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Optimal Integration of Battery Energy Storage Systems in Power Distribution Networks Using Hunger Game Search Algorithm

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Abstract: This paper proposes an integrated method to simultaneously determine the optimal placement and sizing of battery energy storage systems (BESSs) in power distribution networks using the hunger games search algorithm (HGSA). The objective of the proposed method focuses on concurrently reducing power losses and improving the voltage deviation index to improve the distribution system performance while keeping all constraints within permissible limits. The HGSA is a nature-inspired algorithm that simulates the behavior of prey and predators in finding food. In this paper, the HGSA is used to search for the optimal solution in a multi-dimensional search space consisting of the candidate BESS locations and sizes. The proposed method is applied to modified IEEE 69-bus and IEEE 85-bus test distribution systems with five different scenarios, and the results indicate that the HGSA can efficiently determine the optimal placement and sizing of BESSs, resulting in significant power loss reduction (i.e., 69.13-98.08% for the first test system and 52.97-95.03% for the second test system) and voltage deviation improvement (i.e., 94.75-99.89% for the first test system and 12.12-93.37% for the second test system) compared to the base case. Furthermore, the performance of the HGSA is compared with other well-known metaheuristic optimization algorithms (i.e., whale optimization algorithm, chaotic neural network algorithm, genetic algorithm, grey wolf optimizer, and water cycle algorithm), and the results show that the HGSA outperforms these optimization algorithms in attaining the best optimal solution with faster convergence and less number of iterations.

Keywords: Battery energy storage systems, Optimal integration of BESS, Power distribution networks, System power losses, Voltage deviation index.

1. Introduction

The quality and reliability of the power energy delivered to customers must be the most important standards for any distribution system. The unexpected load growth and the presence of distributed generators add significant challenges to fulfilling these standards without violating the operational limitations. Therefore, identifying feasible solutions that enhance distribution systems (DSs) performance without violating operational constraints is so important. Recently, modern DSs have increased interest in battery energy storage systems (BESS) due to their capability to rapidly supply or absorb power to enhance the reliability and performance of DSs. These storage systems can contribute to addressing several operational and environmental challenges. For example, reducing peak demand on the grid by storing excess energy during off-peak hours and releasing it during peak hours, reducing carbon emission, providing rapid backup power during outages, and providing a cost-effective alternative to traditional grid upgrades [1-4]. Furthermore, the BESS can contribute to load management such as peak load shaving and levelling, mitigate voltage magnitude variations, improve voltage stability and voltage deviation, decrease system losses, avoid distribution line overloading, as well as support the system restoration in the islanding mode [5, 6].

Despite the integration of BESS into DSs can bring numerous advantages, inappropriate BESS allocations can impact the performance of DSs, leading to additional system losses and increasing voltage violations. As a result, it is important to find the optimal location and sizing of BESSs without creating such operational problems. To overcome such BESS installation problems, several efficient methods have been developed to identify the best locations and sizes for BESS installation, which in turn leads to improved overall system performance. Some of these studies have used mathematical optimization approaches to address the BESS location and sizing problem. For instance, [7] presents mixed-integer linear programming to find the optimal location and size of BESS. In this paper, the authors aim to minimize generation costs. The authors in [8] utilize an interior point optimization algorithm (OA) to address the BESS location and sizing problem in a distribution system with the objective of minimizing the system operation cost and active power losses.

Although the methods mentioned above relatively improved the DS performance, most mathematical optimization approaches are still struggling to find global optimal solutions because of trapping in local optimal solutions.

In recent decades, several researchers have changed their compass toward meta-heuristic optimization algorithms to handle complex nonlinear optimization problems due to their capability to seek and reach a global solution within a fast convergence time [9, 10]. Several researchers have utilized meta-heuristic optimization approaches to address the respective optimization problem (i.e., the BESS optimum allocation problem). For example, in [11], the optimal size of BESS is determined based on minimum BESS cost that can improve the frequency control of micro-grid using the practical swarm optimization (PSO) algorithm. However, the benefit of reducing the system losses and improving system performance by installing BESS at optimal points along the distribution feeder has not been considered in [11]. The artificial bee colony optimization (ABCO) algorithm is utilized in [12] to obtain the optimal BESS size for improving the frequency response of the network whereas the candidate location of BESS is determined based on a sensitivity analysis of the line loading. However, in this study, the simultaneous BESS optimal location and sizing are not taken into consideration. On the other hand, some researchers only considered the location of BESS [13-16]. For example, in [13], the optimal location of BESS based on decreasing the energy losses is determined using genetic algorithm (GA). An optimal location method using the grey wolf optimization (GWO) algorithm to reduce the system losses is presented in [14]. In [15], the optimal location and control of BESS are determined to improve the system oscillation using the PSO algorithm. The whale optimization (WO) algorithm is introduced in [16] for optimal BESS location to reduce the system losses. However, the improper size of BESS may add a burden on the system's performance and operation. Additionally, in order to consider the advantage of installing both the optimal location and size of BESS simultaneously in DSs, GA and Cuckoo search (CS) meta-heuristic algorithms are proposed in [17] and [18] to reduce energy losses. The simultaneous optimal location and size of BESS with the objective of minimizing the system losses are developed using the coyote optimization (CO) algorithm [19] and WO algorithm [20, 21].

Although the aforementioned studies in [17–21] have efficiently addressed the BESS location and sizing problem, these studies have only covered the impact of injecting active power from BESS on power losses and the voltage profile without taking into account the capability of BESS to inject both active and reactive power. Furthermore, it is well known that meta-heuristic algorithms usually outperform mathematical optimization approaches in terms of providing optimal solutions, especially for complex DSs. Nevertheless, they are still in competition with one another for greater accuracy and faster convergence when it comes to simultaneously determining the BESS's optimal location and size. In this paper, the hunger games search algorithm (HGSA) is proposed to handle the BESS optimal placement and sizing problem to improve active power losses (APL) reduction and voltage deviation index (VDI) in DSs.

The HGSA is categorized as a population-based optimization technique [22]. When utilized to solve complex nonlinear optimization problems with constraints, it is easy to apply. Also, it is stable and effective in concurrently handling discrete and continuous variables in search spaces. In contrast to population-based optimizing algorithms, HGSA offers a simple yet dynamic framework with excellent speed. The HGSA is effective in adjusting weight to simulate the effect of hunger under the logical rules (games) on each search step.

As a result, this weight-adaptive technique based on hunger enhances the balance between HGSA exploration and exploitation without facing the risk of stagnation in local minima [22].

The HGSA is successfully applied in numerous engineering areas in order to address complex optimization problems (e.g., linear and nonlinear optimization problems) with exceptional accuracy and quick convergence. For example, a multi-objective hunger game search optimizer is proposed to optimally select the charging and discharging cycles of the storage energy units injected into the microgrid system. The main goal of this study is to improve grid performance and reliability [23]. The chaotic hunger games search is used to solve the multi-objective optimal power flow problem in power systems with various goal functions [24].

The main purpose of this paper is to present an approach that uses HGSA to simultaneously solve the DS's optimal BESS siting and sizing problem. The objective function considered herein is to reduce APLs and improve the VDI while miniating the operational constraints with acceptable limits. Moreover, several scenarios and comparisons are shown in this paper to further emphasize and demonstrate the efficacy of the proposed method employing HGSA to reduce system losses and improve voltage deviation indexes.

The rest of this paper is arranged as follows. Section 2 describes the problem formulation. Section 3 introduces the proposed HGSA. Section 4 shows the case study. Section 5 gives the numerical results and discussion. Finally, section 6 provides the conclusion.

2. Problem formulation

In this paper, the optimal location and size of the BESS in electrical power distribution networks are simultaneously determined based on the HGSA. The proposed objective function herein represents minimizing APL and VDI while satisfying the system constraints. In this paper, the system performance is analyzed under the influence of injecting the active and reactive power from BESS. In the following subsections, the BESS model, the objective function, and the constraints are explained as follows:

2.1 BESS model

The BESS is modeled in this paper using a current injection model based on the active and reactive power generated from BESS, taking into account the connection bus voltage as given in Eq. (1).

$$I_n^k = \frac{1}{V_n^k}(P_n + jQ_n) \tag{1}$$

Where I_n^k and V_n^k represent the current injection and bus voltage of the k^{th} iteration at n^{th} bus, respectively. P_n and Q_n are the active and reactive power generated from the BESS at n^{th} bus.

2.2 Objective function

To consider the contribution of the proposed optimal allocation of the BESS to decrease both the APLs and the VDI, a single objective function (OF) is formulated using a weighting coefficient as given in Eqs. (2), (3), and (4).

$$OF = \min(\omega f_1 + (1-\omega) f_2) \tag{2}$$

$$f_1 = \frac{1}{P_{Loss_b}} \sum_{i=1}^{N_{br}} \left|I_{b_i}\right|^2 R_i \tag{3}$$

$$f_2 = \sum_{n=1}^{N_b} |V_{rat} - V_n|^2 \tag{4}$$

where ω is the weighting coefficient whose value lies between 0 and 1 (i.e., $\omega = 0.5$); f_1 represents the normalized system active power losses as given in Eq. (3); f_2 indicates the voltage deviation index as indicated in Eq. (4); P_{Loss_b} is the active power losses of the based case system without improvement; I_{b_i} and R_i are the current and the resistance of the i^{th} branch, respectively; V_{rat} and V_n are the rated voltage and the voltage at n^{th} bus, respectively; and N_b and N_{br} are the number of buses and branches in the test system, respectively.

2.3 Operational constraints

The operational constraints adopted in the proposed OA can be divided into equality and inequality constraints that are given in Eqs. (5-8):

I. Inequality constraints

The inequality constraints of the proposed objective function are represented in Eqs. (5-8)

$$V_{min} \le \left|\tilde{V}_n\right| \le V_{max}, \tag{5}$$

$$\left|I_{b_i}\right| \le I_{b_i}^{Max} \quad \forall\, i \in \{1, 2, \dots, Nb\}, \tag{6}$$

$$P_{min}^{BESS} \le P_n^{BESS} \le P_{max}^{BESS}, \tag{7}$$

$$Q_{min}^{BESS} \le Q_n^{BESS} \le Q_{max}^{BESS}, \tag{8}$$

where $\tilde{V}_n$ represents the voltage at n^{th} bus; V_{max} and V_{min} denote the highest and lowest allowable bus magnitude voltages, respectively; $I_{b_i}^{Max}$ is the maximum allowable current to pass through the i^{th} branch; and P_{min}^{BESS}, P_{max}^{BESS}, Q_{min}^{BESS}, and Q_{max}^{BESS} indicate the lowest and highest active and reactive power permissible limits of BESS injected at n^{th} node, respectively.

II. Equality constraints

The equality constraints of the proposed objective function are indicated in Eqs (9) and (10)

$$P_{sub} + \sum_{n=1}^{N_{BESS}} P_{BESS_n} = P_{L_T} + P_{Loss_T} \quad (9)$$

$$Q_{sub} + \sum_{n=1}^{N_{BESS}} Q_{BESS_n} = Q_{L_T} + Q_{Loss_T} \ , \quad (10)$$

where P_{sub} and Q_{sub} are the active and reactive power supplied from the substation, respectively; P_{BESS_n} and Q_{BESS_n} are the BESS active and reactive power injected at n^{th} bus, respectively; N_{BESS} represents the number of BESS installed in the system; P_{L_T} and Q_{L_T} are the total active and reactive power of the system loads, respectively; and P_{Loss_T} and Q_{Loss_T} are the total active and reactive power of the system losses, respectively.

3. Hunger games search algorithm

The HGSA is categorized as a population-based optimization technique. When utilized to resolve optimization issues with constraints, it is easy to apply, stable, and effective [22]. Furthermore, the HGSA was originally proposed by Yang and motivated by animal cooperative behavior. This optimization technique has a remarkable exploration phase called food exploration, which is mainly based on two social performances of animals and how hungry they are. Most animals engage in group cooperation in the first behavior, whereas only a tiny number of them have no participation in collaboration in the second behavior.

The mathematical model is built by Yang et al. based on hunger-motivated actions [22]. The mathematical approach contains two steps. The first step is to approach the meal, where everyone pitches in and cooperates socially. The other step is the hunger role. This step represents the features of characteristics of an individual's hunger in search space. The main steps of the HGSA are summarized as follows:

Step-1: Initialization

The hunger games population (HGP) is generated with a two-dimensional matrix $D \times N_p$ as follows in Eqs. (11) and (12):

$$\mathbf{HGP} = \begin{bmatrix} x_1^1 & \cdots & x_D^1 \\ \vdots & \ddots & \vdots \\ x_1^{N_p} & \cdots & x_n^{N_p} \end{bmatrix} \quad (11)$$

where D is the dimension of search space and N_p represents the population size.

The individuals in the **HGP** are initialized using Eq. (12).

$$x_i^k = \mathrm{x_{l,i}} + (\mathrm{x_{h,i}} - \mathrm{x_{l,i}}) \times U(0,1) \quad (12)$$

Where $\mathrm{x_l}$ and $\mathrm{x_h}$ represents the lowest and highest individual limits.

Step 2: Individual evaluation and classification

In this step, Eq. (2) and power flow are used to evaluate all individuals in Eq. (11) considering problem constraints. Moreover, the evaluated individuals are sorted based on their cost values to find the best one (i.e., minimum value).

Step 3: Approach food

When foraging, social animals frequently work together, however, it is possible that some individuals do not take part in the cooperation based on Yang et al. The primary equation of the HGSA for individual cooperative communication and foraging behavior is represented by the game (G) instructions below shown in Eq. (13):

$$\overrightarrow{M(t+1)} = \begin{cases} G_1: \overrightarrow{M(t)} \,.\, (1 + randn(1)) & , \alpha_1 < l \\ G_2: \overrightarrow{W_1} \,.\, \overrightarrow{M_b} + \vec{S} \,.\, \overrightarrow{W_2} \,.\, \left|\overrightarrow{M_b} - \overrightarrow{M(t)}\right| , \alpha_1 > l \\ , \alpha_2 > K \\ G_3: \overrightarrow{W_1} \,.\, \overrightarrow{M_b} - \vec{S} \,.\, \overrightarrow{W_2} \,.\, \left|\overrightarrow{M_b} - \overrightarrow{M(t)}\right| , \alpha_1 > l \\ , \alpha_2 < K \end{cases} \quad (13)$$

where $\overrightarrow{M(t)}$ represents the location of each individual; $randn(1)$ is a random number selected from a normal distribution; $\overrightarrow{W_1}$ and $\overrightarrow{W_2}$ indicate the weights used to select the hunger behavior; the optimal individual placement at the current iteration of t is indicated by $\overrightarrow{M_b}$; $\vec{S}$ is a controller used to limit the spectrum of hungry activity, thus, it steadily decreases to 0; α_1 and α_2 represents a random number ranging between 0 and 1; l is a number used to improve the algorithm and it is usually less than 0.03; and K is a variation controller that is used to manage animal behavior variation across all locations. The K can be mathematically formulated as:

$$K = hup.func(|F_i - B_F|), i \in (1,2, \dots \dots, x) \quad (14)$$

where $hup.func$ represents a hyperbolic function; F_i is a fitness value of individual i; B_F is the best fitness value among individuals attained during the current iteration process; and x represents the total number of individuals. The controller denoted by $\vec{S}$ can be calculated using Eqs. (15) and (16):

$$\vec{S} = 2 \times \gamma \times \mu - \gamma \tag{15}$$

$$\gamma = 2 \times \left(1 - \frac{t}{Max_{iter}}\right) \tag{16}$$

where μ represents a random number scaled between 0 and 1 and γ is an iteration shrink, and Max_{iter} is the maximum iteration number. To ensure that the whole search space is covered during the exploration phase, individuals in the HGSA use Eq. (1) to find areas that are near the best solution as well as other locations that are far away from the best answer. The control parameters indicated in Eq. (13), the range controller $\vec{S}$ and the weights $\overrightarrow{W_1}$ and $\overrightarrow{W_2}$, govern the individuals' behavior to enhance their seeking abilities.

Step-4: Hunger role

It is possible to formulate the hunger approach in the search space quantitatively, which can be formulated using $\overrightarrow{W_1}$ and $\overrightarrow{W_2}$ as follows:

$$\overrightarrow{W_1(\iota)} = \begin{cases} Case_1: H(i)\ .\ \frac{N_p}{\sum \delta} \times \alpha_4, & \alpha_3 < l \\ Case_2: 1 & \alpha_3 > l \end{cases} \tag{17}$$

$$\overrightarrow{W_2(\iota)} = \left(1 - exp(-|H(i) - \sum \delta|)\right) \times \alpha_5 \times 2 \tag{18}$$

where $H(i)$ represents the hunger level of individual i; δ represents the hunger of each population; N_p is the number of populations; and α_3, α_4, and α_5 are random numbers between 0 and 1. The mathematical formulation of hunger level $H(i)$ is represented as follows:

$$H(i) = \begin{cases} 0, & F_i = B_F \\ H(i) + H_{new}, & F_i \neq B_F \end{cases} \tag{19}$$

$$H_{new} = \begin{cases} H_l \times (1 + \alpha_7), & H_g < H_l \\ H_g, & H_g \geq H_l \end{cases} \tag{20}$$

$$H_g = \frac{F_i - B_F}{F_w - B_F} \times \alpha_6 \times 2 \times (U_b - L_b) \tag{21}$$

where H_{new} stands for an additional new hunger in case of the objective function of the i^{th} individual and the corresponding H_{new} of different individuals is not equal; F_w is the worst fitness value so far discovered during the current iteration procedure; upper and lower search space borders are indicated by the symbols U_b and L_b; H_l is the lower limit of hunger level; and α_6 and α_7 are random numbers ranging between 0 and 1.

The main structure of the proposed method based on the HGSA for all proposed scenarios is demonstrated in Fig. 1.

4. Simulation results and discussions

The modified IEEE 69-bus and IEEE 85-bus DSs are utilized to evaluate the performance of the proposed method based on the HGSA. In this paper, the main goal of the proposed method is to simultaneously reduce APL and VDI. This goal can be achieved by concurrently finding the optimal placement and sizing of BESS based on HGSA while preserving all operational constraints within acceptable limits. The two IEEE test systems used are shown in Figs. 2 and 3. The line and load system data for both test radial DSs are provided in [25,26]. The basic data of these systems is presented as follows: the modified IEEE 69-bus DS operates with the voltage at the substation 12.66 kV (or 1 p.u); the maximum active and reactive power loads are 3.802 MW and 2.694 MVAr (i.e., considering nominal load conditions), respectively; the modified IEEE 85-bus DS works with the voltage at the substation 11 kV (or 1 p.u); the maximum active and reactive power loads are 2.570 MW and 2.623 MVAr (i.e., considering nominal load conditions), respectively. All scenarios and compared OAs including HGSA have the same criteria regarding population size and the maximum number of iterations. The population size and the maximum number of iterations are set to 50 and 200, respectively, while the voltage constraints of the test systems are between 0.95 (p.u) and 1.05 (p.u). In this paper, A backward-forward sweep power flow is utilized to compute the proposed objective function for all proposed scenarios and evaluate DS limits.

Furthermore, five scenarios are considered and applied to test DSs utilizing the proposed HGSA in order to assess the HGSA's viability and effectiveness in solving optimum BESS installation challenges. In this paper, three BESSs are suggested to be installed on the test systems. However, any number of BESS can be installed. These five simulated scenarios are divided into the following categories:

- ***Base case***: Without considering the BESS installation.
- ***Scenario 1***: Optimal BESS location and sizing using unity power factor and only propose APL as an objective function.
- ***Scenario 2***: Optimal BESS location and sizing using unity power factor and propose APL and VDI as an objective function.

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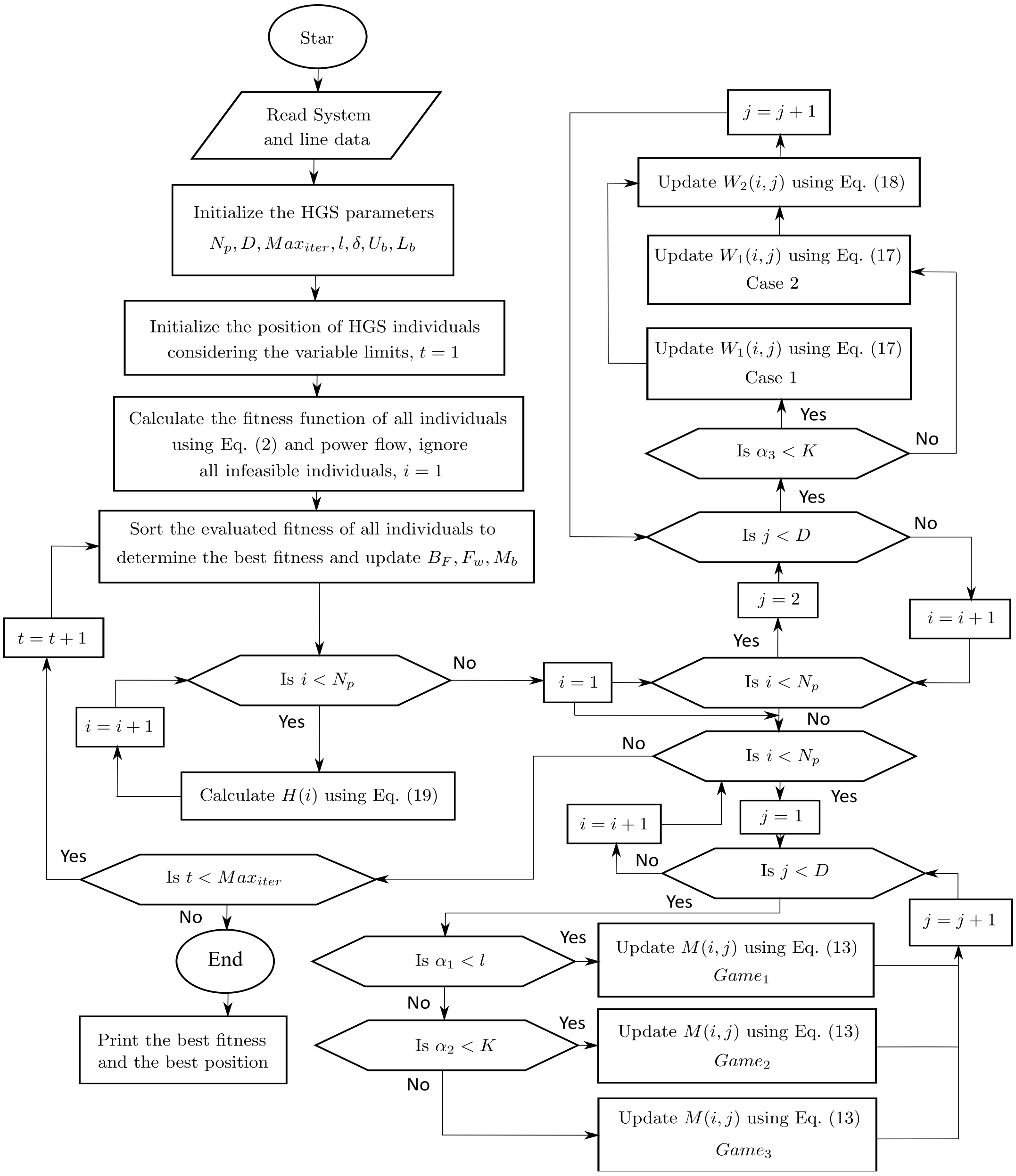

Figure. 1 Flowchart of the proposed HGSA

- ***Scenario 3*****:** Optimal BESS location and sizing, considering active and reactive power injections and only proposing APL as an objective function.
- ***Scenario 4*****:** Optimal BESS location and sizing, taking into account active and reactive power injections and considering minimizing APL and VDI as an objective function.

A comparative analysis is conducted on test DSs based on scenario 4 to demonstrate the outperformance of the proposed HGSA compared to other OAs in addressing the proposed problem with the goal of minimizing APL and VDI. The following is a brief description of these comparable OAs:

- The Whale Optimization Algorithm (WOA) is a metaheuristic OA inspired by the social behavior of humpback whales during bubble-net feeding, which is a cooperative hunting technique used by humpback whales to capture prey [27].
- The chaotic neural network algorithm (CNNA) is a metaheuristic OA in which artificial neural networks and randomness are combined to solve complex optimization problems [28].

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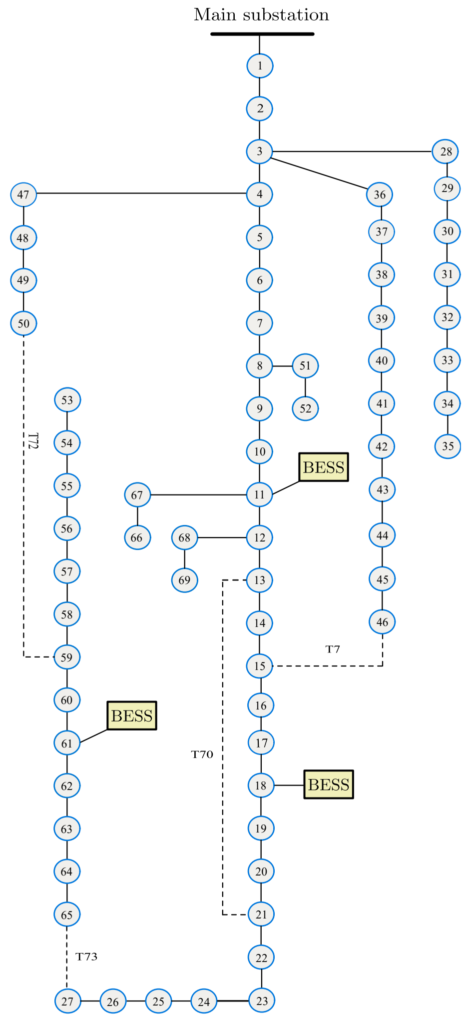

Figure. 2 The optimal BESS locations for the modified IEEE 69-bus test DS (i.e., scenario 4)

- The genetic algorithm (GA) is an evolutionary algorithm inspired by the biological evolution process and survival of the fittest in nature [29].
- The grey wolf optimizer (GWO) is a metaheuristic OA that imitates the social structure and hunting strategy of grey wolves in the wild [30].
- The water cycle algorithm (WCA) is a metaheuristic OA inspired by the movement of water in nature [31].

The simulation results achieved using HGSA are demonstrated in Tables 1 and 2, including the five scenarios that were previously discussed. In these tables, the basic case is the case without BESS injection and is regarded as the worst case to which other scenarios will be compared in terms of APL and VDI reduction. Scenario 1 is also indicated in Tables 1 and 2. In this scenario, the proposed HGSA is successful in identifying the optimal BESS location

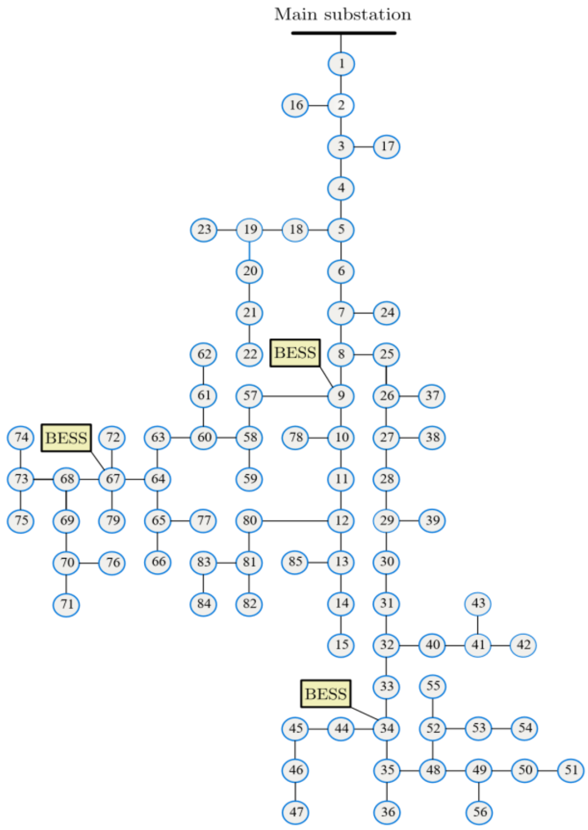

Figure. 3 The optimal BESS locations for the modified IEEE 85-bus test DS (i.e., scenario 4)

and size, where the reductions of APL and VDI are significantly reduced by 69.13% and 94.75 for the modified IEEE 69-bus, respectively, and 52.97% and 12.12% for the modified IEEE 85-bus, respectively, in comparison to the base case. Another conclusion that can be drawn from this scenario is that, although using APL as the objective function in this scenario, the voltage magnitudes of all buses are likewise enhanced to be within allowed limits. This is expected because the BESS systems are placed directly to the load which leads to reducing voltage drops and APLs. Scenario 2 is also presented in Tables 1 and 2. This scenario is similar to scenario 1 except that the APL and VDI are considered as the objective function. In this scenario, the proposed HGSA made an optimal selection of BESS location and sizing while keeping all voltage magnitudes of buses with acceptable limits as shown in Tables 1 and 2. However, this selection results in less APL reduction for both test systems of nearly 0.58% and 3.16%, respectively, and more improvement in the VDI of nearly 50% and 56.32%, respectively, compared with scenario 1. This is expected because the APL and VDI are weighted equally in the objective function. Scenario 3 is also shown in Tables 1 and 2. This scenario demonstrates that the proposed HGSA attains more significant results than scenarios

Table 1. Simulation results of the proposed HGSA with different scenarios for IEEE 69-bus

Case	No. of BESS	Best BESS location	BESS size (MW+jMvar)	APL (kW)	APL reduction (%)	Vmax/Vmin (p.u)	VDI (p.u)
Base case	-----	-----	------	224.50	0	1/ 0.9094	0.0990
Scenario 1	3	11, 18, 61	0.527, 0.380, 1.719	69.30	69.13	1/0.9790	0.0052
Scenario 2	3	18, 61, 66	0.477, 1.843, 0.519	70.60	68.55	1/ 0.9838	0.0026
Scenario 3	3	18, 61, 69	0.396+j0.264, 1.703+j1.216, 0.312+j0.222	5.10	97.73	1/ 0.9943	0.0002
Scenario 4	3	11, 18, 61	0.500+j0.358, 0.387+j0.254, 1.681+j1.198	4.30	98.08	1.004/0.9943	0.0001

Table 2. Simulation results of the proposed HGSA with different scenarios for IEEE 85-bus

Case	No. of BESS	Best BESS location	BESS size (MW+jMvar)	APL (kW)	APL reduction (%)	Vmax/Vmin (p.u)	VDI (p.u)
Base case	-----	-----	------	316.103	0	1/ 0.8713	0.1287
Scenario 1	3	9, 34, 67	1.095, 0.676, 0.524	148.66	52.97	1/0.9524	0.1131
Scenario 2	3	11, 35, 64	0.748, 0.933, 0.924	158.64	49.81	1/ 0.9709	0.0494
Scenario 3	3	9, 34, 67	0.972+j0.988, 0.662+j0.671, 0.519+j0.527	15.30	95.16	1/ 0.9899	0.0018
Scenario 4	3	9, 34, 67	1.085+j1.066, 0.665+j0.673, 0.519+j0.527	15.72	95.03	1.004/0.992	0.0008

1 and 2 when injecting active and reactive power into the test DSs. Furthermore, in this scenario, the APL reduction and VDI for both test DSs are improved by 97.73% and 99.79% for test system 1, respectively, and 95.16% and 98.60% for test system 2, respectively, compared with the base case, whereas all voltage magnitudes are within acceptable limits. Tables 1 and 2 also indicate scenario 4. This scenario is regarded as the proposed method in this paper. It can be observed from this scenario that the proposed HGSA can attain the optimal BESS location and sizing while maintaining all voltage magnitude with acceptable limits as shown in Tables 1 and 2. Moreover, in this scenario, the optimal locations of BESS for both test DSs are shown in Figs. 2 and 3. Also, the reductions of APL and VDI for both test DSs are considerably improved by 98.08 and 99.89% for test system 1, respectively, and 95.03% and 99.37% for test system 2, respectively, compared with the base case. This happens as a result of taking the APL and VDI as the objective function in this scenario. The voltage profiles of all scenarios for both test DSs, including the base case, are plotted and compared as shown in Figs. 4 and 5. It is evident from these figures that the voltage magnitudes of all system buses fall within allowable bounds in every scenario, except the base case.

The effectiveness of the proposed HGSA is compared with other OAs mentioned in section 4 as shown in Tables 3 and 4. In this comparison, scenario 4 is only used with the same metrics as indicated in Tables 1 and 2 in addition to the number of iterations. Furthermore, to get a fair comparison, the OAs have the same initial optimization settings, which are applied to both test DSs. From Table 3, the proposed HGSA surpassed the other OAs in terms of the APL and VDI when compared to the base case. Additionally, the proposed HGSA shows faster convergence speed and less number of iterations to attain the optimal solution. Table 4 also shows the strong performance of the proposed HGSA. In this table, the proposed HGSA, IGWO, and WCA exhibit better performance compared to other OAs. This is expected because these OAs have used an amazing approach to investigate search space for feasible regions. However, the HGSA has better performance in terms of convergence speed and the number of iterations due to utilizing a weight-adaptive technique based on hunger that enhances the balance between HG exploration and exploitation without facing the risk of stagnation in local minima.

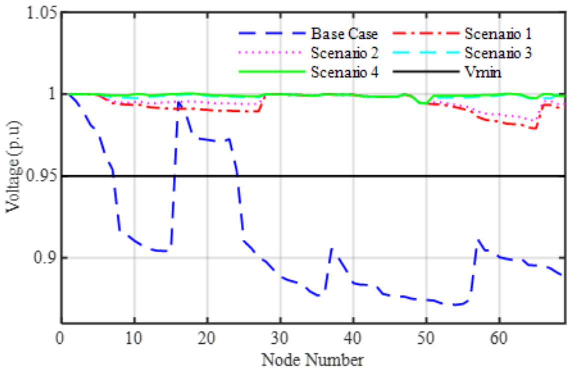

Figure. 3 Voltage magnitude profile of the 69-bus DS for all scenarios

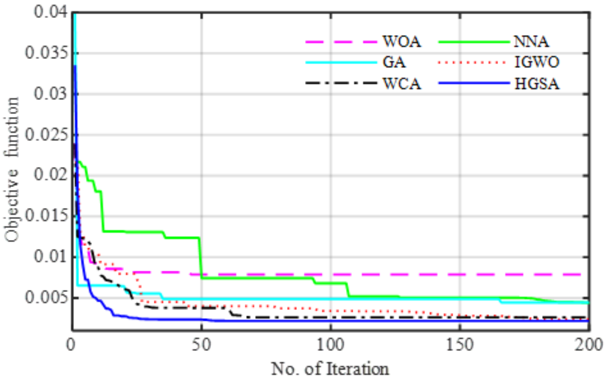

Figure. 5 Comparison of convergence curves of the modified 69-bus DS using compared algorithms

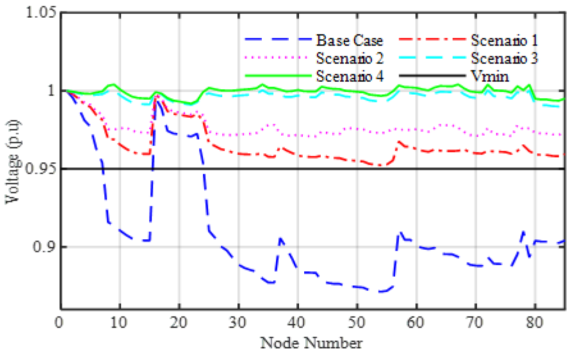

Figure. 4 Voltage magnitude profile of the 85-bus DS for all scenarios

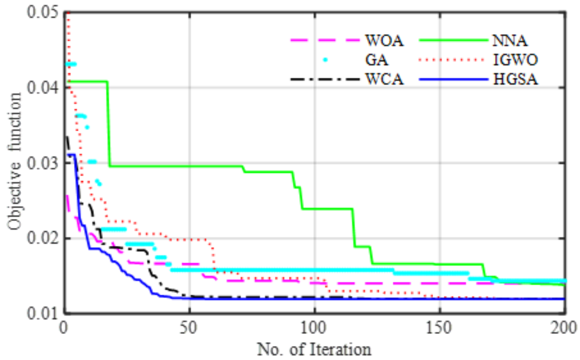

Figure. 6 Comparison of convergence curves of the modified 85-bus DS using compared algorithms

Table 3. Simulation results of the proposed HGSA for Scenario 4 in a comparison with other compared algorithms for IEEE 69-bus

Methods	No. of BESS	Best BESS location	Best BESS size (MW+jMvar)	APL (kW)	APL reduction (%)	Vmax/Vmin (p.u)	VDI (p.u)	No. of iter.
Base case	-----	-----	------	224.50	0	1.000/ 0.9094	0.0990	-----
WOA	3	12, 61, 63	1.271+j0.422, 0.857+j0.999, 0.494+j0.197	14.40	93.59	1.005/ 0.987	0.0013	46
NNA	3	13, 48, 61	0.694+j0.567, 0.954+j0.719, 1.725+j1.219	8.20	96.35	1.002/ 0.993	0.0006	198
GA	3	12, 21, 61	1.031+j0.093, 0.065+j0.325, 1.684+j1.123	8.70	96.12	1.004/0.994	0.0002	166
IGWO	3	18, 61, 66	0.411+j0.262, 1.690+j1.204, 0.428+j0.328	4.60	97.95	1.001/ 0.994	0.0001	178
WCA	3	17, 50, 61	0.543+j0.362, 0.720+j0.516, 1.749+j1.246	4.90	97.81	1.001/ 0.995	0.0003	68
HGSA	3	11, 18, 61	0.501+j0.358, 0.387+j0.254, 1.681+j1.199	4.30	98.08	1.004/0.994	0.0001	54

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Table 4. Simulation results of the proposed HGSA for Scenario 4 in a comparison with other compared algorithms for IEEE 85-bus

Methods	No. of BESS	Best BESS location	Best BESS size (MW+jMvar)	APL (kW)	APL reduction (%)	Vmax/Vmin (p.u)	VDI (p.u)	No. of iter.
Base case	-----	-----	------	316.103	0	1.000/ 0.871	0.8211	-----
WOA	3	9, 34, 68	0.999+j1.303, 0.888+j0.422, 0.392+j0.486	19.70	93.77	1.007/ 0.992	0.0010	103
NNA	3	9, 34, 69	0.202+j0.450, 1.210+j1.045, 0.823+j0.722	18.94	94.01	1.009/ 0.992	0.0021	200
GA	3	8, 35, 72	1.559+j1.319, 0.524+j0.697, 0.491+j0.269	22.08	93.02	1.009/0.993	0.0016	171
IGWO	3	9, 34, 68	1.147+j1.126, 0.665+j0.673, 0.457+j0.463	15.72	95.03	1.004/ 0.992	0.0008	172
WCA	3	9, 34, 67	1.100+j1.070, 0.665+j0.673, 0.519+j0.527	15.72	95.03	1.004/ 0.992	0.0008	127
HGSA	3	9, 34, 67	1.085+j1.066, 0.665+j0.673, 0.519+j0.527	15.72	95.03	1.004/0.992	0.0008	61

5. Conclusion

The optimal placement and sizing of battery energy storage systems (BESSs) is a complex multi-objective optimization problem that requires an efficient meta-heuristic algorithm. This paper proposes a solution to this problem using the hunger games search algorithm (HGSA). The proposed method determines the optimal BESS location and sizing concurrently and considers all operational constraints. In this paper, the proposed method focuses on reducing active power loss (APL) and improving the voltage deviation index (VDI) simultaneously in the proposed test DSs based on HGSA. The HGSA is applied to modified IEEE 69-bus and IEEE 85-bus radial DSs with different scenarios. The proposed method can effectively reduce APL and improve VDI as shown in the simulation results. These obtained results show significant power loss reduction (i.e., 69.13-98.08% for the first test system and 52.97-95.03% for the second test system) and voltage deviation improvement (i.e., 94.75-99.89% for the first test system and 12.12-93.37% for the second test system) compared to the base case. To validate the effectiveness of the proposed method, The performance of the HGSA is compared with the well-known metaheuristic OAs. The simulation results demonstrate that the HGSA outperforms other OAs in terms of APL and VDI improvement, with the fastest convergence and the least number of iterations.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, S.I. and S.A., methodology, S.I. and S.A. software, S.I., validation S.I. and S.A.; data collection, S.I., writing, S.I.; visualization and investigation, S.I. and S.A.; supervision S.I.; review and editing, S.I., S.A., and A.J.K.

Nomenclature

Acronym	Description
BESS	Battery energy storage systems
DSs	Distribution systems
OA	Optimization algorithm
PSO	Practical swarm optimization
ABCO	Artificial bee colony optimization
GA	Genetic algorithm
GWO	Grey wolf optimization
WOA	Whale optimization algorithm
CS	Cuckoo search
CO	Coyote optimization
HGSA	Hunger games search algorithm
APL	Active power loss
VDI	Voltage deviation index

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CNNA	Chaotic neural network algorithm
WCA	Water cycle algorithm
HGP	Hunger Games Population
Parameter List	
Parameter	**Description**
I_n^k	Current injection of the k^{th} iteration at n^{th} bus
V_n^k	Bus voltage of the k^{th} iteration at n^{th} bus
P_n	Active power generated from the BESS at n^{th} bus.
Q_n	Reactive power generated from the BESS at n^{th} bus.
ω	Weighting coefficient
f_1	Normalized system active power losses
f_2	Voltage deviation index equation
P_{Loss_b}	Active power losses of the based case system
I_{b_i}	Current of the i^{th} branch
R_i	Resistance of the i^{th} branch
V_{rat}	Rated voltage
V_n	Voltage at n^{th} bus
N_b	Number of buses in the test system
N_{br}	Number of branches in the test system
V_{max}	Highest allowable bus magnitude voltages
V_{min}	Lowest allowable bus magnitude voltages
$I_{b_i}^{Max}$	Maximum allowable current to pass through the i^{th} branch
P_{min}^{BESS}	Lowest active permissible limit of BESS injected at n^{th} node
P_{max}^{BESS}	Highest active power permissible limit of BESS injected at n^{th} node
Q_{min}^{BESS}	Lowest reactive power permissible limit of BESS injected at n^{th} node
Q_{max}^{BESS}	Highest reactive power permissible limit of BESS injected at n^{th} node
P_{sub}	Active power supplied from the substation
Q_{sub}	Reactive power supplied from the substation
P_{L_T}	Total active power of the system loads
Q_{L_T}	Total reactive power of the system loads
P_{Loss_T}	Total active power of the system losses
Q_{Loss_T}	Total reactive power of the system losses
D	Dimension of search space
N_p	Population size
$\mathrm{x_l}$	Lowest individual limits
$\mathrm{x_h}$	Highest individual limits
$\overrightarrow{M(t)}$	Location of each individual
$\overrightarrow{W_1}$ and $\overrightarrow{W_2}$	Weights used to select the hunger behavior
t	Current iteration
$\overrightarrow{M_b}$	Optimal individual placement at the current iteration of t
$\vec{S}$	Controller used to limit the spectrum of hungry activity
α_1 and α_2	Random numbers ranging between 0 and 1
K	Variation controller used to manage animal behavior variation across all locations
F_i	Fitness value of individual i
B_F	Best fitness value
μ	Random number between 0 and 1
γ	Iteration shrink
Max_{iter}	Maximum iteration
$H(i)$	Hunger level of individual i
δ	Hunger of each population
α_3, α_4, α_5	Random numbers between 0 and 1
H_{new}	Additional new hunger
F_w	Worst fitness value
U_b and L_b	Upper and lower search space borders
H_l	Lower limit of hunger level
α_6 and α_7	Random numbers ranging between 0 and 1

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