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Self-Adaptive Dragonfly Algorithm for Optimal Allocation of Multiple Energy Storage Systems with VAr Support for Islanded Microgrid Operation

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Abstract: Microgrid (MG) operation is one of the operational requirements of modern utilities for not only maintaining reliable and uninterrupted supply under faulty conditions but also for achieving desired economic goals in the competitive electricity market environment. Under faulty conditions, the electrical distribution system (EDS) becomes islanded microgrid (IMG) with either micro turbine (MT) or renewable energy (RE) based distribution generation (DG) units. However, the power generation from RE based DGs is stochastic nature and it may become either surplus or deficit to the network connected load. Also, the reactive power (VAr) support from DGs is limited. Under this scenario, there is a need for the integration of energy storage systems (ESSs) and reactive power compensators like switched/ fixed capacitor banks (CBs). In this paper, a novel optimization approach for determining the locations and capacities of ESSs combined with CBs along with DGs is proposed based on improved variant of dragonfly algorithm (DFA). Different performance variables of basic DFA are tuned by a self-adaptive mechanism in SADFA for attaining the global solution with least computational efforts. Simulation results on IEEE 33-bus are compared with literature works and also other algorithms namely basic DFA, PSO, BOA, and FSA. The islanded network is suffered with a loss of 97.1229 kW, whereas, it is reduced to 74.2305 kW, 47.3380 kW and 37.6792 kW, by integrating CBs, DGs and simultaneous CBs and DGs, respectively. Based on the comparative analysis, SAFDA is dominated literature works and all other simulated algorithms. Also, the proposed method for ESSs, CBs and DGs integration is shown its effectiveness for serving the IMG energy requirements with reduced losses and increased economic benefits and its suitability for practical applications.

Keywords: Electrical distribution system, Energy storage system, Capacitor banks, Islanding mode, Dragonfly algorithm, Microgrid, Renewable energy.

1. Introduction

One of the operational needs for modern utilities is the operation of a microgrid (MG), which is necessary for both attaining targeted economic goals in the competitive power market setting as well as ensuring a dependable and uninterrupted supply under defective conditions. When something goes wrong, the electrical distribution system (EDS) transforms into an island microgrid (IMG) that uses distribution generation (DG) units powered by micro-turbines (MT) or renewable energy (RE). However, because RE-based DG power generation is stochastic in nature, it could either produce more or less energy than the network-connected load. Additionally, DGs can only provide so much reactive power (VAr) support. Energy storage systems (ESSs) and reactive power compensators, such as switching or fixed capacitor banks, must be integrated in this situation (CBs).

The problem of optimal integration of RE based DGs and CBs in EDSs has been addressed using various heuristic approaches in the literature. Gravitational search algorithm (GSA) [1], shark smell optimization (SSO) [2], flower pollination algorithm (FPA) [3], whale optimization algorithm [4], polar bear optimization algorithm [5], spotted hyena optimizer (SHO) [6], salp swarm algorithm (SSA) [7], water cycle algorithm (WCA) [8],

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multiverse optimizer [9], and vortex search algorithm (VSA) [10], are recent examples of CBs allocation. A comprehensive literature survey on other related works can be seen in [11].

On the other hand, marine predators algorithm [12], manta ray foraging optimization algorithm (MRFO) [13], sine-cosine algorithm (SCA) [14], artificial bee colony (ABC) [15], hybrid grey wolf optimizer (HGWO) [16], stud krill herd (SKH) [17], whale optimization algorithm (WOA) [18], flower pollination algorithm (FPA) [19], ant lion optimization (ALO) [20], grey wolf optimization (GWO), manta ray foraging optimization (MRFO), satin bower bird optimization (SBO) and whale optimization (WOA) [21], wild horse optimization (WHO) [22], Archimedes optimization algorithm (AOA) [23], and future search algorithm (FSA) [24] are other heuristic approaches employed for RE based DGs allocation in EDS. Similarly, a comprehensive review of various other approaches can be seen [25].

CBs and/or DGs can improve EDS performance through DG allocation work in terms of loss reduction [1-24], voltage profile improvement [1-24], VDI reduction [12, 19, 20, 21], voltage stability enhancement [2, 8, 12, 14, 17, 18, 20, 21, 24], GHG emission reduction [8, 14, 23, 24], net savings maximisation [14, 15, 17, 18], and reliability improvement [22, 23]. In addition, major objective functions handled in the CBs allocation problem include the cost of real power distribution loss [1–10], operational cost [2–10], and installation cost [1, 2, 5, 7]. Some works use real power loss sensitivity factors (RLSFs) [1, 9, 20], reactive power loss sensitivity factors (QLSFs) [5, 6], and normalised voltage magnitudes (NVMs) [1] to determine the pre-defined search space in order to improve the performance of heuristic algorithms. For the CB/DG allocation problem to be solved, both discrete variables (like locations) and continuous variables (like sizes) must be taken into account. The objective function is subjected to various equal and unequal constraints.

However, RE-based DGs are highly dependent on climatic conditions; thus, they are intermittent in nature and unreliable for islanding conditions. In these aspects, it is essential to incorporate ESSs into EDSs. In recent times, optimal sizing of ESSs has been addressed considering various likelihood uncertainties. In [26], various heuristic approaches along with COA are adapted for determining the ESSs for loss reduction while MG is operating in grid-connected mode. Different climatic conditions and economic aspects are considered while determining the various types of energy sources, including ESSs towards uninterrupted power supply in the IMG using turbulent flow water-based optimization (TFWO) [27]. In [28], interline-photovoltaic (I-PV) systems embedded with ESS and CBs are evaluated using COA by considering one-day-long IMG requirements. Similarly, various other heuristic approaches for energy management in IMG can be found in [29]. The following are the major research gaps, which serve as the primary motivation for this study: (i) Existing literature works on CBs/DGs allocation are only concerned with grid-connected operations. In real-time, there is a need for planning studies for managing islanding conditions; (ii) since RE-base DGs are non-dispatchable generation sources, there is a need for ESSs towards reliable, stable, and economic operation. However, literature reviews are not focused on islanding operational requirements for achieving all these aspects. The following are the major contributions in this regard:

- To locate and sizing the optimal ESS with VAr support for serving the islanding operational requirements of MG.
- Minimization of real power distribution loss and maximization of net-savings are considered for developing the multi-objective function.
- An advanced variant of dragonfly algorithm with self-adaptive mechanism (SADFA) for global optima is proposed as a solution methodology.
- Simulation results of SADFA on IEEE 33-bus system are shown its computational efficiency than basic DFA, PSO, butterfly optimization algorithm (BOA) and FSA.

The remainder of the paper is structured out as follows: Different kinds of DGs and load modelling considering voltage dependency are explained in section 2. In section 3, it presents different objective functions with detailed equal and unequal constraints. Section 4 explains the modelling of the self-adaptive dragonfly algorithm (SADFA). In section 5, the simulation results for IEEE 33-bus and IEEE 69-bus EDSs are discussed. Finally, in section 6, major research findings are comprehensively discussed.

2. Mathematical modelling of concepts

In this section, the mathematical modelling of DGs and CBs and hybrid ESS+CBs are explained suitably for backward/forward load flow [30].

2.1 DGs/CBs modeling

In general, the RE-based DGs connects to the grid via power electronics converters. In this work, a common power injection modelling (PIM) suitably

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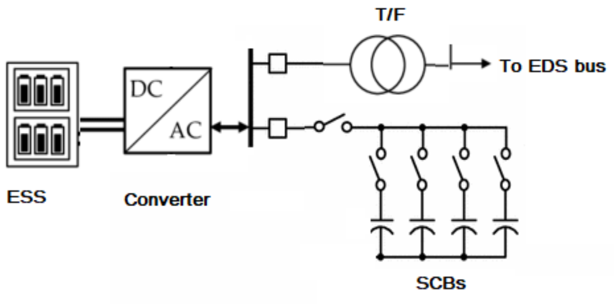

Figure. 1 ESS with Switched CBs

for different kinds of DGs are presented as follows:

$$\bar{P}^h_{D(k)} = P^h_{D(k)} - P^h_{DG(k)} \tag{1}$$

$$\bar{Q}^h_{D(k)} = Q^h_{D(k)} - P^h_{DG(k)} \times tan\left(\theta^h_{DG(k)}\right) \tag{2}$$

$$\bar{Q}^h_{D(k)} = Q^h_{D(k)} - Q^h_{CB(k)} \tag{3}$$

where $\bar{P}^h_{D(k)}$ and $\bar{Q}^h_{D(k)}$ are the net active and reactive power loads of node-k at time-h, respectively; $P^h_{DG(k)}$ and $Q^h_{CB(k)}$ are the active power injection by a DG and reactive power injection by a CB at bus-k at hour-h, respectively; $\theta^h_{DG(k)}$ is the power factor angle of the DG-k's converter at time-h.

The VAr support by a photovoltaic (PV)/ fuel cell (FC) type DGs is negligible and thus $\theta^h_{DG(k)} = 0$, whereas it can be controlled between 0.3 and 1 for wind turbine (WT)/ micro turbines (MT) type DGs. Eq. (5) is defined for only CBs integrated buses for VAr compensation.

2.2 ESS-CBs modeling

The ESS is mainly active power source and it is also capable to provide reactive power via its converter. Under this condition, its back-up time may reduce significantly. In order to meet the reactive power loading of the network under islanding mode, switched CBs are also integrated at the same bus. Thus, by having a tap-changer further, the voltage at ESS-CB location can be maintained constant and continuously. Thus, this entire set-up can be treated as a dispatchable DG when it is operating under grid-connected mode and it can be modelled as a generator bus according to load flow theory, as shown in Fig. 1. Also, when the network is subjected to islanding conditions, it can be treated as a slack bus by which, the deficit power in the network can be met.

Identification of such location by which network can operate with good performance low distribution losses and adequate voltage profile is a challenging task as network size increases.

3. Problem formulation

This section provides the proposed objective functions for (i) CBs allocation, (ii) DGs allocation and (iii) ESS-CBs allocation, separately.

3.1 CB allocation under normal mode

In CBs allocation problem, the objective function F_{CB} is formulated for maximizing the energy loss cost savings. In each simulation hour, the CB operational cost is different due to change in kVAr settings. Similarly, there is a change in active power loss w.r.t. uncompenation losses. Thus, the overall net-savings are evaluated for a 24-hr time span, as follows:

$$F_{CB} = max\left[\sum_{h=1}^{24}\left\{\kappa_L \bar{P}^h_{LR} - \sum_{k}^{ncb} \kappa_{CB} Q_{CB(k)}\right\}\right] \tag{4}$$

where $\bar{P}^h_{LR} = \left(\bar{P}^h_L - \bar{P}^b_L\right)$, $\bar{P}^h_L$ and $\bar{P}^b_L$ are the total active power distribution losses before and after VAr injection by CBs, respectively; $\bar{P}^h_{LR}$ is the reduced loss, κ_L is the cost of grid-power in \$/kW, κ_{CB} is the cost of CBs [4], $Q_{CB(k)}$ is the VAr rating of CB at bus-k.

3.2 DG allocation under normal mode

The objective function for DGs allocation is formulated for minimizing active power distribution losses, and GHG emission reduction, as follows:

$$F_{DG} = min\left[\sum_{h=1}^{24}\left(\bar{P}^h_L + GHG^h_{em}\right)\right] \tag{5}$$

where GHG^h_{em} are the net GHG emission from the conventional power plants associated with main grid [8].

3.3 Simultaneous ESS+DG+CBs allocation under islanding mode

The objective function for ESS-CBs is defined to meet the deficit apparent power demand by maintain proper voltage profile and low distribution losses under islanding conditions.

$$F_{ESS-CB} = min \left[\sum_{h=1}^{24}\left\{\left(\bar{S}^h_D - S^h_{DG}\right) + \bar{P}^h_L + \sum_{k=1}^{nbus}\left(1 - \left|V^h_k\right|\right)\right\}\right] \tag{6}$$

where $\bar{S}^h_D$ and S^h_{DG} are the apparent power demand of the network and total DGs power generation at time-h, respectively, $nbus$ is the number of buses in the network.

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3.4 Constraints

The following are the major operational and planning constraints considered while solving the proposed objective functions.

$$|V_k|_{min} \leq \left|V_k^h\right| \leq |V_k|_{max} \quad (7)$$

$$\sum_k^{ncb} Q_{CB(k)} + \sum_{k=1}^{ndg} Q_{DG(k)}^h \leq Q_D^h + \bar{Q}_L^h \quad (8)$$

$$\sum_k^{ness} P_{ESS(k)} + \sum_{k=1}^{ndg} P_{DG(k)}^h \leq P_D^h + \bar{P}_L^h \quad (9)$$

where $\bar{P}_L^h$ and $\bar{Q}_L^h$ are the active and reactive powers losses of the network, respectively; P_{DG}^h and Q_{DG}^h are the active and reactive power generations by all DGs and CBs, respectively; P_{ESS} is the active power rating of ESS, $|V_k|_{min}$ and $|V_k|_{max}$ are the minimum and maximum voltage profile limits, respectively.

4. Self-adaptive dragonfly algorithm

Dragonfly swarming patterns are used to develop the dragonfly algorithm (DFA) algorithm's exploration and exploitation stages. These phases represent meta-heuristic optimization's search and discovery. DFA generates a swarm of randomly distributed dragonflies. The swarm of dragonflies separates, aligns, and coheres to survive by attracting and distracting. By modelling these unique features, DFA was developed as a global optimization algorithm [31]. In this section, the fundamental concept of DFA and its improvement using self-adaptive mechanisms are explained.

4.1 Constraints modeling of DFA phases

In the search space, *i*th dragonfly is represented by a vector of search variables as given by,

$$x_i = \left[x_i^1, x_i^2, x_i^3, \ldots, x_i^j, \ldots, x_i^{ds}\right] \quad (10)$$

where x_i^j is the position of *j*th search variable of *i*th dragonfly, ds is the dimension of solution variables of the optimization problem.

Each variable is constrained by lower and upper limits by,

$$x_i^j = \left[x_{i(lb)}^j, x_{i(ub)}^j\right]; j = 1,2, \ldots, ds \quad (11)$$

Initially, the search region of the problem is generated by using uniformly distributed random number theory, given by,

$$x_i^j = x_{i(lb)}^j + \left[x_{i(ub)}^j - x_{i(lb)}^j\right] \times rand \quad (12)$$

where $x_{i(lb)}^j$ and $x_{i(ub)}^j$ are the lower and upper bounds of jth solution variable of ith dragonfly, respectively; $rand$ is a random number in the range of 0 and 1.

A dragonfly's position in the solution space represents each optimization solution or fitness. The movement of dragonflies for the next iteration is modelled by velocity vector using various parameters as by,

$$v_{i(k+1)}^j = \left(w_s S_i + w_a A_i + w_c C_i + w_f F_i + w_e E_i\right) + w_i v_{i(k)}^j \quad (13)$$

where w_s, w_a, w_c, w_f, w_e, and w_i are the weighting factors for separation (S_i), alignment (A_i), cohesion (C_i), food (F_i) and enemy (E_i), and inertia, respectively.

$$S_i = -\sum_{j \in \varphi}\left(x_i^i - x_j^i\right) \quad (14)$$

$$A_i = \frac{1}{nh}\sum_{j \in \varphi} v_i^j \quad (15)$$

$$C_i = \left(\frac{1}{nh}\sum_{j \in \varphi} x_j^i\right) - x_i^i \quad (16)$$

$$F_i = x_{i(best)}^j - x_i^j \quad (17)$$

$$E_i = x_{i(worst)}^j + x_i^j \quad (18)$$

where φ is the neighboring individual swarm, v_i^j is the velocity of jth solution variable of ith dragonfly, nh is the number of neighbors, $x_{i(best)}^i$ is the best dragonfly / food source so far, $x_{i(worst)}^j$is the worst dragonfly / enemy so far.

The position of ith dragonfly for the next iteration is updated by.

$$x_{i(k+1)}^j = x_{i(k)}^j + v_{i(k+1)}^j \quad (19)$$

When there is no surrounding solution, dragonflies use a random walk (Levy's flight) to improve randomization, stochastic behavior, and exploration.

$$x_{i(k+1)}^j = x_{i(k)}^j + L_{fl} \times x_{i(k)}^j \quad (20)$$

$$L_{fl}(x) = 0.01 \times \frac{(r_1 \times \alpha)}{|r_2|^\beta} \times x_{i(k)}^j \quad (21)$$

Table 1. Optimal CB allocation under normal mode

Method	**CBs (kVAr) /bus #**	**P_{loss} (kW)**	**F_{CB} ($)**
–	–	210.9976	–
GSA [1]	350/26 450/13 800/15	198.1421*	1846.12
FPA [3]	450/13 450/24 900/30	139.0876	11744.28
DVSA [10]	450/24 450/12 1050/30	138.429	11780.07
SADFA	400/13 550/24 1050/30	138.285	11811.7

$$\alpha = \left(\frac{\Gamma(1+\beta) \times sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\frac{1}{\beta}} \quad (22)$$

$$L_{fl}(x) = (x-1)! \quad (23)$$

where r_1 and r_2 are the random numbers in the range of 0 and 1, respectively; β is the constant.

4.2 Self-adaptive mechanism

The computation efficiency of basic DFA is dependent on different weighting parameters as seen earlier. In order to escape local trap and to achieve global solution with better exploitation phase, the search variables influenced by using dynamically in SADFA [32], as follows:

$$x_i = \left[x_i^1, \ldots, x_i^{ds}, w_s, w_a, w_c, w_f, w_e, w_i, \varepsilon_i\right] \quad (24)$$

where ε_i is a factor used to control the radius ($\mathcal{R}$) and is given by,

$$\mathcal{R}_i^j = \left(x_{i(ub)}^j - x_{i(lb)}^j\right) \times \varepsilon_i \quad (25)$$

The lower and upper limits for w_s, w_a, w_c, w_f, w_e, ε_i and w_i are [0, 0, 0, 0, 0, 0, 0] and [0.15, 0.15, 0.15, 2, 0.15, 1, 1], respectively [32].

In this way, each dragonfly that possesses the extra criteria goes through the entire search procedure. When searching, the SADFA provides superior offspring with less computing work.

5. Results and discussion

The simulations are performed in MATLAB environment on IEEE 33-bus test system. It consists of 33 buses interconnected by 32 branches, and total real and reactive power demands of 3715 kW and 2300 kVAr respectively. By choosing the base values of 100 MVA and 12.66 kV, the BW/FW load flow [30] is performed to assess the network performance.

Simulations are performed for two scenarios. Scenario 1 for normal grid connected mode with two different case studies as (i) only CBs allocation, and (ii) only DGs allocation. Scenario 2 for islanding mode with two different case studies as (i) only ESS+CBs allocation, and (ii) only ESS+CB+DGs allocation.

5.1 Simulations considering normal mode

The uncompensated system has suffered 210.5484 kW of real power loss and 142.7439 kVAr of reactive power loss. It has the lowest voltage of 0.9039 p.u. at bus-18. In this case, the overall operating cost is $3,537.14. The cost of real power loss is selected as 168 cents per kWh per year. The CBs' operating costs are estimated using the shape-preserving interpolate method by considering the cost details of practically available capacitor sizes in kVAr and their prices in $/kVAr [4].

5.1.1 Only CBs allocation for normal mode

In this case study, the network performance is analysed by integrating three CBs optimally into the network. The objective function expressed in Eq. (6) is optimised using the proposed SADFA. The obtained results are compared with those in the literature.

The total reactive power load of the network is 2300 kVAr. The limits for search variables in this test system are chosen as follows: The lower limit and upper limit for locations are [2, 2, 2] and [33, 33, 33], respectively. The lower limit and upper limit for sizes are [0, 0, 0] and [2300, 2300, 2300], respectively. The computational characteristics of PSO, BOA, FSA, DFA and SADFA are provided in Fig. 2. The best results obtained by SADFA are explained here and compared with literature works in Table 1.

The best locations are 14, 30, and 24, and correspondingly, the best sizes in kVAr are 400, 550, and 1050, respectively. The network active power loss decreased to 138.1954 kW from 210.5484 kW, which accounted for a 34.36% reduction. The operating cost is reduced to 11811.7 $from 35373.14 $. In comparison to the base case, it is around a 66.67% reduction. The savings seem to be high with the results of GSA [1], but the network is poorly operating with higher losses, where as SADFA is

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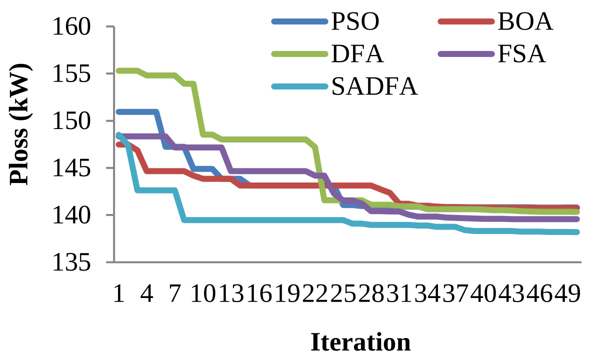

Figure. 2 Convergence characteristics while solving CBs allocation problem under normal mode

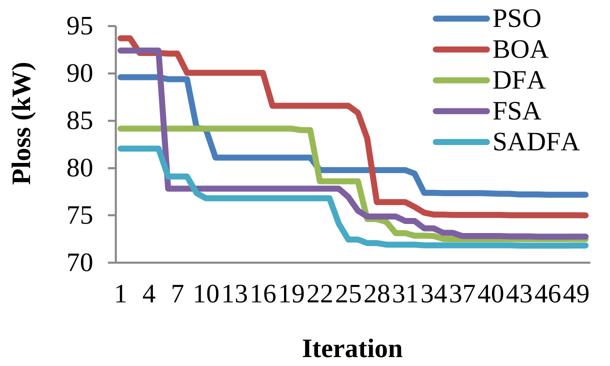

Figure. 3 Convergence characteristics while solving DGs allocation problem under normal mode

Table 2. Optimal DG allocation under normal mode

Method	DGs (kW) /bus #	P_{loss} (kW)	GHG_{em}^{h} (lb/h)
–	–	210.9976	8039.113
MOSCA [15]	514.9/14 948.9/28 635.16/23	90.1385*	3493.673
FPA [19]	1033.9/12 1086.6/30	87.4771	3444.117
WOA [18]	1072.83/30 772.448/25 856.678/13	73.7566	2225.398
MRFO [13]	788.28/13 1017.1/24 1035.3/30	72.8993	1939.591
SKH [17]	1054.64/30 1091.39/24 801.8/13	72.7869	1719.946
HGWO [16]	802/13 1090/24 1054/30	72.7865	1723.693
SADFA	775.4/14 1081.36/24 1077.24/30	71.815	1746.275

highly competitive to FPA [3] and DVSA [10] in terms of reduced losses and net-savings.

5.1.2. Only DGs allocation for normal mode

The total active power load of the network is 3715 kW. Since there are no DGs in the network, the GHG emissions for total load and losses are equal to lb. The SADFA is now working to improve Eq. (7), which is designed to reduce loss and GHG emissions simultaneously. The following are the search variable limits in this test system: The limits for locations are the same as in Section 5.1.1.

The lower limit and upper limit for sizes are [0, 0, 0] and [3715, 3715, 3715], respectively. The computational characteristics of PSO, BOA, FSA, DFA and SADFA are provided in Fig. 3. The best results obtained by SADFA are explained here and compared with literature works in Table 2. The best locations are 14, 24, and 30, and correspondingly, the best sizes in kW are 775.4, 1081.36, and 1077.24, respectively. The network active power loss decreased to 71.815 kW from 210.5484 kW, which accounted for a 34.36% reduction. The GHG emissions were reduced to 1746.275 lb/h from 8039.113 lb/h.

In comparison to the base case, it is around a 78.28% reduction. The results obtained by SADFA are highly competitive with MOSCA [15], FPA [19], WOA [18], MRFO [13], SKH [17], and HGWO [16].

5.2 Simulations considering islanding mode

In this Case-3, the network is assumed to be in islanding mode. Thus, one of the best locations should be modelled as a slack bus, and such a bus should be selected for hybrid ESS with CBs in the network. In this case study, the network performance is analysed by integrating two CBs optimally into the network along with one hybrid ESS with CBs as slack buses. The objective function expressed in Eq. (8) is optimised using the proposed SADFA. The best location for a slack bus is identified as bus-6, and the network performance is as follows: At bus-18, the real power loss was 97.1299 kW, the reactive power loss was 75.9895 kVAr, and the minimum voltage magnitude was 0.9568 p.u.

5.2.1. Only DGs allocation for islanding mode

Considering bus-6 as a slack bus, the locations and sizes of two CBs are optimized. The hybrid ESS at bus-6 is (3789.23+j822.81) kVA, and the two CBs in kVAr are: 896.42/30 and 639.82/24, respectively.

Correspondingly, the network performance is improved as follows: The real power loss is 74.2305 kW; the reactive power loss is 59.0521 kVAr; the minimum voltage magnitude is 0.9568 p.u. at bus-18. The overall VDI is reduced to 0.6986 from 0.8308.

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Table 3. Optimal allocation of single hybrid ESS, CBs and DGs under islanding mode

Case #	Hybrid ESS/ bus #	CBs (kVAr) / bus #	DGs (kVAr) / bus #	P_{loss} (kW)	Q_{loss} (kVAr)	V_{min} (p.u.) / bus #	VDI
Base	3790.99/ 2375.99/ 6	–	–	97.1229	75.9895	0.9568/ 18	0.8308
1	3789.23/ 822.81/ 6	896.42/30 639.82/24	–	74.2305	59.0521	0.9568/ 18	0.6986
2	1829.83/ 2337.324/ 6	–	1280.39/24 652.11/14	47.3380	37.3240	0.9687/ 33	0.4168
3	1347.87/ 663.27/ 6	780.75/4 888.67/30	1624.98/4 779.82/30	37.6792	32.68	0.9568/ 18	0.4357

5.2.2. One hybrid ESS with DGs allocation

Considering bus-6 as a slack bus, the locations and sizes of two DGs are optimized. The hybrid ESS at bus-6 is (1829.83+j2337.32) kVA, and the two DGs in kW are: 1280.39/24 and 652.11/14, respectively.

Correspondingly, the network performance is improved as follows: The real power loss is 47.338 kW; the reactive power loss is 37.324 kVAr; the minimum voltage magnitude is 0.9687 p.u. at bus-33. The overall VDI is reduced to 0.4168 from 0.8308.

5.2.3. One hybrid ESS with DGs+CBs allocation

Considering bus-6 as a slack bus, the locations and sizes of two DGs and two CBs are optimized. The hybrid ESS at bus-6 is (1347.87+j663.27) kVA, and the two DGs in kW are: 1624.98/4 and 779.82/30, respectively. The two CBs in kVAr are: 780.75/4 and 888.67/30, respectively.

Correspondingly, the network performance is improved as follows: The real power loss is 37.6792 kW; the reactive power loss is 32.68 kVAr; the minimum voltage magnitude is 0.9568 p.u. at bus-18. The overall VDI is reduced to 0.4357 from 0.8308.

5.3 Discussion and future scope

The simulation results presented in sections 5.1 and 5.2 show that the electrical distribution networks can be operated effectively by integrating CBs and DGs at optimal locations with appropriate sizes. However, there is a possibility to improve the operational conditions by using reconfiguration along with DGs and CBs allocation. In [34], the mayfly algorithm (MFA) is introduced for optimally sizing and locating hybrid RE systems with storage for islanding conditions. In comparison to this work, there is a possibility for comparative study with DSTATCOM and CBs.

On the other hand, network reconfiguration along with DGs and CBs can further improve the network performance. [35], mixed-integer particle swarm optimization (MIPSO) [36], genetic algorithm [37], self-adaptive butterfly algorithm (SABOA) [38], and honey badger algorithm [HBA] [39], and many other algorithms as seen in [40], have been used for simultaneous DGs/CBs allocation and network reconfiguration. In this connection, the current work can be further extended for reconfiguration.

6. Conclusion

In this paper, a novel optimization method based on an enhanced version of the dragonfly algorithm (DFA) is proposed for calculating the locations and capacities of ESSs combined with CBs. For the global solution to be reached with the least amount of computational work, different basic DFA performance variables are tuned through a self-adaptive mechanism in SADFA. The simulation findings on the IEEE 33-bus are contrasted with published studies and other algorithms, such as the fundamental DFA, PSO, BOA, and FSA. According to the comparison analysis, SAFDA is dominated by literary works and all other simulated algorithms. When the network is islanded, there is a need for an ESS of 3791 kW/h with a CB of 2376 kVAr. On the other hand, by strategically placing CBs and DGs in the network, the ESS size is reduced to 1348 kW/h with a 663.27 kVAr CB. This results in a loss of 97.12 kW to 37.68 kW. Additionally, it is demonstrated that the suggested strategy for ESS, CBs, and DGs integration is effective in meeting IMG energy requirements with lower losses, greater economic benefits, and applicability for real-world applications.

Conflicts of interest

Authors declare that no conflicts of interest.

Author contributions

Ooha L: Conceptualization, software, investigation, simulation, writing—original draft preparation, Radha Rani K and Kotaiah N.C: validation, formal analysis, and supervision.

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