Journal of Energy Storage 26 (2019) 100892

Contents lists available at ScienceDirect

Journal of Energy Storage

journal homepage: www.elsevier.com/locate/est

Optimal placement and sizing of battery energy storage system for losses reduction using whale optimization algorithm

Ling Ai Wong[a,b,*], Vigna K. Ramachandaramurthy[a], Sara L. Walker[c], Phil Taylor[c], Mohammad Javad Sanjari[d]

[a] Institute of Power Engineering, Department of Electrical Power Engineering, College of Engineering, Universiti Tenaga Nasional, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia
[b] School of Engineering & Technology, University College of Technology Sarawak, 96000 Sibu, Sarawak, Malaysia
[c] School of Engineering, Newcastle University, Newcastle Upon Tyne, NE1 7RU, United Kingdom
[d] School of Engineering, Griffith University, Gold Coast, QLD 4222, Australia

ARTICLE INFO

Keywords:
Meta-heuristic optimization algorithm
Whale optimization algorithm
BESS

ABSTRACT

This paper proposes an approach for optimal placement and sizing of battery energy storage system (BESS) to reduce the power losses in the distribution grid. A meta-heuristic optimization algorithm known as Whale Optimization Algorithm (WOA) is introduced to perform the optimization. In this paper, two different approaches are presented to achieve the optimal allocation of the BESS. The first approach is to obtain the optimal location and sizing in two steps while the second approach optimizes both location and sizing simultaneously. The performance of the proposed technique has been validated by comparing with two other algorithms namely firefly algorithm and particle swarm optimization. The results show that WOA has outstanding performance in attaining the optimal location and sizing of BESS in the distribution network for power losses reduction.

1. Introduction

The Battery Energy Storage System (BESS) has gained popularity in the electrical power field in recent years due to its ability to improve the stability and flexibility of power system, provide ride through capability during loss of generation, perform energy arbitrage as well as mitigate the effect of intermittency caused by the renewable energy sources such as solar and wind [1,2]. Despite the advantages of BESS, the optimal planning of BESS, e.g., the optimal location and the optimal sizing is essential since it is not an economic option to install BESS at every bus especially in a large network [3]. Besides, the installation of oversized BESS may further burden the utilities with higher investment cost [4,5]. However, to determine the locations and sizes of BESS simultaneously is a complex non-deterministic polynomial-time problem. Furthermore, there is no preferred solution for the optimal location and sizing of BESS in the network due to the different BESS technologies and different power network requirements with different total load demand, total generation capacity and the network topology [2].

A method employing a second-order cone programming optimal power flow has been proposed in [6] to decide the optimal sizes and location of energy storage systems (ESSs) in the electricity distribution network. The results showed that the placement of ESS at optimal locations avoids significant control on distributed generation (DG) operation which defers the employment of large control facilities. In [7], a technique was suggested for the optimal placement and capacity of BESS in a radial electricity network using clustering and sensitivity analysis. It was found that BESS units were always placed at critical bus irrespective of the number of clusters. An optimal ESS allocation method based on the long-term Wind Power Time Series was proposed in [8] to allocate the ESS considering the charging and discharging cycles of ESS. The proposed time-domain based dynamic simulation required less complicated mathematic equation derivations, which reduced the computation effort. Also, a method was suggested in [9] for the optimal allocation of BESS in low voltage grids using Receding Horizon Control and Benders decomposition algorithm. The algorithm improved the optimization of BESS allocation performance by dividing the problem into a master problem and sub-problems, where the sub-problems were solved successively after the master problem due to the nature of the optimization problem. In [10], the optimal allocation of BESS has been modelled as mixed-integer non-linear programming which is then solved using DICOPT solver. A demand response program (DRP) was employed to perform load shifting process which indirectly

* Corresponding author at: Institute of Power Engineering, Department of Electrical Power Engineering, College of Engineering, Universiti Tenaga Nasional, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia.
E-mail address: ling.ai.wong@ucts.edu.my (L.A. Wong).

https://doi.org/10.1016/j.est.2019.100892
Received 8 May 2019; Received in revised form 26 July 2019; Accepted 3 August 2019
Available online 18 September 2019
2352-152X/

Nomenclature

Acronym list

BESS	Battery energy storage system
DG	Distributed generation
ESS	Energy storage system
FA	Firefly algorithm
GA	Genetic algorithm
NOB	Number of bits
PSO	Particle swarm optimization
PV	Photovoltaic
WOA	Whale optimization algorithm

Parameter list

$\vec{A}$	Coefficient vector
$\vec{C}$	Coefficient vector
$\vec{D}$	Relative position between a search agent and the best candidate
$\vec{D}^t$	Distance between the whale and the prey
$\vec{X}(t)$	Current position vector
$\vec{X}(t+1)$	Position vector for next iteration
$\vec{X}^*(t)$	Position vector for the best current solution
$\vec{X}_{rand}$	Random position vector
I_k^i	Equivalent current injection at bus k at ith iteration
P_k	Active power at bus k
Q_k	Reactive power at bus k
V_k^i	Node voltage at bus k at ith iteration
I_i	Current magnitude of ith branch
R_i	Resistance of ith branch
N_{br}	Number of branches
P_{BESS}	BESS power
$P_{BESS,min}$	Minimum BESS power
$P_{BESS,max}$	Maximum BESS power
V_i	Bus voltage at bus i
V_{min}	Minimum bus voltage
V_{max}	Maximum bus voltage

reduces the system losses and the related cost. It was found that the total cost reduction was higher when DRP was included in the optimization process.

In addition to the aforementioned analytical optimization techniques, some work also focused on artificial intelligence and meta-heuristic methods since these techniques are relatively simple and do not require a complicated mathematical model. Moreover, meta-heuristic algorithms possess better global search ability with relatively shorter computational time [11]. Although the effectiveness of the meta-heuristic algorithms in obtaining the optimal solution is not guaranteed, a proper-designed heuristic algorithm can always achieve the solution which is very close to optimal points [12]. The artificial neural network was recommended in [13,14] for the optimal sizing and control of BESSs in both solar and wind power applications. In [14], the peak load shaving was carried out by comparing the actual and forecasted PV generation. The results demonstrated that the usage of BESS with optimal capacity can shave the peak load and reduce the electricity bill effectively. In [15–18], the genetic algorithm (GA) was proposed for the optimal sizing and placement of ESS to improve the power output fluctuation, and reduce the network losses and net present value of the smart grid. The particle swarm optimization (PSO) was employed in various work [19–22] for the optimal placement and sizing of ESS in order to produce stable power output and enhance system performance. Furthermore, studies to optimally allocate the BESS in the electricity system have been done using the firefly algorithm (FA) [3,23,24], bat algorithm [25], bee colony algorithm [26], as well as the harmonic search algorithm [27].

Nevertheless, algorithms such as GA, PSO and FA are known for the issues of being trapped in the local optimal points and slow convergence rate [28–30]. These issues can be solved by employing an optimization algorithm with better exploration and exploitation capabilities.

Therefore in this paper, an effective meta-heuristic optimization algorithm known as whale optimization algorithm (WOA) [31] with high exploration and exploitation capabilities is introduced to determine the optimal placement and sizing of BESS in a distribution system in order to minimize the total system losses. Although the existing enhanced version of WOA [32] might give better optimization results compared to the original WOA, it is not considered in this work. Two different approaches are proposed in this paper to determine the optimal BESS allocation with the WOA, and the performances of the two approaches are then compared and analysed. The first approach is the optimal sizing of BESS after the attainment of the optimal BESS locations in the network, while the second approach optimizes both locations and sizing simultaneously. The main contributions of this paper can be listed as follow:

1 The optimal location and placement of BESS which are crucial for optimal distribution network performance are determined using WOA with high exploration and exploitation abilities. Two different approaches are considered in this work and the optimal results achieved are compared and analysed. It is proven that the simultaneous optimization approach is more effective than the two-step approach.
2 Different swarm-based meta-heuristic algorithms are employed for the optimization process and the performance of each algorithm are compared and analysed. It is shown that the WOA has superior performance in obtaining the optimal BESS location and sizing for maximum power losses reduction.
3 Different case studies, e.g., distribution network with different numbers of BESS and PV are carried out to investigate the effects of each case on optimal BESS placement and sizing in order to achieve minimum power losses. It can be concluded with equal total capacity, the optimal placement of multiple BESS is more effective in reducing the total system losses than the optimal placement of single BESS.

The study is structured as follows. The basic principle of the WOA is presented in the succeeding section, followed by a brief explanation of the application of the WOA in BESS placement and sizing. Subsequently, results from the WOA based on simulation data are provided and discussed. Lastly, conclusions are drawn on the effectiveness of the WOA.

2. Whale optimization algorithm

Whale optimization algorithm was proposed by [31] based on the hunting behaviour of humpback whales. This algorithm was divided into two important parts, namely exploration stage and exploitation stage.

2.1. Exploitation stage

The mathematical model for the exploitation stage is derived from the bubble-net behaviour of humpback whales where two elements known as shrinking encircling mechanism and spiral updating position were introduced in this stage.

2.1.1. Shrinking encircling mechanism

The humpback whales are able to detect the position of their prey and then encircle them. As the position for the optimal solution in the search space is not known beforehand, the WOA will assume that the solution obtained by the current best candidate is the target prey or it is near to the optimal solution. Once the best candidate is decided, the other searching agents will then update their positions with respect to the best candidate. This behaviour can be formulated as follows:

$$\vec{D} = |\vec{C} \cdot \vec{X}^*(t) - \vec{X}(t)| \tag{1}$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \tag{2}$$

where $\vec{D}$ represents the position of a search agent relative to the position of the best candidate, t denotes the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{X}^*$ is the position vector for the best current solution and $\vec{X}$ is the position vector. Meanwhile, the vectors $\vec{A}$ and $\vec{C}$ can be determined through the following equations:

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \tag{3}$$

$$\vec{C} = 2 \cdot \vec{r} \tag{4}$$

where $\vec{r}$ represents a random vector within the range of zero to one, while $\vec{a}$ is linearly reduced from two to zero throughout the iteration.

The shrinking encircling mechanism is realized through the decreasing of $\vec{a}$ which then decreases the variation for $\vec{A}$ throughout the iteration process. It can be seen that $\vec{A}$ is a random number within the interval $[-a, a]$. The next updated position for a search agent can be any point between the current position of the agent and the position of

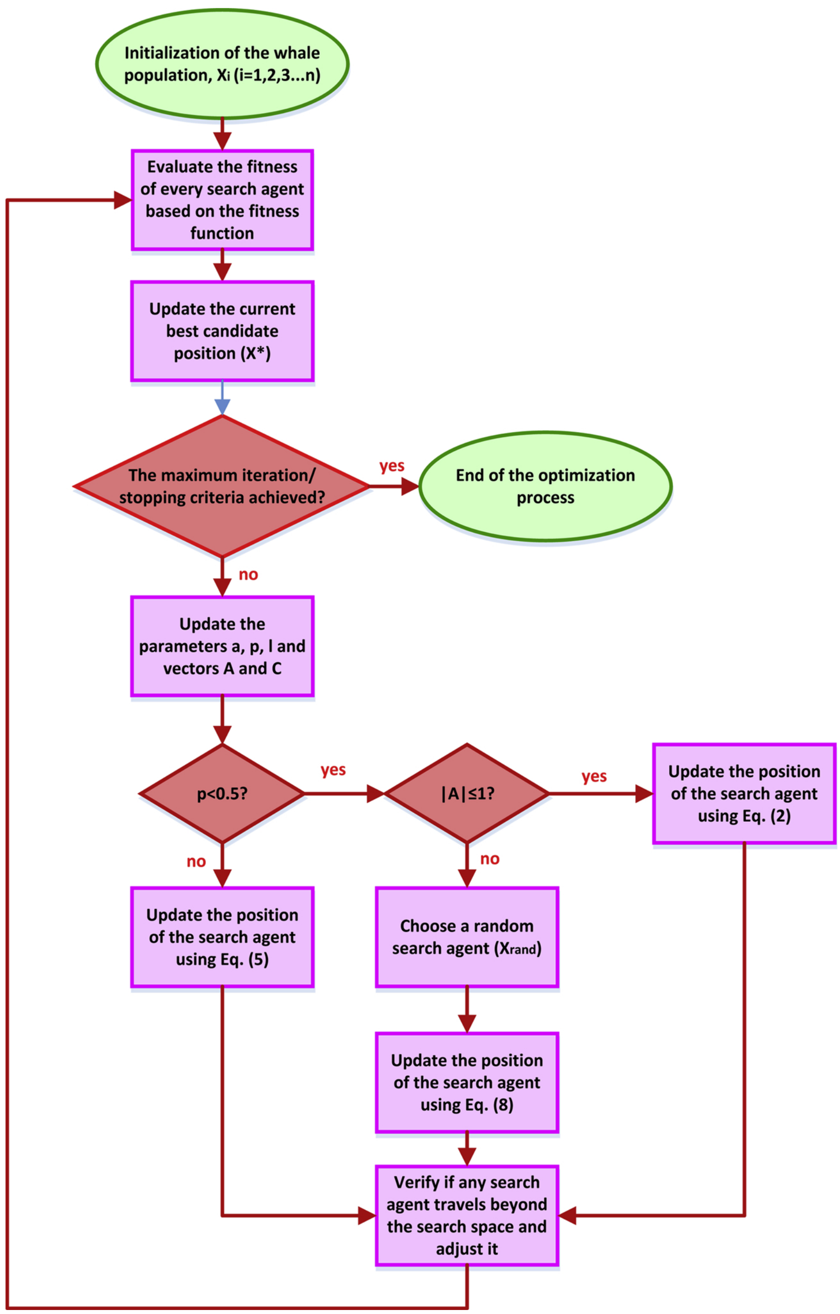

Fig. 1. Flowchart for WOA [31].

the current best candidate when $|\vec{A}| \le 1$.

2.1.2. Spiral updating position

The spiral updating approach utilizes a spiral equation as shown in (5) where the equation imitates the helix-shaped movement of humpback whales based on the location of whales and prey.

$$\vec{X}(t+1) = \vec{D^t} \bullet e^{bl} \bullet cos(2\pi l) + \vec{X^*}(t) \tag{5}$$

where $\vec{D^t}$ denotes the distance between the whale and the prey at ith iteration which can be formulated as $\vec{D^t} = |\vec{X^*}(t) - \vec{X}(t)|$, b represents a constant that define the shape of the logarithmic spiral, while l represents a random number within interval $[-1,1]$.

Since the humpback whales move around the prey in a shrinking circle and at the same time, they move along the spiral-shaped path, it is assumed in the optimization that there is a probability of 0.5 on the preference of whale to use either the shrinking encircling technique or the spiral model to update the positions. The overall position updating equation based on the hunting behaviour of humpback whales in the exploitation stage is shown as follows:

$$\vec{X}(t+1) = \begin{cases} \vec{X^*}(t) - \vec{A} \bullet \vec{D} \ if\ p < 0.5 \\ \vec{D^t} \bullet e^{bl} \bullet cos(2\pi l) + \vec{X^*}(t) \ if\ p \ge 0.5 \end{cases} \tag{6}$$

2.2. Exploration stage

The exploration stage is the stage when the humpback whales are searching for prey randomly based on the position of each other. In this stage, the same technique using the variation of $\vec{A}$ vector is employed where the $|\vec{A}|$ with a random value larger than 1.0 drives the search agents to travel farther from a reference whale. Unlike the exploitation stage, the positions of the search agents in the exploration stage are updated based on a randomly selected search agent rather than the best candidate obtained. This process enables the WOA to carry out a global search with the mathematical equations as shown below:

$$\vec{D} = |\vec{C} \bullet \vec{X}_{rand}(t) - \vec{X}(t)| \tag{7}$$

$$\vec{X}(t+1) = \vec{X}_{rand}(t) - \vec{A} \bullet \vec{D} \tag{8}$$

where $\vec{X}_{rand}$ denotes a random position vector selected from the current population. The flowchart for the WOA is depicted in Fig. 1.

3. Optimization problem formulation

BESS helps to enhance the performance of the distribution grid by supplying the power to the local loads nearby. When the local loads are supported by BESS, less power is needed from the grid and hence the power losses in the grid can be reduced.

The lithium ion BESS is modelled in this study based on real current injection as shown in Fig. 2 where at each bus k, the corresponding equivalent current injection at i^{th} iteration of the solution is shown in (9) [33].

$$I_k^i = \left(\frac{P_k + jQ_k}{V_k^i}\right) \tag{9}$$

where P_k and Q_k are the active and reactive power respectively at bus k, j is the square root of -1, V_k^i is the node voltage at bus k and the i^{th} iteration and I_k^i is the equivalent current injection at bus k at the i^{th} iteration. In this study, since only the active power is involved in the power losses calculation, the output current from the BESS is assumed to supply only active power while the reactive power is considered as zero.

3.1. Optimal BESS placement and sizing in two steps

In this part of the work, the optimal locations and sizing of BESS are obtained in two steps. First, the optimal locations of the BESS in the distribution grid are determined by pre-setting the BESS sizes at a fixed value. After the optimal allocation of the BESS, the size of BESS is optimized by placing the BESS at the locations obtained from the previous step. The purpose of the optimization is to minimize the total power losses. To evaluate the fitness, the objective function, *OF* is formulated as shown in (10), subject to the constraints given in (11) and (12).

$$OF = \min\left(\sum_{i=1}^{N_{br}} |I_i|^2 R_i\right) \tag{10}$$

$$P_{BESS,min} \le P_{BESS} \le P_{BESS,max} \tag{11}$$

$$V_{min} \le V_k \le V_{max} \tag{12}$$

where N_{br} is the number of branches in the distribution system, I_i and R_i are the current magnitude and resistance of the *ith* branch respectively, P_{BESS} is the BESS power and V_k is the bus voltage at bus k.

For the optimization algorithm, the dimensions of the search agents in WOA (number of bits, *NOB*) are decided based on the number of BESSs. For the case with single BESS, the *NOB* is one, representing the possible location or sizing for the single BESS. For the case with two BESSs, the *NOB* is two where the first and second bits represent the possible location or sizing for the first and second BESS respectively.

3.2. Simultaneous optimal BESS placement and sizing

In this part, the optimal BESS locations and capacity in the distribution network are simultaneously determined to minimize the total power losses in the distribution network. The same objective function, *OF* and optimization constraints as given from (10) to (12) are employed to evaluate the fitness of the optimization output. For the optimization process, the *NOB* is decided based on the number of BESSs involved in the optimization as depicted in (13). For the case with a single BESS, the *NOB* equals to two. The first bit represents the possible BESS location while the second bit represents the possible BESS sizing. For the case with two BESSs, the *NOB* is four where the first two bits represents the possible locations for BESS 1 and BESS 2, while the 3rd and 4th bit represent the possible sizing for BESS 1 and BESS 2 respectively.

$$NOB = (number\ of\ BESSs) \times 2 \tag{13}$$

For both approaches explained in Sections 3.1 and 3.2, two scenarios are considered. In the first scenario, the placement and the sizing of BESS in the conventional (no PV) electricity distribution system are considered, while solar photovoltaic (PV) systems are integrated into the electricity distribution system at high load demand buses for the second scenario. Two cases are studied for both scenarios: the first case optimizes the location and size of a single BESS; the latter one determines the optimal placement and sizing for two BESSs. The impact in power loss reduction for different scenarios and cases are then compared and studied. The overview of scenarios and cases in this work is illustrated in Fig. 3.

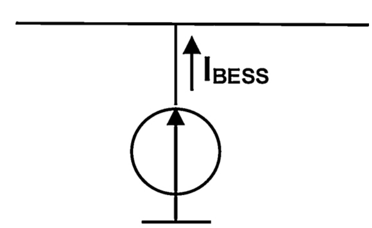

Fig. 2. Steady state BESS model.

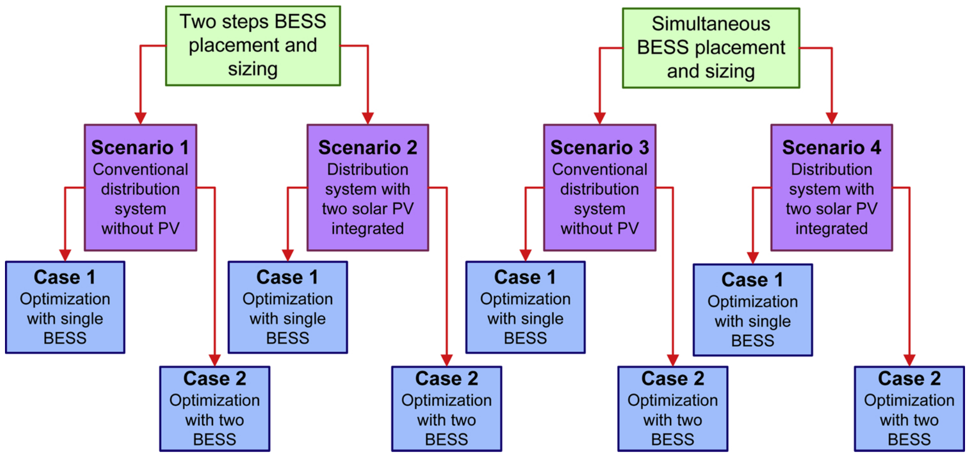

Fig. 3. Overview of scenarios and cases for the optimal BESS placement and sizing.

4. Method of implementation of WOA for power losses reduction

The procedures for the proposed two steps optimization and simultaneous BESS placement and sizing optimization using WOA are summarized as follows.

4.1. Implementation steps for optimal BESS placement and sizing

a For scenario 1, model the generic distribution network with single BESS using Simulink.
b Generate the initial population of whale search agents which represent the possible locations (or size) for the BESS.
c Run the power flow in Simulink considering the candidate solutions proposed in step (b).
d Evaluate the fitness function, *OF* through the data obtained from the power flow.
e Update the current best position (or size) of the whale search agents.
f Update the parameters required for the next iteration.
g Repeat step (c)–(f) until the stopping criteria is achieved where in this work, the maximum iteration number is considered as the stopping criteria.
h Store the best solution as the optimal BESS locations (or sizes) obtained.
i Repeat step (a)–(h) for optimal sizing problem assuming the BESS is at the optimal locations obtained from step (h).
j Repeat step (a)–(i) where another BESS is added into the network.

Repeat the procedures (a)–(j) for scenario 2 with two solar PV integrated in the distribution network model.

4.2. Implementation steps for simultaneous optimal BESS placement and sizing

a For scenario 3, model the generic distribution network with single BESS using Simulink.
b Generate the initial population of whale search agents which represent the possible locations and sizes for the BESS.
c Run the power flow in Simulink considering the candidate solutions proposed in step (b).
d Evaluate the fitness function, *OF* through the data obtained from the power flow.
e Update the current best position of the whale search agents.
f Update the parameters required for the next iteration.
g Repeat step (c) and (f) until the stopping criteria is achieved where in this work, the maximum iteration number is considered as stopping criteria.
h Store the best solution as the optimal BESS locations and sizes obtained.
i Repeat step (a)–(h) where another BESS is added into the network.

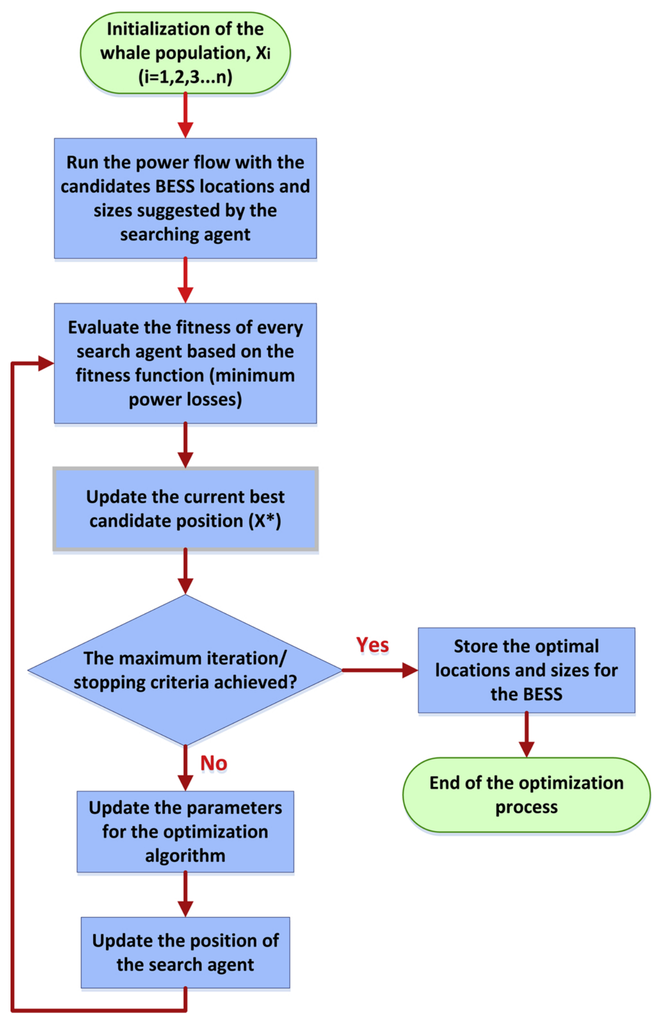

Fig. 4. The flowchart for the optimal allocation of BESS.

Repeat the procedures (a)–(i) for scenario 4 with two solar PV integrated in the distribution network model. The flowchart for the proposed simultaneous BESS allocation method is illustrated in Fig. 4.

4.3. The electricity distribution model, and power loss calculation

The electricity distribution system with nominal voltage of 11 kV as shown in Fig. 5 is used for this analysis. There are 48 buses in the system with total active and reactive load of 3.83 MW and 1.35 MVar respectively. Load data for this generic distribution system is shown in Table A1 in Appendix A, and branch data is shown in Table A2 in Appendix A. For the cases with solar PV involved, two PVs are installed at the centre of two different feeders, at bus 18 and bus 30 with relatively higher load of 192.45 kW and 35.13 kW, respectively if compared to the buses nearby. The modelling of the electricity distribution system and the load flow in this analysis are performed using the software Simulink where the total system losses for each load flow can be computed using the powergui load flow tool. The total system losses for the base case (without any PV and BESS) in this analysis is 130.84 kW.

5. Results and discussions

The results for optimal BESS placement and sizing using WOA are explained in this section. The WOA optimization method is then compared with an existing algorithm known as firefly algorithm (FA) [34] to demonstrate the performance of WOA in solving the same problem. Parameters such as the population size, number of maximum iteration and parameters for each optimization algorithm are decided through trial and error procedure and experimentation considering the performance of the algorithms. For WOA, the initial value of vector $\vec{a}$ is 2 and the value for constant b is set to 1. For PSO, the cognitive and social coefficient are both set to 2. For FA, randomization parameter, α are set to 0.2 with the decreasing factor of 0.97 in the following iteration, and both the attractiveness, βo and light absorption coefficient, γ are set to 1.

For the distribution grid, the generic distribution system as shown in Fig. 5 is employed for the simulation of all scenarios where the system data for the generic distribution system can be found in Appendix A.

5.1. Optimal BESS placement and sizing in two steps

In this part, the number of dimension (D) for the optimized parameters are one-D (location/capacity of one BESS) and two-D (locations/capacities of two BESS) for scenario 1 and scenario 2 respectively. Both the population size and the number of maximum iterations for the optimization algorithms, WOA, PSO and FA are fixed to 50. Optimization process for each case is repeated 5 times where the BESS locations and sizing that yield the minimum total system losses are considered as the optimal solution.

5.1.1. Two steps optimal placement and sizing of BESS in conventional distribution system

The first scenario in this work is the WOA two steps optimization for optimal location and sizing of BESS in the conventional distribution system without any PV. Firstly, the optimal locations are obtained as bus 19 for the case 1 with single BESS while for the case 2 with two BESS in the system, the optimal locations are given at bus 20 and bus 24. These buses chosen for the BESS placement are either the buses with high load demand or the buses that are connected to more buses with high load demand. After the BESS are placed at the optimal locations obtained in the first step, the optimization for the BESS sizing is carried out. For case 1, by using WOA, the optimal sizing is found to be 1.74 MW with 62.58 kW total system loss. This shows a reduction of 68.26 kW in losses compared to the base case. For case 2 with two BESS in the system, the optimal BESS sizes are given as 0.99 MW and 0.66 MW for BESS placed at bus 20 and bus 24 respectively where the

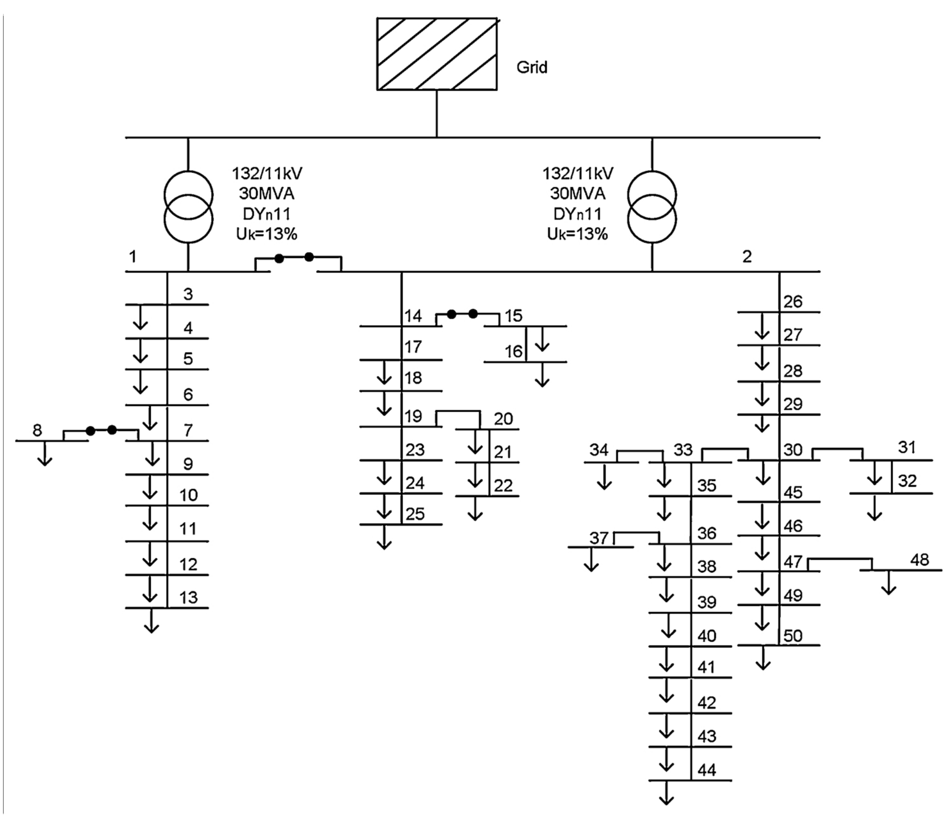

Fig. 5. Single line diagram for distribution system model.

total system losses are 63.62 kW. Since the total capacity of the BESS in case 2 is 1.65 MW, which is smaller than the size of single BESS in case 1, the 2 BESS case is slightly less effective in reducing the power losses. On the other hand, for the optimization using FA, the optimal sizing for single BESS in case 1 is given as 1.76 MW at bus 19, with the total system losses of 62.59 kW. For case 2, the optimal BESS sizes are 1.05 MW and 0.59 MW for BESS at bus 20 and bus 24 respectively with the total system losses of 63.68 kW. Both cases in this scenario have shown that the WOA has better performance than the FA, since it achieves a smaller BESS size and reduced power loss. Meanwhile, for PSO, the optimal sizing obtained for single BESS in case 1 is 1.74 MW at bus 19, with the total system losses of 62.58 kW. For case 2, the optimal BESS sizes are 0.98 MW and 0.68 MW for BESS at bus 20 and bus 24 respectively with the total system losses of 63.61 kW. Even though the total BESS capacity obtained by PSO is 0.01 MW bigger than the one obtained by WOA, it can be seen that in terms of minimizing the total system losses, the performances of PSO and WOA are identical. The performance of WOA, FA and PSO in obtaining the optimal BESS allocations in this scenario is presented in Table 1.

5.1.2. Two steps optimal placement and sizing of BESS in PV integrated distribution system

For the second scenario, the two-step optimization is performed to obtain the optimal location and sizing of BESS in the distribution system with two PV of 0.5 MW each integrated into the power system at bus 18 and bus 30. For case 1 with single BESS, the optimal location attained using WOA is bus 24 while for case 2 with two BESS in the system, the optimal locations achieved are bus 14 and bus 24. The optimization for the BESS sizing is carried out by placing the BESS at the optimal locations obtained from the previous step. For case 1 with single BESS, the optimal sizing obtained using WOA is found to be 1.09 MW with 54.76 kW of total system losses. For case 2 with two BESS in the system, the optimal BESS sizes are given as 0.99 MW and 0.52 MW for BESS placed at bus 14 and bus 24 respectively where the total system losses are further reduced to 47.77 kW. Meanwhile, for the optimization using FA, the optimal sizing for single BESS in case 1 is given as 1.08 MW with the total system losses of 54.77 kW. For case 2, the optimal BESS sizes are 0.76 MW and 0.67 MW for BESS at bus 14 and bus 24 respectively with the total system losses of 48.12 kW. In this scenario, the WOA has achieved slightly higher total loss reduction than the FA for both cases, where the optimal BESS sizes obtained by using WOA are slightly greater than the one obtained using FA. For PSO, the optimal sizing for single BESS in case 1 is given as 1.09 MW with the total system losses of 54.77 kW. For case 2, the optimal BESS sizes are 0.99 MW and 0.53 MW for BESS at bus 14 and bus 24 respectively with the total system losses of 47.77 kW. Similar with the previous scenario (Scenario 1), the performance of PSO is comparable to the performance of WOA. The performance of WOA, FA and PSO in obtaining the optimal BESS allocations in this scenario is presented in Table 2.

5.2. Simultaneous optimal BESS placement and sizing

For the simultaneous optimal BESS placement and sizing, the number of dimension (D) for the optimized parameters are two-D (location and capacity for one BESS) and four-D (locations and capacities of two BESS) for scenario 3 and scenario 4 respectively. The population size and the number of maximum iterations for the optimization algorithm are fixed to 50 and 80 respectively for all scenarios. The optimization process for each case is repeat five times where the BESS allocations that yield minimum total system losses are considered as the optimal solution.

5.2.1. Simultaneous optimal placement and sizing of BESS in conventional distribution system

The third scenario is the simultaneous optimal placement and sizing of BESS in the distribution system feeders without any PV. Case 1 in this scenario investigates the optimal placement and sizing of single BESS in distribution network whereas for case 2, the optimal locations and sizing for two BESS are determined. The performance of WOA, FA and PSO in obtaining the optimal BESS allocations in this scenario is presented in Table 3.

It can be observed from Table 3 that both WOA and PSO have achieved the same solution where in case 1, the BESS is placed optimally at one of the highly loaded buses, bus 18 where the optimal size is given as 1.82 MW. Meanwhile, the total power loss is reduced to 61.87 kW, which is 68.97 kW less than the base case (without BESS and PV). For case 2, two BESS are to be optimized. The optimal buses to place the BESS are found to be bus 7 and bus 18 with the optimal sizes of 0.68 MW and 1.81 MW respectively. The corresponding power losses are further reduced to 48.88 kW, which is a reduction of 12.99 kW compared with case 1. It is found that the BESS in both cases is placed at the buses or feeder with high load demand. In the meantime, the FA demonstrates an optimization of less total loss reduction compared to the output from the WOA for both cases.

5.2.2. Simultaneous optimal placement and sizing of BESS in PV integrated distribution system

In scenario 4, as with scenario 3, an additional two PV of 0.5 MW each are integrated into the power system at bus 18 and bus 30. Again, both WOA and PSO have achieved similar solution. For case 1 with only one BESS, the optimization outcome suggested that the BESS can be optimally placed at bus 15 with the size of 1.50 MW. In this case, the total system losses are reduced to 51.15 kW. For case 2 with two BESS to be optimized, the optimization outcome has suggested the BESS to be placed at bus 7 and bus 15 given the optimal sizes of 0.67 MW and 1.50 MW respectively. The corresponding total losses are 38.20 kW. Similar to the previous scenarios, the optimal locations proposed in this scenario for BESS placement are the buses with high load demand. For FA, it can be seen that the proposed optimal BESS locations for both cases are different than the one proposed by WOA and PSO. Although the BESS sizes proposed by FA are smaller, the solutions yield higher power losses. The performance of WOA, FA and PSO in obtaining the optimal BESS allocations in scenario 4 is summarized in Table 4.

5.3. Comparison of the performances for different scenarios

It can be observed from the optimization results that the optimal placement and sizing reduces the total system losses effectively. The

Table 1
BESS optimal placement and sizing result (Scenario 1).

	Number of BESS	Optimal BESS Location	Optimal BESS size (MW)			Power Loss (kW)		
			WOA	FA	PSO	WOA	FA	PSO
	0	NA	NA			130.84		
Case 1	1	Bus 19	1.74	1.76	1.74	62.58	62.59	62.58
Case 2	2	Bus 20, Bus 24	0.99, 0.66	1.05, 0.59	0.98, 0.68	63.61	63.68	63.61

Table 2
BESS optimal placement and sizing result (Scenario 2).

	Number of BESS	PV Location	PV Size (MW)	Optimal BESS Location	Optimal BESS size (MW)			Power Loss (kW)		
					WOA	FA	PSO	WOA	FA	PSO
Case 1	1	Bus 18, Bus 30	0.5 × 2	Bus 24	1.09	1.08	1.09	54.76	54.77	54.76
Case 2	2	Bus 18, Bus 30	0.5 × 2	Bus 14, Bus 24	0.99, 0.52	0.76,0.67	0.99, 0.53	47.77	48.12	47.77

Table 3
Simultaneous BESS optimal placement and sizing result (Scenario 3).

	Number of BESS	Optimal BESS Location			Optimal BESS size (MW)			Power Loss (kW)		
		WOA	FA	PSO	WOA	FA	PSO	WOA	FA	PSO
	0	NA			NA			130.84		
Case 1	1	Bus 18	Bus 19	Bus 18	1.82	1.76	1.82	61.87	62.59	61.87
Case 2	2	Bus 7, Bus 18	Bus 16, Bus 35	Bus 7, Bus 18	0.68, 1.81	1.97, 0.49	0.68, 1.81	48.88	55.01	48.88

reduction of the entire system losses is due to the local power supply provided by BESS to the buses nearby, thereby less power is transmitted from the main grid and the line losses are reduced as a consequence.

The total system losses obtained for each case in all scenarios are illustrated in Fig. 6. It can be seen from the bar chart in Fig. 6 that the simultaneous optimization on optimal location and sizing of BESS has better performance than two step optimization since the optimal location and sizing are considered together in the power flow during the optimization process. Meanwhile, the total optimal BESS capacities obtained are smaller when PVs are integrated into the power system (as part of the loads are already supplied by the PV generation). Also, it can be concluded from all scenarios (except scenario 1) that the distributed placement of multiple BESSs has better performance in reducing total system losses compared to the placement of only a single BESS in the distribution system.

The performance of WOA is validated by comparing with FA and PSO. As shown in Figs. 7 and 8 , the total system losses obtained through WOA and PSO are identical, while the total system losses for each case obtained by WOA are lower than those obtained using FA. The difference in total system losses reduction becomes more obvious when the dimension of the optimization problem increased with the increase of the number of BESS.

5.4. Comparison of convergence characteristic between WOA, FA and PSO

In this section, the convergence characteristics between the optimization algorithms, namely WOA, FA and PSO are compared. Since the convergence characteristics for all cases display similar patterns, only two cases are chosen and discussed. Fig. 9 shows the convergence characteristics of WOA, FA and PSO for the study with two BESSs in a conventional (no PV) electricity distribution system (scenario 3, case 2) while Fig. 10 illustrates the convergence characteristics of WOA, FA and PSO for the study with two BESSs in an electricity distribution system with PV (scenario 4, case 2).

It can be observed from Figs. 8 and 9 that both the WOA and the PSO has the ability to converge towards the optimal solution in less than 20 iterations while FA does not perform well in the optimization since it does not converge to the optimal solution within the stopping criteria given (maximum iteration number of 80). This can be accounted for by the poor ability of FA to escape from local optimal points. Meanwhile, WOA and PSO has a better convergence characteristic compared to FA, since the algorithms can escape from local optima and therefore give better results. Although the literature has claimed that PSO has limited ability to escape from local optimal point, the results showed that PSO has good performance in this application [30,35].

On the other hand, the performance of each algorithm in terms of achieving minimum solution (total system losses) is analysed using a box plot with five repetition of data. The scenarios for simultaneous BESS optimal sizing and placement (Scenario 3 and Scenario 4) are studied in this part since these scenarios involve higher dimension of search space in the optimization process. Figs. 11 and 12 show the box plot for the data obtained from case 1 and case 2 of Scenario 3 respectively. It can be seen from Fig. 11 that the performance of WOA and PSO are very consistent in achieving the minimum solution while FA has less consistency with wider interquartile range. From Fig. 12, it can be seen that the interquartile range for all three data set increases compared to the one in Fig. 11 when the dimension of the search space increased from 2-D to 4-D. It can be observed that WOA has slightly better performance in achieving the minimum solution since the

Table 4
Simultaneous BESS optimal placement and sizing result (Scenario 4).

	Number of BESS	PV Location	PV Size (MW)	Optimal BESS Location			Optimal BESS size (MW)			Power Loss (kW)		
				WOA	FA	PSO	WOA	FA	PSO	WOA	FA	PSO
Case 1	1	Bus 18, Bus 30	0.5 × 2	Bus 15	Bus 14	Bus 15	1.50	1.38	1.50	51.15	51.42	51.15
Case 2	2	Bus 18, Bus 30	0.5 × 2	Bus 7, Bus 15	Bus 7, Bus 22	Bus 7, Bus 15	0.67, 1.50	0.37, 0.72	0.67, 1.50	38.20	48.83	38.20

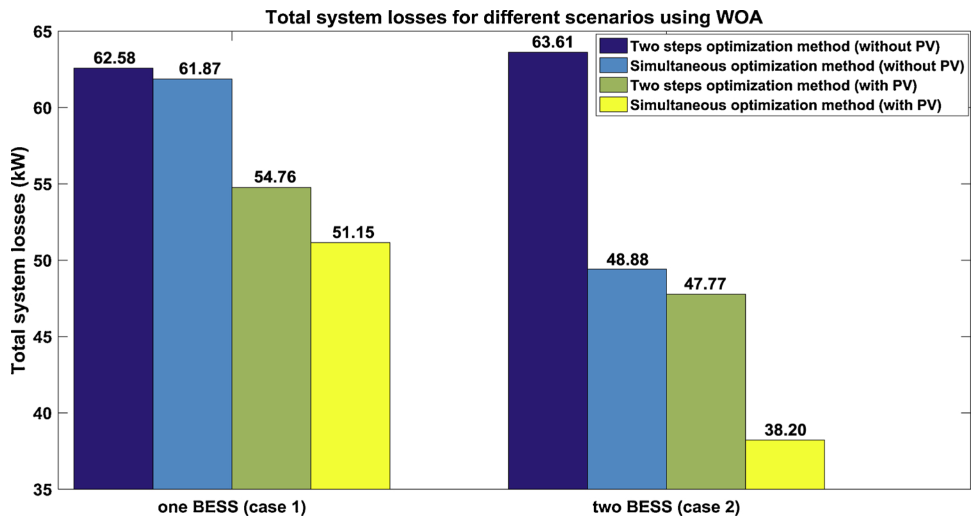

Fig. 6. Total system losses for different scenarios using WOA.

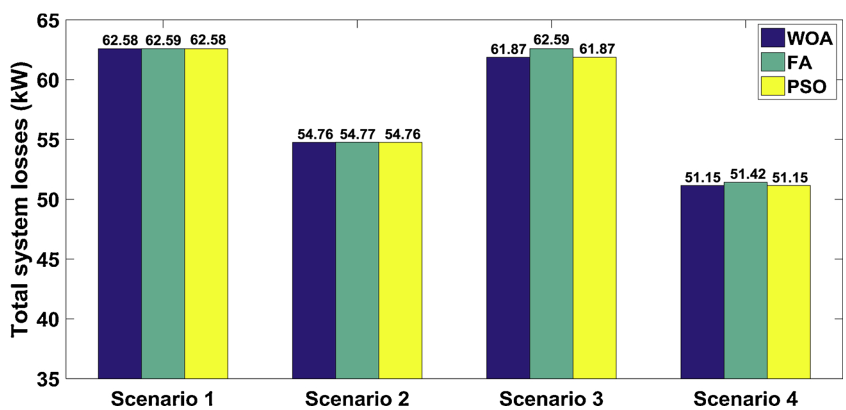

Fig. 7. Comparison of performance between WOA, FA and PSO for different scenarios with one BESS (case 1).

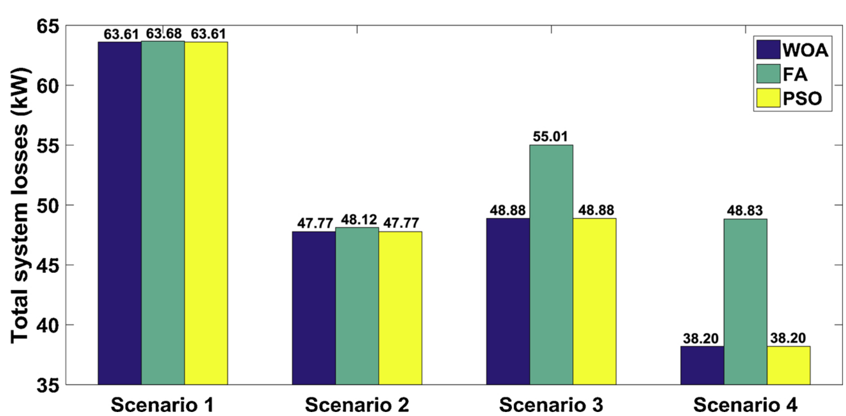

Fig. 8. Comparison of performance between WOA, FA and PSO for different scenarios with two BESS (case 2).

median of the WOA data lean closer to the minimum solution compared to that of PSO. Again, FA data give higher total system losses and bigger interquartile range compared to both WOA and PSO.

Meanwhile, Figs. 13 and 14 illustrate the box plot for the data obtained from case 1 and case 2 of Scenario 4 respectively. Again, the performance of WOA and PSO in the case 1 (Scenario 4) as shown in Fig. 13 are equal and outperformed FA where these two data set show almost no deviation in the minimum solution obtained for all the

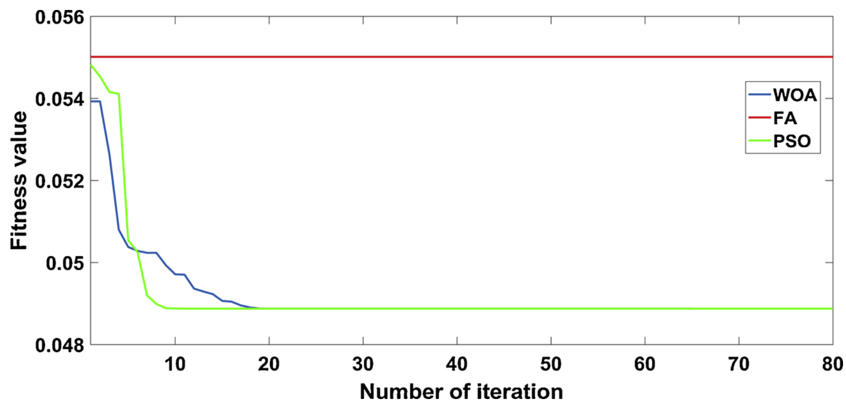

Fig. 9. Convergence characteristic of WOA, FA and PSO for the scenario 3 (case 2).

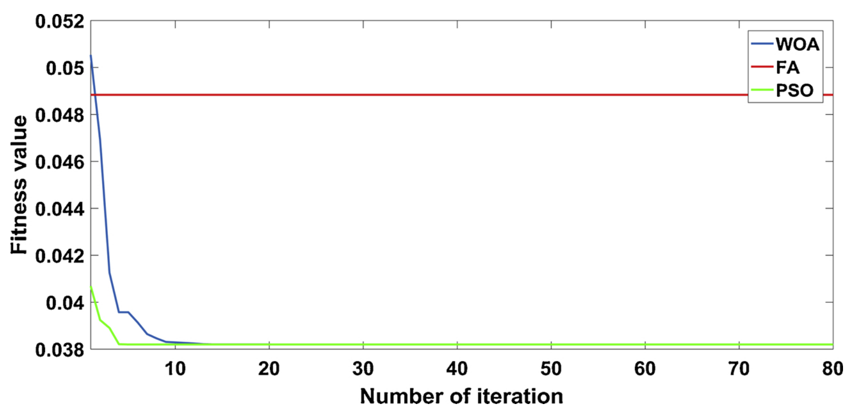

Fig. 10. Convergence characteristic of WOA, FA and PSO for scenario 4 (case 2).

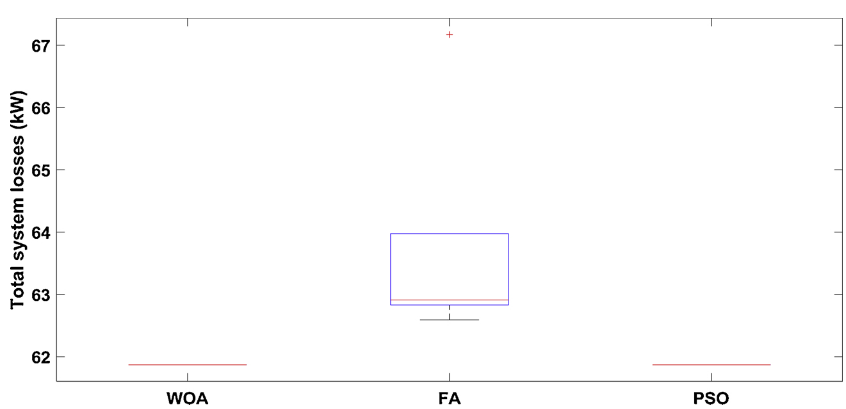

Fig. 11. Performance of WOA, FA and PSO in obtaining the optimal locations and sizing to achieve minimum total system losses (Scenario 3, case 1).

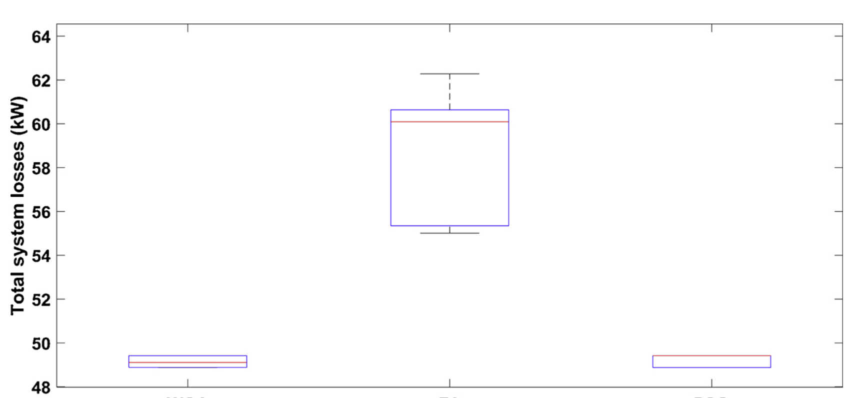

Fig. 12. Performance of WOA, FA and PSO in obtaining the optimal locations and sizing to achieve minimum total system losses (Scenario 3, case 2).

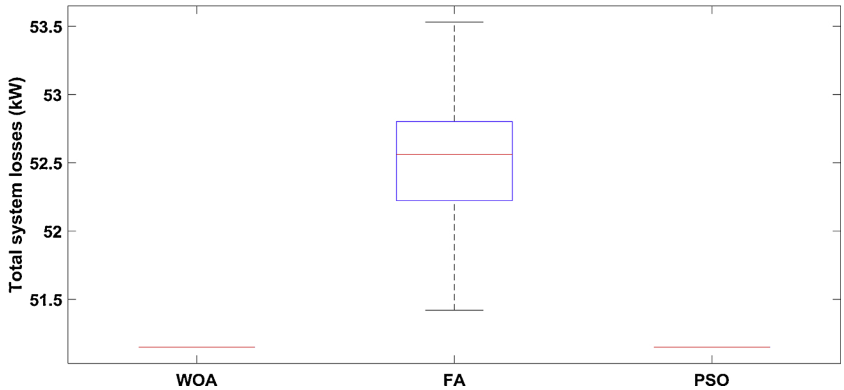

Fig. 13. Performance of WOA, FA and PSO in obtaining the optimal locations and sizing to achieve minimum total system losses (Scenario 4, case 1).

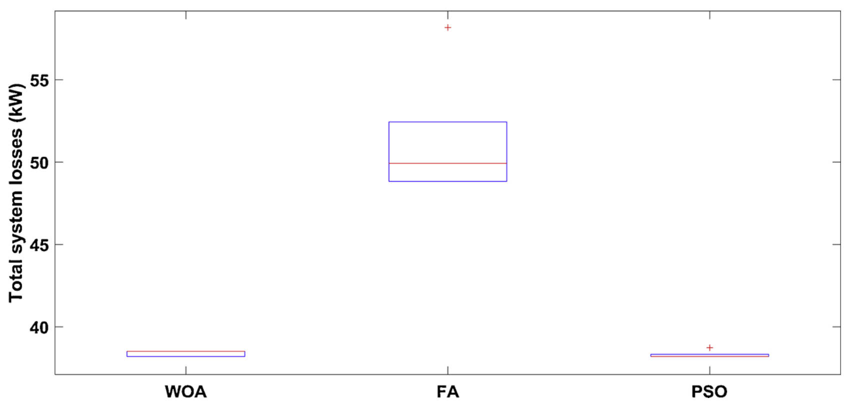

Fig. 14. Performance of WOA, FA and PSO in obtaining the optimal locations and sizing to achieve minimum total system losses (Scenario 4, case 2).

repetition. When the dimension of the search space was increased from 2-D (case 1) to 4-D (case 2), the interquartile range for all data set increased as shown in Fig. 14. In this case, WOA is considered to have better performance than the PSO since there is an outlier for the PSO data which decreases the consistency of the PSO. Again, FA shows the worse performance out of three algorithms with wider data distribution and higher total system losses.

6. Conclusion

In this work, the optimal allocation and sizing of BESS in the distribution system have been performed using the WOA optimization algorithm. The purpose of this work was to use the algorithm to optimise the size and location of BESS to minimize the power losses in the electricity distribution system. Four scenarios with a different number of BESSs, with and without PV integration in the distribution system, were considered and the results can be concluded as follow:

- In Scenario 1, the power losses reduction for case 1 with only one BESS was higher than that of case 2 with two BESS.
- Meanwhile, Scenario 2 depicted the employment of two BESS which produced better outcome in reducing the power losses than the case with only one BESS. This outcome contradicted the outcome of Scenario 1. The outcome for Scenario 1 and Scenario 2 was not consistent since during the first stage of optimal placement, the capacity of BESS was assumed as a particular value and most of the time, this value would not be the optimal capacity of the BESS. This affected the attainment of actual optimal BESS location. Thus, the optimal solution for power losses reduction may not be achieved in this two-stage method.
- It was shown that for both Scenario 3 and Scenario 4, the case with two BESS (case 2) has better performance than the case with only one BESS (case 1) when both the placement and sizing were optimized simultaneously. The findings obtained in these two scenarios are consistent and the simultaneous BESS allocation optimization was proved to be more effective than the two steps optimization method.
- For the performance of different algorithms, both WOA and PSO showed outstanding performances in convergence rate and the ability to escape from local optima points. The WOA slightly outperformed the PSO in terms of consistency in achieving the optimal solution. Meanwhile, the FA did not show good performance in this application.

Lastly, it can be concluded that the optimal placement and sizing of BESS in the electricity distribution system helps in reducing the power losses, and the distributed placement of multiple BESS is more effective in reducing losses than installing a single BESS.

Acknowledgments

This research was supported by the Long Term Research Grant (LRGS), Ministry of Education Malaysia for the program titled “Decarbonisation of Grid with an Optimal Controller and Energy Management for Energy Storage System in Microgrid Applications”.

Appendix A. Data for generic distribution system

Table A1
Load data for generic distribution system.

Bus Number	PL(kW)	QL (kVAr)	Bus Number	PL(kW)	QL (kVAr)
1	–	–	**26**	364.79	182.39
2	–	–	**27**	35.13	17.56
3	22.4	12.8	**28**	31.2	19.5
4	18.9	10.5	**29**	35.13	17.56
5	30.5	21.2	**30**	35.13	17.56
6	30.87	15.4	**31**	36.9	12.9
7	313.55	–375.40	**32**	29.8	14.3
8	154.48	15.21	**33**	31.1	14.9
9	30.87	15.4	**34**	22.1	10.1
10	25.7	14.3	**35**	35.1	18.0
11	19.8	12.17	**36**	35.13	17.56
12	25.4	14.3	**37**	35.13	17.56
13	38.2	14.1	**38**	44.2	20.8
14	–	–	**39**	21.6	13.7
15	789.12	394.56	**40**	30.4	18.2
16	13.35	6.67	**41**	35.13	17.56
17	192.45	96.23	**42**	29.5	18.1
18	192.45	96.23	**43**	33.2	12.8
19	–	–	**44**	30.2	17.5
20	120.28	60.15	**45**	35.13	17.56
21	135.28	70.15	**46**	38.2	18.6
22	85.28	54.9	**47**	35.13	17.56
23	144.34	72.17	**48**	31.4	19.6
24	144.34	72.17	**49**	35.13	17.56
25	144.34	72.17	**50**	31.2	15.4

Table A2
Branch data for generic distribution system.

Sending end bus	Receiving end bus	R (Ω)	X (Ω)
1	3	0.5313	0.3267
3	4	1.127	0.693
4	5	0.9338	0.5742
5	6	0.4267	0.2624
6	7	0.4154	0.2554
7	9	0.4347	0.2673
9	10	0.8211	0.5049
10	11	0.1449	0.0891
11	12	0.161	0.099
12	13	0.7406	0.4554
2	14	1.0363	1.143
15	16	0.053	0.0212
14	17	0.5275	0.2575
17	18	0.1055	0.0515
18	19	0.2321	0.1133
19	20	0.3798	0.1854
20	21	0.1899	0.0927
21	22	0.211	0.103
19	23	0.211	0.103
23	24	0.4853	0.2369
24	25	0.211	0.103
2	26	0.422	0.206
26	27	0.211	0.103
27	28	0.2532	0.1236
28	29	0.422	0.206
29	30	0.844	0.412
30	31	0.1477	0.0721
31	32	0.3798	0.1854
30	33	1.6669	0.8137
33	34	0.5275	0.2575
33	35	0.9073	0.4429
35	36	0.5908	0.2884
36	37	0.211	0.103
36	38	0.211	0.103
38	39	0.422	0.206
39	40	0.211	0.103

(*continued on next page*)

Table A2 (*continued*)

Sending end bus	Receiving end bus	R (Ω)	X (Ω)
40	41	0.633	0.309
41	42	0.325	0.108
42	43	0.975	0.324
43	44	0.3575	0.1188
30	45	0.211	0.103
45	46	0.7596	0.3708
46	47	0.5697	0.2781
47	48	0.6541	0.3193
47	49	0.633	0.309
49	50	0.4431	0.2163

References

[1] F.J. De Sisternes, J.D. Jenkins, A. Botterud, The value of energy storage in decarbonizing the electricity sector, Appl. Energy 175 (2016) 368–379.

[2] L.A. Wong, V.K. Ramachandaramurthy, P. Taylor, J. Ekanayake, S.L. Walker, S. Padmanaban, Review on the optimal placement, sizing and control of an energy storage system in the distribution network, J. Energy Storage 21 (2019) 489–504.

[3] L.A. Wong, H. Shareef, A. Mohamed, A.A. Ibrahim, Optimal battery sizing in photovoltaic based distributed generation using enhanced opposition-based firefly algorithm for voltage rise mitigation, Sci. World J. 2014 (2014) 1–11.

[4] A. Oudalov, D. Chartouni, C. Ohler, Optimizing a battery energy storage system for primary frequency control, IEEE Trans. Power Syst. 22 (2007) 1259–1266.

[5] Y. Yang, H. Li, A. Aichhorn, J. Zheng, M. Greenleaf, Sizing strategy of distributed battery storage system with high penetration of photovoltaic for voltage regulation and peak load shaving, IEEE Trans. Smart Grid 5 (2014) 982–991.

[6] M. Nick, R. Cherkaoui, M. Paolone, Optimal allocation of dispersed energy storage systems in active distribution networks for energy balance and grid support, IEEE Trans. Power Syst. 29 (2014) 2300–2310.

[7] A. Giannitrapani, S. Paoletti, A. Vicino, D. Zarrilli, Optimal allocation of energy storage systems for voltage control in LV distribution networks, IEEE Trans. Smart Grid (2016) 1–12.

[8] H. Zhao, Q. Wu, S. Huang, Q. Guo, H. Sun, Y. Xue, Optimal siting and sizing of energy storage system for power systems with large-scale wind power integration, PowerTech, 2015 IEEE Eindhoven, (2015), pp. 1–6.

[9] P. Fortenbacher, A. Ulbig, G. Andersson, Optimal placement and sizing of distributed battery storage in low voltage grids using receding horizon control strategies, IEEE Trans. Power Syst. 33 (2018) 2383–2394.

[10] A. Akbari-Dibavar, S. Nojavan, K. Zare, Optimal sitting and sizing of energy storage systems in a smart distribution network considering network constraints and demand response program, J. Energy Manage. Technol. 3 (2019) 14–25.

[11] A. Kaveh, Applications of Metaheuristic Optimization Algorithms in Civil Engineering, Springer, 2017.

[12] A. Kaveh, Advances in Metaheuristic Algorithms for Optimal Design of Structures, Springer, 2014.

[13] T.K.A. Brekken, A. Yokochi, A. Von Jouanne, Z.Z. Yen, H.M. Hapke, D.A. Halamay, Optimal energy storage sizing and control for wind power applications, Sustain. Energy IEEE Trans. 2 (2011) 69–77.

[14] B.R. Ke, T.T. Ku, Y.L. Ke, C.Y. Chuang, H.Z. Chen, Sizing the battery energy storage system on a university campus with prediction of load and photovoltaic generation, IEEE Trans. Ind. Appl. 52 (2016) 1136–1147.

[15] G. Carpinelli, G. Celli, S. Mocci, F. Mottola, F. Pilo, D. Proto, Optimal integration of distributed energy storage devices in smart grids, IEEE Trans. Smart Grid 4 (2013) 985–995.

[16] M. Ghofrani, A. Arabali, M. Etezadi-Amoli, M.S. Fadali, A framework for optimal placement of energy storage units within a power system with high wind penetration, Sustain. Energy, IEEE Trans. 4 (2013) 434–442.

[17] M. Farsadi, T. Sattarpour, A.Y. Nejadi, Optimal placement and operation of BESS in a distribution network considering the net present value of energy losses cost, Electrical and Electronics Engineering (ELECO), 2015 9th International Conference, (2015), pp. 434–439.

[18] B. Khaki, P. Das, Sizing and Placement of Battery Energy Storage Systems and Wind Turbines by Minimizing Costs and System Losses, arXiv preprint arXiv:1903.12029 (2019).

[19] S. Wen, H. Lan, Q. Fu, C.Y. David, L. Zhang, Economic allocation for energy storage system considering wind power distribution, IEEE Trans. Power Syst. 30 (2015) 644–652.

[20] Q. Zhong, N. Yu, X. Zhang, Y. You, D. Liu, Optimal siting & sizing of battery energy storage system in active distribution network, IEEE PES ISGT Europe 2013, (2013), pp. 1–5.

[21] S.B. Karanki, D. Xu, Optimal capacity and placement of battery energy storage systems for integrating renewable energy sources in distribution system, 2016 National Power Systems Conference (NPSC), (2016), pp. 1–6.

[22] L. Rui, W. Wei, C. Zhe, W. Xuezhi, Optimal planning of energy storage system in active distribution system based on fuzzy multi-objective bi-level optimization, J. Mod. Power Syst. Clean Energy 6 (2018) 342–355.

[23] W. Ling Ai, H. Shareef, A.A. Ibrahim, A. Mohamed, Optimal battery placement in photovoltaic based distributed generation using binary firefly algorithm for voltage rise mitigation,", Power and Energy (PECon), 2014 IEEE International Conference, (2014), pp. 155–158.

[24] L.A. Wong, H. Shareef, A. Mohamed, A.A. Ibrahim, Optimum placement and sizing of battery storage systems to voltage rise mitigation in radial distribution with Pv generators, Aust. J. Basic Appl. Sci. 8 (2014) 41–43.

[25] B. Bahmani-Firouzi, R. Azizipanah-Abarghooee, Optimal sizing of battery energy storage for micro-grid operation management using a new improved bat algorithm, Int. J. Electr. Power Energy Syst. 56 (2014) 42–54.

[26] C.K. Das, O. Bass, G. Kothapalli, T.S. Mahmoud, D. Habibi, Optimal placement of distributed energy storage systems in distribution networks using artificial bee colony algorithm, Appl. Energy 232 (2018) 212–228.

[27] C.K. Nayak, M.R. Nayak, Optimal battery energy storage sizing for grid connected PV system using IHSA, Signal Processing, Communication, Power and Embedded System (SCOPES), 2016 International Conference, (2016), pp. 121–127.

[28] T. Yafei, G. Weiming, Y. Shi, An improved inertia weight firefly optimization algorithm and application, 2012 International Conference on Control Engineering and Communication Technology (ICCECT), (2012), pp. 64–68.

[29] M. Eslami, H. Shareef, M. Khajehzadeh, Optimal design of damping controllers using a new hybrid artificial bee colony algorithm, Int. J. Electr. Power Energy Syst. 52 (2013) 42–54.

[30] A.R. Jordehi, Enhanced leader PSO (ELPSO): a new PSO variant for solving global optimisation problems, Appl. Soft Comput. 26 (2015) 401–417.

[31] S. Mirjalili, A. Lewis, The whale optimization algorithm, Adv. Eng. Softw. 95 (2016) 51–67.

[32] A. Kaveh, M.I. Ghazaan, Enhanced whale optimization algorithm for sizing optimization of skeletal structures, Mech. Based Des. Struct. Mach. 45 (2017) 345–362.

[33] T. Jen-Hao, A network-topology-based three-phase load flow for distribution systems, Proc. Natl. Sci. Counc. ROC(A), (2000), pp. 259–264.

[34] X.S. Yang, Firefly algorithms for multimodal optimization, Stoch. Algorithms: Found. Appl., Proc. 5792 (2009) 169–178.

[35] M.U. Farooq, A. Ahmad, A. Hameed, Opposition-based initialization and a modified pattern for Inertia Weight (IW) in PSO, 2017 IEEE International Conference on INnovations in Intelligent SysTems and Applications (INISTA), (2017), pp. 96–101.