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Optimal Placement and Sizing of Battery Energy Storage System Considering the Duck Curve Phenomenon

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ABSTRACT This paper suggests a method to place and size the battery energy storage system (BESS) optimally to minimise total system losses in a distribution system. Subsequently, the duck curve phenomenon is taken into consideration while determining the location and sizing. The locations and sizing of BESS were optimised using a metaheuristic algorithm with high exploration and exploitation ability which is known as the Whale Optimisation Algorithm (WOA). Meanwhile, the performance of WOA was validated using other algorithms, i.e., Particle Swarm Optimisation and Firefly Algorithm. The results demonstrated the capability of WOA to determine the optimal BESS location and sizing for all cases, with and without considering the duck curve issue for loss reduction. Besides that, the duck curve issue can be mitigated by appropriately optimising the energy storage system (ESS) to reduce the steep ramp of the duck neck and ducktail and to lift the duck belly. In conclusion, although less loss reduction was achieved as a tradeoff to fulfil the constraint on net load ramp limit, the required BESS sizing was much smaller than the case without those constraints and charging operation, which makes this solution economically viable.

INDEX TERMS Battery energy storage, duck curve, optimal size, optimal location.

I. INTRODUCTION

A. MOTIVATION AND INCITEMENT

Power systems are experiencing a change from the conventional passive system to the active system through the integration of distributed generations and energy storage. Such a change is attributed to the need to reduce greenhouse gas emissions, deferral of transmission and distribution system expansion together with the improvement of power system reliability and quality [1]. Having said that, the energy storage systems (ESSs) are recognised for their contribution to the power systems due to the ability to store and release energy according to the power systems' requirement. The ESSs are capable of providing different functions in the power systems such as spinning reserve, peak shaving, generation output smoothing, voltage control, reverse power flow reduction, power losses reduction and uninterruptible power supply. These functions depend on the technical characteristics of the ESSs, including storage capacity, efficiency, cost, lifetime and power rating [2], [3]. Therefore, key aspects like the optimal placement and capacity of ESS should not be neglected to maximize the benefits provided by the ESS [4]. Optimal planning of ESS in the power systems ensures overall reliability and performance while reducing the investment and operation cost [5], [6].

B. LITERATURE REVIEW

Various methods have been proposed in the extant literature on the optimal allocation of ESS in the power systems. For instance, an approach using mixed-integer linear

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programming was proposed in [7] for optimal placement and sizing of the battery energy storage system (BESS) to alleviate the transmission network congestion. The study revealed that the location of the distributed generation in the network did not affect the overall capacity of the BESS, but changed the optimal placement of the BESS. In another study [8], the optimal size of ESS was obtained using an interior point algorithm, particularly the Jacobian analytical gradient to enhance the optimisation outcome by minimising the system operation cost. Furthermore, a scenario-based two-stage method was introduced [9] to attain optimal ESS sizing to minimise the installation and operation cost. The first stage of the work focused on the optimisation of ESS sizing, while the second stage focused on the optimal control of ESS. This two-stage scenario reduction approach was identified to have performed better than that of the conventional clustering method proposed in a separate study [10] as it exploited the structure of the optimisation problem [2]. Apart from the analytical and mathematical optimisation methods, meta-heuristic optimisation methods were also proposed for optimal ESS allocation. The meta-heuristic optimisation methods are popular optimisation approaches compared to other conventional optimisation methods due to its advantages including simplified implementation, reduced complexity of calculation and ability to thoroughly explore the search space [11], [12]. Another method was proposed in [13] to obtain the optimal location of the BESS using genetic algorithm (GA) to reduce the net present value related to system power losses. In addition, a GA based two-level optimisation algorithm was introduced in [14] for optimal BESS allocation to reduce the voltage fluctuation of the power systems. The first stage involved the BESS optimal allocation, followed by the second stage which determined the BESS dispatch curves during the steady-state power flow analysis. On the other hand, a fuzzy particle swarm optimisation was employed in another study [15] for optimal ESS placement and sizing to minimise the power losses in the distribution network. The study also included a detailed study on cost-benefit based on energy arbitrage through the reduction of operation cost to increase the profit of the service provider. Meanwhile, some other studies proposed and employed the firefly algorithm [5], [16], [17] to solve the BESS allocation problem to mitigate the voltage fluctuation in the distribution system. The studies demonstrated that the BESS should be located close to the photovoltaic distributed generation (PVDG) to best mitigate voltage fluctuation. On the other hand, optimal placement and sizing of the BESS were determined using whale optimization algorithm (WOA) to minimise total system losses [18]. Based on case studies with different numbers of photovoltaic (PV) and BESS in the distribution system, it was concluded that the BESS should be placed close to a heavy load for effective total losses reduction.

C. CONTRIBUTION AND PAPER ORGANIZATION

This paper proposes a method to obtain the optimal location and sizing of BESS to minimise total system losses. WOA, a meta-heuristic optimisation method [11], was proposed to perform all the optimisation processes in this work because it has good exploration and exploitation abilities. The main contributions of this study are summarised as follows:

- The novelty of the proposed method is the incorporation of the duck curve mitigation for the optimisation process. Hence, the proposed method is expected to optimally locate and size the BESS to solve the duck curve issue and simultaneously minimise total system losses.
- The modelling of the duck curve is performed according to the Malaysia PVDG generation and load pattern with issues like steep ramp rate and over-generation. BESS's potential in alleviating the duck curve issue is validated through optimal placement and sizing of BESS.
- This work is carried out in a dynamic time-domain, whereby the simulation included the hourly data collected for up to one month (28 days). Hence, the research outcome will be more operationally relevant compared to those reported in previous literature.
- The effectiveness of the proposed approach will be validated with other well-known optimisation algorithms.

As Section I represents the introduction, Section II describes the duck curve phenomenon. Section III presents an overview of the optimisation algorithm, WOA. While Section IV demonstrates the problem formulation of the optimisation work. Section V presents the implementation of the optimisation process including the flowchart, while the results and discussion are presented in Section VI. Finally, Section VII concludes the findings of the study.

II. DUCK CURVE PHENOMENON

In year 2013, the Californian Independent System Operator presented the net load for a spring day, as shown in Fig.1, by considering different levels of PVDG penetration [19]. The net load at a specific point on the network represents the differences between the estimated load and the forecasted electricity produced from different generation sources (including PVDG) connected at (or below) that point. The mathematical link between the generation, load and net load is depicted in (1). Based on Fig. 1, the middle part of the curves forms a belly shape during daylight hours, in which the curves ramp up quickly looking like the neck of a duck. Hence, the chart is known as the 'duck curve'.

$$Net\ load = Estimated\ load - PVDG \tag{1}$$

The sinking 'duck-belly' indicates the risk of over-generation when the net load decreases with the increased PV generation that is estimated for future years (Fig. 1). Generally, the local power generation exceeds the local load when over-generation occurs. This condition can cause the increment of the rotational speed of other generators connected to the distribution system leading to damages. The effects

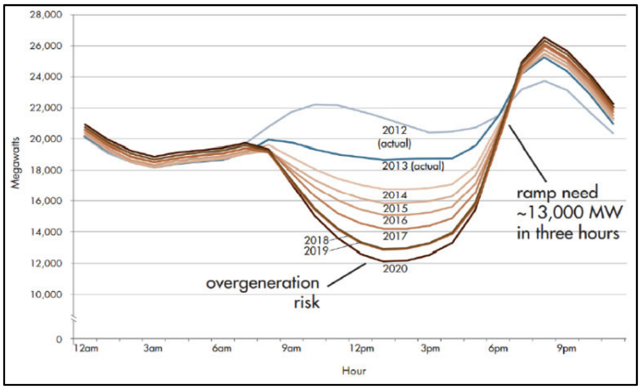

FIGURE 1. The duck curve [19].

can be harmful if the excess power generated by the PV is not regulated by reducing the output of other conventional generators. On the other hand, the 'duck neck' reflects a steep ramp-up in net load as the PV generation decreases due to the reduced solar radiation, combined with a typical evening load increase. Therefore, the utility needs to bring on or shut down more generation sources quickly to fulfil the load, which then significantly affects the efficiency and the daily operation cycles of the generators [20], [21].

Some approaches that have been proposed to solve the duck curve problem include adjusting the orientation of solar panel [22], employing the combination of ESS and demand side's controllable generator [23], besides replacing the conventional thermal generation with the concentrated solar power generation [24]. However, this study proposes the BESS to mitigate the duck curve problem while minimising the total system losses in the distribution network.

III. WHALE OPTIMIZATION ALGORITHM

The optimisation formulation of WOA was modelled based on the hunting pattern of the humpback whales [11]. This algorithm consists of two main elements namely, exploration and exploitation processes.

A. EXPLOITATION PROCESS

Bubble-net feeding is one behaviour of the humpback whales which happens in groups. Hence, this behaviour inspired the mathematical modelling of the exploitation process. The exploitation process can be further divided into two parts which are the shrinking encircling pattern and the spiral position update.

1) SHRINKING ENCIRCLING PATTERN

After detecting the prey, the humpback whales encircle their prey in which each whale is denoted as a search agent. In the current context, however, no prior knowledge of the optimal location (solution) in the search space is available. Hence, the location obtained by the current best search agent will be considered as the target prey. Other search agents will then update their locations according to the location of the current best agent. This pattern can be modelled as:

$$\vec{Y} = \left|\overline{C2} \cdot \overline{X^*}(t) - \vec{X}(t)\right| \tag{2}$$

$$\vec{X}(t+1) = \overline{X^*}(t) - \overline{C1} \cdot \vec{Y} \tag{3}$$

where t denotes the current iteration, $\overline{C1}$ and $\overline{C2}$ are the coefficient vectors, $\overline{X^*}$ is the position vector for the current best solution and $\vec{X}$ is the position vector. The expressions for vectors $\overline{C1}$ and $\overline{C2}$ are indicated as follows:

$$\overline{C1} = 2\vec{c} \cdot \overline{rn} - \vec{c} \tag{4}$$

$$\overline{C2} = 2 \cdot \overline{rn} \tag{5}$$

where $\overline{rn}$ is a random vector within the interval [0,1], while $\vec{c}$ is a vector decreasing linearly from two to zero along with the iteration.

$\overline{C1}$ is a random number within the range $[-c, c]$, where the shrinking encircling pattern is demonstrated through the reduction of the variation for $\overline{C1}$ during the iteration process. When the magnitude of $\overline{C1}$ is less or equal to one, the updated location for the subsequent search agent will fall between the current location of the agent and the location of the current best agent.

2) SPIRAL POSITION UPDATE

The spiral position update equation was modelled based on the spiral movement of humpback whales as illustrated in (6).

$$\vec{X}(t+1) = \overline{Y^t} \cdot e^{bl} \cdot cos(2\pi l) + \overline{X^*}(t) \tag{6}$$

where $\overline{Y^t}$ represents the distance between the whale and the prey at jth iteration with the formula, $\overline{Y^t} = \left|\overline{X^*}(t) - \vec{X}(t)\right|$, while b denotes a logarithmic spiral shape constant and l is a random number between the interval $[-1, 1]$.

However, during the location update process, the same probability is assumed for the whale to employ either the shrinking encircling pattern or the spiral model. The overall equation to update the location of the humpback whales in the process of exploitation is presented as:

$$\vec{X}(t+1) = \begin{cases} \overline{X^*}(t) - \overline{C1} \cdot \vec{Y} & if\ p < 0.5 \\ \overline{Y^t} \cdot e^{bl} \cdot cos(2\pi l) + \overline{X^*}(t) & if\ p \geq 0.5 \end{cases} \tag{7}$$

B. EXPLORATION PROCESS

The humpback whales search for their prey randomly based on their relative locations from other agents during the exploration process. This process employs the same approach based on the variation of $\overline{C1}$ vector. When the value of $\left|\overline{C1}\right|$ is randomly allocated to be larger than 1, the search agents are driven to move away from a reference whale. The updated locations are then decided according to a randomly chosen search agent. The global search process deployed by WOA can be illustrated using the mathematical expressions below:

$$\vec{Y} = \left|\overline{C2} \cdot \overline{X_{rnd}}(t) - \vec{X}(t)\right| \tag{8}$$

$$\vec{X}(t+1) = \overline{X_{rnd}}(t) - \overline{C1} \cdot \vec{Y} \tag{9}$$

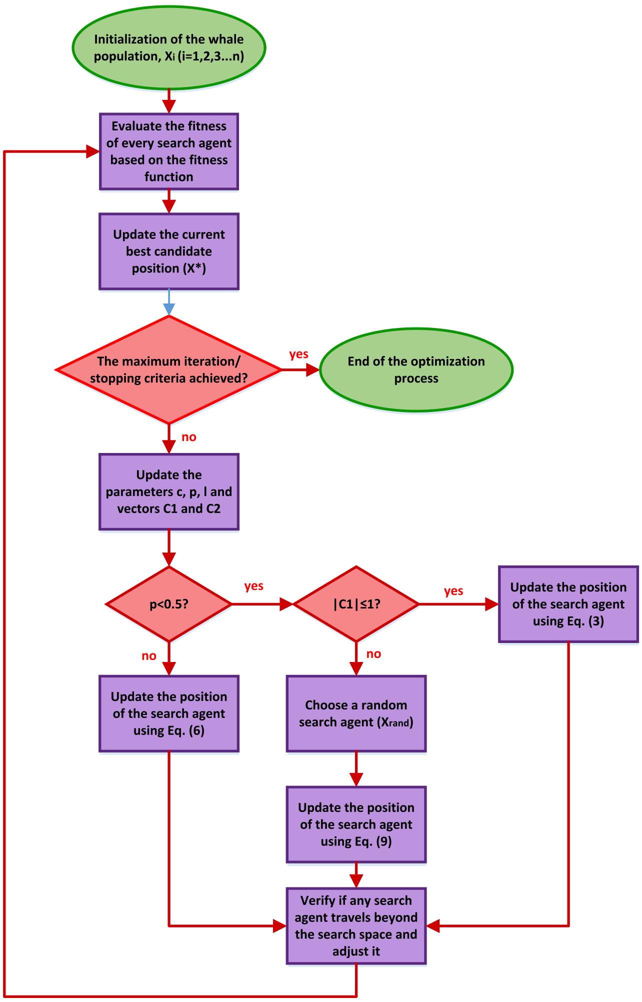

FIGURE 2. The flowchart of WOA.

where $\overline{X_{rnd}}$ denotes a position vector selected randomly from the current population. The concept of WOA is further illustrated in Fig. 2.

IV. FORMULATION OF OPTIMIZATION PROBLEM

The first part of the work involved the formulation of the optimization problem to obtain the optimal BESS placement and sizing to reduce total system losses. While the latter part added the constraint of the duck curve problem to the problem formulation. Then, the outcome and the system performance for both parts were compared.

A. OPTIMAL BESS PLACEMENT AND SIZING FOR TOTAL SYSTEM LOSSES REDUCTION

The placement and sizing of BESS in the distribution system were simultaneously optimised to reduce the total system losses. The objective function, $ObjF$ that was formulated in (10) is bound by the constraints specified in (11) and (12).

$$ObjF = \min \sum_{ith=1}^{N_{branch}} |I_{ith}|^2 R_{ith} \tag{10}$$

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

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

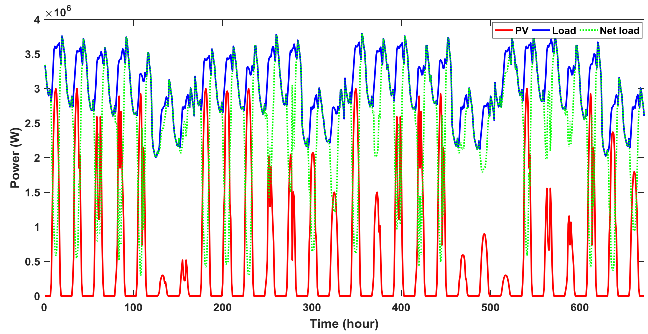

FIGURE 3. Monthly net load curve based on typical PVDG and load profile.

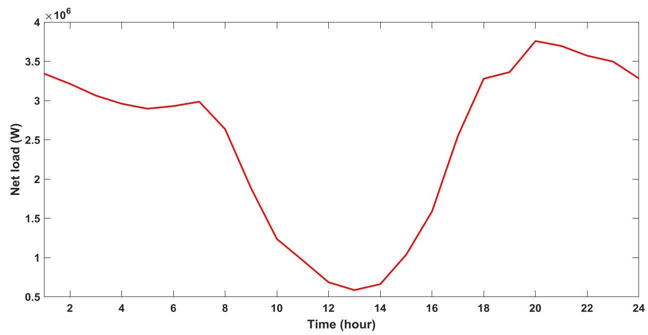

FIGURE 4. Daily net load curve in a microgrid.

where N_{branch} denotes the total number of branches in the system, I_{ith} is the current magnitude of the ith branch, R_{ith} is the resistance of the i-th branch, while P_{BESS} and V_k represent the BESS power and the bus voltage at bus k, respectively.

B. OPTIMAL BESS PLACEMENT AND SIZING TO REDUCE TOTAL SYSTEM LOSSES CONSIDERING DUCK CURVE PHENOMENON

The typical monthly profile of a PVDG [25] adopted in this study includes some fluctuations that were added to represent the intermittent nature of PVDG generation. The PVDG generates power from 7 am until 7 pm. The weekly load profile in Malaysia is created based on the general electricity usage pattern in an urban area. The weekly net load curve is plotted assuming a microgrid with maximum load demand of 3.83 MW and the maximum output of PVDG power of 3 MW (Fig. 3). Fig. 4 illustrates the daily net load pattern. Based on the curve, the shape of a duck starts with a ducktail in the morning, followed by the duck belly in the middle of the curve and the duck neck. Both the duck belly and duck neck denote the over-generation and steep ramping problem as faced by the California Independent System Operator.

The second part of the work considered the duck curve phenomenon in the optimisation process. As mentioned earlier, the major problems posed by the duck curve include the sudden ramp up and ramp down of the net load (the load to be supplied by conventional generator) along with the over-generation due to PVDG in the power systems. Therefore, the ramp rate control is required to solve these issues. This study incorporates BESS to control the ramp rate by absorbing or injecting the necessary amounts of power when the hourly ramp rate exceeds the ramp limit of the conventional generator. Thus, apart from the objective function and constraints stated in (10) – (12), an additional constraint considering the ramp limit of the conventional generator as given in (13) was added to the optimisation process. Hence, the net load equation following the introduction of BESS in the system is demonstrated in (14).

$$ramp_{netload,min} \leq ramp_{net\ load} \leq ramp_{netload,max} \tag{13}$$

$$Netload_{BESS} = Estimated\ load - PVDG\ generation - total\ BESS\ power \tag{14}$$

where $ramp_{netload}$ is the hourly ramp rate of the net load curve, $ramp_{netload,min}$ and $ramp_{netload,max}$ represent the ramp down and ramp up limits of the generator respectively, $Net\ load_{BESS}$ represents the net load with BESS introduced in the power systems. Meanwhile, positive and negative values of total BESS power represent the total BESS power during discharging and charging operation, respectively.

V. IMPLEMENTATION OF WOA FOR BESS APPLICATION

The implementation steps to obtain the optimal location and sizing using WOA are presented as follows:

A. PROCEDURES TO OBTAIN THE OPTIMAL BESS LOCATION USING WOA FOR TOTAL SYSTEM LOSSES REDUCTION

Even though only optimal location is obtained in this step, both location and sizing of BESS for every hour are optimized simultaneously, since assuming a non-optimal BESS sizing will affect the optimal BESS location. However, the final optimal BESS sizing is decided in the following part upon deciding on the optimal location.

a. The first part of optimisation involves the modelling of the BESS and PVDG integrated generic distribution network in Simulink.
b. The optimisation process is initiated from the first hour of the time domain.
c. The whale population (searching agents) representing the possible BESS locations and sizing is initiated.
d. The power flow in Simulink is run with the proposed solutions given by the whale searching agents.
e. The performance is evaluated based on the objective function, *ObjF* after obtaining the data from the power flow.
f. The parameters and the current best positions for the population of whale searching agents are updated.
g. Optimisation process from steps (d) to (f) is repeated until a maximum number of iterations are fulfilled.
h. The optimal location and sizing obtained for the first hour are stored. Steps (c) to (g) are repeated for the subsequent hours.

Fig. 5 provides a more detailed flow of the first part of the optimisation process. The optimal locations for each hour

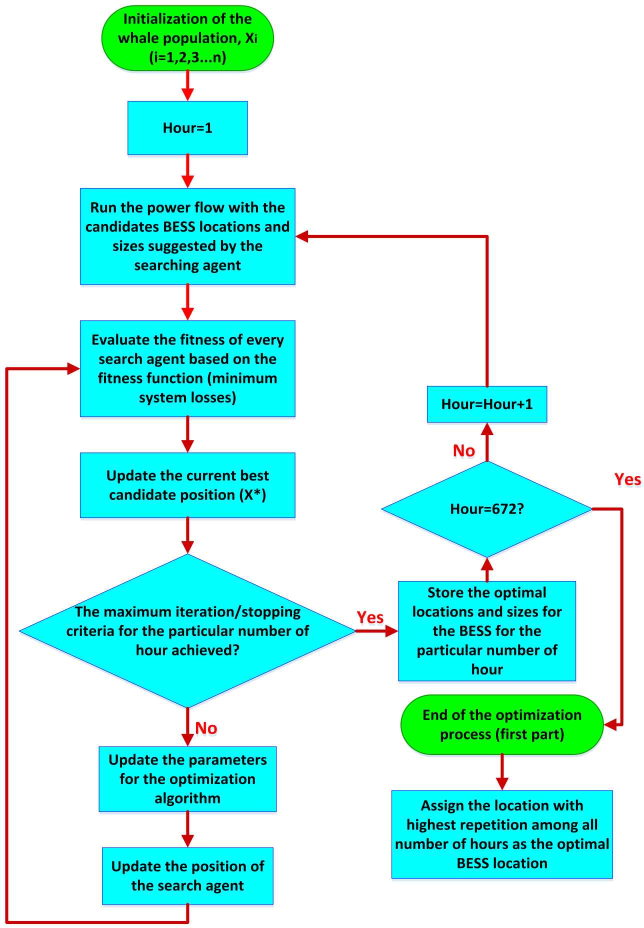

FIGURE 5. Flowchart for the optimal BESS location using WOA (first part).

are compared following the first part of optimisation. The location with the highest repetition throughout all the hours is assigned as the final optimal location. Then, BESS is placed at the final optimal location for the second part of the optimisation process to determine the optimal BESS sizing needed for each hour using the same distribution network. Steps (b) to (h) were repeated (only to optimise the BESS sizing) for the second part of optimisation. The flowchart for the second part of the optimisation process is illustrated in Fig. 6.

B. PROCEDURES TO OBTAIN THE OPTIMAL BESS PLACEMENT AND SIZING USING WOA FOR TOTAL SYSTEM LOSSES REDUCTION AND CONSIDERING DUCK CURVE PROBLEM

To ensure that the ramp rate for each hour does not exceed the ramp limit, the possible location proposed by the search agent is subjected to the optimisation of BESS sizing continuously for each hour. The procedures are as follow:

a. The BESS and PVDG integrated generic distribution network are modelled in Simulink.
b. Whale searching agents representing the possible BESS locations are initialised.

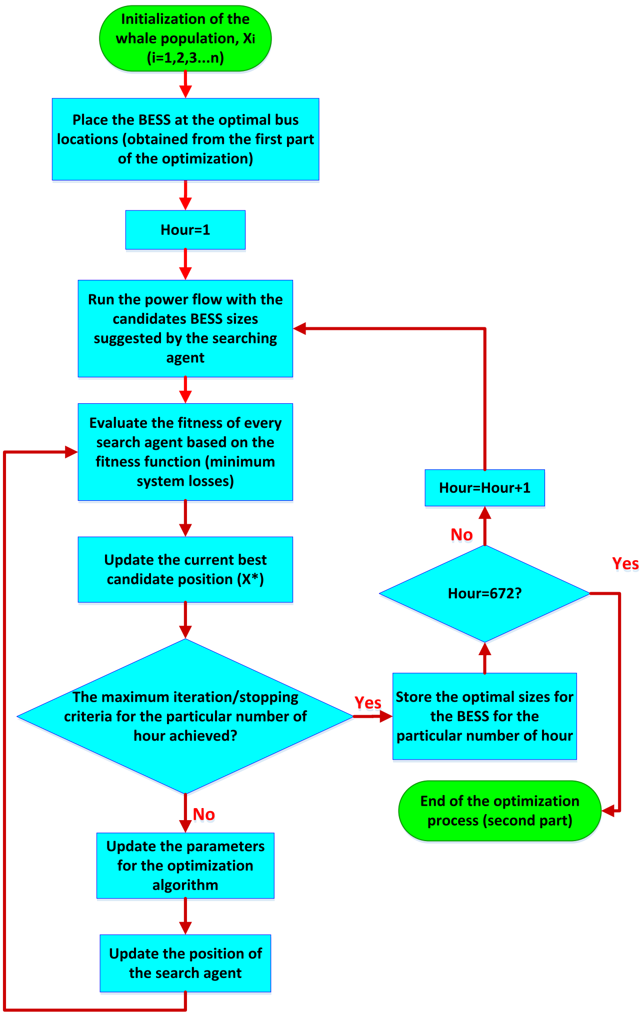

FIGURE 6. **Flowchart for the optimal BESS location using WOA (second part).**

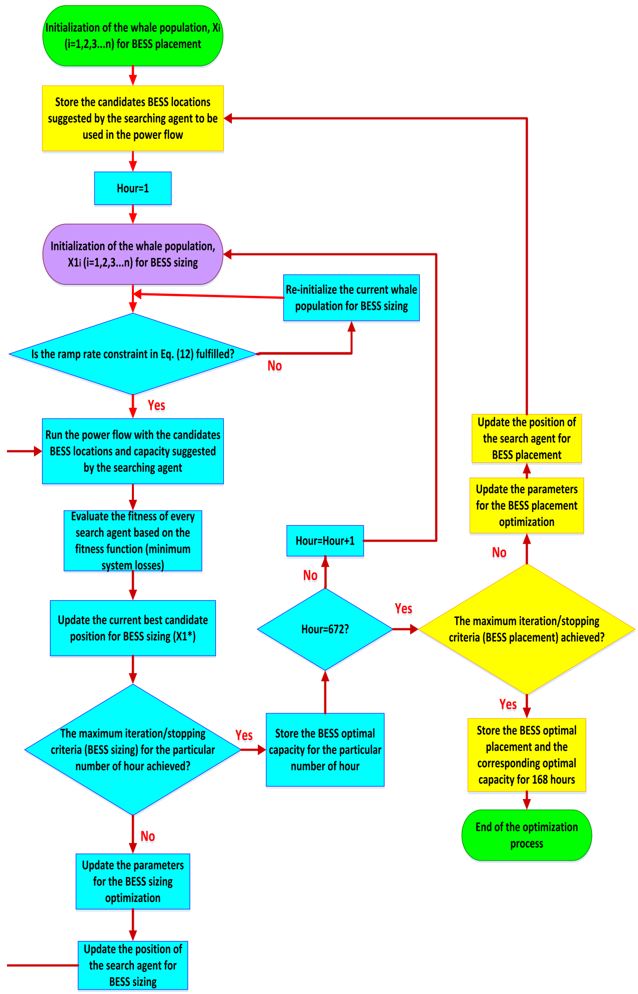

FIGURE 7. **Flowchart for the optimal BESS placement and sizing by considering the duck curve problem.**

c. The suggested/updated BESS locations to be used in the power flow are stored.
d. The BESS sizing optimisation process is initiated from the first hour of the time domain with the suggested locations from step (c).
e. Whale searching agents representing the possible BESS sizing is initialised.
f. The net load ramp rate are examined and maintained within the ramp limit.
g. The power flow is run in Simulink with the proposed locations and sizing provided by the whale searching agents.
h. The performance is evaluated based on the objective function, *ObjF* after obtaining the data from the power flow.
i. The parameters and the current best positions for the population of whale searching agents for BESS sizing are updated.
j. The optimisation process from steps (f) to (i) was repeated until the maximum number of iterations is fulfilled.
k. The suggested optimal sizing with the corresponding BESS locations obtained for step (c) is stored. Steps (e) to (j) were repeated for subsequent hours.
l. Parameters and the current best positions for the population of whale searching agents for BESS locations are updated.
m. The optimisation process from steps (c) to (l) is repeated until a maximum number of iterations is fulfilled.

Fig. 7 illustrates the flowchart of the BESS placement and sizing optimisation processes by considering the duck curve problem.

VI. RESULTS AND DISCUSSION

This section discusses the outcomes for BESS placement and sizing optimisation obtained using WOA. The performance of WOA was compared with that of the simulation results from other algorithms namely particle swarm algorithm (PSO) [26] and firefly algorithm (FA) [27]. The parameter settings of the initial value of the vector $\vec{c}$ and constant b in WOA were set at 2 and 1, respectively. Meanwhile, the cognitive and social

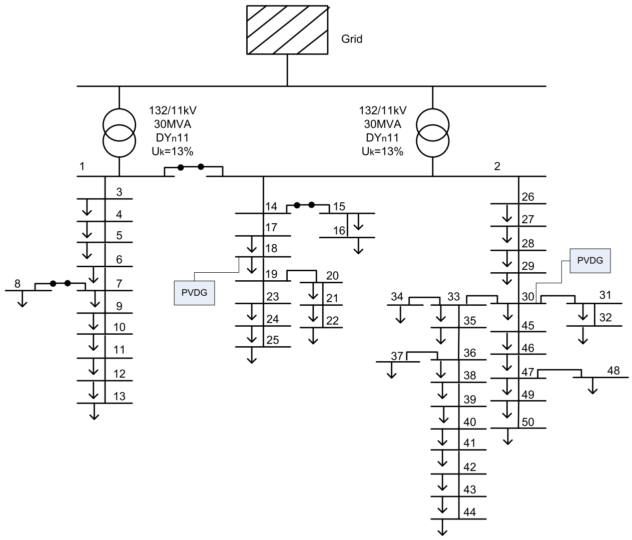

FIGURE 8. Single line diagram of the generic distribution system.

coefficient for PSO was set at 2. As for FA, the random factor α (0.2) decreased with a factor of 0.97 in the subsequent iterations, while the attractiveness βo and light absorption coefficient γ were both set to 1.

On the other hand, Fig. 8 represents the generic distribution system that was employed in this study. The nominal voltage of the distribution system was 11 kV with the load and branch data adapted from [18]. In total, there were 48 buses in the system with a total active and reactive load of 3.83 MW and 1.35 MVAr, correspondingly. Moreover, two PVDGs with a capacity of 1.50 MW each were installed in bus 18 and bus 30. Simulink was used to model the distribution system and to perform the load flow analysis.

A. OPTIMAL BESS PLACEMENT AND SIZING FOR TOTAL SYSTEM LOSSES REDUCTION

The first part of the optimisation process considered four optimization variables (locations and sizing for two BESS), while for the second part considered two optimisation variables (sizing for two BESS). The population capacity and the maximum iteration number for all algorithms (WOA, PSO and FA) were set to 50. The optimisation processes were repeated five times for both parts of the work, where solutions with the least total system losses are acknowledged as the optimal solutions.

1) OPTIMIZATION TO OBTAIN OPTIMAL BESS LOCATIONS FOR EACH HOUR

The optimal placement of BESS 1 and BESS 2 for each hour (total of 672 hours for one month) was decided during the first part of the optimisation. Locations with maximum repetition were then considered as optimal locations for BESS 1 and BESS 2. Table 1 summarises the repetition results.

The result indicated that bus 7 and bus 18 were considered as the optimal bus locations for BESS 1 and BESS 2 (Table 1) based on WOA and PSO for up to 67 and 48-hour repetitions, respectively (from a total of 672 hours). Meanwhile, FA yielded a maximum repetition of only 5 times. Since FA's outcome was not convincing due to poor repeatability, the bus locations obtained here will be excluded from the optimal solution. Once the optimal bus locations were determined, the second part of the optimisation determined the optimal BESS power for each hour.

TABLE 1. BESS bus location with maximum repetition.

Optimization algorithm	Optimal bus location	Number of hours with these bus locations (total 672 hours)
WOA	Bus 7, Bus 18	67
PSO	Bus 7, Bus 18	48
FA	Bus 5, Bus 18	5

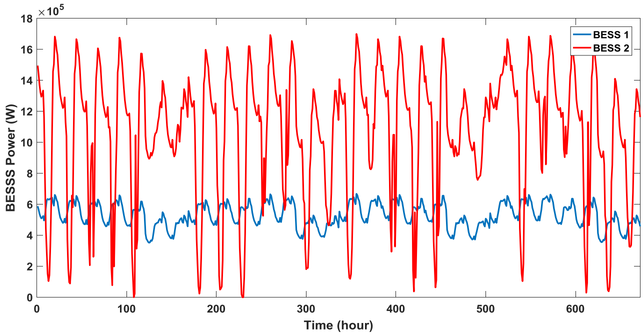

FIGURE 9. Hourly BESS power for total system losses reduction.

2) OPTIMIZATION TO OBTAIN OPTIMAL BESS POWER FOR ALL HOURS

In the second part of the optimisation, BESS 1 and BESS 2 were placed at bus 7 and bus 18 based on the observation from the previous optimisation. The optimal BESS power for each hour was optimised to minimise total system losses as depicted in Fig. 9. BESS 1 at bus 7 supplies less power for loss reduction compared to BESS 2 at bus 18 because the total load at the feeder for bus 18 was much higher than that of bus 7.

The total BESS energy required for all hours to achieve total losses reduction using WOA, PSO and FA is summarized in Table 2. Based on the observation, WOA and PSO possessed similar ability in searching for the optimal solutions, however, the total BESS energy attained using FA for 672 hours was higher than that was attained using WOA and PSO. Table 3 also revealed that FA achieved less total losses reduction compared to WOA and PSO. WOA and PSO lost 42.91% from the original value (without BESS), while FA lost 1.91% more than the former methods.

B. OPTIMAL BESS PLACEMENT AND SIZING FOR TOTAL SYSTEM LOSSES REDUCTION CONSIDERING DUCK CURVE PROBLEM

In this section, the number of dimension involved in the optimization are two-D (locations/ sizing for two BESS) for both

TABLE 2. Total BESS energy required for all hours obtained using WOA, PSO and FA for total system losses reduction.

Optimization algorithm	BESS 1 energy for 672 hours (MWh)	BESS 2 energy for 672 hours (MWh)	Total (MWh)
WOA	357.70	722.27	1079.97
PSO	357.69	722.28	1079.97
FA	368.84	735.96	1104.80

TABLE 3. Total system losses reduction achieved by WOA, PSO and FA for 672 hours.

Optimization algorithm	Total system losses (MWh)	Losses reduction (MWh)
Without BESS	47.77	N/A
WOA	20.50 (42.91% of original loss)	27.27
PSO	20.50 (42.91% of original loss)	27.27
FA	21.41 (44.82% of original loss)	26.36

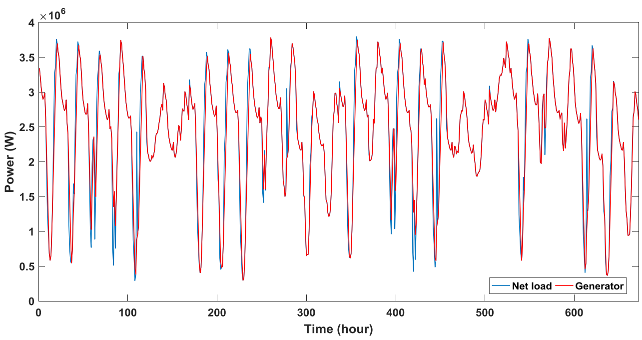

FIGURE 10. Mismatch between net load and actual generator generation for 672 hours.

BESS placement and sizing optimization processes. The population capacity and maximum iterations for all algorithms were set to 30 and 20, respectively. Moreover, the optimisation processes were repeated five times before the solutions with the least total system losses were acknowledged as the optimal solutions.

The power generator used to supply the load in this study was assumed to be a small scale run-of-the-river system with a capacity of 3.83 MW and a ramp rate of 25.6% per hour [28]. The mismatch between the actual generator generation and the net load is illustrated in Fig. 10. Due to the ramp limit of the generator, the actual generation did not meet the net load requirement at a certain time. Thus, two BESS were placed in the distribution to solve the net load mismatch problem and also to minimise the power system losses by considering the constraint given in (12).

On the other hand, Table 4 indicates the total losses reduction achieved by different algorithms after optimisation.

TABLE 4. Total system losses reduction achieved by WOA, PSO and FA for 672 hours considering the duck curve problem.

Optimization algorithm	Total system losses (MWh)	Losses reduction (MWh)
Without BESS	47.77	N/A
WOA	20.59 (43.10% of original loss)	27.18
PSO	20.62 (43.17% of original loss)	27.15
FA	21.11 (44.19% of original loss)	26.66

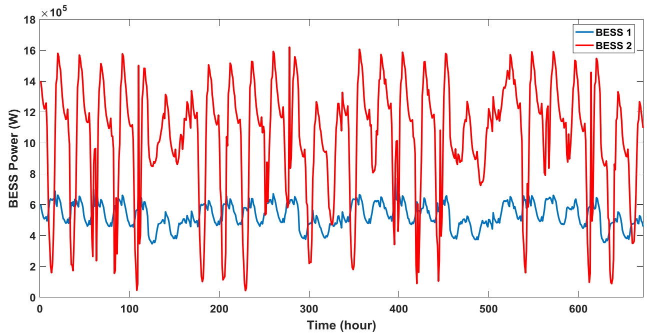

FIGURE 11. Optimal BESS power required for each hour obtained by WOA.

TABLE 5. Optimal locations for BESS 1 and BESS 2 based on WOA, PSO and FA considering duck curve issue.

Optimization algorithm	Optimal bus location
WOA	Bus 7, Bus 19
PSO	Bus 8, Bus 19
FA	Bus 9, Bus 18

Based on the results, WOA yielded the highest losses reduction of 27.18 MWh compared to PSO and FA with losses reduction of 27.15 MWh and 26.66 MWh, respectively. With BESS location and sizing determined using WOA, losses were estimated at 43.10% of their original value, with an improvement in performance by 0.07% and 1.09% for PSO and FA, respectively.

Therefore, it can be concluded that WOA performed better than the other two methods in obtaining the optimal BESS allocation to reduce the total system losses while maintaining the ramp limit of the net load curve. Thus, the optimal allocations obtained by WOA was considered as the optimal solutions for this problem, where the optimal locations of BESS 1 and BESS 2 were assigned as bus 7 and bus 19 (Table 5). Meanwhile, Fig. 11 illustrates the optimal BESS power required for each hour obtained by WOA. Nevertheless, BESS 1 at bus 7 supplied less power for losses reduction compared to BESS 2 at bus 19, since bus 19 is located at a feeder with higher load demand.

The total BESS energy required at all hours for losses reduction considering the duck curve problem using WOA,

TABLE 6. Total BESS energy required for all hours considering the duck curve problem.

Optimization algorithm	BESS 1 energy for 672 hours (MWh)	BESS 2 energy for 672 hours (MWh)	Total (MWh)
WOA	358.44	691.76	1050.20
PSO	358.33	689.07	1047.40 (0.27% lower than WOA)
FA	327.41	724.04	1051.45 (0.12% higher than WOA)

PSO and FA is provided in Table 6. The optimisation outcome of WOA suggested a slightly higher total BESS energy of 1050.20 MWh compared to PSO with 1047.40 MWh, 0.27% lower than of WOA. However, the FA was observed to have performed poorly since it required a higher total BESS energy of 1051.45 MWh, approximately 0.12% higher than WOA.

Referring to Table 2 and Table 6, when the duck curve problem involving the net load ramp rate is considered in the losses reduction optimisation process, the total BESS energy required to solve the optimisation problem was estimated at 1050.20 MWh using WOA. This value was 2.76% lesser than the case for losses reduction only (1079.97 MWh). The reduction in total BESS energy is a result of achieving different BESS optimal locations after the net load ramp rate was added as an optimisation constraint. This new set of optimal locations required less BESS energy to minimise total system losses. However, the reduced total BESS energy required did not significantly influence total system losses, since the losses were only 0.19% greater when Table 3 was compared to Table 4.

Fig. 12 illustrates the comparison of net load curve, where the net load at the base case (power to be supplied by generator when no BESS in the network, blue curve) was reduced (red curve) after BESS were added into the network considering the duck curve problem.

1) ANALYSIS CONSIDERING BESS DAILY CHARGING CAPACITY

It is essential to charge the BESS for several hours to sustain the BESS operation. In this case, BESS was charged during the low net load period from 8 am to 6 pm (10 hours) every day. During this period, all the discharged amount of the same day is divided equally to be charged among the charging hours. However, based on Fig. 13, a large amount of BESS charging energy (to cover all the discharged energy) causes the BESS charging to exceed the generator ramp limit

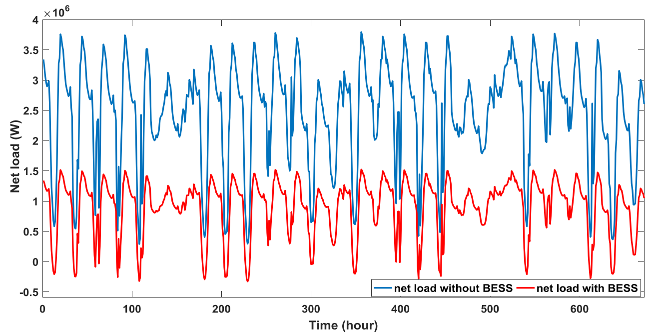

FIGURE 12. Comparison of net load curve for cases with and without BESS.

TABLE 7. Total system losses reduction based on the charging of BESS for 672 hours.

Optimization algorithm	Total system losses (MWh)	Losses reduction (MWh)
Without BESS	47.77	N/A
WOA	46.02 (96.34% of original losses)	1.75
PSO	46.05 (96.40% of original loss)	1.72
FA	46.37 (97.07% of original loss)	1.40

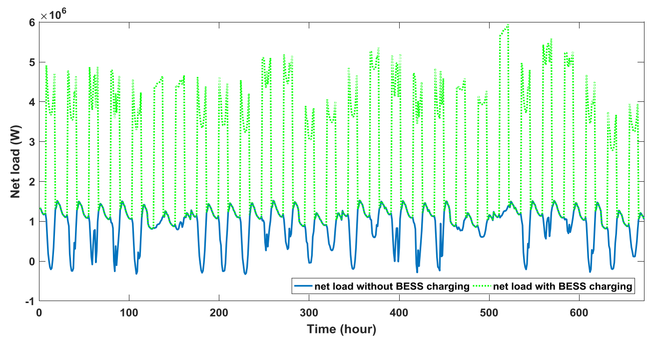

FIGURE 13. Net load curve with BESS charging exceeding the ramp limit.

especially for the first and last hours of the daily charging period. The violation of the net load ramp limit is denoted by the high rising edge of the green dotted curve. To solve the net load ramp limit violation, total BESS discharging power was reduced to 10% of the suggested optimal amount.

The reduced BESS power of the BESS charging and the respective net load curve is illustrated in Fig. 14 and Fig. 15, respectively.

Fig. 16 exhibits the net load curve comparison for only one day to observe the changing of the net load pattern. The observation revealed that with the BESS operation, the net load curve was flattened, whereby a steeper ramp at the ducktail and duck neck was reduced apart from elevating the duck belly. On the other hand, the total losses reduction achieved by each optimisation algorithm considering the duck curve problem is presented in Table 7. Based on Table 8,

TABLE 8. Daily BESS energy obtained using WOA, PSO and FA including BESS discharging and charging operations.

	Optimization algorithm	Total Load demand (MWh)	Total PV generation (MWh)	Total generator generation (MWh)	BESS 1 charge/ discharge (MWh)	BESS 2 charge/ discharge (MWh)
Day 1	WOA	80.38	20.70	59.68	1.38	6.34
	PSO				1.33	6.32
	FA				1.14	6.70
Day 2	WOA	77.91	19.26	58.65	1.10	5.71
	PSO				1.30	5.82
	FA				1.08	5.91
Day 3	WOA	76.12	15.19	60.93	0.92	5.20
	PSO				1.02	5.11
	FA				1.09	6.27
Day 4	WOA	76.27	16.22	60.05	0.97	5.22
	PSO				1.06	5.33
	FA				1.09	5.17
Day 5	WOA	72.70	17.89	54.81	0.88	5.24
	PSO				0.81	4.97
	FA				0.61	5.44
Day 6	WOA	60.87	19.26	41.61	0.85	2.13
	PSO				0.90	2.12
	FA				1.11	2.59
Day 7	WOA	62.08	30.37	31.71	0.63	2.03
	PSO				0.76	2.15
	FA				1.05	2.85
Day 8	WOA	76.36	20.70	55.66	0.97	5.45
	PSO				1.03	5.48
	FA				1.21	6.45
Day 9	WOA	75.57	19.40	56.17	0.91	5.14
	PSO				0.90	5.27
	FA				1.16	5.40
Day 10	WOA	74.88	20.70	54.18	0.96	5.42
	PSO				1.00	5.39
	FA				1.13	5.92
Day 11	WOA	77.03	11.36	65.67	1.03	5.44
	PSO				0.96	5.44
	FA				1.05	6.18
Day 12	WOA	78.40	12.52	65.88	1.11	5.91
	PSO				1.20	5.92
	FA				1.37	6.62
Day 13	WOA	62.08	13.59	48.49	0.65	2.37
	PSO				0.60	2.39
	FA				0.66	2.66
Day 14	WOA	61.70	10.35	51.35	0.57	2.18
	PSO				0.57	2.14
	FA				1.11	2.32
Day 15	WOA	79.47	20.70	58.77	1.26	6.09
	PSO				1.11	6.10
	FA				1.30	7.32
Day 16	WOA	77.91	9.63	68.28	1.08	5.78
	PSO				1.12	5.65
	FA				1.42	5.42

TABLE 8. ***(Continued)*** **Daily BESS energy obtained using WOA, PSO and FA including BESS.**

Day 17	WOA	80.38	15.19	65.19	1.37	6.37
	PSO				1.41	6.46
	FA				1.21	7.39
Day 18	WOA	74.88	16.22	58.66	0.95	5.27
	PSO				0.95	5.20
	FA				1.02	5.64
Day 19	WOA	77.12	17.89	59.23	1.19	5.77
	PSO				1.23	5.85
	FA				1.12	6.04
Day 20	WOA	62.08	3.88	58.20	0.63	2.03
	PSO				0.68	2.18
	FA				0.95	2.62
Day 21	WOA	60.46	6.21	54.25	0.73	1.69
	PSO				0.79	1.76
	FA				1.01	1.51
Day 22	WOA	77.91	2.07	75.84	1.10	5.80
	PSO				1.12	5.75
	FA				1.82	6.37
Day 23	WOA	80.38	19.26	61.12	1.37	6.36
	PSO				1.59	6.22
	FA				1.88	6.95
Day 24	WOA	79.92	9.11	70.81	1.25	6.16
	PSO				1.28	6.18
	FA				1.25	6.43
Day 25	WOA	74.88	6.49	68.39	0.89	5.35
	PSO				0.77	5.51
	FA				1.15	6.34
Day 26	WOA	74.74	17.89	56.85	1.04	5.27
	PSO				0.80	4.94
	FA				1.02	5.48
Day 27	WOA	61.47	15.53	45.94	0.81	2.83
	PSO				0.78	2.84
	FA				1.07	3.50
Day 28	WOA	62.08	12.42	49.66	0.64	2.26
	PSO				0.71	2.34
	FA				0.80	2.81

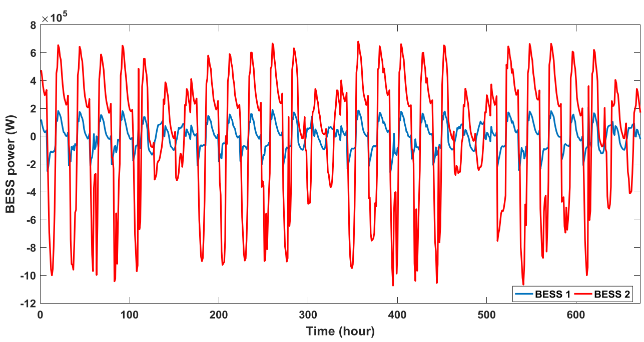

FIGURE 14. **Reduced BESS power for 672 hours with BESS charging.**

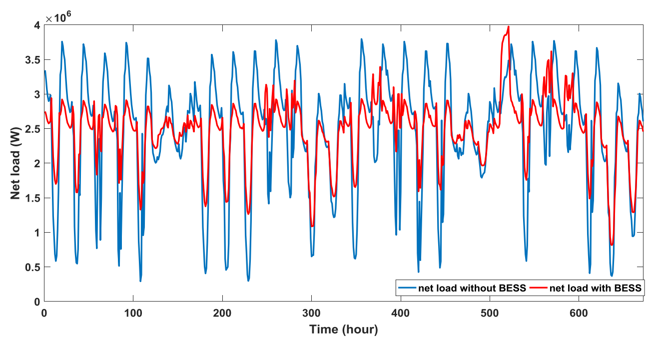

FIGURE 15. **Net load curve comparison for cases with and without BESS with BESS charging.**

the total losses increased when the BESS power for each hour was reduced to fulfil the net load ramp limit. Among all algorithms, the performance of WOA was the best with the highest total losses reduction of 1.75 MWh, followed by PSO and FA with total losses reduction of 1.72 MWh and 1.40 MWh, respectively. The losses recorded with BESS

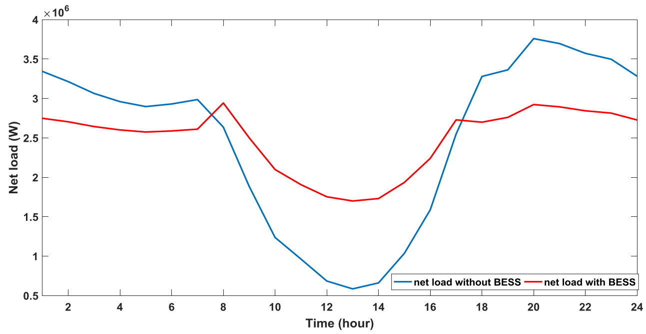

FIGURE 16. Improved duck curve phenomenon with elevated duck belly and reduced ramp at duck neck after BESS were placed in the power system.

location and sizing using WOA that was 96.34% of their original value, is an improvement of approximately 0.06% of PSO and 0.73% of FA. The decrease in the performance of total losses reduction is a tradeoff between the losses reduction and maintenance of the net load ramp limit.

The daily BESS energy for discharging and charging of BESS is summarised in Table 7. For BESS 1, the highest daily sizing required was 1.38 MWh, 1.59 MWh and 1.88 MWh for WOA, PSO and FA, respectively. While for BESS 2, the highest sizing required was 6.37 MWh, 6.46 MWh and 7.39 MWh for WOA, PSO and FA, respectively. WOA yielded the smallest sizing with 13.20% less than PSO and 26.60% less than FA for BESS 1, compared to 1.39% and 13.80% less than PSO and FA, respectively, for BESS 2. In brief, WOA was the best in losses reduction while maintaining the net load ramp limit. Since WOA was deemed the best performer in the optimal sizing problem, the results obtained using WOA was adopted as the optimal solution. According to the BESS minimum and maximum state of charge (SOC) (20% and 80%, respectively) following BESS operation, the optimal sizing for BESS 1 and BESS 2 was estimated at 2.30 MWh and 10.62 MWh, respectively.

VII. CONCLUSION

In conclusion, WOA performed well in achieving the optimal BESS placement and sizing for losses reduction with and without considering the duck curve problem. Although PSO achieved similar optimisation results with WOA to minimise the power losses, it did not perform as well as WOA when the constraints for the duck curve problem were considered. Comparatively, FA performed poorly in achieving the optimal BESS allocation. Therefore, the optimal BESS location and sizing proposed by WOA was acknowledged as the optimal solutions for all studies.

For the first study involving the optimisation for total system losses reduction alone, the BESS was proposed to be placed optimally at bus 7 and bus 18 with total BESS energy of 1079.97 MWh. As for the latter study involving the duck curve problem, the optimal locations were proposed to be at bus 7 and bus 19 with total BESS energy of 1050.20 MWh, which is 2.76% lesser than the former case. Meanwhile, the total losses reduction achieved by both studies were not significantly different with 27.18 MWh and 27.27 MWh, for studies with and without the implementation of the duck curve problem, respectively.

Nevertheless, when BESS daily charging was considered as an effort to maintain BESS operation, the BESS discharging power was required to be reduced up to 90% of the initially proposed amount to maintain the net load ramp limit. Also, the SOC of the BESS was considered in deciding the sizing of the BESS. Finally, BESS are placed optimally at bus 7 and bus 19 with a total-sizing of 12.92 MWh, to minimise the total system losses and solve the duck curve problem. Even though the performance on power losses reduction decreased as a tradeoff to maintain the net load ramp limit, the proposed BESS sizing for the charging and ramp rate constraint was still lesser compared to the case without constraints and charging operation.

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