

Searching Optimal Placement and Operations of Energy Storage Systems Based on Equilibrium Optimizer

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ABSTRACT

Renewable energy integration in Distribution Networks (DN) presents significant opportunities for enhancing stability, reliability, and operational efficiency. To address the challenges that arise from this integration, the use of a Battery Energy Storage System (BESS) within the DN can be very effective. This study explores the optimization of a BESS in order to reduce the system costs and improve the overall DN performance. To facilitate this optimization, the present study proposes two innovative methods: an Equilibrium Optimizer (EO) and a Newton-Raphson-based Optimizer (NRBO). These methods were applied to an IEEE 18-bus distribution network through various case scenarios. The findings demonstrate that an effective BESS integration can significantly bolster DN performance. Furthermore, the EO method was compared with alternative approaches and its effectiveness in solving optimization challenges was validated. This research underscores the potential for advancements in renewable energy integration, paving the way for more efficient and reliable DNs.

Keywords- battery energy storage system optimization; equilibrium optimizer; photovoltaic power; distributed generation; IEEE-18 bus distribution network

I. INTRODUCTION

Modern technology evolution has brought important breakthroughs in many scientific fields. In factories and enterprises, major advancements were experienced. Specifically in the field of energy, new and effective design techniques for Distributed Generation (DG) evolved, which resulted in DG integration into DNs more and more every day. The majority of DG is about Photovoltaic Power Energy (PPE) and Wind Power Energy (WPP). DG technologies bring many benefits, such as energy reduction, electrical quality improvement, and system overload reduction.

However, the existence of PPE and WPP, impacts a DN significantly because of the intermittent nature of wind speed and solar irradiation. This leads to a high risk regarding the imbalance between power supply and load demand [1].

During a day, the power load and supply demands are different and changing. Therefore, a day should be divided into peak, off-peak, and standard peak hours, to optimize system operation and maximize electricity usage. However, the activities and the amount of consumers per time, for living purposes or manufacturing processes, are often different, leading to a significant difference in electricity prices between

peak and off-peak hours, which also causes inefficiency in DN operations.

To solve this problem, the use of energy storage is proposed as an effective way to improve the economic efficiency of the power system. With the rapid advancement of storage technology, various types of storage systems have emerged, including sodium-sulfur batteries [2], lead-acid batteries [3], electrochemical storage [4], lithium-ion batteries [5], etc. Among these, BESS is the most popular due to its independent nature, quick testability, and rapid response capability [6].

BESS plays a vital role in managing the intermittent nature of energy production. It optimizes energy use, participates in arbitrage, supports steady and flexible DN development, provides backup energy during power outages, and reduces the challenges associated with peak demand [7]. BESS can effectively manage the balance between supply and demand by storing surplus energy efficiently and delivering it when needed. As a result, the proper installation and operation of BESS is crucial for maximizing its benefits in the power grid, both economically and technologically. In terms of technique, its benefits include a reduction in power loss, line load, and voltage deviation. Additionally, BESS permits the efficient integration of renewable energy and enhances energy management. From an economic perspective, its major advantages are the decrease in energy deficit costs, minimization of investments, and reductions in both production and annual operating costs.

When it comes to operating DNs, choosing the wrong location or size, can decrease efficiency and lead to waste. In the case of BESS placement, installing and operating BESS, presents a complex, non-linear, and discrete computational challenge. As a result, this area has attracted significant interest from researchers [8]. Several conventional approaches are proposed for solving the problem of BESS placement, including linear programming [9] and mixed-integer programming [10, 11]. These methods are applied globally as a solution to the aforementioned problem and require high computational efficiency. However, such methods may have difficulties in solving large and complex problems, ignoring the non-linearities and multi-dimensional interactions, and making good use of the massive computations that occur intensively.

Recently, some metaheuristic methods have emerged as popular ones in engineering applications due to their easy implementation, high flexibility, and fast convergence. They include solutions based on Genetic Algorithm (GA) [12, 13], Particle Swarm Optimization (PSO) [14], Parallel Implementation of the Particle Swarm Optimizer (PPSO) [15], Coyote Optimization Algorithm (COA) [16], Gravity Search Algorithm (GSA) [17], Whale Optimization Algorithm (WOA) [18], Newton-Raphson Algorithm (NRA) [19] and Mixed Integer Linear Programming (MILP) algorithm [20].

In [12], GA is proposed to enhance the accuracy and efficiency of load forecasting modules in micro-grids. This optimization aims to improve the operation of BESS through economic dispatch and therefore answer to the challenges posed by the intermittent nature of Renewable Energy Sources (RES).

In [15], the proposed energy management system uses a master-slave strategy, formed by the parallel implementation of the Particle Swarm Optimizer (PPSO). Authors in [17], propose an extended inverse model of the BESS inverter based on the Back Propagation (BP) neural network. GSA is also used to search for the initial values of the network parameters during training. Authors in [18] introduce WOA, known for its strong exploration and exploitation capabilities. The goal is to determine BESS's optimal location and size, within the distribution network in order to minimize losses. In [20], the MILP algorithm is implemented to optimize the BESS schedule in order to achieve the lowest operating costs for RES. This optimization takes into consideration factors, such as electricity prices, variable prices for photovoltaic generation, BESS costs, and the goal of maximizing self-consumption.

In the current study, EO [21] is presented as an innovative optimization technique known for its robust exploration and exploitation strategies. The EO is designed to effectively identify the optimal placement and sizing of BESS within a distribution network. Its goal is to minimize the total electricity cost of the system. This study concentrates on the original EO to explore its effectiveness and potential benefits, even though there is an enhanced version of EO available nowadays, which may offer superior optimization outcomes.

In addition to EO, an NRBO [22] is applied. The key contributions are:

- Successful implementation of the EO and NRBO meta-heuristic algorithms to address the problem of BESS placement.
- Assessment of the EO algorithm's effectiveness by comparing it with NRBO and other methods.
- Successful reduction of voltage deviation, power loss minimization, and peak demand decrease within an 18-bus DN.

II. PROBLEM MODELING

The goal when facing the BESS placement problem is to determine the optimal location for the charged and discharged BESS power, in order to minimize electricity costs (EC). The solution must adhere to a set of specified constraints. This objective is formulated by:

$$\text{Minimize EC} = \sum_{i=1}^{24} P_{sb,i} \cdot Pr_i \cdot i; i = 1, \dots, 24 \quad (1)$$

where $P_{sb,i}$ is the power from the supply station at bus 1 of DN, i is the time at each hour, and Pr_i is the hourly energy pricing in \$/kW.

The following section outlines the system constraints that should be considered during BESS installation and operation:

A. Power Balance of DN

The constraint shows a relation between the supply power side, consisting of P_{sb} , and the power of DG (P_{dg}) and the load side, including power loss in DN (P_{pl}), load demand (P_{ld}), and the power of BESS (P_{bess}), using:

$$P_{sb,i} + P_{dg,i} = P_{pl,i} + P_{ld,i} + P_{bess,i} \quad (2)$$

B. Voltage and Current Constraints

These constraints are presented by [23]:

$$V_{a,i}^{\min} \leq V_{a,i} \leq V_{a,i}^{\max}; a = 1, \dots, N \quad (3)$$

$$I_{l,i} \leq I_{l,i}^{\max}; l = 1, \dots, N_l \quad (4)$$

where N is the number of nodes in DN, $V_{a,i}^{\min}$ and $V_{a,i}^{\max}$ are the lower and upper voltage at the a^{th} node, N_l is the number of branches in DN, and $I_{l,i}^{\max}$ is the maximum current running the l^{th} branch.

C. BESS Constraints

The power of BESS as charged and discharged at each hour, must be smaller than the rated power of BESS ($P_{\text{bess,rated}}$):

$$|P_{\text{bess},i}| \leq P_{\text{bess,rated}}; i = 1, \dots, 24 \quad (5)$$

From $P_{\text{bess},i}$, the capacity of BESS is calculated by:

$$C_{\text{bess},i} = C_{\text{bess},i-1} + P_{\text{bess},i} \cdot \mu_c \cdot i; \quad (6)$$

if (Charge) $P_{\text{bess},i} \geq 0$

$$C_{\text{bess},i} = C_{\text{bess},i-1} - \frac{P_{\text{bess},i}}{\mu_{dc}} \cdot i; \quad (7)$$

if (Discharge) $P_{\text{bess},i} < 0$

where μ_c and μ_{dc} are the charging and discharging efficiency of BESS, $C_{\text{bess},i}$ is the capacity of BESS at interval i^{th} , and is limited by its boundaries, as it shown in:

$$C_{\text{bess},i}^{\min} \leq C_{\text{bess},i} \leq C_{\text{bess},i}^{\max}; i = 1, \dots, 24 \quad (8)$$

III. THE EQUILIBRIUM OPTIMIZER

The EO was developed in 2020 based on the concept of mass balance. This method was created by utilizing specific coefficients from the mass balance function, along with key factors associated with the characteristics of such meta-heuristic algorithms. In this algorithm, each solution represents a concentration within an adjustment volume of EO. The adjustment variables in the solutions, take the role of the main parameters for the concentrations of EO. The Fitness Function (FF) for each solution in the meta-heuristic framework, must be determined and used as a primary criterion for comparing the quality of the solutions. The detailed description of EO is given below.

A. Initial Population Generation

With the number of population denoted as N_p , each solution or a concentration is denoted by X_i (i is from 1 to N_p). All solutions in population are randomly initialized by:

$$X_i = X^{\min} + \text{rand.}(X^{\max} - X^{\min}); i = 1, \dots, N_p \quad (9)$$

where X^{\min} and X^{\max} are the lower and upper boundaries of X_i

1) The Update Mechanism

Based on the FF of each solution, initial solutions are sorted randomly to determine the first, second, third, and fourth best solutions (X_{best1} , X_{best2} , X_{best3} and X_{best4}). An average solution is assigned by:

$$X_{\text{aver}} = (X_{\text{best1}} + X_{\text{best2}} + X_{\text{best3}} + X_{\text{best4}})/4 \quad (10)$$

From the old and the five solutions mentioned, the new solution is updated by :

$$X_i^{\text{new}} = X_e + (X_i - X_e) \times N_x + \frac{D_r \times N_x}{\beta} (1 - N_x) \quad (11)$$

where X_e is randomly chosen from the top four and average solutions, X_i is an old one, and β ranges in (0,1). N_x and D_r denote an exponential term and a mass generation rate, given by:

$$N_x = 2 \text{sign}(\bar{I})(e^{-\mu L} - 1) \quad (12)$$

$$D_r = D_{rc} \cdot (X_e - zX_i) \quad (13)$$

D_{rc} is presented by:

$$D_{rc} = \begin{cases} 0.5z_1, & z_2 \geq 0.5 \\ 0, & \text{else} \end{cases} \quad (14)$$

In addition, I ranges in (-0.5,0.5), μ , z , z_1 , and z_2 in (0,1).

2) The Selection Mechanism

This mechanism is applied by comparing the old and new FF (F_i and F_i^{new}) of each solution, to keep the better one. Its formulation is:

$$X_i = \begin{cases} X_i; & \text{if } F_i^{\text{new}} > F_i \\ X_i^{\text{new}}; & \text{if } F_i^{\text{new}} < F_i \\ X_i^{\text{new}}; & \text{if } F_i^{\text{new}} = F_i \end{cases} \quad (15)$$

3) Applying EO to the Problem

To apply the EO algorithm to solve such a problem, the FF is built from the sum of the objective function and penalty term, formulated as:

$$\text{FF} = \text{EC} + K_1 \cdot \sum_{a=1}^N (V_a - V_a^{\text{lim}})^2 + K_2 \cdot \sum_{l=1}^{N_l} (I_l - I_l^{\text{lim}})^2 + K_3 \cdot (C_{\text{bess}} - C_{\text{bess}}^{\text{lim}})^2 \quad (16)$$

where K_1 , K_2 , and K_3 are penalty factors, V_a^{lim} and I_l^{lim} are the limit voltage at a^{th} node and the limit current at l^{th} branch, and $C_{\text{bess}}^{\text{lim}}$ is the limit capacity of BESS.

The implementation steps of EO for the problem are:

- Step 1: Set parameters: N_p and MI.
- Step 2:
 - Produce initial position and power of BESS using (9).
 - Set Current Iteration (CI) to 1.
- Step 3: Run Matpower to calculate EC using (1).
- Step 4: Calculate FF using (16).
- Step 5:
 - Find the best four solutions.
 - Determine the average solution using (10).
- Step 6: Determine N_x , D_r , and D_{rc} using (12-14).
- Step 7: Update new solution using (11).

- Step 8: Compare the old and new solutions to keep the better one using (15).
- Step 9: If $CI=MI$, save the best solution X_{best} and stop the searching procedure. Otherwise, set $CI = CI + 1$ and go back to Step 3.

IV. RESULTS

This section presents the results obtained by EO and NRBO, which were implemented on a DN of 18 buses, to find the position and power of BESS, and thus minimize energy cost. Figure 1 displays the structure of a DN of 18-bus in which DN's data are obtained from [8]. The load demand is plotted in Figure 2 and the power output of DG under the type of PPE, is portrayed in Figure 3. The performances of EO and NRBO are compared to assign the best one. In addition, these results are compared to Harris Hawks Optimizer (HHO), and Artificial Ecosystem Optimization (AEO) [8].

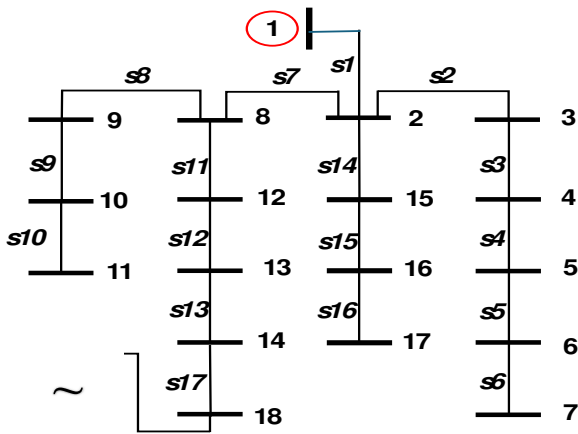


Fig. 1. The structure of DN of 18-bus.

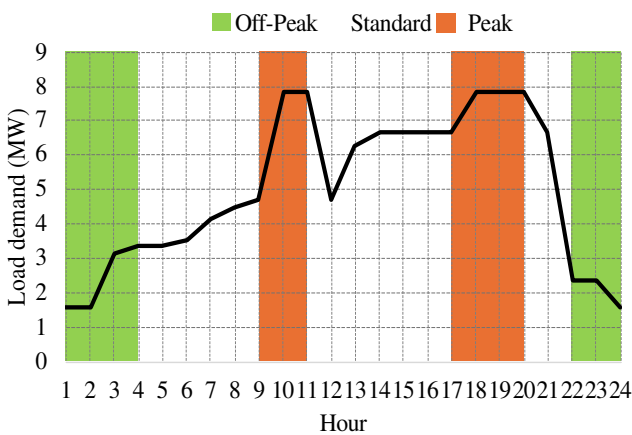


Fig. 2. Load demand for one day.

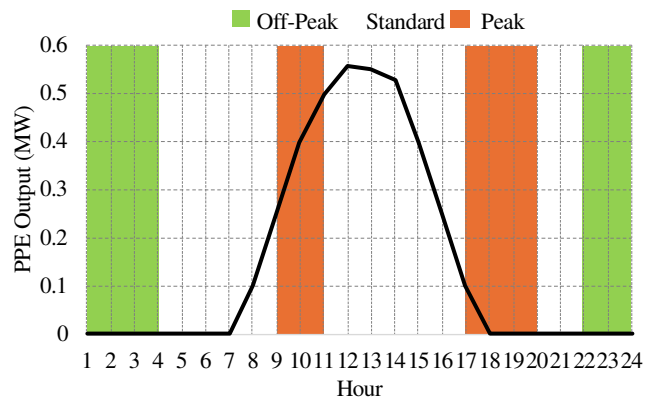


Fig. 3. Power output of PPE for one day.

To assess effectively the operational efficiency of the BESS in conjunction with DG, two key scenarios are explored:

Scenario 1: Optimizing the BESS for the system without DG.

Scenario 2: Optimizing the BESS for the system with DG.

A. Results of Scenario 1

For a fair comparison, the surveys of parameters (N_p and MI) of EO and NRBO are implemented with different values. From N_p and MI , Total Fitness Evaluation (TFE) is calculated by multiplying N_p , MI , and the Number of Evaluation times (NE). It is noted that the NE of EO and NRBO, is 1.

Figures 4 and 5 show the results of over 50 runs of EO and NRBO with different TFEs selected. The EO curve is represented in red and the NRBO curve in blue, with the corresponding TFE of 22,500 providing the best solutions among all other curves. The best EO and NRBO curves are illustrated in Figure 6 to prove their strong ability.

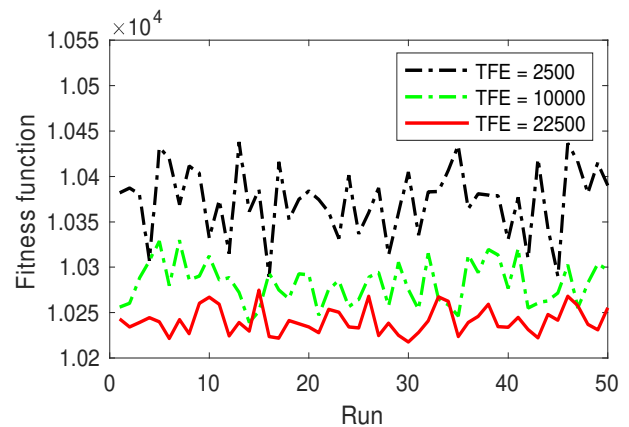


Fig. 4. Results from EO with different TFEs for Scenario 1.

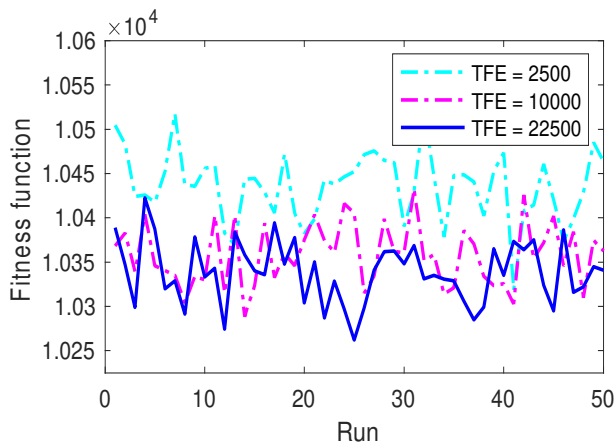


Fig. 5. Results from NRBO with different TFEs for Scenario 1.

Figure 6 depicts the results after 50 runs, with 50 values obtained by EO under those from NRBO. It is proved that the solution-searching ability of EO for Scenario 1 is strong.

Figure 7 shows the charge and discharge power process of BESS found by EO. BESS focuses on discharging power in the 9th, 10th, 18th, 19th, and 20th hour, when the electricity price is the highest corresponding to the peak load. The charged power of BESS concentrates on the off-peak load times.

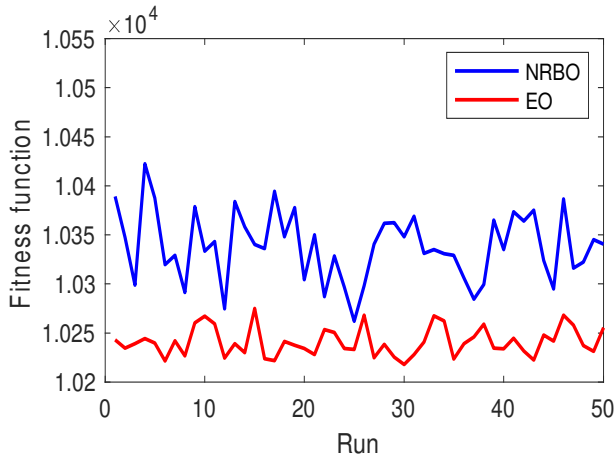


Fig. 6. Result comparison of EO and NRBO with 50 runs for Scenario 1.

BESS presence has a significant impact on the power supply side of DN. As BESS charges power, the supply station curve in red has higher power than the black load curve because of BESS's power plus. On the other hand, the red supply station curve has lower power than the black load curve due to a part of load supplied by BESS's power.

Figure 8 present BESS capacity over one day, where the BESS hourly value is within the minimum and maximum power of 1.0 and 4.5.

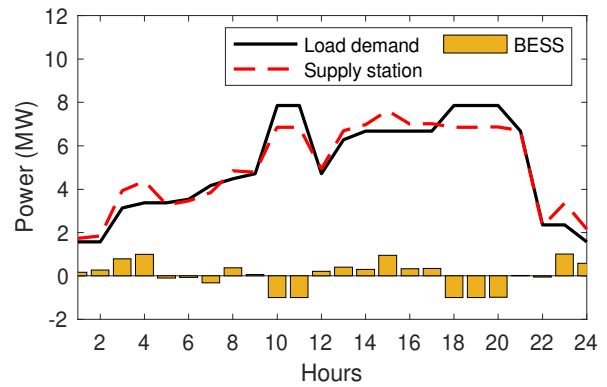


Fig. 7. Charged and discharged power of BESS for Scenario 1.

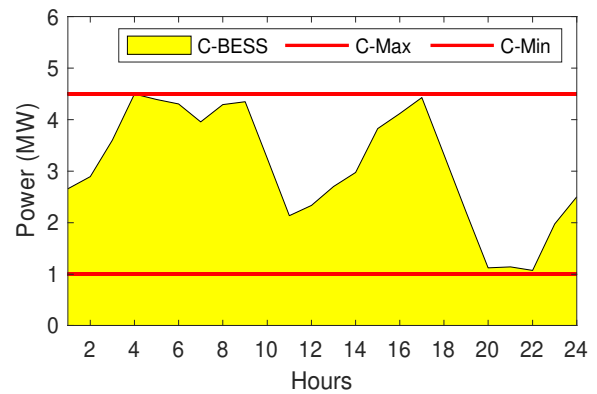


Fig. 8. BESS capacity over one day for Scenario 1.

B. Results of Scenario 2

In this scenario, DG under the type of PPE is located at bus 18, with the power output of DG over one day being depicted in Figure 3. EO and NRBO are applied to the search solutions of the problem. The results after 50 runs, given by EO and NRBO, are plotted in Figure 9, where the powerful performance of EO over NRBO is proved again.

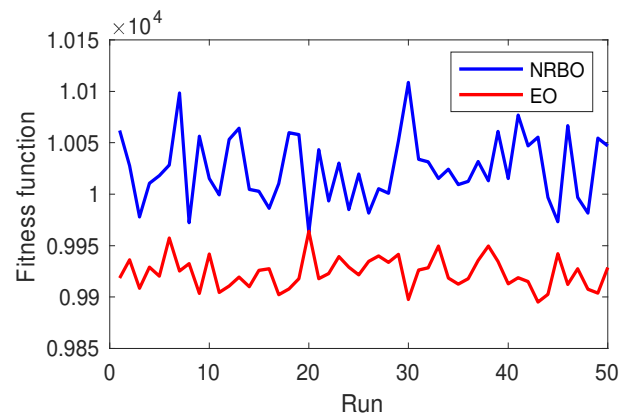


Fig. 9. Result comparison of EO and NRBO with 50 runs for Scenario 2.

Figure 10 presents the process of discharged and charged power of BESS for one day, and Figure 11 displays the capacity of BESS.

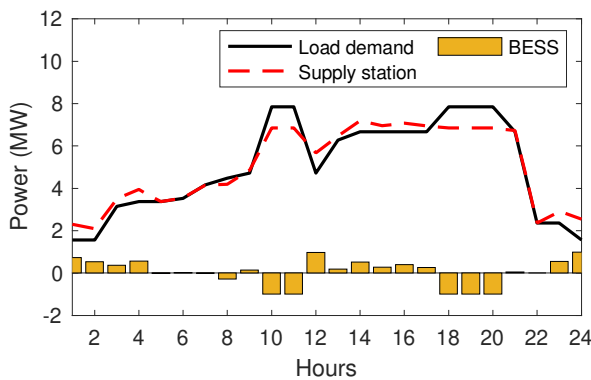


Fig. 10. Charged and discharged power of BESS for Scenario 2.

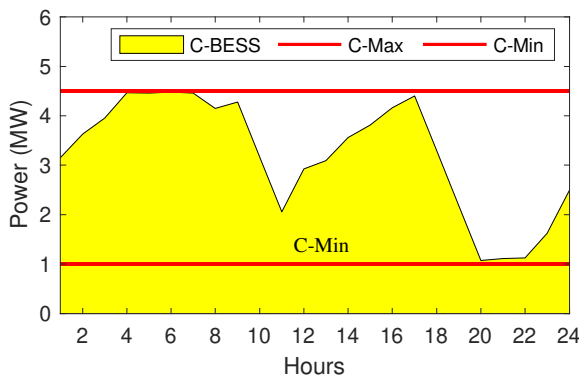


Fig. 11. BESS capacity over one day for Scenario 2.

C. Comparison and Discussion

This section provides the results given by EO and NRBO to reach the position and power of BESS for two Scenarios (without and with DG). The results are reported in Table I.

TABLE I. RESULT COMPARISON OF EO WITH OTHERS

Scenario	Method	Position	Electricity purchasing cost (\$)	Energy loss cost (\$)
Base	-	-	10521.9306	158.8160
Scenario 1	AEO [8]	13	10309.4292	149.6858
	HHO [8]	9	10479.7916	156.9045
	NRBO	13	9943.1730	137.9375
	EO	9	9898.2562	138.6364
Base	-	-	10202.0919	146.7873
Scenario 2	AEO [8]	18	9992.9038	137.0386
	HHO [8]	18	10152.3872	144.2172
	NRBO	6	9962.8039	143.2763
	EO	5	9895.1156	138.6269

For Scenario 1 with BESS being absent, the system has the cost for purchasing electricity of \$ 10521.9306 and the cost for paying energy loss of \$ 158.8160. When BESS is installed, the cost for purchasing electricity and paying energy loss found by EO, are \$ 9898.2562 and \$ 138.6364, respectively. Those from NRBO are \$ 9943.1730 and \$ 137.9375. In terms of electricity cost, the reduction of EO over the base scenario is \$ 632.6744, while that of NRBO over the base scenario is \$ 9921.2424.

Clearly, saving EO cost is significant to NRBO. Regarding energy loss cost, the one of EO is \$ 138.6364, which is better than AEO [8] (\$149.6858), HHO [8] (\$ 156.9045), and slightly higher than NRBO (\$137.9375).

In comparison to other methods, the electricity cost of EO is less than AEO (\$ 410.903) and also less than HHO (\$ 581.2654), as shown in [8]. In terms of BESS's located position, EO and HHO find the same position of bus 9, while NRBO and AEO find bus 13.

For Scenario 2, the electricity cost of EO (\$ 9895.1156) is the smallest, while that of HHO (\$ 10152.3872) is the biggest. Considering the energy loss cost, the value from EO is \$ 138.6269. AEO is \$137.0386, HHO is \$144.2172 and NRBO is \$143.2763. The BESS's position found by EO is bus 5, which is different to those acquired from other methods.

From the result analysis for the two Scenarios, it can be concluded that EO is an effective method for the BESS placement problem.

V. CONCLUSION

This study discusses the optimal installation and operation of Battery Energy Storage System (BESS) within the IEEE 18-node Distribution Networks (DNs), including Distributed Generation (DG). The goal is to minimize overall system costs while improving network performance. The analysis is divided into two scenarios: one with DG and the other without DG. Equilibrium Optimizer (EO) and Newton-Raphson-based Optimizer (NRBO) methods are employed to address the problem of placing BESS.

When comparing the results obtained, it is shown that the EO algorithm is the most effective one in enhancing system performance in all aspects. The EO algorithm also showed its capability in tackling complex optimization challenges in DN.

Additionally, BESS integration into the distribution network demonstrates significant improvements in system performance in terms of reducing power loss and peak demand.

Although the solutions found by the optimization algorithm always satisfy the constraints, the execution time is very long for each run of the method. This is a real challenge when the test system is a large-scale one. In the future, the optimal determination of DG location and capacity in the BESS problem, will be applied to reduce losses and electricity purchasing costs.

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