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A simulation-metaheuristic approach for finding the optimal allocation of the battery energy storage system problem in distribution networks

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ABSTRACT

This paper proposes a simulation study to solve the optimal allocation of the Battery Energy Storage System (BESS) problem in distribution networks. The effect of BESS's installation in the selected distribution networks is surveyed for a 24-hour period, where time-of-use electricity charges are divided into three periods: standard, peak, and off-peak hours. This study will use Teaching Learning-Based Optimization (TLBO) as the main optimizer for the problem simulation. The objective function is to minimize the combined cost of purchasing electricity and energy loss, where the optimal location of BESS and its operated power at each hour are treated as the control variables to be optimized. Two distribution systems are utilized, viz. 18-node and 33-node systems are considered to assess the performance of TLBO in solving the mentioned problem, where a comparison with other recent metaheuristic algorithms also have been conducted. The study's findings demonstrated the promising results of TLBO in terms of minimizing the energy cost and significantly reducing the peak loads during peak hours in the 24 h. The simulations also show that TLBO can be used as an effective tool for position and power of BESS optimization solution, where for the 18-node system, there is about 3.7 % cost reduction and for the 33-node system, about 12% cost saving for power purchased for the surveyed 24-h period.

1. Introduction

The electrical power infrastructures from generation to the distribution are facing significant impediment due to the rapid growth of the technological advancements, penetration of renewable energy resources into existing networks, decarbonization initiatives, enforcement towards zero net greenhouse gas emissions, as well as breaking the interdependence of economic development with the consumption of natural resources. The world is now approaching toward carbon emission reduction along with the promotion of clean energy development a top priority. Among the efforts to cater these issues is by introducing the Battery Energy Storage System (BESS) which can be applied to the Electrical Distribution Systems (EDS) to increase the effectiveness and elevate the reliability. One of the important yet complex tasks that attract the researchers is the determination of optimal sizing of an effective BESS system, which requires considering various factors such as optimal charging and discharging, cost efficiency, capacity limits, power balance, carbon emission, power oscillation and ageing [1].

To date, there are quite numerous studies proposed in the literature to solve the optimal allocation of BESS, especially utilizing the metaheuristic approaches. Metaheuristic approaches have become a popular solution for solving optimization problems across many fields such as in engineering [2–8], computer science [9–13], community detection in social networks [14,15], ecology [16], steel industry [17], integrated energy system (IES) [18], and even in biology and medicine [19,20] and many more. The implementation of Whale Optimization Algorithm (WOA) into BESS optimal placing and sizing has been proposed in [21], and the improved version of Nondominated Sorting Genetic Algorithm-II (NSGA-II) for BESS placement and capacity selection has been proposed in [22]. Ref. [23] proposed the determination of the best allotment of the Interline-Photovoltaic-Battery Energy Storage System (I-PV-BESS) system in islanded electrical distribution system using Coyote Optimization Algorithm (COA). Cuckoo Search Algorithm for optimal placement of the BESS problem also has been proposed in [24]. Recent work on hybrid Arithmetic Optimization Algorithm and Sine Cosine Algorithm (AOA-SCA) for BESS integration in distribution networks for loss minimization has been discussed in [25].

From the mentioned approaches, it can be seen that the usage of metaheuristic algorithms still can be explored especially in solving the BESS allocation problem or in energy storage problems in general. Thus, this paper takes the initiative to propose the optimal allocation

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of BESS and its operation for 24-h period using Teaching Learning Based Optimization (TLBO) approach. In this paper, the objective is to minimize the combine cost of purchasing electricity and energy loss charged by the utility so that the electricity usage during peak-hours can be reduced. TLBO is often considered as an optimizer due to its simplicity or sometime known as parameter free algorithm, as it requires tuning only two parameters: the population size and the maximum number of iterations. This simplicity is a key advantage of TLBO over other metaheuristic algorithms for solving optimization problems. However, it is important to note that TLBO's effectiveness may vary depending on the specific problem being solved, as it may not perform well for optimization problems that are subject to the No Free Lunch (NFL) theorem. To date, there are numerous research that have been proposed that use TLBO as a choice of solution such as in Optimal Power Flow (OPF) problems that have been presented in [26], TLBO as an optimizer of Enhanced Neural Network (ENN) in Terminal voltage prediction of Li-Ion batteries [27], optimal sizing of a grid-connected photovoltaic (PV)/battery system [28], optimization of in-core fuel loading pattern of material test reactor [29], modified version of TLBO for optimal design of an electric vehicle charging station [30], economic dispatch of power generation [31] as well as in energy management system (EMS) [32]. Similar work in energy storage using TLBO that emphasize on the reliability improvement of Radial Distribution System (RDS) has been proposed in [33]. It can be observed that the TLBO is still a viable option for tackling optimization challenges owing to its simplicity and efficacy.

The rest of the paper is organized as follows: Section 2 discusses the problem formulation. A brief description of the implementation of TLBO for the stated problem is presented in Section 3 followed by the results and discussion in Section 4. Section 5 states the conclusion of the paper.

2. Problem formulation

One of the effective solutions for minimizing the costs especially during the peak hours with high demand and high prices charged by the utility is the proper BESS's installation in the EDS. In this paper, the concept is simple where the BESS supplies the EDS at peak hours while at off-peak hours, it will store the energy. This approach led to higher efficiency in the operation of the EDS as well as economical. Apart from that, the proper determination of suitable location of BESS also serves an important role in reducing the total power loss and cost of the EDS operation. Thus, the objective function (*OF*) for the optimization problem is to minimize the combine cost of power purchased and loss cost for the 24-h period, as follows [24]:

$$OF(L_{BESS}, x_i) = \sum_{i=1}^{24} \left(P_{x,i} + P_{Loss,i}\right) \cdot Cost_i \tag{1}$$

where $P_{x,i}$, $P_{Loss,i}$ and $Cost_i$ are the real power purchased from the utility, total power loss for the system and the power price at ith interval, respectively. L_{BESS} represents the location of BESS which also included as the control variables to be optimized, x that and can be expressed as follows:

$$x = \left[L_{BESS}, x_1, \ldots, x_{24}\right] \tag{2}$$

where the x_1 to x_{24} are the percentage of BESS from the rated power for each interval of 24-h. The optimal solution obtained in (2) must fulfill the equality constraint which is the storage capacity in the surveyed period of 24-h must equal to zero so that the BESS can be fully operated for the next planning day. On the other hand, the storage capacity of BESS, viz. $BESS_{cap}$ can be calculated from the equality constraint that has been identified, where the following expressions are used to depict the situation:

$$\sum_{i=1}^{24} P_{BESS,i} = 0 \tag{3}$$

$$BESS_{cap} = \max[cumsum(x_1, \ldots, x_{24})] \tag{4}$$

where $P_{BESS,i}$ is the operating power of BESS in the ith hour and *cumsum* is the sequence function to calculate partial sums of the vector $[x_1,\ldots, x_{24}]$ [24]. In this paper, the capacity of the BESS is determined based on the test system which will be revealed in the next section. On the other hand, for the inequality constraints, the solution obtained must not violate the maximum and minimum of the voltage magnitude at each bus or node in the EDS, which is defined follows:

$$V_k^{min} \le V_k \le V_k^{max} \quad k = 1, \ldots, N \tag{5}$$

where V_k *and* N are the voltage magnitude at each bus and the number of nodes in the system, respectively. In order to ensure the results obtained are not violating the mentioned constraints, the penalty function, (PF) is enforced in Eq. (1), as follows:

$$Obj = OF + PF\left[max\left(0.9 - V_k^{min}, 0\right) + max\left(V_k^{max} - 1.1, 0\right) + \left|\sum_{i=1}^{24} P_{BESS,i}\right|\right] \tag{6}$$

where *PF* is set to 1000. In this study, PF is used to incorporate all the mentioned constraints into the objective function, *OF* allowing the optimization algorithm to find a feasible solution that satisfies the constraints. From the experiments that have been conducted, we found that the value of 1000 provided a good balance between imposing a strong penalty on infeasible solutions and preserving the overall performance of the objective function. In addition, to ensure accurate results obtained and no violation of the constraints, the power flow solution program namely MATPOWER [34] is used to include the required results into the objective function.

3. Application of Teaching Learning Based Optimization (TLBO) into optimal allocation of BESS

TLBO is inspired by the analogy of teaching and learning between teacher and students in the classroom that has been proposed by [35,36]. It can be classified as one of the well-known algorithms from the human-based group that does not require any tuning parameter apart from the number of populations and maximum iterations. In TLBO, two phases are proposed namely teacher and student phases. During each phase, new solutions are generated and evaluated. The best solution is then selected using a greedy selection method. This method selects the solution with the best performance so far, whether it was created in the teacher or student phase.

The teacher phase in the TLBO algorithm is a critical component of the optimization process. During this phase, the teacher tries to improve the performance of the population by generating new solutions that are more promising than the current best solution. The teacher's behavior is influenced by a teaching factor (*TF*), which is a key parameter in the algorithm. This factor controls the teacher's impact on the population and is updated at every iteration based on the performance of the population. The value *TF* is influenced by the mean student in the population. The mean student is a representation of the average performance of the population. If the mean student is high, it implies that the population is performing well, and the teacher's influence should be reduced. On the other hand, if the mean student is low, it implies that the population is not performing well, and the teacher's influence should be increased. The operation of TLBO with the equations used are presented in pseudo code shown in Fig. 1 [35,36].

The implementation of TLBO into the optimal allocation of BESS is depicted in Fig. 2. The proposed TLBO algorithm requires several inputs to be set before the optimization process can begin. These include the number of running simulations, the number of populations, and the maximum number of iterations. Additionally, the function

Initialize the population X_i and calculate the fitness of the population
Identify the best result so far among the population, X_{best}
while *(l < Maximum iterations)*
  Calculate the mean of the population, Mean
  Teacher phase: select the teacher, X_T (current best solution)
  for *each population*
    Generate TF randomly between 1 & 2
    Generate new solution: $X_{new} = X_i + rand * [X_T - TF * M]$ (7)
    Check the new solution within boundaries
    Calculate the objective function of new solution
    if *X_{new} better than X_i*
      $Xi = X_{new}$
      if *X_{new} better than X_{best}*
        $X_{best} = X_{new}$
      end if
    end if
  end for
  Learner phase
  for *each population*
    Randomly select learner, X_j where $X_j \neq X_i$
    if *cost of X_i better than X_j*
      Generate new solution: $X_{i,new} = X_i + rand * [X_i - X_j]$ (8)
    else
      Generate new solution: $X_{i,new} = X_i + rand * [X_j - X_i]$ (9)
    end if
    Check the new solution within boundaries
    Calculate the objective function of new solution
    if *$X_{i,new}$ better than X_i*
      $X_i = X_{i,new}$
      if *$X_{i,new}$ better than X_{best}*
        $X_{best} = X_{i,new}$
      end if
    end if
  end for
  $l=l+1$
end while
Return X_{best}

Fig. 1. Pseudo code of TLBO.

details such as the lower and upper bounds and the dimensions of the problem must be identified. The load flow study is then executed for each hour for each population as an evaluation process to obtain the objective function results. During the optimization process, TLBO generates new solutions for the control variables within the boundaries. The best solution found so far is recorded, and the optimization process continues until the maximum iteration and simulation run settings are reached. Once completed, the best solution from the simulation run is identified, and the performances of the TLBO are compared to other selected metaheuristic algorithms, which will be presented in the next section.

By setting the necessary inputs and conducting a thorough evaluation process, the proposed TLBO algorithm is able to optimize the control variables to achieve the best possible outcome within the specified boundaries. Its ability to generate new solutions and record the best found so far ensures that the optimization process is efficient and effective. The comparison with other metaheuristic algorithms provides a useful benchmark for evaluating the performance of the TLBO algorithm in solving the optimization problems.

4. Results and discussion

All simulations for this study are executed using MATLAB 2019b on a MacBook Pro Processor 2.40 GHz Quad-Core Intel Core i5, 8 GB RAM. To assess the performance of TLBO in optimal allocation and operating of BESS, two test systems are used, viz. 18-node and 33-node systems. For both cases, 25 control variables are to be optimized consist of the components that have been discussed in the previous section. The assumptions for both cases are made referred to [24,37–39], where (1) three categories of loads are considered at each node of the system: residential, commercial, and industrial loads; and (2) the load at each node is treated as the average load per hour. The load flow solution is executed using the MATPOWER toolbox developed by [34] to obtain the information of converged power flow such as voltage magnitude at each bus as well as total power loss at each hour for a 24-h period. The performances of the proposed TLBO are compared with other metaheuristic algorithms namely Barnacles Mating Optimizer (BMO) [40–42], Salp Swarm Algorithm (SSA) [43], Gradient-Based Optimizer (GBO) [44], Particle Swarm Optimization (PSO) [45] as well as Cuckoo Search Algorithm (CSA) that has been proposed in [24]. For fair comparison, all algorithms will be set the similar number of population and maximum number of iterations, which are 30 and 100, respectively. The corresponding prices for electricity are referred to [24].

4.1. The 18-node system

This distribution system consists of 18-node where node 1 is treated as a substation with the voltage level of the whole system is 10 kV.

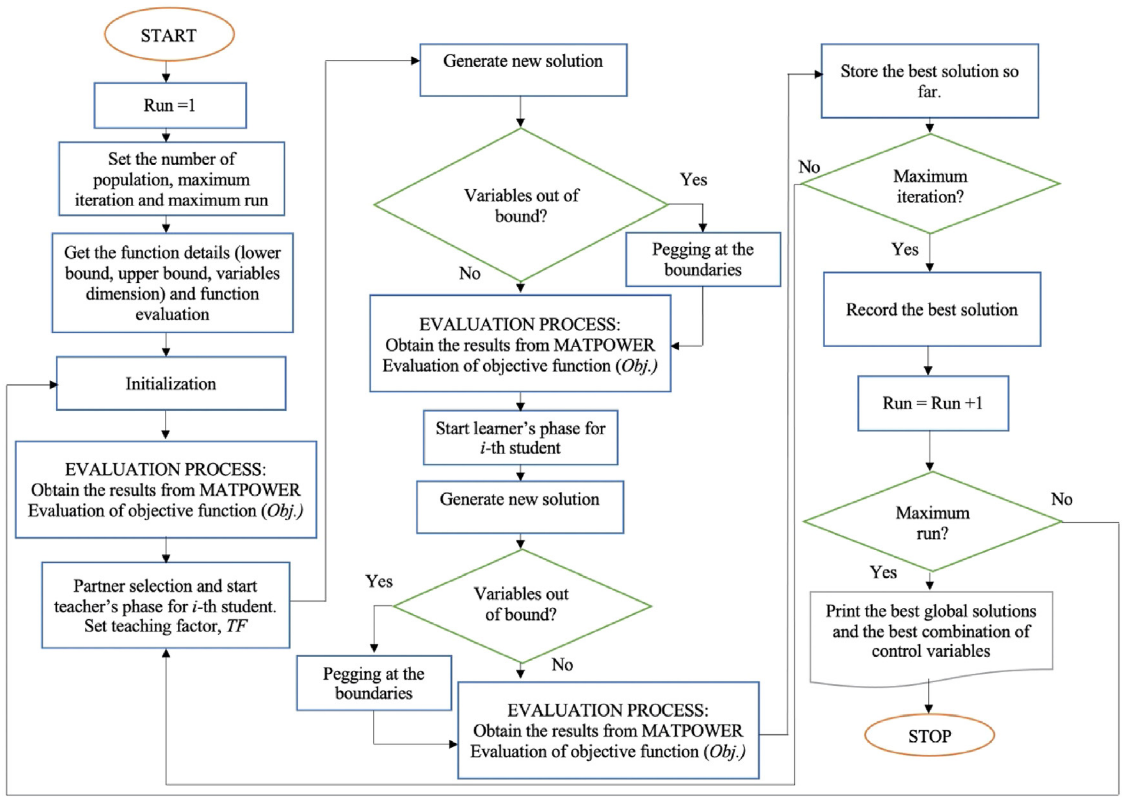

Fig. 2. TLBO for optimal allocation of BESS for 24-h period.

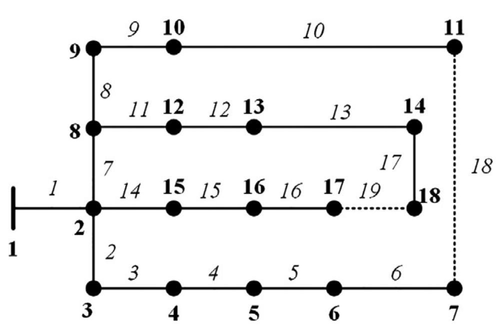

Fig. 3. Single line diagram of the 18-node system [24].

The single-line diagram for this system is visualized in Fig. 3. This system consists of 19 branches, 17 sectionalizing switches with 2 tie switches represented in dot lines. The peak load at each nodes and the line parameters are based on [37]. The simplified load profile for this system for the surveyed 24-h period is shown in Fig. 4 and the detailed load data for real and reactive power is tabulated in Table A.1. It is evident that the peak hours occur at hours 10.00–11.00 and 18.00–20.00, where the peak power is recorded at 7850 kW for these hours. The minimum power is at 1570 kW which is occurred at hours 0.00–01.00, 01.00–02.00 and 23.00–24.00.

From the simulation, the optimal location for installing the BESS obtained by TLBO is at node 18 where the optimal operating power of BESS in percentage for the 24-h are tabulated in Table 1. From the table, it can be confirmed that the cumulative power for 24-h period is equal to zero, as follows: [100 200 100 200 100 157 57 157 169 69 −31 68 168 74 164 88 188 88 −12 −112 −12 −112 −12 0] so that the BESS can effectively operate for the next day. It also can be noticed that the operating power of BESS (%) at each interval hour does not violate the rated limits that have been set. From this result also can be noted that the maximum value in the cumulative sum array for this system is 200% which means that the capacity of the BESS obtained by TLBO is 2 MWh which has been discussed in Eq. (4). The comparison results obtained by other algorithms also have been included in this table where TLBO outperformed others in terms of obtaining the minimum cost of objective function which is highlighted in bold. It is worth to highlight that the results obtained by CSA are taken directly from [24] where the objective function is recalculated for confirmation of using the similar set-up for all algorithms under studied.

The optimal results of BESS's power for this case study for the 24-h period are depicted in Fig. 5, where it can be confirmed that at each interval, the operating power of BESS does not exceed the rated limits of 2 MWh that has been set up for all simulations. This result ensures that the BESS can operate for the next day plan, which are conformed with the results presented in Table 1 for TLBO. The impact of BESS's power contribution to the original load profiles before and after BESS's installation at node 18 is visualized in Fig. 6. From this figure, it can be noticed that during peak hours especially at hours 10th, 11th, 18th, 19th, and 20th, the power is totally supplied by the BESS (fully discharge) which is 100% of its rated power. This will reduce the cost incurred for power purchasing from the utility. It also can be seen that the BESS is fully charged during the standard-hour and off-peak hour, where the detail charged distributions shown at the 1st, 2nd, 4th, 6th, 8th, and 9th intervals with 100%, 100%, 100%, 57%, 100% and 12% from its rate power, respectively. Therefore, it can be concluded that the appropriate installation of BESS into the optimal node of the distribution system has contributed significantly to minimize the peak of the load profiles during peak hours.

Further analysis of the statistical results from 30 run of simulations obtained by TLBO together with the compared algorithms are tabulated

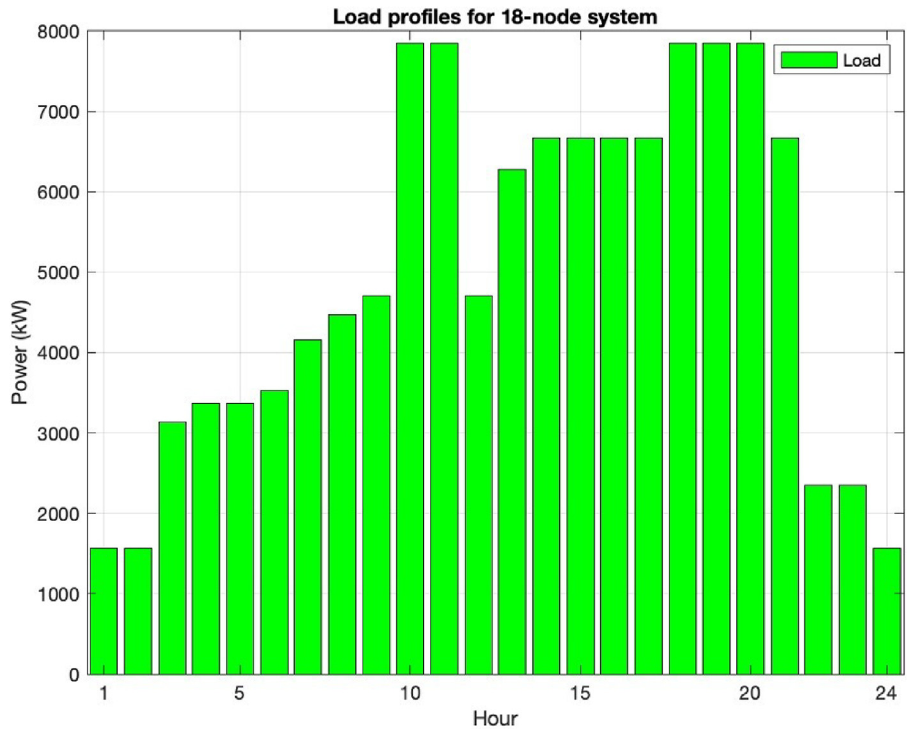

Fig. 4. Load profile for the 18-node system for the 24-h period.

Table 1
Detail results obtained by TLBO and compared algorithms for the 18-node system.

Hour\Algorithms	TLBO	BMO	SSA	GBO	PSO	CSA*
Bus	18	4	18	18	13	15
1	100	9	98	100	50	−24
2	100	100	−89	0	−57	49
3	−100	−11	45	100	100	24
4	100	38	26	−100	93	100
5	−100	−29	69	100	−10	−25
6	57	−16	−79	−100	−100	−8
7	−100	28	66	100	61	−37
8	100	39	4	−100	21	81
9	12	−44	6	100	−83	3
10	−100	−100	−100	−100	−97	−38
11	−100	−18	−24	−100	−100	−100
12	99	100	95	−100	68	42
13	100	19	18	100	77	−35
14	−94	39	−99	100	−100	1
15	90	−75	67	100	99	−66
16	−76	68	−20	−7	97	11
17	100	−100	72	−100	44	28
18	−100	−97	−100	−100	−100	−82
19	−100	27	−99	−93	−100	−97
20	−100	−100	−100	−100	−85	−4
21	100	25	27	100	96	9
22	−100	−3	97	−100	−89	48
23	100	100	−68	100	95	100
24	12	1	88	100	20	20
Obj. function ($)	**10 135.04**	10 281.49	10 230.80	10 142.99	10 148.61	10 254.00

in Table 2. From the table, it is proven that TLBO outperformed others by obtaining the best results in terms of the minimum, average, worst and standard deviation of objective function results which are highlighted in bold. The second-best results were obtained by GBO which obtained about $ 7.95 more than TLBO. The worse result is obtained by BMO, which is produced more than $ 146 compared to TLBO for the best objective function. Details cost analysis for the initial case as well as the improvements obtained by all algorithms are tabulated in Table 3. It can be observed that the cost of the purchased power has decreased from $10, 363.11 to $ 9991.90 obtained by TLBO. After installation of the BESS at node 18, the cost of the purchased power has been reduced to $371.21 which is equal to 3.72% for the surveyed 24-h period. In terms of total power loss, even though the total energy loss for TLBO is slightly higher than the initial case, the cost of energy loss obtained by TLBO ranked as second best which is after SSA that obtained the minimum cost of energy loss among all algorithms.

Fig. 7 shows the energy loss and the cost of energy loss incurred obtained by the TLBO for 24-h period. From this figure, it can be

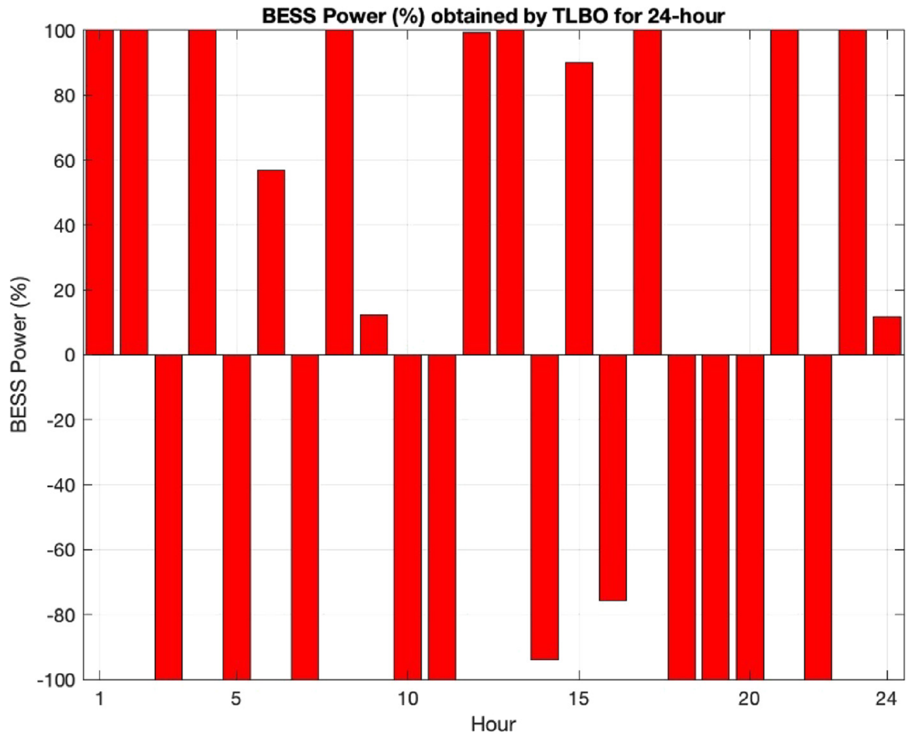

Fig. 5. BESS power obtained by TLBO for the 24-h period.

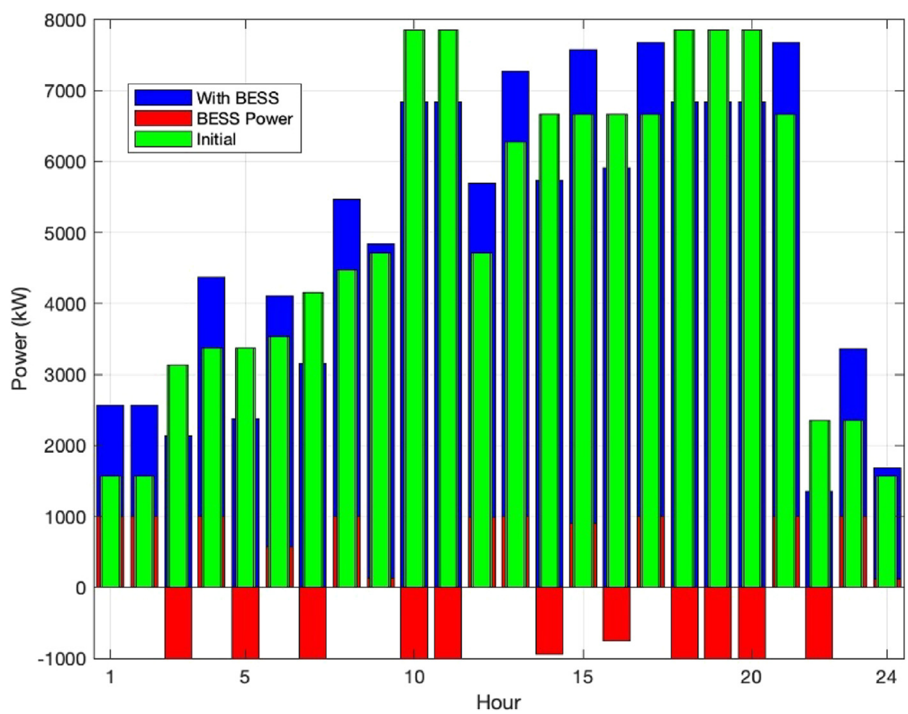

Fig. 6. Purchased power before and after BESS placement at node 18.

proved that cost of energy loss incurred have been reduced for the peak hours after the BESS's installation at node 18. Despite the fact that energy loss and cost may increase at certain hours following the implementation of BESS, the overall energy loss and cost are minimized due to the influence of the electricity tariff during those hours. The voltage profiles for initial and after BESS installation determined by TLBO at hour 20 are depicted in Fig. 8. As visualized in the figure, a slight improvement of voltage magnitude is occurred at each node of the 18-node system. The minimum voltage magnitude after load flow solution obtained by MATPOWER is 0.9605 per unit, which is occurred

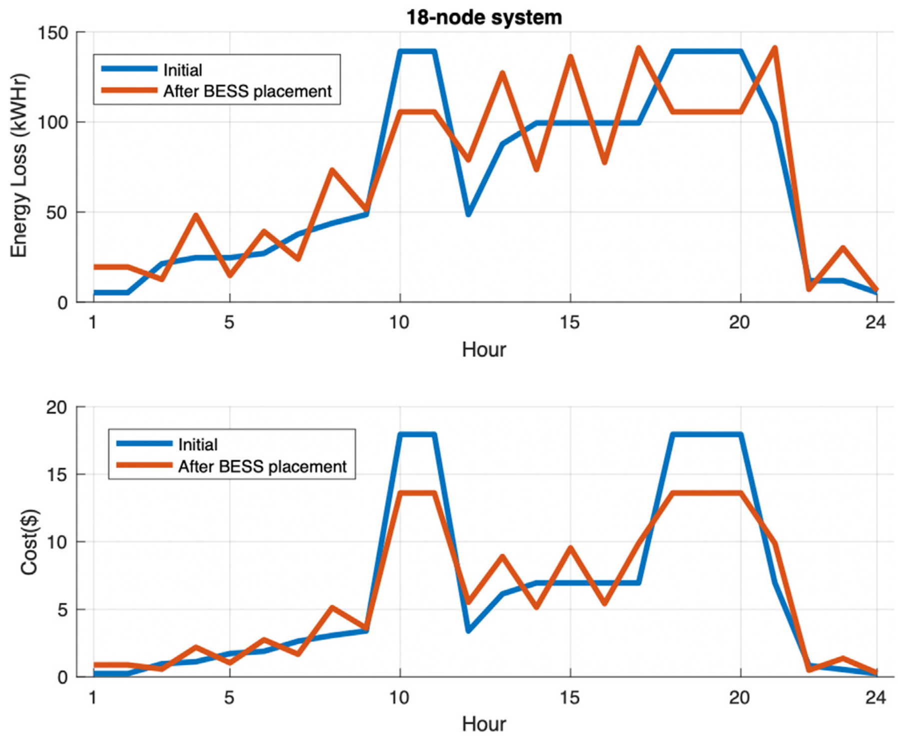

Fig. 7. Energy loss and cost before and BESS placement at node 18.

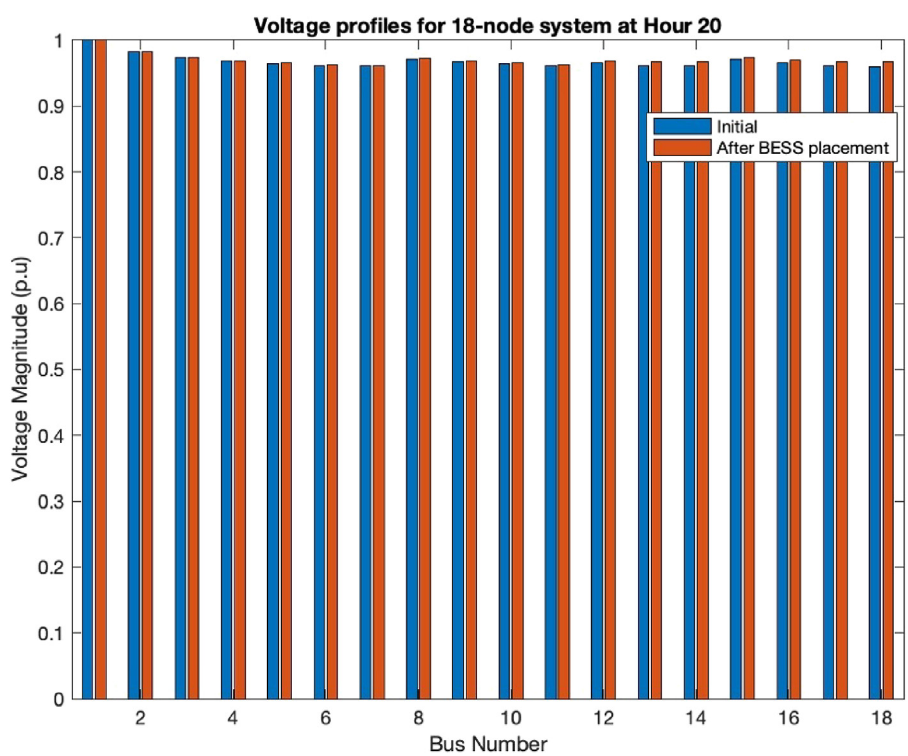

Fig. 8. Voltage profiles before and after BESS installation.

at node 18 before the BESS installation. Following the discharging of the BESS into the system, the voltage magnitude at node 18 increased to 0.9675 per unit, which represents an improvement of approximately 0.73% compared to its original value. Although the improvements in voltage magnitude may seem small, they can have a significant impact on the reliability and stability of power system networks.

The best convergence curve out of 30 runs for all algorithms is shown in Fig. 9. The figure shows that TLBO converged after 70 iterations and produced the best result among all compared algorithms. From this figure, it can be observed that PSO converged just before 100 iterations while BMO produced the worst results compared to all other algorithms. This performance proves that the TLBO is able to obtain

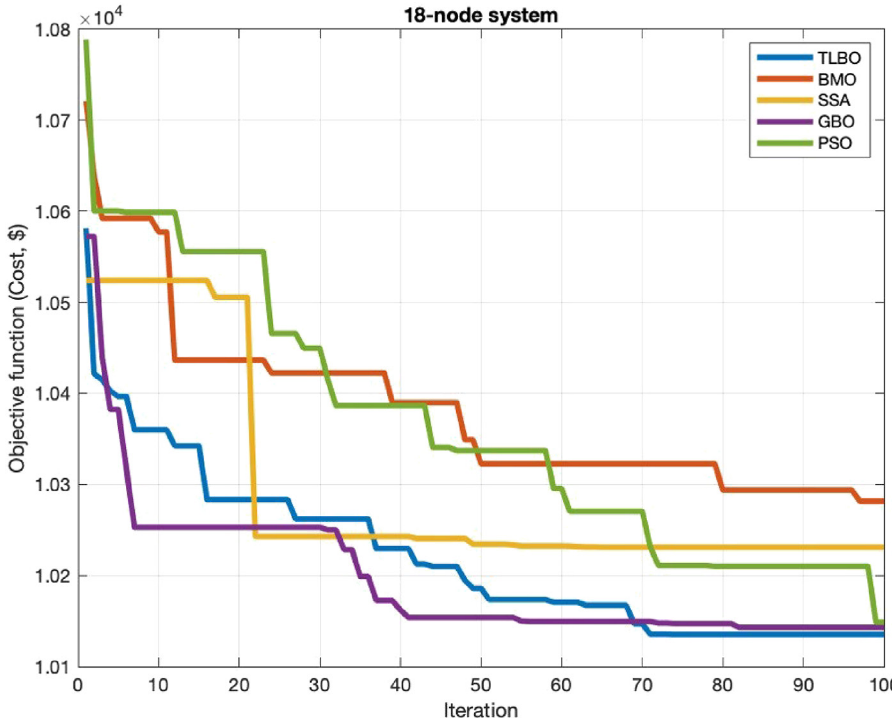

Fig. 9. Convergence curve for all algorithms for the 18-node system.

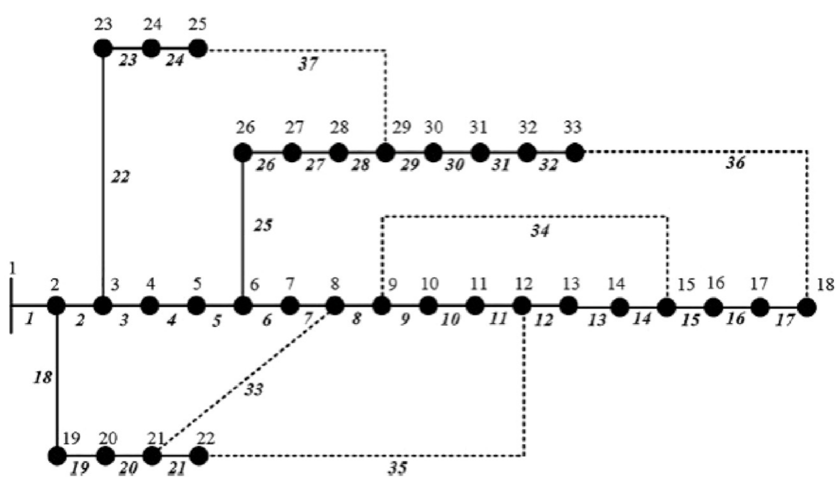

Fig. 10. Single line diagram of the 33-node system [24,38].

Table 2
Statistical results obtained by TLBO and compared algorithms for the 18-node system.

Algorithm	Best	Average	Worst	Std. Dev.
TLBO	**10 135.0414**	**10 218.479**	**10 292.6935**	**43.4480003**
BMO	10 281.4908	10 384.6603	10 505.984	58.7509288
SSA	10 230.7974	10 361.0335	10 457.6433	58.4136445
GBO	10 142.9884	10 268.8343	10 383.022	61.2313359
PSO	10 148.6087	10 274.5138	10 584.4591	87.9008337

better results in optimizing the BESS's location and operating power compared to the results obtained by BMO, SSA, GBO and PSO.

4.2. The 33-node system

This distribution system consists of 33 nodes with a voltage level of 12.66 kV as depicted in Fig. 10. This system consists of 37 branches, 32 sectionalizing switches with 5 tie switches represented in dot line. The load profiles and the transmission line parameters can be obtained in [38]. Fig. 11 shows the load profiles for this system where the peak loads occurred at hours 20 and 21, while the minimum load is recorded at hour 4, which is 345.7 kW. In this system, the capacity of the BESS is set up to 300% of its rated limit or 3 MWh for each interval period. The optimal location for BESS installation obtained by TLBO is at node 26 where the BESS power in terms of percentage is depicted in Fig. 12. Due to minimum load at hour 4, the BESS power for this hour is not used whether to charge or discharge. It means that the BESS capacity is remaining 100% from the previous hour and the power from the node 1 is adequate to supply the total load for this hour. The BESS power levels in each time interval for the 33-node system are similar to those in the 18-node system, in that they do not exceed their rated limits, which represented in percentage as follows: [99, 100, 100, 0, −100, 100, −98, −80, 81, −100, −100, 100, −87, −6, −29, 28, 100, −100, −100, −98, −100, 94, 100, 96] for the 24-h period and their

Table 3
Cost analysis by TLBO and compared algorithms for the 18-node system.

Algorithm	The capacity of BESS in MWhr	Objective function in $	Cost of the purchased power in $	Cost saving in $	Energy loss in kWh	Cost of energy loss in $
Initial	–	10 514.04	10 363.11	–	1596.40	150.93
TLBO	2.00	**10 135.04**	**9991.90**	**371.21**	1649.10	143.18
BMO	1.58	10 281.49	10 135.00	228.11	1588.50	146.31
SSA	1.55	10 230.80	10 089.00	274.11	1593.00	**141.43**
GBO	2.00	10 142.99	9998.90	364.21	1658.80	144.05
PSO	1.86	10 148.61	10 005.00	358.11	1638.50	143.44
CSA*	1.77	10 253.74	10 108.00	255.11	**1577.60**	145.87

Table 4
Cost analysis by TLBO and compared algorithms for the 33-node system.

Algorithm	The capacity of BESS in MWhr	Objective function in $	Cost of the purchased power in $	Cost saving in $	Energy loss in kWh	Cost of energy loss in $
Initial	–	3991.50	3855.00	–	1495.50	136.49
TLBO	2.99	**3569.36**	3439.90	415.10	1626.70	129.49
BMO	2.29	3652.83	3517.20	337.80	1494.90	135.61
SSA	2.66	3658.84	3530.60	324.40	1610.50	**128.25**
GBO	2.94	3590.69	3456.60	398.40	1690.90	134.08
PSO	3.00	3573.92	3438.20	416.80	1499.20	135.72
CSA*	3.73	3687.90	3552.00	303.00	1495.90	135.91

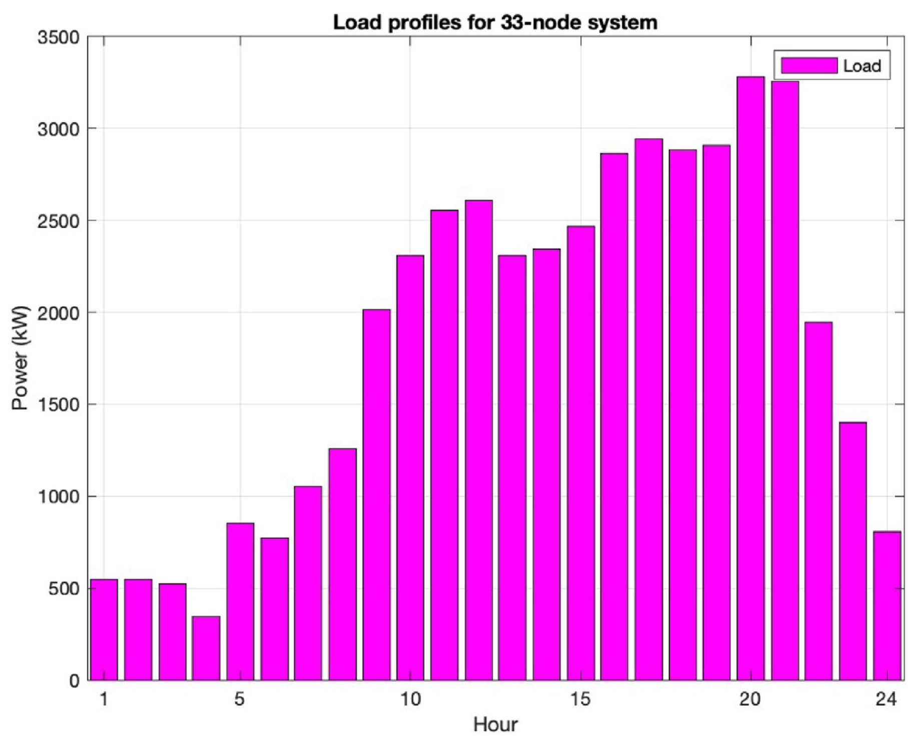

Fig. 11. Load profiles for the 33-node system.

total power over the survey period sums to zero. The combined optimal power output as represented by the cumulative sum of its components, is as follows: [99, 199, 299, 299, 199, 299, 201, 121, 202, 102, 2, 102, 15, 9, −20, 8, 108, 8, −92, −190, −290, −196, −96, 0] with a maximum value of 299. Therefore, the storage capacity of the BESS required for the operation is 2.99 MWh, which is less than the maximum capacity viz. 3 MWh.

Fig. 13 shows the initial, before and after BESS installation at node 26. As highlighted previously, the aim of the proper optimal installation and operating power of BESS is not only can reduce the cost of purchased power, but also can reduce the peak load profiles during peak hours. This is proved by the results shown in Tables 4 and 5 where all the algorithms managed to reduce the power purchased when installing the BESS at the respective node. From the tables also show the superiority of TLBO compared to other algorithms by obtaining the minimum objective function as well as the second highest cost saving for power purchased for the surveyed 24-h period, which is about 12.07% cost reduction. Table 4 indicates that the outcomes are comparable to those of the 18-node system. In both cases, the SSA algorithm was the most effective in generating the lowest energy loss cost, at $128.25, with the TLBO algorithm being the second-best option, yielding $129.49. In order to measure the robustness of the proposed solution, 30 runs of simulations have been performed for all algorithms and the statistical results obtained by all algorithms are tabulated in Table 6. TLBO emerged as the best algorithm followed by the PSO, GBO, BMO and SSA if the best result is taken as the reference of the analysis. This table also demonstrates that TLBO achieved reliable outcomes in relation to objective functions, as evidenced by its low standard deviation, making it superior to all other algorithms considered. While Table 4 reveals that SSA performed the best in minimizing the cost of energy loss, it also yielded the poorest objective function results, viz. $3658.84, which was the lowest among all algorithms evaluated.

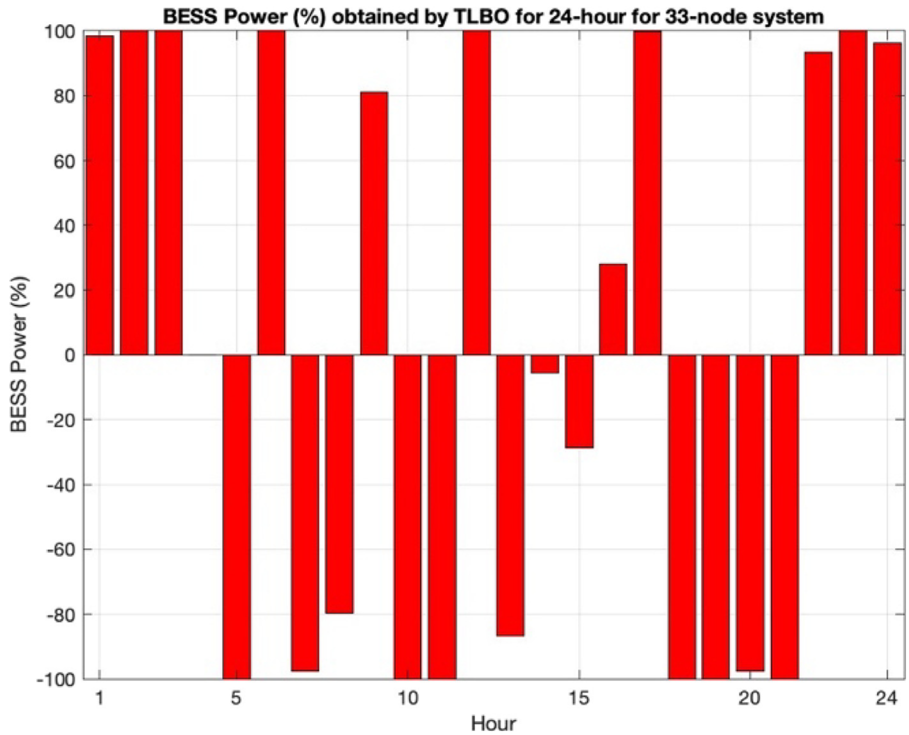

Fig. 12. BESS power obtained by TLBO for the 24-h period.

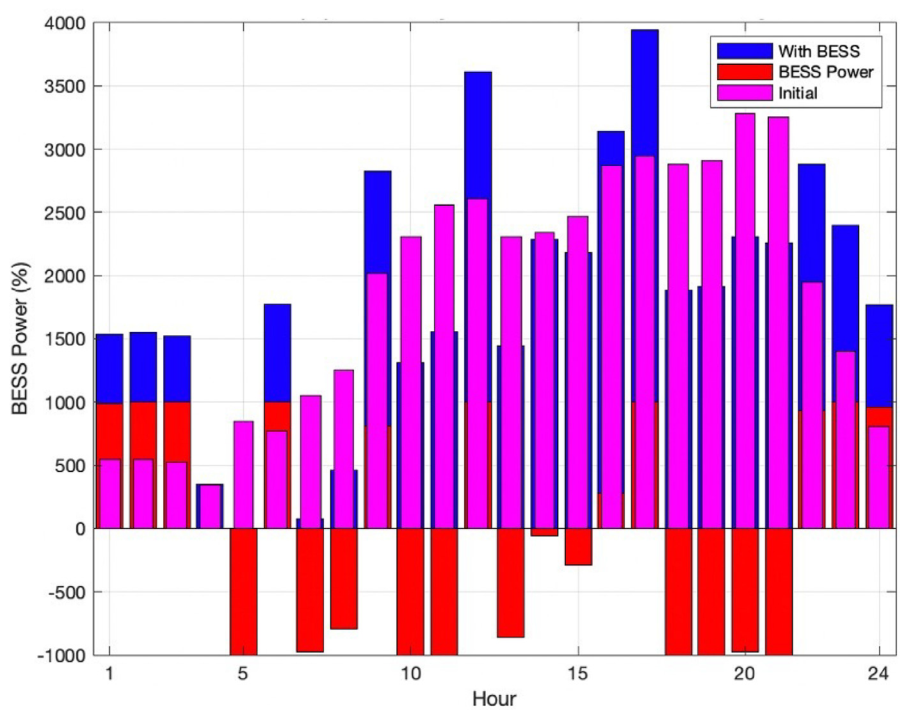

Fig. 13. Purchased power before and after BESS placement at node 26.

Fig. 14 shows the graph of the energy loss and the cost of energy loss obtained by the TLBO during 24-h period for the 33-node system. Again, it can be observed that the cost of energy loss incurred have been reduced for the peak hours after the BESS's installation at node 26. Even though the energy loss peaked at hour 17 after BESS placement, the cost of energy loss is compensated for the peak hours which are at hours 20 and 21. Thus this will minimize the total loss cost overall. The voltage profiles for initial and after BESS installation determined by TLBO at hour 20 is visualized in Fig. 15. Slight improvements of voltage magnitude at each node of the 33-node system can be seen in this figure. The load flow solution obtained by MATPOWER found that the voltage at node 18 had a minimum magnitude of 0.9243 per unit

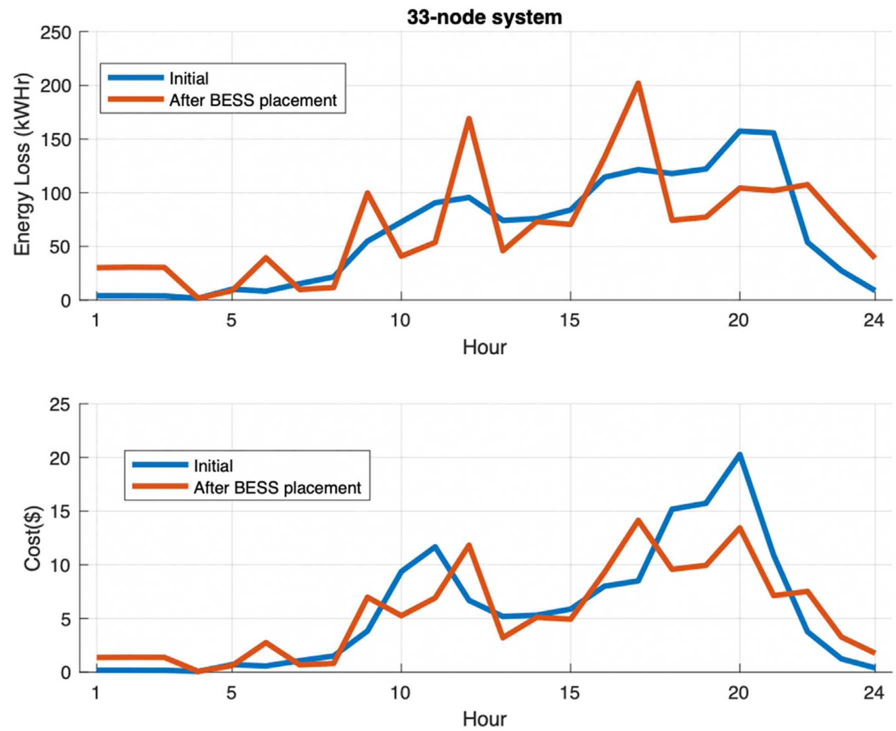

Fig. 14. Energy loss and cost before and BESS placement at node 26.

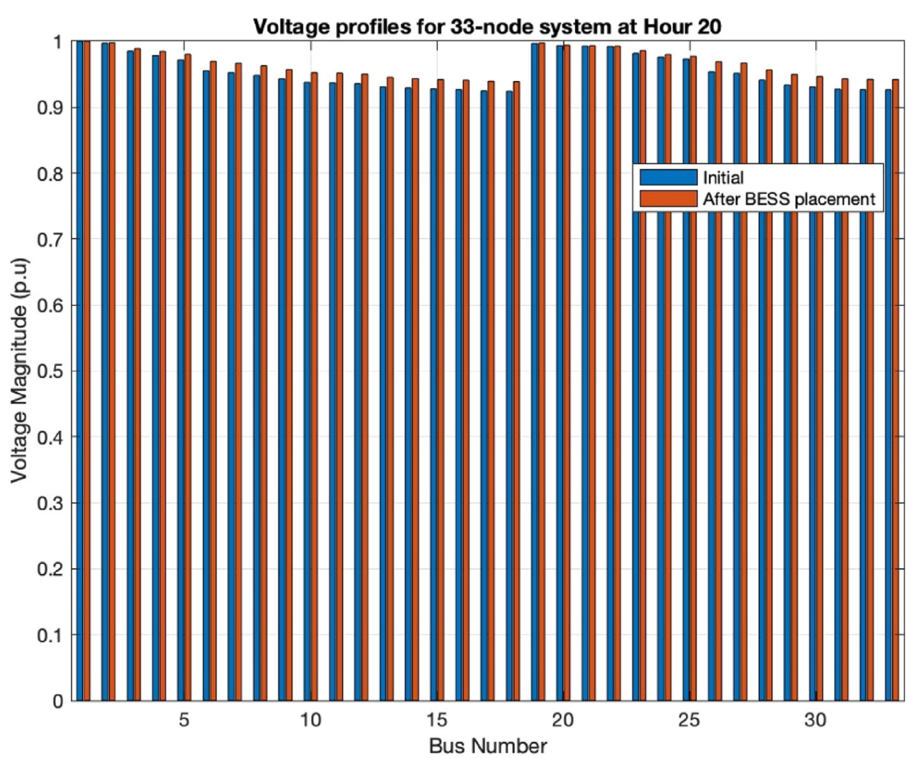

Fig. 15. Voltage profiles before and after BESS installation.

before the installation of BESS. However, after the BESS was discharged into the system, the voltage magnitude at node 18 increased to 0.9390 per unit, resulting in a slight improvement. Even though the increase in voltage magnitude may seem insignificant, again, similar with case 18-node system, it can greatly affect the reliability and stability of power systems.

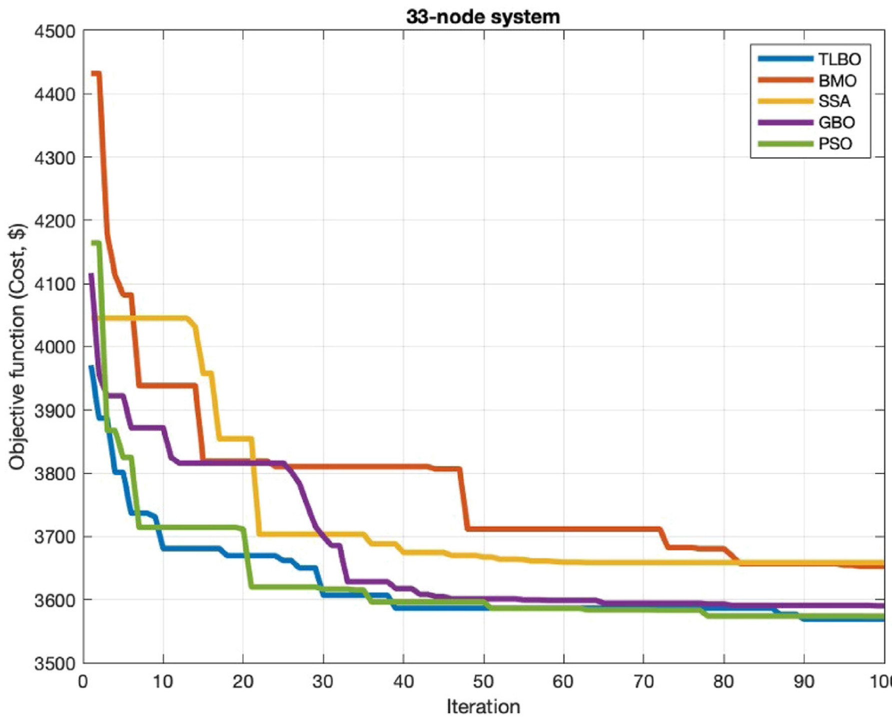

Fig. 16. Convergence curve for all algorithms for the 33-node system.

Table 5
Detail results of obtained by TLBO and compared algorithms for the 33-node system.

Hour\Algorithms	TLBO	BMO	SSA	GBO	PSO	CSA*
Bus	26	2	28	27	2	2
1	99	48	−25	100	46	82
2	100	88	98	32	100	100
3	100	0	30	62	99	100
4	0	93	−64	100	55	91
5	−100	−50	95	−95	−26	−34
6	100	−2	28	−75	−100	−38
7	−98	−15	22	93	−87	−100
8	−80	−65	72	−95	100	86
9	81	100	10	100	−100	−65
10	−100	−100	−76	−97	−100	−81
11	−100	−92	−100	−77	−100	−100
12	100	90	81	100	−17	7
13	−87	−93	71	−87	100	100
14	−6	100	−59	−88	−100	−100
15	−29	−32	−59	75	100	−100
16	28	2	68	91	100	−100
17	100	16	16	97	100	100
18	−100	−74	−91	−96	−100	81
19	−100	−32	−100	−100	−100	−100
20	−98	−100	−86	−100	−100	−75
21	−100	15	−100	−100	33	46
22	94	−88	−26	−40	−100	−100
23	100	100	98	100	100	100
24	96	91	97	100	97	100
Obj. function ($)	**3569.36**	3652.83	3658.84	3590.69	3573.92	3687.90

Table 6
Statistical results obtained by TLBO and compared algorithms for the 33-node system.

Algorithm	Best	Average	Worst	Std. Dev.
TLBO	**3569.36406**	**3650.5059**	**3733.37627**	**42.4387709**
BMO	3652.83304	3835.46741	3980.44114	86.1931174
SSA	3658.83554	3778.83585	3943.28947	73.9830472
GBO	3590.68641	3730.40353	3858.77577	70.1401471
PSO	3573.92121	3649.64632	3859.15245	75.8697652

Fig. 16 shows the best convergence curve out of 30 runs for all algorithms. The figure shows that all algorithms converged within 100 iterations and TLBO emerged as the best result among all compared algorithms. This shows that TLBO is able to obtain consistent and robust results compared to others in solving the optimal allocation and operating power of the BESS, which have been proved in both test cases, 18- and 33-node systems.

5. Conclusion

This paper proposed a Teaching-Learning-Based Optimization (TLBO) algorithm for the optimal allocation of Battery Energy Storage Systems (BESS) in distribution network systems. The aim was to minimize the combined cost of power purchased and energy loss for a 24-h period. The proposed method was tested on two case systems, an 18-node and 33-node systems, using time-of-use electricity charges that were divided into three periods: standard, peak, and off-peak hours. The simulation results showed that the TLBO algorithm outperformed other selected algorithms for both cases in terms of optimizing the placement and operation of BESS units. Additionally, the results from all algorithms demonstrated that determining the optimal location of BESS units and their suitable operating power significantly reduced costs while also curbing peak loads for the 24-h period. The simulations indicate that TLBO is a useful technique for optimizing the position and power of BESS. The results demonstrate that using TLBO can lead to cost reductions of approximately 3.7% for the 18-node system and savings of about 12% for the 33-node system power purchased for the surveyed 24-h period. However, this study also has some limitations that need to be addressed in future research. For example, the uncertainties in energy prices were not considered. In terms of practical implications, the proposed TLBO algorithm also can be applied into energy sector to optimize the placement and capacity of BESS units in microgrids that consider the renewable energy sources, leading to reduced operational costs and improved performance. The results of this study can also provide valuable insights for energy planners and policymakers who are interested in implementing BESS units in microgrids. Future research should focus on addressing the limitations and expanding the scope of the study to include more complex scenarios.

Table A.1
Real and reactive power demand for 18-node system for 24-hour period.

Hour\Load (kW)	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18
1	100	100	100	100	80	90	100	80	80	80	100	80	120	120	120	120
2	100	100	100	100	80	90	100	80	80	80	100	80	120	120	120	120
3	200	200	200	200	160	180	200	160	160	160	200	160	240	240	240	240
4	215	215	215	215	172	193.5	215	172	172	172	215	172	258	258	258	258
5	215	215	215	215	172	193.5	215	172	172	172	215	172	258	258	258	258
6	225	225	225	225	180	202.5	225	180	180	180	225	180	270	270	270	270
7	265	265	265	265	212	238.5	265	212	212	212	265	212	318	318	318	318
8	285	285	285	285	228	256.5	285	228	228	228	285	228	342	342	342	342
9	300	300	300	300	240	270	300	240	240	240	300	240	360	360	360	360
10	500	500	500	500	400	450	500	400	400	400	500	400	600	600	600	600
11	500	500	500	500	400	450	500	400	400	400	500	400	600	600	600	600
12	300	300	300	300	240	270	300	240	240	240	300	240	360	360	360	360
13	400	400	400	400	320	360	400	320	320	320	400	320	480	480	480	480
14	425	425	425	425	340	382.5	425	340	340	340	425	340	510	510	510	510
15	425	425	425	425	340	382.5	425	340	340	340	425	340	510	510	510	510
16	425	425	425	425	340	382.5	425	340	340	340	425	340	510	510	510	510
17	425	425	425	425	340	382.5	425	340	340	340	425	340	510	510	510	510
18	500	500	500	500	400	450	500	400	400	400	500	400	600	600	600	600
19	500	500	500	500	400	450	500	400	400	400	500	400	600	600	600	600
20	500	500	500	500	400	450	500	400	400	400	500	400	600	600	600	600
21	425	425	425	425	340	382.5	425	340	340	340	425	340	510	510	510	510
22	150	150	150	150	120	135	150	120	120	120	150	120	180	180	180	180
23	150	150	150	150	120	135	150	120	120	120	150	120	180	180	180	180
24	100	100	100	100	80	90	100	80	80	80	100	80	120	120	120	120
Hour\Load (kVAR)	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18
1	40	40	40	40	30	30	40	30	30	30	40	30	40	40	40	40
2	40	40	40	40	30	30	40	30	30	30	40	30	40	40	40	40
3	80	80	80	80	60	60	80	60	60	60	80	60	80	80	80	80
4	86	86	86	86	64.5	64.5	86	64.5	64.5	64.5	86	64.5	86	86	86	86
5	86	86	86	86	64.5	64.5	86	64.5	64.5	64.5	86	64.5	86	86	86	86
6	90	90	90	90	67.5	67.5	90	67.5	67.5	67.5	90	67.5	90	90	90	90
7	106	106	106	106	79.5	79.5	106	79.5	79.5	79.5	106	79.5	106	106	106	106
8	114	114	114	114	85.5	85.5	114	85.5	85.5	85.5	114	85.5	114	114	114	114
9	120	120	120	120	90	90	120	90	90	90	120	90	120	120	120	120
10	200	200	200	200	150	150	200	150	150	150	200	150	200	200	200	200
11	200	200	200	200	150	150	200	150	150	150	200	150	200	200	200	200
12	120	120	120	120	90	90	120	90	90	90	120	90	120	120	120	120
13	160	160	160	160	120	120	160	120	120	120	160	120	160	160	160	160
14	170	170	170	170	127.5	127.5	170	127.5	127.5	127.5	170	127.5	170	170	170	170
15	170	170	170	170	127.5	127.5	170	127.5	127.5	127.5	170	127.5	170	170	170	170
16	170	170	170	170	127.5	127.5	170	127.5	127.5	127.5	170	127.5	170	170	170	170
17	170	170	170	170	127.5	127.5	170	127.5	127.5	127.5	170	127.5	170	170	170	170
18	200	200	200	200	150	150	200	150	150	150	200	150	200	200	200	200
19	200	200	200	200	150	150	200	150	150	150	200	150	200	200	200	200
20	200	200	200	200	150	150	200	150	150	150	200	150	200	200	200	200
21	170	170	170	170	127.5	127.5	170	127.5	127.5	127.5	170	127.5	170	170	170	170
22	60	60	60	60	45	45	60	45	45	45	60	45	60	60	60	60
23	60	60	60	60	45	45	60	45	45	45	60	45	60	60	60	60
24	40	40	40	40	30	30	40	30	30	30	40	30	40	40	40	40

Declaration of competing interest

Only data for 18-node system is included in the paper. For 33-bus system, the load profiles and the transmission line parameters can be obtained in [38] M. E. Baran and F. F. Wu, ‘‘Network reconfiguration in distribution systems for loss reduction and load balancing,’’ IEEE Transactions on Power Delivery, vol. 4, no. 2, pp. 1401–1407, 1989, http://dx.doi.org/10.1109/61.25627.

Data availability

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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Appendix

See Table A.1.

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