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Solving the active power loss reduction problem in distribution networks by placing both wind farms and shunt capacitors using novel meta-heuristic algorithms

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Abstract
This research applied two novel meta-heuristic algorithms, including the driving-train-based optimization and the average and subtract-based optimization, to determine the optimized sizes and locations of wind farms and shunt capacitors in the IEEE-33 node distribution network for active power loss reduction. The results obtained by the two applied methods are evaluated on different criteria, such as Min TPWL, Aver TPWL, Max TPWL, and Std. ASBO completely outperforms DTBO in all criteria. Particularly, the higher percentages of ASBO over DTBO on each criterion are, respectively, 0.44%, 31.16%, 25.40%, and 33.71%. Through all results and comparisons, ASBO proves itself to be an efficient search method. We highly suggest using ASBO to deal with the problem of active power loss reduction by placing wind farms and shunt capacitors into the distribution network. Moreover, the presence of both wind farms and shunt capacitors found by ASBO has reduced the active power loss of the original IEEE-33 node from 211 kW to 28,76281 kW, corresponding to 86.37%.

Keywords: Distribution network, renewable energy source, wind farm, shunt capacitor, power loss, voltage improvement

1. Introduction

Distribution networks (DNs) are acknowledged to be the most crucial parts of the whole power system [1]. In general, most electrical customers or loads fulfill their power demand by integrating directly with DNs. Consequently, the operational characteristics of DS highly affect the working status of all connected loads. That means that a minor fluctuation in DS operation can cause unthinkable damage at load in terms of engineering and economics [2]. Recently, the unprecedented rise in electrical demand has added more difficulties to the task of maintaining the normal working status for DS while all electrical customers must be powered continuously. Besides, the power loss in the distribution lines is also larger due to the rise in distribution line quantities. On top of that, all the traditional generating sources, such as thermal power plants, hydropower plants, etc., have run out of their designed capability. To operate the DNs effectively and economically in these circumstances, the placement of distributed generators, especially wind power, solar energy, and shunt capacitors, is admitted as an affordable solution with a low capital cost [3].

By fully understanding the benefits of placing renewable generators such as wind farms, solar generators, and shunt capacitors in DNs, many researchers have published their studies about how to optimize the size and location of these kinds of distributed sources in DNs by applying a wide range of meta-heuristic algorithms. The use of meta-heuristic algorithms by researchers can be classified into two approaches: 1) applying the original version of the algorithms, and 2) applying the modified versions of the algorithms. The applications of the meta-heuristic algorithms with their original versions can be listed, such as the analytical algorithm (AA) [4–6], the artificial bee colony algorithm (ABC) [7], the ant lion optimization algorithm (ALO) [8], the cuckoo search algorithm (CSA) [9], the crow search algorithm (CRSA) [10], the whale optimization algorithm (WOA) [11], the moth-flame algorithm (MFA) [12], the pathfinder algorithm (PA) [13], the krill herd algorithm (KHA) [14], sine and cosine algorithm (SCA) [15]. The implementations of the modified version of the original algorithm can be viewed as the adaptive cuckoo search (ACS) [16], the improved whale optimization algorithm (IWOA) [17], the multi-objective modified symbiotic organisms search (MOMSOS) [18], quasi-oppositional chaotic symbiotic organisms search (QOCSOS) [20], and the modified version of teaching and learning optimization algorithms (MTLOA) [21].

The use of the meta-heuristic algorithms becomes more and more popular for several reasons such as: quick response with affordable solutions, easy to apply for different optimization problem, do not require a series of complicated calculations, feasible to deal with the large-scale optimization problem with complex constraints. By deeply acknowledging the advantages of the meta-heuristic algorithms, we applied two novel meta-heuristic algorithms in this research, including the driving-train-based optimization (DTBO) [22] and the average and subtract-based optimization (ASBO) [23], to reduce the total power loss (TPWL) in the IEEE-33 bus distribution network by optimizing the placement of windfarms (WFs) and shunt capacitors (ShCs). DTBO is proposed for mid-2022 by simulating the human driving training process, while ASBO is accepted for online publishing in early 2022 by using the average information of the best and the worst individuals to navigate the whole optimization process.

The key contributions of the research can be listed as follows:

- Successfully apply two novel meta-heuristic algorithms, including driving-train-based optimization (DTBO) and the average and subtract-based optimization (ASBO), to optimize the placement of both windfarms and shunt capacitors in the IEEE-33 node for active power loss reduction.
- Clarify the contribution of placing renewable energy generators (REGs) in distribution system operation over the original configuration where REGs are not connected.
- Indicate and prove the superiority of the ASBO over the DTBO in the comparisons with different criteria.
- Demonstrate the feasibility of implementing ASBO to solve engineering problems such as the one considered in this research.

In addition to the introduction, the main objective function and all related constraints are described in Section 2 – the problem formulation section; the mathematical models of the applied methods are presented in Section 3; the results obtained by the two applied methods are shown in Section 4; and the final conclusions are disclosed in Section 5.

2. Problem formulation

2.1 The mathematical expression of the main objective function

As mentioned earlier, the main task of this research is to reduce the active power loss in the whole distribution network. The mathematical model of the task is expressed as follows:

$$\text{Reduce } TPWL = 3\sum_{l=1}^{N_{CD}} I_{WTShC,l}^2 . RCD_l \qquad (1)$$

Where, $TPWL$ is the total active power loss in the whole network; $I_{WTShC,l}$ is the current amplitude in the conductor *l* after placing both WFs and ShCs with $l = 1, \ldots, N_{CD}$ and N_{CD} is the number of conductors in the whole network, RCD_l is the resistance value of the conductor *l*.

2.2 The Constraints

Besides the objective function, there are important constraints which must be strictly respected while solving the problem. The detail and the expression of these constraints will be presented in the next subsections:

2.2.1 The power balance constraint

The mathematical expression of this constraint is given as follows:

$$P_{N1} + \sum_{p=1}^{N_{WF}} PWF_p - \sum_{m=2}^{N_D} P_{DM,m} - TPWL = 0 \qquad (2)$$

$$Q_{N1} + \sum_{p=1}^{N_{WF}} QWF_p + \sum_{q=1}^{N_{ShC}} Q_{ShC,q} - \sum_{m=2}^{N_D} Q_{DM,m} - TQWL = 0 \qquad (3)$$

And

$$TQWL = 3\sum_{l=1}^{N_{CD}} I_{WTShC,l}^2 . XCD_l \qquad (4)$$

In the Equations (2) to (4), P_{N1} and Q_{N1} are the amount of active and reactive power at the slack bus or node 1; $\sum_{p=1}^{N_{WF}} PWF_p$ and $\sum_{p=1}^{N_{WF}} QWF_p$ are the total active and reactive power supplied by all wind farms (WFs); $\sum_{m=2}^{N_D} P_{DM,m}$ and $\sum_{m=2}^{N_D} Q_{DM,m}$ are the total active and reactive power that needed to fulfill load demand; $\sum_{q=1}^{N_{ShC}} Q_{ShC,q}$ are the reactive power supplied by shunt capacitors (ShCs); $TPWL$ and $TQWL$ are the total active and reactive power loss caused by the transmission process; XCD_l is the reactance value of the conductor *l*.

2.2.2 Voltage magnitude limit

To maintain the normal working conditions of all electrical devices integrated with the grid, the allowed voltage magnitude of every single node in the whole network must be located inside the limit as described in the equation below:

$$VN_{min} \le VN_i \le VN_{max}; i = 1, \ldots, N_{NO} \qquad (5)$$

Where, VN_{min} and VN_{max} are respectively the lowest and the highest value of voltage at nodes, VN_i is the voltage magnitude at node i^{th}; N_{NO} is the number of nodes in the whole network.

2.2.3 Current amplitude limit

For safety reasons, the current amplitude of all conductors in the whole network must not be higher than the allowed values.

$$I_{CD,l} \le I_{CD,l}^M; l = 1, \ldots, N_{CD} \qquad (6)$$

Where, $I_{CD,l}$ is the current amplitude circulating through conductor *l*; $I_{CD,l}^M$ is the highest current value allowed to run through the conductor *l*.

2.2.4 The site installation limit

This constraint is about the site installation of wind farms

(WFs) and shunt capacitors (ShCs) in the grid. That means, both WFs and ShCs must be placed following the expression as follows:

$$2 \le LS_{WT,p} \le N_{NO} \quad (7)$$

$$2 \le LS_{ShC,q} \le N_{NO} \quad (8)$$

Where, $LS_{WT,p}$ and $LS_{ShC,q}$ are respectively the legal site of WF p and ShC q in the grid

2.2.5 The operational limits of WFs and ShCs

This constraint is regarding the amount of active and reactive power injected to the grid by both WFs and ShCs. The mathematical model of this limit is presented by the equations below:

$$P_{WF}^{min} \le P_{WF,p} \le P_{WF}^{max} \; with \; p = 1, \ldots, N_{WF} \quad (9)$$

$$Q_{WF}^{min} \le Q_{WF,p} \le Q_{WF}^{min} \; with \; p = 1, \ldots, N_{WF} \quad (10)$$

$$Q_{ShC}^{min} \le Q_{ShC,q} \le Q_{ShC}^{min} \; with \; p = 1, \ldots, N_{ShC} \quad (11)$$

In the equations (9) to (11), P_{WF}^{min} and P_{WF}^{max} are the lowest and the highest active power injected to grid by WF, Q_{WF}^{min} and Q_{WF}^{max} are the lowest and the highest reactive power injected to grid by WF, Q_{ShC}^{min} and Q_{ShC}^{max} are the lowest and the highest reactive power supplied by ShC, $P_{WF,p}$ is the amount of active power supplied by WF p, $Q_{WF,p}$ and $Q_{ShC,q}$ are respectively the reactive power supplied by WF p and ShC q.

* Supposed that, the all the WFs deployed in this research are DFIG type which can supply both active and reactive power to the grid.

3. The solving method

3.1 The Driving training-based optimization

The Driving training-based optimization (DTBO) uses three phases to fulfill its update process for new solutions. The mathematical model of each phase will be given in the next subsections below:

3.1.1 Phase 1

In the first phase, the generation of the new solutions is executed by using the mathematical model as shown below:

$$D_m^{new,P1} = \begin{cases} D_i + \gamma \times (RD_n - RS \times D_i), & \text{if } F_{RD_n} < F_{D_i} \\ D_i + \gamma \times (D_i - RD_n), & \text{else} \end{cases} \quad (12)$$

Where, $D_m^{new,P1}$ is the new updated solution m in Phase 1 with m = 1, …, PZ and PZ is the initial population; γ is a random value between 0 and 1; RD_n is the driving trainer n with n = 1, …, TR and TR is the number of driving trainer; RS is the random value between 0 and 1; F_{RD_n} and F_{D_i} is the fitness value of the solution RD_n and the current solution D_i. The quantity of TR is calculated by using the expression as shown below:

$$TR = 0.1 + PZ \times \left(1 - \frac{CT}{CT^{max}}\right) \quad (13)$$

Where, CT and CT^{max} are respectively, the current iteration and the maximum number of iterations.

3.1.2 Phase 2

In this phase, the new solutions are updated by using the equation below:

$$D_m^{new,P2} = RI \times D_i + (1 - RI) \times RD_n \quad (14)$$

Where, $D_m^{new,P2}$ is the new updated solution m in Phase 2 with m = 1, …, PZ and PZ is the initial population; RI is the reference index and the determination of RI is calculated by using the equation as follows:

$$RI = 0.01 + 0.9 \times \left(1 - \frac{CT}{CT^{max}}\right) \quad (15)$$

3.1.3 Phase 3

The final step of the whole update for new solution of DTBO is conducted by using the equation below:

$$D_m^{new,P3} = D_i + (1 - \gamma) \times CS \times \left(1 - \frac{CT}{CT^{max}}\right) \quad (16)$$

Where, $D_m^{new,P3}$ is the new updated solution in the Phase 3; CS is the shrinking factor.

3.2 The Average and subtraction-based optimizer

Similar to DTBO, the update for new solutions of the Average training - based optimization (ASBO) also uses three phases which are described in the next subsection below:

3.2.1 Phase 1

The update for new solutions in this phase is conducted following the expression as follows:

$$A_i^{new,st1} = \begin{cases} A_i + \omega(MA^{st1} - SF * A_i), & if \; F(MA^{st1}) < F(A_i) \\ A_i + \omega(A_i - MA^{st1}), & else \end{cases} \quad (17)$$

With

$$MA^{st1} = \frac{A_{hq} + A_{lq}}{2} \quad (18)$$

In the Equations (17) – (18) above, $A_i^{new,st1}$ is the newly updated solution t in Phase 2 with t = 1, …, PZ and PZ is the number of the initial population; ω is the random value picked up in the interval between 0 and 1; SF is the stage factor; MA^{st1} is the average solution; A_{hq} and A_{lq} are, respectively, the highest and the lowest quality solution.

3.2.2 Phase 2

After that, all solutions of the population will be update following the equation below:

$$A_i^{new,st2} = A_i - \omega_2 DA^{st2} \tag{19}$$

With

$$DA^{st2} = A_{hq} - A_{lq} \tag{20}$$

Where, $A_i^{new,st2}$ is the newly updated solution *t* in Phase 2 with t = 1, *PZ* and *PZ* is the number of the initial population; DA^{st2} is the differential solution.

3.2.3 Phase 3

In this last phase, the new solutions are generated by executing the equations below:

$$A_i^{new,st3} = A_i - \omega_3\left(A_i - SF * A_{hq}\right) \tag{21}$$

Where, $A_i^{new,st3}$ is the new solution updated in Phase 3 at the next iteration, ω_3 is a random value in the interval of 0 and 1.

4. The results

In this section, both driving-training-based optimization (DTBO) and average and subtract-based optimizer (ASBO) will be applied to find the most suitable size and location for both wind farms (WFs) and shunt capacitors (ShCs) on the grid. This work is aimed at reducing the total power loss (TPWL) in the whole distribution system. The IEEE-33 node is selected to conduct the research. The original configuration of the selected DN is described in Figure 1. In summary, the basic specifications in terms of the rated voltage and the allowed deviation of voltage at all nodes are, respectively, 12.66 kW and 5%. Besides, the active and reactive power of all load demand are, respectively, 3175 kW and 2300 kVar. The base losses in terms of active and reactive power are, respectively, 210.9974 kW and 143.0324 kVar. On top of that, the base load of the original network is 69.125 kW. All this information is cited in [7].

To ensure that both the two applied methods are fairly compared in the whole research, we have set the same initial control parameters about population size (*PZ*) and maximum number of iteration (CT^{max}) by 20 and 30, respectively. In addition, DTBO and ASBO are executed 50 independent runs to obtain the best solution.

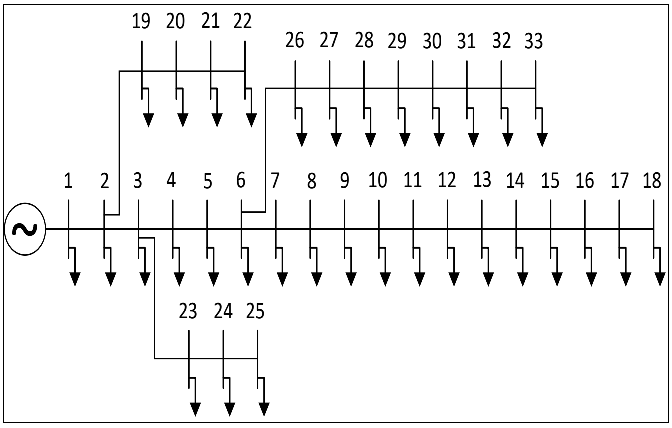

Fig 1: The description of the IEEE-33 bus distribution system

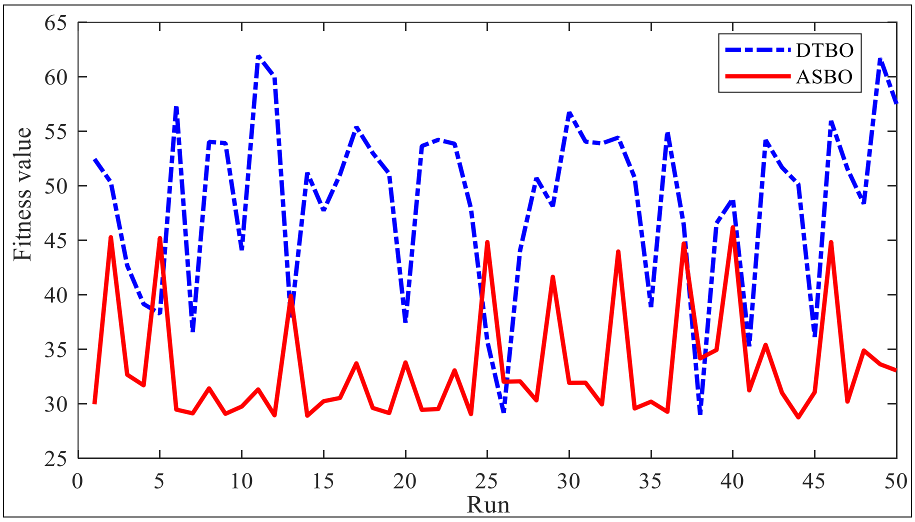

Fig 2: The results obtained by DTBO and ASBO after 50 independent runs

Figure 2 shows the results obtained by the three applied methods after 50 independent runs. The blue line stands for the results given by DTBO, while the red line describes the results obtained by ASBO. It is easy to realize that ASBO can find more optimal results than DTBO among 50 independent runs. That also means that the ASBO shows a better performance than the DTBO. This claim is more enhanced while observing the data shown in Figure 3 and Figure 4. Specifically, Figure 3 shows the best convergences obtained by the two applied methods among 50 independent runs, while Figure 4 presents the worst convergences of these methods. Similar to Figure 2, in both Figures 3 and 4, the blue lines represent DTBO, while the red ones stand for ASBO.

The observation from Figure 3 shows that ASBO also uses over 25 iterations to reach the optimal value for the main objective function, while DTBO cannot achieve the same results even when the last iteration is used. This means that ASBO can find the optimal solution faster and more effectively than DTBO. For more evidence, the maximum value of fitness function determined by ASBO in Figure 4 is much lower than the one found by DTBO.

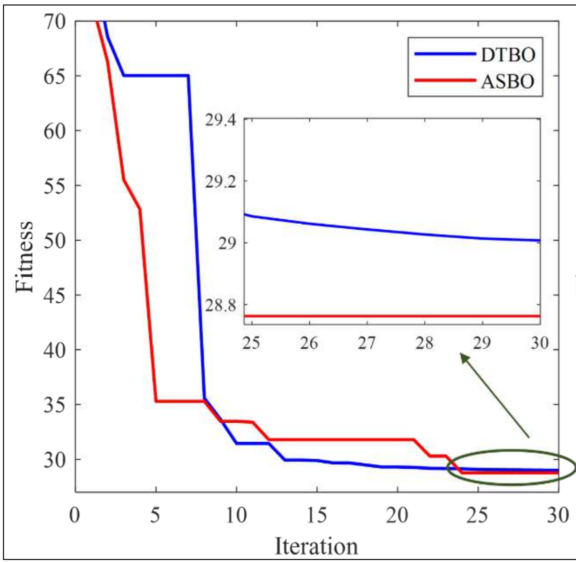

Fig 3: The best convergences given by ASBO and DTBO among 50 independent runs

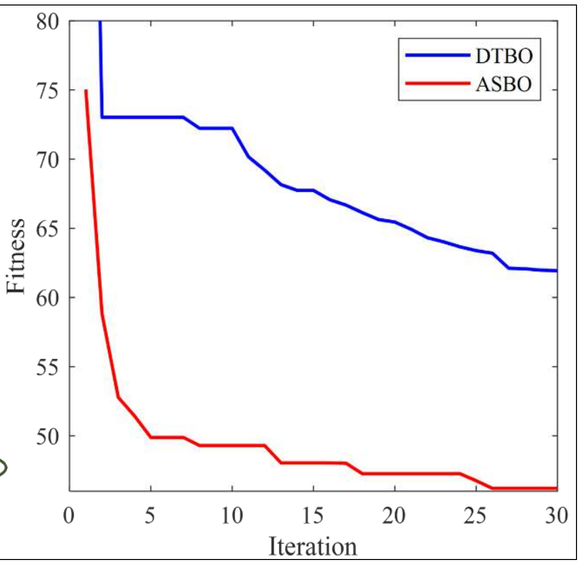

Fig 4: The maximum convergences given by ASBO and DTBO among 50 independent runs

Figure 5 shows the comparison between DTBO and ASBO on different criteria, including Minimum power loss value (Min TPWL), Average power loss value (Aver TPWL), Maximum power loss value (Max TPWL), and standard deviation (Std). The data shown in the figure indicates that ASBO is totally superior to DTBO in all comparison criteria. Specifically, while the Min TPWL and Std. achieved by ASBO are only 28.76281 kW and 5.37258, the similar values obtained by DTBO are 29.00771 kW for the Min TPWL and up to 8.10524 for the Std. Other remaining criteria also point out the high efficiency of ASBO over DTBO. By converting into percentages, the superiority of the ASBO over the DTBO on each criterion is 0.84% for the Min TPWL, 31.16% for the Aver TPWL, 25, 40% for the Max TPWL, and up to 33.71% for the Std. Moreover, the presence of both WTs and ShCs on the IEEE-33 node has substantially reduced the active power loss compared to the original configuration. Particularly, according to [4], the active power loss on the original configuration of the IEEE-33 node is approximately 211 kW. While DTBO and ASBO are both applied, the active power losses obtained by these two applied methods are only 29.0071 kW and 28.76821 kW. These values correspond to 86.25% and 86.37% reduced percentages.

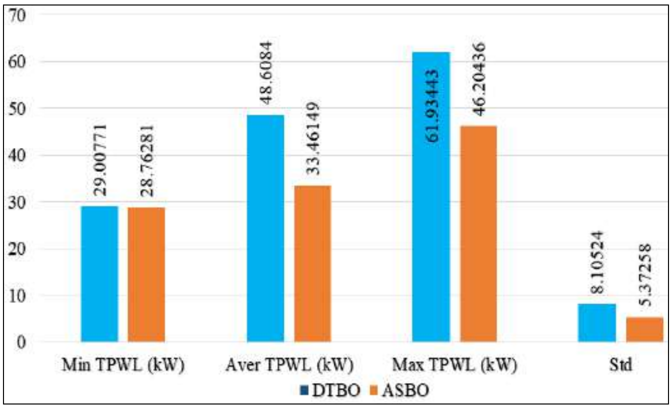

Fig 5: The comparison on different aspects of the between DTBO and ABSO

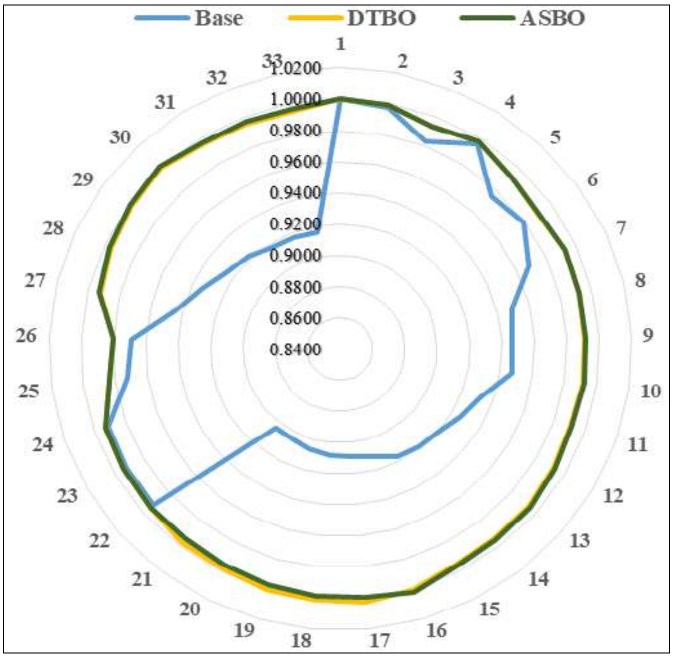

Fig 6: Voltage magnitudes at nodes results by the two applied methods

Appendix

Table A1: The optimal solution found by the two applied methods

Algorithm	DTBO	ASBO
Location 1	30	16
PWF1 (kW)	1156.889	816.128
QWF1 (kVAr)	871.158	89.5736
Location 2	17	30
PWF2 (kW)	801.1036	1157.822
QWF2 (kVar)	328.1485	661.2355
Location 3	25	2
QShC (kVar)	125.4333	377.4734

*** Note:** that, the specific sizes and locations of the WFs and ShCs connected with grid are presented in Table A1 in the Appendix

Figure 6 shows the voltage values at all nodes of the IEEE-33 node distribution network. In the figure, the blue line represents the original configuration without WFs and ShCs, while the orange and green lines are illustrated for the voltage values achieved by DTBO and ASBO with both WFs and ShCs. Because the main objective function of the research is to reduce the total power loss rather than improve the voltage profile, the superiority of ASBO over DTBO is not clearly shown. However, the voltage values at all nodes are substantially improved over the original configuration, where both WFs and ShCs are not connected.

5. Conclusion

In this research, two novel meta-heuristic algorithms, including the Driving-train-based optimization (DTBO) and the Average and subtract-based optimization (ASBO), are successfully applied to determine the optimal size and location of wind farms and shunt capacitors on the IEEE-33 node for active power loss reduction. The results obtained by the two applied methods are compared on different criteria, including the Min TPWL, Aver TPWL, Max TPWL and Std. As evaluated in Section 4, ASBO is totally superior to DTBO in all criteria. Specifically, the better percentages of ASBO over DTBO on the four criteria as mentioned earlier are, respectively, 0.44%, 31.16%, 25.40%, and 33.71%. Moreover, the presence of wind farms and shunt capacitors on the IEEE-33 node has reduced the active power loss value from 211 kW in the original configuration to 28.67281 kW as reached by ASBO. By evaluating the results of ASBO, the method proved itself to be an effective search method. Therefore, we highly recommend using ASBO to solve the problem of placing wind farms and shunt capacitors into distribution networks for active power loss reduction. In the future, the problem of reducing active power loss should be implemented in the larger scale of distribution network such as the IEEE-57, IEEE-85 or a real distribution network in practice. In addition to that, the ASBO also needs to be enhanced for higher efficiency in terms of time response, optimal value and standard deviation.

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