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Modified differential evolution algorithm to finding optimal solution for AC transmission expansion planning problem

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ABSTRACT

The transmission expansion planning (TEP) problem primarily aims to determine the appropriate number and location of additional lines required to meet the increasing power demand at the lowest possible investment cost while meeting the operation constraints. Most of the research in the past solved the TEP problem using the direct current (DC) model instead of the alternating current (AC) model because of its non-linear and non-convex nature. In order to improve the effectiveness of solving the AC transmission expansion planning (ACTEP) problem, a modified version of the differential evolution (DE) is proposed in this paper. The main idea of the modification is to limit the randomness of the mutation process by focusing on the first, second, and third-best individuals. To prove the effectiveness of the suggested method, the ACTEP problem considering fuel costs is solved in the Graver 6 bus system and the IEEE 24 bus system. Moreover, the result of each system is compared to the original DE algorithm and state-of-the-art methods such as the one-to-one-based optimizer (OOBO), the artificial hummingbird algorithm (AHA), the dandelion optimizer (DO), the tuna swarm optimization (TSO), and the chaos game optimization (CGO). The results show that the proposed algorithm is more effective than the original DE algorithm by 1.86% in solving the ACTEP problem.

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1. INTRODUCTION

Transporting electricity from the producing resources to the consumer is the primary function of a power transmission system. However, the integration of renewable energy resources and the expected growth in load demand have placed stress on the power transmission network in recent years [1]. Numerous methods have been researched to address this issue. Nevertheless, for the long-term planning horizon, transmission expansion planning is one of the most appropriate approaches. The primary goal of the transmission expansion planning (TEP) problem is to determine the location and number of additional lines that should be added to the power system with the minimum investment cost while meeting the power system operation constraints.

In general, there are two major models used to solve the TEP problem: the direct current (DC) and alternating current (AC) models. The DC power flow (PF) is used in the DC model and is known as a linearized version of the AC PF [2]. Since the TEP problem is a non-linear and large-scale combinatorial optimization problem, the number of viable solutions grows with the system size. Therefore, the DC model has been used as a simple version of the AC model in many studies in the past [3]–[8] to decrease the complexity of the TEP problem. However, there are three factors that affect the accuracy of the TEP problem using DC model. Firstly, the system voltage on all buses is fixed at 1 p.u., leading to an unacceptable value for the AC system. Secondly, the thermal limit of the transmission line may be exceeded because the reactive power flow is not taken into account. Thirdly, it is hard to evaluate the power loss of a system using a DC model [9]. In order to increase the accuracy of the TEP problem, many studies have solved the TEP problem using the AC model in recent years. The multistage technique is normally applied for solving AC transmission expansion planning (ACTEP) problem [9]–[13]. Although these studies have successfully given the optimal solution for the ACTEP problem, a huge amount of simulation time is required. Moreover, solving the ACTEP problem using a multistage technique required a highly reliable algorithm because the final optimal solution is dependent on the previous optimal solution. Therefore, finding an effective technique for addressing the ACTEP problem is an important goal for research groups. On the other hand, the above issues can be solved by applying the ACOPF formulation, which is allowed to solve the ACTEP problem in a single stage, as presented in study [14]. The load-shedding process is considered in this approach and serves as a penalty value to eliminate the unrealistic transmission topologies. Based on the load-shedding strategy, the AC optimal power flow (ACOPF) formulation is widely applied in the papers [15]–[17] for solving the ACTEP problem. Paper [16] compares the meta-heuristic algorithm approach to addressing the ACTEP problem with mathematical optimization-based approaches. The dynamic TEP problem using the ACOPF formulation is addressed in study [17] utilizing a meta-heuristic approach in large-scale systems.

The optimization methods for solving TEP problem can be divided into two basic approaches: mathematical and meta-heuristic. In a mathematical approach, the TEP problem is solved by using linear programming (LP) [18], branch and bound (B&B) [19], and bender decomposition (BD) [12]. In general, the solution is successfully given by using a mathematical approach in a short time. Although this approach is effective in a small-scale problem, the convergence process may be a weakness in a large-scale problem. On the other hand, meta-heuristic algorithms are powerful at solving large-scale problems. However, the generation, evaluation, and selection of candidates in the population follow a logical rule [15]. Thus, a huge simulation time is required even for small-scale problems. Another challenge for the researcher when using meta-heuristic algorithms is the initial parameters. Some papers applied meta-heuristic algorithms with initial parameters for solving the TEP problem, such as particle swarm optimization (PSO) [14], improved zebra optimization algorithm (IZOA) [20], and social spider (SS) [7]. Besides, the TEP problem is solved using meta-heuristic algorithms without initial parameters, which can be listed as: symbiotic organisms search (SOS) [3], Kepler optimization algorithm (KOA) [5]. Basically, the above algorithms were successfully applied to solving the simplified TEP problem. On the other hand, many studies modified the initial method to handle the complex TEP problem. In [15], the hybridization between differential evolution algorithm and population based incremental learning algorithm called DE-PBILc is proposed for solving the ACTEP problem, considering the fuel cost of generation. The proposed algorithm has a high convergency rate. However, the required control parameters of the DE-PBILc algorithm are very huge, while the differential evolution (DE) algorithm requires only two parameters. The improvement of the binary bat algorithm (IBBA) is proposed in [21] for solving both static and dynamic ACTEP problems. However, the simulation time of the proposed algorithm is huge, even with a small system. Based on the literature review, the existing optimization algorithms are able to solve the ACTEP problem. However, they require several control parameters and huge simulation times, which increase the algorithm’s complexity and computation cost. Therefore, developing an efficiency optimization method for solving the ACTEP problem is still an open question for many studies.

Based on the above analyses, a new modification of the differential evolution algorithm called MDE is proposed in this work to handle the ACTEP problem in the scenario of fuel cost consideration. The DE algorithm is known for its direct parallel search feature based on mutation and crossover processes. Moreover, the efficiency of the DE method in solving the TEP problem is proven in [22], [23]. However, the optimality and convergency speed of this algorithm may be a problem because of the randomness in the mutation process, which can be improved by focusing on the best individuals at each interaction. Therefore, the new individual at the mutation process is created based on the characteristics of the best individual instead of three random individuals in the population in this modification. The efficiency of the proposed MDE algorithm is proved in two well-known models: the Graver 6 bus system and the IEEE 24 bus system. Moreover, the results of the MDE method are compared with the original DE [24] and five different methods: the one-to-one-based optimizer (OOBO) [25], the artificial hummingbird algorithm (AHA) [26], the dandelion optimizer (DO) [27], the tuna swarm optimization (TSO) [28], and the chaos game optimization (CGO) [29].

2. MATHEMATICAL FORMULATION
2.1. Objective function
The objective function of the ACTEP problem included the investment costs of addition lines and generation fuel costs as in [15] is presented in this section. This objective function can be calculated as (1):

$$Minimize\colon C_{total} = \sum_{n_{ij} \in \Omega} c_{ij} \times n_{ij} + 8760 \times \sum_{\forall k \in N_{gen}} (\alpha_k \times P_k) \times CF_k;\ \forall i,j \in N_{bus};\ i \neq j \quad (1)$$

where c_{ij} and n_{ij} are the cost and number of additional lines that need to be added to the power system. α_k, P_k, and CF_k are the generation cost ($/MWh), the total active power of generation, and the capacity factor of the generator at node k, respectively. Ω, N_{bus}, and N_{gen} are the set of candidate lines, the set of all system buses, and the set of all generator buses, respectively.

2.2. Constraints
2.2.1. Equation constraints
The AC PF equation constraints of the ACTEP problem are described in (2)-(7), which contain the power balancing equation for both active and reactive power, as well as the power flow in branches. Equations (2) and (3) provide the active and reactive power balances

$$P(V,\theta) + P_D = P_G \quad (2)$$

$$Q(V,\theta) + Q_D = Q_G + q_s \quad (3)$$

The equation (4) presents the active power flow.

$$P_i(V,\theta) = V_i \sum_{i,j \epsilon N_{bus}} V_j \left[g_{ij} \cos\theta_{ij} + b_{ij} sin\theta_{ij}\right] \quad (4)$$

The reactive power flow is shown in (5).

$$Q_i(V,\theta) = V_i \sum_{i,j \epsilon N_{bus}} V_j \left[g_{ij} \sin\theta_{ij} + b_{ij} cos\theta_{ij}\right] \quad (5)$$

The complex power flow in both terminals is proposed in (6) and (7).

$$S_{ij}^{from} = \sqrt{\left(P_{ij}^{from}\right)^2 + \left(Q_{ij}^{from}\right)^2} \quad (6)$$

$$S_{ij}^{to} = \sqrt{\left(P_{ij}^{to}\right)^2 + \left(Q_{ij}^{to}\right)^2} \quad (7)$$

2.2.2. Inequation constraints
Equations (8)-(14) depict the ACTEP problem's inequality constraints, which include active/reactive generating power, voltage, shunt compensation, installation circuits, and power flow in branches. The allowed active and reactive generations are presented in (8) and (9).

$$P_G^{min} \le P_G \le P_G^{max} \quad (8)$$

$$Q_G^{min} \le Q_G \le Q_G^{max} \quad (9)$$

The voltage amplitude is presented in (10).

$$V_i^{min} \le V_i \le V_i^{max} \quad (10)$$

The limitation of shunt compensation is proposed in (11).

$$q_s^{min} \le q_s \le q_s^{max} \quad (11)$$

The maximum number of additional lines at each right-of-way is presented in (12).

$$0 \le n_{ij} \le n_{ij}^{max} \quad (12)$$

The equations (13) and (14) introduce the transmission line capacity.

$$S^{from} \leq S^{max} \tag{13}$$

$$S^{to} \leq S^{max} \tag{14}$$

where P_G, P_G^{min}, P_G^{max}, Q_G, Q_G^{min}, Q_G^{max}, P_D, and Q_D are the exiting, minimum, and maximum vectors of active and reactive power of the generator and load demand, respectively. q_s, q_s^{min}, q_s^{max} are the exiting, minimum, and maximum of shunt compensation, respectively. The calculation of g_{ij}, b_{ij}, P_{ij}^{from}, P_{ij}^{to}, Q_{ij}^{from}, and Q_{ij}^{to} can be found in [13]. V_i, V_i^{min}, and V_i^{max} are the exiting, minimum, and maximum of voltage, respectively. n_{ij}, n_{ij}^{max} and S^{max} are the addition, maximum number of new lines, and maximum capacity of each branch.

3. OPTIMIZATION METHOD

3.1. Modified differential evolution algorithm

The differential evolution algorithm is first presented in [25]. The main idea of this algorithm is based on the evolution process. This algorithm is known as the effective method for solving the TEP problem due to its direct parallel search strategy. In this algorithm, each characteristic of a new individual is inherited from the previous individual or from the individual created from the mutation process. In the mutation process, a new individual is created based on the characteristics of three random individuals in the population. This process can be described as:

$$v^m = x_a^{ini} + F \times \left(x_b^{ini} - x_c^{ini}\right) \tag{15}$$

where v^m is the new individual created in the mutation process, x_a^{ini}, x_b^{ini}, and x_c^{ini} are the three random individuals in the initial population. F is the mutation factor, which is in the range [0, 2]. Although the DE algorithm successfully solves the TEP problem [22], [23], the optimization may not be guaranteed because of the randomness of the mutation process. Therefore, a new equation based on the three best individuals is suggested in this study to replace (15). This equation is expressed as:

$$v^m = x_{best}^{ini} + F \times \left(x_b^{ini} - x_c^{ini}\right) \tag{16}$$

The difference between (15) and (16) is the x_{best}^{ini}, which is the random choice of the first, second, and third elite individuals ($x_{best}^{ini,1st}$, $x_{best}^{ini,2nd}$, $x_{best}^{ini,3rd}$).

The proposed equation not only improves the exploitation strategy of DE algorithms but also avoids the local optimal solution by randomly selecting first, second, and third-best individuals, as presented in Figure 1. In this figure, the search space of the suggested algorithm focuses on the three best individuals who enhance the exploitation process over the previous approach. In addition, the exploration method may be guaranteed by the random selection of these three best individuals.

Applying the proposed MDE to solve the ACTEP problem can be described in the steps:

Step 1: Read data from the chosen system and choose the control specified parameters of the MDE method: max iter, pop-size (Pop), F, and Cr.

Step 2: Generating the random initial population (17):

$$x_i^{ini} = lb + rand \times (ub - lb), i = 1, \dots Pop \tag{17}$$

where Pop is the maximum number of individuals in the population. ub and lb are the upper bound and lower bound of ACTEP problem. These values are described in (18)-(19).

$$lb = \left[x_1^{min,line} \dots x_\Omega^{min,line}, x_1^{min,vol} \dots x_{N_{gen}}^{min,vol}, x_1^{min,gen} \dots x_{N_{gen}}^{min,gen}\right] \tag{18}$$

$$ub = \left[x_1^{max,line} \dots x_\Omega^{max,line}, x_1^{max,vol} \dots x_{N_{gen}}^{max,vol}, x_1^{max,gen} \dots x_{N_{gen}}^{max,gen}\right] \tag{19}$$

where $x^{min,line}$, $x^{max,line}$, $x^{min,vol}$, $x^{max,vol}$, $x^{min,gen}$ and $x^{max,gen}$ are the lower and upper bounds of candidate transmission lines voltages and active generators output, respectively.

Step 3: Run the AC PF for all initial individuals and check the AC constraints based on the fitness value. The fitness value is calculated following (20):

$$fit = C_{total} + k_p \times \sum P_{pen}^{G} + k_q \times \sum Q_{pen}^{G} + k_s \times \sum S_{pen}^{B} + k_v \times \sum V_{pen} \tag{20}$$

where P_{pen}^{G}, Q_{pen}^{G}, S_{pen}^{B}, and V_{pen} are the penalty values of the generation active power, reactive power, power flow in branches, and voltage, respectively. k_p, k_q, k_s, and k_v are the penalty factors, respectively, which are set of 10^6.

Step 4: Evaluate the population and point out first, second and third elite individuals $\left(x_{best}^{ini,1st}, x_{best}^{ini,2nd}, x_{best}^{ini,3rd}\right)$.

Step 5: Create the mutation individual based on the mutation process using the proposed (16).

Step 6: Generate the new individual based on the crossover (Cr) factor. This process can be described by (21):

$$x_i^{new} = \begin{cases} v_{ij}^{m}, r < Cr \,||\, j = j_0 \\ x_{ij}^{ini}, else \end{cases} \tag{21}$$

where Cr is the crossover factor, which is the random value in the range [0, 1]. j_0 is the random value in the range $[1, Pop]$.

Step 7: Run AC PF and calculate the fitness value of the new individual following the (20).

Step 8: Selected the individual for the new population by (22):

$$x_i^{ini+1} = \begin{cases} x_i^{new}, fit(x_i^{new}) < fit\left(x_i^{ini}\right) \\ x_i^{ini}, else \end{cases} \tag{22}$$

Step 9: Examine the stop condition. If the maximum iteration is reached, go to the next step. Otherwise, go to step 4.

Step 10: Stop and print out the optimal solution.

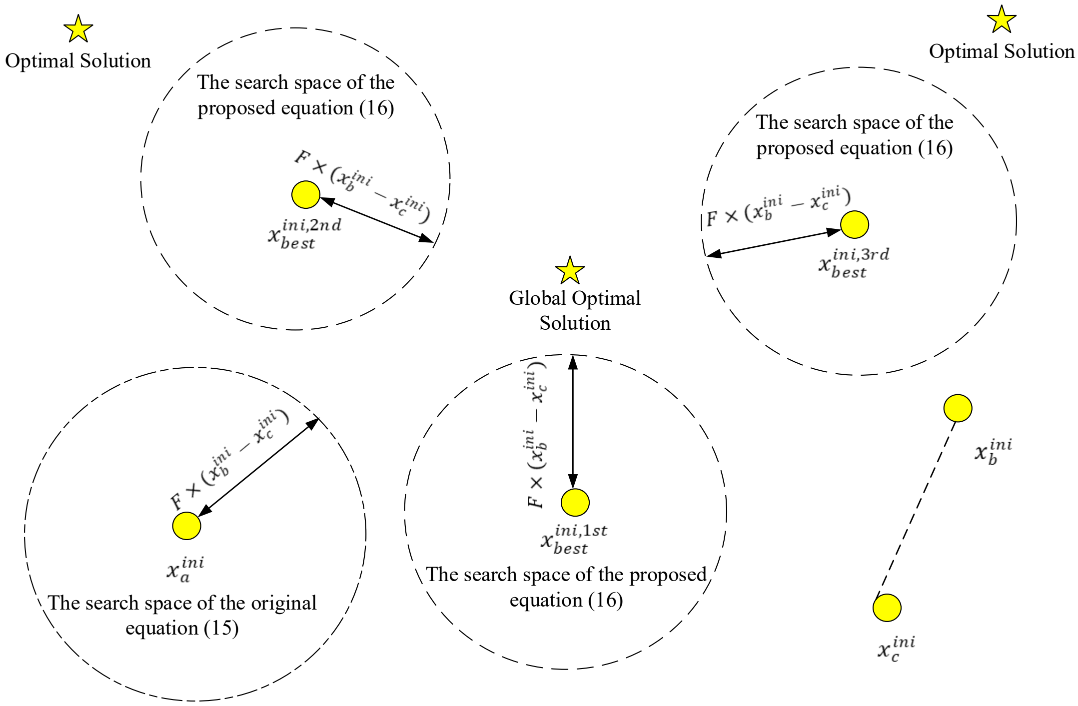


Figure 1. The search space of the proposed MDE algorithm

4. SIMULATION RESULTS

The evaluation of the proposed MDE algorithm for solving the ACTEP problem is performed in this section. Two systems are used in this section, including the Graver 6 bus system and the IEEE 24 bus system.

In each system, the static ACTEP problem considering fuel cost with shunt compensation integration is solved using the MDE algorithm. Moreover, a comparison of the proposed method with other methods such as DE [24], OOBO [25], AHA [26], DO [27], TSO [28], and CGO [29] is performed to prove its effectiveness for solving the mentioned problem. The program is performed in a MATLAB environment, running on a computer with an Intel® Core TM i5-12500H CPU at 3.10 GHz and 16 GB of RAM. The AC power flow is calculated using the MATPOWER [30] toolbox. The optimal solution of all methods is given after 30 trials. The control parameters of each algorithm are presented in Table 1.

Table 1. The operation parameters of used algorithms

Method	Parameter
MDE	F=[0.2,0.8], Cr=0.6, Pop=60
DE	F=[0.2,0.8], Cr=0.6, Pop=60
OOBO	Pop=60
AHA	Pop =60
AHA	Pop =60
TSO	α=0.7, z=0.05, Pop=60
CGO	Pop =60

4.1. The Graver 6 bus system

This system contains 6 buses, 15 rights-of-ways, and 3 generators, with maximum power generation and total load demand of 1100 MW, 760 MW, and 152 MVAr, respectively. The allowed number of addition lines in each rights-of-ways is 4. The detail data for this system can be found in [15]. In order to calculate the fuel cost, the capacity factors, the operating costs of each generator, and the limit of shunt compensation are set as in [15]. The maximum interactions (max iter) of all methods in this system are 150. The simulation results of the ACTEP problem of this system are given in Table 2. Observed from this table, total cost obtained by using the proposed MDE algorithm is 30,395.36×10^3\$, including additional line investment costs (250×10^3\$) and generator fuel costs (30,145.36×10^3\$). This value is lower than the solution given by OOBO (30,399.16×10^3\$), AHA (30,464.63×10^3\$), and TSO (30,399.79×10^3\$), respectively. The solutions given by the MDE, DE, DO, and CGO methods are equal. However, the convergency rate of the DO algorithm is 96.7%, which is lower than the MDE algorithm. Although the solution given by the CGO method is the same as the MDE method, the simulation time of the CGO method is 228.26 s, which is higher than that of the MDE method (149.88 s). The result obtained by the proposed MDE method is not much different compared to the original DE method because the size and the search space of the considered system are quite small. In addition, the convergence curve of all used methods and the results of the ACTEP problem after 30 trials are shown in Figures 2. According to Figure 2(a), the convergence speed of the MDE technique is faster than that of the original DE technique based on the proposed equation. Moreover, the results achieved after 30 trials of the MDE method are more stable than other methods, as shown in Figure 2(b). The new addition lines and total active generation found by the suggested MDE algorithm are equal to the DE-PBILc [15] algorithm. Thus, the total cost given by the MDE algorithm is very close to the compared algorithm.

Table 2. The results of ACTEP problem in Graver 6 bus system

	MDE	DE	OOBO	AHA	DO	TSO	CGO	DE-PBILc [15]
Addition lines	$l_{2-3}=2$ $l_{3-5}=3$ $l_{2-6}=2$ $l_{4-6}=3$	$l_{2-3}=2$ $l_{3-5}=3$ $l_{2-6}=2$ $l_{4-6}=3$	$l_{2-3}=2$ $l_{3-5}=3$ $l_{2-6}=2$ $l_{4-6}=3$	$l_{2-3}=2$ $l_{3-5}=3$ $l_{2-6}=2$ $l_{4-6}=3$	$l_{2-3}=2$ $l_{3-5}=3$ $l_{2-6}=2$ $l_{4-6}=3$	$l_{2-3}=2$ $l_{3-5}=4$ $l_{2-6}=2$ $l_{4-6}=4$	$l_{2-3}=2$ $l_{3-5}=3$ $l_{2-6}=2$ $l_{4-6}=3$	$l_{2-3}=2$ $l_{3-5}=3$ $l_{2-6}=2$ $l_{4-6}=3$
No. addition lines	10	10	10	10	10	12	10	10
Total generation (MW)	766.51	766.51	766.58	766.81	766.51	765.64	766.51	766.51
Total shunt compensation (MVAr)	193.14	192.22	177.45	157.9	194.16	184.49	193.14	191.03
Lines addition cost (10^3 \$)	250	250	250	250	250	300	250	250
Fuel cost (10^3 \$)	30,145.36	30,145.36	30,149.16	30,214.63	30,145.36	30,099.79	30,145.36	30,145.32
Worst cost (10^3 \$)	30,399.8	30,396.4	31,355.3	30,979.5	30,670.8	31,879	31,015	_
Mean cost (10^3 \$)	30.395.61	30,395.48	30,497.16	30,390.05	30,480.24	30,802.83	30,513.53	_
Best cost (10^3 \$)	30,395.36	30,395.36	30,399.16	30,464.63	30,395.36	30,399.79	30,395.36	30,395.32
Simulation time (s)	149.88	151.64	157.73	161.81	154.78	173.15	228.26	_
Convergency rate (%)	100	100	100	100	96.7	90	100	100

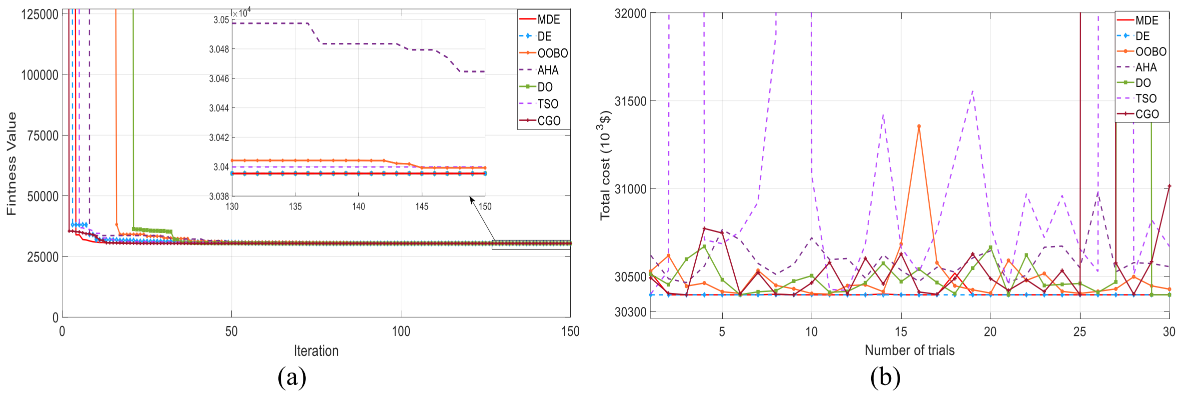


Figure 2. The result obtained by the proposed MDE method: (a) The convergence curve and (b) total cost of ACTEP problem in Graver 6 bus after 30 runs

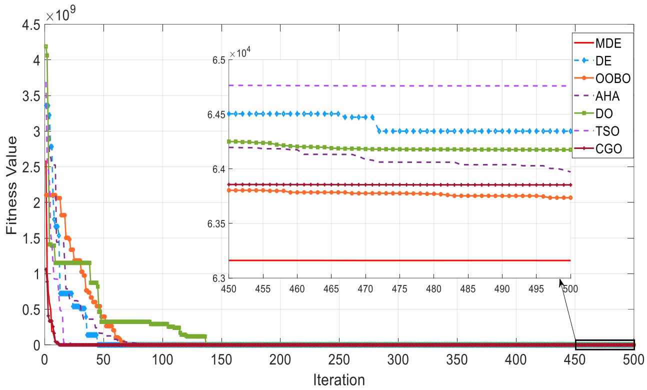
4.2. The IEEE 24 bus system

The chosen system has 24 buses, 10 generators, and 41 rights-of-way. The total values of load demand are 8,550 MW and 1,740 MVAr, with the maximum generation capacity being 10,215 MW. In each rights-of-ways, 4 is the maximum of additional circuits. The completed data for considered system can be seen in [20]. Similarly to the previous system, the shunt compensation limit, the capacity factors, and the operating costs of each generator are set following [15]. In this system, the maximum interaction is set at 500 (max iter). Table 3 presents the simulation results of the considered problem in this system.

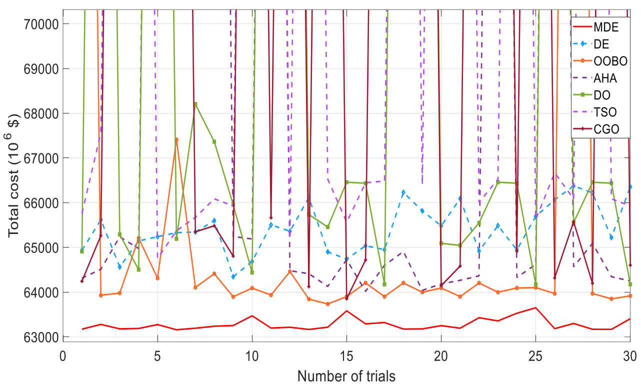
Table 3. The results of ACTEP problem in IEEE 24 bus system

	MDE	DE	OOBO	AHA	DO	TSO	CGO	DE-PBILc [15]
Addition lines	$l_{1-2}=1$ $l_{3-24}=1$ $l_{4-9}=1$ $l_{5-10}=1$ $l_{6-10}=3$ $l_{7-8}=3$ $l_{10-12}=1$ $l_{12-13}=1$ $l_{15-21}=1$ $l_{15-24}=1$ $l_{14-23}=1$	$l_{1-2}=1$ $l_{1-3}=1$ $l_{1-5}=1$ $l_{2-6}=1$ $l_{4-9}=2$ $l_{5-10}=1$ $l_{6-10}=3$ $l_{7-8}=2$ $l_{9-11}=1$ $l_{9-12}=1$ $l_{10-11}=1$ $l_{10-12}=1$ $l_{11-13}=1$ $l_{15-16}=2$ $l_{17-18}=2$ $l_{21-22}=1$ $l_{1-8}=1$ $l_{6-7}=1$ $l_{14-23}=3$	$l_{1-2}=1$ $l_{2-4}=2$ $l_{3-24}=1$ $l_{4-9}=1$ $l_{5-10}=1$ $l_{6-10}=2$ $l_{7-8}=2$ $l_{9-11}=1$ $l_{10-12}=2$ $l_{11-14}=1$ $l_{12-13}=2$ $l_{13-23}=1$ $l_{14-16}=1$ $l_{15-21}=1$ $l_{15-24}=1$ $l_{15-17}=1$ $l_{14-23}=1$	$l_{3-9}=1$ $l_{3-24}=1$ $l_{4-9}=1$ $l_{5-10}=1$ $l_{6-10}=2$ $l_{7-8}=2$ $l_{10-12}=1$ $l_{12-13}=1$ $l_{12-23}=1$ $l_{15-16}=1$ $l_{15-21}=1$ $l_{6-7}=1$ $l_{14-23}=1$	$l_{3-24}=1$ $l_{4-9}=2$ $l_{5-10}=1$ $l_{6-10}=1$ $l_{10-12}=1$ $l_{12-13}=1$ $l_{13-23}=1$ $l_{15-16}=2$ $l_{15-21}=2$ $l_{15-24}=2$ $l_{6-7}=1$ $l_{14-21}=1$	$l_{1-2}=3$ $l_{2-4}=2$ $l_{3-24}=2$ $l_{4-9}=3$ $l_{5-10}=1$ $l_{6-10}=3$ $l_{7-8}=1$ $l_{9-11}=2$ $l_{10-11}=1$ $l_{11-13}=3$ $l_{11-14}=1$ $l_{14-16}=2$ $l_{15-24}=3$ $l_{16-17}=2$ $l_{17-18}=1$ $l_{19-20}=2$ $l_{2-8}=3$ $l_{6-7}=3$ $l_{16-23}=3$ $l_{19-23}=2$	$l_{1-2}=1$ $l_{3-24}=2$ $l_{4-9}=2$ $l_{5-10}=1$ $l_{6-10}=3$ $l_{7-8}=3$ $l_{8-9}=3$ $l_{8-10}=2$ $l_{9-11}=1$ $l_{10-12}=1$ $l_{11-13}=1$ $l_{12-13}=1$ $l_{12-23}=1$ $l_{14-16}=1$ $l_{15-21}=3$ $l_{15-24}=1$ $l_{16-17}=1$ $l_{20-23}=1$ $l_{1-8}=1$ $l_{6-7}=1$ $l_{16-23}=1$	$l_{1-2}=2$ $l_{4-9}=1$ $l_{5-10}=1$ $l_{6-10}=2$ $l_{7-8}=4$ $l_{10-11}=1$ $l_{11-13}=1$ $l_{15-21}=1$ $l_{15-24}=1$ $l_{14-23}=2$
No. addition lines	16	27	22	15	16	43	32	16
Total generation (MW)	8,725.97	8,762,14	8,740.1	8,754.32	8,728.56	8,748.08	8,697,77	8,731.68
Total shunt compensation (MVAr)	1,973.5	2,075.36	1,910.55	2,874.07	2,101.89	2,872.12	1,660.43	1,830.82
Lines addition cost (10^6 \$)	627	1138	1009	721	878	2034	1452	580
Fuel cost (10^6 \$)	62,533.73	63,216.84	62,727.32	63,251.84	63,297.56	62,726.41	62,401.65	62,582.97
Worst cost (10^6 \$)	63,652.05	66,376.91	67,410.85	65,244.51	68,204.26	67,561.41	65,663.34	_
Mean cost (10^6 \$)	63,280.88	65,411.54	64,202.03	64,556.94	65,630.58	66,035.08	64,740.48	_
Best cost (10^6 \$)	63,160.73	64,354.84	63,736.32	63,972.84	64,175.56	64,760.41	63,853.65	63,162.97
Simulation time (s)	580.66	576.89	589.23	587.17	594.04	581.36	815.01	_
Convergency rate (%)	100	100	93.3%	76.7	76.7	66.7	56.7	70

Table 3 shown that the new lines investment cost found by DE-PBILc (580×106$) [15] method is smaller than the MDE (627×106$) method, but the fuel cost obtained by MDE method is 62,533.73×106$, which is lower than DE-PBILc (62,582.97×106$) [15] method. This fuel cost is optimized by the meta-heuristic algorithm (MDE) instead of the interior point method as in the study [15]. Therefore, the result obtained by the suggested MDE algorithm is 63,160.73×106$, which is smaller than the DE, OOBO, AHA, DO, TSO, CGO, and DE-PBILc [15] algorithms by 1.86%, 0.9%, 1.27%, 1.58%, 2.47%, 1.08%, and 0.0035%, respectively. Moreover, the MDE and DE are two techniques that have a 100% convergency rate after 30 trials, as shown in Figure 3. The convergence curve of all used methods in this system is presented in Figure 3(a). Observed from this Figure, the convergence speed of the proposed MDE algorithm is higher than the compared algorithms. In addition, the results given by the MDE method in 30 trials achieve high stability compared to others, as shown in Figure 3(b).



(a)



(b)

Figure 3. Simulation results: (a) the convergence curve and (b) total cost of ACTEP problem in IEEE 24 bus after 30 runs

5. CONCLUSION

In this research, the modified DE algorithm is presented for solving the ACTEP problem considering fuel cost. The efficiency of the proposed technique is proven by solving this problem using the Graver 6 bus system and the IEEE 24 bus system. Moreover, the results found by the MDE algorithm in each system are compared with DE and other meta-heuristics. In the Graver 6 bus system, the solution given by the MDE method is similar to the DE, DO, and CGO methods. However, the convergence speed of the MDE method is faster than that of the other methods mentioned. In a more complex system, such as the IEEE 24 bus system, the solution suggested by the MDE technique has a total cost lower by 1.86%, 0.9%, 1.27%, 1.58%, 2.47%, and 1.08% compared to other techniques. In addition, the improvement of the proposed MDE algorithm is confirmed by the comparison with the original DE algorithm and the DE-PBLIc method in literature. Therefore, this algorithm can be applied to solve the ACTEP problem in large-scale systems (IEEE 118 bus, IEEE 300 bus) and the complex TEP problems in our future works.

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