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Using Improved DDAO Algorithm to Solve Economic Emission Load Dispatch Problem in Presence of Wind Farms

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ABSTRACT

In power systems planning, economic load dispatch considering the uncertainty of renewable energy sources is one of the most important challenges that researchers have been concerned about. Complex operational constraints, non-convex cost functions of power generation, and some uncertainties make it difficult to solve this problem through conventional optimization techniques. In this article, an improved dynamic differential annealed optimization (IDDAO) meta-heuristic algorithm, which is an improved version of the dynamic differential annealed optimization (DDAO) algorithm has been introduced. This algorithm has been used to solve the economic emission load dispatch (EELD) problem in power systems that include wind farms, and the performance of the proposed technique was evaluated in the IEEE 40-unit and 6-unit standard test systems. The results obtained from numerical simulations demonstrate the profound accuracy and convergence speed of the proposed IDDAO algorithm compared to conventional optimization algorithms including, PSO, GSA, and DDAO, while independent runs indicate the robustness and stability of the proposed algorithm.

I. Introduction

Due to the ever-increasing progress of industries and the expansion of cities, the need for electric energy and consequently, thermal power generation has significantly increased. In recent years, the emission of harmful gases such as sulfur oxide and nitrogen oxide, which have caused atmospheric pollution and intensified global warming, has become a critical issue. One of the ways to limit the emission of these gases is to apply stricter policies on thermal units [1, 2]. To apply new regulations and tax considerations for excessive greenhouse gas emissions, a problem combining load economic dispatch and emission constraints known as the load economic emission dispatch problem is introduced [2].

Economic load dispatch has an important and sensitive task in the operation and planning of power systems in such a way that it requires the generation units to meet the load demand while the total power generation cost is minimized and various technical and operational limitations of this process are met [2, 3].

One of the most important solutions to reduce environmental pollutants is to replace fossil fuels with renewable energy, and one of the most important and cost-effective sources of renewable energy is wind energy [4]. The use of wind energy in the generation of electrical energy does not cause environmental pollution, and its maintenance cost is reasonable compared to other renewable energy sources. However, due to the random nature of wind speed forecasting,

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solving the problem of economic load dispatch with the participation of wind units has many challenges [5, 6].

Classical optimization methods such as gradient descent, Landa's iteration method, linear programming method and dynamic programming in the simple economic load dispatch problem provide suitable results when the cost function is smooth, continuous, and differentiable [7]. These methods don't provide suitable answers when the cost function is non-convex, discontinuous, and non-derivative and there are various electrical and mechanical constraints such as the effect of the input valve, generation and consumption balance constraints, generation limits, prohibited zones, the limit of the permitted rate of change of power and the losses of the transmission network. These problems have led researchers to use intuitive optimization algorithms to solve this problem [8-13].

In recent years, different optimization algorithms have been used to solve the problem of economic load dispatch by considering the effect of wind units, including the PSO optimization algorithm and its improved variants called EMOPSO [10], or the gravitational acceleration enhanced particle swarm optimization (GAEPSO) algorithm [14], CMOPEO-EED algorithm [15], EMA algorithm [16], NSGA-II algorithm [17], CSCA algorithm [18], IMOBSO algorithm [19], NSGWO algorithm [20], MQLSA algorithm [21], MODE algorithm [22], WMA algorithm [23], COOT algorithm [24] and CRO algorithm [25]. In the following, some of the articles presented in this regard are mentioned.

In [26], a hybrid method combined with linear and non-linear programming is employed to tackle with non-convexity of economic dispatch, considering the valve point effects. The woodpecker mating algorithm (WMA) is used by [23] to solve the economic dispatch problem considering the nonlinear properties of generators. In the presence of RESs, the chaotic slap swarm optimization algorithm has been applied to cope with the non-convexity caused by the valve point loading effect [27]. The quasi-oppositional-based political optimizer has been implemented by [28], which has minimized the costs and emissions as well. However, with an increase in the number of units, the proposed technique requires a higher number of iterations to reach a desirable solution. The kernel search optimization algorithm and PSO with Cauchy perturbation [29] are also used to solve economic dispatch problem with non-convexity of valve point loading effect. Results indicate that the proposed methodology is robust and flexible. [30] introduced an improved mayfly algorithm incorporating levy flight to resolve the combined economic emission dispatch problem encountered in microgrids with thermal, solar, and wind generation. Although this reference, successfully minimizes total cost and emission for four different scenarios, the speed of the solution has not been discussed. Quasi-oppositional learning-based chaos-assisted sine cosine algorithm has been applied in [31] for dynamic economic emission dispatch in hybrid energy systems. In this reference, the participation of wind and solar energy resources led to a reduction of 20.84% and 8% in generation costs, respectively. [32] evaluates the implementation of the grasshopper optimization algorithm with the binary approach to solve heat and power economic emission dispatch considering the valve point loading effect, ramp-rate constraints, prohibited zones, and transmission losses. This reference has additionally introduced a new case study to examine the effectiveness of the proposed strategy. To increase convergence performance and solution speed in solving the problem of hybrid dynamic economics emissions dispatch, an improved COOT optimization algorithm is utilized [24]. Adaptive chaotic class topper optimization algorithm [33], exchange market algorithm (stock ticker EMA) [34], and chemical reaction optimization (CRO) [25] are also applied to solve combined economic emission dispatch problem.

Solving the EELD problem along with uncertainties about renewable energy sources has been associated with many challenges in recent years. Even though the literature is enriched with the optimization techniques employed to solve it but still a lot of papers are being published incorporating the problem through the variants of metaheuristic optimization techniques.

In this paper, the EELD problem has been solved by presenting an improved dynamic differential annealed optimization algorithm, which is an improved version of the DDAO algorithm. The main contributions of this work are as follows:

- An improved dynamic differential annealed optimization algorithm is proposed to enhance the performance of the conventional DDAO optimizer.
- The efficacy of the proposed algorithm to solve the EELD problem in 6-unit and 40-unit test systems is validated.
- The competence and effectiveness of the proposed IDDAO in terms of robustness, quality of the solution, and computational efficiency are compared with various methods suggested in the literature.

The remainder of this article is organized as follows:

The EELD problem is formulated in section 2. In part 3, the proposed IDDAO algorithm is introduced, followed by section 4 which discusses and evaluates the performance and effectiveness of the proposed IDDAO algorithm in 6-unit and 40-unit test systems to solve EELD with the presence of wind generation. Section 5 is dedicated to the conclusion.

II. The problem of economic emission load dispatch

With the increase in the demand for electric power generation and the reduction of power resources and the increase in pollution, the optimization issues in modern power systems have received more attention from researchers. Considering the output power of wind units, one of the most important optimization issues in power systems related to loading management on the demand side for calculation of the optimal output of generators on the generation side. In terms of the generated power of thermal units, the power plants do not have the same specifications and have different fuel costs, and are located at different distances from the load centers, and the lines that connect them to the loads have different specifications. In addition to these problems, the generation capacity of power plants is more than the total demand of loads and system losses in normal operating conditions, leading to the issue that there are different choices for the amount of power generated by each power plant [3].

In power systems analysis, economic load dispatch has an important role, as it requires the generation units to meet the load demand while the total cost of power generation is minimized, and various non-linear and complex constraints of this process are met. In the simplest possible case, the economic load dispatch problem has the objective function of relation (1) [25].

$$F_c = \sum_{i=1}^{N} (a_i + b_i P_i + c_i P_i^2) \tag{1}$$

Where the total production power of thermal power plants is represented by F_c, N represents the number of thermal units, and a_i, b_i, and c_i are the cost coefficients of each unit. Considering the effect of the steam valve, the cost function changes as follows [25].

$$\mathrm{F_c} = \sum_{\mathrm{i}=1}^{\mathrm{N}} \Big(\mathrm{a_i} + \mathrm{b_i P_i} + \mathrm{c_i P_i^2} + \left| \mathrm{e_i} \times \sin\left(\mathrm{f_i}\left(\mathrm{P_i^{min}} - \mathrm{P_i}\right)\right)\right| \Big) \tag{2}$$

Where the coefficients f_i and e_i are related to the effect of the steam valve and the lower limit of the generation of each unit. For each thermal unit, the cost of the total emission is expressed as the following relationship [25]:

$$E_c = \sum_{i=1}^{N} 10^{-2} (\alpha_i + \beta_i P_i + \gamma_i P_i^2) + \eta_i \exp(\delta_i P_i) \tag{3}$$

where α_i, β_i, γ_i, η_i, and δ_i are the emission coefficients of each generator.

The cost of power generated by wind units in the following relationship consists of three parts [35]. The first part is related to the cost paid to the owner of wind turbines. The second part is related to the conditions in which the output power of the wind unit is greater than its estimated value, so some of the generated power will be wasted or the power of other units must be reduced by redistributing load so that the difference between the planned power of the wind unit and the output of the wind unit should be applied in the cost function. The third part of the cost function is related to the conditions in which the output power of the wind unit is less than the planned value for it. In this case, to balance the generation and consumption power, the revolving reserve capacity should be used [35].

$$F_W = \sum_{j=1}^{M} d_j w_j + k_{P,j} \int_{w_j}^{w_{r,j}} (w - w_j) f_w(w) dw + k_{R,j} \int_0^{w_j} (w_j - w) f_w(w) dw \tag{4}$$

In the above relation, the number of wind units and the factor of the planned power cost of the wind unit is shown by M, and d_j. In the second and third parts, $k_{P,j}$ shows the penalty factor for generating more power than the planned amount, and $k_{R,j}$ shows the penalty factor for generating less than the planned amount. In this relationship, $f_W(w)$ represents the probability density function of the output power of the wind turbine, which is calculated from the following relationships [16, 35].

$$f_W(w) = \frac{klv_i}{c} \left(\frac{(1 + \rho l) v_i}{c} \right)^{k-1} * \exp\left(- \left(\frac{(1+\rho l) v_i}{c} \right)^k \right) \tag{5}$$

$$l = \left(\frac{(v_r - v_i)}{v_i} \right) \tag{6}$$

$$\rho = \frac{w}{w_r} \tag{7}$$

Where w is the output power of the wind turbine, v is the wind speed, ρ is the ratio of the output power to the nominal wind power, and l is the ratio of the linear range of the wind speed to the connection speed of the wind turbine.

A. Objective function

The objective function implemented in this paper is as follows:

$$T_c = Minimaze \quad (F_c + E_c + F_W) \tag{8}$$

B. System limitations

The EELD problem has several constraints. The first constraint is the balance of the power system's generation and consumption power so that the set of power generation at any time is equal to the set of consumption power and network losses. This issue is defined as the following relationship. It should be noted that the system losses are considered a function of the power generation, whose value is calculated from the following equations.

$$\sum_{i=1}^{N} P_i = P_{\text{Demand}} + P_{\text{Loss}} \tag{9}$$

$$P_{\text{Loss}} = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{i0} P_i + B_{00} \tag{10}$$

Where, the required power is indicated by P_{Demand}, and the losses of the power system are indicated by P_{Loss}. B_{00}, B_{i0}, and B_{ij} are the network loss coefficients, and constants during normal operating conditions [28].

The second constraints indicate the minimum and maximum of generated power by thermal and wind power plants as follows [35]:

$$P_i^{min} \le P_i \le P_i^{max} 0 \le w_j \le w_{r,j} \tag{11}$$

where the upper and lower limit of the power generation of each thermal unit is indicated by P_i^{max} and P_i^{min}, and the rated power and output power for each wind unit are indicated by $w_{r,j}$, and w_j.

III. The proposed optimization algorithm

Introducing the DDAO algorithm, the proposed improved algorithm has been discussed in this section.

A. Dynamic differential annealed optimization algorithm (DDAO)

The dynamic differential annealing optimization (DDAO) algorithm presented in reference [36] is inspired by the optimal production process of two-phase annealed steel. This algorithm is effective in solving optimization problems. The processes of this algorithm are briefly described below:

The first stage includes the production of the initial population. At this stage, the initial population of solutions is generated randomly. This population includes candidate answers and general answers. In the second step, for the production of two-phase steel, the temperature decreases randomly. The random process of temperature reduction causes the formation of different phases of steel that have different energies. These energies are proportional to the value of the cost function. In the third stage, the two-phase steel cooling process is done in three ways, which are: air cooling, accelerated cooling system, and slow cooling system. This procedure can be represented by the following equation.

$$N_S^J = R_{GS} + [R_{CS}^K + R_{CS}^I] \qquad J = 1, \ldots, N \tag{12}$$

where N_S^J and R_{GS} represent the new solution in the Jth iteration and the random solution of production, respectively. R_{CS}^K and R_{CS}^I represent the randomly selected solution according to K and I index.

In the fourth stage which is related to reducing the differential temperature, the steel is exposed to the forging process. Because during the forging process, the dynamic characteristic of the hammer fluctuates between 1 and R, this process can be formulated according to the following equation.

$$F_G = \begin{cases} 1; if\ Re(I,2) = 1 \\ R[0,1]; if\ Re(I,2) = 0 \end{cases} \tag{13}$$

where, F_G, R, and Re represent the forging parameter, the random value, and the remainder divided by 2, respectively. Forging processes and differential cooling processes are integrated in the following equation.

$$N_S^J = R_{GS} + [R_{CS}^K + R_{CS}^I] * F_G \tag{14}$$

In the annealing process, the probability of forming a new phase with higher quality is higher than that of a weaker base. This process is defined by the acceptance probability, Pr, according to the following relations:

$$Pr = e^{\frac{-\Delta D}{t}} \tag{15}$$

$$\Delta D = \frac{C(N_S^J) - C(P_M)}{C(P_M)} \tag{16}$$

In this regard, ΔD represents the difference between the merit value of the potential responses resulting from equation (14) and the merit value corresponding to the P_M index. The values of p and t represent the population size and temperature variable, respectively. The best solution is selected by satisfying the following equation:

$$Pr > R \in [0,1] \tag{17}$$

Based on equation (12),

$$Pr = \begin{cases} 1 \ \ If\ t\ is\ high \\ 0 \ \ If\ t\ is\ low \end{cases} \tag{18}$$

The mentioned stages are repeated until reaching the stopping condition of the algorithm, which can be the maximum number of iterations or reaching a certain cost function.

B. Improved dynamic differential annealed optimization algorithm (IDDAO)

Investigations imply that the forging parameter, F_G, has a significant effect on the overall efficiency of the DDAO algorithm in solving mathematical optimization problems. For some cases, setting F_G=1 in equation (14), the random value improves while for some sets of problems, the random value becomes worse. This may reversely happen in other cases. equation (13) provides a solution for this algorithm in which F_G = 1 for half of the iterations while for other iterations F_G is a random number in the interval [0, 1]. Investigations also show that the randomness of the value of F_G causes the algorithm not to desirably perform in reaching the optimal solution; therefore, equations (13) and (14) are considered as follows.

$$F_G{}^{J+1} = W_e . F_G{}^J + C.rand(N_S^{best} - N_S^J) \tag{19}$$

$$N_S^{J+1} = N_S^J + F_G{}^{J+1} \tag{20}$$

In these equations, W_e is defined as a weighting factor, C is a learning factor (a number between 1.5-2) and rand is a random number between [0, 1]. Also, to prevent the divergence of F_G, its final value is limited.

Equation (19) contains two terms. The first term is a ratio of the forging parameter for each phase, and its role is similar to the momentum in the neural network. The second term is proportional to the difference between the obtained answer compared to the best existing answer (N_S^{best}), which increases the speed of guiding the answer toward the optimal answer. In the proposed improved algorithm, the degree of accuracy and convergence is highly dependent on W_e, so its value is considered dynamically and linearly according to equation (21). In the beginning, by choosing large values for W_e, it is possible to find good solutions in the early stages, while in the final stages, the smallness of W_e causes better convergence.

$$w_e^{J+1} = w_e^J + [w_e^{min} + w_e^{max}]/N_{iteration} \tag{21}$$

In this equation, w_e^{max}, w_e^{min} and $N_{iteration}$ are the maximum weighting factor, minimum weighting factor, and the number of iterations in the algorithm, respectively. The pseudo-code of this algorithm is shown in Figure 1.

IV. The EELD Based on IDDAO Algorithm

To evaluate the performance of the proposed improved

IDDAO algorithm, the EELD problem for 6-unit and 40-unit standard IEEE test systems has been applied, and the results have been compared with those of PSO, GSA, and DDAO algorithms. In the proposed algorithm, the position vector is considered as the following equation.

$$x = [P_1, P_2, \dots, P_{NG}]^T \tag{22}$$

where x is the power generated by each power plant.

In this study simulations have been done in MATLAB R2021b software, using a Core i7, 2.30 GHz processor, and a 4G Ram. The number of populations is 150, the number of iterations is 100, and the number of independent runs is 30. The best solution of all independent runs is considered the optimal solution of the algorithms.

A. EELD for 6-unit IEEE test system

For the standard IEEE 6-unit test system with a load demand of 2,834 p.u., cost function coefficients, the generation constraints units, thermal unit emission cost coefficients, and wind turbine data are given in Tables 1 to 3 respectively [16,37].

Considering the permitted range of power generation of power plants, the fuel cost of thermal power plants, the cost function of pollution, and two wind farms, the output power of power plants along with the optimal values of the objective function for the proposed IDDAO algorithm and PSO, GSA, DDAO algorithms are given in Table 4.

***Pseudocode*: IDDAO Algorithm**

Input: size of the population, variable temperature t, dimensions

Population Initialization x_K $(K = 1, \dots. N)$;
Initialization of cooling rate and temperature parameters;
Evaluating fitness for every solution;
Best solution $(N_S^{best}) = x_B$;
While $T < I_{MAX}$
    Initialization of sub population R_{CS};
    Evaluating the cost function for every R_{CS};
    Sorting of R_{CS}
    Select the best solution in sub population;
    Selection of two random solutions;
    Evaluation of N_S^J from equation (20);
    Population sorting;
    for (each solution within the population)
        if (there occurs enhancement)
            $x_K = N_S^J$
        else
            Replacement of worst solution using equation (15) and (16);
        end if
    end for
Updating of x_B ;
$T = T^* \, rate \; of \; cooling$
$T = T + 1$
end while
Return x_B

Output: Best solution

Fig. 1. The pseudo-code of the IDDAO algorithm.

TABLE 1
COST FUNCTION COEFFICIENTS OF THE 6-UNIT SYSTEM.

Unit i	Generation limits		Fuel cost coefficients				
	$P_{i,\min}$	$P_{i,\max}$	a_i	b_i	c_i	e_i	f_i
1	0.05	0.5	10	200	100	–	–
2	0.05	0.6	10	150	120	–	–
3	0.05	1.0	20	180	40	–	–
4	0.05	1.2	10	100	60	–	–
5	0.05	1.0	20	180	40	–	–
6	0.05	0.6	10	150	100	–	–

TABLE 2
EMISSION COEFFICIENTS OF THE 6-UNIT SYSTEM.

Unit i	Emission coefficients				
	α_i	β_i	γ_i	η_i	δ_i
1	4.091	−5.554	6.490	2.0e−4	2.857
2	2.543	−6.047	5.638	5.0e−4	3.333
3	4.258	−5.094	4.586	1.0e−6	8.000
4	5.326	−3.550	3.380	2.0e−3	2.000
5	4.258	−5.094	4.586	1.0e−6	8.000
6	6.131	−5.555	5.151	1.0e−5	6.667

TABLE 3
THE PARAMETERS OF WIND TURBINES.

	k	C	$c_{un,j}$	d	W_{min} (MW)	W_{max} (MW)	v_o (m/s)	v_i (m/s)	v_r (m/s)
WT1	2.2	15	100	120	10	100	45	5	15
WT2	2.2	15	100	150	10	100	45	5	15

TABLE 4
BEST SOLUTION FOR 40-UNIT TEST SYSTEM.

Outputs (MW)	PSO [14]	GSA [14]	DDAO	IDDAO
TU 1	0.02	0.1445	0.2896	0.2941
TU 2	0.3006	0.5346	0.3258	0.3325
TU 3	0.2824	0.2387	0.3501	0.3478
TU 4	0.3129	0.06	0.3625	0.3581
TU 5	0.4032	0.2548	0.3521	0.3795
TU 6	0.4161	0.2267	0.6258	0.6295
WT 1	0.8	0.5771	0.5289	0.4919
WT 2	0.302	0.8	0.2896	0.2941
Fuel cost ($/h)	624.97	588.46	571.99	565.89
EC (ton/h)	0.2043	0.2133	0.2049	0.2019
Total cost ($/h)	1836	1853	1776	1674

B. EELD for 40-unit IEEE test system

For the IEEE 40-unit test system, the cost function coefficients, power generation limits, and pollution coefficients are stated in Tables 5 and 6, respectively [37].

Considering the permitted range of power generation, the cost of fuel consumed by thermal power plants, and the cost function of pollution, the simulation of EELD based on the PSO, GSA, DDAO, and IDDAO algorithm was carried out, and results are summarized in Table 7.

V. Numerical results and discussions

Based on Tables 4 and 7, the total cost reduction achieved by the IDDAO algorithm compared to DDAO, GSA, and PSO algorithms for the 6-unit test system is 102 $/h, 179 $/h, and 162 $/h and for a 40-unit test system equals 1332 $/h, 7828 $/h, and 2810 $/h, respectively. Results demonstrate the superiority of the proposed algorithm in reaching the optimal solution over other algorithms.

TABLE 5
COST FUNCTION COEFFICIENTS OF THE 40-UNIT SYSTEM.

Unit i	Generation limits		Fuel cost coefficients				
	$P_{i,min}$	$P_{i,max}$	a_i	b_i	c_i	e_i	f_i
1	36	114	94.705	6.73	0.00690	100	0.084
2	36	114	94.705	6.73	0.00690	100	0.084
3	60	120	309.54	7.07	0.02028	100	0.084
4	80	190	369.03	8.18	0.00942	150	0.063
5	47	97	148.89	5.35	0.01140	120	0.077
6	68	140	222.33	8.05	0.01142	100	0.084
7	110	300	287.71	8.03	0.00357	200	0.042
8	135	300	391.98	6.99	0.00492	200	0.042
9	135	300	455.76	6.60	0.00573	200	0.042
10	130	300	722.82	12.90	0.00605	200	0.042
11	94	375	635.20	12.90	0.00515	200	0.042
12	94	375	654.69	12.80	0.00569	200	0.042
13	125	500	913.40	12.50	0.00421	300	0.035
14	125	500	1760.40	8.84	0.00752	300	0.035
15	125	500	1760.40	8.84	0.00752	300	0.035
16	125	500	1760.40	8.84	0.00752	300	0.035
17	220	500	647.85	7.97	0.00313	300	0.035
18	220	500	649.69	7.95	0.00313	300	0.035
19	242	550	647.83	7.97	0.00313	300	0.035
20	242	550	647.81	7.97	0.00313	300	0.035
21	254	550	785.96	6.63	0.00298	300	0.035
22	254	550	785.96	6.63	0.00298	300	0.035
23	254	550	794.53	6.66	0.00284	300	0.035
24	254	550	794.53	6.66	0.00284	300	0.035
25	254	550	801.32	7.10	0.00277	300	0.035
26	254	550	801.32	7.10	0.00277	300	0.035
27	10	150	1055.10	3.33	0.52124	120	0.077
28	10	150	1055.10	3.33	0.52124	120	0.077
29	10	150	1055.10	3.33	0.52124	120	0.077
30	47	97	148.89	5.35	0.01140	120	0.077
31	60	190	222.92	6.43	0.00160	150	0.063
32	60	190	222.92	6.43	0.00160	150	0.063
33	60	190	222.92	6.43	0.00160	150	0.063
34	90	200	107.87	8.95	0.00010	200	0.042
35	90	200	116.58	8.62	0.00010	200	0.042
36	90	200	116.58	8.62	0.00010	200	0.042
37	25	110	307.45	5.88	0.01610	80	0.098
38	25	110	307.45	5.88	0.01610	80	0.098
39	25	110	307.45	5.88	0.01610	80	0.098
40	242	550	647.83	7.97	0.00313	300	0.035

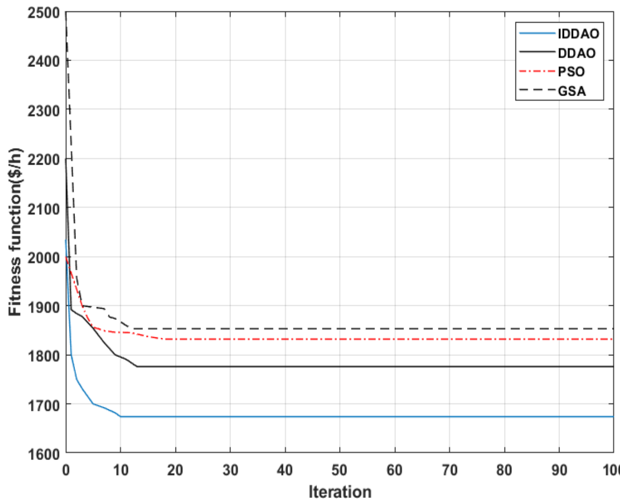

Fig 2. Convergence behaviors of fitness function for the 6-unit test system.

The convergence curve of the proposed improved algorithm for the best solution obtained for the 6-unit and 40-unit test systems is shown in Figures 2 and 3. The IDDAO algorithm has converged to a more optimal solution after a smaller number of iterations compared to other algorithms. PSO, GSA, and DDAO algorithms have a lower convergence speed and are stuck in the local solution. Hence, it can be concluded that the performance of the proposed algorithm is satisfactory for solving the EELD problem.

TABLE 6
EMISSION COEFFICIENTS OF THE 40-UNIT SYSTEM.

Unit i	Emission coefficients				
	α_i	β_i	γ_i	η_i	δ_i
1	60	−2.22	0.0480	1.3100	0.05690
2	60	−2.22	0.0480	1.3100	0.05690
3	100	−2.36	0.0762	1.3100	0.05690
4	120	−3.14	0.0540	0.9142	0.04540
5	50	−1.89	0.0850	0.9936	0.04060
6	80	−3.08	0.0854	1.3100	0.05690
7	100	−3.06	0.0242	0.6550	0.02846
8	130	−2.32	0.0310	0.6550	0.02846
9	150	−2.11	0.0335	0.6550	0.02846
10	280	−4.34	0.4250	0.6550	0.02846
11	220	−4.34	0.0322	0.6550	0.02846
12	225	−4.28	0.0338	0.6550	0.02846
13	300	−4.18	0.0296	0.5035	0.02075
14	520	−3.34	0.0512	0.5035	0.02075
15	510	−3.55	0.0496	0.5035	0.02075
16	510	−3.55	0.0496	0.5035	0.02075
17	220	−2.68	0.0151	0.5035	0.02075
18	222	−2.66	0.0151	0.5035	0.02075
19	220	−2.68	0.0151	0.5035	0.02075
20	220	−2.68	0.0151	0.5035	0.02075
21	290	−2.22	0.0145	0.5035	0.02075
22	285	−2.22	0.0145	0.5035	0.02075
23	295	−2.26	0.0138	0.5035	0.02075
24	295	−2.26	0.0138	0.5035	0.02075
25	310	−2.42	0.0132	0.5035	0.02075
26	310	−2.42	0.0132	0.5035	0.02075
27	360	−1.11	1.8420	0.9936	0.04060
28	360	−1.11	1.8420	0.9936	0.04060
29	360	−1.11	1.8420	0.9936	0.04060
30	50	−1.89	0.0850	0.9936	0.04060
31	80	−2.08	0.0121	0.9142	0.04540
32	80	−2.08	0.0121	0.9142	0.04540
33	80	−2.08	0.0121	0.9142	0.04540
34	65	−3.48	0.0012	0.6550	0.02846
35	70	−3.24	0.0012	0.6550	0.02846
36	70	−3.24	0.0012	0.6550	0.02846
37	100	−1.98	0.0950	1.4200	0.06770
38	100	−1.98	0.0950	1.4200	0.06770
39	100	−1.98	0.0950	1.4200	0.06770
40	220	−2.68	0.0151	0.5035	0.02075

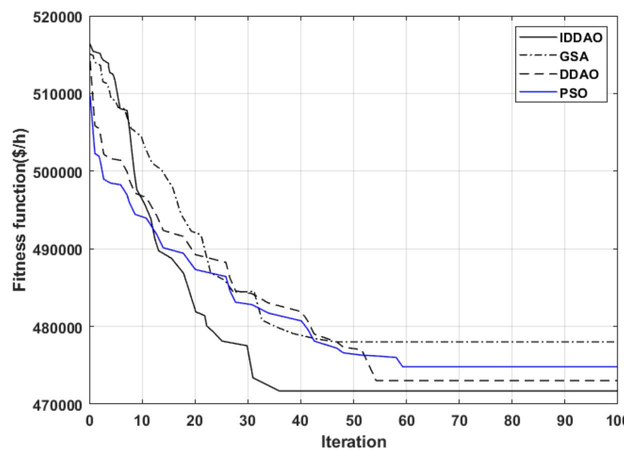

Fig 3. Convergence behaviors of fitness function for the 40-unit test system.

To check the compatibility of the proposed improved algorithm, the values of the best solution, the worst solution, and the average solution along with the standard deviation (STD) considering 30 independent runs for PSO, GSA, DDAO, and IDDAO algorithms for 6-unit and 40-unit test system are given in Table 8. Results show that the standard deviation of the optimal solutions obtained by the IDDAO algorithm is smaller than other algorithms, which indicates its higher robustness and stability to different parameters of algorithms. Comparing the average time required to run the proposed algorithm with other algorithms, it can also be concluded that the solution speed of the IDDAO algorithm surpasses those of other algorithms.

TABLE 7
BEST SOLUTION FOR THE 40-UNIT TEST SYSTEM.

Outputs (MW)	PSO [25]	GSA [25]	DDAO	IDDAO
TU 1	114.0000	112.0124	113.2849	112.152051
TU 2	106.2356	102.0546	112.9873	110.6585
TU 3	118.2564	65.3624	118.9851	119.1124
TU 4	182.6634	189.0000	172.3033	172.5485
TU 5	97.0000	81.4570	96.9899	97.0000
TU 6	102.1987	140.0000	120.7941	118.5487
TU 7	134.0531	178.9692	297.9866	240.5487
TU 8	292.2256	261.0062	298.0531	299.1473
TU 9	290.1165	144.0886	289.9833	290.2548
TU 10	133.8941	268.6632	141.9755	138.2546
TU 11	101.2368	262.5468	290.8744	278.2351
TU 12	154.7289	338.0018	295.8873	299.2548
TU 13	308.2166	357.2549	428.9894	425.365
TU 14	368.3325	402.6638	421.9738	425.9854
TU 15	371.2215	481.0378	430.9884	424.2154
TU 16	381.2681	426.7826	416.9725	398.8547
TU 17	416.2678	468.2594	449.7641	448.6354
TU 18	482.9655	411.0338	451.0875	451.5241
TU 19	506.2201	452.7650	463.4483	466.9878
TU 20	516.2468	485.3309	424.9509	420.6662
TU 21	502.7719	410.7262	418.7534	417.2154
TU 22	435.4741	446.8291	438.5739	448.754
TU 23	482.1264	410.5897	415.5968	442.1187
TU 24	538.0536	429.6281	429.0083	430.2522
TU 25	545.0089	355.4008	442.8693	447.6584
TU 26	426.2278	497.2740	421.7939	400.2215
TU 27	121.2238	110.0368	29.6631	38.2654
TU 28	126.0343	103.0191	20.9746	50.2654
TU 29	106.2268	135.4494	28.2672	102.5245
TU 30	96.0892	67.2264	95.0546	90.2154
TU 31	172.0086	160.2286	183.1982	178.2654
TU 32	181.6147	156.2273	169.8629	168.1145
TU 33	170.1243	162.1683	183.2297	175.2654
TU 34	191.3843	150.6824	184.8734	190.2487
TU 35	189.5371	163.4874	190.2495	192.3659
TU 36	172.0034	173.7898	197.8624	186.2658
TU 37	97.6206	99.3548	102.6921	99.1212
TU 38	94.4833	96.1757	103.2485	104.3256
TU 39	86.0853	99.0471	100.2394	95.3298
TU 40	462.2264	484.1232	432.0381	420.6965
WT 1	46.0468	66.2162	41.5432	45.2185
WT 2	80.0468	94.0293	32.1267	40.2354
Fuel cost($/h)	142 068	143562.68	141241.46	141025.41
EC (ton/h)	178432	180028.22	171953.76	171902.52
Total cost($/h)	474934	479405	473456	472124

TABLE 8
STATISTICAL COMPARISON BETWEEN IDDAO AND DIFFERENT.

Test systems	Algorithms	Best($/h)	Worst($/h)	Average($/h)	STD	Average of run time(s)
6-unit	PSO	1836	1880	1856	15.1471	3.542
	GSA	1853	1914	1886	20.5487	4.754
	DDAO	1776	1831	1793	11.2514	4.124
	IDDAO	1674	1724	1685	7.2135	3.562
40-unit	PSO	474934	495356	481108	6451.7854	26.2541
	GSA	479405	503375	489951	8721.2145	34.524
	DDAO	473456	492394	479610	1425.5215	34.854
	IDDAO	472124	490064	478733	501.2341	25.43

VI. Conclusions

In this article, to solve the EELD problem with the participation of wind farms, a novel strategy based on the IDDAO algorithm has been introduced. The limitations such as generation-demand balance, uncertainty, and the non-convexity of cost functions for thermal power plants have also been considered. The performance of the proposed algorithm to solve the EELD problem for two standard test systems of 6-unit and 40-unit were compared and evaluated. The minimum reduction of the total cost function obtained by the proposed IDDAO algorithm Compared to the DDAO, GSA, and PSO algorithms was 102 $/h and 1332 $/h for 6-unit and 40-unit test systems, respectively. These results demonstrate that the new approach developed in this paper can efficiently reduce the expected cost of the integrated thermal-wind system. Moreover, to check the robustness and stability of the proposed algorithm, the EELD problem was implemented for 30 independent runs. The results indicate the superiority of the proposed algorithm in the speed of convergence and proper performance compared to other studied algorithms.

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