Emission Constrained Optimal Allocation of Generation using AWDO Technique

Swaraj Banerjee and Dipu Sarkar*

Abstract—**The current work introduces a meta-heuristic solution of an emission constrained optimal generation scheduling problem on the Distributed Energy Resources (DERs). The Combined Economic Emission Dispatch (CEED) problem reflects the environmental effects from the gaseous pollutants from fossil-fueled power generating plants. The CEED is a method for scheduling the generation considering both emission and generation cost meeting the needs of satisfying all operational constraints and load demand as well. The CEED problem has been formulated as a multi-objective problem and that later has been converted into a single objective function using price penalty factor. A comparatively new meta-heuristic nature-inspired global optimization method, Adaptive Wind Driven Optimization (AWDO), has been proposed to solve the CEED problem solution. The key objective is to solve the CEED problem with the proposed algorithm and analyze its effectiveness of with the help of the simulation results which later have been compared with other existing algorithms for two test systems (10 thermal units and 40 thermal units) and AWDO has proved to be the best and most powerful amongst them.**

Index Terms—**adaptive wind has driven optimization, economic load dispatch, constrained minimization, multi-objective, valve-point effect, environmental dispatch.**

I. Introduction

THE objective of the Economic Dispatch Problem (EDP) is determining the optimal generation for each generator at minimum fuel costs, conditional on equality constraints on power balance and inequality constraints on power outputs. In addition, transmission losses, higher order non-linear valve point effect may also be considered.

A diversity of techniques has been used by earlier researchers to solve ED (Economic Dispatch) problems of which several are based on classical optimization methods, for example, the linear or quadratic programming, whereas others are based on artificial intelligence or heuristic algorithms.

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During the last two decades, the different conventional techniques such as Lambda-iteration method [1], Gradient method used by Chang et al. in [2], Coleman et al. in [3], Base-point participation factor method [4] have been applied through the techniques have some limitations. The demerits are high computational time, several local minima and oscillatory in nature [5].

Contemporary Stochastic Search Algorithms such as PSO used by El-Sawy et al. in [6], Vlachogiannis et al. in [7], Selvakumar et al. in [8], Park et al. in [9], Sreenivasan et al. in [10], Shahinzadeh et al. in [11]; GA used by Damousis et al. in [12], Walters et al. in [13], Nanda et al. in [14]; Direct Search used by Chen et al. in [15] and Differential Evolution used by Balamurugan et al. in [16], Noman et al. in [17]; Simulated Annealing used by Vishwakarma et al. in [18], Basu et al. in [19]; Gravitational Search used by Mondal et al. in [20], Hota et al. in [21]; Cuckoo Search used by Tran et al. in [22], Sekhar et al. in [23]; Binary successive approximation-based evolutionary search used by Dhillon et al. in [24], Mallikarjuna et al. in [25] have been applied for solving the ELD problem. However, the above-mentioned optimization techniques in literature are also accompanying with their own limitations such as local optimal solution and requirement of common controlling parameters like population size, executions of many repeated stages, execution speed etc. Jaya optimization algorithm used by Rao in [26] is a relatively newly developed class of algorithm. Trust-Region-Reflective Algorithm used by Bisheh et al. in [27] is another very effective algorithm that has strong potential to solve the constrained optimization problem. This is also a new algorithm. In the present work Wind Driven Optimization (WDO) Algorithm has been proposed to solve the CEED problem. It's a global optimization technique that is inspired by nature and its working principle is based on atmospheric motion. The technique is population-based heuristic global optimization algorithm which can be used for multi-dimensional and multi-modal problems. The technique has the ability to implement constrained optimization in the search domain.

II. Problem Formulation

The combined environmental economic dispatch problem is to minimize two objective functions, fuel cost, and emission, simultaneously while satisfying all equality and inequality constraints. The mathematical formulation of the problem is described as follows:

A. *Economic dispatch formulation with valve-point effect*

The cost function of economic load dispatch problem is defined as follows where P_G is the total generation:

$$F_C(P_G) = \sum_{i=1}^{N_g}(a_i P_i^2 + b_i P_i + c_i) + \left| d_i \sin(e_i(P_i^{\min} - P_i)) \right| \quad (1)$$

where N_g is the number of generating units. a_i, b_i, c_i, d_i and e_i are the cost coefficients of the i^{th} generating unit. P_i is the real power output of the i^{th} generator.

B. Emission dispatch formulation

The emission function of economic load dispatch problem is defined as follows:

$$E(P_g) = \sum_{i=1}^{n} 10^{-2}(\alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^2) + \xi_i \exp(\lambda_i P_{gi}) \quad (2)$$

where α_i, β_i, γ_i, ξ_i, and λ_i are coefficients of the i^{th} generator emission characteristics.

C. Minimization of fuel cost and emission

The multi-objective combined economic and emission problem with its constraints can be mathematically formulated as a nonlinear constrained problem as follows:

$$OF = \omega \sum_{i}^{n} F(P_{gi}) + (1-\omega)\sum_{i=1}^{n} E(P_{gi}) \quad (3)$$

The solution of the problem is achieved by minimizing the objective function (*OF*), the fuel cost rate ($/h) is shown with $F(P_{gi})$ and NO_x emission rate (ton/h) with $E(P_{gi})$.

D. Power balance constraint

Generation should cover the total demand and the active power losses that occur in the transmission system,

$$\sum_{j=1}^{N_g} P_i = P_d + P_{loss} \quad (4)$$

where P_d is the total demand load and P_{loss} is the total transmission losses computed using a quadratic approximation,

$$P_{loss} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P_i B_{ij} P_j \quad (5)$$

where B_{ij} is the loss coefficient matrix. This paper assumes B-matrix as constant.

Power generation limits. Each unit should generate power within its minimum and maximum limits,

$$P_i^{\min} \le P_i \le P_i^{\max} \quad (6)$$

III. Adaptive Wind Driven Optimization Algorithm

The Wind-Driven Optimization is a nature-inspired population-based iterative heuristic global optimization method. One of the important property of this algorithm is the Covariance matrix adaptive evolutionary strategy (CMAES). It means the technique does not need parameters for tuning which is obtained internally without getting input from the user side other than the population size.

The algorithm is following the physical equations describing the trajectory of an individual air parcel. The air parcel is influenced by various natural forces in our atmosphere in hydrostatic balance.

Atmospheric motion by the Eulerian description is considered for solving this algorithm. In this Eulerian description, it is assumed that air parcel infinitesimally small and its motion follows Newton's second law of motion. Using Eulerian description, it is possible for computation the velocity and position of the air parcel within the N-dimensional search space.

To achieve the best computational efficiency in an N-dimensional optimization problem some consideration has been taken accordingly. In case of high level of abstraction of wind description, the horizontal movement of air is stronger than the vertical movement hence equations are derived accordingly where a certain level of simplifications has modified to achieve computational efficiency in an N-dimensional optimization problem. A detailed description of the algorithm and the parameter analysis can be found in [28] and [29]. The velocity and the position update rules follow the below-written equations. The velocity update equation is expressed as,

$$\overrightarrow{u_{new}} = (1-\alpha)\overrightarrow{u_{cur}} - g(\overrightarrow{x_{cur}}) + \left|1 - \frac{1}{i}\right| RT(x_{\max} - x_{cur}) + \frac{c u_{cur}^{otherdim}}{i} \quad (7)$$

In the expression (7) presented the rank of the air parcel between all population members based on the pressure value at its location in the search space.

The velocity update equation contains α which presents the friction coefficient, g that presents the gravitational constant, R which presents the universal gas constant, T, that presents the temperature and c which presents a constant that represents the rotation of the Earth.

Initially, each parameter is fixed to a constant value. From equation (7), it is clearly seen that the updated velocity (u_{new}) can be obtained by using velocity at the current iteration (u_{cur}), current location of the search space (x_{cur}), distance from the highest pressure point (x_{max}) and as well as the velocity at one of the other dimensions ($u_{otherdim}^{cur}$). After updating the velocity of the parcel using equation (7), consequently, the position also is updated by the following equation (8),

$$\overrightarrow{x_{new}} = \overrightarrow{x_{cur}} + (\overrightarrow{u_{new}} \times \Delta t) \quad (8)$$

where x_{new} indicates the updated position for each air parcel for the next iteration. It is assumed that for all iterative cases unity time step $\Delta t = 1$.

The total algorithm has been explained by the Flowchart as shown in Fig. 1.

IV. Results and Discussions

The practical applicability of AWDO has been applied for two case studies (10 and 40 thermal units) where the objective functions were non-smooth due to the valve-point effects. The AWDO has been applied through coding in MATLAB 7.9.0 (MathWorks, Inc.) and compared with other optimization methods available in the literature. All the simulations have been worked out on a 2.2-GHz Intel Pentium processor with 4 GB of RAM.

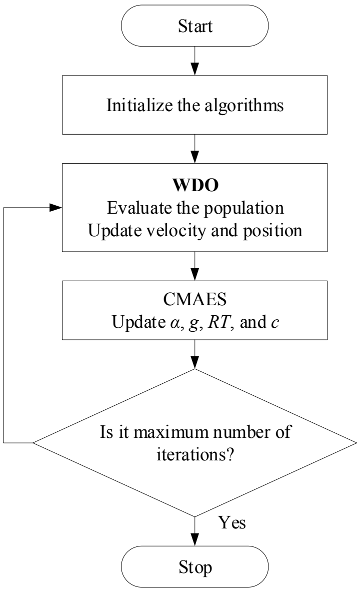

Fig. 1. Flowchart of the Adaptive Wind Driven Optimization Algorithm.

A. *Case-study – 1 for 10 generating systems*

This case study has been performed for a test system of 10 thermal units considering the effects of valve-point loading. The relevant data for this system has been shown in Table I [30]. In the present study, the load demand is PD=2000 MW (considering transmission losses). The results for Case Study-1 applying AWDO are shown in Table II and the program, ELD_Solution_AWDO_Algo_10_gen.m, has been written in an m-file. Here the termination criterion has been set as 100 iterations.

The m-file has been loaded in the current MATLAB folder. The lower and upper bounds, linear equalities have been set as per the data are given in Table I. From the successive runs the best results were logged and all the best outputs were written in a tabular form (shown in Table II) for their comparative analysis.

B. *Case-study – 2 for 40 generating systems*

A case of 40 thermal units was also carried out to check the the effectiveness of the present algorithm. The required data is shown in Table III [30]. The load demand to be satisfied was PD = 10,500MW (without considering transmission losses). To find the optimal generation of power for 40 generating units, the proposed technique has been utilized. The population size, maximum and minimum generation limits and iteration count for the present study have been fixed. The same procedure was followed as in the previous case.

The program for AWDO, ELD_Solution_AWDO_Algo_40_gen.m, has been written in a MATLAB m-file and kept in the current MATLAB directory. The termination criterion has been set as 2000 iterations. Table IV shows the most feasible results for 40 generating units using different methods. The comparative analysis, out of the results in Table IV, puts forth AWDO to be one of the reliable techniques while the valve-point effect is considered.

To investigate the effectiveness of this approach, it is seen that in both the two cases the results obtained from AWDO are almost the same with the results of other existing methods. From Table II and IV, it is seen that AWDO gives viable results in both the cases. For 10 thermal units (Case-study – 1), AWDO decreased the fuel cost as well as total transmission loss. The B-matrix for test system-1 is shown in Box I.

TABLE I
TYPE DATA FOR THE 10 THERMAL UNITS [30]

Unit	P_i^{min}(MW)	P_i^{max}(MW)	a_i (\$/h)	b_i (\$/MWh)	c_i (\$/(MW)^{2}h)	d_i (\$/h)	e_i (rad/MW)	α_i(lb/h)	β_i(lb/MWh)	γ_i(lb/(MW)^{2}h)	ξ_i(lb/h)	λ_i (1/MW)
1	10	55	1000.403	40.5407	0.12951	33	0.0174	360.0012	-3.9864	0.04702	0.25475	0.01234
2	20	80	950.606	39.5804	0.10908	25	0.0178	350.0056	-3.9524	0.04652	0.25475	0.01234
3	47	120	900.705	36.5104	0.12511	32	0.0162	330.0056	-3.9023	0.04652	0.25163	0.01215
4	20	130	800.705	39.5104	0.12111	30	0.0168	330.0056	-3.9023	0.04652	0.25163	0.01215
5	50	160	756.799	38.539	0.15247	30	0.0148	13.8593	0.3277	0.0042	0.2497	0.012
6	70	240	451.325	46.1592	0.10587	20	0.0163	13.8593	0.3277	0.0042	0.2497	0.012
7	60	300	1243.531	38.3055	0.03546	20	0.0152	40.2669	-0.5455	0.0068	0.248	0.0129
8	70	340	1049.998	40.3965	0.02803	30	0.0128	40.2669	-0.5455	0.0068	0.2499	0.01203
9	135	470	1658.569	36.3278	0.02111	60	0.0136	42.8955	-0.5112	0.0046	0.2547	0.01234
10	150	470	1356.659	38.2704	0.01799	40	0.0141	42.8955	-0.5112	0.0046	0.2547	0.01234

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$$B = \begin{bmatrix}
0.000049 & 0.000014 & 0.000015 & 0.000015 & 0.000016 & 0.000017 & 0.000017 & 0.000018 & 0.000019 & 0.000020 \\
0.000014 & 0.000045 & 0.000016 & 0.000016 & 0.000017 & 0.000015 & 0.000015 & 0.000016 & 0.000018 & 0.000018 \\
0.000015 & 0.000016 & 0.000039 & 0.000010 & 0.000012 & 0.000012 & 0.000014 & 0.000014 & 0.000016 & 0.000016 \\
0.000015 & 0.000016 & 0.000010 & 0.000040 & 0.000014 & 0.000010 & 0.000011 & 0.000012 & 0.000014 & 0.000015 \\
0.000016 & 0.000017 & 0.000012 & 0.000014 & 0.000035 & 0.000011 & 0.000013 & 0.000013 & 0.000015 & 0.000016 \\
0.000017 & 0.000015 & 0.000012 & 0.000010 & 0.000011 & 0.000036 & 0.00012 & 0.000012 & 0.000014 & 0.000015 \\
0.000017 & 0.000015 & 0.000014 & 0.000011 & 0.000013 & 0.000012 & 0.000038 & 0.000016 & 0.000016 & 0.000018 \\
0.000018 & 0.000016 & 0.000014 & 0.000012 & 0.000013 & 0.000012 & 0.000016 & 0.000040 & 0.000015 & 0.000016 \\
0.000019 & 0.000018 & 0.000016 & 0.000014 & 0.000015 & 0.000014 & 0.000016 & 0.000015 & 0.000042 & 0.000019 \\
0.000029 & 0.000018 & 0.000016 & 0.000015 & 0.000016 & 0.000015 & 0.000018 & 0.000016 & 0.000019 & 0.000044
\end{bmatrix}$$

TABLE II
TYPE DATA FOR THE 10 THERMAL UNITS [30]

Unit	P_i^{min}(MW)	P_i^{max}(MW)	a_i ($/h)	b_i ($/MWh)	c_i ($/(MW)^{2}h)	d_i ($/h)	e_i (rad/MW)	α_i(lb/h)	β_i(lb/MWh)	γ_i(lb/(MW)^{2}h)	ξ_i(lb/h)	λ_i (1/MW)
1	10	55	1000.403	40.5407	0.12951	33	0.0174	360.0012	-3.9864	0.04702	0.25475	0.01234
2	20	80	950.606	39.5804	0.10908	25	0.0178	350.0056	-3.9524	0.04652	0.25475	0.01234
3	47	120	900.705	36.5104	0.12511	32	0.0162	330.0056	-3.9023	0.04652	0.25163	0.01215
4	20	130	800.705	39.5104	0.12111	30	0.0168	330.0056	-3.9023	0.04652	0.25163	0.01215
5	50	160	756.799	38.539	0.15247	30	0.0148	13.8593	0.3277	0.0042	0.2497	0.012
6	70	240	451.325	46.1592	0.10587	20	0.0163	13.8593	0.3277	0.0042	0.2497	0.012
7	60	300	1243.531	38.3055	0.03546	20	0.0152	40.2669	-0.5455	0.0068	0.248	0.0129
8	70	340	1049.998	40.3965	0.02803	30	0.0128	40.2669	-0.5455	0.0068	0.2499	0.01203
9	135	470	1658.569	36.3278	0.02111	60	0.0136	42.8955	-0.5112	0.0046	0.2547	0.01234
10	150	470	1356.659	38.2704	0.01799	40	0.0141	42.8955	-0.5112	0.0046	0.2547	0.01234

TABLE III
COMPARISON OF BEST RESULTS OF DIFFERENT OPTIMIZATION TECHNIQUES FOR CASE STUDY-1, PD = 2000 MW

Unit	MODE [30]	PDE [30]	NSGA-II [30]	SPEA [30]	GSA [31]	TLBO	JOA	AWDO
P1(MW)	54.9487	54.9853	51.9515	52.9761	54.9992	54.4285	55.0000	54.9441
P2(MW)	74.5821	79.3803	67.2584	72.8130	79.9586	78.9558	78.4112	79.7300
P3(MW)	79.4294	83.9842	73.6879	78.1128	79.4341	79.5993	80.3464	80.1338
P4(MW)	80.6875	86.5942	91.3554	83.6088	85.0000	85.4390	84.6690	86.2269
P5(MW)	136.8551	144.4386	134.0522	137.2432	142.1063	143.7134	143.8600	143.5906
P6(MW)	172.6393	165.7756	174.9504	172.9188	166.5670	166.9796	167.4608	165.9426
P7(MW)	283.8233	283.2122	289.4350	287.2023	292.8749	293.3021	292.4104	292.7701
P8(MW)	316.3407	312.7709	314.0556	326.4023	313.2387	312.9163	313.2630	312.4573
P9(MW)	448.5923	440.1135	455.6978	448.8814	441.1775	440.4352	440.4677	440.3041
P10(MW)	436.4287	432.6783	431.8054	423.9025	428.6306	428.1624	428.0384	427.8155
Cost (x 10^5 $)	1.1348	1.1351	1.1354	1.1352	1.1349	1.1333	1.1333	1.1330
Emission (lb)	4124.9	4111.4	4130.2	4109.1	4111.4000	4108.1000	4105.3000	4108.8000
Loss (MW)	84.3271	83.9331	84.2496	84.0612	83.9869	83.9317	83.9270	83.9150

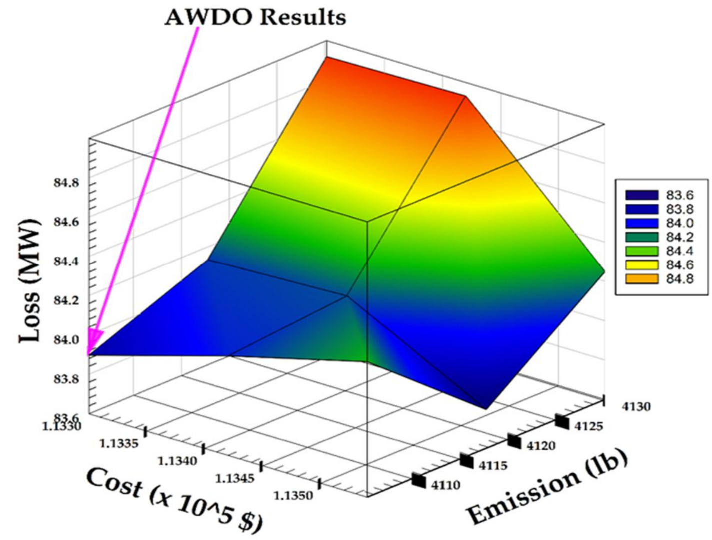

Fig. 2. Comparative Analysis of results from Table II

TABLE IV
DATA FOR THE 40 THERMAL UNITS [30]

Unit	P_i^{min}(MW)	P_i^{max}(MW)	a_i (\$/h)	b_i (\$/MWh)	c_i (\$/(MW)^{2}h)	d_i (\$/h)	e_i (rad/MW)	α_i(ton/h)	β_i(ton/MWh)	γ_i(ton/(MW)^{2}h)	ξ_i(ton/h)	λ_i (1/MW)
1	36	114	94.705	6.73	0.0069	100	0.084	60	-2.22	0.048	1.31	0.0569
2	36	114	94.705	6.73	0.0069	100	0.084	60	-2.22	0.048	1.31	0.0569
3	60	120	309.54	7.07	0.02028	100	0.084	100	-2.36	0.0762	1.31	0.0569
4	80	190	369.03	8.18	0.00942	150	0.063	120	-3.14	0.054	0.9142	0.0454
5	47	97	148.89	5.35	0.0114	120	0.077	50	-1.89	0.085	0.9936	0.0406
6	68	140	222.33	8.05	0.01142	100	0.084	80	-3.08	0.0854	1.31	0.0569
7	110	300	287.71	8.03	0.00357	200	0.042	100	-3.06	0.0242	0.655	0.02846
8	135	300	391.98	6.99	0.00492	200	0.042	130	-2.32	0.031	0.655	0.02846
9	135	300	455.76	6.6	0.00573	200	0.042	150	-2.11	0.0335	0.655	0.02846
10	130	300	722.82	12.9	0.00605	200	0.042	280	-4.34	0.425	0.655	0.02846
11	94	375	635.2	12.9	0.00515	200	0.042	220	-4.34	0.0322	0.655	0.02846
12	94	375	654.69	12.8	0.00569	200	0.042	225	-4.28	0.0338	0.655	0.02846
13	125	500	913.4	12.5	0.00421	300	0.035	300	-4.18	0.0296	0.5035	0.02075
14	125	500	1760.4	8.84	0.00752	300	0.035	520	-3.34	0.0512	0.5035	0.02075
15	125	500	1760.4	8.84	0.00752	300	0.035	510	-3.55	0.0496	0.5035	0.02075
16	125	500	1760.4	8.84	0.00752	300	0.035	510	-3.55	0.0496	0.5035	0.02075
17	220	500	647.85	7.97	0.00313	300	0.035	220	-2.68	0.0151	0.5035	0.02075
18	220	500	649.69	7.95	0.00313	300	0.035	222	-2.66	0.0151	0.5035	0.02075
19	242	550	647.83	7.97	0.00313	300	0.035	220	-2.68	0.0151	0.5035	0.02075
20	242	550	647.81	7.97	0.00313	300	0.035	220	-2.68	0.0151	0.5035	0.02075
21	254	550	785.96	6.63	0.00298	300	0.035	290	-2.22	0.0145	0.5035	0.02075
22	254	550	785.96	6.63	0.00298	300	0.035	285	-2.22	0.0145	0.5035	0.02075
23	254	550	794.53	6.66	0.00284	300	0.035	295	-2.26	0.0138	0.5035	0.02075
24	254	550	794.53	6.66	0.00284	300	0.035	295	-2.26	0.0138	0.5035	0.02075
25	254	550	801.32	7.1	0.00277	300	0.035	310	-2.42	0.0132	0.5035	0.02075
26	254	550	801.32	7.1	0.00277	300	0.035	310	-2.42	0.0132	0.5035	0.02075
27	10	150	1055.1	3.33	0.52124	120	0.077	360	-1.11	1.842	0.9936	0.0406
28	10	150	1055.1	3.33	0.52124	120	0.077	360	-1.11	1.842	0.9936	0.0406
29	10	150	1055.1	3.33	0.52124	120	0.077	360	-1.11	1.842	0.9936	0.0406
30	47	97	148.89	5.35	0.0114	120	0.077	50	-1.89	0.085	0.9936	0.0406
31	60	190	222.92	6.43	0.0016	150	0.063	80	-2.08	0.0121	0.9142	0.0454
32	60	190	222.92	6.43	0.0016	150	0.063	80	-2.08	0.0121	0.9142	0.0454
33	60	190	222.92	6.43	0.0016	150	0.063	80	-2.08	0.0121	0.9142	0.0454
34	90	200	107.87	8.95	0.0001	200	0.042	65	-3.48	0.0012	0.655	0.02846
35	90	200	116.58	8.62	0.0001	200	0.042	70	-3.24	0.0012	0.655	0.02846
36	90	200	116.58	8.62	0.0001	200	0.042	70	-3.24	0.0012	0.655	0.02846
37	25	110	307.45	5.88	0.0161	80	0.098	100	-1.98	0.095	1.42	0.0677
38	25	110	307.45	5.88	0.0161	80	0.098	100	-1.98	0.095	1.42	0.0677
39	25	110	307.45	5.88	0.0161	80	0.098	100	-1.98	0.095	1.42	0.0677
40	242	550	647.83	7.97	0.00313	300	0.035	220	-2.68	0.0151	0.5035	0.02075

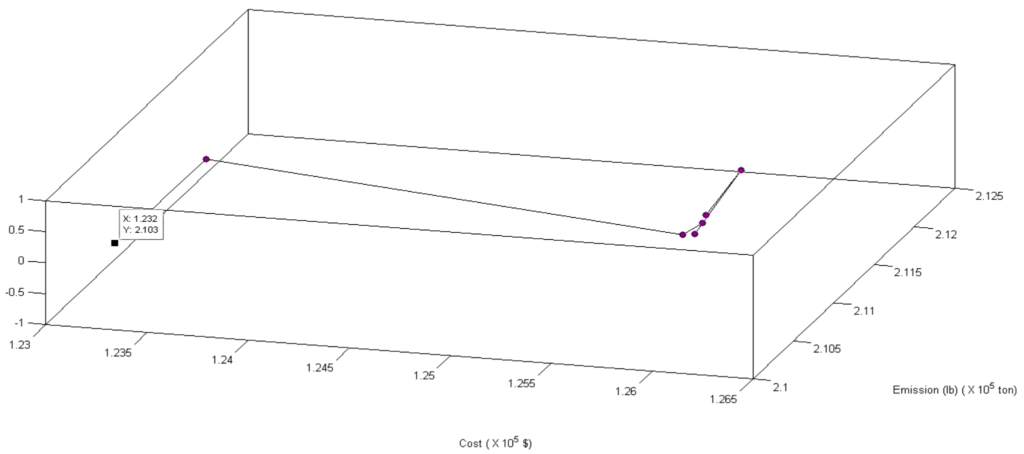

Fig. 3. Comparison of best results of different Optimization Techniques for Case Study-2 (from Table II)

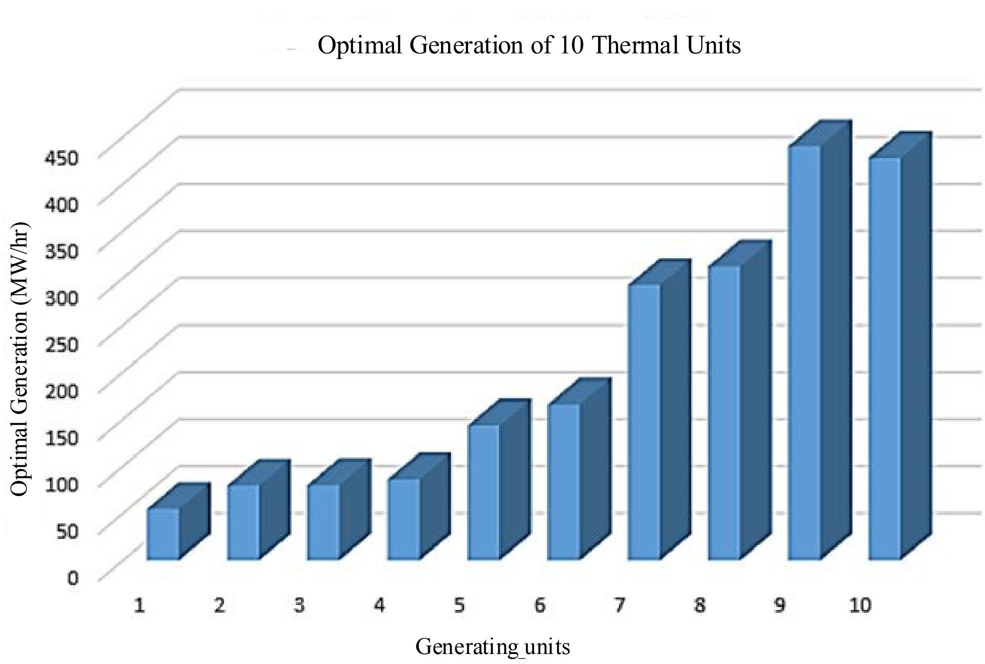

Fig. 4. Optimal Generation of Case Study-1

TABLE V
COMPARISON OF BEST RESULTS OF DIFFERENT OPTIMIZATION TECHNIQUES FOR CASE STUDY-2, PD=10,500 MW

Unit	MODE [30]	PDE [30]	NSGA-II [30]	SPEA [30]	GSA [31]	TLBO	AWDO
P1(MW)	113.5295	112.1549	113.8685	113.9694	113.9989	113.9637	113.7032
P2(MW)	114	113.9431	113.6381	114	113.9896	114.0000	114.0000
P3(MW)	120	120	120	119.8719	119.9995	119.2759	119.9368
P4(MW)	179.8015	180.2647	180.7887	179.9284	179.7857	181.0562	180.5315
P5(MW)	96.7716	97	97	97	97	96.4756	97.0000
P6(MW)	139.276	140	140	139.2721	139.0128	137.7332	138.3124
P7(MW)	300	299.8829	300	300	299.9885	299.4274	300.0000
P8(MW)	298.9193	300	299.0084	298.2706	300	299.6958	300.0000
P9(MW)	290.7737	289.8915	288.889	290.5228	296.2025	298.0269	297.1393
P10(MW)	130.9025	130.5725	131.6132	131.4832	130.385	131.0000	130.9194
P11(MW)	244.7349	244.1003	246.5128	244.6704	245.4775	245.1809	245.2199
P12(MW)	317.8218	318.284	318.8748	317.2003	318.2101	319.6045	318.0639
P13(MW)	395.3846	394.7833	395.7224	394.7357	394.6257	394.8243	394.2374
P14(MW)	394.4692	394.2187	394.1369	394.6223	395.2016	395.6854	396.4756
P15(MW)	305.8104	305.9616	305.5781	304.7271	306.0014	306.6104	306.8609
P16(MW)	394.8229	394.1321	394.6968	394.7289	395.1005	393.7669	393.9455
P17(MW)	487.9872	489.304	489.4234	487.9857	489.2569	489.3632	489.8599
P18(MW)	489.1751	489.6419	488.2701	488.5321	488.7598	489.2599	488.5698
P19(MW)	500.5265	499.9835	500.8	501.1683	499.232	499.3462	497.9881
P20(MW)	457.0072	455.416	455.2006	456.4324	455.2821	455.8277	454.8535
P21(MW)	434.6068	435.2845	434.6639	434.7887	433.452	433.3401	432.5556
P22(MW)	434.531	433.7311	434.15	434.3937	433.8125	432.5457	434.2654
P23(MW)	444.6732	446.2496	445.8385	445.0772	445.5136	445.5808	444.7076
P24(MW)	452.0332	451.8828	450.7509	451.897	452.0547	453.4598	452.8684
P25(MW)	492.7831	493.2259	491.2745	492.3946	492.8864	493.0912	492.2676
P26(MW)	436.3347	434.7492	436.3418	436.9926	433.3695	434.2457	434.1368
P27(MW)	10	11.8064	11.2457	10.7784	10.0026	11.2841	10.7532
P28(MW)	10.3901	10.7536	10	10.2955	10.0246	10.6029	11.1086
P29(MW)	12.3149	10.3053	12.0714	13.7018	10.0125	10.9478	11.1915
P30(MW)	96.905	97	97	96.2431	96.9125	96.2683	97.0000
P31(MW)	189.7727	190	189.4826	190	189.9689	189.5610	189.2526
P32(MW)	174.2324	175.3065	174.7971	174.2163	175	174.3280	174.6346
P33(MW)	190	190	189.2845	190	189.0181	188.7028	188.8095
P34(MW)	199.6506	200	200	200	200	198.2413	200.0000
P35(MW)	199.8662	200	199.9138	200	200	198.3432	198.6563
P36(MW)	200	200	199.5066	200	199.9978	200.2483	200.4569
P37(MW)	110	109.9412	108.3061	110	109.9969	109.5386	109.4282
P38(MW)	109.9454	109.8823	110	109.6912	109.0126	108.7831	110.0000
P39(MW)	108.1786	108.9686	109.7899	108.556	109.456	110.0000	108.5079
P40(MW)	422.0682	421.3778	421.5609	421.8521	421.9987	420.7631	421.7822
Cost (X 10^5 $)	1.2579	1.2573	1.2583	1.2581	1.2578	1.2323	1.2322
Emission (lb) (X 10^5 ton)	2.1119	2.1177	2.1095	2.111	2.1093	2.114	2.103

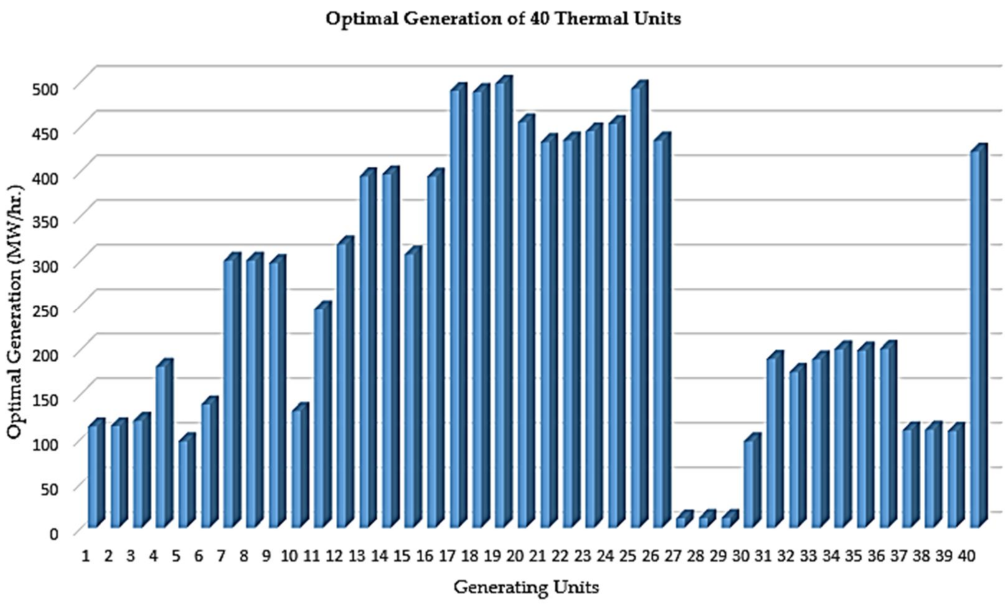

Fig. 5. Optimal Generation of Case Study-2

In case study-2 (Test system-2) AWDO has worked effectively decreasing both generation cost and emission. Table V and Table VI show the Standard Deviation and Variance of Case Study-1 and Case Study-2 respectively and in both the cases AWDO proved to be effective.

TABLE VI
STANDARD DEVIATION AND VARIANCE OF CASE STUDY-1

Algorithms	Standard Deviation	Variance
MODE	151.959504	23091.691
PDE	147.906896	21876.45
NSGA-II	153.3645944	23520.699
SPEA	151.2236031	22868.578
GSA	148.6411264	22094.184
TLBO	148.4512366	22037.77
JOA	148.3717562	22014.178
AWDO	148.0821708	21928.329

TABLE VII
STANDARD DEVIATION AND VARIANCE OF CASE STUDY-2

Algorithms	Standard Deviation	Variance
MODE	155.6019909	24211.97957
PDE	155.5304779	24189.72956
NSGA-II	155.4116327	24152.77559
SPEA	155.4551195	24166.29418
GSA	155.5556727	24197.56731
TLBO	155.6011394	24211.71459
AWDO	155.4083704	24151.7616

V. CONCLUSION

The current work emphases on the application of Adaptive Wind Driven Optimization Algorithm (AWDOA) for multi-objective CEED problem solution for examining the performances of two test cases (10 thermal units and 40 thermal units). Satisfactory results are obtained by adopting the program. Simulation results are also compared with other existing algorithms for the above two test cases and AWDO has proved to be the best and most powerful amongst them.

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