GWO BASED AWDO TECHNIQUE FOR EMISSION CONSTRAINED OPTIMAL GENERATION OF ALLOCATION

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The current work focuses on a meta-heuristic solution of a multi-objective CEED (Combined Economic Emission Dispatch) problem on the Distributed Energy Resources (DERs). The proposed algorithm is based on a hybrid optimization technique, Grey Wolf Optimization-based-Adaptive Wind Driven Optimization (GWO -AWDO) where the search agents are initiated and randomized by GWO but position vectors are governed by AWDO. The CEED problem focuses on both the environmental effects from the gaseous pollutants from fossil-fueled power generating plants and generation cost meeting the needs of satisfying all operational constraints and load demand as well at the same time. Therefore, CEED problem has been formulated as a multi-objective, non-linear, non-smooth problem and that has later been converted into a single objective function using price penalty factor. 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) where in both cases GWO-AWDO has proved to be the best and outperformed other existing methods.

Keywords: adaptive wind driven optimization, economic load dispatch, constrained minimization, multi objective, valve-point effect, environmental dispatch

1. Introduction

Distributed Energy Resources (DERs) are small-scale or large-scale, two-way power flow electric utilities those are directly connected to host facility in and within a local distribution system. The key objective of the Emission Constrained Optimal Dispatch Problem (ECODP) is to determine the optimal generation on DERs for each utility at minimum possible fuel costs and to bring down the pollution at its lowest possible rate simultaneously considering all operational constraints to be satisfied. ECODP follows the method of CEED solution. The generating units can be of coal-fired or non-conventional type but current work only points to coal-fired stations. Each generating unit is associated with two major factors i.e. generating cost and gaseous emission. Gaseous emission depends on the ignition of hydrocarbon fuels. More amount of generation directly reflects to more addition of carbon byproducts in the

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environment and thereby improving greenhouse impacts. Therefore, it is highly needed to reduce it at its minimal potential value considering it as a generation constraint. Higher order non-linear valve-point effects and transmission losses may also be considered at the same time.

Earlier diverse techniques have already been used to check their applicability and effectiveness to solve ECODP or single-objective Economic Load Dispatch (ELD) problems. Out of these methods, several are based on classical optimization methods for example, the heuristic algorithms or artificial intelligence whereas others are based on the linear or quadratic programming. During the recent innovation during last two decades, the different conventional techniques such as Lambda-iteration method [1], Gradient method used by Chang et al. in [2] have been applied though the techniques have some limitations. The demerits are several local minima, high computational time and oscillatory in nature [3]. Contemporary Stochastic Search Algorithms such as PSO used by Layth Al-Bahrani et al. in [4], Shahinzadeh et al. in [5]; GA used by Damousis et al. in [6]; Direct Search used by Chen et al. in [7] and Differential Evolution used by Cătălin Florin Ionescu et al. in [8]; Gravitational Search used by Mondal et al. in [9]; Whale optimization Algorithm used by Subramanian R. et al. in [10]; Florin Ionescu et al. in [11]; Cuckoo Search used by Tran et al. in [12], Interior Search Algorithm by N. Karthik et al. in [13] 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 [14] is a relatively newly developed class of 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 from 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 search domain.

2. 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:

2.1. 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:

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

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 ith generating unit. P_i is the real power output of the ith generator.

2.2. Emission dispatch formulation

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

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

Where α_i, β_i, γ_i, ξ_i and λ_i are coefficients of the ith generator emission characteristics.

2.3. 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:

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

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 $E(P_{gi})$.

2.4. 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 quadratic approximation:

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

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: $P_i^{min} \le P_i \le P_i^{max}$

3. Used Algorithm

3.1. GWO Algorithm

Grey Wolf Optimizer (GWO) algorithm [15] mimics the leadership hierarchy and hunting technique used by grey wolves to catch their prey until stopping its movement. The algorithm starts with a given number of wolves whose positions are randomly generated.

3.2. Steps of GWO Algorithm

The grey wolves maintain a hierarchy while praying and that can be divided into four groups. The most responsible and dominant group which care about decision making is at the top namely (Λ). All other groups will follow its higher order group(s) in a fashion:

$$(\rho) \text{ and } (\delta) \longrightarrow (\Upsilon) \longrightarrow (\Psi) \rightarrow (\Phi) \rightarrow (\Lambda)$$

(Λ)'s are considered to be the leader of the hierarchy chain and considered to be the fittest solution. The main steps associated with the original GWO algorithm are:

a. Initialization of the search agents.
b. Assign the values of Λ, Φ and Ψ by their fitness they hold.
c. Capturing the prey: represented by a circular area out around the best solution (i.e. prey). The following equations represents this step:

$$F = \left|Q.\vec{Z}_P(i) - Z(i)\right|; \qquad Z(i+1) = \left|\vec{Z}_P(i) - P.F\right|$$

Where, $\vec{Z}_P$= prey's position vector. $(\vec{P})$ and $(\vec{Q})$, are vectors given by the following equations: $q = 2(1 - i/I_{max})$; $\vec{P} = 2.qr_1 - q$; $\vec{Q} = 2r_2$ Where, i= current iteration; I_{max}= total iterations. r_1 and r_2 are random vectors in the range [0, 1].

d. Hunting step: the encircling process comes to the second step involving hunting guided by the alpha wolf group. The following equations represent this step:

$$F_\Lambda = |Q_1.Z_\Lambda(t) - Z(t)|, \qquad F_\Phi = |Q_2.Z_\Phi(t) - Z(t)|,$$
$$F_\Psi = |Q_3.Z_\Psi(t) - Z(t)|,\ Z_1 = Z_\Lambda - P_1.F_\Lambda Z_2,\ Z_2 = Z_\Phi - P_2.F_\Phi Z_3,$$
$$Z_3 = Z_\Psi - P_3.F_\Psi, \qquad Z(i+1) = (Z_1 + Z_2 + Z_3)/3.$$

e. Attacking the prey.
f. Steps b to e are repeated until the maximum of iteration count is reached.

3.3. Adaptive Wind Driven Optimization Algorithm

The Wind Driven Optimization [16] is a nature inspired technique. It tends to its global solution through search based iterative process. The velocity and the position update rules follow the below written equations. The velocity update equation is expressed as:

$$\overrightarrow{u_{new}} = (1-\alpha)\overrightarrow{u_{cur}} - g(\overrightarrow{x_{cur}}) + \left|1 - {}^{1}/_{i}\right| RT(x_{max} - x_{cur}) + {}^{c\, u_{cur}^{otherdim}}/_{i} \quad (6)$$

In the expression (6) presented the rank of the air parcel between all population members based on the pressure value at its location in the search space.

α = friction coefficient, g = gravitational constant, R = universal gas constant, T = temperature and c = constant that represents the rotation of the Earth. After updating the velocity of the parcel using equation (6), consequently the position also is updated by the following equation (7),

$$\overrightarrow{x_{new}} = \overrightarrow{x_{cur}} + (\overrightarrow{u_{new}} \times \Delta t) \quad (7)$$

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, Δt = 1, x_{cur}= current location of the search space, u_{new}=updated velocity.

3.4. Pseudo Code for GWO-AWDO Algorithm

a. **Initialize** *the grey wolf candidate solutions;* Z_r; $r = 1 \ldots n$;
b. **Initialize** *Iter_count =0 and Max_Iter=100;*
c. **Initialize** *parameters; q, P, and Q;*
d. **Calculate** *the fitness of each Search_Agent;* Z_Λ*=the best search_agent;* $Z_\ddagger$*=the second best search_agent;* Z_Ψ *the third best search_agent;*
e. **While** *Iter ≤ Max_Iter*
For *j∈{search space}*
Sort *the grey wolves' population in accordance with their fitness;*
Select *Set of best population (search parcels);*
Update *the velocity of each search parcel using Eq. (6);*
Find x_{new} *from Eq. (7);*
Update *a, g, RT and c;*
Update *the position of search parcel;*
Calculate *the fitness of the new search agents; Iter_count=Iter_count+1;*
f. **End For** *Find best solution got so far and return,* x_{new};
g. **End While**

4. Results and discussions

The practical applicability of the proposed algorithm has been applied for two case studies (10 and 40 thermal units) where the objective functions were nonlinear dynamic in nature due to the valve-point effects. The coding is done in MATLAB 7.9.0 (MathWorks, Inc.) in an environment of a 2.2-GHz Intel Pentium processor with 4 GB of RAM and simulation results are compared with other optimization methods available in literature.

4.1. Case-study – 1 for 10 thermal units

This case study consists of 10 thermal units with a load demand of P_D=2000 MW (considering transmission losses). The relevant data along with the B-matrix for this test case has been taken from [17]. The comparative results for this Case Study-1 are shown in Table 1. The termination criterion has been set as 100 iterations. Fig. 1 shows the comparative analysis of the results using different methods in a 3D plot where X, Y and Z axes are assigned as Optimal Cost, Emission and Loss respectively. Results from Table 1 puts GWO-AWDO forth to be most efficient algorithm.

4.2. Case-study – 2 for 40 thermal units

The required data for 40 thermal units with a load demand of P_D = 10,500MW (without considering transmission losses) has been taken from [17].

The termination criterion has been set as 2000 iterations. Table 2 shows the most feasible results of this test case.

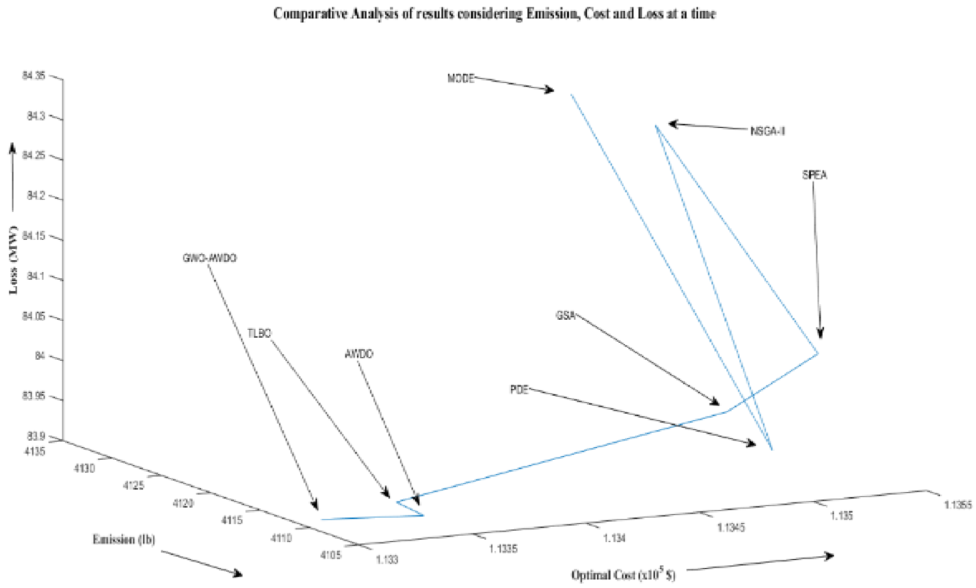

Fig. 1. Comparative Analysis from Table 1

Fig. 2 shows the optimal generation for 40 different units satisfying both generation cost and emission. Fig. 3 shows the convergence curve of different methods out of which GWO-AWDO converges fastest amongst all.

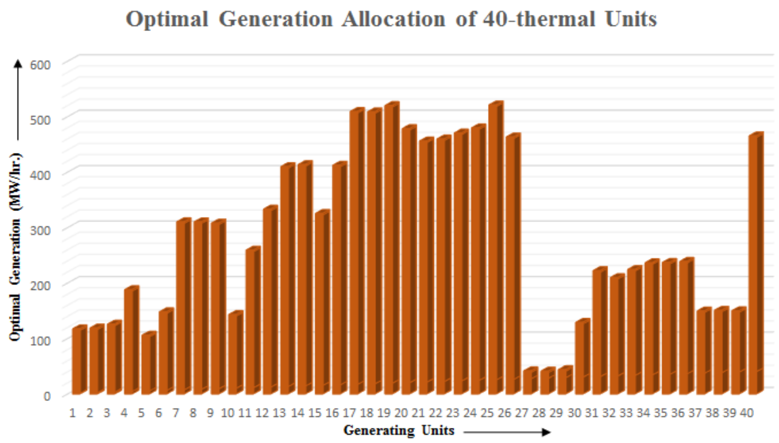

Fig. 2. Optimal Generation of Case Study-2

Table 1

Comparison of best results of different Optimization Techniques for Case Study-1, P_D = 2000 MW

Unit	MODE [17]	NSGA-II [17]	SPEA [17]	TLBO	AWDO	GWO-AWDO
P1(MW)	54.9487	51.9515	52.9761	54.4285	55.0000	54.9441
P2(MW)	74.5821	67.2584	72.8130	78.9558	78.4112	79.7300
P3(MW)	79.4294	73.6879	78.1128	79.5993	80.3464	80.1338
P4(MW)	80.6875	91.3554	83.6088	85.4390	84.6690	86.2269
P5(MW)	136.8551	134.0522	137.2432	143.7134	143.8600	143.5906
P6(MW)	172.6393	174.9504	172.9188	166.9796	167.4608	165.9426
P7(MW)	283.8233	289.4350	287.2023	293.3021	292.4104	292.7701
P8(MW)	316.3407	314.0556	326.4023	312.9163	313.2630	312.4573
P9(MW)	448.5923	455.6978	448.8814	440.4352	440.4677	440.3041
P10(MW)	436.4287	431.8054	423.9025	428.1624	428.0384	427.8155
Cost (x 10^5 $)	1.1348	1.1354	1.1352	1.1333	1.1333	1.1330
Emission (lb)	4124.9	4130.2	4109.1	4108.1000	4105.3000	4108.8000
Loss (MW)	84.3271	84.2496	84.0612	83.9317	83.9270	83.9150
Standard Dev.	151.95950	153.36459	151.22360	148.451236	148.371756	148.082170
Variance	23091.691	23520.699	22868.578	22037.77	22014.178	21928.329

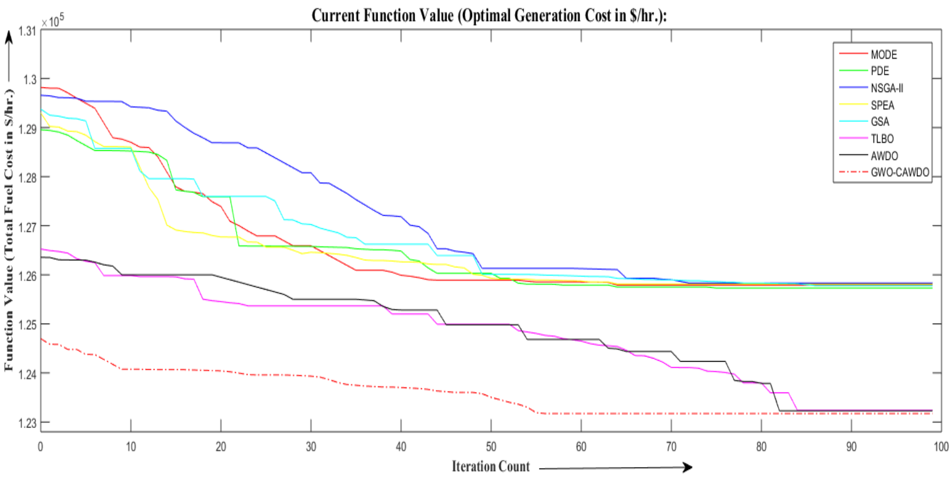

Fig. 3. Comparison of convergence characteristics of Case Study-2

Table 2

Comparison of best results of different Optimization Techniques for Case Study-2, P_D=10,500 MW

Unit	MODE [17]	NSGA-II [17]	SPEA [17]	TLBO	AWDO	GWO-AWDO
P1(MW)	113.5295	113.8685	113.9694	113.9637	113.7032	113.5420797
P2(MW)	114	113.6381	114	114	114	114.0232174
P3(MW)	120	120	119.8719	119.2759	119.9368	119.8085748
P4(MW)	179.8015	180.7887	179.9284	181.0562	180.5315	181.147694
P5(MW)	96.7716	97	97	96.4756	97	97.94031922
P6(MW)	139.276	140	139.2721	137.7332	138.3124	139.2048631
P7(MW)	300	300	300	299.4274	300	300.4398333
P8(MW)	298.9193	299.0084	298.2706	299.6958	300	299.3478885
P9(MW)	290.7737	288.889	290.5228	298.0269	297.1393	296.1599331
P10(MW)	130.9025	131.6132	131.4832	131	130.9194	130.2445827
P11(MW)	244.7349	246.5128	244.6704	245.1809	245.2199	245.3229693
P12(MW)	317.8218	318.8748	317.2003	319.6045	318.0639	318.2684193
P13(MW)	395.3846	395.7224	394.7357	394.8243	394.2374	393.9149241
P14(MW)	394.4692	394.1369	394.6223	395.6854	396.4756	396.6966906
P15(MW)	305.8104	305.5781	304.7271	306.6104	306.8609	307.5914615
P16(MW)	394.8229	394.6968	394.7289	393.7669	393.9455	393.400511
P17(MW)	487.9872	489.4234	487.9857	489.3632	489.8599	489.3805933
P18(MW)	489.1751	488.2701	488.5321	489.2599	488.5698	487.7686129
P19(MW)	500.5265	500.8	501.1683	499.3462	497.9881	497.9932221
P20(MW)	457.0072	455.2006	456.4324	455.8277	454.8535	455.4430073
P21(MW)	434.6068	434.6639	434.7887	433.3401	432.5556	432.1031255
P22(MW)	434.531	434.15	434.3937	432.5457	434.2654	434.7887324
P23(MW)	444.6732	445.8385	445.0772	445.5808	444.7076	444.5295997
P24(MW)	452.0332	450.7509	451.897	453.4598	452.8684	452.917454
P25(MW)	492.7831	491.2745	492.3946	493.0912	492.2676	493.1878035
P26(MW)	436.3347	436.3418	436.9926	434.2457	434.1368	434.4643366
P27(MW)	10	11.2457	10.7784	11.2841	10.7532	11.64144815
P28(MW)	10.3901	10	10.2955	10.6029	11.1086	10.24850627
P29(MW)	12.3149	12.0714	13.7018	10.9478	11.1915	11.93565907
P30(MW)	96.905	97	96.2431	96.2683	97	96.06486078
P31(MW)	189.7727	189.4826	190	189.561	189.2526	188.4472109
P32(MW)	174.2324	174.7971	174.2163	174.328	174.6346	174.8440261
P33(MW)	190	189.2845	190	188.7028	188.8095	188.4976833

P34(MW)	199.6506	200	200	198.2413	200	199.5871191
P35(MW)	199.8662	199.9138	200	198.3432	198.6563	199.1956633
P36(MW)	200	199.5066	200	200.2483	200.4569	200.0082842
P37(MW)	110	108.3061	110	109.5386	109.4282	109.591098
P38(MW)	109.9454	110	109.6912	108.7831	110	109.8719191
P39(MW)	108.1786	109.7899	108.556	110	108.5079	108.04106
P40(MW)	422.0682	421.5609	421.8521	420.7631	421.7822	422.3950125
Cost (X 10^5 $)	1.2579	1.2583	1.2581	1.23237841	1.2322875	1.2317218
Emission (lb) (X 10^5 ton)	2.1119	2.1095	2.111	2.11453	2.1035762	2.1019425
Stan. Dev.	155.6019	155.5304	155.4116	155.60113	155.408370	155.41198

In case study-2 (Test system-2) GWO-AWDO has worked effectively decreasing both generation cost and emission.

5. Conclusion

As Negative emissions technologies (NETs) technologies are still at discussion level, it is highly required to bring down the hydrocarbon emission largely at industrial belt to circumvent significant global warming effects. Environmental emission is a concerning trend in recent scenario and also Independent System Operator (ISO) tries to make profit with minimal fuel consumption. Therefore, it is of prior most important thing to reduce both the fuel cost and pollution from hydrocarbon ignition. But in the process of reducing generation cost, it is observed that the emission increases. As power system demands to reduce both generating cost and emission concurrently, the concept of CEED is adopted. Keeping in view of the bi-objective non-linear CEED problem solution, the test system results enlighten that side of industrial application where the proposed technique can produce promising results. Transmission system operator (TSO) is concerned about effective decrement in line loss. But line loss is an explicit dependent function of generation for which it increases. Therefore, it is highly necessary to allocate generation in such a way that transmission loss becomes minimum. It is seen from the first test case that the proposed algorithm has been able to dispatch optimally with minimal line loss. The results show that the meta-heuristic GWO-AWDOA has outperformed the existing methods concerning all the three factors viz. generation cost, emission and line loss. It ensures the non-divergence characteristics and timely solutions too. Therefore, it can be recommended for large-scale coal-fired power generating stations. Satisfactory results from Table 1 and 2 have accentuated the applicability of the proposed approach which can give better solution than other stochastic techniques.

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