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Grey Wolf Optimization for Economic Load Dispatch with Valve-Point Effects

Fuazen[1], Hardiansyah[2]

Department of Mechanical Engineering, Universitas Muhammadiyah Pontianak, Indonesia[1]

Department of Electrical Engineering, University of Tanjungpura, Indonesia[2]

ABSTRACT:Grey Wolf Optimization (GWO) is a new meta-heuristic inspired by grey wolves. The leadership hierarchy and hunting mechanism of the grey wolves is mimicked in GWO. In this paper, GWO is proposed to solve the economic load dispatch (ELD) problem with valve-point effects. To demonstrate the effectiveness of the proposed approach, the numerical studies have been performed for twostandard test systems, i.e. six andfifteen generating unit systems, respectively. The results show that performance of the proposed approach reveal the efficiently and robustness when compared results of other optimization algorithms reported in literature.

KEYWORDS: Grey wolf optimization, economic load dispatch, non-smooth cost functions, valve-point effects.

I.INTRODUCTION

Electrical power system plays a pivotal role in the modern wold to satisfy various needs.Most of power system optimization problems including economic load dispatch (ELD) which have complex and nonlinear characteristics with heavy equality and inequality constraints. The objective of the ELD of electric power generation is to schedule the committed generating unit outputs so as to meet the required load demand at minimum operating cost while satisfying all unit and system equality and inequality constraints. Several classical optimization techniques such as lambda iteration method, gradient method, Newton's method, linear programming, Interior point method and dynamic programming have been used to solve the basic economic dispatch problem [1]. These mathematical methods require incremental or marginal fuel cost curves which should be monotonically increasing to find global optimal solution. In reality, however, the input-output characteristics of generating units are non-convex due to valve-point loadings and multi-fuel effects, etc. Also there are various practical limitations in operation and control such as ramp rate limits and prohibited operating zones, etc. Therefore, the practical ELD problem is represented as a non-convex optimization problem with equality and inequality constraints, which cannot be solved by the traditional mathematical methods. Dynamic programming method [2] can solve such types of problems, but it suffers from so-called the curse of dimensionality. Over the past few decades, as an alternative to the conventional mathematical approaches, many salient methods have been developed for ELD problem such as genetic algorithm (GA) [3, 4], improved tabu search (ITS) [5], simulated annealing (SA) [6], neural network (NN) [7, 8], evolutionary programming (EP) [9]-[11], particle swarm optimization (PSO) [12]-[18], and intelligent tuned harmony search (ITHS) [19].

In this paperGWO algorithm has been used which is a recently developed new algorithm technique inspired from the leadership hierarchy and hunting mechanism of grey wolf in nature proposed by Mirjalili etal. [20]. The ELD solutionwhich was performed using GWOalgorithm was tested on the standard 6-unit and 15-unit test system. The performance of the solution results was compared with those of the existing methods available in the literature.

II.PROBLEM FORMULATION

2.1. ELD Problem

The objective of an ELD problem is to find the optimal combination of power generations that minimizes the total generation cost while satisfying equality and inequality constraints. The fuel cost curve for any unit is assumed to be approximated by segments of quadratic functions of the active power output of the generator. For a given power system

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network, the problem may be described as optimization (minimization) of total fuel cost as defined by (1) under a set of operating constraints.

$$F_T = \sum_{i=1}^{n} F(P_i) = \sum_{i=1}^{n} \left(a_i P_i^2 + b_i P_i + c_i \right) \tag{1}$$

where F_T is total fuel cost of generation in the system ($/h), a_i, b_i, and c_i are the cost coefficient of the ith generator, P_i is the power generated by the ith unit and n is the number of generators.
The cost is minimized subjected to the following constraints:
Generation capacity constraint,

$$P_{i,\min} \le P_i \le P_{i,\max} \quad \text{for } i = 1,2,\cdots,n \tag{2}$$

Power balance constraint,

$$P_D = \sum_{i=1}^{n} P_i - P_{Loss} \tag{3}$$

where $P_{i,\,min}$ and $P_{i,\,max}$ are the minimum and maximum power output of the ith unit, respectively. P_D is the total load demand and P_{Loss} is total transmission losses. The transmission losses P_{Loss}can be calculated by using **B** matrix technique and is defined by (4) as,

$$P_{Loss} = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00} \tag{4}$$

where B_{ij} is coefficient of transmission losses.

2.2. ELD Problem Considering Valve-Point Effects

For more rational and precise modeling of fuel cost function, the above expression of cost function is to be modified suitably. The generating units with multi-valve steam turbines exhibit a greater variation in the fuel-cost functions [14]. The valve opening process of multi-valve steam turbines produces a ripple-like effect in the heat rate curve of the generators.

The significance of this effect is that the actual cost curve function of a large steam plant is not continuous but more important it is non-linear. The valve-point effects are taken into consideration in the ELD problem by superimposing the basic quadratic fuel-cost characteristics with the rectified sinusoid component as follows:

$$F_T = \sum_{i=1}^{n} F(P_i) = \sum_{i=1}^{n} \left(a_i P_i^2 + b_i P_i + c_i + \left| e_i \times \sin\left(f_i \times \left(P_{i,\min} - P_i \right) \right) \right| \right) \tag{5}$$

where F_T is total fuel cost of generation in ($/h) including valve point loading, e_i, f_i are fuel cost coefficients of the ith generating unit reflecting valve-point effects.

III.GREY WOLF OPTIMIZATION

Grey Wolf Optimizer (GWO) is a new population based meta-heuristic algorithm proposed by Mirjalili et al. in 2014 [20].The grey wolves mostly like to live in a pack and one of the most important features is their very strict social hierarchy. The main leader of the pack is called alpha. The alpha wolf is the most predominant wolf in the pack as his/her orders were followed by rest of the pack. The alpha wolf is one of the most important members in terms of managing the pack.

The second important one is called beta. They are also known as sub-ordinate wolves as they help alpha in their respective work. They act as advisor to alpha and commander to the rest of the wolves in the pack. The third ones are called Delta. They submitted themselves to the alphas and betas but dominate the omegas. The fourth one which are lower ranking wolves are called omega. They have to submit themselves to all other members in the pack.
In another important thing among the grey wolves is their hunting mechanism which includes tracking, chasing, encircling and harassing the prey until they stop moving. Then they attack the prey. The mathematical model of this model is discussed as following.

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3.1. Social Hierarchy

When mathematical model of GWO is designed we will consider the first fitness solution as alpha (α),secondbest solution as beta (β), and the third best solution as delta (δ). The rest of the solutions are assumed as omega (ω). The hunting mechanism is decided by α, β, and δ, and the ω wolves have to follow them.

3.2. Encircling Prey

As the grey wolves encircle prey during the hunt, so their mathematical model which represents their encircling behavior are discussed as below:

$$D = (C.X_p(t)-X_w(t)) \tag{6}$$

$$X_w(t+1) = X_p(t)-A.D \tag{7}$$

where 't' indicates the current iteration, A and C are coefficient vectors, X_p is the position of prey and X_w is the position of grey wolf.
The vector A and C are given as:

$$A = 2a.r_1-a \tag{8}$$

$$C = 2.r_2 \tag{9}$$

Here r_1, r_2 are random vector between 0 to 1, andvalue of 'a' is linearly decreased from 2 to 0.
The grey wolf can update their position according to equation (6) and (7).

3.3. Hunting

As we know that the grey wolf firstly recognizes the prey and then encircles them to hunt. The hunt is usually decided by alpha and beta, delta also participate in hunting occasion. So mathematically in the hunting procedure we take alpha, beta and delta as the best candidate solution and omega have to update its position according to the best search agent. The mathematical model for hunting is shown below:

$$D_\alpha = (C_1.X_\alpha(t)-X(t)) \tag{10}$$

$$D_\beta = (C_2.X_\beta(t)-X(t)) \tag{11}$$

$$D_\delta = (C_3.X_\delta(t)-X(t)) \tag{12}$$

$$X_1 = X_\alpha - A_1.D_\alpha \tag{13}$$

$$X_2 = X_\beta - A_2.D_\beta \tag{14}$$

$$X_3 = X_\delta - A_3.D_\delta \tag{15}$$

$$X(t+1) = (X_1+X_2+X_3)/3 \tag{16}$$

3.4. Search for Prey

As we know that the grey wolves finish their hunt by attacking the prey. In mathematical model we have 'A' a random variable having values in the range [-2a, 2a] where 'a' is decreased from 2 to 0. When the value of 'A' lies within [-1, 1] then the next position of search agent is between its current position and position of prey.The pseudo code of the GWO algorithm is presented in Table 1.

Table 1 Pseudo code of GWO [20]

Grey Wolf Optimizer
Initialize the grey wolf population X_i (i=1, 2, ..., n)
Initialize a, A, and C
Calculate the fitness of each search agent
X_α= the best search agent
X_β = the second best search agent
X_δ = the third best search agent
while *(t < Max number of iterations)*
for *each search agent*
Update the position of the current search agent by equation (6)
end for
Update a, A, and C
Calculate the fitness of all search agents

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Update X_α, X_β, and X_δ
t=t+1
end while
Return X_α

IV.SIMULATION RESULTS

To verify the feasibility of the proposed method, two different power systems were tested: (1) 6-unit system with valve-point effects and transmission losses, (2) 15-unit system with valve-point effects and transmission losses. The population taken in each case was 30 and maximum numbers of iterations performed were 200 in test case 1 and 500 iterations in test case 2.

Test Case 1: 6-unit system

The system consists of six thermal generating units with valve point effects. The total load demand on the system is 1263 MW. The parameters of all thermal units are presented in Table 2 [12, 18].

Table 2 Fuel cost cooefficients and power limits (6-units)

Unit	$P_{i,\,min}$ (MW)	$P_{i,\,max}$ (MW)	a	b	c	e	f
1	100	500	0.0070	7.0	240	300	0.035
2	50	200	0.0095	10.0	200	200	0.042
3	80	300	0.0090	8.5	220	200	0.042
4	50	150	0.0090	11.0	200	150	0.063
5	50	200	0.0080	10.5	220	150	0.063
6	50	120	0.0075	12.0	190	150	0.063

The transmission losses are calculated by B matrix loss formula which for 6-unit system is given as [12]:

$$B_{ij} = \begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0.0000 & -0.0010 & -0.0006 \\ -0.0001 & 0.0001 & 0.0000 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.0010 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.0150 \end{bmatrix}$$

$$B_{0i} = 1.0e^{-3} * [-0.3908 \;\; -0.1297 \;\; 0.7047 \;\; 0.0591 \;\; 0.2161 \;\; -0.6635]$$

$$B_{00} = 0.056$$

The obtained results for the 6-unit system using the GWO method are given in Table 3 and the results are compared with other methods reported in literature, including GA, PSO, PSO-LRS, NPSO, and NPSO-LRS [17]. It can be observed that GWO algorithm can get total generation cost of 15442.3953 ($/h) and power losses of 12.3980 (MW), which is the best solution among all the methods. Note that the outputs of the generators are all within the generator's permissible output limit. A convergence characteristic of six-generator system is shown in Fig. 1.

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Table 3 Comparison of the best results of each method (P_D = 1263 MW)

Unit Output	GA	PSO	PSO-LRS	NPSO	NPSO-LRS	GWO
P1 (MW)	474.8066	447.4970	447.4440	447.4734	446.9600	447.7683
P2 (MW)	178.6363	173.3221	173.3430	173.1012	173.3944	173.2517
P3 (MW)	262.2089	263.0594	263.3646	262.6804	262.3436	263.5518
P4 (MW)	134.2826	139.0594	139.1279	139.4156	139.5120	138.6975
P5 (MW)	151.9039	165.4761	165.5076	165.3002	164.7089	165.2461
P6 (MW)	74.1812	87.1280	87.1698	87.9761	89.0162	86.8826
Total power output (MW)	1276.03	1276.01	1275.95	1275.95	1275.94	1275.398
Total generation cost ($/h)	15459	15450	15450	15450	15450	15442.3953
Power losses (MW)	13.0217	12.9584	12.9571	12.9470	12.9361	12.3980

Test Case 2: 15-unit system

This system consists of 15 generating units and the input data of 15-generator system are given in Table 4 [12, 18]. Transmission loss B-coefficients are taken from [16, 18]. In order to validate the proposed GWOalgorithm, it is tested with 15-unit system having non-convex solution spaces, and the load demand is 2630 MW.

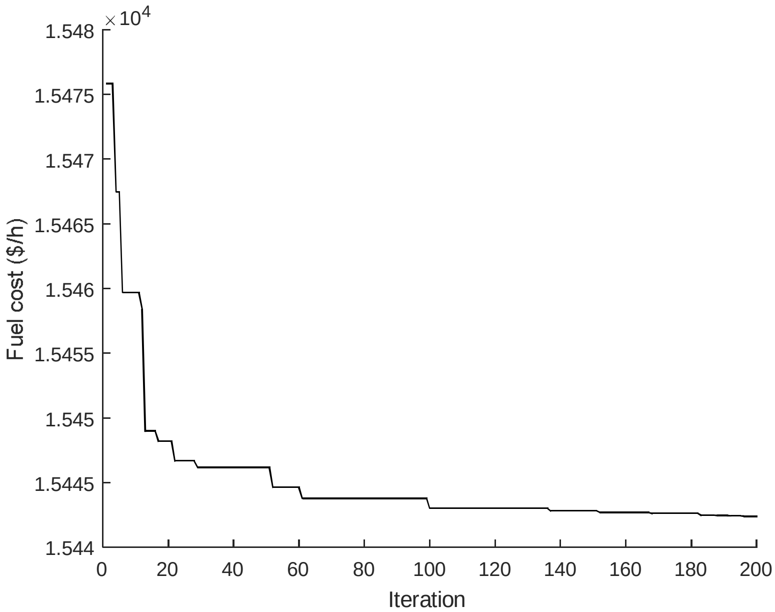

Fig. 1 Convergence characteristic by GWO forsix-generator system

The best fuel cost result obtained from proposed GWO and other optimization algorithms are compared in Table 5 for load demands of 2630 MW. In Table 5, generation outputs and corresponding fuel cost and losses obtained by the proposed GWO are compared with those of GA, PSO, and ITHS [18, 19]. The proposed GWO provide better solution (total generation cost of 32552.1192 $/h and power losses of 26.7291 MW) than other methods while satisfying the system constraints. We have also observed that the solutions by GWO always are satisfied with the equality and

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inequality constraints by using the proposed constraint-handling approach. A convergence characteristic of fifteen-generator system is shown in Fig. 2.

Table 4 Fuel cost cooefficients and power limits(15-units)

Unit	$P_{i,\,min}$ (MW)	$P_{i,\,max}$ (MW)	a	b	c	e	f
1	150	455	0.000299	10.1	671	100	0.084
2	150	455	0.000183	10.2	574	100	0.084
3	20	130	0.001126	8.8	374	100	0.084
4	20	130	0.001126	8.8	374	150	0.063
5	150	470	0.000205	10.4	461	120	0.077
6	135	460	0.000301	10.1	630	100	0.084
7	135	465	0.000364	9.8	548	200	0.042
8	60	300	0.000338	11.2	227	200	0.042
9	25	162	0.000807	11.2	173	200	0.042
10	25	160	0.001203	10.7	175	200	0.042
11	20	80	0.003586	10.2	186	200	0.042
12	20	80	0.005513	9.9	230	200	0.042
13	25	85	0.000371	13.1	225	300	0.035
14	15	55	0.001929	12.1	309	300	0.035
15	15	55	0.004447	12.4	323	300	0.035

Table 5 Best solution of 15-unit systems (P_D = 2630 MW)

Unit power output	GA	PSO	ITHS	GWO
P1 (MW)	415.3108	439.1162	454.8399	454.9044
P2 (MW)	359.7206	407.9729	379.9939	455.0000
P3 (MW)	104.4250	407.9729	130.0000	130.0000
P4 (MW)	74.9853	129.9925	130.0000	130.0000
P5 (MW)	380.2844	151.0681	169.9483	229.3028
P6 (MW)	426.7902	459.9978	459.9727	460.0000
P7 (MW)	341.3164	425.5601	430.0000	465.0000
P8 (MW)	124.7876	98.5699	79.9210	61.4777
P9 (MW)	133.1445	113.4936	51.9794	26.4398
P10 (MW)	89.2567	101.1142	157.9175	30.1173
P11 (MW)	60.0572	33.9116	79.7113	79.3693
P12 (MW)	49.9998	79.9583	79.2993	78.6134
P13 (MW)	38.7713	25.0042	25.0001	25.4279
P14 (MW)	41.4140	41.4140	16.0608	15.7897
P15 (MW)	22.6445	36.6140	15.0000	15.2867
Total power output (MW)	2668.2782	2662.4306	2659.6442	2656.7291
P_{Loss} (MW)	38.2782	32.4306	29.6492	26.7291
Total generation cost ($/h)	33113	32858	32694.73561	32552.1192

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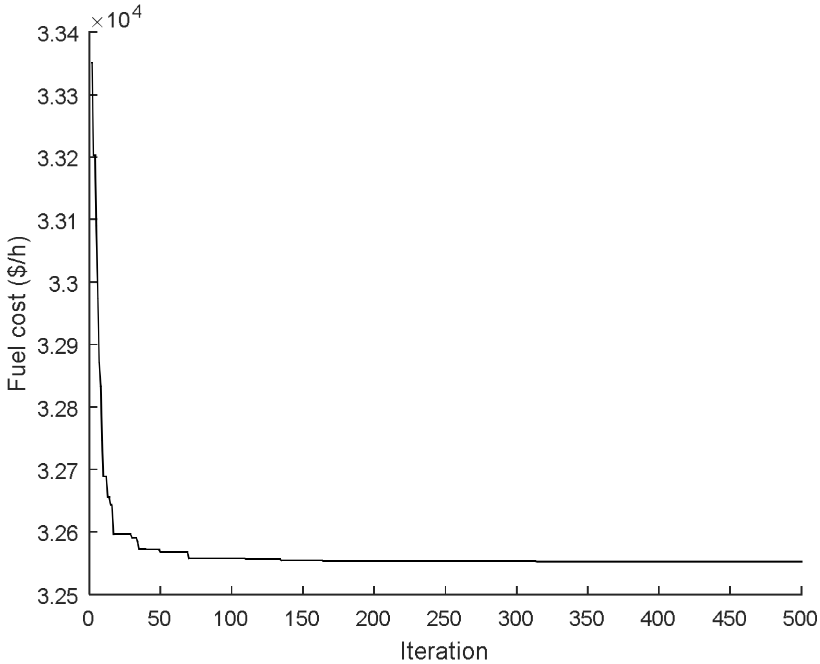

Fig. 2 Convergence characteristic by GWO for fifteen-generator system

V.CONCLUSION

This paper presents a new approach for solving ELD problems with valve-point effects using GWO technique. The GWO technique has provided the global solution in the 6-unit, and 15-unit test system and the better solution than the previous studies reported in literature. Also, the equality and inequality constraints treatment methods have always provided the solutions satisfying the constraints. Although the proposed GWO algorithm had been successfully applied to ELD with valve-point effects, the practical ELD problems should consider multiple fuels as well as prohibited operating zones. This remains a challenge for future work.

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