Application of Grey Wolf Optimization Algorithm on Higher Order Economic Load Dispatch Problems

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***Abstract*— Economic Load Dispatch (ELD) is the main work in distributing the required energy load to the available generating units at minimum fuel price. In order to solve such non-convex ELD problem with Cubic Cost Functions (CCF), a new approach based on Grey Wolf Optimization (GWO) Algorithm is proposed in this article. the algorithm is based on the hunting behavior of the Grey wolf. To compute minimized fuel cost and to demonstrate the superiority of the proposed algorithm, one widely adopted test system is employed and the simulation results are compared with the state-of-the-art algorithms.**

***Index Terms*— Cubic cost function, Economic load dispatch problem, Grey wolf optimization, Meta heuristic algorithm.**

I. INTRODUCTION

The economic load dispatch (ELD) problem is a significant optimization task in power system operation, aiming to determine the optimal allocation of power generation among different units while considering fuel economic costs. A crucial component in the ELD problem is the fuel cost function, which characterizes the relationship between power generation and the associated fuel cost. Traditionally quadratic functions are used to represents the fuel cost relation of the thermal generators, but accuracy of this method is not up to the level of expectation. So the cubic fuel function is a commonly used mathematical model in the ELD problem. In early decades various mathematical techniques are used to solve the ELD problems but it has the limitation of reaching local optimal point and difficulties in handling large numbers of constraints. Meta heuristic based optimization methods are able to handle these difficulties easily. Numerous types of swarm based optimization methods are available in the literature to solve the cubic cost function economic load dispatch (CCFELD) problems.

The CCFELD problem has been solved by algorithms such as Dynamic Programming (DP) [1], Evolutionary Programming (EP) [2], Particle Swarm Optimization (PSO) [3], Simulated Annealing [4], Grasshopper Optimization Algorithm (GOA) [5], Improved dynamic harmony search algorithm(IDHSA) [6], Teaching Learning Based Optimization (TLBO) [7], Firefly Algorithm [8], Equal Embedded Algorithm (EEA) [9], Pattern Search (PS) [10], Swarm Based Mean-Variance Mapping Optimization (MVMO) [11]. In this research article, a new meta-heuristic algorithm named Grey Wolf Optimization (GWO) algorithm was proposed by Mirjalili, Seyedali et.al. [12]. The GWO algorithm models the forging activities of golden jackals. In order to validate the effectiveness of the GWO method one test systems with fuel cost function is analyzed. The outcomes have been contrasted with several other optimization approaches reported in literature.

The rest of the sections of the article are structured as follows: Explanation and expression of ELD issues with cubic fuel cost functions are given in Section 2. The Grey Wolf optimization algorithm is briefly discussed, and the implementation of GWO for cubic cost function Economic load dispatch problems is presented in Section 3. Section 4 presents the simulation results and discusses the outcomes. Finally, Section 5 provides the conclusion of the research work.

II. ELD PROBLEM FORMULATION

The main aim of ELD problem is to find out the optimal power generation combination that reduces the total generation cost while meeting with inequality and equality constraints. The industry common practice of representing generator fuel cost curves is by polynomial functions. In real-time, fuel cost function parameters significantly impacts the economic load dispatch solution's accuracy. Higher-order generating cost functions can significantly enhance ELD solutions. The cubic cost function clearly presents the real response time of thermal generators. The cubic fuel cost function is stated as follows

$$F_i(P_i) = d_i P_i^3 + c_i P_i^2 + b_i P_i + a_i \quad (1)$$

Here *a*,*b*,*c* and *d* are the fuel cost coefficients of thermal generators.

Fuel cost function for different orders of thermal generators are shown in Fig. 1.

The objective function of ELD is represented as below

$$minimize\ F = \sum_{i=1}^{N} F_i(P_i) \quad (2)$$

Where $F_i(P_i)$ is the representation of i^{th} unit fuel cost, P_i is the i^{th} unit power output and *N* represents the total number of generating units in the power system.

A. System Constraint

In this section, various types of system constraints considered in the simulation studies are discussed in details.

a. Power balance constraints

The total power generation should be equal to the system power demand in addition to the transmission network loss. It is provided by the following equation

$$\sum_{i-1}^{N} P_i = P_D + P_L \quad (3)$$

Here P_D is the total load demand and P_L is the Transmission loss of the system.

The method based on the B coefficient and constant loss formula coefficient is used to compute the system loss. The transmission losses in the power system are expresses as

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{oi} P_i + B_{oo} \quad (4)$$

B_{ij}, B_{oi}, B_{oo} are the loss coefficient of the Transmission system.

b. Generator capacity Constraints

Every generation unit's power output should be within its permitted range of minimum and maximum limits. Thus, each generator in operation has to meet the following inequality condition.

$$P_i^{min} \le P_i \le P_i^{max} \quad (5)$$

Where P_i^{max} and P_i^{min} are the upper and lower limit of the power generated by the *i* th generator.

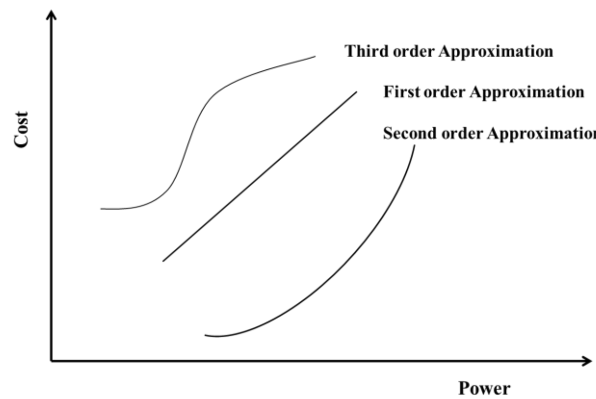

Fig 1: Cost function approximation

III. GREY WOLF OPTIMIZATION ALGORITHM

If Grey wolf optimization algorithm (GWO) is a new population based meta-heuristic algorithm proposed by Mirjalili et al. in 2014 [12]. The method imitates the hunting behavior and social hierarchy of grey wolves. On the basis of behavior of grey wolves, GWO is implemented where a specific number of grey wolves in a pack move through a multi-dimensional search space to look for prey. In this optimization algorithm, the positions of grey wolves are considered as different position variables and the distances of the prey from the grey wolves determine the fitness value of the objective function. The movement of each individual is influenced by four processes, namely searching for prey (exploration), Encircling prey, Hunting, Attacking prey (exploitation).

These operators are briefly explained and mathematically expressed in the following subsection.

A. Searching for prey (exploration)

The grey wolves diverge from each other position for searching a victim. Make use of AM with random values to compel the search agent to diverge from the victim. The component CM provides random weights for searching prey in the search space. Hence exploration through AM and CM permits this algorithm to globally search the area. CM vector also presents the effect of obstacles to impending the prey.

B. Encircling prey

The alpha, beta and delta estimate the position of the three best wolves and other wolves updates their positions using the positions of these three best wolves. Encircling behavior can be represented by DM. The expected boundary is mathematically represented by the following equations:

$$DM = |CM.XP(t) - X(t)| \tag{8}$$

$$X(t+1) = XP(t) - AM.DM \tag{9}$$

Here *t* indicates the current iteration, AM and CM are coefficient vectors, *XP(t)* is the position vector of prey, *X(t)* represents the position vector of a grey wolf. r_1 and r_2 are random vectors in [0, 1].*a* is linearly decreased from 2 to 0.

$$AM = 2a * r_1 - a \tag{10}$$

$$CM = 2 * r_2 \tag{11}$$

C. Hunting

Conservation of regional habitat connectivity has the potential to facilitate recovery of the grey wolf. After encircling, alpha wolf guides for hunting. Later, the delta and beta wolves join in hunting. It is tough to predict about the optimum location of prey. The hunting behavior of grey wolf, based on the position of alpha, beta, gamma (candidate solution) wolf can be represented by

$$DM_\alpha = |CM_\alpha.XP_\alpha(t) + X| \tag{12}$$

$$DM_\beta = |CM_\beta.XP_\beta(t) + X| \tag{13}$$

$$DM_\delta = |CM_\delta.XP_\delta(t) + X| \tag{14}$$

Finally, the position of various categories of wolves is modified as follows:

$$X_{\alpha 1} = X_\alpha - AM.DM_\alpha \tag{15}$$

$$X_{\beta 1} = X_\beta - AM.DM_\beta \tag{16}$$

$$X_{\delta 1} = X_\delta - AM.DM_\delta \tag{17}$$

$$X(t+1) = \frac{X_{\alpha 1} + X_{\beta 1} + X_{\delta 1}}{3} \tag{18}$$

D. Attacking prey (exploitation)

The grey wolves stop the hunting by attacking the prey when it stop moving. It depends on the value of *a* AM* is a random value in the interval [-*2a*, *2a*]. In GWO, search agents update their positions based on the location of alpha, beta, delta wolves mentioned in hunting phase and attack towards the prey.

E. Grey wolf optimization applied to CCFELD

The different steps of GWO algorithm for solving CCFELD problems are described below.

Step 1: Active power generation of all the generating units initialized randomly within their lower and upper real power operating limits

Step 2: Evaluate fitness of each solution of current population using (1)–(3). Each fitness value represents the distance of the individual wolf from the prey.

Step 3: Sort the population from best to worst. The best, second best and third best solutions respectively, represent the positions of α, β and δ categories of wolves.

Step 4: Modify the position of each search agents using the searching prey, encircling prey, hunting and attacking prey concepts. The position of each search agent represents a potential solution comprised of active power generation of CCFELD problem.

Step 5: Check whether the operating limits of the active power of all generating units except last unit are violated or not. If any power generation is less than the minimum level, it is made equal to minimum value. Similarly, if it is greater than the maximum level, it is assigned its maximum value. The infeasible solutions are exchanged by the best feasible solutions.

Step 6: Go to Step 2 until termination criteria is met. The GWO is stopped executing when the maximum number of iterations (generations) is reached or there is no noteworthy improvement in the solution. In this paper, the ending criterion is the maximum number of iterations for which most of the grey wolves or search agents are idle.

IV. CASE STUDIES AND NUMERICAL RESULTS

In order to validate the feasibility of the proposed GWO method for the CCFELD problems, it is employed on a power system consisting of 5 generating units. The load demand used in the simulations is 1800 MW. The data for cubic fuel cost coefficients and different other power generation limits are taken from [3], and these are listed in Table 1. Transmission power loss is neglected for this case analysis. In order to justify the efficacy of the proposed algorithm, the developed algorithm is simulated and tested in MATLAB 7.1 Software on 2 GHz Pentium IV, 1 GB RAM personal computer. The population size and the maximum iteration number are taken as 50 and 500 respectively for the test systems under consideration. The obtained results for the ELD problem by the GWO are contrasted with those from FA, GA, and PSO, which is tabulated in Table 2. GWO algorithm reaches the optimal fuel cost of 18609.69 ($/hr) which is lesser than the other heuristic methods. A graphical representation of the best result is shown in Fig. 2. The results attained by the GWO meets the constraints, and the GWO provides a lower total cost than other algorithms.

Table 1: Parameters of Test system

Gen	a_i	b_i	c_i	d_i	P_{max}	P_{min}
P1	749.55	6.95	9.68E-04	1.27E-07	800	320
P2	1285	7.05	7.38E-04	6.45E-08	1200	300
P3	1531	6.531	1.04E-03	9.98E-08	1100	275
P4	749.55	6.95	9.68E-04	1.27E-07	800	320
P5	1285	7.05	7.38E-04	6.45E-08	1200	300

Table 2: Comparison of Economic Load Dispatch Result of Test system

Unit	GA[3]	PPSO[3]	FA[8]	IDHSA[6]	GWO
1	320	320	327.8004	320	320
2	343.74	343.7	341.989	343.7101	345.088
3	472.6	472.6	460.4217	472.5799	472.277
4	320	320	327.8004	320	320
5	343.74	343.7	341.989	343.71	342.634
Pd	1800	1800	1800	1800	1800
Fuel cost ($/hr)	18611.07	18610.4	18610	18610.38	18609.69

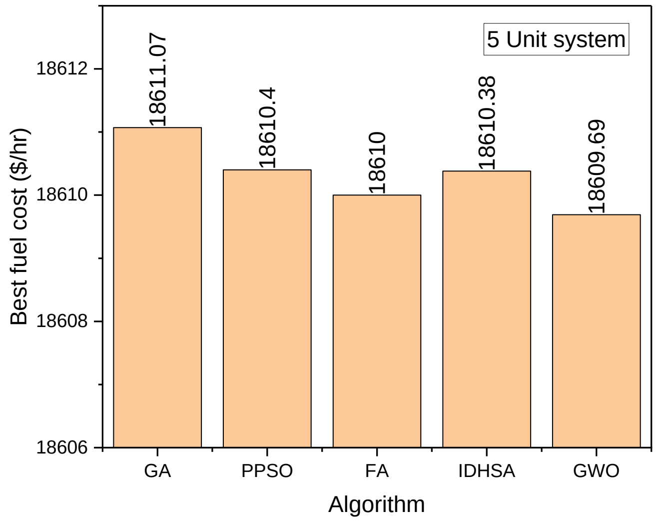

Fig 2: Comparison of test result for test system

V. CONCLUSION

The cubic cost function economic emission load dispatch (CCFELD) problem is very important problem in power system optimization. It is used to minimize the fuel cost of the generator to obtain the best optimal generation schedule. In this research work GWO is utilized to find the best optimal solution for the CCFELD problem and it is applied to the 5 unit test case. The results show that the GWO produces the best optimal solution then the compared algorithms such as GA, PPSO, FA and IDHA. Hence the applied GWO algorithm can be a potential meta-heuristic algorithm for the CCFELD problems in power system.

REFERENCES

[1] Z.-X. Liang and J. D. Glover, "A zoom feature for a dynamic programming solution," *IEEE Trans. Power Syst.*, vol. 7, no. 2, pp. 544–550, 1992.

[2] Kit Po Wang and J. Yuryevich, "Evolutionary-programming-based algorithm for environmentally-constrained economic dispatch," *IEEE Trans. Power Syst.*, vol. 13, no. 2, pp. 301–306, May 1998, doi: 10.1109/59.667339.

[3] T. Adhinarayanan and M. Sydulu, "Particle swarm optimisation for economic dispatch with cubic fuel cost function," *IEEE Reg. 10 Annu. Int. Conf. Proceedings/TENCON*, vol. 00, pp. 6–9, 2006, doi: 10.1109/TENCON.2006.344059.

[4] I. Ziane and F. Benhamida, "Solving the Generation Scheduling with Cubic Fuel Cost Function using Simulated Annealing," *Int. J. Energy, Inf. Commun.*, vol. 7, no. 2, pp. 1–8, 2016, doi: 10.14257/ijeic.2016.7.2.01.

[5] R. Karthikeyan, S. Subramanian, and E. B. Elanchezhian, "Grasshopper optimization algorithm on combined economic emission dispatch problem involving cubic functions," *Int. J. Eng. Adv. Technol.*, vol. 9, no. 1, pp. 808–817, 2019, doi: 10.35940/ijeat.A9337.109119.

[6] B. Houari, L. Mohammed, B. Hamid, A. A. N. El Islam, M. Sara, and S. Abdallah, "Improved dynamic harmony search optimization for economic dispatch problems with higher order cost functions," *Univers. J. Electr. Electron. Eng.*, vol. 6, no. 5, pp. 303–313, 2019, doi: 10.13189/ujeee.2019.060501.

[7] E. B. Elanchezhian, S. Subramanian, and S. Ganesan, "Cost Effective Operating Strategy for Unit Commitment and Economic Dispatch of Thermal Power Plants with Cubic Cost Functions Using TLBO Algorithm," *J. Power Energy Eng.*, vol. 03, no. 06, pp. 20–30, 2015, doi: 10.4236/jpee.2015.36003.

[8] N. A. Amoli, S. Jadid, H. A. Shayanfar, and F. Barzipour, "Solving economic dispatch

problem with cubic fuel cost function by firefly algorithm," *ICTPE Conf. Tech. Phys. Probl. Power Eng.*, vol. 1, no. July 2019, pp. 1–5, 2012.

[9] K. Chandram, N. Subrahmanyam, and M. Sydulu, "Equal embedded algorithm for economic load dispatch problem with transmission losses," *Int. J. Electr. Power Energy Syst.*, vol. 33, no. 3, pp. 500–507, 2011, doi: 10.1016/j.ijepes.2010.12.002.

[10] J. S. Al-Sumait, J. K. Sykulski, and A. K. Al-Othman, "Solution of different types of economic load dispatch problems using a pattern search method," *Electr. Power Components Syst.*, vol. 36, no. 3, pp. 250–265, 2008, doi: 10.1080/15325000701603892.

[11] K. H. Truong, P. Vasant, M. S. Balbir Sing, and D. N. Vo, "Swarm Based Mean-Variance Mapping Optimization for Solving Economic Dispatch with Cubic Fuel Cost Function," pp. 3–12, 2015, doi: 10.1007/978-3-319-15705-4_1.

[12] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," *Adv. Eng. Softw.*, vol. 69, pp. 46–61, Mar. 2014, doi: 10.1016/j.advengsoft.2013.12.007.