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Optimizing ELD in power systems applying GWO: A Practical Approach

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Abstract

Addressing the Economic load Dispatch (ELD) Problem in power systems is crucial for minimizing generation cost and transmission losses while meeting the load demand. This research explores the application of Grey Wolf Optimization (GWO) to solve the ELD problem, leveraging 'GWO's inspiration from grey wolf social behavior. Through simulation, 'GWO's superior convergence speed and solution quality compared to traditional techniques is demonstrated. The finding highlights 'GWO's effectiveness in enhancing the economic and operational efficiency of power systems, offering promising avenues for sustainable energy management strategies.

Keywords: Economic Dispatch Problem, Optimization technique, Grey Wolf Optimization Algorithm

1. Introduction

In recent years, the optimization of power system operation has garnered significant attention due to the growing demand for electricity and the imperative for sustainable energy practices. The ELD issue, which entails figuring out the best way to distribute generation resources to fulfill demand while reducing operating costs and abiding by system limits, is one of the main obstacles in power system optimization [1].

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Traditional optimization techniques such as gradient-based methods and evolutionary algorithms have been extensively explored for addressing the ELD problem [2]. However, these methods often suffer from limitations such as slow convergence and sensitivity to initial conditions. In order to surmount these obstacles, researchers have resorted to nature-inspired optimization algorithms, which replicate the characteristics of organic systems in order to effectively investigate solution spaces [3].

One such algorithm that has gained traction in recent years is the GWOA proposed by Mirjalili[4]. Grey wolf social structure and hunting behavior serve the inspiration for GWO, a potentially effective method for resolving optimization issues like ELD. Grey wolf hunting techniques are simulated using GWO, which achieves stable convergence features and higher performance over conventional approaches by striking a balance between exploitation and exploration [5].

In this research, a comprehensive study on the application of GWO to solve the ELD problem in power systems is presented. We leverage insights from recent research to enhance the performance and applicability of GWO in the context of ELD optimization [6]-[12]. The proposed methodology has been validated using MATLAB based simulation environment. The results revealed that the proposed methodology offers optimal solutions with good convergence rate.

2. Problem Formulation

The economic load distribution among the various generating units has enabled a minimal cost operation to be carried out; hence, it is necessary to explain the unit's running cost in terms of power production. The fuel-cost function has the mathematical shape of a second order curve (2.1) in most studies. The ED's goal function will be to minimize

$$f(FC) = \min \Sigma_{i=1}^{n} FC_i$$

$$FC_i = a_i P_i^2 + b_i P_i + c_i \tag{2.1}$$

Within the limitations of:

“$P_{i\,min} \leq P_i \leq P_{i\,max}$ i= 1,…..,n”

$$P_L = \Sigma_{i=1}^{n}\Sigma_{j=1}^{n} P_i B_{ij} P_j + \Sigma_{j=1}^{n} B_{oj} P_j + B_{00} \quad (2.2)$$

$$P_D = \Sigma_{i=1}^{n} P_i - P_L \quad (2.3)$$

Where,

FCi- unit(i) fuel cost in $/h .

Pi- generator i real power output

a,b,c are cost coefficients.

n - Number of units.

$P_{i\ min}$ and $P_{i\ max}$ is the minimum and maximum limit i^{th} generating unit

P_L- "Total power loss in MW".

P_D- 'Total demand in MW".

B- Loss coefficients.

3. Grey Wolf Optimization Algorithm

A. Introduction

The GWOA method was inspired by the hunting techniques of grey wolves. The way alphas guide the pack toward prey relates to their social order. The program simulates the behaviors of wolves—circling, tracking, and attacking their prey—using mathematical formulas. These behaviors are then applied to an optimization issue to find the optimal solution. Other wolves in the pack follow the movements of alpha, beta, and delta wolves, which finally directs them to the best option. The following are the primary stages of grey wolf hunting:

- Tracking, pursuing, and getting close to the target Challenging, encircling, and pestering the target until it gives up make an attack on the target.

B. Formulary Synopsis

The below section shows the mathematical modeling of the foraging behavior of the grey wolves.

C. Social Hierarchy

"In building GWO, we consider the best suited solution, which we call the alpha (α), to simulate the social structure of wolves quantitatively. So, we call the second and third best solutions beta (β) and delta (δ), respectively. The other possible solutions are considered omega (ω). In the GWO algorithm, alpha (α), beta (β), and delta (δ) guide the optimization process".

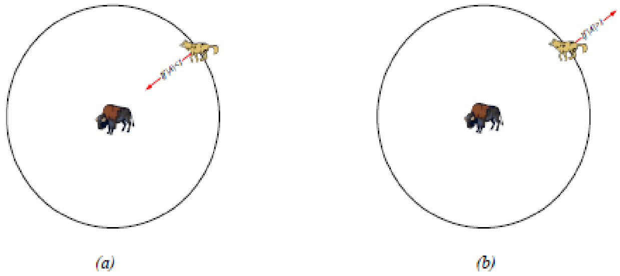

Figure 1. Exploitation and Exploration Strategy

D. Encircling Prey

As we already know, the prey is surrounded by the wolves while hunting. This encircling behavior, is analysed using the equations provided below. :

$$\vec{D} = \left|\overrightarrow{x_P}(t).\vec{C} - \vec{x}(t)\right| \tag{3.1}$$

$$\vec{x}(t+1) = \overrightarrow{x_P}(t) - \vec{D}.\vec{A} \tag{3.2}$$

"Within this framework, 't' denotes the current iteration, 'A ⃗' and 'C ⃗' are coefficient vectors, '(x_P)' ⃗ signifies the prey's position vector, and 'x ⃗' indicates a gray wolf's position vector, with vectors 'A' and 'C' calculated using equations (3.3) and (3.4)."

$$\vec{A} = \vec{a}(2\overrightarrow{rand_1}-1) \tag{3.3}$$

$$\vec{C} = 2.\overrightarrow{rand_2} \tag{3.4}$$

E. Hunting

Gray wolves are skilled at tracking down and following their prey. Usually, the alpha leads the hunt, with the beta and delta occasionally joining. However, we lack information about where the best (prey) might be in a general search space. o mathematically simulate gray wolves' hunting behavior, we prioritize the alpha, beta, and delta agents for their superior prey-tracking abilities, adjusting other agents' positions accordingly, as depicted by the relevant equations.

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1} \cdot \overrightarrow{x_\alpha} - \vec{x}\right|,\ \overrightarrow{D_\beta} = \left|\overrightarrow{C_2} \cdot \overrightarrow{x_\beta} - \vec{x}\right|,\ \overrightarrow{D_\delta} = \left|\overrightarrow{C_3} \cdot \overrightarrow{x_\delta} - \vec{x}\right| \quad (3.5)$$

$$\vec{x}_1 = \vec{x}_\alpha - \vec{A}_1 \cdot \left(\overrightarrow{D_\alpha}\right), \vec{x}_2 = \overrightarrow{x_\beta} - \vec{A}_i \cdot \left(\overrightarrow{D_\beta}\right), \overrightarrow{x_3} = \overrightarrow{x_\delta} - \overrightarrow{A_3} \cdot \left(\overrightarrow{D_\delta}\right) \quad (3.6)$$

$$\vec{x}(t+1) = \frac{\overrightarrow{x_1} + \overrightarrow{x_2} + \overrightarrow{x_3}}{3} \quad (3.7)$$

F. Prey Attack (Exploitation)

“As mentioned earlier, gray wolves finalize their search by attacking their prey once it halts. We adjust vector 'a ⃗' to mathematically simulate approaching the prey. Notably, reducing 'a ⃗' also narrows the range of fluctuation for 'A ⃗'During each iteration, 'A ⃗' symbolizes a random value within the interval [-a, a], with 'a' diminishing from 2 to 0; when 'A ⃗' falls within [-1, 1], the future position of a search agent can vary between its current position and the prey's position, as illustrated in Fig. 1(a), where if |A|<1, the wolves are driven to attack towards the prey”.

G. Search for Prey (Exploration)

Gray wolves primarily rely on the alpha, beta, and delta’s position to guide their searches. They venture out individually to locate prey and then regroup to attack it. To simulate divergence mathematically, We employ vector 'A ⃗' with random values beyond 1 or below -1, prompting the search agent to move away from the prey. This prioritizes exploration and enhances the global search capability of the GWO algorithm. Fig. 1(b) illustrates how |A|>1 prompts gray wolves to separate from their prey in search of a potentially better meal. Another component of GWO, 'C ⃗', fosters exploration. Equation (3.4) demonstrates that 'C ⃗' holds random values within the range [0, 2]. By assigning random weights to the prey, this section stochastically amplifies (if 'C' > 1) or diminishes (if 'C' < 1) the influence of the prey in determining distance (as per Equation 3.1), promoting unpredictability in GWO's optimization process, aiding in discovery, and circumventing local optima. It's worth noting that unlike 'A', 'C' does not decrease linearly. To encourage exploration throughout both initial and final rounds, we intentionally mandate 'C' to consistently provide random values. '$\vec{C}$' can be likened to the effect of natural obstacles encountered by wolves during their hunt for prey.

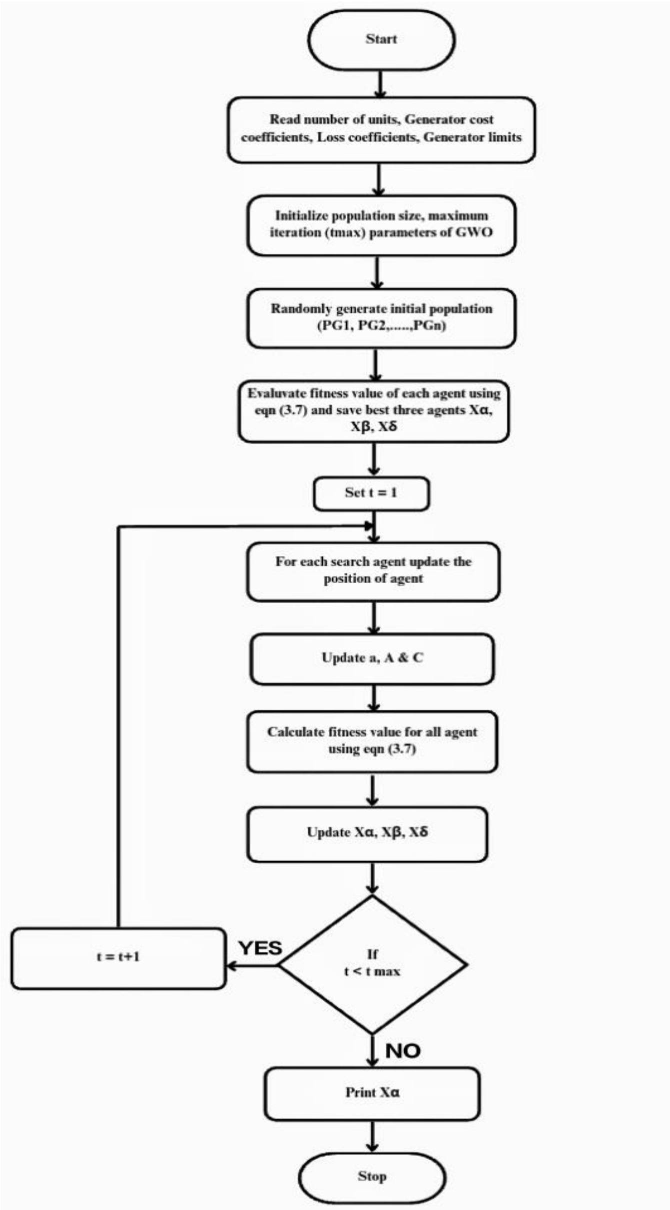

Figure 2. Flowchart of GWO

4. Simulation Results

The suggested method has been applied to the IEEE 30-Bus standard test system and its three generator units. MATLAB is used for all simulation-related tasks.

Case A: Three generator units

Fuel cost coefficients and the operational limits of generators are given in Table 1.

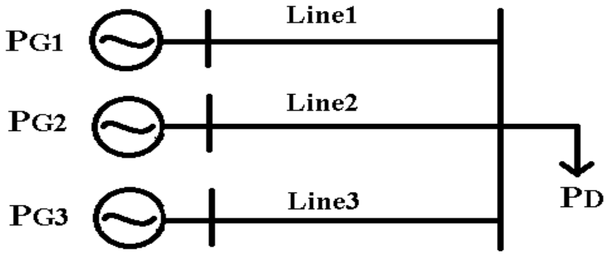

Figure 3. Three Generator System

Table 1. System Specifications of Three Generator Units

Unit No.	Fuel Cost Coefficients			Generation Limits	
	a ($/MW²h)	b ($/MWh)	c ($/h)	P_{min} (MW)	P_{max} (MW)
1	0.008	7.0	200	10	85
2	0.009	6.3	180	10	80
3	0.007	6.8	140	10	70

Loss Coefficients

$$B_{ij}=\begin{bmatrix} 0.000218 & 0 & 0 \\ 0 & 0.000228 & 0 \\ 0 & 0 & 0.000179 \end{bmatrix}$$

The optimal solutions of EDC problem using GWO method for the system demand of 150 MW at the end of 500th iterations for the population size of 20 are summarized in Table 2. GWO strategy produces a superior answer than the gradient descent method, which is evident from the simulation results.

Table 2. Comparisons- Three Generator Case (PD=150 MW)

Optimization methods	**Gradient Descent [1]**	**GWO**
P1 (MW)	35.0907	36.6967
P2 (MW)	64.1317	61.7718
P3 (MW)	52.4767	53.1541
Total loss (MW)	1.699	1.622
Total Cost ($/h)	1592.65	1592.40

Case B: IEEE 30- Bus Test System

This system has a base load of 283.4 MW, 6 generation units, and 41 transmission lines. Table 3 lists the necessary data for this test system.

Table 3. System Specifications of IEEE 30 Bus

Unit No.	Fuel Cost Coefficients			Generation Limits	
	a ($/MW²h)	b ($/MWh)	c ($/h)	Pmin (MW)	Pmax (MW)
1	0.00375	2.00	0	50	200
2	0.01750	1.75	0	20	80
3	0.06250	1.00	0	15	50
4	0.00834	3.25	0	10	35
5	0.02500	3.00	0	10	30
6	0.02500	3.00	0	12	40

$$B = \begin{vmatrix} 0.000218 & 0.000103 & 0.000009 & -0.00010 & 0.000002 & 0.000027 \\ 0.000103 & 0.000181 & 0.000004 & -0.000015 & 0.000002 & 0.000030 \\ 0.000009 & 0.000004 & 0.000417 & -0.000131 & -0.000153 & -0.000107 \\ -0.00010 & -0.000015 & -0.000131 & 0.000221 & 0.000094 & 0.000050 \\ 0.000002 & 0.000002 & -0.000153 & 0.000094 & 0.000243 & -0.00000 \\ 0.000027 & 0.000030 & -0.000107 & 0.000050 & -0.00000 & 0.000358 \end{vmatrix}$$

B0= -0.000003 0.000021 -0.000056 0.000034 0.000015 0.000078

B00= 0.000014

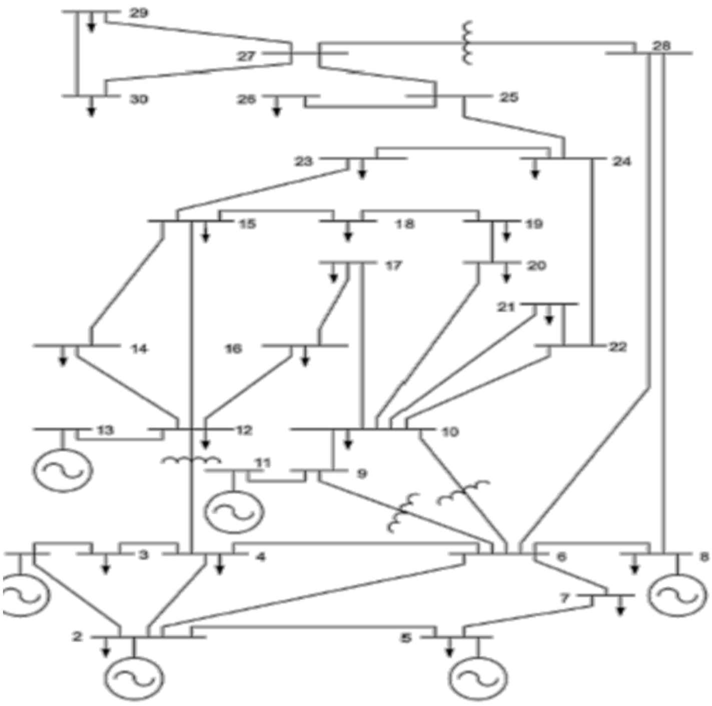

Figure 4. IEEE 30 Bus System [13]

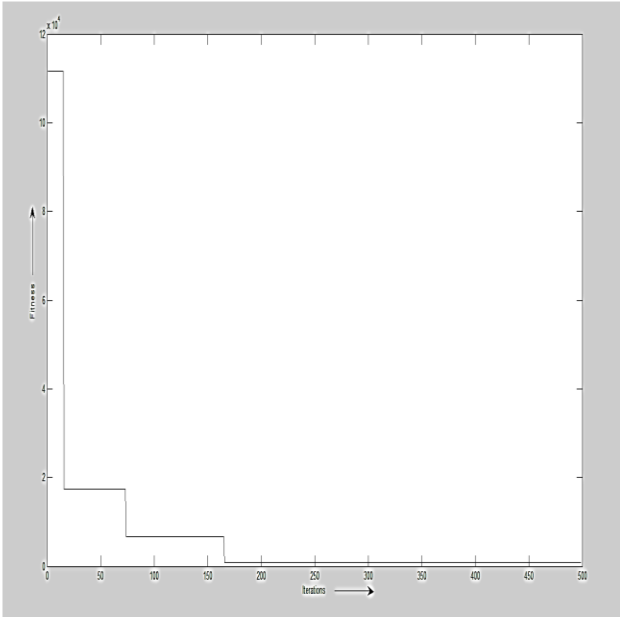

Figure 5. Convergence Characteristic of GWO for System Demand of 283.4 MW

The EDC problem has been solved using GWO method and the figure 5 shows the convergence characteristic for 500 iterations. It is discovered that in each independent trial, the GWO approach consistently produces solutions. Comparison findings between the novel approach GWO and those from [13,14,15] are displayed in Tables 4 and 5. The findings show that power outputs, total losses, and total cost have significantly converged.

Table 4. Comparative Results of Optimal Generations-IEEE 30-Bus system (PD=283.4 MW).

Optimization methods	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)
WOA [13]	174.4379	47.8294	21.4578	25.6931	10.1262	12.1515
PSO[14]	176.94	48.71	21.27	21.09	11.83	12.00
GA[15]	179.367	44.24	24.61	19.9	10.71	14.09
ACO[15]	177.863	43.8366	20.893	23.1231	14.0255	13.1199
GWO	**163.0912**	**44.8092**	**21.5202**	**26.7506**	**12.7692**	**21.8856**

Table 5. Comparative Results of EDC for IEEE 30- Bus (PD-283.4 MW).

Optimization methods	Power Loss (MW)	Total Cost ($/h)
WOA[13]	8.2972	800.2825
PSO [14]	8.4382	798.43
GA [15]	9.5177	803.699
ACO [15]	9.4616	803.123
GWO	**7.4260**	**802.8866**

From Table 5, it is evident that GWO approach results good solution than other soft computing techniques reported in the literatures. Further, solutions to EDC problem for various demands using proposed GWO method are summarized in Table 6.

Table 6. Outcomes for Various Load Demand using GWO-Case B

Demand	Generation						Total Loss (MW)	Total cost ($/h)
P_D (MW)	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)		
150	67.710	28.613	17.448	11.2603	14.072	12.511	1.6159	379.7618
200	111.22	29.905	20.084	14.4589	13.350	14.561	3.5858	524.3892
250	124.00	40.425	27.075	22.4091	23.156	17.578	4.6463	698.2926
275	158.09	41.880	21.533	23.5786	20.239	16.592	6.9146	773.2976
300	151.90	55.089	24.396	33.3539	14.919	27.537	7.2009	871.0429
400	198.56	72.281	43.367	34.5029	26.926	37.117	12.756	1290.60

5. Conclusion

In this work, GWO has been implemented to find the best solution for ELD problem. The IEEE 30 Bus system and three generating units system is considered for validation. To verify the efficacy of the suggested strategy, comparisons have been done between the outcomes of the GWO method and other optimization strategies documented in the literature. When compared to previous optimization strategies, it is discovered that the suggested technique produces best solutions to the EDC problem with good rate of convergence characteristics.

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