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An Efficient Solution for Economic Load Dispatch Using Cheetah Optimizer with Opposition-Based Learning and Adaptive Weighting Factor

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Abstract: The multi-objective economic load dispatch problem (ELDP) with non-smooth cost functions and ramp-rate limits presents a challenging optimization task in power systems. This paper proposes the use of a modified cheetah optimizer (MCO) that incorporates opposition-based learning (OBL) and a dynamic adaptive weighting factor to efficiently solve this problem. The simulations are conducted on standard test systems using MATLAB programming. A comparative study is performed, evaluating the performance of the MCO against basic CO and other similar heuristics. The results demonstrate the effectiveness of the MCO in achieving optimal solutions for the multi-objective ELDP with non-smooth cost functions and ramp-rate limits. The proposed approach offers a promising solution for addressing the complex optimization requirements in power system operation and planning. The optimal cost is determined using multi-criterion optimization (MCO) in 3-bus system as \$6,838.6434/h, \$7,738.789/h, and \$8,252.033/h for 700 MW, 800 MW and 850 MW demand levels respectively. The optimal cost is evaluated as \$17,988.96/h for the 13-bus test system considering a total demand of 1800 MW. The optimal cost is evaluated as 121960.30 \$/hr, for the 40-bus test system considering a total demand of 10500 MW. These outcomes demonstrate the efficacy of MCO in resolving the ELDP with generator and valve controls.

Keywords: Optimal power flow, Electric vehicle fleets, Open access trading, Wind farms, Skill optimization algorithm, Opposition-based learning.

1. Introduction

The economic load dispatch problem (ELDP) is pivotal in power systems, optimizing energy generation to minimize production costs while meeting demand. It ensures efficient resource utilization, grid stability, and reduced operational expenses by allocating power from generators economically and reliably [1]. A country's economic growth and power system efficiency are intertwined: expanding economies demand more electricity, while a stable power supply fosters industrial growth, enabling productivity, attracting investments, and supporting technological advancements. ELDPs come in various forms—Classical ELD minimizes costs with operational constraints, Multi-objective ELD optimizes multiple goals, Dynamic ELD considers time-varying demands and constraints, Security-Constrained ELD emphasizes stability, and Stochastic ELD manages uncertainties like load forecasts and renewable variations [2]. Solutions involve classical methods (lambda iteration, gradient, newton-raphson) offering quick but limited solutions and modern optimization techniques providing robust, efficient solutions for complex ELDPs, accommodating non-linear constraints and diverse objectives in power system optimization [2].

In recent times, various researchers have been motivated to solve ELDPs using various meta-heuristics. In [3], crow search algorithm (CSA_1) and differential evolution (DE) were used to solve ELDP considering only quadratic cost curves and generator limits. In [4], gradient-based optimizer (GBO) is employed for solving ELDP along with emission control and transmission loss. The study considers the generator limits and valve settings. In [5], an improved symbiosis particle swarm optimization (ISPSO) is proposed for ELDP focusing on cost minimization by handling MW limits and valve controls. In [6], salp swarm algorithm (SSA) and β-hill climbing optimizer (βHO) are hybridized to formulate hybrid salp swarm algorithm (HSSA) and solved ELDP for cost reduction. In [7], dynamic particle swarm optimization (DPSO) and grey wolf optimizer (GWO) were employed for ELDP in multi-area power system by aiming cost reduction. In [8], deep neural network (DNN) is trained by using different solution data set of ELDPs using λ-iteration optimization algorithm by considering only MW limits. In [9], an enhanced exploratory whale optimization algorithm (EEWOA) is utilized for solving multi-period ELDP. In [10], quasi oppositional population based global particle swarm optimizer with inertial weights (QPGPSO-W) is introduced by aiming cost and loss reducing while solving ELDP with MW limits and valve controls. In [11], memory-based gravitational search algorithm (MBGSA) is introduced for solving ELDP considering photovoltaic power generation and load demand variations. The study considered only cost minimization and MW limits. In [12], chameleon swarm algorithm (CSA_2) is employed for solving ELDP and combined emission economic load dispatch (CEEDP) with MW limits by considering cost and loss minimization. In [13], total operating cost (includes fuel, maintenance, emission, power loss, and wind power costs) is optimized while solving ELDP using DNN and novel genetic algorithm (nGA). Notably, the study was also considered ramp rate and spinning reserve limits. In [14], evolutionary simplex adaptive Hooke-Jeeves algorithm (ESAHJ) is developed by hybridizing GA and modified Hooke and Jeeves methods. In [15], an innovative hybrid algorithm (ihPSODE) by combining novel PSO (nPSO) and DE (nDE) is developed for solving ELDP with multiple objectives and constraints. In [16], arithmetic optimization algorithm (AOA) is proposed with six elementary mathematic functions for balancing exploration and exploitation for solving ELDP by aiming cost and loss reduction. In [17], modified krill herd algorithm (MKHA) is proposed by embedding crossover and mutation features for solving ELDP with multiple constraints. In [18], salp swarm algorithm (SSA) is introduced for ELDP subjected to MW limits, valve points and ramp rate limits. It is aimed to reduce operating cost and total transmission loss. In [19], oppositional based learning (OBL) is employed to improve pigeon-inspired optimizer (PIO) for solving ELDP focusing on cost minimization. In [20], symbiotic organism search with disruption operator (DSOS) is presented for ELDP for ensuring better exploration features. In [21], search and rescue optimization algorithm (SRA) is proposed for ELDP is solved by aiming cost and loss reducing with MW limits and valve controls. In [22], multigroup marine predator algorithm (MGMPA) based ELDP is presented to reduce cost of generation and transmission lines. The problem is constrained by generator limits and valve controls. In [23], a novel artificial ecosystem-based optimization (AEO) is employed for solving ELDP with MW limits and valve controls. In [24], author proposes a novel approach based on the chaotic slime mould algorithm (CSMA) for solving the ELD problem. The algorithm's effectiveness is demonstrated through comprehensive experiments, and it shows promising results in optimizing the economic load dispatch problem. In [25], a hybrid Harris Hawks optimizer (HHHO) combines the Harris Hawks optimization algorithm with other metaheuristics to enhance exploration and convergence for the economic load dispatch problem. Experimental results demonstrate HHHO's superiority over existing techniques. In [26], a memetic sine cosine algorithm (MSCA) is proposed, combining the global search of sine cosine algorithm with local search to improve solution quality for economic load dispatch. In [27], a hybrid capuchin search algorithm (HCSA) is introduced, combining Capuchin Search Algorithm and gradient search for balanced exploration-exploitation in economic load dispatch. Results show HCSA's effectiveness. In [28], a Quasi-oppositional-based political optimizer (QOBPO) handles non-convex economic emission load dispatch with valve-point loading via quasi-oppositional learning and political optimization. QOBPO achieves better economic-emission trade-offs.

From the comparison of literature listed in Table 1, meta-heuristics, while versatile, might converge slowly or get stuck in local optima. The no free lunch theorem (NFLT) [29] states anyone algorithm works for all problems, justifying the need for new approaches. In recent times, migration-crossover algorithm (MCA) [30], four directed search algorithm (FDSA) [31], total interaction algorithm (TIA) [32], walk-spread algorithm (WSA) [33], and attack leave optimizer (ALO) [34] are have been introduced for solving various optimization problems. However, a reliable metaheuristic demonstrates stability and resilience by consistently identifying near-optimal or ideal solutions even when faced with changes in problem landscapes or algorithm settings [35]. Cheetah optimizer [36], is one such another recent efficient metaheuristic and adapted in this work for the first time. Since this work is focused on only economic aspects and thus emission is not considered. Further, the tie-line limit is required for only when ELDP is handling in multi-area power system. On the other hand, spinning reserve is required for ensuring reliability under generators failure, but can cause for extra operating cost. Thus, this work is not handled tie-line and spinning reserve constraints.

Within this context, this work presents the following significant contributions:

- Introduction of the cheetah optimizer (CO) for the economic load dispatch problem (ELDP) within power systems, marking a pioneering application.
- Incorporation of opposition-based learning (OBL) algorithm to enhance search capabilities and initialize the population for improved optimization.
- Effective handling of valve point limits and ramp rate limits during the resolution of ELDP.
- Optimization of multiple objectives, specifically total fuel cost and transmission losses, enhancing the comprehensiveness of the solution.
- Conducting simulations on standard three-unit and thirteen-unit test systems to validate the proposed methodologies.
- Augmentation of the analysis by deploying various meta-heuristics alongside the modified cheetah optimizer (MCO) for a comprehensive quantitative evaluation of computational efficiency.

Paper organized as: Generator fuel cost curves and valve controls are covered in section 2. Section 3 describes the multi-objective function with equal and unequal constraints. Section 4 explains CO and the modified cheetah optimizer. Section 5 compares conventional test system simulation findings. Section 6 concludes the investigation on valve controls, multi-objective functions, optimizer upgrades, and simulation assessments.

2. Modelling of concepts

The curve typically slopes upwards due to factors like start-up costs, fuel expenses, maintenance, and other operational costs. At lower power outputs, the cost per unit of generated power tends to be higher due to start-up or minimum generation costs. As the output increases, the marginal cost of generating additional power decreases until reaching a certain point where it might plateau or slightly increase due to factors like efficiency limitations or fuel expenses.

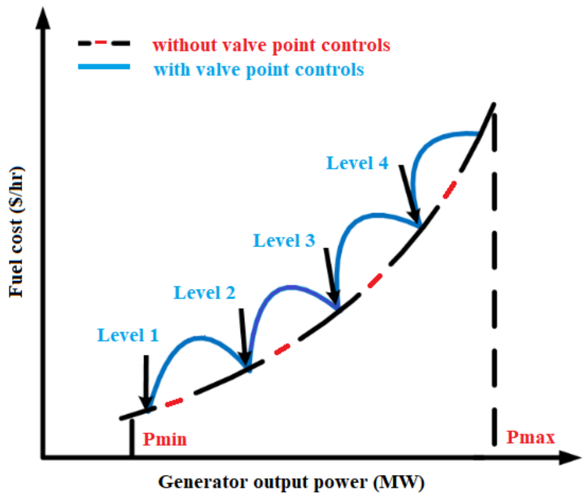

Figure. 1 Non-smooth fuel cost curve with valve controls

This curve is crucial in ELD as it helps in determining the optimal allocation of power output among generators to meet demand while minimizing the overall production cost. The objective is to find the combination of generator outputs that satisfy the demand at the lowest possible cost, considering various constraints and operating conditions. The following Eq. (1) and Eq. (2) are the expressions for generators cost curve without and with valve point controls, respectively.

$$f_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{1}$$

$$f_i(P_i) = \left(a_i P_i^2 + b_i P_i + c_i\right) + \left|d_i \times sin\left[e_i \times \left(P_i^{min} - P_i\right)\right]\right| \tag{2}$$

where P_i is the output power of a generator-i, a_i, b_i, c_i, d_i and e_i are the coefficients of cost curve, respectively; f_i is the fuel cost of a generator-i, P_i^{min} and P_i^{max} are the minimum and maximum MW limits of a generator-i, respectively.

Valve settings and ramp rates are crucial to ELD. Valve modifications affect thermal generator efficiency and flexibility. Increased operational maneuverability may reduce efficiency, whereas lower settings maximize efficiency. Ramp rates allow rapid power output changes to suit demand but may strain equipment. ELD valve settings and ramp rates should be balanced for effective load tracking, grid stability, resource use, system dependability, and equipment stress.

3. Problem formulation

The power plants use multi-valve steam turbines to regulate the power output of their generating units. These turbines, with their frequent valve openings, create fluctuations in the generator's fuel cost function. To address this issue in examining the Economic Dispatch problem, a rectified sinusoidal component needs incorporation into the standard quadratic cost function. Consequently, the quadratic cost function for generating units affected by valve point loading is outlined below.

$$F_c = \sum_{i=1}^{ng} \{ (a_i P_i^2 + b_i P_i + c_i) + |d_i \times sin[e_i \times (P_i^{min} - P_i)]| \} \quad (3)$$

In ELDP, equal constraints typically refer to equality constraints that maintain the balance between power generation and demand (load + losses).

$$P_D = \sum_{i=1}^{ng} P_i \quad (4)$$

$$P_D + P_{loss} = \sum_{i=1}^{ng} P_i \quad (5)$$

$$P_{loss} = \sum_{i=1}^{ng} \sum_{j=1}^{ng} P_i B_{ij} P_j + \sum_{i=1}^{NG} B_{0i} P_i + B_{00} \quad (6)$$

Unequal constraints, on the other hand, involve inequality conditions, often related to generator limits, transmission line capacities, and various operational limits. These constraints ensure that the generated power remains within the capacity limits of the generators and transmission lines, considering factors like minimum and maximum generation limits, ramp rates, and other operational restrictions.

$$P_i^{min} \leq P_i \leq P_i^{max} \quad (7)$$

$$P_i - P_i^0 \leq UR_i \quad (8)$$

$$P_i^0 - P_i \leq DR_i \quad (9)$$

where F_c is the total fuel cost of all generators in the system, P_i^0 is the earlier output power of a generator-i, UR_i and DR_i are the up-ramp and down-ramp limits, respectively; ng is the number of generators, P_D is the total demand on system, P_{loss} is the total transmission loss, B_{ij} , B_{0i} an B_{00} are the B-coefficients of transmission system, respectively.

Table 1. Objective functions, constraints and solution techniques used ELDPs in literature

Method	Objectives			Limits				
	Cost	Loss	Emission	MW limits	Valve points	Ramp rate	Tie-line	Spinning Reserve
CSA_1 & DE [3]	x	-	-	x	-	-	-	-
MBGSA [11]	x	-	-	x	-	-	-	-
DNN [8]	x	-	-	x	-	-	-	-
EEWOA [9]	x	-	-	x	x	-	-	-
ISPSO [5]	x	-	-	x	x	-	-	-
HSSA [6]	x	-	-	x	x	-	-	-
GWO [7]	x	-	-	x	x	-	x	-
OPIO [19]	x	-	-	x	x	x	-	-
QPGPSO-W [10]	x	x	-	x	x	-	-	-
ESAHJ [14]	x	x	-	x	x	-	-	-
ihPSODE [15]	x	x	-	x	x	-	-	-
AOA [16]	x	x	-	x	x	-	-	-
MKHA [17]	x	x	-	x	x	x	-	-
MKHA [18]	x	x	-	x	x	x	-	-
DSOS [20]	x	x	-	x	x	x	-	-
CSA_2 [12]	x	x	x	x	-	-	-	-
GBO [4]	x	x	x	x	x	-	-	-
nGA [13]	x	x	x	x	x	x	-	x
SAR [21]	x	x	-	x	x	-	-	-
MGMPA [22]	x	x	-	x	x	-	-	-
AEO [23]	x	x	-	x	x	-	-	-
CSMA [24]	x	x	-	x	x	-	-	-
HHO-AβHC [25]	x	x	-	x	x	-	-	-
SCA-βHC [26]	x	x	-	x	x	-	-	-
IHCSA [27]	x	x	-	x	x	-	-	-
QOPO [28]	x	x	-	x	x	-	-	-
Proposed	x	x	-	x	x	-	-	-

4. Solution methodology

The solution methodology of ELDP is developed based on recent metaheuristic cheetah optimizer (CO) with opposition-based learning (OLB) and an adaptive weighting factor.

4.1 Cheetah optimizer

The CO algorithm, inspired by the cheetah's hunting methods [36], offers advantages like minimal parameter adjustments, swift convergence, and simplified calculations. It follows three key stages: searching, waiting, and attacking, streamlining the optimization process.

4.1.1. Searching phase

With a vigilant gaze, the cheetah keenly observes its environment, leveraging its hunting instincts to seek optimal prey according to the current environmental dynamics. The mathematical model at this stage is outlined as follows:

$$C_{pq}^{k+1} = C_{pq}^{k} + r \times R_{pq}^{k} \tag{10}$$

$$R_{pq}^{k} = 0.001 + \frac{k}{k_{max}}(u_{lim} - l_{lim}) \tag{11}$$

where C_{pq}^{k} signifies the current position of cheetah-p at iteration k while C_{pq}^{k+1} represents its updated position at the subsequent iteration, r denotes a randomly chosen number from the range (0, 1), R_{pq}^{k} refers to a random step length, and u_{lim} and l_{lim} represent the upper and lower bounds of variable q. k stands for the current iteration, and k_{max} denotes the maximum iteration count.

4.1.2. Sitting and waiting phase

While foraging, each cheetah movement bears the risk of alerting and potentially startling its prey, leading to escape. Cheetahs adopt a strategy of staying low or camouflaging in bushes, patiently awaiting prey within striking distance. During the sitting and waiting stage, the cheetah maintains its position unchanged, represented mathematically as follows:

$$C_{pq}^{k+1} = C_{pq}^{k} \tag{12}$$

4.1.3. Attacking phase

Cheetahs' prowess lies in their precise timing during prey attacks, relying on remarkable speed and agility. In the attacking stage, they swiftly close the distance, using speed to destabilize prey strategically. Attacks, solitary or group-based, involve tactical positioning based on prey movements and group dynamics. The mathematical representation for this stage follows:

$$C_{pq}^{k+1} = C_{Hq}^{k} + X_{pq} \times Y_{pq}^{k} \tag{13}$$

$$X_{pq} = |r_{pq}|^{exp\left(\frac{r_{pq}}{2}\right)} \times sin(2\pi r_{pq}) \tag{14}$$

$$Y_{pq}^{k} = C_{rq}^{k+1} - C_{pq}^{k} \tag{15}$$

where C_{Hq}^{k} signifies the prey's position, while X_{pq} and Y_{pq}^{k} represent the turning factor and interaction factor, respectively, r_{pq} stands for a randomly chosen value from a normal distribution. Additionally, C_{rq}^{k+1} and C_{pq}^{k} denote the positions of cheetahs r and j at iteration k, respectively.

4.2 Modified cheetah optimizer

In the proposed modified cheetah optimizer (MCO), the searching phase is improvised using opposition based learning for population diversity, promoting convergence toward the global optimum.

$$\bar{C}_i = u_{lim} + l_{lim} - C_i \tag{16}$$

where $\bar{C}_i$ is a population initiated in the opposite direction.

Later, in the attacking phase, the cheetah employs a dynamic weighting factor, γ, for ongoing position updates. Initially, γ holds a higher value, facilitating an efficient global search. As the iteration progresses, γ gradually decreases adaptively [37], modifying Eq. (13) as follows:

$$C_{pq}^{k+1} = C_{Hq}^{k} + \gamma_{pq} \times Y_{pq}^{k} \tag{17}$$

Here dynamic weighting factor γ_{pq} is dependent on ∂ as defined by:

$$\partial = \frac{k}{k_{max}} \tag{18}$$

$$\gamma_{pq} = \frac{e^{4(1-\partial)} - e^{-4(1-\partial)}}{\left[e^{2(1-\partial)} + e^{-2(1-\partial)}\right]^2} \tag{19}$$

$$Y_{pq}^{k} = C_{rq}^{k+1} - C_{pq}^{k} \tag{20}$$

By these modifications, the basic CO can experience better search characteristics, and can balance

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Table 2. Comparison for a demand of 700 MW

	DSOS [20]	MCO	CO
G1	322.94	323.36	322.875
G2	99.33	98.99	98.401
G3	277.73	277.66	278.724
Cost	6838.4143	6838.4133	6838.6434
Mean	-	6838.627	6838.639
SD	-	0.00232	0.00286

Table 3. Comparison for a demand of 800 MW

	DSOS [20]	MCO	CO
G1	369.94	368.459	369.758
G2	114.54	115.555	114.507
G3	315.52	315.986	315.735
Cost	7738.5035	7738.503	7738.789
Mean	-	7738.79	7738.792
SD	-	0.0046	0.00711

exploration and exploitation phases by avoid local trap or optima, resultant for global solution.

5. Results and discussion

The computational efficacy of the proposed MCO is verified while solving ELDP on standard test systems [27]. Two test systems are considered for analyzing the impact of valve-point loading effects and ramp-rate limits on ELDP solution.

5.1 Three units test system

For this test system, the transmission loss is ignored and considered only cost optimization with valve point controls. The demand levels are taken as 700 MW, 800 MW and 850 MW and the results of CO, MCO are given in Table 2, Table 3 and Table 4, respectively. The mean and standard deviation (SD) of 25 independent runs are also tabulated. Further, the results of CO and MCO are compared with DSOS [20]. The optimal cost is determined as 6838.4133 \$/hr and 6838.6434 \$/hr with MCO and CO. In comparison to CO, MCO has resulted best solution and it is very competitive with DSOS [20]. Similarly, MCO has shown superiority than CO and DSOS [20] for a demand of 800 MW and also for 850 MW, the results are better than DSOS [20] and ISPSO [5].

Further, the computational features of MCO are quantified over 25 independent runs by considering load demand as 850 MW. Also, basic CO, cuckoo search algorithm (CSA) [38], teaching learning based optimization (TLBO) [39], artificial rabbits optimization (ARO) [40], grasshopper optimization algorithm (GOA) [41], prairie dog optimization (PDO) [42], butterfly optimization algorithm (BOA) [43], and firefly algorithm (FA) [44] are used for comparative study. The results are given in Table 4 and it can be seen that the MCO has been outperformed than other algorithms with least global optima.

5.2 Thirteen units test system

In this scenario, simulations are performed on a 13-units power system considering a total demand of 1800 MW considering both limits. The results of MCO over 25 independent runs along with other comparative algorithms are given in Table 3. From the results, MCO is outperformed than other compared algorithms by its global best, 17988.96 \$/hr.

Further, a comparison with literature is given in Table 5. In order to cross verify the results which are reported in literature works, we have used brute force technique by considering the reported schedule in the cost curve for evaluating the total cost. The corrected values are given in Table 6. As per the comparison of corrected cost functions, MCO is highly comparative with QOPO [28], whereas superior to CSMA [24], HHO-AβHC [25], SCA-βHC [26], and IHCSA [27].

Table 4. Comparison of different algorithms for three units system with P_d = 850 MW

Algorithm	**Schedule (MW)**			**Cost (\$/hr)**				
	$\mathbf{P_{g1}}$	$\mathbf{P_{g2}}$	$\mathbf{P_{g3}}$	**Best**	**Worst**	**Mean**	**Median**	**SD**
MCO	395.309	301.993	152.698	8252.033	8978.065	8645.213	8640.494	118.043
CO	499.665	300.335	50.000	8273.702	8954.948	8627.167	8633.250	132.755
CSA	501.219	298.781	50.000	8302.129	8918.455	8640.373	8645.926	134.717
TLBO	496.697	303.303	50.000	8310.748	8956.688	8639.265	8642.703	119.056
ARO	502.430	297.570	50.000	8324.201	8905.957	8637.363	8640.514	128.980
GOA	406.277	297.860	145.863	8349.217	8985.551	8641.163	8644.257	124.027
PDO	406.503	293.470	150.028	8351.280	8980.821	8647.461	8642.544	135.055
BOA	494.175	305.825	50.000	8354.220	8885.906	8641.583	8643.591	129.922
FA	497.564	152.436	200.000	8354.990	8981.300	8631.659	8638.399	121.617
PSO	399.747	377.391	72.862	8365.966	8970.968	8642.211	8647.447	123.065

Table 5. Comparison of different algorithms for thirteen units system with P_d = 1800 MW

Item	FA	BOA	PDO	GOA	ARO	TLBO	CSA	CO	MCO
P_{g1}	628.0021	627.67	539.35	629.23	626.41	626.48	628.23	628.74	628.44
P_{g2}	0.001185	297.00	360.00	299.55	300.99	307.35	360.00	360.00	1.56
P_{g3}	359.142	298.99	299.36	220.58	293.41	226.37	1.39	216.69	359.97
P_{g4}	159.7312	60.01	60.01	60.90	60.18	60.00	60.00	60.00	111.48
P_{g5}	60	60.00	60.00	60.00	60.72	60.92	60.00	60.00	109.86
P_{g6}	60	60.00	109.88	60.36	62.30	60.00	159.80	60.32	160.05
P_{g7}	60	60.06	60.00	159.26	60.14	60.00	60.03	60.00	60.00
P_{g8}	60	60.14	60.04	60.00	60.10	154.39	110.51	105.43	114.25
P_{g9}	159.7479	60.00	60.00	60.57	60.02	60.00	161.24	60.45	60.00
P_{g10}	103.4461	66.17	40.17	40.00	40.00	40.37	40.51	40.00	40.17
P_{g11}	40	40.01	40.14	40.31	40.12	40.40	48.31	40.41	44.70
P_{g12}	55	55.08	56.17	55.67	82.43	55.26	55.00	55.53	55.65
P_{g13}	55	55.15	55.00	55.15	55.77	55.00	55.00	55.00	55.05
Best	17992.45	17991.58	17990.62	17997.17	17999.62	17989.19	17977.27	17999.90	17988.96
Worst	18329.65	18262.73	18291.86	18322.55	18328.25	18286.21	18280.85	18277.89	18333.46
Mean	18168.77	18155.43	18177.04	18176.77	18217.28	18166.82	18184.36	18172.64	18162.21
Median	18195.08	18152.99	18162.40	18175.59	18247.03	18162.69	18215.96	18182.81	18133.31
SD	89.91886	75.16	68.69	69.89	75.41	73.84	72.66	80.90	85.57

Table 7. Comparison of different algorithms for forty units system with P_d = 10500 MW

Unit #	P_{g1}	P_{g2}	P_{g3}	P_{g4}	P_{g5}	P_{g6}	P_{g7}	P_{g8}	P_{g9}	P_{g10}
Schedule (MW)	114.00	114.00	120.00	190.00	97.00	140.00	280.67	290.42	292.51	130.00
Unit #	P_{g11}	P_{g12}	P_{g13}	P_{g14}	P_{g15}	P_{g16}	P_{g17}	P_{g18}	P_{g19}	P_{g20}
Schedule (MW)	168.80	168.80	214.76	304.52	304.52	394.28	489.28	489.28	511.28	511.28
Unit #	P_{g21}	P_{g22}	P_{g23}	P_{g24}	P_{g25}	P_{g26}	P_{g27}	P_{g28}	P_{g29}	P_{g30}
Schedule (MW)	523.28	523.71	523.28	523.28	523.82	523.28	13.84	11.78	10.19	94.83
Unit #	P_{g31}	P_{g32}	P_{g33}	P_{g34}	P_{g35}	P_{g36}	P_{g37}	P_{g38}	P_{g39}	P_{g40}
Schedule (MW)	190.00	181.90	187.16	164.81	180.46	199.99	108.24	90.29	89.20	511.28

Table 6. Comparison of literature for 13-units system

Method	Reported cost ($/hr)	Corrected cost ($/hr)
CSMA [24]	18701.49	19081.62
HHO-AβHC [25]	17,960.43	18424.86
SCA-βHC [26]	17960.39	18425.00
IHCSA [27]	17,960.37	18425.00
QOPO [28]	17988.99	18450.00
Proposed	17988.96	17988.96

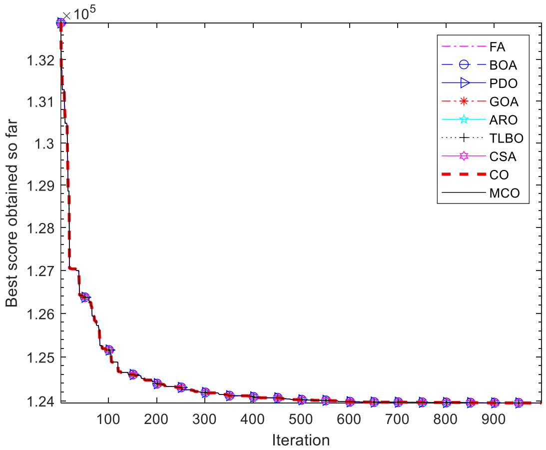

Figure. 2. Convergence characteristics of different algorithms in 40-bus system

5.3 Forty units test system

In this test system, 40 units are supposed to supply 10500 MW demand. The best results of MCO over 25 independent runs are alone given in Table 7. The corresponding operating cost is 121960.30 $/hr, which is very competitive with the result HSSA of 121960.27 $/hr [6]. The convergence characteristics of different algorithms are given in Fig. 2.

6. Conclusion

The multi-objective economic load dispatch problem (ELDP) poses a significant challenge in power systems due to its non-smooth cost functions and ramp-rate limits. This study introduces a solution using a modified cheetah optimizer (MCO) that integrates opposition-based learning (OBL) and a dynamic adaptive weighting factor. This method efficiently tackles the complexity of the ELDP. By conducting simulations on standard test systems through MATLAB programming, a comparative analysis is performed. The MCO's performance is evaluated against other algorithms, showcasing its effectiveness in delivering optimal solutions for the

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multi-objective ELDP with non-smooth cost functions and ramp-rate limits. The optimal cost is determined using MCO in 3-bus system as 6838.6434 \$/h, 7738.789 \$/h, and 8252.033 \$/h for 700 MW, 800 MW and 850 MW, respectively. Similarly, the optimal cost is evaluated as 17988.96 \$/h for 13-bus test system considering a total demand of 1800 MW. The optimal cost is evaluated as 121960.30 \$/hr, for the 40-bus test system considering a total demand of 10500 MW. These results have shown the effectiveness of MCO in solving ELDP.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, methodology, software and original draft preparation are done by V. Sai Geetha Lakshmi; supervision, review, and formal analysis are done by M. Vanithasri and M. Venu Gopal Rao.

Notations

P_i	Output power of a generator-*i*
a_i, b_i, c_i, d_i and e_i	Cost coefficients of cost curve
f_i	Fuel cost of a generator-*i*
F_c	Total fuel cost of all generators in the system
P_i^{min}	Minimum MW limits of a generator-*i*
P_i^{max}	Maximum MW limits of a generator-*i*
P_i^0	Earlier output power of a generator-*i*
UR_i	Up-ramp limit
DR_i	Down-ramp limit
ng	Number of generators
P_{loss}	Total transmission loss
B_{ij}, B_{0i} an B_{00}	B-coefficients of transmission system

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