

# Economic Load Dispatch with Practical Constraints using Mountaineering Team-Based Optimization Technique

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**Abstract:** In order to resolve the issue of economic load dispatch (ELD), this research presents a novel metaheuristic optimization approach called mountaineering team based optimization (MTBO). The MTBO approach, which prioritizes human connection and teamwork, takes into account regular incidents on a mountain peak route. These kinds of techniques assess the leader's expertise, the complexity of the climb, and the potential for the team as a whole to become stuck in a suboptimal state of performance. The organization and social support of the organization are also thought to protect members against widespread calamities. The effectiveness of the proposed strategy was evaluated using six ELD instances by including various practical limitations like valve-point effect (VPE), prohibited operating zone (POZs) and ramp rate limit (RRL). The ELD problem are solved using the MTBO in conjunction with other optimization techniques, such as the ant lion optimization (ALO), grey wolf optimization (GWO) and flower pollination algorithm (FPA), and. The MTBO method is superior to other approaches in terms of its efficacy in optimising global solutions, as well as its robustness and ease of application.

**Keywords:** ant lion optimization, economic load dispatch, flower pollination algorithm, grey wolf optimization, mountaineering team based optimization, prohibited operating zone, valve-point effect.

## 1. Introduction

The disparity between electricity consumption and production has widened in recent years. It would be more expensive to build and store new power plants than to make greater use of the existing power plants. Economic load dispatch (ELD) [1] issues are solved by using optimization techniques in order to determine the optimal allocation of power for generating units in order to reduce generation costs. An ELD problem is described as a quadratic function in the literature [2]. In a more practical context, transmission losses, ramp rate restrictions (RRLs), prohibited operating zones (POZs), and the valve point effect (VPE) are all taken into consideration as prospective elucidations to the ELD problem [3–5]. The ELD problem is non-convex and nonsmooth as a result of these practical constraints [6, 7].

The issues with ELD have been addressed using conventional methods such the lambda-iteration and Newton technique [8], gradient method [9], and base-point method [10]. The preferred method for resolving ELD problems in recent years has been metaheuristic optimization algorithms [11–13]. Taking into account the practical restrictions, the genetic algorithm (GA) [14], particles swarm optimization (PSO) [15], artificial bee

colony (ABC) algorithm [16], and differential evolution (DE) [17] were used to solve the multi-objective ELD. The Butterflies and Bat Algorithms are combined in the Hybrid Approach (HYB) [18], and GA and PSO are combined [19]: The modified frog-leaping method (MSFLA) and the MOSHEPO [20, 21] are two variations of the frog-leaping approach that are often employed to tackle ELD problems.

It has been proposed that the metaheuristic optimization technique known as mountaineering team based optimization (MTBO) [22] method used to solve the ELD problem. This exploration examines six distinct test cases for the ELD issue in order to estimate the efficacy of the suggested method in a variety of actual contexts. The MTBO is contrasted with a wide range of optimizer algorithms, including ant lion optimizer (ALO) [23], flower pollination algorithm (FPA) [24], and grey wolf optimization (GWO) [25], in order to address the ELD problem.

## 2. Problem Formulation

### 2.1. Economic Load Dispatch (ELD)

The traditional method for solving the ELD Problem ignores any practical limitations and works to decrease the fuel costs of the generators that must supply the whole load demand at a specific power output. In the majority of formulations of the traditional ELD problem, the valve-point effect is neglected, resulting in a quadratic fuel cost function. The cost function associated with each generating unit  $i$  can be expressed as a quadratic function in its

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simplest form.

Minimize

$$F_T = \min f = \sum_{i=1}^n F_i(P_i) \quad (\$/h) \quad (1)$$

$$F_i(P_i) = \sum_{i=1}^N (a_i \times P_i^2 + b_i \times P_i + c_i) \quad (2)$$

### 2.1.1 Equality Constraints

The addition of power consumed, transmission losses, and electricity generated by generators must always equal zero. The power equality equation is

$$\sum_{i=1}^N P_i = P_{Dem} + P_{Los} \quad (3)$$

Losses must be accounted for if economical dispatch is to be attained. The relationship between power output and transmission loss is direct. Use equation (4) to approximate your economic losses.

$$P_L = \sum_{i=1}^N \sum_{j=1}^N P_i \times B_{ij} \times P_j + \sum_{i=1}^N B_{0i} \times P_i + B_{00} \quad (4)$$

### 2.1.2 Inequality Constraints

The actual power output of each generator is limited by its utmost and minimum power limitations, respectively. In Equation (5), an inequality restricts the producing power to a particular range.

$$P_{i\min} \leq P_i \leq P_{i\max} \quad (5)$$

### 2.2. ELD with Valve-point effect (ELDVPE)

The generator-produced heat rate curve is not linear in higher order due to the sequential valve opening mechanism used in multivalve steam turbines. The cost function is non-convex and has a lot of minima due to the action of the valve point. The accuracy of mathematical equations (ELDVPE) is increased by modifying the impact of the valve points using the sine function. Commonly, the cost objective function of the ELD problem is expressed as the addition of a sinusoidal function and a quadratic cost function when the effects of valve-point impacts are considered (ELDVPE).

The time necessary to open the valve is included in the cost function, which can be expressed as

$$F_2 = F_1(P_i) = a_i \times P_i^2 + b_i \times P_i + c_i + |e_i \times \sin(f_i \times (P_{\min} - P_i))| \quad (6)$$

### 2.3. ELD with Ramps rate limit (ELDRRL)

In reality, the ramp rate limitation diminishes the operational period in which online units may change the

operation of the generator throughout each of two operating periods. Consequently, the range depicted below is the utmost range within which the power output of a practical generator can be rapidly adjusted.

$$\begin{cases} (P_i - P_{0i}) \leq UR_i & \text{when generation increases} \\ (P_{0i} - P_i) \leq DR_i & \text{when generation decreases} \end{cases} \quad (7)$$

The following equation provides a mathematical expression for the operational ramp-rate limitations of units:

$$P_{i\min,r} \leq P_i \leq P_{i\max,r} \quad (8)$$

$$\text{Where } \begin{cases} P_{i\min,r} = \max(P_{i\min}, P_{0i} - DR_i) \\ P_{i\max,r} = \min(P_{i\max}, P_{0i} + UR_i) \end{cases} \quad (9)$$

### 2.4. ELD including Prohibited Operating Zone (ELDPOZ)

The generators might not be able to operate within a limited range due to mechanical limitations like a damaged condensation valve or extremely loud pulsation in the shaft bearings. As a result, the cost curvatures have gaps that symbolize the small working domains. The unit must be at or above the zone's verge to function properly inside a restricted region. A non-convex set consists of at least two convex regions separated by prohibited regions. However, near the limited zone, disturbance in real-world performance testing or operational data could obscure the input-output curve's contour. In actuality, it is more economical not to dispatch any employees there.

$$P_i = \begin{cases} P_{i\text{minimum}} \leq P_i \leq P_{i,l}^1 \\ P_{i,j-1}^u \leq P_i \leq P_{i,j}^l, j = 2, \dots, n_i \\ P_{i,n_i}^u \leq P_i \leq P_{i\text{maximum}} \end{cases} \quad (10)$$

### 3. Mountaineering Team Based Optimization

The MTBO method takes into consideration natural phenomena as well as human conduct and collaboration, thanks to input from mountaineers. The authors report a dearth of previous work on this unconventional approach to optimization studies. The main goal of this study is to conclude the MTBO algorithm performs for typical problems and tasks in engineering design. The competence of the MTBO algorithm is evaluated in association to other popular modern algorithms.

#### 3.1 Inspiration

A new metaheuristic approach that considers natural events and is motivated by collaboration and social behaviour. In a wide variety of practical applications, its MTBO optimization performance is preferable to that of other

well-known techniques. It has an advantage over more contemporary methods because it converges to a globally optimal solution rapidly and adequately. Below are the logical steps of the MTBO algorithm, which originated in order to make it easier for the team to climb the mountain carefully and in unity despite the natural calamities.

### 3.2 Mathematical model

#### 3.2.1 Cooperative mountaineering is the first phase

Typically, the climber with the most experience is in command, similar to how optimization researchers select the optimal algorithmic option at any given time. This position is filled by the algorithm's top performer or the ascending team. To reach the pinnacle or obtain the best solution overall, the finest, or the entire group, follows this individual's direction. As a result, group members progress in the methods outlined below.

$$X_i^{new} = X_i + \text{rand}(X_{leader} - X_i) \quad (11)$$

A mountaineering team's leader is in charge of overseeing all activities, and members are typically evaluated from best to worst. In addition to serving as the group's commander, the individual in front of them also acts as a guide and director. Follow the individual who is in front of themselves until everyone is evaluated from best to worst is an analogous MTBO method.

$$X_i^{new} = X_i + \text{rand}(X_{leader} - X_i) + \text{rand}(X_{ii} - X_i) \quad (12)$$

In the context of optimization, it is believed that each action will occur at random with a probability of  $L_i$ . This is the resulting pseudo-code:

$$\begin{aligned} &\text{if } \text{random} < L_i \\ &X_i^{new} = X_i + \text{random}(X_{leader} - X_i) + \text{random}(X_{ii} - X_i) \quad (13) \\ &\text{end} \end{aligned}$$

#### 3.2.2 Natural disaster effects at the second stage

If natural calamities occur while hikers are on the trail, they risk injury or death, thereby securing the residents' optimal environment. The MTBO algorithm significantly depends on the occurrences of avalanches and clifffalls. Avalanches have a significant impact on the MTBO's optimization strategy. Therefore, it is more probable that an avalanche will begin at this time than at any other. Avalanches have a significant impact on the MTBO's optimization strategy. Permitting the individual to depart on foot discourages them from remaining at the optimal solution's local maximum.

$$X_i^{new} = X_i - \text{rand}(X_{Avalanche} - X_i) \quad (14)$$

Given the assumption that the avalanche probability is equal to  $A_i$ , the pseudocode as follows:

$$\begin{aligned} &\text{if } \text{rand} < A_i \\ &X_i^{new} = X_i - \text{rand}(X_{Avalanche} - X_i) \quad (15) \\ &\text{end} \end{aligned}$$

#### 3.2.3 The third stage is an integrated and coordinated response to natural disasters

The highly effective and well-informed manner in which members assist and guide one another distinguishes human communities from other phenomena and species. For a climbing expedition to be successful, the group's ability to collaborate is crucial. If a climbing team member falls or becomes entangled, the others will strive to extricate them. The  $i$ th team member is assumed to be in the same position as the remainder of the team, which is either  $X_{mean}$  or  $X_{Team}$ , depending on the measure employed.

$$X_i^{new} = X_i + \text{rand}(X_{Team} - X_i) \quad (16)$$

In this phase, the pseudo-code assumes that  $M_i$  equals the probability of locating the optimal local response or the prospect of rescuing someone from a landslide.

$$\begin{aligned} &\text{if } \text{rand} < M_i \\ &X_i^{new} = X_i + \text{rand}(X_{Team} - X_i) \quad (17) \\ &\text{end} \end{aligned}$$

#### 3.2.4 Potential Member Loss in the Fourth Stage

The MTBO technique takes this into attention by randomly selecting a new member to replace the departing one using the equation below.

$$X_i^{new} = X(X_{max} - X_{min}())_{min} \quad (18)$$

### 3.3 Mathematical Complexity of MTBO

The MTBO method calculations are done in three steps: initialization, fitness assessment, and updation of population.  $O(NPP)$  intricate computation is required to initiate the procedure with NPP entities. The evaluation difficulty of the enhancement method is evaluated as  $O(\text{itera max} \times NPP) + O(\text{itera max} \times NPP \times \text{Diff})$ . The practice comprises adjusting the position vector for all populations and looking for the best site, where  $\text{Iteramax}$  is the maximum no. of allowed iterations and  $\text{Diff}$  is the difficulty of the problem.

$$O(\text{MTBO}) = O(NPP * (\text{itera max} + \text{itera max} * D + 1)) \quad (19)$$

## 4. Results and Discussion

### 4.1 Introduction

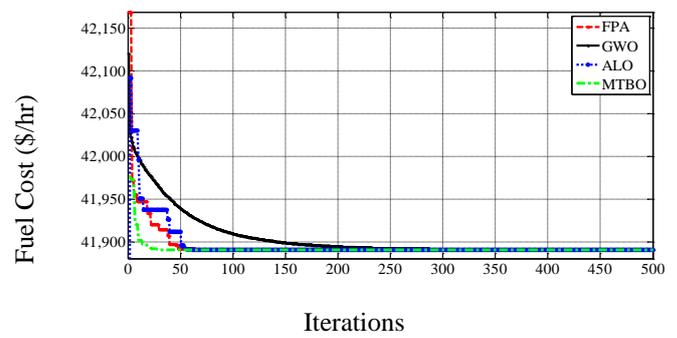
The suggested MTBO has successfully included six test cases to solve ELD problem. Consideration is given to

transmission losses, ramp rates, ramp amplitudes, VPE, and POZ. Table 1 contains a listing of the characteristics utilised in these six evaluations. MTBO's effectiveness in comparison to other optimization techniques like ALO, FPA, and GWO should be evaluated.

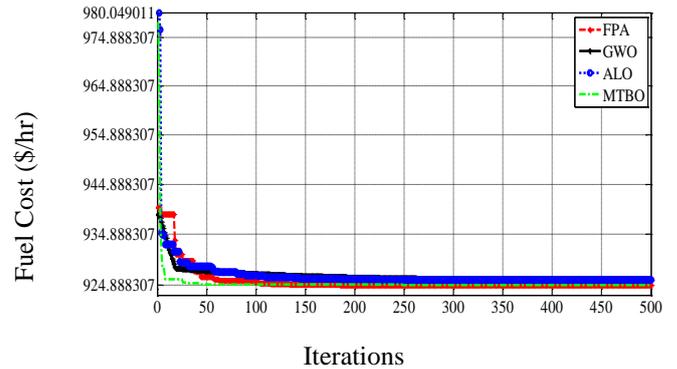
**Table 1.** Six Case Studies Characteristic

Test cases	PL	VPE	RRL	POZ	PD (MW)	Units
Case 1	√				800	6 [40]
Case 2	√	√			283.4	6 [42]
Case 3	√	√			1263	6 [48]
Case 4	√	√	√		1263	6 [48]
Case 5	√	√		√	1263	6 [48]
Case 6	√	√	√	√	1263	6 [48]

Table 2 provides the optimal results obtained by various methods. Among all the methods MTBO provides better results interms of power losses and operating cost. Figure 1 indicates the characteristics of convergence to proposed methods like FPA, ALO, GWO, and MTBO. The MTBO converge faster as compare with remaining three methods even though all methods provide better cost as 41890.5076 \$/hr.



**Fig. 1.** Characteristics of Convergence in Case 1



**Fig. 2.** Characteristics of Convergence in Case 2

Case 2 calculates and compares the optimal fuel expenditure and power distribution for generators using a variety of methodologies. NSO-GA [29], MSG-HP [30], TLBO [32], ALO, GWO, and FPA are among these methods. This investigation was prompted by the proposed MTBO. Listed below are the collated results. MTBO's hourly rate is the lowest, at 924.8776 dollars. Figure 2 depicts the cost convergence curve for FPA, ALO, GWO and MTBO, which reveals that MTBO has a better convergence rate than the other three methods.

**Table 2.** Optimal results of Test System (Case 1)

	PSO (26)	CSA (27)	FFA (28)	ALO	GWO	FPA	MTBO
P1 (MW)	32.67	50.6613	32.5861	33.9086	33.9061	33.9125	33.9122
P2 (MW)	14.45	32.5863	14.4843	14.4444	14.4940	14.4023	14.4027
P3 (MW)	141.73	14.4843	141.548	141.2628	141.2544	141.2750	141.2749
P4 (MW)	136.56	136.0450	136.045	135.6417	135.6336	135.6481	135.6478
P5 (MW)	257.37	243.0090	257.664	257.3038	257.2812	257.3120	257.3118
P6 (MW)	242.54	253.3120	243.009	242.6118	242.6020	242.6245	242.6251
PL (MW)	25.3200	25.3300	25.3309	25.1731	25.1714	25.1744	25.1744
PT (MW)	825.32	825.3300	825.3309	825.1731	825.1714	825.1744	825.1744
FC(\$/hr)	41896.66	41896.90	41896.7	41890.5076	41890.5076	41890.5076	41890.5076

**Table 3.** Optimal results of Test System (Case 2)

	NSO-GA [29]	MSG-HP [30]	TLBO [32]	GWO	ALO	FPA	MTBO
P <sub>1</sub> (MW)	182.4784	199.6331	197.8648	199.5996	199.5997	199.5996	199.5996
P <sub>2</sub> (MW)	48.3525	20.0000	50.3374	20.0117	20.0000	20.0000	20.0002
P <sub>3</sub> (MW)	19.8553	23.7624	15.0000	23.8450	23.9611	23.8091	239.9650
P <sub>4</sub> (MW)	17.1370	18.3934	10.0000	19.1505	19.2833	19.1764	19.4335
P <sub>5</sub> (MW)	13.6677	17.1018	10.0000	18.1232	17.5607	18.0782	18.3433
P <sub>6</sub> (MW)	12.3487	15.6922	12.0000	13.6590	14.0130	13.7322	13.0357
P <sub>Loss</sub> (MW)	10.4395	11.1830	11.8022	11.0140	11.0428	11.0208	11.0125
PT(MW)	293.8395	294.5829	295.2022	294.4140	294.4428	294.4208	294.4125
FC(\$/hr)	984.9365	925.6406	925.7581	924.9248	924.8993	924.8883	924.8776

**Table 4.** Optimal Costs Comparison of case 3, 4, 5 and 6 Studies to 6-unit system

	MTBO	FPA	ALO	GWO
CASE 3 (ELD)	15433.2734	15433.2734	15433.2734	15433.2734
CASE 4 (ELDRRL)	15452.6753	15452.6754	15452.6753	15452.6873
CASE 5 (ELDPOZ)	15433.1343	15433.1344	15433.1343	15433.1343
CASE 6 (ELDRPOZ)	15442.6753	15442.6754	15442.6753	15442.6753

**Table 5.** Optimal results of Test System (Case 6)

	BSA[34]	EMA[35]	MCS[36]	ALO	GWO	FPA	MTBO
P <sub>1</sub> (MW)	447.4902	447.3872	447.3997	447.0456	447.0748	447.0442	447.0448
P <sub>2</sub> (MW)	173.3308	173.2524	173.2392	173.1781	173.2096	173.1765	173.1765
P <sub>3</sub> (MW)	263.4559	263.3721	263.3163	263.9637	264.0014	263.9632	263.9628
P <sub>4</sub> (MW)	139.0602	138.9894	138.0006	139.0554	139.0073	139.0645	139.0569
P <sub>5</sub> (MW)	165.4804	165.3650	165.4104	165.5877	165.5685	165.5863	165.5902
P <sub>6</sub> (MW)	87.1409	87.0781	87.0798	86.5854	86.5551	86.5810	86.5847
P <sub>LS</sub> (MW)	12.9583	12.4430	12.4460	12.4156	12.4164	12.4155	12.4154
PT(MW)	1275.958	1275.4430	1275.4460	1275.4156	1275.4164	1275.4155	1275.4154
FC(\$/hr)	15449.89	15443.075	15443.090	15442.675	15442.675	15442.675	15442.675

Case 3 (ELD) examines a 6-unit system devoid of peak rate limits and POZs. In this scenario, the optimal hourly cost for the entire MTBO system is 15433.2734 dollars. Case 4 investigates the ramp rate limitations (ELDRRL) of the same system without POZs. When ramp rate constraints are accounted for, the optimal hourly cost increases to a maximum of 15452.6753 dollars

Case 5 is the result of replacing the transition rate limits in Case 3's POZs with ELDPOZs. Due to the participation of the POZs, the greatest rate is 15433.1343 \$/h. Case 6

(ELDRPOZ) describes the system from Case 3 with rise rate limitations and POZs. When escalation rate limitations and POZs are considered, operational costs increase to 15442.6753 dollars per hour, which is less than case 4 but greater than case 3. Figure 3 depicts the characteristics of convergence in case 6. The comparison of cases 3, 4, 5, and 6 is shown in Table 4. The comparative analysis makes use of BSA [34], EMA [35], MCS [36], GWO, ALO, and FPA. Table 5 shows the results of applying these strategies and the suggested MTBO to the generation units.

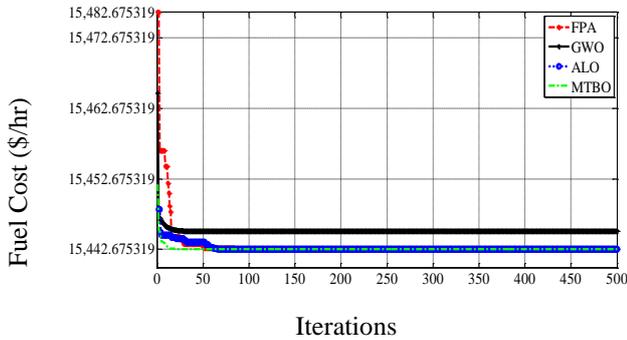


Fig. 3. Characteristics of Convergence in Case 6

## 5. Conclusions

This work introduces a unique mountaineering team-based optimization (MTBO) method for addressing economic load dispatch (ELD) issues in the power system. By using this method, human conduct is brought into line with ecological and technological advancement. The proposed algorithm accounts for the four phases of coordinated climb, the consequences of natural disasters, the importance of a strong front in the face of chaos, and the potential for individual avalanche fatalities. The ant lion optimization (ALO), grey wolf optimization (GWO), and flower pollination algorithm (FPA) optimization approaches have also been used to address the ELD and CEED issues in addition to the MTBO method. Limited acceleration and limited zones also contribute to the ELD issue, in addition to gearbox losses. The MTBO approach was shown to be the most efficient based on data from six instances of the ELD problem. Real-time simulator software can be used to evaluate the method under consideration. Using this method, it is possible to analyse in real time an extensive and complex power system network using actual parameters. The analysis of the results reveals that the proposed method can be used to address an extensive range of single and multi-objective problems in numerous fields of study. In the upcoming, the MTBO algorithm and prominent evolutionary algorithms may function better together.

## References

[1] E. Ali and S. A. Elazim, "Mine blast algorithm for environmental economic load dispatch with valve loading effect," *Neural Comput. Appl.*, vol. 30, no. 1, pp. 261–270, 2018. doi.org/10.1007/s00521-016-2650-8

[2] L. Gholamghasemi, Maedeh, et al. "A new solution to the non-convex economic load dispatch problems using phasor particle swarm optimization." *Applied Soft Computing* 79, 111-124, 2019. doi.org/10.1016/j.asoc.2019.03.038

[3] T. T. Nguyen and D. N. Vo, "The application of one rank cuckoo search algorithm for solving economic

load dispatch problems," *Appl. Soft Comput.*, vol. 37, pp. 763–773, Dec. 2015. doi.org/10.1016/j.asoc.2015.09.010

[4] B. Dey, S. K. Roy, et al, "Solving multi-objective economic emission dispatch of a renewable integrated microgrid using latest bio-inspired algorithms," *Eng. Sci. Technol. Int. J.*, vol. 22, no. 1, pp. 55–66, 2019. doi.org/10.1016/j.jestch.2018.10.001

[5] K. Bhattacharjee, A. Bhattacharya, and S. H. N. Dey, "Backtracking search optimization based economic environmental power dispatch problems," *Int. J. Elect. Power Energy Syst.*, vol. 73, pp. 830–842, Dec. 2015. doi.org/10.1016/j.ijepes.2015.06.018

[6] Q. Zhang, D. Zou, N. Duan, and X. Shen, "An adaptive differential evolutionary algorithm incorporating multiple mutation strategies for the ELD problem," *Appl. Soft Comput.*, vol. 78, pp. 641–669, May 2019. doi.org/10.1016/j.asoc.2019.03.019

[7] Amann M et al. "Reducing global air pollution: the scope for further policy interventions", *Philos Trans A Math Phys Eng Sci.* 378(2183), , October 2020. doi: 10.1098/rsta.2019.0331

[8] A. J. Wood, B. F. Wollenberg, and G. B. Sheblé, *Power Generation, Operation, and Control.* Hoboken, NJ, USA: Wiley, 2013.

[9] K. Lee, Y. Park, and J. Ortiz, "Fuel-cost minimisation for both realand reactive-power dispatches," *IEE Proc. C, Gener. Transm. Distrib.*, vol. 131, no. 3, pp. 85–93, May 1984. DOI: 10.1049/ip-c.1984.0012

[10] C.-L. Chen and S.-C. Wang, "Branch-and-bound scheduling for thermal generating units," *IEEE Trans. Energy Convers.*, vol. 8, no. 2, pp. 184–189, Jun. 1993. DOI: 10.1109/60.222703

[11] A. Gogna and A. Tayal, "Metaheuristics: Review and application," *J. Exp. Theor. Artif. Intell.*, vol. 25, no. 4, pp. 503–526, 2013. doi.org/10.1080/0952813X.2013.782347

[12] Y. V. K. Reddy, M. L. Devi, A. V. S. Reddy and P. V. Kumar, "Economic dispatch solutions with piecewise quadratic cost functions using Spotted hyena Optimizer," *2021 IEEE Madras Section Conference (MASCON), Chennai, India, 2021, pp. 1-6, doi: 10.1109/MASCON51689.2021.9563437.*

[13] Ramanaiah, M. Laxmidevi, and M. Damodar Reddy. "Optimal placement of unified power quality conditioner using ant lion optimization method." *International Journal of Applied Engineering Research* 12.13 (2017): 3708-3713.

- [14] Y. Xiang, Y. Zhou, L. Tang, and Z. Chen, "A decomposition-based manyobjective artificial bee colony algorithm," *IEEE Trans. Cybern.*, vol. 49, no. 1, pp. 287–300, Jan. 2019. doi.org/10.1016/j.asoc.2019.105879
- [15] Z.-J. Wang et al., "Dynamic group learning distributed particle swarm optimization for large-scale optimization and its application in cloud workflow scheduling," *IEEE Trans. Cybern.*, vol. 50, no. 6, pp. 2715–2729, Jun. 2020. doi:10.1109/TCyB.2019.2933499
- [16] H. Ma, M. Fei, Z. Jiang, L. Li, H. Zhou, and D. Crookes, "A multipopulation-based multiobjective evolutionary algorithm," *IEEE Trans. Cybern.*, vol. 50, no. 2, pp. 689–702, Feb. 2020. DOI:10.1007/s12293-022-00360-1
- [17] J. Wang, G. Liang, and J. Zhang, "Cooperative differential evolution framework for constrained multiobjective optimization," *IEEE Trans. Cybern.*, vol. 49, no. 6, pp. 2060–2072, Jun. 2019. doi.org/10.3390/math10050813
- [18] H. Liang, Y. Liu, F. Li, and Y. Shen, "A multiobjective hybrid bat algorithm for combined economic/emission dispatch," *Int. J. Elect. Power Energy Syst.*, vol. 101, pp. 103–115, Oct. 2018. DOI:10.3390/en14196376
- [19] Gong et al., "Genetic learning particle swarm optimization," *IEEE Trans. Cybern.*, vol. 46, no. 10, pp. 2277–2290, Oct. 2016. doi 10.1109/TCyB.2015.2475174
- [20] G. Dhiman, "Moshepo: A hybrid multi-objective approach to solve economic load dispatch and micro grid problems," *Appl. Intell.*, vol. 50, pp. 119–137, Jan. 2020. doi.org/10.1007/s10489-019-01522-4
- [21] E. E. Elattar, "Environmental economic dispatch with heat optimization in the presence of renewable energy based on modified shuffle frog leaping algorithm," *Energy*, vol. 171, pp. 256–269, Mar. 2019. DOI:10.1109/SCES50439.2020.9236742
- [22] Faridmehr, I.; Nehdi, M.L.; Davoudkhani, I.F.; Poolad, A. "Mountaineering Team-Based Optimization: A Novel Human-Based Metaheuristic Algorithm" *Mathematics* 2023, 11, 1273. https://doi.org/10.3390/math11051273.
- [23] Seyedali Mirjalili, "The Ant Lion Optimizer", *Advances in Engineering Software, Elsevier, Vol.83*, pp. 80–98, 2015. doi.org/10.1016/j.advengsoft.2015.01.010
- [24] Xin-She Yang "Flower Pollination Algorithm for Global Optimization", *Soft Computing Techniques. pp.1-13, 2014*. doi.org/10.3390/math9141661
- [25] Seyedali Mirjalili, "Grey Wolf Optimizer", *Advances in Engineering Software, Elsevier, Vol.69*, pp.46–61, March 2014. doi.10.1016/j.advengsoft.2013.12.007
- [26] Hardiansyah, Junaidi and Yohannes MS, "Solving Economic Load Dispatch Problem Using Particle Swarm Optimization Technique", *International journal of intelligent systems and applications, Vol.12*, pp.12-18, 2012. DOI:10.5815/ijisa.2012.12.02
- [27] K. Sudhakara Reddy and M. Damodar Reddy, "Economic Load Dispatch Using Firefly Algorithm", *International Journal of Engineering Research and Applications, Vol. 2, Issue4*, pp.2325-2330, July-August 2012. doi.10.22214/ijraset.2019.6297
- [28] A.Hima Bindu and M. Damodar Reddy, "Economic Load Dispatch Using Cuckoo Search Algorithm", *International Journal of Engineering Research and Applications, Vol. 3, Issue 4*, pp. 498-502, Jul-Aug 2013. doi.10.22214/ijraset.2019.6297
- [29] Tahir Nadeem Malik and Azzam ul Asar, "A New Hybrid Approach for the Solution of Nonconvex Economic Dispatch Problem with Valve-Point Effects", *Electric Power Systems Research, Vol. 80*, pp.1128–1136, 2010. DOI:10.1016/j.epsr.2010.03.004
- [30] Celal Yasar and Serdar Ozyon, "A New Hybrid Approach for Nonconvex Economic Dispatch Problem with Valve-Point Effect", *Energy (Elsevier Journal), Vol. 36*, pp.5838-5845, 2011. Doi: 10.1016/j.energy.2011.08.041
- [31] Serhat Duman and Nuran Yorukeren, "A Novel Modified Hybrid PSO/GSA based on Fuzzy Logic for Non-Convex Economic Dispatch Problem with Valve-Point Effect", *Energy Systems, Vol.64*, pp.121–135, 2015. DOI:10.1080/23311916.2015.1076983
- [32] Sumit Banerjee and Deblina Maity, "Teaching Learning Based Optimization for Economic Load Dispatch Problem Considering Valve Point Loading Effect", *Electrical Power and Energy Systems., vol.73*, pp.456–464, 2015. DOI:10.1109/ITCE.2018.8316665
- [33] Zwe-Lee Gaing, "Particle Swarm Optimization to Solving the Economic Dispatch Considering the Generator Constraints", *IEEE transactions on power systems, Vol. 18, no. 3, august 2003*. DOI:10.1109/TPWRS.2004.831709
- [34] Mostafa Modiri-Delshad and S. Hr. Aghay Kaboli, "Backtracking Search Algorithm for Solving Economic Dispatch Problems with Valve-Point

- Effects and Multiple Fuel Options”, *Energy*, Vol. 116, pp.637-649, 2016. DOI: 10.1016/j.energy.2016.09.140
- [35] Naser Ghorbani and Ebrahim Babaei, “Exchange Market Algorithm for Economic Load Dispatch”, *Electrical Power and Energy Systems (Elsevier Journal)*, Vol. 75, pp.19–27, 2016. DOI:10.1109/KBEL.2019.8734963
- [36] Jian Zhao and Shixin Liu, “Modified Cuckoo Search Algorithm to Solve Economic Power Dispatch Optimization Problems”, *IEEE/CAA journal of automatica sinica*, Vol. 5, no. 4, pp.794-807, july 2018. DOI:10.1109/JAS.2018.7511138
- [37] Rao, M. S. ., Kumar, S. P. ., & Rao, K. S. . (2023). A Review on Detection of Medical Plant Images. *International Journal on Recent and Innovation Trends in Computing and Communication*, 11(4), 54–64. <https://doi.org/10.17762/ijritcc.v11i4.6381>
- [38] Esposito, M., Kowalska, A., Hansen, A., Rodríguez, M., & Santos, M. Optimizing Resource Allocation in Engineering Management with Machine Learning. *Kuwait Journal of Machine Learning*, 1(2). Retrieved from <http://kuwaitjournals.com/index.php/kjml/article/view/115>
- [39] Anupong, W., Azhagumurugan, R., Sahay, K. B., Dhabliya, D., Kumar, R., & Vijendra Babu, D. (2022). Towards a high precision in AMI-based smart meters and new technologies in the smart grid. *Sustainable Computing: Informatics and Systems*, 35 doi:10.1016/j.suscom.2022.100690