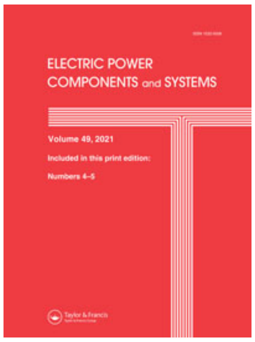

Taylor & Francis
Taylor & Francis Group

Electric Power Components and Systems

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/uemp20

Solving Economic Dispatch using Artificial Eco System-based Optimization

Kuntal Bhattacharjee, Kathan Shah & Jatin Soni

Electric Power Components and Systems, 0(0): 1–18, 2021

ISSN: 1532-5008 print / 1532-5016 online
DOI: 10.1080/15325008.2021.2013995

Solving Economic Dispatch using Artificial Eco System-based Optimization

Kuntal Bhattacharjee, Kathan Shah, and Jatin Soni
Department of Electrical Engineering, Institute of Technology, Nirma University, Ahmedabad, Gujarat, India

CONTENTS

Abstract—Economic Load Dispatch (ELD) is the most inherent necessity in power system operation to minimize the cost as well as the accomplishment of load demand abundantly. The main purpose of ELD is to satisfy load demand with the minimization of cost. Distinct techniques have been used for resolving the ELD problem. This paper introduces a robust and effective technique named Artificial Eco System Optimization (AEO) Algorithm to solve ELD. AEO is a population-based optimizer stimulated by the flow of energy into the Earth's ecosystem. This algorithm shows three distinct functions of living organisms, including production, consumption, and decomposition. By accomplishing three operator producer, consumer, and decomposer whole algorithm works and balances between the exploitation and the exploration phases of the technique. For solving the ELD problem, AEO has been implemented on multiple test systems with an account of different restrictions and AEO has given better results than different several novels, previous and hybrid optimization techniques. The outcomes confirm the robustness, expediency, effectiveness, and efficacy of AEO in terms of computational time and vicinity to the global optimum solution.

1. INTRODUCTION

Economical Load Dispatch (ELD) is a usual problem in the domain of power system optimization. The ELD serves the load demand by allotting a particular generation to each generator with an account of various physical and operational constraints. The main purpose of ELD is to minimize the generation cost of power in the plant. Despite that, it also helps to make the system more reliable by dealing with multiple constraints.

For solving ELD problem by assuming linear increasing cost function, several classical optimization methods such as quadratic programming [1], Dynamic Programming [2], Linear Programming [3], gradient method [4], Lagrangian relaxation [5], Hopfield framework [6] are used successfully. But the problem with the classical way is that it tends to converge more toward local optima and then begins to diverge from the global optimal solution. Dynamic programming has its limitation such as more

Keywords: artificial eco system, generation scheduling, prohibited operating zone, valve point loading, economic load dispatch, electrical power system optimization

Received 7 January 2021; accepted 31 October 2021

Address correspondence to Kuntal Bhattacharjee, Department of Electrical Engineering, Institute of Technology, Nirma University, Ahmedabad, Gujarat 382481, India. E-mail: kuntal.bhattacharjee@nirmauni.ac.in

programming efforts needed because of large dimensions requirements. As the ELD problem comes with inclusion various constraints and restriction (non-linear equations) such as non-smooth cost function, ramp rate limit, and discontinues prohibited operating zone classical methods fails to achieve the global optimum solution. Also due to non-linear characteristics of the ELD classical method trapped in local minima and fails to achieve the global solution. So, it becomes a necessity to come out from the disadvantages of classical methods and develop an optimization method that can move directly toward a globally optimal solution without trapping into local minima. With the rise of computational intelligence and efficient computers many heuristics and meta-heuristics optimization techniques are discovered such as improvise version of very well-known Genetic Algorithm [7], group search based optimization technique such as Search Group Optimization (SGO) [8], Back Tracking Search Algorithm [9,10], Hybrid Version Particle Swarm Optimization With Mutation [11], Bacterial Forge Optimization [12],Combination of three techniques including Particle swarm, Gravitational search with fuzzy logic [13], modified version of linear programming such as mixed-integer linear programming [14], optimization techniques based on mathematical functions like Sine Cosine Algorithm [15], Differential evaluation with multi population [16], organism based algorithm like A Modified Symbiotic Organisms Search [17], chemical reaction based technique such as Real Coded Chemical Reaction Optimization with Oppositional approach [18], Optimization method based on bird behavior Cuckoo Search Algorithm [19], Swarm Base Optimization [20], Crisscross Search Method [21], Jaya Algorithm with self-adaptive approach [22], Water Inspired Algorithm [23], Two-phase mixed integer programming [24], nature inspired Tree Root Based Optimization [25], market based optimization link Exchange Market Algorithm [26], Teaching And Learning Inspired Method [27], probability based approach using Artificial Bee Colony [28], Differential Evolutionary Algorithm with multiple mutation [29], Gray Wolf Optimization (GWO) [30], Evolutionary Approach For Particle Swarm Optimization (EPSO) [31], Evolutionary Programming (EP) [32], Evolutionary Approach With Density Enhancement [33], another variety of PSO Phasor Particle Swarm Optimization (PPSO) [34], Gravitational Search Optimization [35], optimization method based on Lightning Flash [36], Multiple strategies based Orthogonal Design Particle Swarm Optimizer [37], chaotic approach toward BAT algorithm [38], Molecule Based Optimization [39], Immune Algorithm [40], Oppositional Approach For Weed Optimization [41], Turbulence Based Water Optimization [42], Ameliorated Gray Wolf Optimization [43], Teaching And Learning Exercise Based Technique [44], Chemical Reaction Based Technique [45], Group Leader Optimization [46], Salp Swarm Optimization [47] All above set of techniques are inclusion of novel, previous, hybrid, evolutionary, multi population, multi mutation and many more. Use of optimization methods other than electrical engineering is also noticeable like the use of learning machine technique predict moment rotation for the precast beam to column connection [48], Metaheuristic Optimization Algorithms for optimal active control of structures and its comparative analysis [49], UML diagrams for dynamical monitoring of rail vehicles [50], Moment-rotation estimation of steel rack connection using extreme learning machine [51].

All mentioned techniques have all their conveniences and prejudice, but some of them have a problem with local minima it can easily divert toward local minima. Some hybrid and modified techniques are complicated to understand also. So, it becomes essential to use a novel powerful method for solving Economical Load Dispatch. In this paper novel Artificial Eco System [34] technique is used for solving Economical Load Dispatch. AEO is mainly motivated by energy flow in Earth's Eco System. AEO mimics the production, consumption, and decomposition behaviors of living organisms. Another important thing about AEO is a parameter-free algorithm. In this paper, AEO is used to solve the ELD problem on various complex test systems.

Section 2 of the paper presents a concise description and mathematical formulation of various types of ELD problems. Section 3 explains the proposed AEO algorithm. Simulation studies are shown and discussed in Section 4. The conclusion is drawn in Section 5.

2. PROBLEM FORMULATION

The ELD problem can be explained as a convex and non-convex problem with the inclusion of linear and nonlinear constraints. The objective function for the ELD problem in the quadratic cost function

$$C_F = \min\left(\sum_{i=1}^{n} X_i + Y_i P_i + Z_i P_i^2\right) \tag{1}$$

For the application of realistic and practical ELD problems, the smooth quadratic price function has been

Case	1	2	3	4	5	6
No. of generator units	10	13	15	38	40	110
Input data	[7]	[13]	[9]	[29]	[32]	[41]
Total demand (MW)	2700	2520	2630	6000	10500	15000
Valve point loading	Yes	No	No	No	Yes	No
Ramp rate	No	No	Yes	No	No	No
Prohibited operating zone	No	No	Yes	No	No	No
Transmission loss	No	Yes	Yes	No	No	No
Multi fuel option	Yes	No	No	No	No	No

TABLE 1. Details of test systems.

Unit	Fuel type	Generator output		
		AEO	SGO [8]	BSA [9]
1	2	218.087158	217.0407	218.5777
2	1	211.901553	211.8944	211.2153
3	1	283.683701	281.6792	279.5619
4	3	239.686989	238.2056	239.5024
5	1	277.098481	279.8321	279.9724
6	3	240.198181	239.2547	241.1174
7	1	286.783891	290.2798	289.7965
8	3	240.089756	240.2228	240.5785
9	3	426.529535	425.5958	426.8873
10	1	275.940755	275.9942	272.7907
Fuel Cost($/hr.)		**623.885662**	623.9170	623.9016

TABLE 2. Power output of 10 generator units for test case 1. (Power demand: 2700 MW).

modified by adding input-output curves of sine terms with a valve point effect. The ELD cost function based on the valve-point effect is given below:

$$C_F = \min\left(\sum_{i=1}^{n} \begin{array}{c} X_i + Y_iP_i + Z_iP_i^2 + \\ \left|k_i*\sin\{C_i*(P_i^{min} - P_i)\}\right| \end{array}\right) \quad (2)$$

P_i is power generation of unit i, X_i, Y_i, Z_i, C_i, k_i are fuel cost constants of i^{th} generator and n is the number of generators of a power plant. For each generator unit, the maximum and minimum limit is specified that limit should not be disrupted to avoid instability of the entire system.

$$P_i^{maximum} \leq P_i \leq P_i^{minimum} \quad (3)$$

With consideration of equality constraint equation (4) and (5) is below,

$$\sum_{i=1}^{n} P_i = P_d \quad (4)$$

$$\sum_{i=1}^{n} P_i - P_d - P_{loss} = 0 \quad (5)$$

In Eq. (4), the transmission losses have been ignored and Eq. (5) is with the consideration of transmission loss. P_d is the total power demand and P_{loss} is the total transmission loss, which can be calculated using the coefficient of B-matrix.

$$P_L = \sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{n} P_iB_{ij}P_j + \sum\nolimits_{i=1}^{n} B_{0i}P_i + B_{00} \quad (6)$$

By considering another constraint named ramp rate limit. Ramp rate limit constraint is essential to enhance the life of the generator. A sudden change of generation at some instance may lead to huge load to generator and it is harmful to the generator. So, Power generation change should be restricted and it should be within the specified upper and lower values. For this upper ramp rate limit (U_{RLi}) and lower ramp rate limit (L_{RLi}) are shown below:

$$P_i - P_{i0} \leq U_{RLi} \text{ (as generation rises)} \quad (7)$$

$$P_{i0} - P_i \leq L_{RLi} \text{ (as generation falls)} \quad (8)$$

$$max(P_i^{min},\ P_{i0} - L_{RLi}) \leq \min(P_i^{max}, P_{i0} + U_{RLi}) \quad (9)$$

P_{i0} is the power generation of i^{th} previous interval U_{RLi} and L_{RLi} are upper ramp limit lower ramp limit respectively.

Prohibited operating zone (POZ) is the range of generator output power where the operation creates turbine shaft vibrations occurs. Normally, such vibrations occur at the point of opening or closing of the steam valve, which can damage the shaft and bearings. It is challenging to determine POZ with actual operational records. Operations in such regions are normally evaded.

$$\left.\begin{array}{l} P_i^{min} \leq P_i \leq P_{i,1}^{l} \\ P_{i,k-1}^{u} \leq P_i \leq P_{i,k}^{l} \\ P_{i,n}^{u} \leq P_i \leq P_i^{max} \end{array}\right\} \quad (10)$$

k represents the number of operating zones of i^{th} unit, $P_{i,k}^{l}$

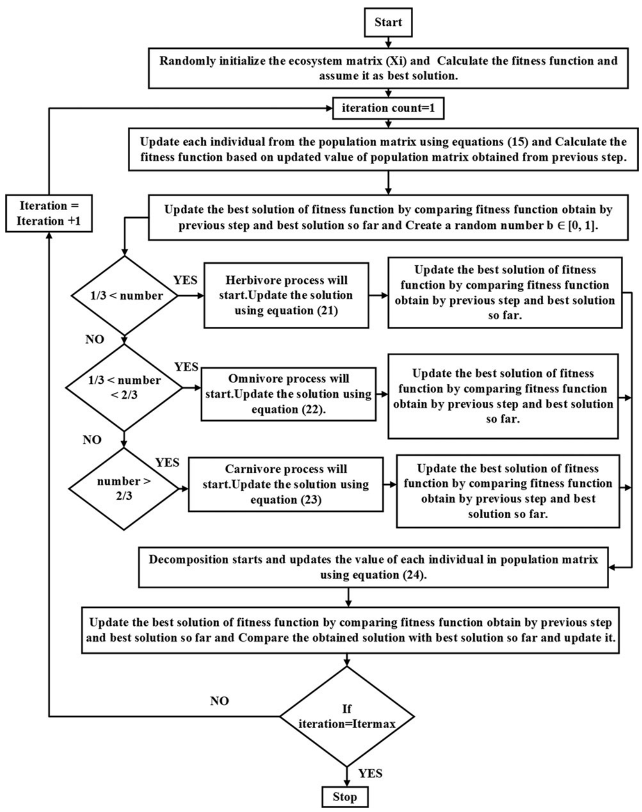

FIGURE 1. Flowchart for AEO.

and $P^{u}_{i,k-1}$ is lower and upper limit respectively is the total number of operating zones for k^{th} unit.

The systems with n number of generators have P_f fuel options for every unit. So, the cost function can be redesigned as

$$F_{ip}(E_i) = X_{ip} + Y_{ip} + Z_{ip}P_i^2 + \Big|e_{ip} \times \sin\left\{f_{ip} \times \left(P_{ip}^{min} - P_i\right)\right\}\Big|; \quad p = 1, 2, 3......, \; \text{Nf} \tag{11}$$

The calculation for slack generation is also an important aspect of the ELD problem. If n is the number of units then calculate generation output subject to balance and capacity constraints for n–1 generator units. So, the Power level of the slack generator(n) is given by:

$$E_d - \sum_{i=1}^{n} E_i = E_n \tag{12}$$

$$E_d + E_{loss} - \sum_{i=1}^{n} E_i = E_n \tag{13}$$

E_{loss} is subject to (6). Modified (13) as below,

$$B_{NN}P_N^2 + E_n\left(2\sum\nolimits_{i=1}^{n-1} B_{ni}E_i + \sum\nolimits_{i=1}^{n-1} B_{0n} - 1\right) + \Big(E_d + \sum\nolimits_{i=1}^{n-1}\sum\nolimits_{j=1}^{n-1} E_iB_{ij}E_j + \sum\nolimits_{i=1}^{n-1} B_{0i}E_i - \sum\nolimits_{i=1}^{n-1} E_i + B_{00}\Big) = 0 \tag{14}$$

3. ARTIFICIAL ECO-SYSTEM BASED OPTIMIZATION (AEO)

AEO [52] is population-based, inspired by flow energy in ecosystem techniques. Overall AEO works based on three operators Production, Consumption, Decomposition. Each operator has its role in the algorithm. Production will balance exploration and exploitation. Consumption will enhance exploration. Decomposition will improve exploitation. Eco System population has three kinds of organism producer, consumer, decomposer. Producers and decomposers are only one in the population. Other individuals are consumers, consumers are divided into three types carnivore, herbivore, omnivore. The energy level of each population is evaluated by fitness function or objective function value. Detailed explanation with pseudo-code of AEO is mentioned in [52]. In this study, the authors described the algorithm with the flowchart in Figure 1.

Mainly AEO can be divided into three processes.

3.1. Production

The producer is individual in Eco system it will generate food energy with carbon dioxide, water, and sunlight as well as nutrition provided by decomposers. Process of production assists AEO to produce individual solutions drifting from randomly generated position to best position with the increase in iteration. This process will also guide the consumption process further. This behavior contributes greatly to the balance between the explorative and exploitative search. The mathematical model for production,

$$X_1(t+1) = (1-a)X_n(t) + aX_{rand} \tag{15}$$

$$a = \left(1 - \frac{t}{T}\right)r_1 \tag{16}$$

$$X_{rand} = r(U-L) + L \tag{17}$$

Where n is the size of the population. T is the maximum iterations, U and L is the upper and lower bound limit. In Eq. (15) a is the weight coefficient. r_1 is a random number

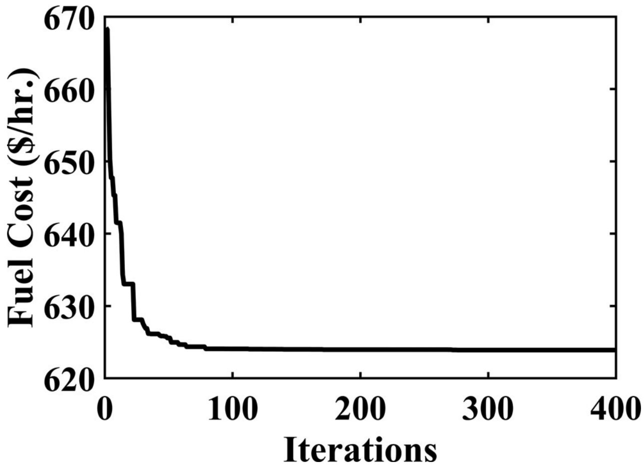

FIGURE 2. Convergence characteristics for test case 1.

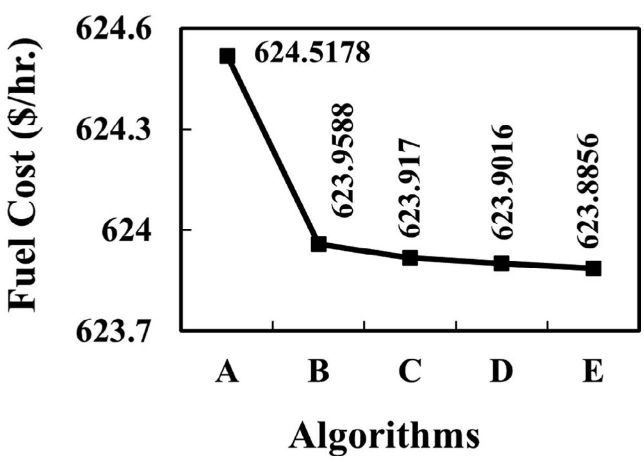

FIGURE 3. Comparison of minimum fuel cost with different algorithms (A-IGA-MU [12], B- CBPSO-RVM [11], C- SGO [8]. D- BSA [9], E- AEO).

between 0 to 1. r is the random vector between 0 to 1. X_{rand} is the position of the individual which is produced randomly in search space. $X_1(t+1)$ is the previous equation.

3.2. Consumption

After the producer accomplishes production operator all the consumers will act on the consumption factor. Each consumer may eat producer or consumer with lower energy even it can eat both. Herbivore can eat producer only. Similar way Carnivore can eat only consumers with higher energy levels and omnivore can eat producers and consumers both. The consumption process allows AEO to update the solution of an individual concerning the solution provided by the producer or the solution of the randomly chosen individual with a higher energy level, or both. The

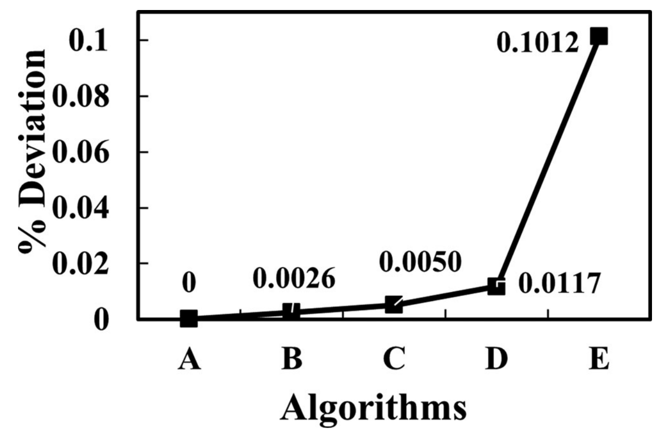

FIGURE 4. Change in Percentage deviation concerning other optimization techniques (A-AEO, B- BSA [9], C- SGO [8], D- CBPSO RVM [11], E- IGA MU [12]).

random number b ∈ [0, 1] is going to be created. If b is lesser than 1/3 then the performance of Herbivore can be done. If the value of b lies within 1/3 to 2/3 performance of consumption can be occur using the Omnivore procedure. If the value of b is exceeding 2/3 then the Carnivore process can be performed. This process will enhance the exploration process. Consumption factor,

$$C = \frac{1}{2} V_1 / |V_2| \tag{18}$$

$$V_1 \sim N(0,\ 1) \tag{19}$$

$$V_2 \sim N(0,\ 1) \tag{20}$$

N (0, 1) is a normal distribution with mean = 0 and the standard deviation = 1. Herbivore: If the consumer is randomly chosen herbivore, Herbivore eats only producer. The mathematical model is shown below:

$$X_i(t+1) = X_i(t) + C*\left(X_i(t) - X_j(t)\right), \quad i \in [2, \ldots\ldots\ldots, n] \tag{21}$$

Carnivore: If the consumer is randomly chosen a carnivore, Carnivore can eat only consumers with higher energy levels. Equation modeling is as below,

$$X_i(t+1) = X_i(t) + C*\left(X_i(t) - X_j(t)\right), \quad i \in [2, \ldots, n];\ j = randi([2\ \ i-1]) \tag{22}$$

Omnivore: If a consumer is randomly chosen omnivore, it can eat both a consumer with a higher energy level randomly and producer.

$$X_i(t+1) = X_i(t) + C*(r_2*(X_i(t) - X_1(t)) + (1-r_2)\left(X_i(t) - X_j(t)\right); \quad i = 3, \ldots n;\ j = randi[2\ \ i-1] \tag{23}$$

Method	Minimum fuel cost ($/hr.)	Maximum fuel cost ($/hr.)	Average fuel cost ($/hr.)	Simulation time	Number of hits to best solution	Standard deviation
AEO	**623.8856**	**623.8856**	**623.8856**	**0.40**	**50**	**0**
SGO [8]	623.9170	625.5478	623.9170	0.51	49	NA
BSA [9]	623.9016	624.0838	623.9757	NA	NA	NA
CBPSO-RVM [11]	623.9588	624.2930	624.0816	NA	NA	NA
IGA-MU [12]	624.5178	630.8705	625.8692	NA	NA	NA

TABLE 3. Comparison of the result obtained by AEO and other techniques for test case 1.

Unit	Generator output		
	AEO	SCA [15]	F-MLP [14]
1	628.318405	628.3179	628.318530
2	299.198640	299.1992	299.199300
3	297.447763	297.4468	299.199300
4	159.732882	159.7327	159.733100
5	159.732945	159.7327	159.733100
6	159.732810	159.7328	159.733100
7	159.733154	159.7331	159.733100
8	159.732762	159.7325	159.733100
9	159.732888	159.7328	159.733100
10	77.397909	77.3995	77.399912
11	114.799627	114.7993	113.49589
12	92.399962	92.3997	92.399912
13	92.399872	92.4000	92.399912
Total Power Generate (MW)	2559.8000	2559.8000	2560.811356
Total Loss (MW)	**39.8000**	39.8000	40.811358
Fuel Cost($/hr.)	**24512.6073**	24512.6085	24,515.2258

TABLE 4. The power output of 13 generator units for test case 1. (Power demand: 2520 MW).

3.3. Decomposition

Decomposition is a very vital process in terms of the functioning of an ecosystem, and it provides the required nutrients for the growth of the producer. D is the decomposition factor where e and h are weight co-efficient.

$$X_i(t+1) = X_n(t) + D*(e*X_n(t) - h*X_1(t)), \quad i = 1, \ldots\ldots\ldots, n \tag{24}$$

$$D = 3u, \ u \sim N(0,1) \tag{25}$$

$$e = r_3 * \text{randi}\ ([1\ \ 2]) - 1 \tag{26}$$

$$h = 2 * r_3 - 1 \tag{27}$$

3.4. Solution of ELD using AEO Algorithm

3.4.1. Representation of Population Matrix (X). Since the individual population set for the AEO is considered as the real power output of the generators for the ELD problem. For the initializations, choose the number of generator units n and the total number of population matrix, PopSize. The complete population matrix is represented in the form of the following matrix. Population ecosystem is shown in matrix form as below:

$$X_i = [X_1,\ X_2, \ldots, X_{PopSize}]$$

For the ELD problem above matrix will be as below:

$$X = [P_{i1},\ P_{i2} \ldots, P_{in}];\ \text{n} = \text{ number of generators}$$

3.4.2. Initialization of the Population Matrix. Each element of the population matrix is initialized randomly within the effective real power operating limits. The initialization is based on (3) for generators without ramp rate limits, based on (3), (9) for generators with ramp rate limits, and based on (3), (9), (10) for generators with ramp rate limits and prohibited operating zone.

3.4.3. Evaluation of Objective Function. In the case of the ELD problems, the objective function of each population matrix is represented by the minimization of total fuel cost with the inclusion of all generators. of that given population set matrix. Total fuel cost is calculated using (1) for the system having quadratic fuel cost characteristic; using (2) for the system having a valve-point effect; and using (11) for the system having multi-fuel type fuel cost characteristic. The steps of the algorithm to solve the ELD problems are given as follows:

Step 1: For initialization, choose the number of generator units, n; the number of populations set, PopSize; Specify the maximum and minimum capacity of each generator, power demand, and B coefficients matrix for calculation of transmission loss. Set the maximum number of iterations, Itermax.

Step 2: Finalize each element of the given population matrix (X) should satisfy the equality constraint of (5) according to concept slack generator (12), (13).

Method	Minimum fuel cost	Maximum fuel cost	Average fuel cost	Simulation time (s)	Number of hits to best solution	Standard deviation
AEO	**24512.6073**	**24512.6073**	**24512.6073**	**0.035**	**50**	**0**
F-MLP [14]	24,515.2258	NA	NA	4.24	NA	NA
SCA [15]	24512.6085	24512.6085	24512.6085	0.041	50	NA
MPDE [16]	24514.8756	24514.8756	24514.8756	5	NA	NA
MSOS [17]	24,515.2258	24,515.2258	24,515.2258	2.6535	NA	NA
ORCCRO [18]	24513.91	24513.91	24513.91	0.04	50	NA
MCSA [19]	24514.8756	24514.8756	24514.8756	12.80	NA	NA

TABLE 5. Comparison of a result obtained by AEO and other techniques for test case 2.

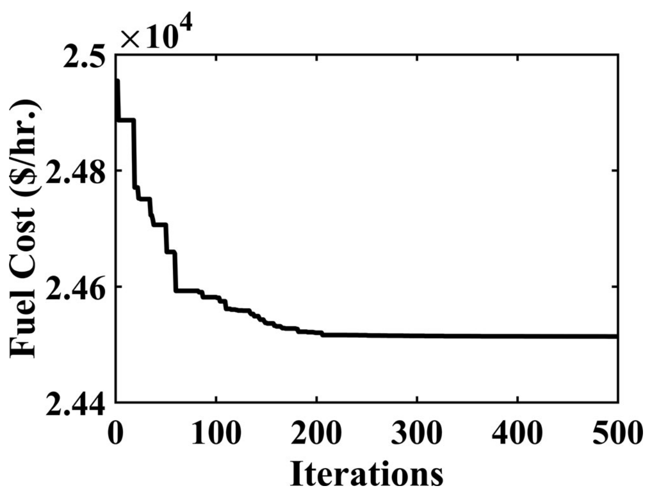

FIGURE 5. Convergence characteristics for test case 2.

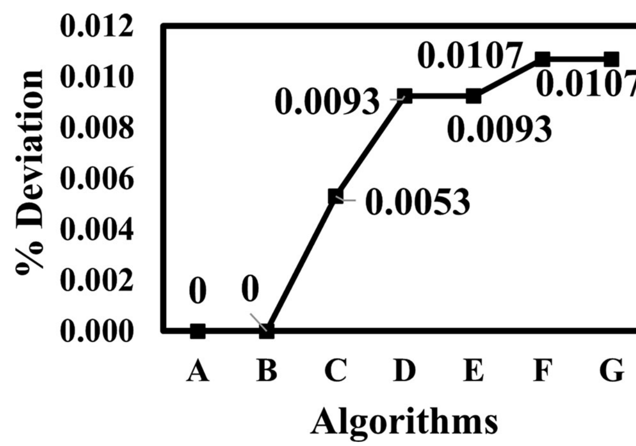

FIGURE 7. Change in Percentage deviation concerning other optimization techniques (A-AEO, B- SCA [15], C- ORCCRO [18], D- MPDE [16], E- MCSA [19], F- FMLP [14], G- MSOS [17]).

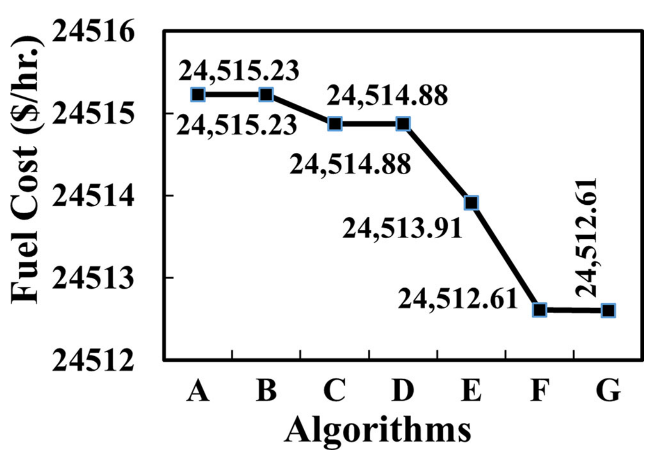

FIGURE 6. Comparison of minimum fuel cost with different algorithms (A-F-MLP [14], B-MSOS [17]. C- MPDE [16], D- MCSA [19], E- ORCCRO [18]. F- SCA [15]. G- AEO).

Step 3: Calculate the objective function value for each population matrix. Initially, it is considered as the best solution based on objective function obtain from each initialized population matrix.

Step 4: Based on the objective function values identify the elite population set. Here, the elite term is used to indicate the population of generator power outputs, which give the best fuel cost.

Step 5: Performance of Production: Update each individual from the population matrix using Eq. (15) of production. Calculate the objective function value after performing production

Step 6: Update population matrix by comparing objective function obtained from production best solution obtain so far.

Step 7: Performance of consumption: Create a random number b ∈ [0, 1]. If b is lesser than 1/3 then the performance of Herbivore can be done using Eq. (21). If the value of b lies within 1/3 to 2/3 performance of consumption can be occur using the Omnivore procedure according to Eq. (22). If the value of b is exceeded 2/3

Unit	Power output AEO	ESSA [20]	Jaya SML[22]
1	455.0000	454.9995	454.9999
2	380.0000	379.9996	380.0000
3	130.0000	130.0000	130.0000
4	130.0000	130.0000	130.0000
5	170.0000	170.0000	170.0000
6	460.0000	460.0000	460.0000
7	430.0000	430.0000	430.0000
8	71.429134	70.1478	71.4456
9	58.596355	60.2593	59.3587
10	160.000000	159.9599	160.0000
11	80.000000	79.9996	79.9997
12	80.000000	79.9999	80.0000
13	25.000000	25.0007	25.0000
14	15.000000	15.0000	15.0000
15	15.000000	15.0009	15.0000
Total power generated (MW)	2660	2660	2660.8039
Total loss (MW)	**30.000**	30.3679	30.8039
Fuel cost ($/hr.)	**32697.2819**	32701.21	32706.3587

TABLE 6. Schedule of generation for test case 3 with 15 generators and power demand 2630 MW.

then the Carnivore process can be performed using Eq. (23). Calculate the fitness of each individual after performing the consumption process

Step 8: Update the best solution by comparing the objective function which is obtained from the consumption process and step 3.

Step 9: Decomposition performance: Decomposition starts and updates the value of each individual in the population matrix using Eq. (24). Calculate the objective function of the individual after performing the decomposition process.

Step 10: Compare the objective function obtained from step 9 with the best solution so far.

Step 11: Go to step 5 for the next iteration. Terminate the process after a predefined number of iterations, $Iter_{max}$.

4. SIMULATION AND RESULTS

Since the proposed algorithm is based on an artificial ecosystem it is essential to check relative effectiveness with the application. To prove the effectiveness of the AEO, six sets of experiments were conducted and the final results were compared both in form of a Table 1 and graphically to the various existing methods.

Details of all Test Cases:

- For Test Case-1, a total of 10 generating units, 2700 MW demand have been taken with consideration of Valve point Loading and Multi-fuel option.
- For Test Case-2 total of 13 generating units, 2520 MW demand have been taken with consideration of Transmission loss.
- For Test Case-3 total of 15 generating units, 2630 MW demand has been taken with consideration of Ramp rate limit, Prohibited operating zone, and Transmission loss.
- For Test Case-4 total of 38 generating units, 6000 MW demand has been taken without any constraints.

Method	Minimum fuel cost	Maximum fuel cost	Average fuel cost	Simulation time (s)	Number of hits to the best solution (50 trials)	Standard deviation
AEO	**32697.2819**	**32697.9898**	**32697.3102**	**0.62**	**48**	**0.13592**
SGO [8]	32697.2819	32698.1574	32697.3344	0.75	47	NA
BSA [9]	32704.4504	32704.5816	32704.4721	NA	NA	NA
ESSA [20]	32701.21	32701.22	32701.22	NA	NA	NA
SSA [20]	32702.43	32911.32	32785.45	NA	NA	NA
C-MIMO-CSOO [21]	32701.21	32701.22	32701.2102	NA	NA	NA
Jaya SML [22]	32706.3578	32707.2925	32706.6774	5.14	NA	NA
WCA [23]	32704.44	32704.51	32704.50	NA	NA	NA
TPMIP [24]	33013.98	NA	NA	NA	NA	NA
RTO [25]	32701.81	32715.18	32704.53	NA	NA	NA
EMA [26]	32704.45	32704.45	32704.45	NA	NA	NA
TLBO [27]	32770.72	33073.88	32819.74	NA	NA	NA

TABLE 7. Comparison of a result obtained by AEO and other techniques for test case 3.

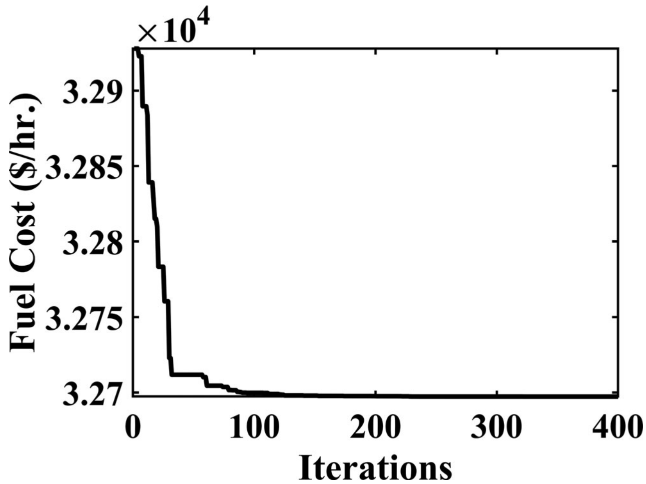

FIGURE 8. Convergence characteristics for test case 3.

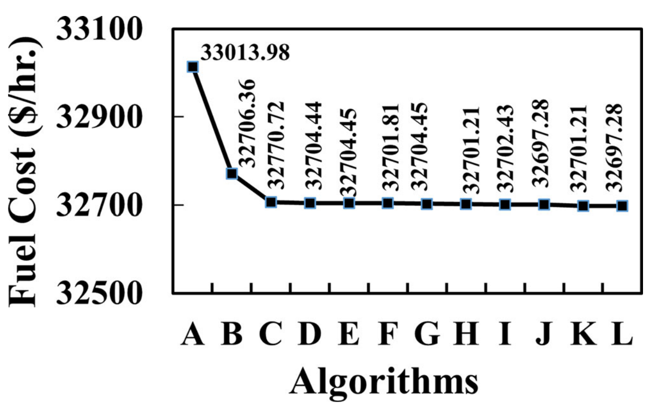

FIGURE 9. Comparison of minimum fuel cost with different algorithms (A-TPMIP [24], B-TLBO [27], C- Jaya SML [22], D- BSA [9], E- EMA [26], F- WCA [23], G-SSA [20], H- RTO [25], I- ESSA [20], J- CMIMO CSOO [21], I- SGO [8], J- AEO).

- For Test Case-5, a total of 40 generating units, 10500 MW demand has been taken with consideration of Valve point Loading.
- For Test Case-6 total of 110 generating units, 15000 MW demand have been taken without any constraints.

The AEO algorithm was applied to ELD problems of power systems with six different test systems with varying levels of complexity to verify its efficacy and feasibility. The program was compiled in MATLAB-2017B and performed on a 1.7 GHz Intel Core i3 computer with 4 GB RAM.

4.1. Test Case-1

In this case, 10 generator units are taken with a power demand of 2700 MW. Here, Multifuel options have been

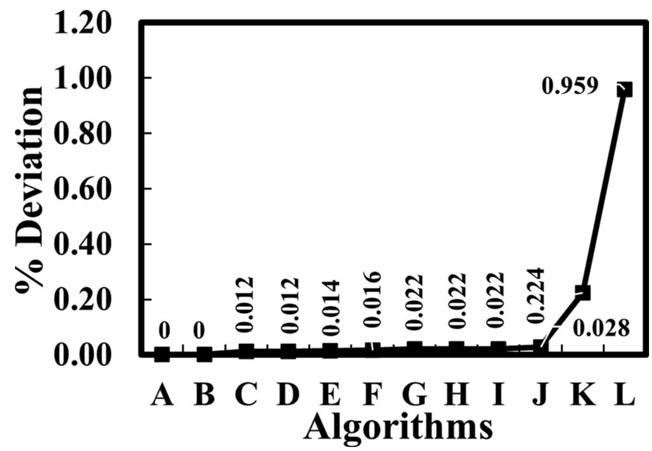

FIGURE 10. Change in Percentage deviation concerning other optimization techniques (A-AEO, B- SGO [8], C- ESSA [20], D- C MIMO CSOO [21], E- RTO [25], F-SSA [20], G- WCA [23], H- EMA [26], I- BSA [9], J-Jaya SML [22], K- TLBO [27], L-TPMIP [24]).

considered along with the valve point loading effect. Transmission losses are neglected. Required input data are taken from [7]. Obtained minimum fuel cost is 623.88566 $/hr which is superior to other existing techniques like BSA [9], SGO [8], CBPSO-RVM [11], IGA_MU [12]. Obtained results are much better than existing techniques as shown in Table 3. The output of each generator is shown in Table 2. Convergence characteristics are shown in Figure 2. Figure 3 shows the Comparison of minimum fuel cost with different algorithms. Figure 4 represents the change in Percentage deviation concerning other optimization techniques. Calculation of change in percentage deviation is given as:

$$\begin{aligned}&\text{Change in \% deviation} =\\&\text{Min.fuel cost obtained from respective algorithm} - \text{Min.}\\&\text{fuel cost obtained from AEO}) * 100/\text{Min.fuel}\\&\text{cost obtained by AEO}\end{aligned} \quad (28)$$

For Example, the change in percentage deviation for BSA with AEO according to (28) is (Table 3)

$$\begin{aligned}&= \{(623.9016 - 623.8856)/623.8856\} * 100\\&= 0.002564507\end{aligned}$$

4.2. Test Case-2

In this case total, 13 generator units are taken with multiple constraints. Power demand is 2520 MW. Transmission losses are considered here. Required input data are taken from [13]. Obtained minimum cost and simulation time are 24512.6073 $/hr. and 0.035 seconds respectively. Obtained results are superior to other existing techniques. The number hits to best

Unit	Power output AEO	Power output ADE-MMS [29]	Unit	Power output AEO	Power output ADE-MMS[29]
1	425.24	426.607294	21	272.0000	272
2	425.2447	426.607294	22	260.0000	260
3	409.9	429.667976	23	134.8666	130.647753
4	412.0	429.658589	24	10.0000	10
5	412.0	429.66264	25	117.1228	113.30554
6	412.0	429.66229	26	90.4443	88.066386
7	412.0	429.664774	27	39.0006	37.504753
8	412.0	429.662296	28	20.0000	20
9	133.01	114.000001	29	20.0000	20
10	133.01	114	30	20.0000	20
11	144.0	119.767436	31	20.0000	20
12	153.53	127.070702	32	20.0000	20
13	110.0000	110	33	25.0000	25
14	96.0000	90	34	18.0000	18
15	82.0000	82	35	8.0000	8
16	120.0000	120	36	25.0000	25
17	161.4117	159.598618	37	22.2781	21.784749
18	65.0000	65	38	22.9413	21.063428
19	65.0000	65	Total Power Generated (MW)	6000	6000
20	272.0000	272	Fuel Cost ($/hr.)	**9416559.0869**	9417235.786502

TABLE 8. Schedule of generation for test case 4 with 38 generators and power demand 6000 MW.

Method	Minimum fuel cost($/hr.)	Maximum fuel cost($/hr.)	Average fuel cost($/hr.)	Simulation time	Number of hits to best solution (50 trials)	Standard deviation
AEO	**9416559.0869**	**9416662.3878**	**9416561.148**	**7.20**	**49**	**20.11**
ADE-MMS [29]	9417235.7865	NA	NA	NA	NA	NA
GWO [30]	9419270.188	9421100	9419978.978	9.457	NA	NA
EPSO [31]	9431139.15	9 470 838.18	9 448 492.98	NA	NA	NA

TABLE 9. Comparison of result obtained by AEO and other techniques for test case 4.

solution are 50 out of 50 trials. The output of each generator unit is shown in Table 4. A comparison of Obtained result is shown in Table 5. Convergence characteristics are shown in Figure 5. Figure 6 shows the Comparison of minimum fuel cost with different algorithms. Figure 7 represents the change in Percentage deviation concerning other optimization techniques.

4.3. Test Case-3

In this case total, 15 generator units are taken with multiple constraints. The prohibited operating zone, ramp rate limit is considered here along with transmission losses. Power demand is 2630 MW. Required input data is taken from [9]. Obtained minimum cost and simulation time are 32697.2819 $/hr. and 0.62 seconds respectively. Obtained results are superior to other existing techniques like ESSA [20], Jaya SML [22], etc. The number hits to best solution are 48 out of 50 trials. The output of each generator unit is shown in Table 6. A comparison of obtained results is shown in Table 7. Convergence characteristics are shown in Figure 8. Figure 9 shows the Comparison of minimum fuel cost with different algorithms. Figure 10 represents the change in Percentage deviation concerning other optimization techniques (Tables 8–11).

4.4. Test Case-4

This includes 38-units of generators with a power demand of 6000 MW with no transmission loss. System Data is

Unit	Power output AEO	Power output PPSO [34]	Unit	Power output AEO	Power output PPSO [34]
1	110.7998	110.7998	22	523.2793	523.2794
2	110.7998	110.7998	23	523.2793	523.2794
3	97.3999	97.3999	24	523.2793	523.2794
4	179.7331	179.7331	25	523.2793	523.2794
5	87.7999	87.7999	26	523.2793	523.2794
6	140.0000	140.0000	27	10.0000	10.0000
7	259.5996	259.5997	28	10.0000	10.0000
8	284.5996	284.5997	29	10.0000	10.0000
9	284.5996	284.5997	30	87.7999	87.7999
10	130.0000	130.0000	31	190.0000	190.0000
11	94.0000	94.0000	32	190.0000	190.0000
12	94.0000	94.0000	33	190.0000	190.0000
13	214.7597	214.7598	34	164.7998	164.7998
14	394.2793	394.2794	35	200.0000	194.3973
15	394.2793	394.2794	36	194.3977	200.0000
16	394.2793	394.2794	37	110.0000	110.000000
17	489.2793	489.2794	38	110.0000	110.000000
18	489.2793	489.2794	39	110.0000	110.000000
19	511.2793	511.2794	40	511.2793	511.2794
20	511.279370	511.2794	Total power generated (MW)	40500	400500
21	523.279370	523.2794	Fuel cost ($/hr.)	**121412.5355**	121,412.5421

TABLE 10. Schedule of generation for test case 5 with 40 generators and power demand 6000 MW.

Method	Minimum fuel cost($/hr.)	Maximum fuel cost($/hr.)	Average fuel cost($/hr.)	Simulation time (sec.)	Number of hits to best solution (50 trials)	Standard deviation
AEO	**121412.5355**	**121413.5000**	**121412.574**	**6.2**	**48**	**0.2971**
DMOA [33]	121412.5443	NA	121420.8076	66.42	NA	NA
PPSO [34]	121412.5421	121413.9525	121412.5890	NA	NA	NA
MPDE [35]	121412.5355	121414.6185	121412.6188	NA	NA	NA
PARPSO [36]	122256.3000	NA	122634.0000	NA	NA	NA
IODPSO-G [37]	121414.93	121426.42	121416.54	17.75	NA	NA
IODPSO-L [37]	121420.98	121431.62	121424.62	18.69	NA	NA
CBA [38]	121412.5468	121436.1500	121418.9826	NA	NA	NA
CSA [39]	121425.6100	NA	NA	NA	NA	NA
IA_EDP [40]	121436.9729	121648.4401	121492.7018	NA	NA	NA

TABLE 11. Comparison of result obtained by AEO and other techniques for test case 5.

taken from [29]. Obtained minimum cost is 9416559.0869 $/hr and the number of hits best solution is 49 out of 50 trails. The obtained result is superior to existing techniques in terms of fuel cost, simulation time, and no hits to the best solution. Convergence characteristics are shown in Figure 11. Figure 12 shows the Comparison of minimum fuel cost with different algorithms. Figure 13 represents the change in Percentage deviation concerning other optimization techniques.

4.5 Test Case-5

This includes 40-units of generators with a power demand of 10500 MW. The valve point loading effect is considered here. Transmission losses are ignored. So, the problem becomes a non-convex optimization problem. Input data is taken from [32]. Obtained minimum cost is 12412.5355 $/hr and the number of hits best solution is 48 out of 50 trails. The obtained result is superior to existing techniques in terms of fuel cost, simulation time, and no hits to the best solution. Convergence

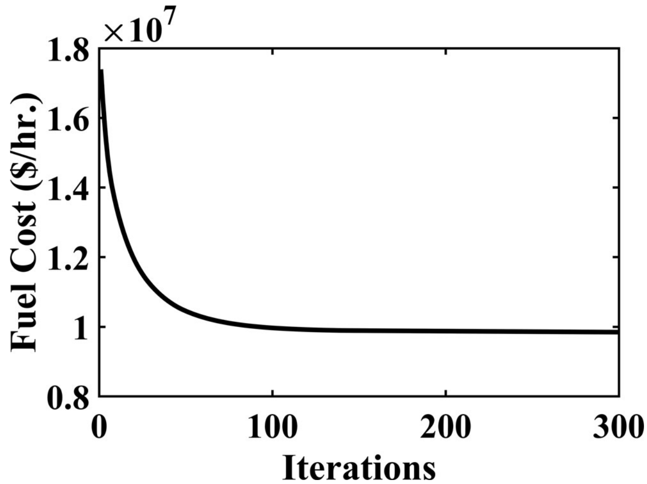

FIGURE 11. Convergence characteristics for test case 4.

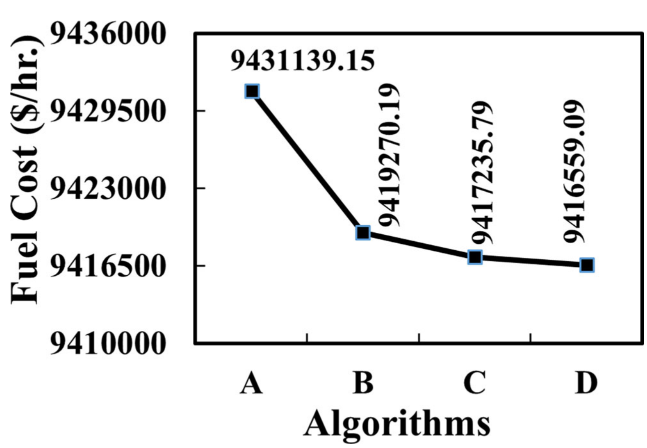

FIGURE 12. Comparison of minimum fuel cost with different algorithms (A-EPSO [31], B- GWO [30], C- ADE MMS [29], D- AEO).

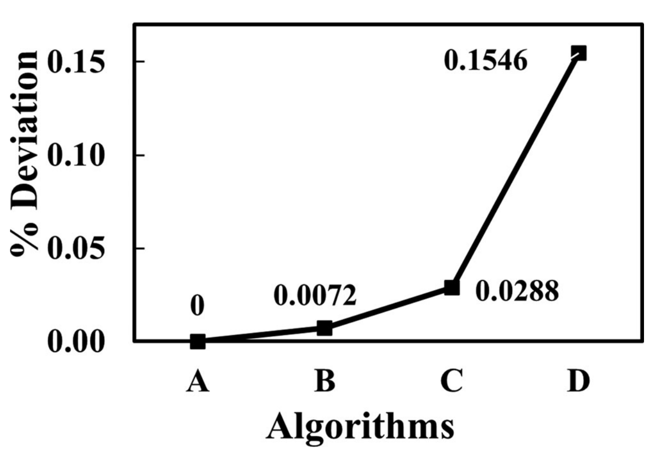

FIGURE 13. Change in Percentage deviation concerning other optimization techniques (A-AEO, B- ADE MMS [29], C- GWO [30], D- EPSO [31]).

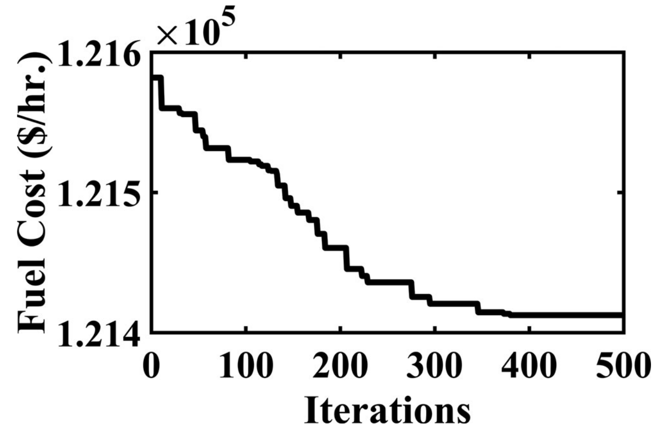

FIGURE 14. Convergence characteristics for test case 5.

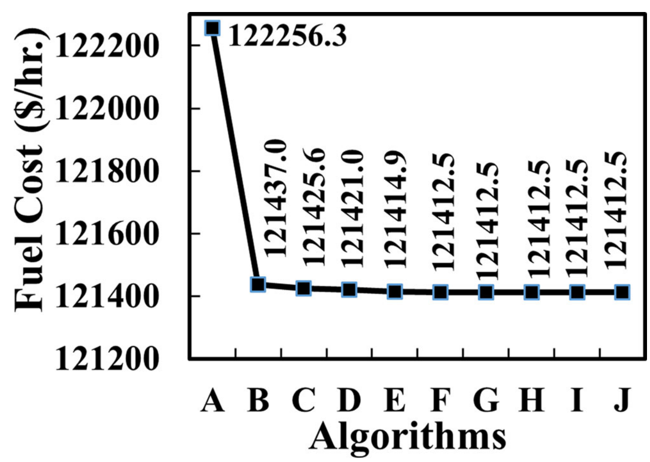

FIGURE 15. Comparison of minimum fuel cost with different algorithms (A-PARPSO [36], B- IA_EDP [40], C- CSA [39], D- IODPSO L [37], E- IODPSO G [37], F- CBA [38], G- DMOA [33], H- PPSO [34], I- MPDE [35], G- AEO).

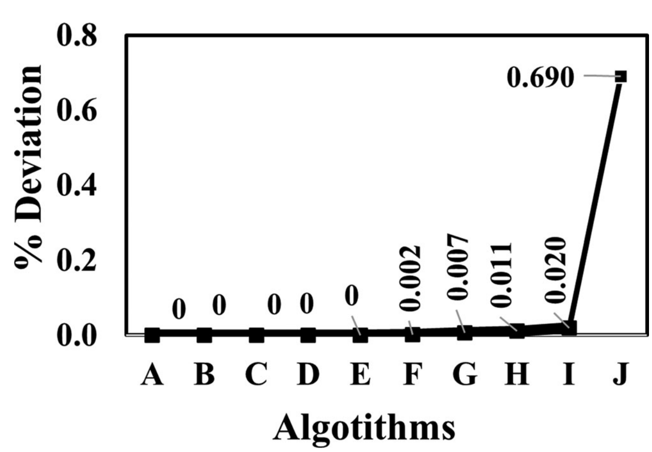

FIGURE 16. Change in Percentage deviation concerning other optimization techniques (A-AEO, B- MPDE [35], C- PPSO [34], D- DMOA [33], E- CBA [38], F- IODPSO G [37], G- IODPSO L [37], H- CSA [39], I- IA_EDP [40], J- PARPSO [36]).

Unit	Power output	Unit	Power output	Unit	Power output
1	2.4000	38	70.0000	75	90.0000
2	2.4000	39	100.0000	76	50.0000
3	2.4000	40	120.0000	77	160.0000
4	2.4000	41	157.1629	78	295.6941
5	2.4000	42	220.0000	79	175.0000
6	2.4000	43	440.0000	80	98.0000
7	2.4000	44	560.0000	81	10.0000
8	2.4000	45	660.0000	82	12.0000
9	2.4000	46	616.4179	83	20.0000
10	64.4151	47	5.4000	84	200.0000
11	62.2148	48	5.4000	85	325.0000
12	36.2838	49	5.4000	86	440.0000
13	56.6329	50	5.4000	87	14.3048
14	25.0000	51	5.4000	88	24.3943
15	25.0000	52	12.0000	89	82.4038
16	25.0000	53	12.0000	90	89.2092
17	155.0000	54	12.0000	91	57.5729
18	155.0000	55	12.0000	92	100.0000
19	155.0000	56	25.2000	93	440.0000
20	155.0000	57	25.2000	94	500.0000
21	68.9000	58	35.0000	95	600.0000
22	68.9000	59	35.0000	96	471.8996
23	68.9000	60	45.0000	97	3.6000
24	350.0000	61	45.0000	98	3.6000
25	400.0000	62	45.0000	99	4.4000
26	400.0000	63	185.0000	100	4.4000
27	500.0000	64	185.0000	101	10.0000
28	500.0000	65	185.0000	102	10.0000
29	200.0000	66	185.0000	103	20.0000
30	100.0000	67	70.0000	104	20.0000
31	10.0000	68	70.0000	105	40.0000
32	20.0000	69	70.0000	106	40.0000
33	80.0000	70	360.0000	107	50.0000
34	250.0000	71	400.0000	108	30.0000
35	360.0000	72	400.0000	109	40.0000
36	400.0000	73	104.9089	110	20.0000
37	40.0000	74	191.3547	**Fuel Cost ($/hr.)**	**197987.7411**

TABLE 12. Schedule of generation for test case 6 with 110 generators and power demand 15000 MW.

Method	Minimum fuel cost ($/hr.)	Maximum fuel Cost($/hr.)	Average fuel Cost($/hr.)	Simulation time (sec.)	No of hits to best solution (50 trials)	Standard deviation
AEO	**197987.7411**	**197987.7411**	**197987.7411**	**0.10**	**50**	**0**
TFWO [42]	197,988.1790	197988.1904	197988.1823	NA	NA	NA
AGWO [43]	197988.00	197988.00	197988.00	NA	NA	NA
ORCCRO [18]	198016.29	198016.89	198016.32	0.15	48	NA
OIWO [41]	197989.14	197989.93	197989.41	NA	NA	NA

TABLE 13. Comparison of the result obtained by AEO and other techniques for test case 6.

characteristics are shown in Figure 14. Figure 15 shows the Comparison of minimum fuel cost with different algorithms. Figure 16 represents the change in Percentage deviation concerning other optimization techniques. The output of each generator unit is shown in Table 8. A comparison of obtained results is shown in Table 9.

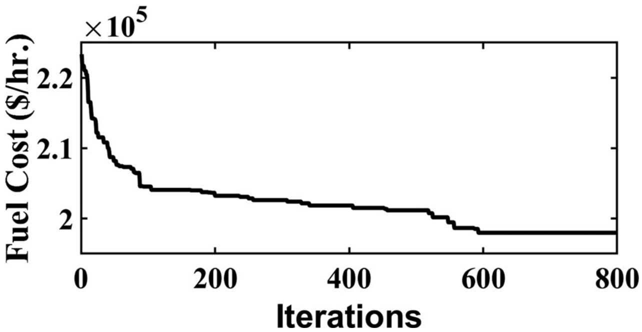

FIGURE 17. Convergence characteristics for test case 6.

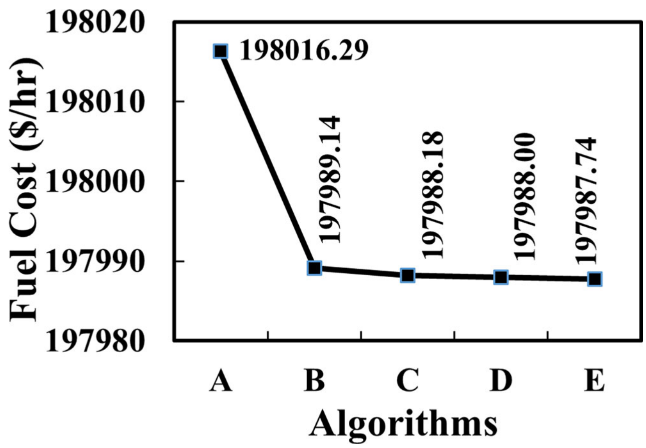

FIGURE 18. Comparison of minimum fuel cost with different algorithms (A-ORCCRO [18], B- OIWO [41], C-TFWO [42], D- AGWO [43], E-AEO).

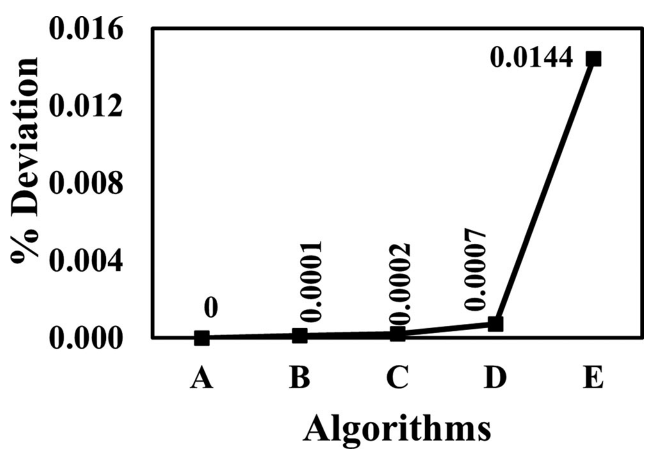

FIGURE 19. Change in Percentage deviation concerning other optimization techniques (A-AEO, B- AGWO [43], C-TFWO [42], D- OIWO [41], E- ORCCRO [18]).

4.6. Test Case-6

In this case total of 110 generators unit are considered. Transmission loss is neglected here. Required input data are taken from [41]. The total Power demand is 15000 MW. Obtained results are shown in Table 12. A comparison of obtained results is in Table 13. Convergence characteristics are shown in Figure 17. Figure 18 shows the Comparison of minimum fuel cost with different algorithms. Figure 19 represents the change in Percentage deviation concerning other optimization techniques (Table 14).

4.7. Result summary

In Test Case 1, the average and minimum fuel costs are 623.8856 $/hr. and 623.8856 $/hr. respectively which is better than other existing techniques like BSA [9], SGO [8], etc. Simulation time and "number of hits to best solution" are 0.40 seconds and 50 (out of 50 trials) using AEO are also superior to BSA [9], SGO [8], etc.

In Test Case 2, the average and minimum fuel costs are 24512.6073 $/hr. and 24512.6073 $/hr. respectively which is better than other existing techniques like SCA [15], F-MLP [14], MPDE [16], etc. Simulation time and "number of hits to best solution" are 0.035 seconds and 50 (out of 50 trials) using AEO are also superior to SCA [15], F-MLP [14], MPDE [16], etc.

In Test Case 3, the average and minimum fuel costs are 32697.4000 $/hr. and 32697.2819 $/hr. respectively which is better than other existing techniques like SGO [8], BSA [9], etc. Simulation time and "number of hits to best solution" are 0.62 seconds and 48 (out of 50 trials) using AEO are also superior to SGO [8], BSA [9], etc.

In Test Case 4, the average and minimum fuel costs are 94165561.14 $/hr. and 9416559.0869 $/hr. respectively which is better than other existing techniques like ADE-MMS [29], GWO [30], etc. Simulation time and "number of hits to best solution" are 7.2 seconds and 49 (out of 50 trials) using AEO are also superior to ADE [29], GWO [30], etc.

In Test Case 5, the average and minimum fuel costs are 121412.5740 $/hr. and 121412.5355 $/hr. respectively which is better than other existing techniques like DMOA [33], PPSO [34], etc. Simulation time and "number of hits to best solution" are 6.2 seconds and 48 (out of 50 trials) using AEO are also superior to DMOA [33], PPSO [34], etc.

In Test Case 6, average and minimum fuel costs are 197987.7411 $/hr. and 197987.7411 $/hr. respectively which is better than other existing techniques like TFWO [42], AGWO [43], etc. Simulation time and "number of hits to best solution" are 0.10 seconds and 50 (out of 50 trials) using AEO are also superior to TFWO [42], AGWO [43], etc.

Test case	No. of generator unit	Total power demand	Minimum fuel cost ($/hr.)	Simulation time(sec)	No. of hits to the best solution (Out of 50 trials)	Power loss (MW) (If applicable)
1	10	2700	623.8856	0.40	50	NA
2	13	2520	24512.6073	0.035	50	39.8
3	15	2630	32697.2819	0.62	48	30
4	38	6000	9416559.0869	7.20	49	NA
5	40	10500	121412.5355	6.2	48	NA
6	110	15000	197987.7411	0.10	50	NA

TABLE 14. Summarized Results of six different cases.

Number of search agent	Number of hits to best solution (Out of 50 trials)	Simulation time (sec)	Minimum fuel cost ($/hr.)	Maximum fuel cost ($/hr.)	Average fuel cost ($/hr.)
20	38	0.09	197998.2569	199856.854	198444.305
50	**50**	**0.10**	**197987.7411**	**197987.7411**	**197987.7411**
100	36	0.35	198120.8526	199851.3654	198605.2020
150	24	0.58	198240.7412	199913.8547	199110.7600
200	20	0.40	198260.8765	199990.3698	199298.5720

TABLE 15. Selection of number of search agents.

4.8. Tuning Parameters and Number of Search Agents

The most significant advantage of AEO is that there are no parameters so, there is no need for tuning it. So, it will take less computational time and it will also enhance the overall efficiency of the algorithm. The selection of search agents is an important task in any optimization technique. In AEO different numbers of search, agents have been taken and shown in Table 15 for test case 6. The most superior values achieved at the number of search agents are 50. A similar process followed for the rest of the test cases.

4.9. Discussion

The effectiveness and preponderance of any algorithm should decide on three terms Solution quality, Computational efficiency, and Robustness.

4.9.1. Solution Quality. The obtained fuel cost for each case is shown in the summarized result. Best fuel cost is achieved for all test cases and it is compared with existing techniques. Obtained fuel cost is superior to the recent technique as well as previous techniques, even obtained cost is better than hybrid and oppositional based techniques, the comparison is shown in Tables 3, 5, 7, 9, 11 and 13. So, from comparison, AEO is superior in terms of solution quality.

4.9.2. Computational Efficiency. It is clear from the summarized result, simulation time required for AEO to obtain the best solution is very less compared to other existing novel and previous techniques. These are shown in Tables 3, 5, 7, 9, 11, and 13. These results prove the computational efficiency of AEO. A convergence characteristic of AEO is smoother and it achieves convergence in very little time.

4.9.3. Robustness. The performance of any algorithms cannot be analyzed by the results of a single run. For better analysis, it is essential to make several trials. By analyzing the result of each trial, the decision regarding the robustness of the algorithm can be taken. An algorithm is said to be robust if it gives consistent results during these trial runs. From Table 14 it is clear the best results obtained out of 50 trials for six test cases are 50, 50, 48, 49,48, 50 respectively. That mean efficiency of AEO to obtain best solution is 100%, 100%, 96%, 98%, 96%, 100% respectively. Therefore, the above results establish the enhanced ability of AEO to achieve superior quality solutions, in a computationally efficient and robust way.

5. CONCLUSION

In this proposed work, an ELD is integrated with AEO. The main goal of ELD is to minimize the total generation cost. Comparing the results obtained by AEO from all different types of test systems with other optimization methods confirm that the recommended AEO can get the lower fuel cost insensibly less computation time with a high number of hits to the best solution.

Therefore, it can be concluded that AEO is a highly effective technique for solving the ELD problems and successful implementation of AEO in the ELD domain has conceived a new track in the area of power systems to solve different and even more complex problems of optimization like Emission minimization, optimal power flow, voltage stability, etc.

ORCID

Kuntal Bhattacharjee http://orcid.org/0000-0001-6934-6702
Kathan Shah http://orcid.org/0000-0002-9285-0613
Jatin Soni http://orcid.org/0000-0002-4939-8481

REFERENCES

[1] K. Aoki and T. Satoh, "Economic dispatch with network security constraints using parametric quadratic programming," *IEEE Trans. Power App. Syst*, vol. PAS-101, no. 12, pp. 4548–4556, 1982. DOI: 10.1109/TPAS.1982.317308.

[2] K. S. Swarup and A. Natarajan, "Constrained optimization using evolutionary programming for dynamic economic dispatch," Proceedings of 2005 International Conference on Intelligent Sensing and Information Processing, 2005.

[3] R. A. Jabr, A. H. Coonick and B. J. Cory, "A homogeneous linear programming algorithm for the security constrained economic dispatch problem," *IEEE Trans. Power Syst.*, vol. 15, no. 3, pp. 930–936, 2000. DOI: 10.1109/59.871715.

[4] M. Ramamoorty, R. N. Dhar and P. K. Mukherjee, "Reduced-gradient method for economic dispatch," *Proc. Inst. Electr. Eng. UK*, vol. 120, no. 11, pp. 1419, 1973. DOI: 10.1049/piee.1973.0287.

[5] A. A. El-Keib, H. Ma and J. L. Hart, "Environmentally constrained economic dispatch using the LaGrangian relaxation method," *IEEE Trans. Power Syst*, vol. 9, no. 4, pp. 1723–1729, 1994. DOI: 10.1109/59.331423.

[6] S. C.-T and C.-T. Lin, "New approach with a Hopfield modeling framework to economic dispatch," *IEEE Trans. Power Syst*, vol. 15, no. 2, pp. 541–545, 2000.

[7] C.-L. Chiang, "Improved genetic algorithm for power economic dispatch of units with valve-point effects and multiple fuels," *IEEE Trans. Power Syst*, vol. 20, no. 4, pp. 1690–1699, 2005. DOI: 10.1109/TPWRS.2005.857924.

[8] K. Bhattacharjee and N. Patel, "An experimental study regarding Economic Load Dispatch using Search Group Optimization," *Sci. Iran*, vol. 27, no. 6, pp. 3175–3189, 2019. DOI: 10.24200/sci.2019.51798.2367.

[9] M. Modiri-Delshad, S. H. Aghay Kaboli, E. Taslimi-Renani and N. A. Rahim, "Backtracking search algorithm for solving economic dispatch problems with valve-point effects and multiple fuel options," *Energy (Oxf.)*, vol. 116, pp. 637–649, 2016. DOI: 10.1016/j.energy.2016.09.140.

[10] K. Bhattacharjee, "Economic dispatch problems using backtracking search optimization," *Int. J. Energy Optim. Eng.*, vol. 7, no. 2, pp. 39–60, 2018.

[11] H. Lu, P. Sriyanyong, Y. H. Song and T. Dillon, "Experimental study of a new hybrid PSO with mutation for economic dispatch with non-smooth cost function," *Int. J. Electr. Power Energy Syst*, vol. 32, no. 9, pp. 921–935, 2010. DOI: 10.1016/j.ijepes.2010.03.001.

[12] B. K. Panigrahi and V. R. Pandi, "Bacterial foraging optimisation: Nelder-Mead hybrid algorithm for economic load dispatch," *IET Gener. Transm. Distrib*, vol. 2, no. 4, pp. 556, 2008. DOI: 10.1049/iet-gtd:20070422.

[13] S. Duman, N. Yorukeren and I. H. Altas, "A novel modified hybrid PSOGSA based on fuzzy logic for non-convex economic dispatch problem with valve-point effect," *Int. J. Electr. Power Energy Syst*, vol. 64, pp. 121–135, 2015. DOI: 10.1016/j.ijepes.2014.07.031.

[14] S. Pan, J. Jian, H. Chen and L. Yang, "A full mixed-integer linear programming formulation for economic dispatch with valve-point effects, transmission loss and prohibited operating zones," *Electric Power Syst. Res*, vol. 180, no. 106061, pp. 106061, 2020. DOI: 10.1016/j.epsr.2019.106061.

[15] K. Bhattacharjee and N. Patel, "A comparative study of economic load dispatch using sine cosine algorithm," *Sci. Iran*, vol. 27, no. 3, pp. 1467–1480, 2018. DOI: 10.24200/sci.2018.50635.1796.

[16] X. Li, H. Zhang and Z. Lu, "A differential evolution algorithm based on multi-population for economic dispatch problems with valve-point effects," *IEEE Access*, vol. 7, pp. 95585–95609, 2019. DOI: 10.1109/ACCESS.2019.2927574.

[17] D. C. Secui, "A modified symbiotic organisms search algorithm for large scale economic dispatch problem with valve-point effects," *Energy (Oxf.)*, vol. 113, pp. 366–384, 2016. DOI: 10.1016/j.energy.2016.07.056.

[18] K. Bhattacharjee, A. Bhattacharya and S. H. N. Dey, "Oppositional real coded chemical reaction optimization for different economic dispatch problems," *Int. J. Electr. Power Energy Syst.*, vol. 55, pp. 378–391, 2014. DOI: 10.1016/j.ijepes.2013.09.033.

[19] J. Zhao, S. Liu, M. Zhou, X. Guo and L. Qi, "Modified cuckoo search algorithm to solve economic power dispatch optimization problems," *IEEE/CAA J. Autom. Sinica*, vol. 5, no. 4, pp. 794–806, 2018. DOI: 10.1109/JAS.2018.7511138.

[20] V. Kansal and J. S. Dhillon, "Emended salp swarm algorithm for multiobjective electric power dispatch problem," *Appl. Soft Comput.*, vol. 90, no. 106172, pp. 106172, 2020. DOI: 10.1016/j.asoc.2020.106172.

[21] M. Kumar and J. S. Dhillon, "A conglomerated ion-motion and crisscross search optimizer for electric power load

dispatch," *Appl. Soft Comput*, vol. 83, no. 105641, pp. 105641, 2019. DOI: 10.1016/j.asoc.2019.105641.

[22] Y. J.-T, C.-H. Kim, A. Wadood, T. Khurshaid and S.-B. Rhee, "Jaya algorithm with self-adaptive multi-population and Lévy flights for solving economic load dispatch problems," *IEEE Access*, vol. 7, pp. 21372–21384, 2019.

[23] M. A. Elhameed and A. A. El-Fergany, "Water cycle algorithm-based economic dispatcher for sequential and simultaneous objectives including practical constraints," *Appl. Soft Comput.*, vol. 58, pp. 145–154, 2017. DOI: 10.1016/j.asoc.2017.04.046.

[24] Z. L. Wu, J. Y. Ding, Q. H. Wu, Z. X. Jing and X. X. Zhou, "Two-phase mixed integer programming for non-convex economic dispatch problem with spinning reserve constraints," *Electric Power Syst. Res.*, vol. 140, pp. 653–662, 2016. DOI: 10.1016/j.epsr.2016.05.006.

[25] Y. Labbi, D. B. Attous, H. A. Gabbar, B. Mahdad and A. Zidan, "A new rooted tree optimization algorithm for economic dispatch with valve-point effect," *Int. J. Electr. Power Energy Syst.*, vol. 79, pp. 298–311, 2016. DOI: 10.1016/j.ijepes.2016.01.028.

[26] N. Ghorbani and E. Babaei, "Exchange market algorithm for economic load dispatch," *Int. J. Electr. Power Energy Syst.*, vol. 75, pp. 19–27, 2016. DOI: 10.1016/j.ijepes.2015.08.013.

[27] S. Banerjee, D. Maity and C. K. Chanda, "Teaching learning based optimization for economic load dispatch problem considering valve point loading effect," *Int. J. Electr. Power Energy Syst.*, vol. 73, pp. 456–464, 2015. DOI: 10.1016/j.ijepes.2015.05.036.

[28] A. G. Abro and J. Mohamad-Saleh, "Enhanced probability-selection artificial bee colony algorithm for economic load dispatch: A comprehensive analysis," *Eng. Optim.*, vol. 46, no. 10, pp. 1315–1330, 2014. DOI: 10.1080/0305215X.2013.836639.

[29] Q. Zhang, D. Zou, N. Duan and X. Shen, "An adaptive differential evolutionary algorithm incorporating multiple mutation strategies for the economic load dispatch problem," *Appl. Soft Comput.*, vol. 78, pp. 641–669, 2019. DOI: 10.1016/j.asoc.2019.03.019.

[30] V. K. Kamboj, S. K. Bath and J. S. Dhillon, "Solution of non-convex economic load dispatch problem using Grey Wolf Optimizer," *Neural Comput Appl.*, vol. 27, no. 5, pp. 1301–1316, 2016. DOI: 10.1007/s00521-015-1934-8.

[31] M. N. Abdullah, A. H. Abu Bakar, N. A. Rahim and H. Moklis, "Economic load dispatch with nonsmooth cost functions using evolutionary particle swarm optimization: Economic load dispatch using evolutionary pso," *IEEJ Trans Elec Electron Eng*, vol. 8, No. S1, pp. S30–S37, 2013. DOI: 10.1002/tee.21915.

[32] N. Sinha, R. Chakrabarti and P. K. Chattopadhyay, "Evolutionary programming techniques for economic load dispatch," *IEEE Trans. Evol. Computat*, vol. 7, no. 1, pp. 83–94, 2003. DOI: 10.1109/TEVC.2002.806788.

[33] J.-Y. Ji, W.-J. Yu, J. Zhong and J. Zhang, "Density-enhanced multiobjective evolutionary approach for power economic dispatch problems," *IEEE Trans. Syst. Man Cybern, Syst*, vol. 51, no. 4, pp. 2054–2067, 2021. DOI: 10.1109/TSMC.2019.2953336.

[34] M. Gholamghasemi, E. Akbari, M. B. Asadpoor and M. Ghasemi, "A new solution to the non-convex economic load dispatch problems using phasor particle swarm optimization," *Appl. Soft Comput*, vol. 79, pp. 111–124, 2019. DOI: 10.1016/j.asoc.2019.03.038.

[35] Z. Younes, I. Alhamrouni, S. Mekhilef and M. Reyasudin, "A memory-based gravitational search algorithm for solving economic dispatch problem in micro-grid," *Ain Shams Eng. J*, vol. 12, no. 2, pp. 1985–1994, 2021. DOI: 10.1016/j.asej.2020.10.021.

[36] M. Kheshti, X. Kang, Z. Bie, Z. Jiao and X. Wang, "An effective Lightning Flash Algorithm solution to large scale non-convex economic dispatch with valve-point and multiple fuel options on generation units," *Energy (Oxf.)*, vol. 129, pp. 1–15, 2017. DOI: 10.1016/j.energy.2017.04.081.

[37] Q. Qin, S. Cheng, Q. Zhang, Y. Wei and Y. Shi, "Multiple strategies based orthogonal design particle swarm optimizer for numerical optimization," *Comput. Oper. Res*, vol. 60, pp. 91–110, 2015. DOI: 10.1016/j.cor.2015.02.008.

[38] B. R. Adarsh, T. Raghunathan, T. Jayabarathi and X.-S. Yang, "Economic dispatch using chaotic bat algorithm," *Energy (Oxf.)*, vol. 96, pp. 666–675, 2016. DOI: 10.1016/j.energy.2015.12.096.

[39] M. Basu, "Kinetic gas molecule optimization for nonconvex economic dispatch problem," *Int. J. Electr. Power Energy Syst.*, vol. 80, pp. 325–332, 2016. DOI: 10.1016/j.ijepes.2016.02.005.

[40] V. S. Aragón, S. C. Esquivel and C. A. Coello Coello, "An immune algorithm with power redistribution for solving economic dispatch problems," *Inf. Sci. (Ny)*, vol. 295, pp. 609–632, 2015. DOI: 10.1016/j.ins.2014.10.026.

[41] A. K. Barisal and R. C. Prusty, "Large scale economic dispatch of power systems using oppositional invasive weed optimization," *Appl. Soft Comput.*, vol. 29, pp. 122–137, 2015. DOI: 10.1016/j.asoc.2014.12.014.

[42] M. Ghasemi, I. F. Davoudkhani, E. Akbari, A. Rahimnejad, S. Ghavidel and L. Li, "A novel and effective optimization algorithm for global optimization and its engineering applications: Turbulent Flow of Water-based Optimization (TFWO)," *Eng. Appl. Artif. Intell.*, vol. 92, no. 103666, pp. 103666, 2020. DOI: 10.1016/j.engappai.2020.103666.

[43] D. Singh and J. S. Dhillon, "Ameliorated grey wolf optimization for economic load dispatch problem," *Energy (Oxf.)*, vol. 169, pp. 398–419, 2019. DOI: 10.1016/j.energy.2018.11.034.

[44] K. Bhattacharjee, A. Bhattacharya and S. H. Nee Dey, "Teaching learning Based Optimization for different Economic dispatch problems," *Sci. Iran.*, vol. 21, no. 3, pp. 870–884, 2014.

[45] K. Bhattacharjee, A. Bhattacharya and S. Halder Nee Dey, "Chemical reaction optimisation for different economic dispatch problems," *IET Generat Trans Distribut*, vol. 8, no. 3, pp. 530–541, 2014. DOI: 10.1049/iet-gtd.2013.0122.

[46] K. Shah, K. Bhattacharjee and S. Godwal, "Solving of economical load dispatch using efficient group leader optimization technique," in *Technologies for Sustainable Development*, London: CRC Press, Taylor & Francis Group, 2020, pp. 181–186. DOI: 10.1201/9780429321573.

[47] K. Bhattacharjee and N. Patel, "A comparative study of Economic Load Dispatch with complex non-linear constraints using Salp Swarm Algorithm," *Sci. Iran*, 2020, in press. DOI: 10.24200/sci.2020.52145.2562.

[48] N. Trung, et al., “Moment-rotation prediction of precast beam-to-column connections using extreme learning machine,” *Struct Eng Mech.*, vol. 70, no. 5, pp. 639–647, 2019.

[49] J. Katebi, M. Shoaei-Parchin, M. Shariati, N. T. Trung and M. Khorami, “Developed comparative analysis of metaheuristic optimization algorithms for optimal active control of structures,” *Eng. Comput*, vol. 36, no. 4, pp. 1539–1558, 2020. DOI: 10.1007/s00366-019-00780-7.

[50] M. Milovančević, et al., “UML diagrams for dynamical monitoring of rail vehicles,” *Physica A*, vol. 531, no. 121169, pp. 121169, 2019. DOI: 10.1016/j.physa.2019.121169.

[51] M. Shariati, N. T. Trung, K. Wakil, P. Mehrabi, M. Safa and M. Khorami, “Steel and composite structures,” *Steel Compos. Struct*, vol. 31, no. 5, pp. 427, 2019.

[52] W. Zhao, L. Wang and Z. Zhang, “Artificial ecosystem-based optimization: A novel nature-inspired meta-heuristic algorithm,” *Neural Comput Appl.*, vol. 32, no. 13, pp. 9383–9425, 2020. DOI: 10.1007/s00521-019-04452-x.

BIOGRAPHIES

Kuntal Bhattacharjee is working as associate professor at the department of electrical engineering, institute of technology, Nirma University. He obtained BE degree in electrical engineering from Burdwan University, West Bengal on the year 2003. He received his MTech and PhD degree in electrical engineering (power system) from NIT, Durgapur and Jadavpur University, Kolkata on the year 2005 and 2015 respectively. He has published 12 international / national journal research papers and 10 international / national conference papers. He is a reviewer of prestigious journals of IET, Elsevier, IEEE Access, Taylor & Fransis and Springer. His areas of interests are - power system optimization, optimization techniques, power system operation and control and hydro-thermal scheduling problems.

Kathan Shah has completed M.Tech in Electrical Engineering with specialization in Electrical Power Systems in May 2020 from Nirma University, Ahmedabad, India. His area of interest is power system optimization, generation scheduling, algorithm development.

Jatin Soni is pursuing a Ph.D. (part-time) in electrical engineering at the Institute of Technology, Nirma University since September 2020. He is working as an assistant professor in the electrical engineering department at Ganpat University, Mehsana. He obtained his B.E. degree from Birla Vishvakarma Mahavidyalaya (BVM) engineering college and M.E. degree from Lukhdhirji engineering college (Govt.), Gujarat from 2016 and 2018 respectively. His areas of research are power system optimization, power system operation and control, optimization technique and hydro-thermal scheduling problems.