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A CUCKOO SEARCH OPTIMIZATION SCHEME FOR NON-CONVEX ECONOMIC LOAD DISPATCH

Mohd Wazir Mustafa and Abdirahman Mohamed Abdilahi
Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Johor Bahru, Johor, Malaysia
E-Mail: abdirahman@fkegraduate.utm.my

ABSTRACT

This paper presents a Cuckoo Search (CS) based algorithm to solve constrained economic load dispatch (ELD) problems. The proposed methodology easily deals with non-smoothness of cost function arising due to the use of valve point effects. The performance of the algorithm has been tested on systems possessing 13 and 40 generating units involving varying degrees of complexity. The findings affirm that the method outperforms the existing techniques, and can be a promising alternative approach for solving the ELD problems in practical power system.

Keywords: economic dispatch, power system operations, valve-point effects, cuckoo search.

1. INTRODUCTION

For most of energy companies, particularly the electricity utilities, the Economic Load Dispatch (ELD) problem is one of the fundamental issues in power system operation. It is the use of the optimization techniques in this power system problem that has served the energy companies to lower their operating generation costs throughout decades. Not only that these optimization methods help them reduce costs, it also assists the utility planners and decision makers to make better and faster decisions that improve the quality of the delivery of the service.

The ELD problem investigates the optimal combination of a set of committed generation units to provide power for a specified load at a given time whilst satisfying system constraints [1]. Earlier researches to tackle this optimization problem have utilized various mathematical programming methods such as the equal-incremental method [2], interior-point method [3], Lagrangian Relaxation method [4], and quadratic programming [5], to name only a few. However, these deterministic numerical methods are either infeasible for practical non-linear or non-convex cost functions or they suffer from the "curse of dimensionality".

In view of that, a wide variety of meta-heuristic algorithms and other soft computing have been emerging as potential algorithms to solve the ELD problems. Even though they do not always guarantee global best solutions, but are often found to achieve fast and near global optimal solutions. The powerful optimization tool called Cuckoo Search (CS) algorithm was proposed recently for highly multimodal problems.

Having known that the challenge for ELD problem is to overcome the problems posed by multiple minima and non-differential points, both of which appear when a non-smooth cost function is present. Finding a powerful search algorithm that can solve these problems is of paramount importance.

2. PROBLEM FORMULATION

ELD operations perform the optimal generation dispatch from a list of selected committed units while satisfying system constraints such as load demand and generator limits. Practically, ELD formulations could also consider more practical operation characteristics such as the valve-point loading effects. The problem is mathematically formulated as an optimization problem with an objective function and two constraints.

2.1. Objective function

For simplicity reasons, the ELD problems are generally modelled approximately by a quadratic cost function of the generator's output. But heat-run tests of the generators indicate that ELD problems are best suited to be modelled as non-linear, non-convex type problem due to the ripple effect produced by valve-point loading as the generator's output is increased[6]. In this paper, the Walter - Sheble model [6] is used to represent this effect. Therefore, the cost function is modified and the rectified sinusoidal function is incorporated into the quadratic function as follows:

$$Minimize F_i = \sum_{i=1}^{n} F_i(P_i) \quad (1)$$

where F_i is the total fuel cost for all committed generators and is defined as follows:

$$F_i = a_i P_i^2 + b_i P_i + c_i + \left| e_i \sin\left(f_i\left(P_i - P_i^{min}\right)\right)\right| \quad (2)$$

where a_i, b_i, and c_i are the fuel-cost coefficients of the i^{th} unit; n is the number of committed generators; e_i and f_i are valve-point loading effects of i^{th} unit.

2.2. Equality constraint

To satisfy the system demand, including the system losses, is a necessity in economic dispatch algorithms in order to maintain the overall system stability. The equality constraint deals with this requirement by balancing the power output ($\sum_{i=1}^{n} P_i$) with demand (P_{Dm}) and losses (P_L) combined.This is expressed mathematically as follows:

$$\sum_{i=1}^{n} P_i - P_{Dm} - P_L = 0 \quad (3)$$

where P_L is obtained using the unit power outputs and the B-coefficients, by the following equation:

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

where B_{00}, B_{0i} and B_{ij} are the B-loss coefficients of the system which is pre-defined by the load flow calculations.

2.3. Inequality constraints

For any allocated power output of every unit, the generator's own limits should not be violated as every unit's capability is known to the operators prior to any dispatch calculations. This is represented mathematically as follows:

$$P_i^{min} \le P_i \le P_i^{max} i = 1,2,\ldots,n \quad (5)$$

where P_i^{min} and P_i^{max} are the lower and upper bounds of the generator limits.

3. METHODOLOGY AND ALGORITHM DESCRIPTION

3.1 Cuckoo search algorithm

Cuckoo Search (CS) algorithm was developed by Xin-She Yang and Suash Deb in 2009 [7]. The algorithm metaphorically uses the theory of Cuckoos, particularly their brood parasitism characteristics in combination with the Levy flight concept.

3.2 Implementation of CS algorithm in ED problem

CS is a swarm-based optimization algorithm that carries out two successive evaluations of the objective function in every iteration. This double evaluation procedure makes the algorithm to be powerful for solving complex, non-linear and non-convex optimization problems. The main steps involved in the process are described below:

Step 1: Initialization: a population of nests is initializedrandomly within the limits using equation (6):

$$P_{g_{ij}} = P_j^{min} + rand_1 * (P_j^{max} - P_j^{min}) \quad (6)$$

Where $rand_1$ is a uniformly distributed random number between 0 and 1.

Step 2: Fitness evaluation: fitness evaluation is then performed for all nests at *t* iteration, based on the following fitness equation:

$$f(P_i) = \sum_{i=1}^{ng} F_i(P_i) + PF\left|\sum_{i=1}^{ng} P_i - P_{Dm} - P_L\right| \quad (7)$$

Where P_{Dm} is the total system demand and P_L is the system loss. The first term represents equation (2) and the second term calculates the error introduced by any equality constraint violations. The parameter PF is the penalty factor multiplier to amplify the error values so that it weakens the goodness of the fitness function when there are equality constraint violations. For every loop, two evaluations are performed in this step because of the two other steps of generating solutions.

Step 3: Generate new solutions using levy flight: In this step, new solutions are generated using the Levy flight process. In this process, the global best index is utilized. In the proposed method, the optimal path for the Levy flights is calculated by Mantegna's algorithm [8]. The updating formula for the Levy flight process is given as follows:

$$P_{g\_flight_i} = P_{g\_best_i} + rand_2 \times \alpha \times Step \quad (8)$$

where α is set to 0.01; $rand_2$ is a normally distributed stochastic number; and the incremental step for every iteration is determined as follows:

$$Step = v \times \frac{\sigma_x(\beta)}{\sigma_y(\beta)} \times \left(P_{g\_best_i} - G_{best}\right) \quad (9)$$

$$v = \frac{rand_x}{|rand_y|^{1/\beta}} \quad (10)$$

where $rand_x$ and $rand_y$ are two normally distributed stochastic variables with standard deviation $\sigma_x(\beta)$ and $\sigma_y(\beta)$ given by:

$$\sigma_x(\beta) = \left[\frac{\Gamma(1+\beta)\times\sin((\pi\beta)/2)}{\Gamma((1+\beta)/2)\times\beta\times 2^{((\beta-1)/2)}}\right]^{1/\beta} \quad (11)$$

$$\sigma_y(\beta) = 1 \quad (12)$$

where $\Gamma(.)$ is the gamma distribution function. For further understanding of the CS, the authors advise to visit reference [9] for readers who are interested to learn the basics of the algorithm.

Step 4: Discovery and randomization: In this step, the action of discovery of an alien egg in a nest of a host bird with the probability of p_a is carried out using the following updating equation:

$$P_{g_i}^{t+1} = P_{g\_best_i} + Stepsize \times K \quad (13)$$

Where K is the updated coefficient determined based on the probability of a host bird to discover an alien egg in its nest and it is calculated as follows:

$$K = \begin{cases} 1, & if Rand_3 > p_a \\ 0, & Otherwise \end{cases} \quad (14)$$

and the incremental step size is determined by:

$$Stepsize = Rand_4 \times \left[Rand_{p_1}\left(P_{g\_best_i}\right) - Rand_{p_2}\left(P_{g\_best_i}\right)\right] (15)$$

Where $Rand_3$ and $Rand_4$ are the distributed random numbers in [0, 1]; $Rand_{p_1}$and $Rand_{p_2}$ are the random perturbation for positions of nests in $P_{g\_best_i}$.

Additionally, in this work, in order increase the efficiency and the robustness of the CS algorithm, an additional constraint handling mechanism adopted from [10] is implemented.

4. IMPLEMENTATION AND NUMERICAL EXPERIMENTS

All the experiments implemented in this paper were carried out using MATLAB 13. Owing to the heuristic nature of the metaheuristic algorithms, their performance requires in-depth statistical analysis. To achieve a meaningful conclusion from the statistics based results, many trials must be run, independently. For each experimental case considered in this paper, 100 trials were run throughout this study, for all the scenarios considered. It is then analysed using descriptive statistical measures such as minimum, mean, maximum, standard deviation (here after referred as Std) and the range (the difference between the maximum and the minimum value).

Two different standard IEEE test systems with thirteen and forty units along with valve loading effects are used to test the algorithm's capability to solve the ED problems. The data of the two test systems are obtained from [11]. In all executed experiments, the stopping criterion was the maximum iteration.

In order to obtain the right parameters of the algorithm, we have carried out a detailed parametric study by varying one parameter at a time. The advantages of the CS algorithm include its nature of having small number of controllable parameters unlike the PSO. The first parameter to be tuned is the fixed number that represents the probability of randomly discovering a Cuckoo's egg in the host nest (donated as P_a). Besides, other inherent parameters such as the population size (donated as N) and the Levy flight exponent - donated as β (Beta) - are tuned. Table 1indicates the settings of the parameter values used during experimentations.

Table-1. Parameter setting in the algorithm design.

Parameter	Description	13 Unit	40 Unit
β	Levy Flight Exponent	1.5	1.5
P_a	Probability of Discovery	0.25	0.25
N	Population Size	50	50
K_φ	Maximum Iteration	$5x10^3$	$5x10^3$
PF	Penalty Factor	100	500

4.1. Determination of probability of discovery (P_a)

In this experiment, the value of P_a was tuned in the range of [0,1] and with the steps of 0.1 and the results are summarised in Table-2. For the thirteen unit system, despite a P_a with 0.9 value has given the best (lowest) optimal cost, the best mean value has been presented by a P_a with a value of 0.8. Additionally, the best range is between 0.6 and 0.8 because these values of P_a give the algorithm's best mean values. They also exhibit the lowest data variability as indicated by the mean, std and range.

Table-2. Determination of the probability of discovery.

	13 Unit					40 Unit				
Pa	Min Cost	Mean Cost	Max Cost	Std Cost	Range	Min Cost	Mean Cost	Max Cost	Std Cost	Range
0	17,965.65	17,994.99	18,045.72	19.39	80.07	121,582.20	122,335.49	123,765.82	415.82	2,183.62
0.1	17,964.26	17,993.39	18,049.49	16.75	85.23	121,734.64	122,321.23	123,631.95	319.15	1,897.31
0.2	17,964.04	17,996.40	18,039.56	18.77	75.52	121,826.36	122,405.56	123,253.16	255.39	1,426.79
0.3	17,968.19	17,990.70	18,053.01	14.22	84.82	121,891.60	122,334.64	122,919.62	191.90	1,028.02
0.4	17,968.43	17,988.01	18,029.16	12.52	60.73	121,924.19	122,275.60	122,724.37	170.99	800.18
0.5	17,965.61	17,983.81	18,010.09	10.31	44.48	121,732.06	122,154.52	122,502.34	136.36	770.28
0.6	17,964.29	17,979.32	18,005.11	8.04	40.82	121,788.78	122,035.06	122,301.28	110.95	512.50
0.7	17,964.03	17,978.82	18,001.68	7.89	37.66	121,673.67	121,882.39	122,104.73	90.57	431.06
0.8	17,964.01	17,978.58	18,005.77	8.80	41.77	121,611.91	121,751.54	121,928.75	68.09	316.85
0.9	17,963.96	17,985.47	18,024.30	13.89	60.35	121,522.84	121,702.83	121,905.23	74.70	382.39
1	17,995.99	18,044.65	18,091.59	19.79	95.60	124,548.58	125,431.99	125,970.83	262.45	1,422.24

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For the forty unit system, a value of P_a in the range of 0.7 and 0.9 gives the best performance in terms of the lowest result variability (measured by the standard deviation (abbreviated as Std Cost) and range). Additionally, a P_a value of 0.9 gives the best optimal value of the experiment.

4.2. Determination of population size (N)

To assess the effect of the population size (N), it has been varied in the range of [10,100] in steps of 10, each constituting a different experiment on its own.The results presented in Table-3show that low range of population size, typically between 10 and 30, are not favourable for both of the systems. However, higher ranges do not give significant effect on the performance of the algorithm. In short, the experiments reveal that the best range should be from 50 to 80, in order to achieve a balanced trade-off between a high computation time and a minimalistic improvement as a result of higher population size.

Table-3. Determination of the population size.

	13 Unit					40 Unit				
N	**Min Cost**	**Mean Cost**	**Max Cost**	**Std Cost**	**Range**	**Min Cost**	**Mean Cost**	**Max Cost**	**Std Cost**	**Range**
10	17,964.61	18,019.44	18,082.71	31.39	118.10	121,593.82	122,302.90	123,391.66	413.71	1,797.84
20	17,966.21	18,007.61	18,058.15	22.35	91.94	121,629.36	122,210.64	122,983.12	249.75	1,353.76
30	17,973.33	18,001.85	18,055.66	20.67	82.33	121,885.28	122,321.96	123,055.98	222.76	1,170.70
40	17,972.98	17,994.03	18,038.63	13.46	65.64	121,875.47	122,346.55	122,810.65	230.61	935.18
50	17,971.11	17,994.34	18,032.30	15.38	61.20	121,868.19	122,353.61	122,854.05	208.65	985.86
60	17,969.68	17,989.55	18,036.60	13.91	66.93	121,936.31	122,393.99	122,915.20	216.24	978.89
70	17,964.57	17,988.67	18,033.15	13.54	68.58	121,961.71	122,406.39	122,867.49	208.00	905.78
80	17,971.83	17,987.27	18,020.13	10.03	48.30	122,013.98	122,400.95	122,765.92	185.07	751.94
90	17,966.99	17,984.78	18,030.63	10.58	63.63	121,964.50	122,436.43	123,170.22	208.11	1,205.73
100	17,969.98	17,981.87	18,008.15	7.61	38.17	121,865.22	122,413.07	122,826.50	183.94	961.28

4.3. Determination of exponent of the levy flight (β)

According to Yang *et al*, the settings of this parameter are normally problem dependent. In order to explore the effect of this parameter on the performance of the algorithm, the experiment summarised in Table-4 was conducted for the shown values of β. The results reveal that a value in the range of [0.3, 1.0] are recommended for CS when tackling ELD problems with values of 0.3 and 0.6 showing the best performance for thirteen and forty unit systems respectively, in terms of the mean cost results.

Table-4. Determination of the levy exponent.

	13 Unit					40 Unit				
Beta	**Min Cost**	**Mean Cost**	**Max Cost**	**Std Cost**	**Range**	**Min Cost**	**Mean Cost**	**Max Cost**	**Std Cost**	**Range**
0.3	17,964.30	17,972.52	17,975.66	1.61	11.36	121,658.67	121,934.07	122,124.13	95.51	465.45
0.4	17,964.07	17,973.09	17,983.05	2.44	18.98	121,559.54	121,687.26	121,807.87	57.34	248.33
0.5	17,963.88	17,980.20	18,016.99	8.42	53.11	121,417.72	121,538.22	121,672.72	58.48	255.00
0.6	17,963.87	17,985.17	18,036.33	11.14	72.47	121,417.84	121,537.68	121,672.54	48.82	254.70
0.7	17,963.91	17,983.67	18,014.17	9.34	50.27	121,434.32	121,556.80	121,733.53	64.12	299.21
0.8	17,965.22	17,983.89	18,010.04	9.00	44.82	121,461.68	121,600.48	121,773.60	69.42	311.92
0.9	17,972.55	17,985.65	18,022.86	11.30	50.31	121,519.33	121,706.03	121,897.93	78.55	378.60
1.0	17,970.25	17,988.26	18,014.50	10.04	44.25	121,578.72	121,836.29	122,080.87	92.70	502.15
1.1	17,966.01	17,988.31	18,035.31	11.62	69.30	121,692.76	121,978.12	122,278.89	138.99	586.13
1.2	17,973.09	17,990.43	18,028.59	12.63	55.50	121,714.33	122,125.54	122,397.63	155.19	683.30
1.3	17,963.98	17,993.95	18,039.72	16.03	75.74	121,835.95	122,194.39	122,722.54	175.60	886.58
1.4	17,969.48	17,991.81	18,028.21	12.10	58.73	121,902.25	122,330.52	122,958.24	221.32	1,055.98

1.5	17,973.05	17,994.03	18,045.37	15.38	72.32	121,854.77	122,372.00	123,061.53	218.11	1,206.76
1.6	17,964.44	17,994.67	18,045.14	16.53	80.70	121,938.35	122,433.46	123,008.21	224.44	1,069.87
1.7	17,973.22	17,991.59	18,041.65	12.91	68.43	121,887.86	122,487.83	123,089.03	254.89	1,201.17
1.8	17,969.10	17,994.83	18,054.14	16.26	85.04	122,074.86	122,587.94	123,175.86	238.81	1,101.01
1.9	17,973.03	17,990.48	18,047.97	13.73	74.93	122,133.90	122,575.41	123,104.77	221.53	970.87
2.0	17,975.40	18,018.80	18,080.06	22.67	104.66	122,252.39	122,643.99	123,406.02	203.71	1,153.62

4.4. Optimal solutions

After the optimal tuning experiments, another final experiment was run with the recommended optimal values for the parameters as described in the previous section with a maximum iteration of 10,000 and 15,000 for the thirteen and forty unit systems. The output settings of the generators are shown in Tables 5and 6 for the thirteen and forty unit systems. The tables also include the results of some other methods presented in recent literature.

Table-5. Best solution output power solution settings for the generators in comparison with other methods in the literature (13-Unit System).

Unit	DEC-SQP[12]	IGA MU [13]	ICA–PSO [14]	QPSO [15]	NSS [16]	SDE[17]	CS
1	628.32	628.32	628.32	538.56	448.80	628.32	628.32
2	149.24	148.10	149.60	224.70	300.50	149.60	222.76
3	223.17	224.27	222.75	150.09	299.20	222.75	149.60
4	109.85	109.86	109.86	109.87	60.00	109.87	109.87
5	109.87	109.86	109.86	109.87	109.90	109.87	109.87
6	109.87	109.86	60.00	109.87	109.90	109.87	60.00
7	109.82	109.86	109.87	109.87	61.90	60.00	109.87
8	109.87	109.87	109.87	109.87	109.90	109.87	109.87
9	60.00	60.00	109.87	109.87	109.90	109.87	109.86
10	40.00	40.00	40.00	77.41	40.00	40.00	40.00
11	40.00	40.00	40.00	40.00	40.00	40.00	40.00
12	55.00	55.00	55.00	55.01	55.00	55.00	55.00
13	55.00	55.00	55.00	55.01	55.00	55.00	55.00
Total cost ($/h)	17,963.94	17,963.98	17,963.88	17,969.01	17,976.95	17,963.83	17,963.8343

Table-6. Best solution output power solution settings for the generators in comparison with other methods in the literature (40-Unit System).

Unit	MPSO[18]	DEC–SQP[12]	QPSO [15]	BBO [19]	NPSO–LRS [20]	SDE[17]	CS
1	114.00	111.76	111.20	110.82	113.98	110.80	110.95
2	114.00	111.56	111.70	111.09	114.00	110.80	111.54
3	120.00	97.40	97.40	97.40	97.42	97.40	97.43
4	182.22	179.73	179.73	179.75	179.73	179.73	179.80
5	97.00	91.66	90.14	88.21	89.65	87.80	94.11
6	140.00	140.00	140.00	139.99	105.40	140.00	140.00
7	300.00	300.00	259.60	259.59	259.75	259.60	259.63
8	299.02	300.00	284.80	284.62	288.45	284.60	284.88
9	300.00	284.60	284.84	284.65	284.65	284.60	284.80
10	130.00	130.00	130.00	130.03	204.81	130.00	130.00
11	94.00	168.80	168.80	94.01	168.83	94.00	168.85
12	94.00	94.00	168.80	94.26	94.00	94.00	94.00
13	125.00	214.76	214.76	304.52	214.77	214.76	214.79

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14	304.49	394.28	304.53	394.26	394.29	394.28	394.35
15	394.61	304.52	394.28	304.51	304.52	394.28	394.28
16	305.32	304.52	394.28	394.25	394.28	394.28	304.53
17	490.27	489.28	489.28	489.33	489.28	489.28	489.31
18	500.00	489.28	489.28	489.30	489.28	489.28	489.27
19	511.40	511.28	511.28	511.31	511.28	511.28	511.29
20	512.17	511.28	511.28	511.25	511.30	511.28	511.29
21	550.00	523.28	523.28	523.32	523.29	523.28	523.31
22	523.66	523.28	523.28	523.31	523.29	523.28	523.48
23	534.67	523.28	523.29	523.36	523.28	523.28	523.30
24	550.00	523.28	523.28	523.29	523.30	523.28	523.32
25	525.06	523.28	523.29	523.30	523.29	523.28	523.30
26	540.16	523.28	523.28	523.28	523.29	523.28	523.34
27	10.00	10.00	10.01	10.03	10.00	10.00	10.00
28	10.00	10.00	10.01	10.00	10.00	10.00	10.03
29	10.00	10.00	10.00	10.03	10.00	10.00	10.00
30	97.00	90.33	88.47	88.15	89.01	87.80	88.20
31	190.00	190.00	190.00	189.99	190.00	190.00	190.00
32	190.00	190.00	190.00	189.99	190.00	190.00	190.00
33	190.00	190.00	190.00	190.00	190.00	190.00	190.00
34	200.00	200.00	164.91	164.85	200.00	164.80	200.00
35	200.00	200.00	165.36	192.99	165.14	200.00	200.00
36	200.00	200.00	167.19	199.99	172.03	194.40	165.31
37	110.00	110.00	110.00	109.99	110.00	110.00	110.00
38	110.00	110.00	107.01	110.00	110.00	110.00	110.00
39	110.00	110.00	110.00	109.98	93.10	110.00	110.00
40	512.96	511.28	511.36	511.28	511.30	511.28	511.30

4.5 Comparison with the existing methods

In order to show CS's effectiveness and suitability in ELD problems, results of different methods for the both systems with valve-point loading effects are shown in Tables 7 & 8. Table 7reports the results of different methods for the 13-unit system. The table summarises the optimal cost result achievement of forty three different methods found in the major energy and engineering databases. In terms of the ability of the method to achieve minimum operating cost out of the set trials, the results of the proposed method are better than those of 80% of the methods listed in the table while it also achieves similar performance for the rest of the methods. A similar performance is observable for the forty unit system in Table-8.

Table-7. Comparison of results for existing methods for a thirteen unit with a demand of 1800MW.

Method	**Min Cost** ($/h)	**Mean Cost** ($/h)	**Max Cost** ($/h)	**SD** ($/h)
MSL [21]	18,158.68			
PSO [22]	18,030.72			
IFEP [11]	17,994.07			
HEP_SQP [22]	17,991.03			
AIS [23]	17,977.0905			
HDE [24]	17,975.73			
DPSO [25]	17,976.31	18,084.99	18,310.43	-
HMAPSO [25]	17,969.31	17,969.31	17,969.31	0.00
NDS [26]	17,976.9512	17,976.9512	17,976.9512	0.0000
SA [26]	-	18,299.2550	-	123.8335
PSO_TVAC [27]	17,963.879	18,154.562	18,358.310	-

NEW PSO [27]	18,120.594	18,227.052	18,427.631	-
IFEP [11]	17,994.07	18,127.06	18,267.42	-
DE [28]	17,963.83	17,965.48	17,975.36	-
PSO-SQP [29]	17,969.93	18,029.99	-	-
EP-SQP [29]	17,991.03	18,106.93	-	-
PSO [29]	18,030.72	18,205.78	-	-
ED-DE [30]	17,963.86	17,972.70	17,975.85	-
ST-HDE [24]	17,963.89	18,046.38	-	-
HDE [24]	17,975.73	18,134.80	-	-
FAPSO [31]	17,963.84	17,969.9187	17,976.35	-
FAPSO-NM [31]	17,963.84	17,963.9577	17,964.21	-
PSO [31]	18,030.72	18,205.9247	18,401.35	-
HGA [32]	17,963.83	17,988.04	-	-
CASO [33]	17,965.15	18,022.04	-	-
FCASO-SQP [33]	17,964.08	18,001.96	-	-
GSA [34]	17,963.84	18,041.21	18,910.31	-
CLPO [35]	17,970.67	18,019.41	18,071.57	22.67055
SQP-CLPSO [35]	17,973.12	18,005.05	18,069.35	23.81023
NPSO [36]	17,976.015	-	-	-
HHS [37]	17,963.8293	17,972.4822	-	2.4185
DEC-SQP [38]	17,963.9401	17,973.1339	17,984.8105	1.9735
BFO [39]	17,974.48	17,997	18,018.75	
GA-PS-SQP [40]	17,964.25	-	18,199	
TSARGA [41]	17,963.94	17,974.31	18,264.23	3.18
ABC [42]	17,963.86	17,987.22	17,995.11	-
aBBOmDE[43]	17,963.8521	17,967.3560	17,975.0552	-
IHSWM [44]	17,963.83	17,976.475	18,041.34	25.6079
MsEBBO/sin [45]	17,963.8292	17,964.0468	17,969.0323	1.9215
MsEBBO[45]	17,963.8292	17,964.0468	17,969.0323	1.9215
θ-PSO [46]	17,963.8297	17,965.2055	17,980.2030	4.3807
FA [47]	17,963.83	18,029.16	18,168.80	148.542
SDE [17]	17,963.83	-	-	-
CS	17,963.83	17,965.43	17,972.81	3.22

Table-8. Comparison of results for existing methods for a forty unit with a demand of 10,500MW.

Method	**Min Cost** ($/h)	**Mean Cost** ($/h)	**Max Cost** ($)	**SD** ($/h)
MODE [48]	121,836.9839	-	-	-
NSGA-II [48]	124,963.5028	-	-	-
HBMO [49]	121,416.03	122,019.65	-	-
IHBMO [49]	121,412.7533	121,875.58	-	-
MBFA [50]	121,415.653	-	-	-
DE [51]	121,840	-	-	-
DEC(2)-SQP(1) [52]	121,741.9793	122,295.1278	122,839.2941	386.1809
EP [29]	122,624.35	123,382.00	-	-
CPSO-SQP [53]	121,458.54	122,028.16	-	-
FCASO-SQP [33]	121,456.98	122,026.21	-	-
θ-PSO [46]	121,420.9027	121,509.8423	-	-
PSO [29]	123,930.45	124,154.49	-	-
PSO [54]	122,588.5093	123,544.8853	124,733.6795	-
PSO [55]	121,800.13	121,899.57	122,000.80	84.21

ACO [55]	121,532.41	121,606.45	121,679.64	45.58
GA [55]	121,996.40	122,919.77	123,807.97	320.31
CSO [54]	121,461.6707	121,936.1926	122,844.5391	-
BBO [56]	121,479.5029	121,512.0576	121,688.6634	-
ABC [42]	121,441.03	121,995.82	122,123.77	-
HDE [24]	121,698.51	122,304.30	-	-
IABC [57]	121,412.75	-	121,503.58	-
IABC-LS [57]	121,412.73	-	121,471.61	-
ABC [58]	121,515.1	124,827.34	-	-
ABCLogistic[58]	121,440.2	123,314.12	-	-
ABCTend[58]	121,418.51	122,831.22	-	-
MABC/P/log [59]	121,412.591816	121,431.576266	121,493.188471	18.16
MABC/D/Cat [59]	121,412.540947	121,431.779282	121,503.755217	19.16
SOH_PSO [60]	121,501.14	121,853.57	122,446.30	-
CS	**121,412.72**	**121,438.17**	**121,492.82**	**16.07**

5. CONCLUSIONS

In this paper, the performance of a CS-based algorithm with an efficient constraint handling approach has been looked at. Two practically-oriented test systems are used during the experimentation of the algorithm. The results indicate the effectiveness of the technique. Additionally, the paper has highlighted the superiority of the method in comparison with some existing and well-established methods that have already been applied in the ELD problems. For further investigations, the testing of the performance of CS under other types of economic dispatch modules are worthy-investigations.

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