

ARTICLE

# OPPOSITIONAL CUCKOO SEARCH FOR SOLVING ECONOMIC POWER DISPATCH

KalaiPriyan Thirugnanasambandam<sup>1\*</sup>, J. Amudhavel<sup>2</sup>, Sujatha Pothula<sup>3</sup>

<sup>1,3</sup>Department of Computer Science, Pondicherry University, Puducherry, INDIA

<sup>2</sup>Department of Computer Science and Engineering, KL University, Andhra Pradesh, INDIA

## ABSTRACT

This paper proposes an efficient oppositional Cuckoo Search Algorithm (OCSA) for solving Economic Power Dispatch (EPD). This variant of Cuckoo Search (CS) is proposed in order to impose exploitation strategy in standard CS. Oppositional based Learning is a heuristic method which induces the intensification process of neighborhood solutions in the given search space. On the other hand, CS lacks in intensification phase since BSRW intuitively more on exploration. Hence in this paper, OCSA is proposed to improve the intensification in non-smooth and non-linear EPD solution space. The proposed algorithm has been evaluated in with three different test systems in order to prove the efficiency of OCSA. For validating the performance of OCSA, different variants of CS and some of the novel evolutionary algorithms are tested in same simulation environment. The results show that the proposed OCSA outperforms existing algorithms and other variants of CS.

## INTRODUCTION

In the field of power systems, EPD is one among the major concern since the need of electric energy in day today life become an essential and its growth towards the need gets increased in exponential manner. Distribution of power load to generation units in an economic way leads the problem to get solved using optimization algorithms. Without the constraints of EPD it seems to be a linear problem where the problem can be solved in polynomial time. But with the constraints like transmission loss total power demand, valve point effects, EPD turns out to be a non-linear optimization problem [1]. There are a number of variants available for distributing the power to generation units which are classified based on its mathematical formulation. Along with the EPD, emission of fossil fuels based generation has been coined as a multi-objective variant called combined economic emission dispatch problem (CEED) [2]. While solving EPD, dynamic models become a factor to be considered with ramp rate limits over 24 hours' horizon [3]. On incorporating renewable energy resources into existing EPD a probabilistic or stochastic formulation becomes essential [4]. In power systems, efficiency with respect to energy conversion can be achieved with the combined approach of heat and power namely Combined Heat and Power Economic Dispatch (CHPED) [5, 6]. Another variant, nonlinear EPD problem has been formulated which imposes ramp limits, valve point effects, prohibition in operation zones and different type of fuels with it [7, 1]. Conventional EPD used quadratic function to compute the total consumed fuel cost of generation units; however, in recent years since some of the generators hold steam valves opening processes sinusoidal points were added to conventional EPD for effective fuel cost consumption function [7]. In some other generators there exists limitation in fixing power ranges due to practical infeasibilities. This addressed issue has been coined as prohibited power zones and turned the search space into disjoint and non-smooth [1].

Researchers contributed numerous techniques to solve EPD and its variants using exact methods such as dynamic programming, linear programming, and so on. These methodologies are time consuming process since the time complexity of the algorithm increases exponentially as the number of generation units increased. Some of the heuristic methods are proposed including lambda iteration method, interior point method for solving conventional EPD problems. These heuristics fail to find best feasible solution when the search space becomes nonlinear. On the other hand, evolutionary algorithms have the trend of finding optimal feasible solution sets in non-linear search space. Genetic Algorithm [8], differential evolution [9] along with swarm based algorithms such as Particle Swarm Optimization [10], Seeker Optimization (SOA) [11], Harmony Search (HS) [12], Artificial Bee Colony (ABC) [13], Group Search Optimizer (GSO) [14], are some of the algorithms by which EPD has been solved. Recently, Zhou, et al [15] solved economic emission dispatch with respect to power security as an objective using Ant Colony Optimization (ACO). Imposing niche search phase in ACO promoted the individuals to result in efficient Pareto front solutions. Jiang, et al [16] addressed stochastic EPD in which wind integrated power system has been considered with demand response. Another proposed work on addressing wind integrated power system by Wang, et al [17] which has been solved using efficient heuristic method. Wei, et al. [18] solved environmental economic dispatch with wind and carbon capture plants using golden selection search algorithm. Qu, et al [19] solved EED using multi-objective evolutionary algorithm which addresses wind generated power system. Shilaja and Ravi [20] addressed EPD problem with solar power plants as power units and tested their approach in standard IEEE 30 and 57 bus systems.

Based on the research contributions made in EPD and its variants, in this approach an attempt to solve EPD using a variant of Cuckoo Search (CS) namely Oppositional Cuckoo Search Algorithm (OCSA) has been made. This method concentrates on intensification phase in standard cuckoo search algorithm where a consistent exploration and exploitation phase is followed throughout the search. CS has been chosen since it is a lightweight algorithm (in terms of memory) [21-26].

### KEY WORDS

Oppositional Cuckoo search, economic power dispatch problem, non-linear search space, exploitation strategy, Opposition based learning.

Received: 11 June 2017  
Accepted: 20 July 2017  
Published: 14 Sept 2017

### \*Corresponding Author

Email: kalaip27@gmail.com  
Tel: +91 9042208508

The reminder of this paper is as follows: Section 2 holds the definition of EPD along with the constraints considered, Section 3 addresses standard CS and OCSA, Section 4 holds the experimental evaluation and result discussion on three different Test systems, Section 5 holds the conclusion and future work.

## EPD PROBLEM FORMULATION

This problem formulation considers EPD as a minimization problem whose objective is to minimize the total generation cost with satisfied equality (power demand) and inequality constraints (power consumption).

### Objective formulation

As stated above the objective is to minimize the total fuel cost consumed by the generators. The cost function for  $i^{th}$  generation unit can be formulated as follows:

$$F_i = a_i P_i^2 + b_i P_i + c_i$$

where  $a, b, c$  are the cost coefficients of  $i^{th}$  generator unit.

On imposing valve point effects on the cost functions which is a variant formulation of EPD, the search space becomes non-smooth and non-linear. The mathematical formulation of EPD with valve point effects can be represented as

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

where  $e$  and  $f$  are the coefficients of valve point effects,  $P_i^{min}$  is the lower bound value of  $P$ . The bound of  $P$  for each generator unit are not same.

Thus, the objective of EPD with valve point effects can be formulated as

$$\text{Minimize } F_G = \sum_{i=1}^n a_i P_i^2 + b_i P_i + c_i + |e_i \sin(f_i (P_i^{min} - P_i))|$$

where  $n$  represents the total number of generators

Constraints

The equality and inequality constraints to be satisfied in economic dispatch problem in terms of generating capacity and power balance are as follows.

### Power balance

The total generated power is the summation of the total power demand and transmission loss in the power system. The constraint is mathematically formulated as.

$$\sum_{i=1}^n P_i = P_D + P_{TL}$$

where  $P_D$  is the total power demand in the system and  $P_{TL}$  is the total transmission loss in the system.

The total transmission loss is calculated using B coefficient and the formulated is represented as follows.

$$P_{TL} = \sum_{i=1}^n \sum_{j=1}^n P_i B_{ij} P_j + \sum_{i=1}^n B_{0i} P_i + B_{00}$$

where  $B_{ij}, B_{0i}$  and  $B_{00}$  are the  $i, j^{th}$  loss coefficient of the symmetric matrix  $B$ ,  $i^{th}$  element of the loss coefficient vector and loss coefficient constant respectively.

### Generating capacity constraint

The power output of each generation must satisfy generating capacity constraints and it is represented as.

$$P_i^{min} \leq P_i \leq P_i^{max}$$

where  $P_i^{min}$  and  $P_i^{max}$  are the minimum and maximum limits of the power output of generator  $i$ .

## CUCKOO SEARCH ALGORITHM

Yang and Deb developed CS based on the inspiration from cuckoo's brood parasitism [27]. CS is simple but yet an effective algorithm which follows Markov chain model (next generation population is based on the current population). Memory-wise, CS is considered to be a powerful lightweight algorithm since there will not be any storage of previous best solutions and global best solutions. In CS, the solutions are generated based on two different strategies Levy Flights Random Walk (LFRW) and Biased/ Selective Random Walk (BSRW).

In a given search space  $X$  where  $x_{d,min}$  and  $x_{d,max}$  are the lower and upper bounds of search space where  $d = [1, 2, \dots, D]$  represents the dimensions of search space. An individual in CS can be represented as

$$Indv = [x_1, x_2, \dots, x_D]$$

and the population of CS can be denoted as

$$pop = [Indv_1, Indv_2, \dots, Indv_N]$$

where  $N$  represents total number of individuals in the population.

Each individual in CS can be generated randomly as

$$Indv = x_{d,min} + rand() \times (x_{d,max} - x_{d,min}) \quad (1)$$

where  $d = [1, 2, \dots, D]$ . After the process of initialization CS goes for LFRW method for searching process in the given search space.

LFRW imposes exploration phase of search in the given search space with the help of Levy Flights whose concentration of randomization can be limited with step size  $\alpha$ . Based on LFRW the generation of random solutions are as follows:

$$Y_i = Indv_i + \alpha \oplus Levy(\beta) \quad (2)$$

where  $Y_i$  is the newly generated solution of  $Indv_i$ .  $Levy(\beta)$  can be represented using the formula of power-law

$$Levy(\beta) = r^{-1-\beta} \quad (3)$$

where  $r$  is the random variable,  $\beta$  ranges (0,2) termed as stability factor During implementation process,  $Levy(\beta)$  is followed as [28]:

$$Levy(\beta) = \frac{\phi \times \mu}{|v|^\beta} \quad (4)$$

where  $\mu$  and  $v$  are the random variables which ranges (0,1) and the value of  $\phi$  can be calculated as

$$\phi = \left[ \frac{\sin(\frac{\pi \times \beta}{2}) \times \Gamma(1+\beta)}{2^{\frac{\beta-1}{2}} \times \Gamma(\frac{1+\beta}{2}) \times \beta} \right]^{\frac{1}{\beta}} \quad (5)$$

where  $\Gamma$  is *gamma function*.

After the process of LFRW, CS imposes the obtained solutions to BSRW where the search has been done based on greedy method. In this search a probability factor  $P_a$  has been defined which limits the total number of individuals by deleting the worst individuals below  $P_a$ .

After the worst solutions are abandoned a new set of solutions will be generated as follows:

$$Z_i = Indv_i + rand \times (Indv_g - Indv_h) \quad (6)$$

where  $i \in |abandon\ solutions|$ ,  $rand$  denotes a random variable range (0,1),  $Indv_g, Indv_h$  represents randomly generated solutions based on Eq. (1).

In standard CS, since the Levy flight is controlled by step size there exists a consistent phase between exploration and exploitation. This leads CS to divergence from optimal solution. Hence the authors of this paper proposed a concept with high exploitation strategy in the given search space which is an essential factor in EPD optimization problem. Pseudo code for standard CS is given in Algorithm 1.

Cuckoo search algorithm:

Input: Population  $pop = [Indv_1, Indv_2, \dots, Indv_N]$

Each  $Indv$  consists of dimensions  $(1, 2, \dots, D)$

$Pop$ , Termination Criteria,  $\alpha, P_a$ , min, max

1: Initialize the population  $pop$

2: for  $i = 1$  to  $Pop_{Nest}$

3:  $Indv_i = (max - min) * rand + min$

4: Compute  $f(Indv_i)$

5: end

6: while (Termination Criteria not satisfied) do

7: Generate random individuals  $Y_i$  based on Eq. (2) where  $i \in 1 \dots N$

8: Compute  $f(Y_i)$  where  $i \in 1 \dots N$

9: for  $i = 1$  to  $N$

10: if  $(f(Y_i) \leq f(Indv_i))$

11:  $Indv_i = Y_i$

12:  $f(Indv_i) = f(Y_i)$

13: end

14: end

15: for  $i = 1$  to  $N$

16: if  $(rand() < P_a)$

17:  $Indv_i =$  Generate  $Z_i$  based Eq. (6)

```

18:         end
19:     end
20:      $f(Indv_{best}) = \min(f(Indv_i))$ 
21:     Track  $Indv_{best}$ 
22: end while
Output:  $Indv_{best}$  and  $f(Indv_{best})$ 

```

**Algorithm 1:** Pseudo code of standard Cuckoo Search Algorithm.

## OPPOSITIONAL BASED LEARNING

Tizhoosh [28] proposed a phase called Oppositional Based Learning (OBL) for improving the convergence speed of optimization techniques towards optimal solution. This concept produces an opposition of current individual and evaluates the performance of the generated individual and current individual based on the jumping rate. This process finds better individual in the given search space to provide optimal solution at the end of initiated search. OBL has been successfully used in more number of meta-heuristics [30, 31] which enhances the convergence speed towards optimal solution. To implement OBL, opposite number of OBL has to be defined.

When  $N$  such that  $N \in [a, b]$  be a real number where  $a$  and  $b$  are the upper and lower bounds of  $N$  the opposite number  $N^0$  can be defined as

$$N^0 = a + b - N$$

When oppositional concept implemented on more than one-dimension problem it has to be formulated as

$$N_d^0 = a_d + b_d - N_d$$

where  $i \in 1 \leq d \leq D$ ,  $D$  represents the number of dimensions,  $N_d \in [a_d, b_d]$ .

## OPPOSITIONAL CUCKOO SEARCH

In OCSA, the standard CS is incorporated with Oppositional based learning in BSRW. When the individuals are generated with BSRW, the concept of extracting information from two different random individuals are replaced with oppositional based learning concept. Thus Eq. (6) can be redefined as

$$Z_{i,d} = Indv_{i,d} + rand \times N_{i,d}^0$$

The pseudo code of proposed OCSA is given in Algorithm 2.

---

Oppositional Cuckoo search algorithm (OCSA)

---

Input: Population  $pop = [Indv_1, Indv_2, \dots, Indv_N]$

Each  $Indv$  consists of dimensions  $(1, 2, \dots, D)$

$Pop$ , Termination Criteria,  $\alpha, P_a$ , min, max

1: Initialize the population  $pop$

2: for  $i = 1$  to  $Pop_{Nest}$

3:  $Indv_i = (max - min) * rand + min$

4: Compute  $f(Indv_i)$

5: end

6: while (Termination Criteria not satisfied) do

7: Generate random individuals  $Y_i$  based on Eq. (2) where  $i \in 1 \dots N$

8: Compute  $f(Y_i)$  where  $i \in 1 \dots N$

9: for  $i = 1$  to  $N$

10: if  $f(Y_i) \leq f(Indv_i)$

11:  $Indv_i = Y_i$

12:  $f(Indv_i) = f(Y_i)$

13: end

14: end

15: for  $i = 1$  to  $N$

16: if  $(rand() < P_a)$

17:  $Indv_i =$  Generate  $Z_i$  based Eq. (7)

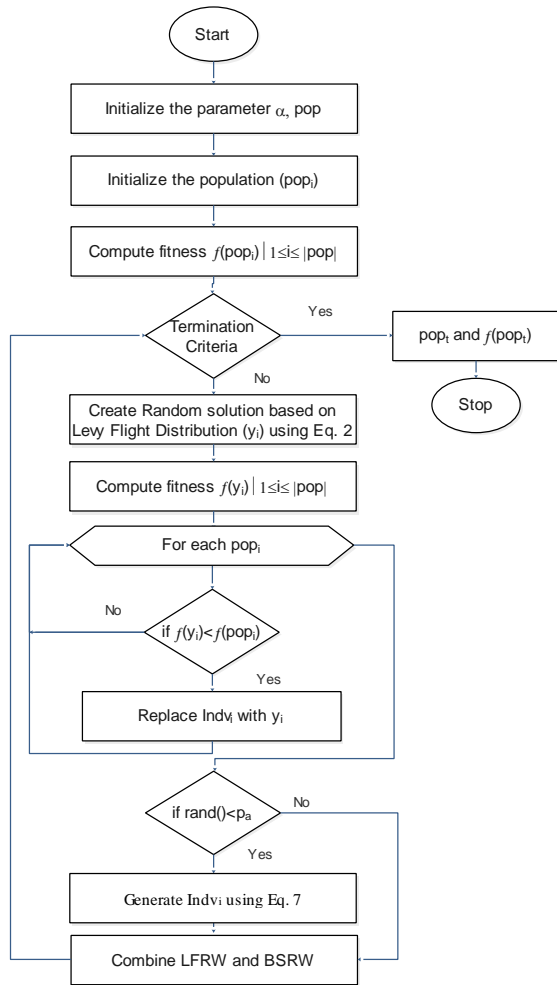
18: end

19: end

20:  $f(Indv_{best}) = \min(f(Indv_i))$

21: Track  $Indv_{best}$   
 22: end while  
 Output:  $Indv_{best}$  and  $f(Indv_{best})$

**Algorithm 2:** Pseudo code of OCSA.



**Figure 1:** Flow chart of oppositional cuckoo search.

### Experimental Evaluations and Result Discussion

To evaluate the performance of the proposed algorithm on EPD, three different power systems which holds 10 power units [31] 13 power units [32] and 40 power units [33] are considered. OSCA and other compared algorithms were implemented in MATLAB 8.3 with the system configuration of Intel core i7 processor with 3.2 GHz speed and 4GB RAM. Parameter settings for experimental results are tabulated in [Table 1].

**Table 1:** Parameter settings for Experimental Evaluation

Type	Method
Total Individuals	100
Maximum Iterations	1000
Heuristic Used	Oppositional based Learning
Termination Condition	Maximum Iterations
Run	20
$\alpha$	0.1

#### Test System 1

In this test system 10 power units are considered for effective power transmission to generation units. The system has been evaluated with power demand 500 MW. The system considers valve point effects along with power balance and transmission loss. Table II holds the simulation results of 10-unit power

systems with a power demand of 500MW. To evaluate the performance of the proposed algorithm on EPD, the results are compared with existing techniques such as GGCS [34], NNCS [35], HSACS [36], PSO [37], Gradient Search [38] and CECS [39]. On comparing the results of proposed algorithm in the simulated environment, the results show that the proposed algorithm outperforms existing techniques in terms of fuel cost consumption. The test data are found in [31]. Evaluation of the performance of OCSA on another case of 10-unit power system which consists of 500MW were done with same test data [31] and the results are tabulated in [Table 2].

**Table 2:** Unit output of different methods for test case 1

Unit	GGCS	OCSA	NNCS	HSACS	CECS	PSO	Gradient search
P1	23.60743	88.20742	24.37497	14.03441	18.90339	12.3000	13.4868
P2	23.07166	13	13.09404	13.16896	13	14.4134	13.5586
P3	10.83128	10	11.69235	24.18451	15.86997	10.0069	12.2281
P4	37.34063	25.90333	33.39361	15	16.82842	26.3741	18.3283
P5	54.80545	54.54007	89.31385	72.00139	72.24111	87.5469	125
P6	14.69713	28.30135	53.91961	33.17024	44.00295	50.5875	20.6141
P7	46.45713	34.71568	20	55.5201	30.1395	86.3165	93.8312
P8	25.61695	25	25	25	33.70554	28.0985	25
P9	150	150	150	150	150	75.9916	34.5543
P10	126.7559	144.8579	92.91588	99.89749	113.9942	110.76	150
Total Loss	13.1836	74.52572	13.70432	1.977099	8.685112	2.21323	2.11552
Total Cost	11069.75	<b>10948.83</b>	11096.99	11076.72	11105.97	11080.5	13340.5

### Test System 2

In this test system 13 power units are considered for effective power transmission to generation units. The system has been evaluated with the power demand 2520 MW. The system considers valve point effects along with power balance and transmission loss. [Table 3] holds the simulation results of 13-unit power systems with a power demand of 2520MW. To evaluate the performance of the proposed algorithm on EPD, the results are compared with existing techniques such as OGOW [40], GWO [41], OIWO [42], SDE [43] and ORCCRO [44]. On comparing the results of proposed algorithm in the given test bed, the results show that the proposed algorithm outperforms existing techniques in terms of fuel cost consumption. The test data are found in [32].

**Table 3:** Unit output of different methods for test case 2

Unit	OGWO	GWO	OIWO	SDE	ORCCRO	OCSA
P1	628.2940	628.1678	628.3185	628.32	628.32	549.5416
P2	299.1803	298.9229	299.1989	299.20	299.20	278.7213
P3	297.5041	298.2269	299.1991	299.20	299.20	359.9482
P4	159.7284	159.7232	159.7331	159.73	159.73	148.0571
P5	159.7325	159.7210	159.7331	159.73	159.73	173.2179
P6	159.7295	159.7270	159.7331	159.73	159.73	179.0255
P7	159.7334	159.7173	159.7330	159.73	159.73	174.535
P8	159.7323	159.6793	159.7331	159.73	159.73	148.8514
P9	159.7327	159.6673	159.7330	77.40	77.40	142.4425
P10	77.3963	77.3971	77.3953	113.12	112.14	66.26028
P11	114.7487	114.6051	113.1079	92.40	92.40	107.6776
P12	92.3974	92.3886	92.3594	92.40	92.40	97.00774
P13	92.3780	92.3550	92.3911	92.40	92.40	91
Total Loss	40.2874	40.2983	40.3686	40.43	39.43	16.286
Total Cost	24512.7250	24514.4774	24514.83	24514.88	24513.91	24320.35

### Test System 3

In this test system 40 power units are considered for evaluating the performance of proposed algorithm in the simulated environment. The system has been evaluated with the power demand 10500 MW. Transmission loss is neglected in 40 generation power systems for comparison purpose of the proposed algorithm. [Table 4] holds the simulation results of 40-unit power systems with a power demand of 10500 MW. To validate the performance of the proposed algorithm on EPD, the results are compared with other variants of Cuckoo search such as [34], NNCS [35], HSACS [36] and CECS [39]. On comparing the results of proposed algorithm in the given test bed, the results show that the proposed algorithm outperforms existing techniques in terms of fuel cost consumption. The test data are found in [33].

**Table 4:** Unit output of different methods for test case 3

Unit	GGCS	NNCS	HSACS	GGCS	CECS	OCSA
P1	50.70948	64.08755	74.42451	36	91.39232	36
P2	114	110.7719	110.7608	113.0483	105.9526	101.9321
P3	120	120	66.37267	71.69646	114.2243	82.0777
P4	190	160.4973	168.8296	146.588	189.7303	168.7644
P5	97	87.13556	97	97	97	97
P6	105.5822	129.7955	137.3084	91.71777	104.5073	84.9458
P7	208.5234	219.6922	300	298.7696	230.0757	297.9823

P8	290.6988	268.0003	291.8245	268.5739	243.3768	290.2042
P9	166.1162	209.1052	177.0825	270.1083	274.1762	245.0909
P10	214.1494	288.5109	182.6113	142.4041	294.3056	182.892
P11	375	299.4434	333.2223	335.1445	159.5352	156.1595
P12	268.3552	328.7383	193.0712	341.1426	94	260.9524
P13	500	329.5528	267.5022	220.3067	368.5003	454.9511
P14	195.7186	370.5926	500	500	195.2312	412.1025
P15	215.1643	331.1107	500	193.1617	376.9174	240.4924
P16	198.575	500	436.8967	438.3321	500	358.4201
P17	500	452.649	499.5347	457.9635	404.5655	500
P18	500	418.0952	498.5542	492.5126	481.227	500
P19	547.7405	318.0209	517.5683	406.1257	495.5848	526.2942
P20	550	462.2571	270.1213	548.2812	522.3797	550
P21	550	549.6432	396.4421	506.9649	485.074	550
P22	447.5882	549.5902	442.9756	260.5514	532.9034	539.2501
P23	550	301.8208	535.9142	528.2371	530.896	550
P24	550	546.6685	549.9532	534.3838	492.7228	333.6466
P25	543.1754	506.7675	533.5099	550	395.0965	549.994
P26	550	548.5131	466.9563	545.9104	544.8522	550
P27	38.9467	38.97291	21.4302	10	29.29106	10
P28	10	42.99519	10	18.56083	49.74159	10
P29	25.19344	17.44346	15.56426	46.20762	36.6943	18.60118
P30	97	97	97	97	97	87.98265
P31	160.2971	190	190	190	190	190
P32	190	190	190	190	190	190
P33	190	190	190	190	190	176.3939
P34	181.8816	115.2958	108.9326	200	187.0463	108.4217
P35	142.4572	200	199.1489	124.8424	182.3224	90
P36	200	156.5702	127.998	176.376	200	90
P37	100.932	53.14813	76.0706	76.09422	76.68901	110
P38	105.0013	72.60135	89.30453	79.88293	106.1308	103.1142
P39	52.85066	104.2112	71.91103	78.7876	109.8352	103.4303
P40	345.9452	510.897	524.6997	549.7684	508.5204	515.4442
TOTAL COST	124053.7	125878.4	124684.6	124885.8	123947.2	<b>123189.6</b>

## CONCLUSION

In this work, an effective OCSA is proposed for solving EPD with valve point effects, equality and non-equality constraints. Three test cases are used in this paper for evaluating and validating the proposed algorithm which consists 10, 13 and 40 power systems. The advantage of oppositional based learning is to intensify the search towards exploitation for obtaining optimal solutions. Experimental results show that OCSA outperforms in terms of fuel cost consumption. The convergence of the proposed algorithm towards optimal solution is higher when compared with other compared algorithms. Future enhancement of this work can be done with more limit factors of EPD.

### CONFLICT OF INTEREST

There is no conflict of interest

### ACKNOWLEDGEMENTS

None

### FINANCIAL DISCLOSURE

None

## REFERENCES

- [1] Ding T, Bo R, Li F, Sun H. [2015] A bi-level branch and bound method for economic dispatch with disjoint prohibited zones considering network losses, IEEE Transactions on Power Systems, 30(6):2841-2855.
- [2] Jadoun VK, Gupta N, Niazi KR, Swarnkar A. [2015] Modulated particle swarm optimization for economic emission dispatch. International Journal of Electrical Power & Energy Systems, 73: 80-88.
- [3] Elattar, Ehab E. [2015] A hybrid genetic algorithm and bacterial foraging approach for dynamic economic dispatch problem. International Journal of Electrical Power & Energy Systems 69: 18-26.
- [4] Dubey, Hari Mohan, Manjaree Pandit, Panigrahi BK. [2015] Hybrid flower pollination algorithm with time-varying fuzzy selection mechanism for wind integrated multi-objective dynamic economic dispatch. Renewable Energy 83: 188-202.
- [5] Jayakumar N, Subramanian S, Ganesan S, Elanchezian EB. [2016] Grey wolf optimization for combined heat and power dispatch with cogeneration systems. International Journal of Electrical Power & Energy Systems, 74:252-264.
- [6] Beigvand, Soheil Derafshi, Hamdi Abdi, Massimo La Scala. [2016] Combined heat and power economic dispatch problem using gravitational

- search algorithm." *Electric Power Systems Research* 133: 160-172.
- [7] Elsayed, Wael T, Ehab F El-Saadany. [2015] A fully decentralized approach for solving the economic dispatch problem. *IEEE Transactions on Power Systems* 30(4): 2179-2189.
- [8] Walters, David C, Gerald B Sheble. [1993] Genetic algorithm solution of economic dispatch with valve point loading. *IEEE transactions on Power Systems* 8(3): 1325-1332.
- [9] Gaing, Zue-Lee. [2003] Particle swarm optimization to solving the economic dispatch considering the generator constraints. *IEEE transactions on power systems* 18(3): 1187-1195.
- [10] Noman, Nasimul, Hitoshi Iba. [2008] Differential evolution for economic load dispatch problems. *Electric Power Systems Research* 78(8): 1322-1331.
- [11] Shaw Bikash, V Mukherjee, Sakti Prasad Ghoshal. [2011] Seeker optimisation algorithm: application to the solution of economic load dispatch problems. *IET generation, transmission & distribution* 5(1): 81-91.
- [12] Wang, Ling, and Ling-po Li. [2013] An effective differential harmony search algorithm for the solving non-convex economic load dispatch problems. *International Journal of Electrical Power & Energy Systems* 44(1): 832-843.
- [13] Secui, Dinu Calin. [2015] The chaotic global best artificial bee colony algorithm for the multi-area economic/emission dispatch. *Energy* 93: 2518-2545.
- [14] Moradi-Dalvand M, Mohammadi-Ivatloo B, Najafi A, Rabiee A. [2012] Continuous quick group search optimizer for solving non-convex economic dispatch problems. *Electric Power Systems Research*, 93: 93-105.
- [15] Zhou J, Wang C, Li Y, Wang P, Li C, Lu P, Mo L. [2017] A multi-objective multi-population ant colony optimization for economic emission dispatch considering power system security. *Applied Mathematical Modelling*.
- [16] Jiang Y, Xu J, Sun Y, Wei C, Wang J, Ke D, Tang B. [2017] Day-ahead stochastic economic dispatch of wind integrated power system considering demand response of residential hybrid energy system. *Applied Energy*, 190: 1126-1137.
- [17] Wang, Xu, Chuanwen Jiang, Bosong Li. [2016] Active robust optimization for wind integrated power system economic dispatch considering hourly demand response. *Renewable Energy* 97: 798-808.
- [18] Wei W, Liu F, Wang J, Chen L, Mei S, Yuan T. [2016] Robust environmental-economic dispatch incorporating wind power generation and carbon capture plants. *Applied Energy*, 183:674-684.
- [19] Qu BY, Lian JJ, Zhu YS, Wang ZY, Suganthan PN. [2016] Economic emission dispatch problems with stochastic wind power using summation based multi-objective evolutionary algorithm. *Information Sciences*, 351: 48-66.
- [20] Shilaja C, Ravi K. [2017] Optimization of emission/economic dispatch using euclidean affine flower pollination algorithm (eFPA) and binary FPA (BFPA) in solar photo voltaic generation. *Renewable Energy* 107: 550-566.
- [21] Nguyen, Thang Trung, Dieu Ngoc Vo, Bach Hoang Dinh. [2016] Cuckoo search algorithm for combined heat and power economic dispatch." *International Journal of Electrical Power & Energy Systems* 81: 204-214.
- [22] Nguyen, Thang Trung, and Dieu Ngoc Vo. [2015] The application of one rank cuckoo search algorithm for solving economic load dispatch problems. *Applied Soft Computing* 37: 763-773.
- [23] Mellal, Mohamed Arezki, Edward J Williams. [2015] Cuckoo optimization algorithm with penalty function for combined heat and power economic dispatch problem. *Energy* 93: 1711-1718.
- [24] Sekhar, Pudi, and Sanjeeb Mohanty. [2016] An enhanced cuckoo search algorithm based contingency constrained economic load dispatch for security enhancement. *International Journal of Electrical Power & Energy Systems* 75: 303-310.
- [25] Basu, M., and A. Chowdhury. [2013] Cuckoo search algorithm for economic dispatch. *Energy* 60: 99-108.
- [26] Nguyen, Thang Trung, and Dieu Ngoc Vo. [2016] An efficient cuckoo bird inspired meta-heuristic algorithm for short-term combined economic emission hydrothermal scheduling. *Ain Shams Engineering Journal*.
- [27] Yang, Xin-She, and Suash Deb. [2010] Engineering optimization by cuckoo search. *International Journal of Mathematical Modelling and Numerical Optimization* 1.4: 330-343.
- [28] Tizhoosh, Hamid R. [2015] Opposition-based learning: a new scheme for machine intelligence. *Computational intelligence for modelling, control and automation, 2005 and international conference on intelligent agents, web technologies and internet commerce, international conference on*. Vol. 1. IEEE.
- [29] Roy, Provas Kumar, Chandan Paul, and Sneha Sultana. [2014] Oppositional teaching learning based optimization approach for combined heat and power dispatch. *International Journal of Electrical Power & Energy Systems* 57: 392-403.
- [30] Roy, Provas Kumar, and Dharmadas Mandal. [2014] Oppositional biogeography-based optimisation for optimal power flow." *International Journal of Power and Energy Conversion* 5(1): 47-69.
- [31] Sen, Tanuj, and Hitesh Datt Mathur. [2016] A new approach to solve Economic Dispatch problem using a Hybrid ACO-ABC-HS optimization algorithm." *International Journal of Electrical Power & Energy Systems* 78: 735-744.
- [32] Črepinšek, Matej, Shih-Hsi Liu, Marjan Mernik. [2013] Exploration and exploitation in evolutionary algorithms: A survey. *ACM Computing Surveys (CSUR)*, 45(3):3.
- [33] Nidul Sinha,, Chakrabarti R, PK. Chattopadhyay. [2003] Evolutionary programming techniques for economic load dispatch. *IEEE Transactions on evolutionary computation* 7(1): 83-94.
- [34] Dhabal, Supriya, Palaniandavar Venkateswaran. [2017] An efficient gbest-guided Cuckoo Search algorithm for higher order two channel filter bank design. *Swarm and Evolutionary Computation* 33: 68-84.
- [35] Wang, Lijin, Yiwen Zhong, Yilong Yin. [2016] Nearest neighbour cuckoo search algorithm with probabilistic mutation. *Applied Soft Computing* 49: 498-509.
- [36] Mlakar Uroš, Iztok Fister.[2016] Hybrid self-adaptive cuckoo search for global optimization. *Swarm and Evolutionary Computation* 29: 47-72.



- [37] Govindharaj I, Karthiga S, Manishalakshmi R, Mary Silvia Theodore R. [2016] Home Power Analyzer with Smart Power Monitoring using IoT", International Research Journal of Advanced Engineering Sciences and Technologies, ISSN: 2455 - 8907, 2(1): 7-13.
- [38] Rajadurai R, Amelia, Aubrey, Anusha A, Danapriya P, Geethashnee D. [2017] Efficient Data Leakage Prevention Strategy using Key Distribution", International Research Journal of Advanced Engineering Sciences and Technologies, ISSN: 2455 - 8907, 3(1): 9-16.
- [39] Anusha B, Noah C. Sivaranjani, Priyanka S, [2015] Predictive analysis of movie reviews using hybrid approach", International Research Journal of Advanced Engineering Sciences and Technologies, ISSN: 2455 - 8907,1(1): 1-7.
- [40] Pradhan, Moumita, Provas Kumar Roy, and Tandra Pal. [2017] Oppositional based grey wolf optimization algorithm for economic dispatch problem of power system. Ain Shams Engineering Journal.
- [41] Wong, Lo Ing, MH Sulaiman, Mohamed MR, Mee Song Hong. [2014] Grey Wolf Optimizer for solving economic dispatch problems. In Power and Energy (PECon) IEEE International Conference on, pp. 150-154. IEEE.
- [42] Bhattacharjee, Kuntal, Aniruddha Bhattacharya, and Sunita Halder nee Dey. [2014] Oppositional real coded chemical reaction optimization for different economic dispatch problems. International Journal of Electrical Power & Energy Systems 55: 378-391.
- [43] Ciornei, Irina, and Elias Kyriakides. [2012] A GA-API solution for the economic dispatch of generation in power system operation. IEEE Transactions on power systems 27(1): 233-242.
- [44] Bhattacharya, Aniruddha, Pranab Kumar Chattopadhyay. [2010] Biogeography-based optimization for different economic load dispatch problems. IEEE transactions on power systems 25(2): 1064-1077.