

Economic Load Dispatch with Multiple Fuel Options and Valve Point Effect Using Cuckoo Search Algorithm with Different Distributions

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Abstract

Cuckoo Search Algorithm (CSA), a new meta-heuristic algorithm based on natural phenomenon of Cuckoo species and Lévy flights random walk has been widely and successfully applied to several optimization problems so far. In the paper two modified versions of CSA, where new solutions are generated using two distributions including Gaussian and Cauchy distributions in addition to imposing bound by best solutions mechanism are proposed for solving economic load dispatch (ELD) problem with multiple fuel options. The advantages of CSA with Gaussian distribution (CSA-Gauss) and CSA with Cauchy distribution (CSA-Cauchy) over CSA with Lévy distribution and other meta-heuristic are fewer parameters. The proposed CSA methods are tested on two systems with several load cases and obtained results are compared to other methods. The result comparisons have shown that the proposed methods are highly effective for solving ELD problem with multiple fuel options and/nor valve point effect.

Keywords: Cuckoo Search algorithm, economic load dispatch, multiple fuel options, valve point effect, Gaussian distribution, Cauchy distribution

Nomenclature

a_{ij}, b_{ij}, c_{ij}	fuel cost coefficients for fuel type j of unit i ;
e_{ij}, f_{ij}	fuel cost coefficients for fuel type j of unit i reflecting valve-point effects;
N	total number of generating units;
m_i	number of fuel types of unit i ;
P_i	power output of unit i ;
$P_{i,max}$	maximum power output of unit i ;
$P_{i,min}$	minimum power output of unit i ;
$P_{ij,min}$	minimum power output for fuel j of unit i ;
P_D	total system load demand;
P_L	total transmission loss;

1. Introduction

The objective of economic load dispatch (ELD) is to minimize total fuel cost of thermal units while satisfying both equality and inequality constraints including load balance constraint, upper and lower generation limit on thermal units [1]. Traditionally, the fuel cost function of thermal unit is approximately represented as one single quadratic curve because each generating unit used only one fossil fuel to produce electricity. However, it is more realistic to represent the fuel function as a segmented piece-wise quadratic functions because several fuels are burned [2].

Several methods have been applied for solving ELD problem with multiple fuel options so far. The lambda-iteration has been valued as a simple and effective one [3]. However, the disadvantages of the method are that the values of lambda and updated step size are randomly chosen initially. This can lead to a non-optimal solution or non-convergence. The best solution has been found after the method has been performed 93 independent runs with various values of lambda and fuel type. The computational time for each trial is short but total time for whole is long. Enhanced Augmented Lagrange Hopfield Network (ALHN) [4] solves ELD problem in two phases and gains good solutions and short simulation time. However, the gained simulation results depend on setting a large number of parameters. The Differential Evolution (DE) [5] algorithm is found to be a powerful evolutionary algorithm for global optimization in many real problems. Self-Adaptive Differential Evolution (SDE) [6] is a good method to solve ELD problem with valve point effects. The application of Hopfield neural network (HNN) [7] with merit of simplicity created difficulties in handling some kinds of inequality constraints. For solving the problem by the enhanced Lagrangian neural network (ELANN) [1] method, the dynamics of Lagrange multipliers including equality and inequality constraints were improved to guarantee its convergence to the optimal solutions, and the momentum technique was also employed in its learning algorithm to achieve fast computational time. Both HNN [7] and ELANN [1] were involved a large number of iterations for convergence.

Particle Swarm Optimization [8] (PSO) is one of the modern heuristic algorithms and has a great potential to solve complex optimization problems. PSO algorithm is highly robust yet remarkably simple to implement. Thus, it is quite pertinent to apply the PSO with new modifications to achieve better optimization and handle the power system problems efficiently [9]. Hierarchical approach based on the numerical method (HNUM) [9] is one of conventional method which is non-effective for solving non-smooth fuel cost function. With a parallel searching mechanism, the improved evolutionary programming (IEP) [11] method has a high probability of finding an optimal solution. By combining equivalent function and Lagrange multiplier theory or Hopfield Lagrange network, two methods including Lambda Iterative (LI) and Hopfield Lagrange network have been proposed for solving economic dispatch [12]. The two methods have obtained good solution quality; however, the applicability of the two ones is restricted on the system with valve point effect on thermal units. The genetic algorithm (GA) [13] is critically dependent on the fitness function and sensitive to the mutation and crossover rates, the encoding scheme of its bits, and the gradient of the search space curve leading toward solutions.

The cuckoo search algorithm (CSA) developed by Yang and Deb in 2009 [14] is a new meta-heuristic algorithm for solving optimization problems inspired from the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds of other species. To verify the effectiveness of the CS algorithm, Yang and Deb compared its performance with particle swarm optimization (PSO) and GA for ten standard optimization

benchmark functions [14]. As observed from the obtained results, the CSA method has been outperformed both PSO and GA methods for all test functions in terms of success rate in finding optimal solution and the number of required objective function evaluations. The highlighted advantages of the CSA method are fine balance of randomization and intensification and less number of control parameters. Recently, CSA has been successfully applied for solving non-convex economic dispatch (ED) problems considering generator and system characteristics including valve point loading effects, multiple fuel options, prohibited operating zones, spinning reserve and power loss [15]. In addition, CSA has been also used for solving the ED and micro grid power dispatch problems [16], economic emission dispatch problems [17], short-term hydrothermal scheduling problems [18] and photovoltaic system [19]. For these problems, CSA has been tested on many systems and obtained better solution quality than several methods in the literature such as HNN, GA, EP, Taguchi method, biogeography-based optimization (BBO), PSO, DE, and Tabu search. Therefore, CSA is an efficient method for solving optimal problems.

In this paper, a cuckoo search algorithm (CSA) with different distributions including Gaussian distribution and Cauchy distribution, and bound by best solutions mechanism [20] are combined in order to solve ELD problems with multiple fuel options neglecting power losses in transmission systems and considering upper and lower generation of thermal units. The advantages of CSA with Gaussian distribution (called CSA-Gauss) and Cauchy distributions (called CSA-Cauchy) over CSA with Lévy distribution (called CSA- Lévy) in [14-18] not only are fewer equations and fewer control parameters but also reduce a step of evaluating fitness function value. The effectiveness of the proposed CSA has been tested on two systems where valve point effect considered with several load cases and the obtained results have been compared to those from other methods available in the literature.

2. Related Work

Conventional CSA has been successfully used for solving economic load dispatch problem in [15-16] and emission economic load dispatch in [17]. The method is slightly modified by using other distributions, Cauchy and Gaussian distributions and bound by best solution mechanism for handling power balance constraint.

3. Problem Formulation

The objective of the ED problem with multiple fuel options is only to minimize the total cost of thermal generating units while satisfying different constraints including power balance and generation limits.

Mathematically, the problem is formulated as follows:

$$\text{Min } F = \sum_{i=1}^N F_i(P_i) \quad (1)$$

Where:

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i + c_{i1}P_i^2, & \text{fuel 1, } P_{i,\min} \leq P_i \leq P_{i1,\max} \\ a_{i2} + b_{i2}P_i + c_{i2}P_i^2, & \text{fuel 2, } P_{i2,\min} \leq P_i \leq P_{i2,\max} \\ \dots \\ a_{ij} + b_{ij}P_i + c_{ij}P_i^2, & \text{fuel } j, P_{ij,\min} \leq P_i \leq P_{ij,\max} \end{cases} \quad (2)$$

when the valve point effect of thermal units are considered, fuel cost function for fuel type j of unit i is determined by:

$$F_i(P_i) = a_{ij} + b_{ij}P_i + c_{ij}P_i^2 + |e_{ij} \times \sin(f_{ij} \times (P_{ij,\min} - P_i))| \quad (3)$$

Subject to:

- *Power balance constraints:* the power generated by all thermal units must be equal to load demand

$$\sum_{i=1}^N P_i - P_D = 0 \quad (4)$$

- *Generator operating limits:*

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

4. Cuckoo Search Algorithm for ELD Problems with Multiple Fuel Options

4.1. Calculation of Generation for Slack Thermal Unit

To guarantee that the equality constraint (4) is always satisfied, a slack generating unit 1 is selected and therefore its power output will be dependent on the power output of remaining $N-1$ generating units in the system. Suppose that the power output of the $N-1$ generating units are known, the power output of the slack unit s is calculated based on (4) as follows:

$$P_1 = P_D - \sum_{i=2}^N P_i \quad (6)$$

4.2. Bound by Best Solutions

In ELD problems, a solution generated may contain some dimensions violating the limits of maximum and minimum generation. The issue is solved by assigning the maximum or minimum generation to the invalid dimensions as the dimension is either higher or lower than upper or lower generation. Instead, a bound by best solutions algorithm is introduced by Ahmed S. Tawfik et al [20]. There is a bound by best ratio r_{bbb} defined as in equation (7) in order to find valid dimensions for the invalid dimensions. A number is then generated randomly. If the random number is less than bound by best ratio, the invalid dimension is initialized in range of minimum and maximum value of it. Otherwise, the invalid one is replaced with another valid dimension drawn randomly from another nest.

$$r_{bbb} = 1 - 1/\sqrt{D} \quad (7)$$

where D is the number of dimensions.

4.3. Cuckoo Search Algorithm Implementation to The Problem

The main steps for the proposed CSA for solving EELD problem are described as follows:

4.3.1. Initialization: A population of N_p host nests is represented by $X = [X_1, X_2, \dots, X_{N_p}]^T$, where each nest $X_d = [P_{d2}, \dots, P_{dN}]$ ($d = 1, \dots, N_p$) representing for power output of from the generating unit 2 to unit N except the slack unit P_{ds1} is initialized by:

$$X_{di} = P_{i\min} + rand_1 * (P_{i\max} - P_{i\min}) \quad (8)$$

where $rand_1$ is a uniformly distributed random number in $[0, 1]$ for each population of the host nests.

Based on the initial population of nests, the fitness function to be minimized corresponding to each nest for the considered problem is calculated:

$$FT_d = \sum_{i=1}^N (F_i(P_{id}) + K_s(P_{d1} - P_s^{\text{lim}})^2) \quad (9)$$

where K_s is a penalty factor for the slack unit; P_{d1} is power output of the slack thermal unit calculated from (6) corresponding to nest d in the population. P_s^{lim} is the limit for the slack unit in (9) is obtained by:

$$P_s^{\text{lim}} = \begin{cases} P_{1\text{max}} & \text{if } P_1 > P_{1\text{max}} \\ P_{1\text{min}} & \text{if } P_1 < P_{1\text{min}} \\ P_1 & \text{otherwise} \end{cases} \quad (10)$$

where $P_{1\text{max}}$ and $P_{1\text{min}}$ are the maximum and minimum power outputs of slack thermal unit 1, respectively.

The initial population of the host nests is set to the best value of each nest $Xbest_d$ ($d = 1, \dots, N_d$) and the nest corresponding to the best fitness function in (9) is set to the best nest $Gbest$ among all nests in the population.

4.3.2. Generation of New Solution via Lévy Flights: The new solution by each nest is calculated as follows:

$$X_d^{\text{new}} = Xbest_d + \alpha \times rand_2 \times \Delta X_d^{\text{new}} \quad (11)$$

Where $\alpha > 0$ is the updated step size; $rand_2$ is a normally distributed stochastic number; and the increased value ΔX_d^{new} is determined by:

$$\Delta X_d^{\text{new}} = \text{sum}(y_j); j=1,2,\dots,N-1 \quad (12)$$

Where:

- For Cauchy distribution:

$$y_j = (\mu + s * ((\text{pi} * rand_3(1, N-1) - 0.5))); \quad (13)$$

- And for Gaussian distribution:

$$y_j = (2 * \sqrt{-\log(rand_4(1, N-1)) * \sin(\pi * rand_5(1, N-1))}); \quad (14)$$

Where N is the number of thermal and hydro units, $rand_3$, $rand_4$ and $rand_5$ are the distributed random numbers in $[0, 1]$.

For the newly obtained solution, its lower and upper limits should be satisfied according to the generating unit's limits by using bound by best solutions algorithm

The fitness function (9) will be calculated for the new eggs and are compared to that of old eggs so as to keep the better ones.

4.3.3. Alien Egg Discovery and Randomization: The action of discovery of an alien egg in a nest of a host bird with the probability of p_a also creates a new solution for the problem similar to the Lévy flights. The new solution due to this action is calculated as follows:

$$X_d^{\text{dis}} = Xbest_d + K \times \Delta X_d^{\text{dis}} \quad (15)$$

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

$$K = \begin{cases} 1 & \text{if } rand_6 < p_a \\ 0 & \text{otherwise} \end{cases} \quad (16)$$

And the increased value ΔX_d^{dis} is determined by:

$$\Delta X_d^{\text{dis}} = rand_7 \times (randp_1(Xbest_d) - randp_2(Xbest_d)) \quad (17)$$

Where $rand_6$ and $rand_7$ are the distributed random numbers in $[0, 1]$ and $randp_1(Xbest_d)$ and $randp_2(Xbest_d)$ are the random perturbation for positions of nests in $Xbest_d$.

Similar to the solution obtained via Lévy flights, this new solution is also redefined as in section 4.2, and each nest $Xbest_d$ and the best value of all nests $Gbest$ are set based on fitness value obtained from (9).

4.3.4. Stopping Criteria: The proposed algorithm is terminated when the current iteration is equal to the maximum number of iteration.

4.3.5. The Overall Procedure: The overall procedure of the proposed CSA for solving the ELD problems is described as follows.

- Step 1: Select parameters for the CSA including number of host nests N_p , probability of a host bird to discover an alien egg in its nest P_a , and maximum number of iterations N_{max} .
- Step 2: Initialize a population of N_p host nests as in Section 4.3.1 and calculate the power output for the slack unit 1 as in Section 4.1.
- Step 3: Evaluate the fitness function using (9) and store the best value for each nest $Xbest_d$ and the best value of all nests $Gbest$ in the population. Set the initial iteration counter $n = 1$.
- Step 4: Generate a new solution via Lévy flights as described in Section 4.3.2 and calculate the power output for the slack unit as in Section 4.1.
- Step 5: Evaluate the fitness function using (9) for the newly obtained solution and determine the new $Xbest_d$ and $Gbest$ via comparing the values of the fitness function.
- Step 6: Generate a new solution based on the probability of p_a as in Section 4.3.3 and calculate the power output for the slack unit 1 as in Section 4.1
- Step 7: Evaluate the fitness function using (9) and determine the newly best $Xbest_d$ and $Gbest$ for the new obtained solution.
- Step 8: If $n < N_{max}$, $n = n + 1$ and return to Step 4. Otherwise, stop.

5. Results and Discussions

The proposed algorithm is coded in Matlab platform and run twenty independent trials for each test case on a 2 GHz Laptop with 2 GB of RAM. There are two 10-unit systems tested to validate the effectiveness of the proposed method. The valve point effect on thermal units is neglected for system one but for system 2. In addition, there are four load cases of 2400, 2500, 2600 and 2700 MW for the first system whereas only 2700 MW load demand is considered for the second one.

5.1. Selection of Parameters

In the proposed CSA method, three main parameters which have to be predetermined are the number of nests N_p , maximum number of iterations N_{max} , and the probability of an alien egg to be discovered P_a .

Among the three parameters, the number of nests significantly effects on the obtained solution quality. Normally, the larger number of N_p is chosen the higher probability for a better optimal solution is obtained. However, the simulation time for obtaining the solution in case of the large numbers is long. Thus, the selection of N_p is an important task. By experience, the number of nests in this paper is set to 30. Similar to N_p , the maximum number of iterations N_{max} also has an impact on the obtained solution quality and computation time. It is chosen based on the complexity and scale of the considered problems. For the test system above, the maximum number of N_{max} is set

to 400. The value of the probability for an alien egg to be discovered can be chosen in the range [0, 1]. However, different values of P_a may lead to different optimal solutions for a problem. For the complicated or large-scale problems, the selection of value for the probability has an obvious effect on the optimal solution. In contrast, the effect is inconsiderable for the simple problems, that is different values of the probability can also lead the same optimal solution. In this paper, the value of the probability is selected in range from 0.1 to 0.9 with a step of 0.1 whereas the number of nests and the maximum number of iterations are predetermined in advance.

5.2. Obtained Results

5.2.1. System with Multiple Fuel Options and without Valve Point Effect : In the section, the two proposed methods have been tested on one system consisting of 10 generating units [1], each with two or three piecewise quadratic cost functions representing different fuel types. Total demands are gradually changed from 2,400 MW to 2,700 MW in steps of 100 MW neglecting power losses. For all test cases, the number of nests and iterations are set to the fixed values of 5 and 400, respectively. In case of 2400 MW load demand, both CSA-Cauchy and CSA-Gauss are performed twenty independent trials for each value of probability P_a ranging in from 0.1 to 0.9. The result obtained including minimum cost, average cost, maximum cost, standard deviation and computational time by the two methods for 2400 MW load demand corresponding to different values of P_a are given in Tables 1 and 2. The best cost for load cases of 2500, 2600 and 2700 MW obtained by CSA-Cauchy and CSA-Gauss at the best value of P_a are summarized in Table 3. The result comparison among the proposed method and others are indicated in Tables 4, 5, 6 and 7 corresponding to 2400 MW, 2500 MW, 2600 MW and 2700 MW load demands. Clearly, CSA-Cauchy and CSA-Gauss can obtain either better cost than or equal cost to others. Note that HNN [7] gets the best cost for 2400 MW, 2500 MW and 2600 MW load demands, however, the power generated by HNN [7] is less than load demand. Besides, all methods take approximate computational time nearly less than one second. Therefore, the proposed method is effective for the ELD problems with multiple fuel options and without valve point effect on thermal units. The best solutions obtained by CSA-Cauchy and CSA-Gauss are shown in Tables 8 and 9, respectively.

Table 1. Result obtained by CSA-Cauchy for 2400 MW Load Case with Different Values of P_a .

Pa	Min total cost (\$)	Average total cost (\$)	Max total cost (\$)	Std. dev. (\$)	Avg. CPU (s)
0.1	481.7228	481.72451	481.7301	0.00212365	0.6
0.2	481.7226	481.7227	481.7229	8.3666E-05	0.59
0.3	481.7226	481.722615	481.7228	4.7697E-05	0.62
0.4	481.7227	481.7227	481.7227	0	0.63
0.5	481.7226	481.7226	481.7226	0	0.6
0.6	481.7226	481.722615	481.7227	3.5707E-05	0.62
0.7	481.7226	481.72263	481.7227	4.5826E-05	0.64
0.8	481.7226	481.72263	481.7227	4.5826E-05	0.62
0.9	481.7226	481.72284	481.726	0.00072622	0.63

Table 2. Result obtained by CSA-Gauss for 2400 MW Load Case with Different Values of P_a .

P_a	Min total cost (\$)	Average total cost (\$)	Max total cost (\$)	Std. dev. (\$)	Avg. CPU (s)
0.1	481.7247	481.75094	481.8777	0.035413972	0.6
0.2	481.7249	481.72995	481.7457	0.005070355	0.59
0.3	481.7229	481.72503	481.7346	0.002623376	0.62
0.4	481.7227	481.72347	481.7252	0.000709295	0.63
0.5	481.7226	481.72284	481.7235	0.000205913	0.6
0.6	481.7226	481.722745	481.723	0.000132193	0.62
0.7	481.7226	481.722675	481.7228	6.22495E-05	0.64
0.8	481.7226	481.722695	481.7228	7.39932E-05	0.62
0.9	481.7226	481.722765	481.7232	0.000173997	0.63

Table 3. Result obtained by CSA-Gauss and CSA-Cauchy for 2500, 2600 and 2700 MW Load Cases

PD (MW)	Method	P_a	Min cost (\$)	Average cost (\$)	Max cost (\$)	Std. dev. (\$)	CPU (s)
2500	CSA-Cauchy	0.5	526.2388	526.2388	526.2388	0	0.62
	CSA-Gauss	0.4	526.2388	526.2388	526.2389	0	0.6
2600	CSA-Cauchy	0.4	574.3808	574.4169	574.7413	0.1081	0.64
	CSA-Gauss	0.4	574.3808	574.3992	574.7413	0.0785	0.66
2700	CSA-Cauchy	0.4	623.8092	624.2982	626.2543	0.9780	0.62
	CSA-Gauss	0.5	623.8092	624.6651	626.2548	1.1662	0.64

Table 4. Comparison of Fuel Cost and CPU Time for Load Demand of 2,400 MW

Method	Total power (MW)	Cost (\$/h)	CT (s)
HNN [7]	2,399.8	481.87	~60
ELANN[1]	2,400	481.74	11.53
SDE [6]	2,400	481.8628	-
ARCGA [13]	2,400	481.743	0.85
IEP [11]	2,400	481.779	-
DE [5]	2,400	481.723	-
ALHN [4]	2,400	481.723	0.008
LI [12]	2,399.9978	481.7217	7.84
HLN [12]	2,400	481.7226	0.124
MPSO [8]	2,400	481.723	-
HNUM [10]	2,401.2	488.50	1.08
CSA-Cauchy	2,400	481.7226	0.6
CSA-Gauss	2,400	481.7226	0.64

Table 5. Comparison of Fuel Cost and CPU Time for Load Demand of 2,500 MW

Method	Total power (MW)	Cost (\$/h)	CT (s)
HNN [7]	2,499.8	526.13	~60
ELANN[1]	2,500	526.27	12.25
SDE [6]	2,500	526.3232	-
ARCGA [13]	2,500	526.259	0.85
IEP [11]	2,500	526.304	-
DE [5]	2,500	526.239	-
ALHN [4]	2,500	526.239	0.043
LI [12]	2,500	526.239	2.508
HLN [12]	2,500	526.2388	0.11
MPSO [8]	2,500	526.239	-
HNUM [10]	2,500.1	526.7	-
CSA-Cauchy	2,500	526.2388	0.62
CSA-Gauss	2,500	526.2388	0.6

Table 6. Comparison of Fuel Cost and CPU Time for Load Demand of 2,600 MW

Method	Total power (MW)	Cost (\$/h)	CT (s)
HNN [7]	2,599.8	574.26	~60
ELANN[1]	2,600	574.41	~9.99
SDE [6]	2,600	574.538	-
ARCGA [13]	2,600	574.405	0.85
IEP [11]	2,600	574.473	-
DE [5]	2,600	574.381	-
ALHN [4]	2,600	574.381	0.047
LI [12]	2,600	574.7412	6.871
HLN [12]	2,600	574.7413	0.152
MPSO [8]	2,600	574.381	-
HNUM [10]	2,599.3	574.03	-
CSA-Cauchy	2,600	574.3808	0.64
CSA-Gauss	2,600	574.3808	0.66

Table 7. Comparison of Fuel Cost and CPU Time for Load Demand of 2,700 MW

Method	Total power (MW)	Cost (\$/h)	CT (s)
HNN [7]	2,700	626.12	~60
ELANN[1]	2,699.7	623.88	21.36
SDE [6]	2,700	623.9225	-
ARCGA [13]	2,700	623.828	0.85
IEP [11]	2,700	623.851	-
DE [5]	2,700	623.809	-
ALHN [4]	2,700	623.809	0.057
LI [12]	2699.9995	623.8089	6.221
HLN [12]	2,700	623.8092	0.225
MPSO [8]	2,700	623.809	-
HNUM [10]	2,702.2	625.18	-
CSA-Lévy [15]	2,700	623.8092	0.679
CGA-MU [20]	2,700	623.8095	19.42
IGA-MU [20]	2,700	623.8093	5.47
CSA-Cauchy	2,700	623.8092	0.62
CSA-Gauss	2,700	623.8092	0.64

Table 8. Best Solutions by CSA-Cauchy for Load Demand Cases

Unit	P _D =2400 MW		P _D =2500 MW		P _D =2600 MW		P _D =2700 MW	
	Fuel	Gen (MW)	Fuel	Gen (MW)	Fuel	Gen (MW)	Fuel	Gen (MW)
1	1	189.7409	2	206.5144	2	216.4785	2	218.2503
2	1	202.3413	1	206.4493	1	210.9338	1	211.6861
3	1	253.8795	1	265.7170	1	278.4871	1	280.6636
4	3	233.0472	3	235.9623	3	239.0739	3	239.6155
5	1	241.7778	1	258.0080	1	275.5404	1	278.5551
6	3	233.0445	3	235.9537	3	239.1303	3	239.6482
7	1	253.2645	1	268.8956	1	285.7381	1	288.5958
8	3	233.0381	3	235.9598	3	239.1013	3	239.6231
9	1	320.4039	1	331.4828	1	343.5123	3	428.5077
10	1	239.4622	1	255.0571	1	272.0043	1	274.8545

Table 9. Best Solutions by CSA-Gauss for Load Demand Cases

Unit	P _D =2400 MW		P _D =2500 MW		P _D =2600 MW		P _D =2700 MW	
	Fuel	Gen (MW)	Fuel	Gen (MW)	Fuel	Gen (MW)	Fuel	Gen (MW)
1	1	189.7509	2	206.5467	2	216.5440	2	218.2236
2	1	202.3556	1	206.4651	1	210.9076	1	211.5977
3	1	253.9436	1	265.6894	1	278.5493	1	280.7745
4	3	232.9954	3	235.9648	3	239.0997	3	239.6140
5	1	241.8100	1	257.8910	1	275.5226	1	278.5130

6	3	233.0387	3	235.9660	3	239.0966	3	239.6407
7	1	253.3112	1	268.9140	1	285.7068	1	288.8672
8	3	233.0327	3	235.9874	3	239.0962	3	239.5967
9	1	320.3529	1	331.4919	1	343.4951	3	428.3415
10	1	239.4091	1	255.0836	1	271.9821	1	274.8311

5.2.2. System with Multiple Fuel Options and Valve Point Effect: In section, a 10-unit system with multiple fuel options and valve point effect on thermal units is considered [21]. The load demand is 2700 MW and the power losses in transmission line are neglected. For implementation of CSA-Cauchy and CSA-Gauss, the number of nest and maximum number of iterations are set to 10 and 1000, respectively. The best value of P_a is found at 0.2 for both CSA-Cauchy and CSA-Gauss. The results obtained by the proposed methods are compared with other methods including improved genetic algorithm with multiplier updating (IGA-MU), conventional genetic algorithm (CGA) with multiplier updating (CGA-MU) [21], new PSO (NPSO), PSO with a simple local random search (PSO-LRS), new PSO with a simple local random search (NPSO-LRS) [22] in Table 10. As observed from the table, CSA-Cauchy and CSA-Gauss can get better cost than all methods. In term of computational time, the proposed methods are faster than CGA-MU [21] and IGA-MU [21] and lightly slower than the rest of methods. The best solution for the proposed methods are indicated in Table 11.

Table 10. Comparison of Fuel Cost and CPU Time for System with Valve Point Effect of Thermal Units

Method	Min cost (\$)	Average cost (\$)	Max cost (\$)	Std. dev. (\$)	Avg. CPU (s)
CSA- Lévy [15]	623.8684	623.9495	626.3666	0.2438	1.587
PSO-LRS [22]	624.2297	625.7887	628.3214	-	0.93
NPSO [22]	624.1624	625.218	627.4237	-	0.41
NPSO-LRS [22]	624.1273	624.9985	626.9981	-	1.08
CGA-MU [21]	624.7193	627.6087	633.8652	-	25.65
IGA-MU [21]	624.5178	625.8692	630.8705	-	7.14
CSA-Cauchy	623.8566	624.1160	626.3440	0.7395	2.1
CSA-Gauss	623.8564	624.3618	626.3474	0.9826	2.2

Table 11. Best Solutions by CSA-Gauss and CSA-Cauchy for System with Valve Point Effect

Unit	CSA_Cauchy		CSA_Gauss	
	Fuel	P _i (MW)	Fuel	P _i (MW)
1	2	218.1322	2	218.1067
2	1	211.4116	1	210.6692
3	1	281.6867	1	280.6682
4	3	238.7456	3	239.9578
5	1	279.8622	1	279.9982
6	3	240.3328	3	239.5265

7	1	287.7978	1	287.7462
8	3	238.3435	3	239.6854
9	3	427.8687	3	427.9883
10	1	275.8188	1	275.6534

6. Conclusion

In this paper, two versions of Cuckoo Search Algorithm including CSA-Cauchy and CSA-Gauss have been implemented for solving economic load dispatch problems with multiple fuel options and valve point effect on thermal units. In stead of using Lévy distribution, the advantages of Cauchy distribution and Gauss distribution over Lévy distribution are fewer parameters and fewer equations. In addition, the bound by best solution algorithm can enable CSA to find better new dimensions in case that the dimensions violate their limits. CSA-Cauchy and CSA-Gauss have been tested on two systems with several load cases and the result comparisons with other methods have indicated that the proposed methods are more efficient and faster than most of methods for solving ELD problem with multiple fuel options and/nor valve point effect.

References

- [1] S. C. Lee and Y. H. Kim, "An enhanced Lagrangian neural network for the ELD problems with piecewise quadratic cost functions and nonlinear constraints", *Electr. Power Syst. Res.*, vol. 60, (2002), pp. 167–177.
- [2] V. N. Dieu, W. Ongsakul and J. Polprasert, "The augmented Lagrange Hopfield network for economic dispatch with multiple fuel options", *Mathematical and Computer Modeling*, vol. 57, (2013), pp. 30-39.
- [3] N. T. Thang, "Solving economic dispatch problem with piecewise quadratic cost functions using lagrange multiplier theory", *Proceedings of the 3rd International Conference on Computer Technology and Development, China (2011) November*, pp. 359-364.
- [4] V. N. Dieu and W. Ongsakul, "Economic Dispatch with Multiple Fuel Types by Enhanced Augmented Lagrange Hopfield Network", *Power System Technology and IEEE Power India Conference*, (2008).
- [5] N. Nasimul and I. Hitoshi, "Differential evolution for economic load dispatch problems", *Electric Power Systems Research*, vol. 78, (2008), pp. 1322-1331.
- [6] R. Balamurugan and S. Subramanian, "Self-Adaptive Differential Evolution Based Power Economic Dispatch of Generators with Valve-Point Effects and Multiple Fuel Options", *World Academy of Science, engineering and technology*, vol. 27, (2007).
- [7] J. H. Park, Y. S. Kim, I. K. Eom and K. Y. Lee, "Economic load dispatch for piecewise quadratic cost function using Hopfield neural network", *IEEE Trans. Power Systems*, vol. 8, (1993), pp. 1030-1038.
- [8] J. B. Park, K. S. Lee, J. R. Shin and K. Y. Lee, "A particle swarm optimization for economic dispatch with nonsmooth cost functions", *IEEE Trans. Power Syst.*, vol. 20, (2005), pp. 34-42.
- [9] P. K. Roy, S. P. Ghoshal and S. S. Thakur, "Combined economic and emission dispatch problems using biogeography-based optimization", *Electr. Eng.* vol. 92, (2010), pp. 173–184.
- [10] C. E. Lin and G. L. Viviani, "Hierarchical economic dispatch for piecewise quadratic cost functions", *IEEE Trans. Power App. Syst.*, vol. PAS-103, no. 6, (1984), pp. 1170-1175.
- [11] Y. M. Park, J. R. Wong and J. B. Park, "A new approach to economic load dispatch based on improved evolutionary programming", *Eng. Intell. Syst. Elect. Eng. Commun.*, vol. 6, (1998), pp. 103–110.
- [12] N. T. Thang, "Economic emission load dispatch with multiple fuel options using Hopfiled Lagrange Network", *International Journal of Advanced Science and Technology*, vol. 57, (2013), pp. 9-24.
- [13] N. Amjady and H. Nasiri-Rad, "Solution of nonconvex and nonsmooth economic dispatch by a new adaptive real coded genetic algorithm", *Expert Syst. Appl.*, vol. 37, (2010), pp. 5239–5245.
- [14] X. S. Yang and S. Deb, "Cuckoo search via Lévy flights", In *Proc. World Congress on Nature & Biologically Inspired Computing (NaBIC 2009)*, India, (2009), pp. 210-214.
- [15] N. V. Dieu, S. Peter and W. Ongsakul, "Cuckoo search algorithm for non-convex economic dispatch", *IET Generation, Transmission & Distribution*, vol. 7, (2013), pp. 645–54.
- [16] M. Basu and A. Chowdhury, "Cuckoo search algorithm for economic dispatch", *Energy*, vol. 60, (2013), pp. 99-108.

- [17] N. T. P. Thao and N. T. Thang, "Environmental Economic Load Dispatch with Quadratic Fuel Cost Function Using Cuckoo Search Algorithm", *International Journal of u- and e- Service, Science and Technology*, vol. 7, no. 2, (2014), pp. 199-210.
- [18] N. T. Thang, V. N. Dieu and T. V. Anh, "Cuckoo search algorithm for short-term hydrothermal scheduling", *Applied Energy*, vol. 132, (2014), pp. 276-287.
- [19] A. Jubaer and S. Zainal, "A maximum power point tracking (MPPT) for PV system using Cuckoo search with partial shading capability", *Applied Energy*, vol. 119, (2014), pp. 118-30.
- [20] S. T. Ahmed, A. B. Amr and F. A. Ibrahim, "One Rank Cuckoo Search Algorithm with Application to Algorithmic Trading Systems Optimization", *International Journal of Computer Applications*, vol. 64, no. 6, (2013), pp. 30-37.
- [21] C. L. Chiang, "Improved genetic algorithm for power economic dispatch of units with valve-point effects and multiple fuel", *IEEE Trans. Power Syst.*, vol. 20, no. 4, (2005), pp. 1690-1699.
- [22] A. I. Selvakumar and K. Thanushkodi, "A new particle swarm optimization solution to nonconvex economic dispatch problems", *IEEE Trans. Power Syst.*, vol. 22, (2007), pp. 42-51.