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Economic Emission Load Dispatch with Multiple Fuel Options Using Cuckoo Search Algorithm with Gaussian and Cauchy 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 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 are proposed for economic emission load dispatch (EELD) 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 are fewer parameters and fewer equations and shorter computational process. The proposed method is tested on one test system consisting of ten generating units with various load demands and compared to other methods. In addition, the best compromise from the set of obtained solutions is found and compared to this from lamda-iteration (LI) method and Hopfield Lagrange Network (HLN). The result comparisons have indicated that the proposed method is a highly effective method.

Keywords: *Cuckoo Search algorithm, environmental economic load dispatch, quadratic fuel cost function*

Nomenclature

a_{ik}, b_{ik}, c_{ik}:	Cost coefficients of thermal unit *i* for *kth* fuel
d_{ik}, e_{ik}, f_{ik}:	Emission coefficients of thermal unit *I* for *kth* fuel
B_{ij}, B_{0i}, B_{00} :	Transmission loss formula coefficients
N:	Number of online generating units
P_D :	Total load demand of the system (MW)
P_L :	Total network loss of the system (MW)
Pi:	Output power of unit *i* (MW)
P_{imin}, P_{imax}:	Lower and upper generation limits of unit *i* (MW)
w_1, w_2	Weights corresponding to the fuel cost and NOx emission objectives.

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1. Introduction

In economic load dispatch (ELD) problems, the main task is to determine thermal generations so that the fuel cost is minimized while satisfying both equality and inequality constraints including load balance constraint, upper and lower generation limit on thermal units. Nowadays, emission control is also an important objective to consider along with fuel cost and utility planners are trying to improve their operating strategies to reduce pollution [1]. In fact, apart from heat, thermal units produce particulates and gaseous emissions. A number of substances such as CO2, SO2, NOx, dust particles etc. are emitted during the operation of thermal units. Society demands adequate and secure electricity not only at the cheapest possible price, but also at minimum level of pollutant's emission [2]. Therefore, the objective of the EELD problem is to minimize both fuel cost and the gaseous emission.

Several methods have been applied for solving ELD problem neglecting emission released into the air so far. The lamda-iteration has been valued as a simple and effective one [3]. However, the disadvantages of the method are that the values of lamda 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 lamda 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.

Traditionally, thermal units used only one fossil fuel to burn and produce electricity. The emissions of CO2, SO2, NOx are taken into account as a main objective in addition to fuel cost. Nowadays, each thermal unit can use several fuels including coal, oil and gas with higher efficiency and shorter time for supply full power to system. The emission corresponding to the burned fuel is different from another. As a result, the ELD problem is expanded more one objective of emission [8]. There are two method performed in [8] where Hopfield Lagrange network (HLN) is proposed and Lamda-iteration method (LIM) is used again to make comparison with HLN. An approximated method used to simplify the fuel cost function with valve point effect represented several single-piecewise functions into one function. The HLN method is faster and more effective than LIM. However, the disadvantage of the HLN method is the task of selection of control parameter, which is in a large none-predetermined range. Therefore, in the paper a Cuckoo Search Algorithm is presented for solving the emission economic dispatch with multi fuel options.

The cuckoo search algorithm (CSA) developed by Yang and Deb in 2009 [9] 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. Several studies of the CSA for solving different optimization problems have been shown for recent years. Yang and Deb [9] have tested the CSA on ten standard optimization benchmark functions. Via comparison with PSO and GA, CSA is judged more effectively with higher successful rate and better solution quality. Several more complex problems were then solved by CSA such as non-convex economic dispatch problems [10], micro grid power dispatch problems [11], economic emission dispatch problems [12], short-term hydrothermal scheduling problems [13] and photovoltaic system [14]. For these problems, CSA has been tested on many systems and obtained better solution quality than several methods like HNN, GA, EP, PSO, DE, etc. 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 is proposed for solving EELD 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 [9-14] 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 one system with several load cases and the obtained results have been compared to those from HLN and LIM.

2. Problem Formulation

The main objective of the EELD problem is to find a suitable fuel for each generating unit in order to minimize both the total cost and the emissions given off from thermal generating while satisfying different constraints including power balance and generation limits.

Mathematically, the problem is formulated as follows:

$$Min\sum_{i=1}^{N}F_i=\sum_{i=1}^{N}\left(w_1F_{1i}(P_i)+w_2F_{2i}(P_i)\right) \tag{1}$$

Where:

$$F_{1i}(P_i)=\begin{cases}c_{i1}P_{i1}^2+b_{i1}P_{i1}+a_{i1} \\ \qquad if\ \ P_{i1}^{\min}\le P_{i1}\le P_{i1}^{\max}\ \ for\ fuel\ 1 \\ \vdots \\ c_{ik}P_{ik}^2+b_{ik}P_{ik}+a_{ik} \\ \qquad if\ \ P_{ik}^{\min}\le P_{ik}\le P_{ik}^{\max}\ \ for\ fuel\ k\end{cases} \tag{2}$$

$$F_{2i}(P_i)=\begin{cases}f_{i1}P_{i1}^2+e_{i1}P_{i1}+d_{i1} \\ \qquad if\ \ P_{i1}^{\min}\le P_{i1}\le P_{i1}^{\max}\ \ for\ fuel\ 1 \\ \vdots \\ f_{ik}P_{ik}^2+e_{ik}P_{ik}+d_{ik} \\ \qquad if\ \ P_{ik}^{\min}\le P_{ik}\le P_{ik}^{\max}\ \ for\ fuel\ k\end{cases} \tag{3}$$

Subject to:

1. Power balance constraints:

$$\sum_{i=1}^{N} P_i - P_L - P_D = 0 \tag{4}$$

$$P_{Lk} = \sum_{i=1}^{N_1}\sum_{j=1}^{N_1} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00} \tag{5}$$

2. Generator operating limits:

$$P_{i\min} \le P_i \le P_{i\max} \tag{6}$$

3. Weight constraint [15]:

$$w_1 + w_2 = 1 \tag{7}$$

where $0 \le w_1, w_2 \le 1$

3. Cuckoo Search Algorithm for EELD Problem

3.1. Calculation of Generation for Slack Thermal Unit

In order to exactly meet power balance equation (4), a slack technique is used in the paper for handling the equality constraint. In fact, the first thermal unit is regarded as the slack unit and needs to be determined based on equation (4) whereas the rest of thermal units from the second to the *Nth* are given before. In the paper, power loss in transmission line is neglected. Therefore, the slack unit 1 is obtained by:

$$P_{s1} = P_D - \sum_{i=2}^{N} P_i \tag{8}$$

3.2. Cuckoo Search Algorithm Impelentation

The EELD probelm solved by using CSA with Cauchy distribution and Gaussian distribution called CSA-Cauchy and CSA-Gauss is described as follows:

1) Initialization: Like other meta-heuristic algorithms, there is a population of host nest, Np in the CSA methods represented by $X = [X_1, X_2, \ldots, X_{Np}]^T$, where each nest $X_d = [P_{d2}, \ldots\ldots, P_{dN}]$ ($d = 1, \ldots, N_p$). Each nest contains from the second thermal unit to the final unit and is initialized randomly as below:

$$X_{di} = P_{i\min} + rand_1 * (P_{i\max} - P_{i\min}) \tag{9}$$

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

Each nest from the initialized population is evaluated based on fitness function in equation (10):

$$FT_d = \sum_{i=1}^{N} \left(w_1 F_{1i}(P_{id}) + w_2 F_{2i}(P_{id}) \right) + K_s (P_{ds1} - P_s^{\lim})^2 \tag{10}$$

where w_1, w_2 must satisfy (7), K_s is a penalty factor for the slack unit; P_{ds1} is power output of the slack thermal unit calculated from section 3.1 and $P_s^{\lim}$ is the limit for the slack unit is obtained by:

$$P_s^{\lim} = \begin{cases} P_{s\max} & if\ P_{ds1} > P_{1\max} \\ P_{s\min} & if\ P_{ds1} < P_{1\min} \\ P_{ds1} & \text{otherwise} \end{cases} \tag{11}$$

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

All initial population of the host nests is set to best value of each nest $Xbest_d$ ($d = 1, \ldots, N_d$) and stored.

2) *Generation of New Solution via Lévy Flights:* The new solution is calculated based on the previous best nests via Lévy flights. In the proposed CSA method, the optimal path for the Lévy flights is calculated and then the new solution by each nest is obtained as follows:

$$X_d^{new} = Xbest_d + \alpha \times rand_2 \times \Delta X_d^{new} \tag{12}$$

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

$$\Delta X_d^{new} = \sum_{j=1}^{N-1}\left(\mu + s*((\mathrm{pi}*\mathrm{rand}(1, \mathrm{N}-1) - 0.5))\right);\ \mathrm{j} = 1, 2, \ldots\ldots, \mathrm{N}-1 \tag{13}$$

$$\Delta X_d^{new} = \sum_{j=1}^{N-1}\left(2*\sqrt{-\log(rand(1, N-1)}*\sin(\pi*\mathrm{rand}(1, \mathrm{N}-1))\right);\ \mathrm{j} = 1, 2, \ldots\ldots, \mathrm{N}-1 \tag{14}$$

The equations (13) and (14) are Cauchy distribution and Gaussian distribution, respectively. The two ones are defined as symmetrical distribution and described in [16-17].

For the newly obtained solution, its lower and upper limits should be satisfied according to the generating unit's limits:

$$X_{di}^{new} = \begin{cases} P_{i\max} & if\ X_{di} > P_{i\max} \\ P_{i\min} & if\ X_{di} < P_{i\min} \\ X_{di} & \text{otherwise} \end{cases} \tag{15}$$

The fitness function (10) will be reevaluated for the new solution. The new eggs are compared to old eggs stored in Section 3.2.1 and the eggs with lower fitness are retained and store.

3) Alien Egg Discovery and Randomization: Like Lévy flights in Section 3.2, the new solution is also generate corresponding to the action of an alien egg discovery with the probability of Pa as follows:

$$X_d^{dis} = Xbest_d + K \times \Delta X_d^{dis} \tag{16}$$

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

$$K = \begin{cases} 1 & \text{if } rand_3 < p_a \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

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

$$\Delta X_d^{dis} = rand_4 \times \left(randp_1(Xbest_d) - randp_2(Xbest_d) \right) \tag{18}$$

where $rand_3$ and $rand_4$ 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 (15), and each nest $Xbest_d$ and the best value of all nests *Gbest* are set based on fitness value obtained from (10).

4) Stopping Criteria: The iterative procedure of the proposed algorithm stops to obtain the final optimal solution as the maximum number of iterations is reached.

3.3. The overall procedure

The overall procedure of the proposed CSA for solving the EELD 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 3.2.1 and calculate the power output for the slack unit 1 as in Section 3.1.

Step 3: Evaluate the fitness function using (10) 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 3.2.2 and calculate the power output for the slack unit as in Section 3.1

Step 5: Evaluate the fitness function using (10) 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 3.2.3 and calculate the power output for the slack unit 1 as in Section 3.1

Step 7: Evaluate the fitness function using (10) 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.

4. Best Compromise Solution by Fuzzy-Based Mechanism

In the environmental economic load dispatch, there often exists a conflict among fuel cost and emission objectives. Thus, the best compromise solution for the EELD problem needs to be determined [8]. A set of optimal solutions is first determined and the best compromise is then calculated by using fuzzy satisfying method [16]. The fuzzy goal is represented in linear membership function as follows [18]:

$$\mu(F_j) = \begin{cases} 1 & if \quad F_j \le F_{j\min} \\ \dfrac{F_{j\max} - F_j}{F_{j\max} - F_{j\min}} & if \quad F_{j\min} < F_j < F_{j\max} \\ 0 & if \quad F_j \ge F_{j\max} \end{cases} \tag{19}$$

Where F_j is the value of objective j; F_{jmax} and F_{jmin} are maximum and minimum values of objective j, respectively.

For each k non-dominated solution, the membership function is normalized as follows [15]:

$$\mu_D^k = \sum_{i=1}^{Nobj} \mu(F_i^k) \Big/ \sum_{k=1}^{Ns} \sum_{i=1}^{Nobj} \mu(F_i^k) \tag{20}$$

where μ^k_D is the cardinal priority of kth non-dominated solution, $\mu(F^k_i)$ is membership function of objective j, N_{obj} is number of objective functions, and N_s is number of Pareto-optimal solutions.

The solution that attains the maximum membership μ^k_D in the fuzzy set is chosen as the ‘best’ solution based on cardinal priority ranking:

$$\text{Max } \{\mu^k_D: k = 1, 2, \dots , N_p\} \tag{28}$$

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. In addition, there are four load cases of 2400, 2500, 2600 and 2700 MW for the system.

In this section, CSA-Cauchy and CSA-Gauss are performed for determining thermal generation for economic dispatch and emission dispatch corresponding to $w_1=1$ and $w_1=0$, respectively. To implement CSA, the number of nest Np and the maximum number of iterations are set to 10 and 450 in advance. The probability Pa is then changed in range from 0.1 to 0.9 with a step of 0.1. For each case, the CSA is run twenty independent trials. For economic dispatch, the obtained results including minimum total cost, average total cost, maximum total cost, standard deviation cost from CSA-Cauchy and CSA-Gauss for load of

2400 MW with different values of Pa are given in Tables 1 and 2. Similarly, the obtained results for emission dispatch are given in Table 3 for CSA-Cauchy and Table 4 for CSA-Gauss. As observed from Tables 1 to 4, the best solution is obtained at Pa=0.2-0.9 for all cases. On the other hand, the standard deviation from the two methods for each case is nearly equal to zero. This information reveals that the methods can get many the same best solutions during the number of independent trials. The convergence characteristic of CSA-Cauchy and CSA-Gauss for economic dispatch with load of 2400 MW is shown in Figure 1. As indicated in the Figure, the CSA-Gauss can obtain better new solution than CSA-Cauchy at each iteration until the maximum number of iteration is reached.

For economic emission dispatch, by using Section 4, a set of 19 non-dominated solutions is determined corresponding to the value of w_1 in eq. (7) ranging in 0 to 1 and shown in Table 5. The solution corresponding to the highest value of μ_D of 0.05805 is considered as the best solution for economic emission dispatch. The Pareto-optimal front for the economic and emission is respectively shown in Figures 2 and 3 for CSA-Cauchy and CSA-Gauss.

Similarly, the best solutions for economic dispatch, emission dispatch and economic emission dispatch are obtained from CSA-Cauchy and CSA-Gauss for the rest of load cases of 2500, 2600 and 2700 with the same manner.

The results obtained by CSA-Cauchy and CSA-Gauss for load cases of 2400, 2500, 2600 and 2700 MW are compared to those by HLN and LIM in [8] in Tables 6 to 9. Clearly, the solution from LIM is better than HLN and the two proposed methods. However, the total power generated by LIM does not satisfy load. Moreover, the computational time by LIM is much more than that from HLN and the two proposed CSA methods. For the load cases of 2500 and 2600 MW, the CSA-Cauchy and CSA-Gauss obtain better cost and emission than HLN and LIM for economic dispatch, emission dispatch and economic emission dispatch. At the 2700 MW load, the two proposed methods get better than LIM and HLN for most cases except emission for compromise dispatch. The best solutions obtained by the two methods are shown in Table 10 and 11 for all load cases.

Table 1. Results obtained by CSA-Cauchy for load 2400 MW with different values of P_a for case of economic dispatch

p_a	Min cost ($)	Avg. cost ($)	Max cost ($)	Std. dev. ($)	CPU (s)
0.1	481.7229	481.7235	481.7247	0.00032	1.3572
0.2	481.7226	481.7226	481.7228	0.00002	1.3262
0.3	481.7226	481.7226	481.7227	0.00002	1.3265
0.4	481.7226	481.7226	481.7226	0.00000	1.3246
0.5	481.7226	481.7226	481.7226	0.00000	1.3454
0.6	481.7226	481.7226	481.7226	0.00000	1.3881
0.7	481.7226	481.7226	481.7226	0.00000	1.3764
0.8	481.7226	481.7226	481.7226	0.00000	1.3245
0.9	481.7226	481.7226	481.7226	0.00000	1.3546

Table 2. Results obtained by CSA-Gauss for load 2400 MW with different values of Pa for case of economic dispatch

p_a	Min cost ($)	Avg. cost ($)	Max cost ($)	Std. dev. ($)	CPU (s)
0.1	481.7233	481.7245	481.7268	0.00096	1.3572
0.2	481.7226	481.7227	481.7232	0.00011	1.3260
0.3	481.7226	481.7226	481.7226	0.0000	1.3260
0.4	481.7226	481.7226	481.7226	0.00000	1.3884
0.5	481.7226	481.7226	481.7226	0.00000	1.3416
0.6	481.7226	481.7226	481.7226	0.00000	1.3884
0.7	481.7226	481.7226	481.7226	0.00000	1.3728
0.8	481.7226	481.7226	481.7226	0.00000	1.3728
0.9	481.7226	481.7226	481.7226	0.00000	1.3572

Table 3. Results obtained by CSA-Cauchy for load 2400 with different values of P_a for case of emission dispatch

p_a	Min cost ($)	Avg. cost ($)	Max cost ($)	Std. dev. ($)	CPU (s)
0.1	4694.43	4694.518	4694.7	0.04271	1.3562
0.2	4694.41	4694.4215	4694.45	0.01083	1.3732
0.3	4694.41	4694.4105	4694.42	0.00216	1.3265
0.4	4694.41	4694.41	4694.41	0.00000	1.3246
0.5	4694.41	4694.41	4694.41	0.00000	1.3554
0.6	4694.41	4694.41	4694.41	0.00000	1.3781
0.7	4694.41	4694.41	4694.41	0.00000	1.3564
0.8	4694.41	4694.41	4694.41	0.00000	1.3345
0.9	4694.41	4694.41	4694.41	0.00000	1.3246

Table 4. Results obtained by CSA-Gauss for load 2400 MW with different values of P_a for case of emission dispatch

p_a	Min cost ($)	Avg. cost ($)	Max cost ($)	Std. dev. ($)	CPU (s)
0.1	4694.47	4694.6015	4694.91	0.12498	1.3573
0.2	4694.42	4694.45	4694.52	0.02948	1.3264
0.3	4694.41	4694.4315	4694.54	0.02922	1.3262
0.4	4694.41	4694.43	4694.69	0.06062	1.3883
0.5	4694.41	4694.412	4694.43	0.00502	1.3412
0.6	4694.41	4694.71	4700.38	1.28973	1.3885
0.7	4694.41	4694.41	4694.41	0.00000	1.3722
0.8	4694.41	4694.41	4694.41	0.00000	1.3758
0.9	4694.41	4694.41	4694.41	0.00000	1.3372

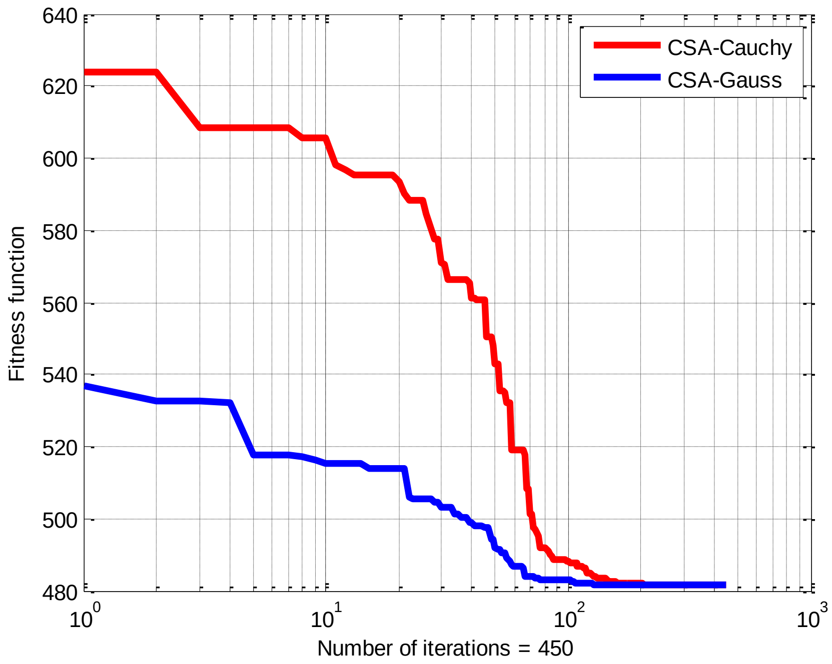

Figure 1. The convergence characteristic for cost for 2400 MW load

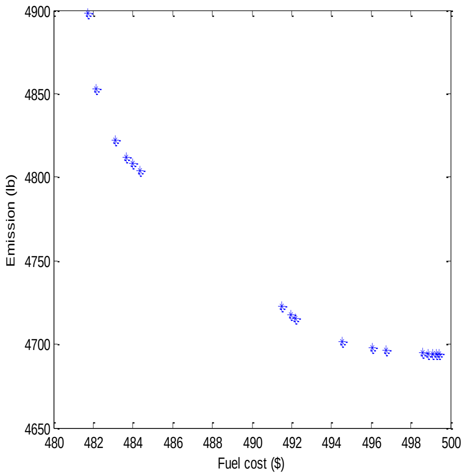

Figure 2. Pareto-optimal front for fuel cost and emission for CSA-Gauss for 2400 MW load case

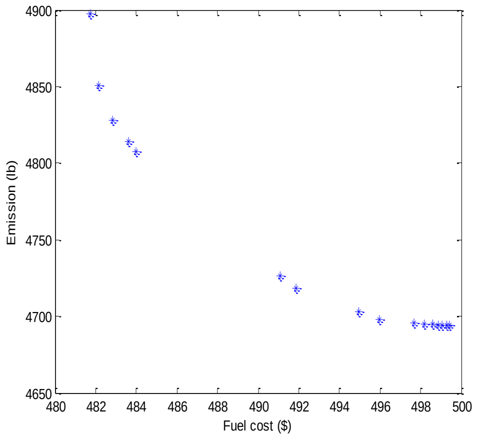

Figure 3. Pareto-optimal front for fuel cost and emission for CSA-Cauchy for 2400 MW load case

Table 5. Results obtained by CSA-Cauchy for load 2400 MW with P_a=0.9 for different values of w_1

w_1	Cost ($)	Emission (kg)	μ_D	CPU (s)
0	499.4154	4694.41	0.0442	1.3572
0.1	499.2667	4694.42	0.0529	1.3416
0.2	499.0888	4694.45	0.0573	1.3728
0.3	498.8615	4694.53	0.0580	1.3416
0.4	498.5747	4694.68	0.0579	1.4196
0.5	496.7409	4696.27	0.0580	1.3884
0.6	**496.0561**	**4697.58**	**0.05805**	1.3416
0.7	494.5513	4701.69	0.0579	1.3572
0.8	492.2086	4715.42	0.0579	1.3416
0.88	491.9597	4717.56	0.0578	1.3260
0.9	491.4769	4722.51	0.0576	1.3260
0.91	491.5362	4721.88	0.0548	1.3416
0.92	491.1350	4726.19	0.0519	1.5444
0.93	484.3506	4804.15	0.0505	1.3260
0.94	483.9891	4808.6	0.0462	1.5132
0.96	483.6498	4812.23	0.0455	1.4040
0.98	483.0956	4821.86	0.0450	1.3884
0.99	482.1261	4853.01	0.0446	1.3728
1	481.7226	4897.82	0.0442	1.3728

Table 6. Result comparison for load 2400 MW

Method	Economic dispatch		Emission dispatch		Compromise dispatch		
	Cost ($)	CPU (s)	Emission (kg)	CPU (s)	Cost ($)	Emission (kg)	CPU (s)
HLN	481.7226	0.7984	4694.407	0.7984	484.9916	4797.629	0.7985
LIM	481.7217	77.2460	4692.545	77.2460	484.9959	4797.669	77.2430
CSA-Cauchy	481.7226	1.3546	4694.41	1.3246	496.0561	4697.58	1.3416
CSA-Gauss	481.7226	1.3572	4694.41	1.3372	491.8798	4718.26	1.3421

Table 7. Result comparison for load 2500 MW

Method	Economic dispatch		Emission dispatch		Compromise dispatch		
	Cost ($)	CPU (s)	Emission (kg)	CPU (s)	Cost ($)	Emission (kg)	CPU (s)
HLN	526.2388	0.7413	5142.302	0.7412	530.3071	5230.867	0.7422
LIM	526.239	56.726	5142.297	56.731	530.3073	5230.868	56.729
CSA-Cauchy	526.2388	1.678	5119.48	1.679	529.9445	5223.29	1.675
CSA-Gauss	526.2388	1.668	5119.94	1.699	529.9278	5223.46	1.693

Table 8. Result comparison for load 2600 MW

Method	Economic dispatch		Emission dispatch		Compromise dispatch		
	Cost ($)	CPU (s)	Emission (kg)	CPU (s)	Cost ($)	Emission (kg)	CPU (s)
HLN	574.7413	1.175	5572.911	1.174	579.2083	5660.883	1.173
LIM	574.7412	60.791	5572.366	60.793	579.2086	5660.885	60.792
CSA-Cauchy	574.3808	1.683	5562.18	1.684	578.7632	5652.55	1.685
CSA-Gauss	574.3808	1.679	5562.27	1.678	578.7232	5653.01	1.679

Table 9. Result comparison for load 2700 MW

Method	Economic dispatch		Emission dispatch		Compromise dispatch		
	Cost ($)	CPU (s)	Emission (kg)	CPU (s)	Cost ($)	Emission (kg)	CPU (s)
HLN	623.8092	2.036	6049.333	2.035	628.2922	6121.833	2.034
LIM	623.8089	53.921	6043.129	53.922	628.4246	6119.806	53.923
CSA-Cauchy	623.8092	1.721	6036.67	1.723	628.2750	6121.99	1.722
CSA-Gauss	623.8092	1.712	6036.62	1.714	628.2942	6121.81	1.713

Table 10. Best Solutions by CSA-Cauchy for Economic Dispatch (w_1=1, w_2=0)

Unit	P_D=2400 MW		P_D=2500 MW		P_D=2600 MW		P_D=2700 MW	
	Fuel	Gen	Fuel	Gen	Fuel	Gen	Fuel	Gen
1	1	189.7428	2	206.5178	2	216.5338	2	218.2422
2	1	202.3417	1	206.4518	3	210.9049	3	211.6598
3	1	253.8912	1	265.7411	1	278.5401	1	280.7264
4	3	233.0456	3	235.9588	3	239.1035	3	239.6422
5	1	241.8298	1	258.0206	1	275.5474	1	278.4955
6	3	233.0489	3	235.9547	3	239.0819	3	239.6317
7	1	253.2800	1	268.8643	1	285.7291	1	288.5673
8	3	233.0471	3	235.9517	3	239.0938	3	239.6295
9	2	320.3866	2	331.4826	2	343.4863	1	428.5335
10	1	239.3862	1	255.0565	1	271.9791	1	274.8720
TP (MW)	2400		2500		2600		2700	
TC ($)	481.7226		526.2388		574.3803		623.8092	
CT (S)	1.747		1.669		1.685		1.7	

Table 11. Best Solutions by CSA-Gauss for Economic Dispatch (w_1=1, w_2=0)

Unit	P_D=2400 MW		P_D=2500 MW		P_D=2600 MW		P_D=2700 MW	
	Fuel	Gen	Fuel	Gen	Fuel	Gen	Fuel	Gen
1	1	189.7405	2	206.5190	2	216.5442	2	218.2499
2	3	202.3427	3	206.4573	3	210.9058	3	211.6626
3	1	253.8953	1	265.7391	1	278.5441	1	280.7228
4	3	233.0456	3	235.9531	3	239.0967	3	239.6315
5	1	241.8297	1	258.0177	1	275.5194	1	278.4973
6	3	233.0456	3	235.9531	3	239.0967	3	239.6315
7	1	253.2750	1	268.8635	1	285.7170	1	288.5845
8	3	233.0456	3	235.9531	3	239.0967	3	239.6315
9	2	320.3832	2	331.4877	2	343.4934	2	428.5216
10	1	239.3969	1	255.0562	1	271.9861	1	274.8667
TP (MW)	2400		2500		2600		2700	
TC ($)	481.7226		526.2388		574.3803		623.8092	
CT (S)	1.73		1.747		1.716		1.825	

6. Conclusions

In the paper, a Cuckoo Search Algorithm and two distributions have been combined for solving economic emission load dispatch problem with multiple fuel options. The advantages of the methods over than others are few parameter and high success rate. Moreover, as Cauchy distribution and Gaussian distribution are used instead of Lévy distribution, the iterative procedure of the proposed methods can reduce a step of calculating and evaluating fitness. The obtained result comparison between the proposed methods and others reported in the paper has shown that the proposed methods are very favorable for solving economic emission load dispatch with multiple fuel option.

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