Indonesian Journal of Electrical Engineering and Computer Science
Vol. 5, No. 1, January 2017, pp. 48 ~ 57
DOI: 10.11591/ijeecs.v5.i1.pp 48-57

Non-convex Economic Load Dispatch using Cuckoo Search Algorithm

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Abstract

This paper presents cuckoo search algorithm (CSA) for solving non-convex economic load dispatch (ELD) problems of fossil fuel fired generators considering transmission losses and valve point loading effect. CSA is a new meta-heuristic optimisation technique inspired from the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds of other species. The strength of the proposed meta-heuristic optimization technique CSA has been tested and validated on the standard IEEE 14-bus, 26-bus and 30-bus system with several heuristic load patterns. The results have indicated that the proposed approach is able to obtain significant economic load dispatch solutions than those of Firefly Algorithm (FFA) and other soft computing techniques reported in the literature.

***Keywords**: Economic load dispatch (ELD), Cuckoo search algorithm (CSA), Firefly Algorithm (FFA), Valve-point loading effect*

1. Introduction

ELD (Economic load dispatch) is one of the most important optimization problems in power system operation and control. ELD allocates the load demand among the committed generators at minimum operating cost while satisfying the physical and operational constraints. The ELD problem is a highly constrained nonlinear non-convex optimization problem [1]. To solve the ELD problem, a number of conventional optimization techniques such as quadratic programming (QP) [2], linear programming (LP) [3], non-linear programming (NLP) [4]-[5], Newton based method [6], interior point methods [6], dynamic programming (DP) [7] and branch and bound [8] and mixed integer programming [9] have been applied. All of these conventional optimization techniques can solve economic load dispatch problem under the assumption that the incremental fuel cost curves of the generating units are monotonically increasing piecewise-linear functions. On the other hand, the ELD problem has the characteristics of high non-convexity and nonlinearity. Also large steam turbines contain a number of steam admission valves which contribute non-convexity in the cost function of the generating units. Classical calculus based optimization techniques fail to address these types of issues satisfactorily and lead to sub optimal solutions making huge revenue loss over time. The classical optimization techniques are not good enough to solve this ELD problem which has inherently nonlinear and discontinuous objective function. Conventional optimization techniques depend on the existence of the first and the second derivatives of the fitness function and on the estimation of these derivatives in large search space. Hence the practical ELD problem can be formulated as non-convex objective function subject to non-linear constraints, which is difficult to be solved by the conventional optimization techniques.

Recently, many attempts have been examined to overcome the limitations of the conventional optimization techniques such as meta-heuristic optimization techniques, for example simulated annealing (SA) [10], tabu search (TS) [11], genetic algorithms (GA) [12], artificial neural networks [13], ant colony optimization (ACO) [14], evolutionary programming (EP) [15], particle swarm optimization (PSO) [16], harmony search algorithm (HSA) [17] and firefly algorithm (FFA) [18]. The application of the meta-heuristic optimization techniques to global optimization problems turn out to be attractive since they have improved global search abilities over conventional optimization techniques. The meta-heuristic optimization techniques appear to be evolving and promising and have become the most extensively used tools for

Received August 29, 2016; Revised November 30, 2016; Accepted December 14, 2016

solving ELD problem. For maximization/minimization problems the meta-heuristic optimization techniques allow to find solutions nearer to the global optimum.

CSA (Cuckoo search algorithm) is a new meta-heuristic optimization technique developed by Yang and Deb in 2009 [19]-[20]. CSA is a new meta-heuristic optimisation algorithm inspired from the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds of other species. In this paper, Cuckoo search algorithm (CSA) is proposed for solving non-convex ELD problems considering system and generator characteristics including valve point loading effects (VPE) and power loss. The proposed CSA is tested on standard IEEE 14-bus, 26-bus and 30-bus system and the obtained results are compared with FFA and other optimization methods in reported in the literature. The convex ELD problem assumes quadratic fuel cost function along with system power demand and operational limit constraints. The practical non-convex ELD problem, in addition, considers generator nonlinearities such as valve point loading effect.

2. Problem Formulation

2.1. ELD Problem without Valve Point Effect

The objective of the economic load dispatch problem is to
Minimize

$$F_{t,cost}=\sum_{i=1}^{N} F_i(P_i) \tag{1}$$

where $F_i(P_i)=a_i+b_iP_i+c_iP_i^2$
without valve point loading effect
and

$$F_i(P_i)=a_i+b_iP_i+c_iP_i^2+|e_i\sin(f_i*(P_{i,min}-P_i)|$$

where $F_{t,cost}$ is the total fuel cost; F_i is the fuel cost of ith generator; a_i, b_i and c_i are the fuel consumption cost coefficients of the ith unit; e_i and f_i are the fuel cost coefficients of the ith unit with valve point loading effect and P_i is the power output of the ith generator in megawatts.

The minimization of the generation cost is subjected to the following equality and inequality constraints:
Real power balance constraint

$$\sum_{i=1}^{N}(P_i-P_D-P_L)=0 \tag{2}$$

where P_D is the total demand, P_L is the total real power transmission losses and N is the total number of the online generators. The traditional B loss matrix formula which is used to determine transmission loss is given in Eq. (3).

$$\sum_{i=1}^{N}\sum_{j=1}^{N} P_iB_{ij}P_j+\sum_{i=1}^{N} B_{0i}P_i+B_{00} \tag{3}$$

where B_{ij} is the ijth element of the loss coefficient square matrix, B_{0i} is the ith element of the loss coefficient vector, and B_{00} is the loss coefficient constant.

Generation limit constraint

$$P_{i,min}\le P_i\le P_{i,\,max} \text{ for } i=1,2,3\ldots N \tag{4}$$

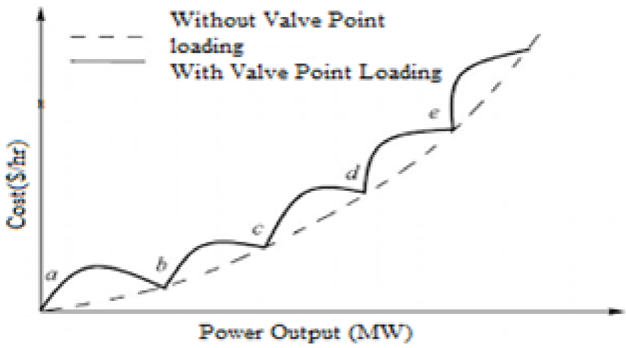

Figure 1. Fuel Cost Curve of Units with Valve-Point Effects

Real power balance: The total real power output of generating units satisfies total real load demand plus power loss, where the power loss PL can be approximated by Kron's formula [3]

Generator capacity limits: The real power output of generating units should be within their upper and lower operating limits as. The cost curve function of units with valve point loading effects is shown in Figure 1.

3. Cuckoo Search Algorithm

Cuckoo search is a meta-heuristic optimization technique developed by Yang and Deb in 2009 [21]. The basic idea of this optimization technique is based on the obligate brood parasitic behaviour of some cuckoo species in combination with the Levy flight behaviour of some birds and fruit flies. Cuckoos are fascinating birds, not only because of the attractive sounds they can make, but also because of their aggressive reproduction strategy. Some species such as the ani and guira cuckoos lay their eggs in communal nests, even if they may remove others' eggs to enhance the hatching probability of their own eggs. Fairly a number of species maintain the obligate brood parasitism by laying their eggs in the nests of other host birds. Some host birds can engage direct conflict with the obtrusive cuckoos. If a host bird discovers the eggs are not its own, it will either throw these alien eggs away or just abandon its nest and build a new nest in a different place. Some cuckoo species such as the new world brood-parasitic Tapera have evolved in such a way that female parasitic cuckoos are often very specific in the mimicry in colour and pattern of the eggs of a few selected host species. This diminishes the probability of their eggs being abandoned and thus enhances their reproductively. In nature, animals try to find food in a random or quasi-random manner. In general, the foraging path of an animal is in fact a random walk because the next move is based on the current location/state and the transition probability to the next location. Which direction it decides depends absolutely on a probability which can be modelled mathematically. A recent study shows that fruit flies or Drosophila melanogaster explore their landscape by means of a series of straight flight paths punctuated by a sudden 90 degrees turn, leading to a Levy-flight-style discontinuous scale-free search pattern.

Cuckoo search is based on three idealized rules [21]:

a) Each cuckoo lays one egg (a design solution) at a time, and abandons its egg in a randomly chosen nest among the fixed number of available host nests;
b) The best nests with high quality of egg (better solution) will be carried over to the next generation;
c) The number of available hosts nests is fixed, and the egg laid by a cuckoo is discovered by the host bird with a probability of pa˛ [0,1]. In this case, it can simply either throw the egg away or abandon the nest and find a new location to build a completely new one.

4. Implementation of Cuckoo Search Algorithm for Economic Load Dispatch Problem

The proposed Cuckoo Search Algorithm (CSA) is a population based method similar to other meta-heuristic optimization techniques. The structure of CSA comprises two most important operations including a direct search based on Levy flights and a random search based on the probability for a host bird to discover an alien egg in its nest. The proposed CSA becomes a more powerful search method than other meta-heuristic optimization techniques for complex and large-scale optimization problems with the combination of two operations. Hence, the proposed CSA is very effective for solving non-convex and large-scale ELD problems.

In the proposed CSA method, each nest corresponds to a solution and a population of nest is utilized for finding the best solution of the problem. The main steps of the proposed CSA algorithm are described as follows:

Step1: Initialisation

A population of N_p host nests is represented by $X = [X_1, X_2,\ldots, X_{Np}]T$, where each nest $X_d = [P_{d1},P_{d2},\ldots, P_{ds-1}, P_{ds+1},\ldots, P_{dN}]$ ($d = 1,\ldots, N_p$) corresponds to power output of units except the slack unit is initialised by

$$X_{di}=P_{i,min}+rand_1*(P_{i,max}-P_{i,min}) \quad (5)$$

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 objective function to be minimised corresponding to each nest for the considered problem is determined.

Step 2: Generation of new solution via Levy flights

The new solution is calculated based on the previous best nests via Levy flights. In the proposed method, the optimal path for the Levy flights is determined by Mantegna's algorithm [28]. The new solution for each nest is calculated as follows:

$$X_i^{new}=Xbest_i+\alpha*rand_2*\Delta X_i^{new} \quad (6)$$

where $\alpha > 0$ is the updated step size and $rand_2$ is a normally distributed stochastic number. ΔX_i^{new} is determined as follows:

$$\Delta X_i^{new}=v*\frac{\sigma_x(\beta)}{\sigma_y(\beta)}*(Xbest_i-Gbest) \quad (7)$$

$$v=rand_x/|rand_y|^{1/\beta} \quad (8)$$

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

where β is the distribution factor $0.3 \le \beta \le 1.99$ and $\Gamma(.)$ is the gamma distribution function.

The newly determined solution should be satisfied according to its upper and lower limits.

Step 3: Alien egg discovery and randomization

The act of discovery of an alien egg in a nest of a host bird with the probability of p_a also builds a new solution for the problem similar to the Levy flights. The new solution due to this action can be determined by the following method.

$$X_i^{dis}=Xbest_i+K*\Delta X_i^{dis} \quad (6)$$

where K is the updated coefficient calculated based on the probability of a host bird to find out an alien egg in its nest

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

The increased value ΔX^{i}_{dis} is determined by
ΔX_i^{dis}=rand$_3$*[randp$_1$(Xbest$_i$)-randp$_2$(Xbest$_i$)]
where rand$_3$ is the distributed random number in [0,1]. randp$_1$(Xbest$_i$) and randp$_2$(Xbest$_i$) are the random perturbation for positions of nests in Xbest$_i$.
Step4: Stopping Criteria
The above algorithm is stopped when the number of iterations reached the predefined value. The flowchart for the proposed CSA is shown in Figure 2.

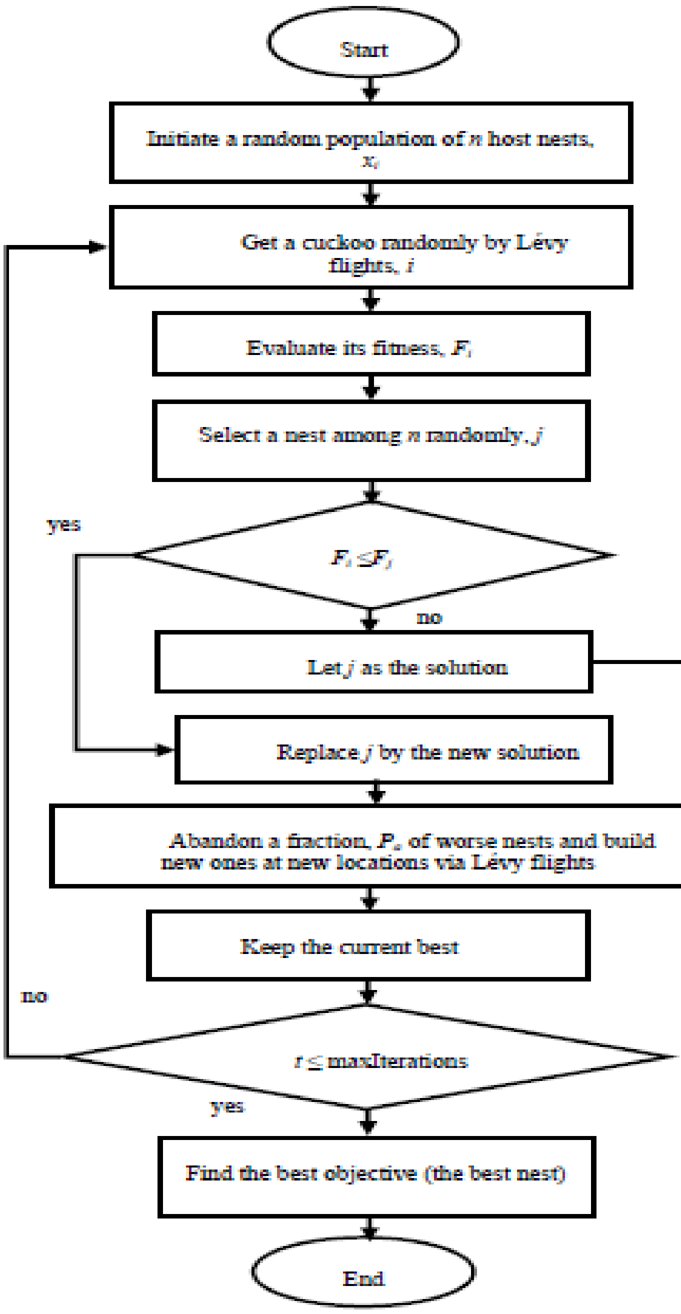

Figure 2. Flowchart for the Proposed CSA

5. Simulation Results

The proposed algorithm has been applied to solve ELD problems for proving its feasibility. The proposed algorithm has been implemented to IEEE 14-bus, 26-bus and 30-bus system using MATLAB software and the results are compared with FFA and other optimization techniques reported in the literature.

Selection of Parameters:

In the proposed CSA approach, four important parameters that have to be predetermined are the number of nests N_p, maximum number of iterations N_{max}, distribution factor β and the probability of an alien egg to be discovered in host nests p_a. Among these parameters, the number of nests can be easily predetermined. Since CSA is a powerful and efficient search method, it requires a small number of nests for dealing with different systems. On the other hand, the maximum number of iterations for the proposed CSA can be also easily predetermined based on the complexity and scale of the considered problems. The maximum number of iterations for the CSA ranges from 300 for small-scale systems up to 10,000 for large-scale systems. The value of distribution factor β can be fixed in the range [0.2, 1.99] as in the Mantegna's algorithm.

Test System 1: IEEE 14-bus System

The IEEE 14-bus system consists of five thermal generating units. The load demand is 289 MW. For this standard test system, the maximum number of iterations, population size (N_p) and the value of probability p_a have been chosen as 500, 20, 0.20 respectively. Results obtained from proposed CSA and FFA have been summarized in Table 1. Table 2 shows the statistical results of CSA and other optimization techniques. It is observed from Table 1 and 2 that the proposed CSA based approach provides the lowest minimum cost among all optimization techniques the cost convergence characteristic of this IEEE 14-bus system obtained from CSA is shown in Figure 2.

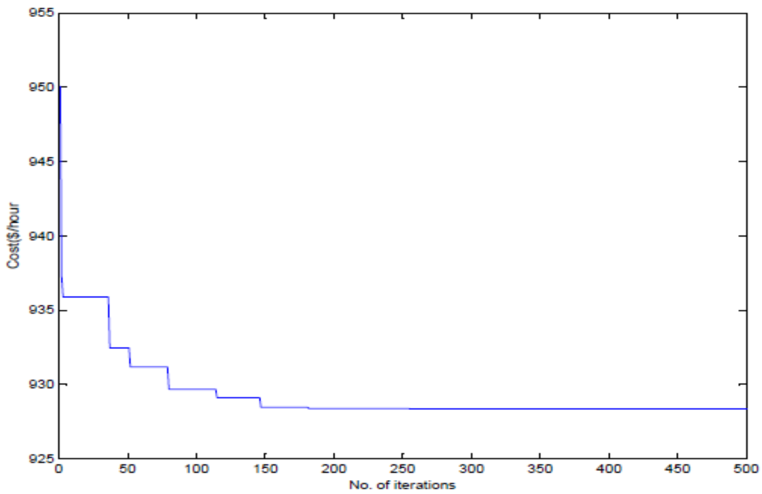

Figure 3. Cost Convergence Characteristic of IEEE 14-bus System

Table 1. Power Output for IEEE 14-Bus System (PD 289 MW)

Unit Power Output (MW)	CSA	FFA
P1	199.59	199.65
P2	20.00	30.81
P3	19.59	22.48
P4	23.22	18.20
P5	30.00	21.27
Total power output (MW)	289.00	289.00
Ploss (MW)	3.41	3.41
Total cost ($/h)	928.00	955.96

Table 2. Statistical Results of Various Algorithms for Test System 1 (IEEE 14-Bus System)

Algorithms	Best Fuel Cost ($/hr)	Average fuel cost ($/hr)	Worst fuel cost cost ($/hr)
IFEP	984.83 [17]	-	-
PSO	982.69 [17]	-	-
HSA	979.22 [17]	-	-
FFA	955.96	961.44	974.96
CSA	928.00	928.407	929.73

Test System 2: IEEE 30-bus System

A six generator system with valve point loading effect is considered here. The load demand is 283.4 MW. For this standard test system, the maximum number of iterations, population size (N_p) and the value of probability p_a have been chosen as 500, 20, 0.20 respectively. Results obtained from proposed CSA and FFA have been summarized in Table III. Table 4 shows the statistical results of CSA and other optimization techniques. It is observed from Table 3 & 4 that the proposed CSA based approach provides the lowest minimum cost among all optimization techniques. The cost convergence characteristic of this IEEE 30-bus system obtained from CSA is shown in Figure 3.

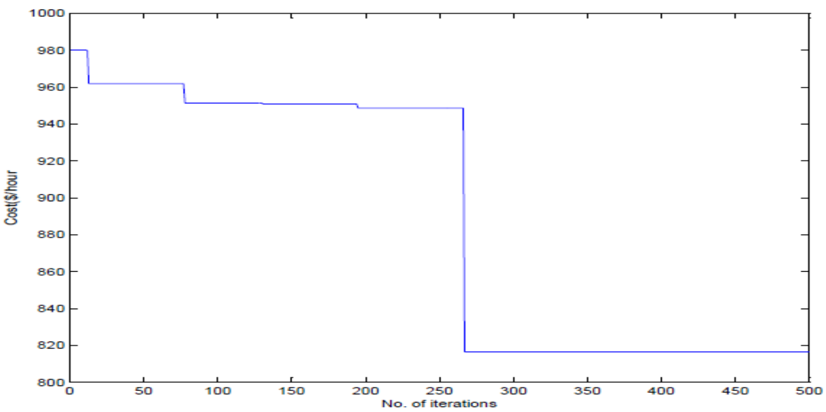

Figure 4. Cost Convergence Characteristic of IEEE 30-bus System

Table 3. Power Output for IEEE 30-Bus System (PD 283.4 MW)

Unit Power Output (MW)	CSA	FFA
P1	120.41	149.52
P2	20.57	48.65
P3	50.00	23.41
P4	35.00	22.26
P5	24.97	19.88
P6	40.00	27.23
Total power output (MW)	283.4	283.4
Ploss (MW)	7.54	7.54
Total cost ($/h)	819.81	973.01

Table 4. Statistical Results of Various Algorithms for Test System 2 (IEEE 30-Bus System)

Algorithms	Best Fuel Cost ($/hr)	Average fuel cost ($/hr)	Worst fuel cost cost ($/hr)
GA [26]	996.0369	-	1117.1285
GA-APO [26]	984.9365	-	992.4815
HGA [26]	996.03	-	1101.49
IFEP [17]	830.39	-	-
PSO [17]	828.15	-	-
HSA [17]	826.86	-	-
FFA	973.01	978.55	981.85
CSA	819.81	821.315	828.99

Test System 3: IEEE 26-bus System

The IEEE 26-bus system consists of six thermal generating units. The load demand is 1263 MW. For this test system, the population size (N_p), maximum number of iterations and the value of probability p_a have been chosen as 20, 500, and 0.20 respectively. Results obtained from proposed CSA, FFA and HSA have been summarized in Table 5. Table 4 shows the statistical results of CSA and other optimization techniques. It is observed from Table 5 & 6 that the proposed CSA based approach provides the lowest minimum cost among all optimization techniques. The cost convergence characteristic of this IEEE 26-bus system obtained from CSA is shown in Figure 3.

Table 5. Power Output for IEEE 26-Bus System (PD 1263 MW)

Unit Power Output (MW)	CSA	FFA
P1	445.87	457.72
P2	164.24	181.23
P3	300.00	255.17
P4	84.18	119.63
P5	164.24	175.06
P6	120.00	89.72
Total power output (MW)	1263.00	1263.00
Ploss (MW)	15.53	15.53
Total cost ($/h)	15349.19	15484.95

Table 6. Statistical Results of Various Algorithms for Test System 3 (IEEE 26-Bus System)

Algorithms	Best Fuel Cost($/hr)	Average fuel cost ($/hr)	Worst fuel cost cost ($/hr)
GA binary [22]	15451.66	15469.21	15519.87
GA [23]	15459.00	15469.00	15469.00
NPSO-LRS [22]	15450.0	15454.00	15455.00
SOH-PSO [24]	15446.02	15497.35	15609.64
GAAPI [22]	15449.78	15449.81	15449.85
NAPSO [24]	15443.765664	15443.765671	15443.765683
FAPSO [22]	15445.244	15448.052	15451.63
PSO [23]	15,450	15,454	15,492
DE [22]	15449.766	15449.777	15449.874
TSA [23]	15451.631	15462.263	15506.451
MTS [23]	15450.06	15451.17	15453.64
SA [22]	15461.1	15488.98	15545.5
KHA-I [22]	15450.7492	15452.8219	15455.4561
KHA-II [22]	15448.2117	15450.8322	15453.4289
KHA-III [22]	15445.3560	15447.2175	15449.6078
KHA-IV [22]	15443.0752	15443.1863	15443.3265
DSPSO-TSA [23]	15,441.57	15,443.84	15,446.22
SA-PSO [24]	15,447	15,447	15,455
HSA	15,449	-	15,449
IHS [25]	15441.6970	15,441.8415	15,442.0873
FFA	15484.95	15510.64	15562.37
CSA	15349.19	15351.81	15357.37

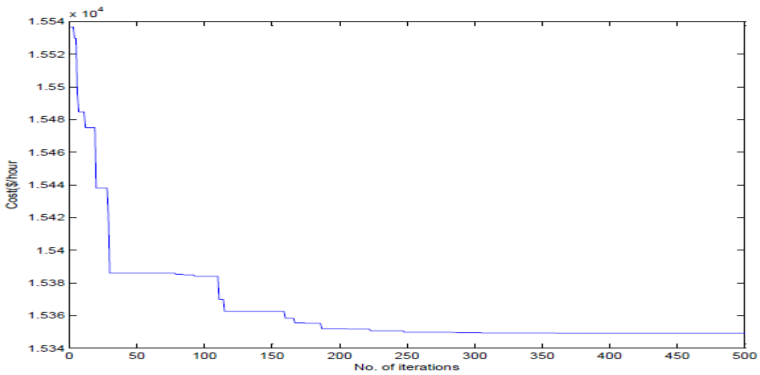

Figure 5. Cost Convergence Characteristic of IEEE 26-bus System

6. Conclusion

In this paper, the CSA method has been successfully implemented for solving non-convex economic load dispatch problem. The proposed algorithm has been tested on IEEE 14-bus, 26-bus and 30-bus system to validate its efficiency. The results of the proposed method were compared with the results of FFA and other evolutionary programming techniques available in the literature. The simulation results indicated that the proposed CSA method can provide cheaper generation cost than FFA and other meta-heuristic optimization techniques. Hence, the performance of the proposed CSA appears to be a powerful and efficient optimization technique to solve highly nonlinear discontinuous cost functions of ELD problem and to achieve globally better optimum solution.

Acknowledgment

The author wish to thank the Management of Hindustan University, Padur Chennai for their support and encouragement to carry out this work.

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