Full Title: A comparative study of Economic Load Dispatch with complex non-linear constraints using Salp Swarm Algorithm

[1]Kuntal Bhattacharjee*
Institute of Technology
Electrical Engineering Department
Nirma University
kuntal.bhattacharjee@nirmauni.ac.in
Ph: +91 9832832822

[2]Nitish Patel
Institute of Technology
Electrical Engineering Department
Nirma University
16meee18@nirmauni.ac.in
Ph: +91 8347208330

Abstract:

Economic Load Dispatch (ELD) is an important part of cost minimization procedure in power system operation. Different derivative and probabilistic methods are used to solve ELD problems. This paper proposes a powerful Salp Swarm Algorithm (SSA) to explain the ELD issue including equality and inequality restrictions. The main aim of ELD is to satisfy the entire electric load at minimum cost. The SSA is a population based probabilistic method which guides its search agents that are randomly placed in the search space, towards an optimal point using their fitness function and also keeps a track of the best solution achieved by each search agent. SSA is being used to solve the ELD problem with their high exploration and local optima escaping technique. This algorithm confirms that the promising areas of the search space are exploited to have a smooth transition from exploration to exploitation using the movement of Salps in the sea. Simulation results prove that the proposed algorithm surpasses other existing optimization techniques in terms of quality of solution obtained and computational efficiency. The final results also prove that SSA is more robust when compared to other techniques in the paper.

Keywords: Economic Load Dispatch, Optimization, Prohibited operating zone, Salp Swarm Algorithm, Valve-point loading

1. Introduction:

Economic Load Dispatch (ELD) is considered to be one of the valued optimization problem in the field of power system operations. The ELD satisfies the total load demand by economically allocating the load demand to each and every generator while satisfying their operation and physical constraints. The ELD helps to satisfy the total load demand in the most economical way. The main aim of the ELD is to make the entire system reliable and to minimize the total generation cost of the thermal power plant. But the ELD also satisfies all the constraints of each and every generator that is considered for the ELD problem.

There are many classic optimization method methods based on gradient method [1], quadratic programming (QP) [2], Lagrangian relaxation [3], Hopfield modeling framework [4], linear programming (LP) [5], dynamic programming (DP) [6] which assume a linear increasing cost function and have been successfully applied to solve the ELD problem. But the main problem with the classical approach is that it tends to converge at a local optima and then begins to diverge from the global optimal solution. The problem with the Dynamic Programming approach is that it requires very large dimensions and so large amount of programming efforts are required. These classical methods are not able to locate the global optimum solution because of the presence of many non-linear equations like the non-smooth cost function, ramp rate limit and discontinues prohibited operating zones. Also due to the non-linear characteristic of the ELD problem, many of the classic optimization method techniques cannot reach the global optimal solution and tend to diverge at a local optima solution. Therefore, it becomes imperative to develop an optimization technique that can overcome these drawbacks of the classical based methods and can give the global optimum solution in the least computation time. Many artificial intelligence algorithms like the Hopfield neural network (HNN) [7] have been used to solve the ELD problem. The problem for artificial intelligence algorithms is that they take huge number of iterations to reach the global optimum solution. This is because the algorithms have to converge towards the global optimum value and the rate of convergence of these algorithms is different. Due to the difference in the rate of convergence, the time taken by the different algorithms is different. Hence, more time is required to reach the global solution. The computer technology has been developed many new population based heuristic optimization techniques like differential evolution (DE) [8], evolutionary programming (EP) [9], hybrid evolutionary programming (HEP) [10], particle swarm optimization (PSO) [11], civilized swarm optimization (CSO) [12], craziness based PSO (CRPSO) [13], hybrid PSO (HPSO) [14], modified PSO (MPSO) [15], genetic algorithm (GA) [16], hybrid GA (HGA)[17], adaptive real coded GA (ARCGA) [18], bacteria foraging optimization (BFO) [19], modified BFO (MBFO) [20], modified artificial bee colony (ABC) [21], seeker optimization algorithm (SOA) [22], ant colony optimization (ACO) [23], tabu search (TS) [24], biogeography based optimization (BBO) [25], and quasi oppositional BBO (QOBBO) [26] , oppositional BBO (OBBO) [27], harmony search algorithm (HSA) [28] for solving ELD problems. Other optimization algorithms have been proposed to solve the ELD problem, like the opposition based harmony search algorithm (OHSA) which was introduced by Chatterjee et al. [29]. Krill herd algorithm (KHA), [30] was also successfully applied to solve the ELD problems. The problem of short term hydrothermal scheduling is solved using the SCA technique in [31]. An enhanced version of the Particle Swarm Optimisation has been proposed in [32] to solve the problem of ELD. A new technique maximum likelihood optima technique has also been used to solve the ELD problem in [33]. Group Leader Optimization [34] has been proposed because of its special ability to solve the non-linear and the non-quadratic equations with greater ease. Even Teaching Learning Based Optimization Technique (TLBO) has been used in [35] to solve the ELD problem. Some of the above mentioned algorithms have problem in finding local optima solution and some have problem in finding the global optimum solution. So to overcome such kind of problem, a new and a powerful optimization technique is needed. Even the Simulated Annealing Algorithm (SAA) has been used to solve the economic emission dispatch problem in [36]. Also the Enhanced vibrating particles system algorithm has been used for identification for any damage in the truss structure in [37]. A new algorithm named Ameliorated grey wolf optimization [38] has been recently introduced which solve the ELD problem. The Hybrid artificial algae algorithm has been used in [39] to solve the ELD problem. In [40] artificial cooperative search algorithm and in [41] phasor particle swarm optimization has been introduced to solve the ELD problem. The authors of [42] have used Opposition-based krill herd algorithm and the authors of [43] have used adaptive differential evolutionary algorithm to find a solution for the ELD problem.

Recently, a new algorithm called Salp Swarm Algorithm (SSA) [44] has been proposed based on the movement of salps in the sea. The search agent having the maximum fitness is made to move towards the global optima. The SSA is considered superior due to its exploration and exploitation property which it utilizes to reach the global optimal value in the least computation time. Due to its exploration and exploitation property it avoids the local optima and tends to move directly towards the global optimum value. Newly some efficient modified and hybrid optimization techniques [45-50] have also used to solve ELD problems with much more efficient manner. With a new concept, there are some recent techniques [51-61] that are actively able to solve the ELD problem with much more complex constraints.

Section 2 of the paper states the problem formulation of various ELD problems with different feasible constraints. The conception of the SSA is described in Section 3. The performance of the SSA under various test systems and the simulation studies are discussed in Section 4. Lastly, the conclusion is drained in Section 5.

2. Problem Formulation

The problems of ELD expressed as convex or non-convex problems with some linear and nonlinear constrained for different applications.

The objective function of ELD with quadratic cost function based on (1) is as follows [44]:

$$F_{Cost} = \min \sum_{a=1}^{N} \left(\alpha_a + \beta_a P_a + \gamma_a P_a^2 \right) \tag{1}$$

For realistic and practical application of ELD problem, the smooth quadratic cost function has been modified by adding a sinusoidal terms of ripples input-output curve with valve point effects. The valve point effect based cost function of ELD is given below [44]:

$$F_{Cost} = \min \sum_{a=1}^{N} \left(\alpha_a + \beta_a P_a + \gamma_a P_a^2 + \left| \delta_a \times \sin\left\{ \varepsilon_a \left(P_a^{\min} - P_a \right) \right\} \right| \right) \tag{2}$$

where α_a, β_a, γ_a, δ_a and ε_a are the constant values of fuel cost function. N is the total number of thermal generators. Power generations from each generators is P_a. Lower limit and higher limit of power generation is characterized by $P_a^{\min}$ and $P_a^{\max}$. Power generations from each unit are followed by following generating capacity constraint:

$$P_a^{\min} \le P_a \le P_a^{\max} \tag{3}$$

This is inequality constraints of ELD problems. The equality constraints or real power balance constraint of ELD is based on (4).

$$\sum_{a=1}^{N} P_a - P_D - P_{Loss} = 0 \tag{4}$$

Where, P_D is the total system active power demand and total transmission loss P_{Loss} is calculated by using the B-matrix loss coefficients which is expressed as [59]:

$$P_{Loss} = \sum_{a=1}^{N} \sum_{b=1}^{N} P_a B_{ab} P_b + \sum_{a=1}^{N} B_{0a} P_a + B_{00} \tag{5}$$

Ramp Rate Limit is another constraint which is considered in ELD problems for increase the life of generators which is given below:

$$P_a - P_{a0} \le UR_a \qquad \text{(as generation rises)} \tag{6}$$

$$P_{a0} - P_a \le DR_a \qquad \text{(as generation declines)} \tag{7}$$

And $\max\left(P_a^{\min}, P_{a0} - DR_a\right) \le \min\left(P_a^{\max}, P_{a0} + UR_a\right)$ (8)

Where P_{a0} is the power generations of a[th] previous interval; UR_a and DR_a are the up-ramp limit and down ramp limit.

Different faults in the machines, boilers, feed pumps, steam valve operation and vibration in the bearing etc. and also the constraints like Prohibited Operating Zone (POZ) have been considered in ELD problems. Mathematically POZ can be expressed as given below:

$$\left.\begin{array}{l} P_a^{\min} \le P_a \le P_{a,1}^{l} \\ P_{a,j-1}^{u} \le P_a \le P_{a,j}^{l} \\ P_{a,n}^{u} \le P_a \le P_a^{\max} \end{array}\right\}; \qquad j=1 \text{ to } n \tag{9}$$

Where $P_{a,j}^{u}$ and $P_{a,j}^{l}$ the upper limit and lower limit of the j^{th} prohibited operating zone of ath unit. Total number of prohibited operating zone of the ath unit is n.

For a system with n number of generators, and having n_F fuel options for each unit, the entire cost function can be expressed as:

$$F_{ip}(P_i) = a_{ip} + b_{ip} P_i + c_{ip} P_i^2 + \left| e_{ip} \times \sin\left\{ f_{ip} \times \left(P_{ip}^{min} - P_i \right) \right\} \right| \tag{10}$$

Where $p = 1,2,\ldots,n_F$

Calculation of slack generator is one of the important part in ELD problem formulations. If N is the total number of generators then initially calculate (N-1) number of power generations randomly based on (3), (6), (7), (8) and (9). The remaining generator (let N^{th}) which is called slack generator has to be calculated using (4). The value of slack generator is given below:

$$P_N = P_D - \sum_{a=1}^{N-1} P_a \quad \text{(Without transmission losses)} \tag{11}$$

$$P_N = P_D + P_{Loss} - \sum_{a=1}^{N-1} P_a \quad \text{(With transmission losses)} \tag{12}$$

Transmission loss (P_{Loss}) is also related to power generations based on (5), therefore (11) is further modified and is given below:

$$B_{NN}P_N^2 + P_N\left(2\sum_{a=1}^{N-1} B_{Na}P_a + \sum_{a=1}^{N-1} B_{0N} - 1\right) + \left(P_D + \sum_{a=1}^{N-1}\sum_{b=1}^{N-1} P_a B_{ab} P_b + \sum_{a=1}^{N-1} B_{0a}P_a - \sum_{a=1}^{N-1} P_a + B_{00}\right) = 0 \tag{13}$$

In this manuscript the authors are considering static ELD problem formulation. Instead of static, dynamical ELD problem with spinning reserve can be considered as complex constraint. Similarly for some durations like for anyone day, i.e. 24 hours, different constraints like start up cost and must run cost can be considered as a constraint in unit commitment problem formulation. Whenever this type of complex constraint are included, the overall problem formulation will be more complex and therefore the SSA algorithm can be applied to this type of complex formulation as well. Due to lack of space, these are not considered in the manuscript.

3. Salp Swarm Algorithm:

The SSA [44] is a population based optimization technique. It is inspired by the movement of the salps in the ocean. They move in a swarm of population. The entire population is divided into two groups: leader and the followers. The leader is the salp which is in front of the chain and the rest of the salps are considered to be the followers. The leader slap guides the entire swarm of salps towards the destination. The position of salps is defined in an n -dimensional search space where n is the number of variables of a given problem. Thus, the position of all salps are stored in a two-dimensional matrix called *x*. It is also assumed that there is a food source called *F* in the search space as the swarm's target.

To update the position of the leader the following equation is proposed:

$$x_j^1 = \begin{cases} F_j + c_1((ub_j - lb_j)c_2 + lb_j) \\ F_j - c_1((ub_j - lb_j)c_2 + lb_j) \end{cases} \tag{14}$$

where x_j^1 shows the position of the first salp (leader) in the jth dimension, F_j is the position of the food source in the jth dimension, ub_j indicates the upper bound of jth dimension, lb_j indicates the lower bound of jth dimension.

This equation proves that the leader updates its position with respect to the food source. The coefficient c_1 is the most important parameter in SSA because it balances exploration and exploitation defined as follows:

$$c_1 = 2 \times e^{\frac{-4l}{L}} \tag{15}$$

where *l* is the current iteration and L is the maximum number of iterations. The parameter c_2 and c_3 are random numbers uniformly generated in the interval of [0, 1] and [-1, 1] respectively. In fact, they dictate if the next position in jth dimension should be towards positive infinity or negative infinity as well as the step size. More details about these parameters can be found in [44].To update the position of the followers, the following equations is utilized:

$$x_j^i = \frac{1}{2}(x_j^i + x_j^{i-1}) \tag{16}$$

Where $i > 2$ and x_j^i shows the position of i^{th} follower salp in j^{th} dimension.

Sequential steps for SSA

i. The lower bound and the upper bound for all the search agents are initialized. Initialization process of different search agents are assigned randomly in the initial stage within their lower and upper bound. Also the total number of iterations is decided and then the number of search agents to be used in the algorithm is decided.

ii. In this stage, the objection function of the system is calculated. This function depends on the independent variables given by the user.

iii. If the fitness function value obtained in the present iteration is less than the previous iteration value, then it can be assigned as the local best. Then the Salp Swarm function starts its processing. Initially, the parameters of SSA are assigned with a fixed value and as the iterations increase the value of these parameters keep on changing. Using SSA algorithm, the changed value of search agents have to be checked their different constraints. If there is any violation, then their values are fixed with their boundary conditions.

iv. As the iteration changes, the value of these three parameter also changes and the search agents collectively move towards the global optimum value (14). After every iteration the fitness value of the search agents also changes. The search agent that is nearest to the global optimum value has the highest fitness. In this way the search agents will move in the search space and will explore the entire search space for the optimized value. Once the location of the optimized value is known to the search agent, then the phase of exploitation will begin. Now the search agents instead of moving in the entire search space, will exploit the regions where the results are promising. In this way the search agents tend to move towards the global optimum value. (15) Once the iteration count is reached or the value of the cost function is obtained within the tolerance limit, then the iteration is terminated. The result obtained at that time is considered to be the sub-global value (16).

v. Once the final iteration count is reached, the algorithm is terminated and the search agents having the highest fitness is considered to be nearest to the global optimum value.
The flow chart of SSA algorithm is shown in Figure 1:

Figure 1

In this subsection, the steps to solve the ELD problem by the implementation of SSA is explained. The detailed sequential steps for solving the ELD problem is explained below:

i. Initialization of various parameters takes place in the first step. Various variables like the *lower bound, upper bound, total power demand* P_D, etc. are initialized. The total number of generators is denoted by, *m* and total number of search agents is denoted by *Popsize*.
The search agent matrix is represented as:
$X = X_i = [X_1, X_2, X_3, \dots X_{Popsize}]$ where i = 1, 2, 3, …, Popsize
For ELD problem search agent matrix is assigned as active power generation and represented as the follows:
$$[X_{ij}] = [X_{i1}, X_{i2}, X_{i3}, \dots, X_{im}] = [P_{i1}, P_{i2}, P_{i3}, \dots, P_{im}] = [P_{ij}]$$
where m = number of generators

ii. Each of the element of the search agent should follow the equations (3), (6), (7), (8) and (9). If various effects like the ramp rate limit and the prohibited operating zone are considered then the equation should be satisfied based on (6), (7), (8) and (9) respectively.

iii. For ELD problem the objective function is considered the fuel cost of power generation and it can be using (1) when quadratic fuel cost function is used and (2) when valve point loading effect is considered. This objective function serves as the base of the algorithm. The function needs to be minimized to minimize the cost for the power generation in the system. The objective function of fuel cost is calculated based on the power generation (P_{ij}) from step (i).

iv. The main working mechanisms of the algorithm begins form (14). The values for the four main parameters of the algorithm are assigned to the concerned variables i.e. c_1 to c_3. These values help the movement of the search agent (X_{ij}) (i.e. power generation (P_{ij})) in the search space. Using (13), (14) and (15), the movement of search agents takes place in the search space.

v. Now the new values of the power generations are obtained. These new values are checked for the constraints given in equations (3), (6), (7), (8) and (9). If various effects like the ramp rate limit and the prohibited operating zone are considered then the equation should be satisfied based on (6), (7), (8) and (9) respectively. If any value violates any of these constraints, then its upper or lower value is considered. And the slack value of power generation can be calculated based on (11) and (12). If there are any violations of any inequality constraint (3), (6), (7), (8) and (9) that are valid for the slack generator, then repeat from step (ii). This process will continue until the ultimate set of power generation matrix is formed.

vi. The new objective function of fuel cost can be calculated based on the newly generated power generation matrix.

vii. Now the current objective values are compared with the values obtained in the previous iterations. If the present objective value is less than the previous value, then the present value is treated as the best local optimized value, but if the current value is not less as compared to previous value, then the previous value remains in the same position of the newly generated value of the power generation matrix. Now the objective function value obtained in the present iteration will be compared to all other values obtained in various iterations and finally the minimum value will be made the global optimum value. This global optimum value will be stored in a different memory location.

viii. Goto step (ii) for the next iteration. Terminate the process after a predetermined value of the iteration count is reached.

4. Simulations and results

To prove the effectiveness of the SSA, six sets of experiments have been conducted and the final results have been compared to various existing methods in a tabular manner as well as graphically.

The SSA algorithm has been applied to four different test systems with varying degrees of complexity for verifying its effectiveness and feasibility. The program has been written in MATLAB-2017B language and executed on a 1.7 GHz Intel core i3 personal computer with 4-GB RAM. All the systems are re-simulated with the same configuration.

Test Case 1: 6 generator units have been considered in Test System 1, where the transmission losses have been taken into account. The total power demand is 1263 MW. Here we have not considered valve point loading effect, ram-rate limit or prohibited operating zone. .The input data is taken from [45] and the system runs for 400 iterations. The number of search agents used are 50 in this case. In test case 1, the results of the SSA algorithm are compared with TLBO[45], CTLBO[45] and AIS[45] optimization techniques. It can be seen from the graph and the table that the minimum cost is first reached by using the SSA algorithm and the rest of the optimization techniques take minimum time as compared to other. In Table 1, the minimum fuel cost for 6 generator units is 15377.8907 $/hr. obtained by the proposed algorithm is better than TLBO[45], CTLBO[45] and AIS[45]. The minimum, maximum and the average fuel cost obtained after 50 trials are presented in Table 2. The convergence characteristics of SSA is shown in Figure 2. The net power delivered to the system comes out to be 1274.0128 MW. Hence the accuracy of the result is 99.99% based on (4).

Table 1	Table 2	Figure 2

Test Case 2: 10 generator units have been considered in Test case 2, where the transmission losses have been neglected. This test case has considered multi fuel cost and valve point loading effect. Here we have not considered ram-rate limit or prohibited operating zone. The total power demand is 2700 MW. The input data is taken from [46]. The number of search agents used are 50 in this case. In this test case, the results obtained using SSA algorithm are compared with PSO-LRS[47], APSO[47], CBPSO-RVM[47] and OKHA[47] optimization techniques to prove the effectiveness of SSA algorithm. In Table 3, the minimum fuel cost for 10 generator units is 623.9170 $/hr. obtained by the proposed algorithm is better than PSO-LRS[47], APSO[47], CBPSO-RVM[47] and OKHA[47]. The minimum, maximum and the average fuel cost obtained after 50 trials are presented in Table 4. It can be seen from the Table 4 that the minimum cost is first reached by using the SSA algorithm and the rest of the optimization techniques take minimum time as compared to other. The convergence characteristic of SSA is shown in Figure 3. The net power delivered to the system comes out to be 2699.9999 MW. Hence the accuracy of the result is 99.9999% based on (4) with transmission losses have been neglected. The fuel cost mentioned of OKHA[47] is 605.6449 $/hr, but based on the mentioned output power generation for each unit with consideration the input data from [46], the actual fuel cost should be 628.8264 $/hr which is much higher as compared to SSA.

Table 3	Table 4	Figure 3

Test Case 3: 13 generator units have been considered in Test System 3, where the transmission losses have been considered. The total power demand is 2520 MW. The input data is taken from [48] and the system runs for 400 iterations. Here we have considered valve point loading. We have neglected ram-rate limit and prohibited operating zone. The number of search agents used are 50 in this case. In this Test Case, the results of the SSA algorithm are compared with ORCCRO [49], SDE [50] and BSA [57] optimization techniques as shown in Table 5. The fuel cost obtained by using SSA comes out to be 24512.6085 $/hr. It can be seen from Table 6 that the minimum cost is first reached by using the SSA algorithm and the rest of the optimization techniques take minimum time as compared to other. The results obtained by the proposed algorithm are better than SDE [50], ORCCRO [49] and BSA [57]. The minimum, maximum and the average fuel cost obtained after 50 trials are presented in Table 6. The convergence characteristic of SSA is shown in Figure 4. The net power delivered to the system comes out to be 2520 MW. Hence the accuracy of the result is 100.00% based on (4).

Table 5	Table 6	Figure 4

Test Case 4: In this Test Case, 40 generator units with valve point loading have been considered. The test case has been splitted into two parts, in test case (a) transmission loss has been neglected and in test case (b) transmission loss has been considered. For both the cases prohibited operating zone and ram-rate limit have been neglected. The details of these two case study have been given below. Here this system can be of two types: one in which the transmission losses have been neglected and second in which the transmission losses have been taken into account.

Case (a): In this case 40 generator units with valve point have been considered. Transmission losses neglected. The input data is taken from [51]. The total load demand is 10500 MW. In the test case 4(a), the results of the SSA algorithm are compared with EMA[51] and QPSO[51] optimization techniques. It can be seen from table 7 that the minimum cost is first reached by using the SSA algorithm and the rest of the optimization techniques take more time. In Table 7, the minimum fuel cost for 40 generator units is 121412.5347 $/hr. obtained by the proposed algorithm is better than EMA[51] and QPSO[51]. The minimum, maximum and the average fuel cost obtained after 50 trials are presented in Table 8. The convergence characteristic of SSA is displayed in Figure 5. The net power delivered to the system comes out to be 10500 MW. Hence the accuracy of the result is 100.00% based on (4) with transmission losses neglected.

Table 7 Table 8 Figure 5

Case (b): In this case 40 generator units have been considered and their transmission losses have been taken into consideration. The total power demand is 10500 MW. The input data is taken from [52] and the system runs for 400 iterations. 50 search agents are used in this case. Only valve-point loading effect is considered as a constraint for this test case. The comparison of the optimum fuel cost obtained using various optimization techniques is given in Table 9. Table 10 illustrates the minimum, maximum and the average fuel cost of various optimization techniques after 50 trials. The convergence characteristic is shown in Figure 6. The minimum fuel cost obtained using SSA comes out to be 136653.0219 $/hr. Looking at the tabular data it is clear that the minimum fuel cost is obtained by using SSA, is better with other techniques like GAAPI [49], DE/BBO[49], SDE [50] and BBO[49]. The net power delivered to the system comes out to be 10500 MW. Hence the accuracy of the result is 100.00% based on (4).

Table 9 Table 10 Figure 6

Test Case 5: To investigate the efficiency of SSA in a large power system, experiments are conducted on the Korean power system. The input data is taken from [58]. This test system is fossil fuel based power system, comprising of forty thermal generating units, fifty-one gas units, twenty nuclear unit and twenty-nine oil units. Out of 140-units, 6 thermal units, four gas units and two oil units have non-convex fuel cost function addressing valve loading effects. The total load demand is 49342 MW. The large and complicated test system of 140 generating units have been considered here with valve point loading effects, ramp rate limits and prohibited operating zones. The system is made to run for 1000 iterations. 50 search agents are used in this case. Since the cost function of each generating unit is considered as the second-order polynomial, the global optimum solution can be obtained using the mathematical programming techniques. Table 11 shows the power generation of each of the 140 generators using the SSA. The total fuel cost obtained by SSA comes out to be 1658384.8872 $/hr. Table 12 compares the minimum, maximum and the average fuel cost obtained using various optimization techniques after 50 trials. Figure 7 shows the convergence characteristic of SSA. The results in Table 11 prove that the minimum fuel cost is obtained using SSA is much better than other algorithms. The net power delivered to the system comes out to be 49342 MW. Hence the accuracy of the result is 100.00% based on (4).

Table 11 Table 12 Figure 7

Tuning of parameters for the SSA

To obtain the optimized solution with the use of SSA, it is imperative to obtain the proper values of parameters c_1, c_2 and c_3. Tuning of these parameters is very important for obtaining the optimized solution. Different values of these parameters give different fuel costs. For one single value of one parameter, other parameters have to be varied for all possible combinations. For single value of c_1 different combinations of c_2 and c_3 have been tried to obtain the minimum fuel cost. Optimum fuel cost obtained for 140 unit test system with all parameters: $c_1 = 0.7886$, $c_2 = 0.4082$ and $c_3 = 0.3452$ is 1658384.8872 $/hr. which is shown in table 13. However the optimum value of fuel cost obtained for other test systems are also with the same value of all parameters. To present all these results for all test system in a table, takes lots of space. Therefore, the detail tuning procedure is not presented here. A brief summarized result is only shown in for the most complex 140 generator system out of five test systems is shown in Table 13.

Also, using large number of search agents or using too less search agents for screening the search space does not give the optimized solution. So a specific number of search agents will only help to obtain the optimized solution. For each number of search agent trials have been run. The output obtained after using various number of search agents is shown in Table 14. Out of these trials, 50 number of search agents achieves the optimized fuel cost. For other number of search agents, no significant improvement in the fuel cost is observed. Moreover, beyond 50 number of search agents, the simulation time also increases.

The optimum values of the tuned parameters are P_{size}=50, c_1=0.7886, c_2=0.4082 and c_3=0.3452.

Simulation Time Comparison: In this section authors have created a table which compares the simulation time of the SSA algorithm with all the other algorithms for all five different test systems. The authors understand that it is not possible to compare the simulation time, as different authors have used different computer configurations, but this table just gives an indication about the superiority of SSA with same computer configurations. The programs have been written in MATLAB-2017B language and executed on a 1.7 GHz Intel core i3 personal computer with 4-GB RAM. All the systems are re-simulated with the same configuration.

Table 13 Table 14

Comparative study

Quality of Solution: Tables 1, 3, 5, 7, 9 and 11 show that the fuel cost obtained by the SSA is the least as compared to other optimization techniques. The cost obtained by SSA is better than the cost obtained by many previously developed algorithms. Like for example, in test case 1, the minimum fuel cost using the SSA is 24512.6085 $/hr. which is less as compared to the minimum fuel cost obtained by using SDE and ORCCRO. The comparison has been made by neglecting the transmission losses as well as by taking the transmission losses into account. Thus, it is clear that the quality of the solution is the best when SSA is applied.

Robustness: The robustness of any optimization algorithm cannot be judged by only running the algorithm for a single time. Number of trials should be conducted in order to prove the robustness of any optimisation technique. It is evident form tables 4 and 6 that SSA achieves the optimal solution for all the 50 trials for various test cases and from other tables 2, 8, 10 and 12, it can be said that SSA gives the minimum fuel cost for the maximum number of trials as compared to other optimization techniques. This proves that the efficiency of the SSA is very high and so the performance of SSA is superior as compared to other optimization techniques. This proves that consistently the algorithm perform well when it is compared to other algorithms.

Computational efficiency: The efficiency of any optimization technique is determined by the time the technique takes to reach the global optimal solution. It is clear from table 15 that the computational time taken for one single iteration is the least for the SSA as compared to other previously developed optimization techniques. Thus, the SSA gives the global optimal results in the least computational time.

Table 15

5. Conclusion

A new algorithm named Salp Swarm Algorithm has been proposed to solve ELD problem. To prove the efficiency of the SSA, five test systems of various kinds of thermal power plants have been considered in which the main objective is the net fuel cost. This objective is obtained by SSA has been shown in tables 1, 3, 5, 7, 9 and 11. The comparison with other techniques is also shown in those tables. The average, minimum and the maximum value obtained for different optimization techniques in various test systems within a particular number of trials is also considered to be important and is to be minimized for any optimization technique. The authors have been able to prove the effectiveness of SSA with other algorithm with the consideration of these components in tables 2, 4, 6, 8, 10 and 12. As simulation time is also important object in soft computing techniques, the authors also considered simulation time for same test system with same other efficient optimization techniques. The authors have considered the simulation time for above discussed Test Systems and have successfully proved that SSA takes minimum computational time. This has been shown in table 15. The results prove that SSA is consistent, feasible, and more effective as compared to other algorithms in terms of efficiency and computational time. The numerical results also prove that the SSA prevents premature convergence and has a stable convergence characteristic. Hence, by using the exploration and exploitation ability of SSA, the problem of ELD has successfully been solved.

References

[1] Dhar R. N. and Mukherjee P. K., "Reduced-gradient method for economic dispatch" Electrical Engineers, Proceedings of the Institution of, Volume: 120, Issue: 5 Pages: 608 – 610 (1973).

[2] Aoki K. and Satoh T., "Economic Dispatch with Network Security Constraints Using Parametric Quadratic Programming" IEEE Power Engineering Review, Volume: PER-2, Issue: 12 Pages: 37 – 38 (1982).

[3] El-Keib AA and Ma H, Hart J.L., "Environmentally constrained economic dispatch using the Lagrangian relaxation method" IEEE Trans Power Syst; 9(4):1723–1729 (1994).

[4] Su C. T. and Lin C. T., "New approach with a Hopfield modeling framework to economic dispatch" IEEE Transactions on Power Systems, Volume: 15, Issue: 2, Pages: 541 – 545 (2000).

[5] Jabr R. A., Coonick A. H. and Cory B. J., "A homogeneous linear programming algorithm for the security constrained economic dispatch problem" IEEE Transactions on Power Systems, Volume: 15, Issue: 3 Pages: 930 – 936 (2000).

[6] Swamp K. S. and Natarajan A., "Constrained optimization using evolutionary programming for dynamic economic dispatch" Proceedings of 2005 International Conference on Intelligent Sensing and Information Processing, 2005, Pages: 314 – 319 (2005).

[7] Farooqi M. Jain R, P. and Niazi K. R.., "Using Hopfield neural network for economic dispatch of power systems" Proceedings. National Power Engineering Conference, PECon 2003. Pages: 5 – 10 (2003).

[8] Reis Nascimento M. H., Nunes M. V. A., Rodriguez J. L. M., Leite J. C., "A new solution to the economical load dispatch of power plants and optimization using differential evolution." Electrical Engineering 99.2: 561-571 (2017).

[9] Khatir A. A., Motamedi A., Sadati N.et al, "Fuzzy economic dispatch and spinning reserve allocation using evolutionary programming" 2008 40th North American Power Symposium, Pages: 1 – 5 (2008).

[10] Bavafa M., Monsef H. and Navidi N., "A New Hybrid Approach for Unit Commitment Using Lagrangian Relaxation Combined with Evolutionary and Quadratic Programming" 2009 Asia-Pacific Power and Energy Engineering Conference, Pages: 1 – 6 (2009).

[11] Wang Y., Zhou J., Xiao W., Zhang Y., "Economic Load Dispatch of Hydroelectric Plant Using a Hybrid Particle Swarm Optimization Combined Simulation Annealing Algorithm" Second WRI Global Congress on Intelligent Systems, Volume: 2 Pages: 231 – 234 (2010).

[12] Anand H. and Narang N., "Civilized swarm optimization for combined heat and power economic emission dispatch" 2016 7th India International Conference on Power Electronics (IICPE), Pages: 1 – 6 (2016).

[13] Chaturvedi K.T., Pandit M. and Srivastava L., "Particle swarm optimization with crazy particles for nonconvex economic dispatch" Appl Soft Comput., 9:962–969 (2009).

[14] Lu H., Sriyanyong P., Song Y.H. and Dillon T., "Experimental study of a new hybrid PSO with mutation for economic dispatch with non smooth cost function" Int J Electr Power Energy Syst.;32:921–935 (2010).

[15] Niknam T., Golestane F. and Bahmanifirouzi B., "Modified adaptive PSO algorithm to solve dynamic economic dispatch" 2011 IEEE Power Engineering and Automation Conference, Volume: 1 Pages: 108 – 111 (2011).

[16] King D. J. and Oezveren Warsono C. S., "A Genetic Algorithm Based Economic Dispatch (GAED) with Environmental Constraint Optimisation Universities" Power Engineering Conference (UPEC), Proceedings of 2011 46th International, Pages: 1 – 6 (2011).

[17] Jamal S. Alsumait and Sykulski Jan K., "Solving economic dispatch problem using hybrid GA-PS-SQP method" IEEE EUROCON 2009, Pages: 333 – 338 (2009).

[18] Amjady N. and Nasiri-Rad H., "Solution of non-convex and non-smooth economic dispatch by a new adaptive real coded genetic algorithm" Expert Syst Appl.; 37:5239–5245 (2010).

[19] Hazra J. and Sinha A.K., "Environmental Constrained Economic Dispatch using Bacteria Foraging Optimization" 2008 Joint International Conference on Power System Technology and IEEE Power India Conference, Pages: 1 – 6 (2008).

[20] Maity D., Banerjee S. and Chanda C.K., "Multi-objective economic emission load dispatch using modified biogeography based optimization algorithm" 2016 IEEE 7th Power India International Conference (PIICON), Pages: 1 – 6 (2016).
[21] Nagur P. N., Raj S. and Jadhav H T, "Modified Artificial Bee Colony algorithm for non-convex economic dispatch problems" 2012 International Conference on Green Technologies (ICGT), Pages: 258 – 262 (2012).
[22] Shaw B., Mukherjee V. and Ghoshal S. P., "Seeker optimisation algorithm: application to the solution of economic load dispatch problems" IET Generation, Transmission & Distribution, Volume: 5, Issue: 1 Pages: 81 – 91 (2011).
[23] Rahmat N. Musirin A., I., Abidin A. F., Ahmed M. R., "Economic load dispatch with valve-point loading effect by using Differential Evolution Immunized Ant Colony optimization technique" 2014 Australasian Universities Power Engineering Conference (AUPEC), Pages: 1 – 6 (2014).
[24] Khamsawang S., Pothiya S. and Boonseng C., "Distributed tabu search algorithm for solving the economic dispatch problem" 2004 IEEE Region 10 Conference TENCON 2004, Vol. 3, Pages: 484 – 487 (2004).
[25] Maity D., Banerjee S. and Chanda C. K., "Multi-objective economic emission load dispatch using modified biogeography based optimization algorithm" 2016 IEEE 7th Power India International Conference (PIICON), Pages: 1 – 6 (2016).
[26] Roy P. K. and Mandal D., "Quasi-oppositional biogeography-based optimization for multi-objective optimal power flow" Electric Power Component System, 40:236–256 (2012).
[27] Bhattacharya A. and Chattopadhyay P. K., "Oppositional Biogeography-Based Optimization for multi-objective Economic Emission Load Dispatch" 2010 Annual IEEE India Conference (INDICON), Pages: 1 – 6 (2010).
[28] Arul R., Velusami S. and Ravi G., "Solving combined economic emission dispatch problems using self-adaptive differential harmony search algorithm" 2014 International Conference on Circuits, Power and Computing Technologies [ICCPCT-2014], Pages: 757 – 762 (2014).
[29] Chatterjee A, Ghoshal S.P. and Mukherjee V., "Solution of combined economic and emission dispatch problems of power systems by an opposition-based harmony search algorithm" Int J Electr Power Energy Syst., 39(1):9–20 (2012).
[30] Ghosh B., Dey B. and Bhattacharya A., "Solving economic load dispatch problem using hybrid Krill Herd algorithm" 2015 International Conference on Energy, Power and Environment: Towards Sustainable Growth (ICEPE)(2015).
[31] Das S., Bhattacharya A. and Chakraborty A. K. , "Solution of short-term hydrothermal scheduling using sine cosine algorithm" Soft Computing (2017).
[32] Qin Q., Cheng S., Chua X., Lei X. and Shi Y., "Solving non-convex/non-smooth economic load dispatch problems via an enhanced particle swarm optimization" Applied Soft Computing Volume 59, Pages 229-242 (2017).
[33] Roy S., "The maximum likelihood optima for an economic load dispatch in presence of demand and generation variability" Energy Volume 147, Pages 915-923 (2018).
[34] Roy S., Bhattacharjee K. and Bhattacharya A., "A Modern Approach to Solve of Economic Load Dispatch using Group Leader Optimization Technique" International Journal of Energy Optimization and Engineering, IGI-Global. Vol-6, Issue-1,Article-4, pp. 66-85 (2016).
[35] Bhattacharjee K., Bhattacharya A. and Halder S., "Teaching Learning Based Optimization for Different Economic Dispatch Problems" International Journal of Science and Technology, Scientia Iranica Volume 21, Issue 3, pp-870-884 (2014).
[36] Júnior A. B., Jorge De, M. V. A. Nunes, M. H. R. Nascimento, J. L. M. Rodríguez, J. C. Leite, "Solution to economic emission load dispatch by simulated annealing: case study". Electrical Engineering, 1-13 J. C. (2017).
[37] Kaveh A., Vaez S. R. H. and Hosseini P., "Enhanced vibrating particles system algorithm for damage identification of truss structures", *Scientia Iranica*, (2017).
[38] Singh D. and Dhillon J.S., "Ameliorated grey wolf optimization for economic load dispatch problem" Energy Volume 169, Pages 398-419 (2019).
[39] Kumara M. and Dhillon J. S., "Hybrid artificial algae algorithm for economic load dispatch" Applied Soft Computing Volume 71, Pages 89-109 (2018).

[40] Aghay Kaboli S. Hr. and Abdullah K. A., “Solving non-convex economic load dispatch problem via artificial cooperative search algorithm” Expert Systems with Applications Volume 128, Pages 14-27 (2019).
[41] Gholamghasemi M., Akbari E. and Asadpoor M. B., “A new solution to the non-convex economic load dispatch problems using phasor particle swarm optimization” Applied Soft Computing Volume 79, Pages 111-124 (2019).
[42] Bulbul Sk Md Ali , Pradhan M. , Roy P. K. , Pal T., “Opposition-based krill herd algorithm applied to economic load dispatch problem” Ain Shams Engineering Journal, Volume 9, Issue 3, Pages 423-440 (2018).
[43] Zhang Q. , Zou D. and Duan N., “An adaptive differential evolutionary algorithm incorporating multiple mutation strategies for the economic load dispatch problem” Applied Soft Computing, Volume 78, Pages 641-669 (2019).
[44] Mirjalili S., Gandomi A. H., Mirjalili S. Z.,et al, “Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems” Advances in Engineering Software 114 (2017) 163–191.
[45] X. He, Y. Rao and J. Huang, “Novel algorithm for economic load dispatch of power systems” Neurocomputing 171(2016)1454–1461
[46] Lu H., Sriyanyong P., Song Y. H., Dhilon T., “Experimental study of a new hybrid PSO with mutation for economic dispatch with non-smooth cost function” Electrical Power and Energy Systems 32 (2010) 921–935
[47] Ali Bulbul S M, Pradhan M., Roy P. K., Pal T., “Opposition-based krill herd algorithm applied to economic load dispatch problem”, Ain Shams Engineering Journal (2016).
[48] Coelho L. D. S. and Mariani V. C. “Combining of chaotic differential evolution and quadratic programming for economic dispatch optimization with valve- point effect” IEEE Trans Power System; 21(2):989–96 (2006).
[49] Bhattacharjee K., Bhattacharya A. and Halder S., “Oppositional Real Coded Chemical Reaction Optimization for different economic dispatch problems” Electrical Power and Energy Systems 55, 378–391 (2014).
[50] Reddy S. and Vaisakh K., “Shuffled differential evolution for large scale economic dispatch” Electric Power Syst Res.; 96:237–245 (2013).
[51] Ghorbani N. and Babaei E., “Exchange market algorithm for economic load dispatch”, Electrical Power and Energy Systems 75, 19–27 (2016).
[52] Sinha N, Chakrabarti R. and Chattopadhyay P. K., “Evolutionary programming techniques for economic load dispatch” IEEE Trans Evol. Comput. 7(1):83–94 (2003).
[53] Bhattacharjee K., Bhattacharya A. and Chattopadhyay P. K., “Discussion on “A GA-API Solution for the Economic Dispatch of Generation in Power System Operation” IEEE transaction on power systems, vol. 28, no. 1, (2013).
[54] Roy S. and Bhattacharjee K., “The use of krill herd based optimization to solve complex economic load dispatch problems” Emerging Devices and Smart Systems (ICEDSS), 2017
[55] Rani S., Roy S., Bhattacharjee K., Bhattacharya A., “Teaching Learning Based Optimization to Solve Economic and Emission Scheduling Problems”, 2016 2nd International Conference on Control, Instrumentation, Energy & Communication (CIEC) (2016).
[56] Bhattacharjee K., Bhattacharya A. and Halder S., “Chemical Reaction Optimization Applied In Economic Dispatch Problems” 1st international conference on automation, control, energy and systems (ACES 14), Academic of technology, Hooghly, India, 1-2, Pages: 1 – 6 (2014).
[57] Bhattacharjee K., “Economic Dispatch Problems using Backtracking Search Optimization” International Journal of Energy Optimization and Engineering, IGI-Global. Vol-7, Issue-2,Article-2, pp. 39-60 (2018).
[58] Park J., Jeong Y., Shin J. et al, “An Improved Particle Swarm Optimization for Non-convex Economic Dispatch Problems” IEEE Transactions on power systems, vol. 25, no. 1 (2010).
[59] Huang, Wei T., et al., "Derivation and Application of a New Transmission Loss Formula for Power System Economic Dispatch" Energies 11.2 (2018): 417.

[60] Moradi-Dalvand M., Mohammadi-Ivatloo B. and Najafi A.,et al, "Continuous quick group search optimizer for solving non-convex economic dispatch problems" Electric Power Systems Research, Volume 93, Pages 93-105 (2012).
[61] Mohammadi-Ivatloo B., Rabiee A., Ehsan S. M., "Iteration PSO with time varying acceleration coefficients for solving non-convex economic dispatch problems" Electrical Power and Energy Systems, Volume 42, Pages 508–516 (2012).

List of Figures

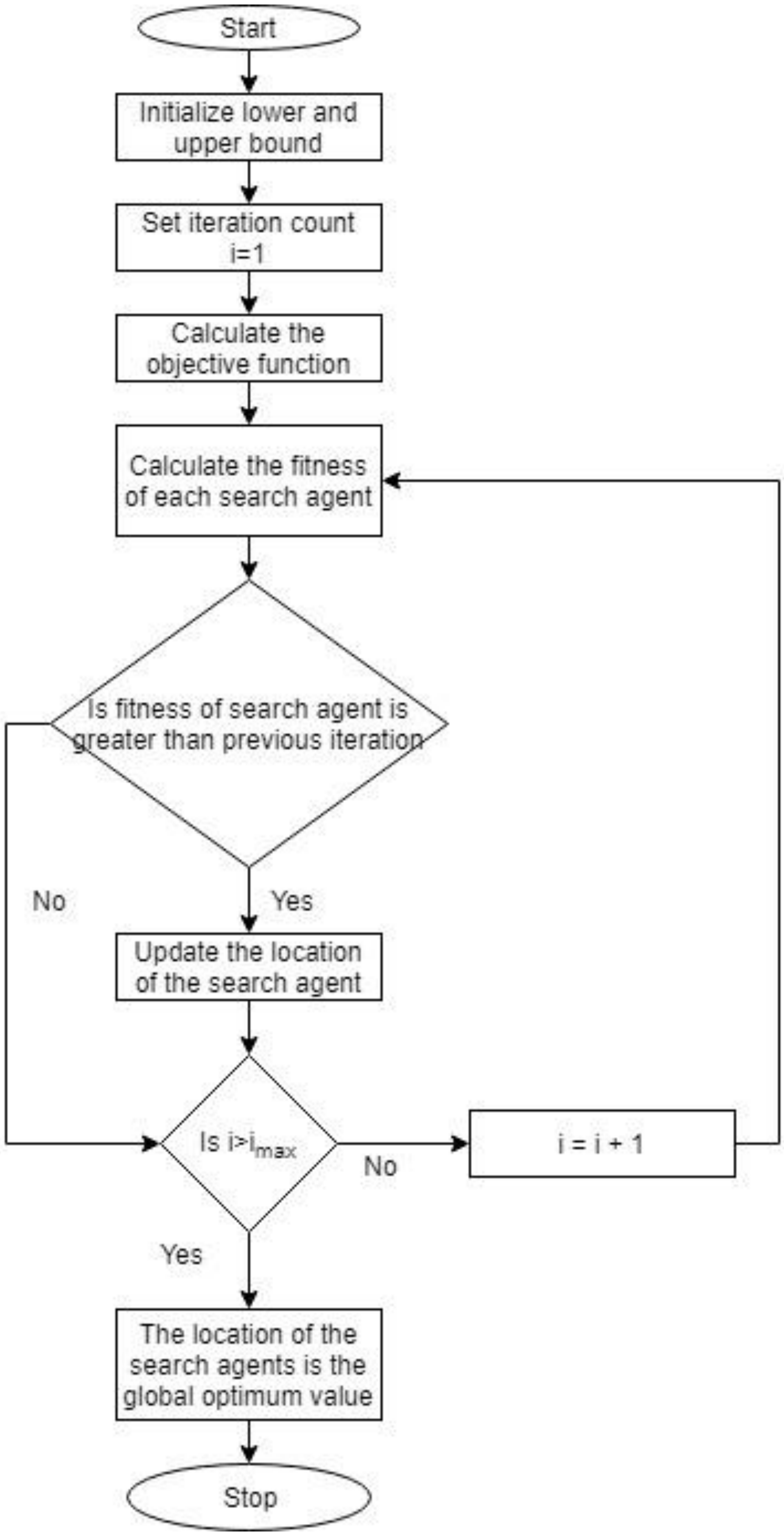

Figure 1: Flowchart

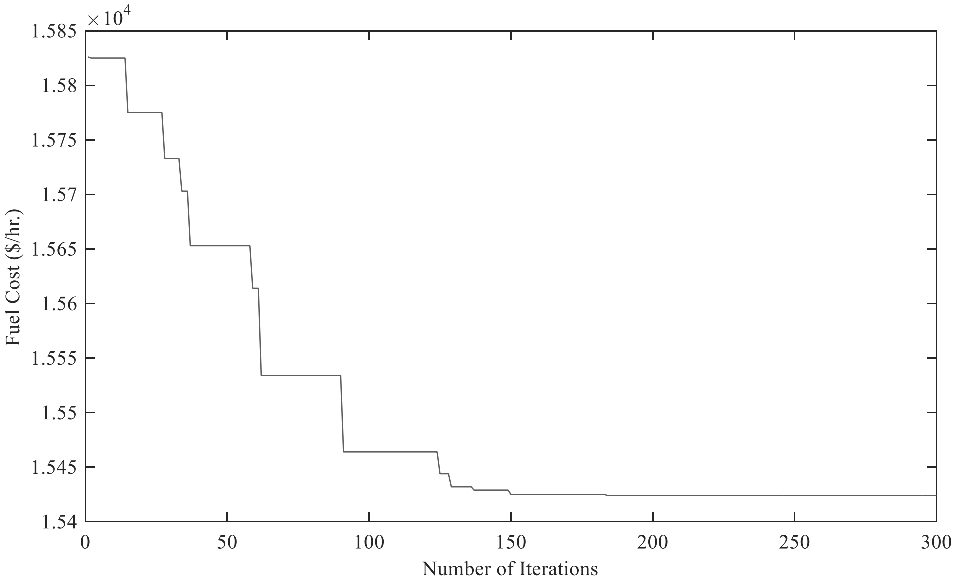

Figure 2: Convergence characteristic of SSA for 6 generator units

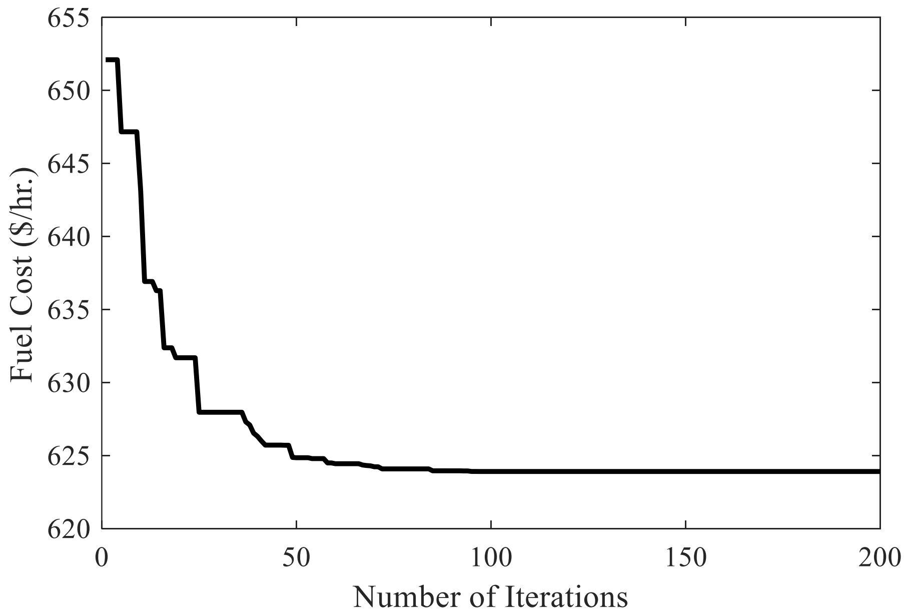

Figure 3: Convergence characteristic of SSA for 10 generator units

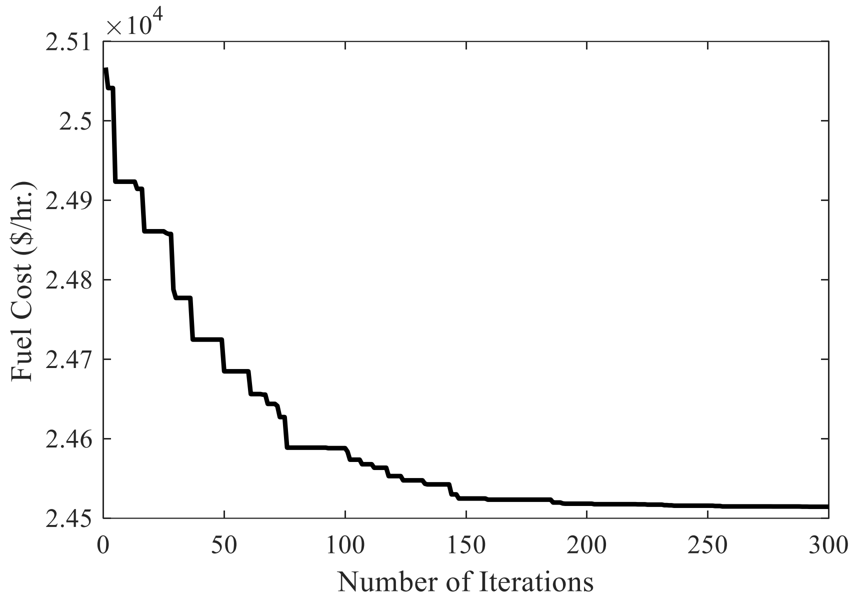

Figure 4: Convergence characteristic of SSA for 13 generator units

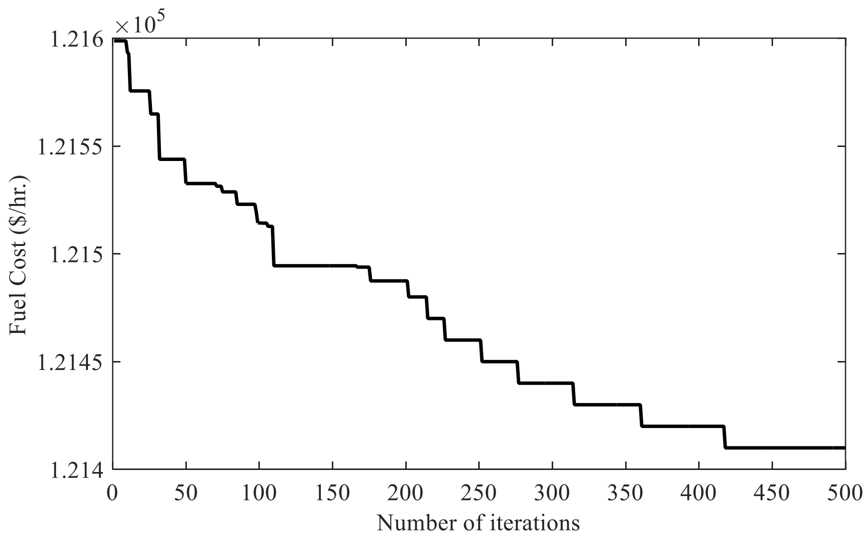

Figure 5: Convergence characteristic of SSA for 40 generator units

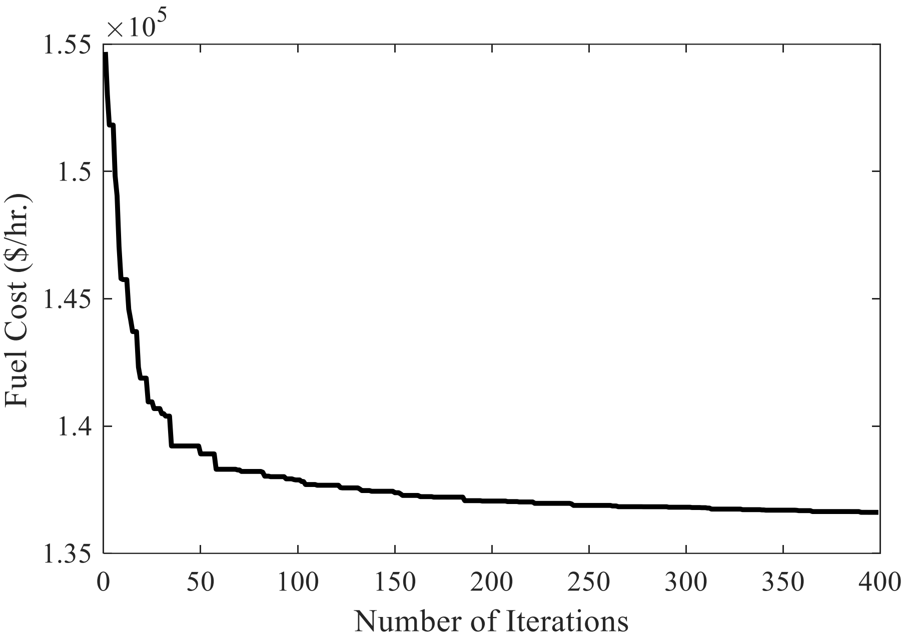

Figure 6: Convergence characteristic of SSA for 40 generating units

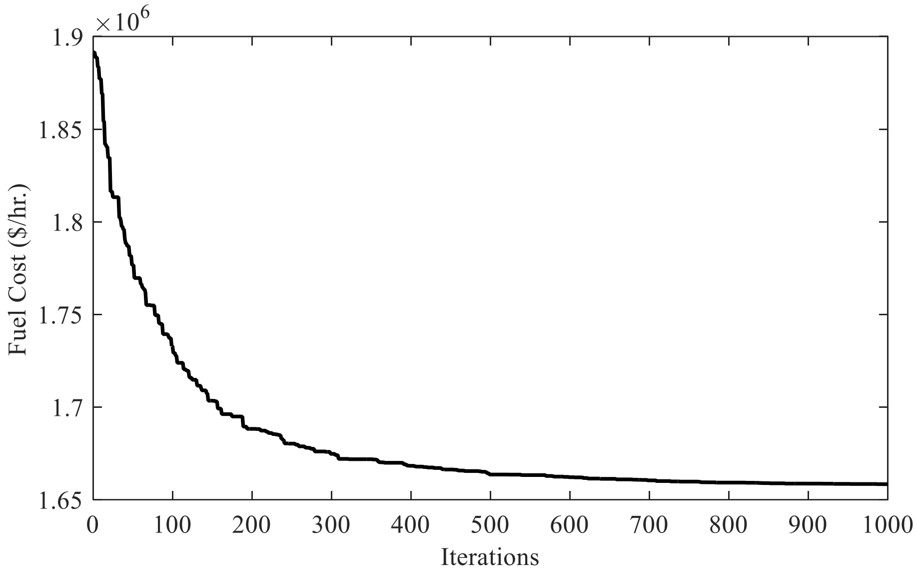

Figure 7: Decreasing cost for 140 generator units using SSA

List of Tables

Table 1: Optimum power output and fuel cost for SSA and other techniques comparison for 6 unit test system

Unit	Power Output (MW)					
	SSA	TLBO[45]	CTLBO[45]	AIS[45]	QGSA[60]	IPSO-TVSC[61]
P_1	442.9518	446.7270	449.4980	458.2904	263.9079	447.5840
P_2	172.7533	173.4890	173.4810	168.0518	173.2418	173.2010
P_3	257.3543	173.4890	264.9700	262.5175	263.9079	263.3310
P_4	136.1425	138.8320	127.4610	139.0604	139.0529	138.8520
P_5	162.5341	165.6500	173.8420	178.3936	165.6013	165.3280
P_6	102.0713	86.9460	86.2390	69.3416	86.5357	87.1500
Transmission Loss (MW)	11.0128	12.4180	12.4900	13.1997	12.4163	12.4460
Power Generated (MW)	1274.0128	1275.4180	1275.4900	1275.6550	1275.4163	1275.4460
Fuel Cost ($/hr.)	15424.0734	15,442.5200	15,441.6970	15,448.0000	15,442.6608	15443.0630

Table 2: Minimum maximum and average cost obtained by SSA and various optimization techniques for 6 generator units (50 trials)

Methods	Generation cost ($/hr.)			No. of hits to minimum solution	Standard Deviation
	Maximum	Minimum	Average		
SSA	15427.0734	15424.0734	15424.2534	47	0.06
TLBO[45]	15450.3685	15442.5200	15445.8163	29	0.42
CTLBO[45]	15449.0236	15441.6970	15445.9464	21	0.58
AIS[45]	NA	623.9588	NA	NA	NA
QGSA[60]	15,442.6630	15,442.6608	15,442.6614	NA	NA
IPSO-TVSC[61]	155445.1140	15443.0630	15443.5820	NA	NA

*NA-Not available

Table 3: Optimum power output and fuel cost for SSA and other techniques comparison for 10 unit test system

Unit	Power Output (MW)									
	Fuel type	SSA	Fuel type	PSO-LRS [47]	Fuel type	APSO [47]	Fuel type	CBPSO-RVM[47]	Fuel type	OKHA [47]
P_1	2	217.0407	2	219.0155	2	223.3377	2	219.2073	2	214.4684
P_2	1	211.8944	1	213.8901	1	212.1547	1	210.2203	1	208.9873
P_3	1	281.6792	1	283.7616	1	276.2203	1	278.5456	1	332.0575
P_4	3	238.2056	3	237.2687	3	239.4176	3	239.3704	3	238.1622
P_5	1	279.8321	1	286.0163	1	274.6411	1	276.412	1	269.2157
P_6	3	239.2547	3	239.3987	3	239.7953	3	240.5797	3	238.5653
P_7	1	290.2798	1	291.1767	1	285.5406	1	292.3267	1	280.6120
P_8	3	240.2228	3	241.4398	3	240.6270	3	237.7557	3	237.6241
P_9	3	425.5958	3	416.9721	3	429.3104	3	429.4008	3	413.8705
P_{10}	1	275.9942	1	271.0623	1	278.9553	1	276.1815	1	266.4366
Fuel Cost ($/hr.)		623.9170		624.2297		624.0145		623.9588		605.6449*

*The precise fuel cost of generation in [47] is 628.8264 $/hr. which is much higher than that reported in [47].

Table 4: Minimum maximum and average cost obtained by SSA and various optimization techniques for 10 generator units (50 trials)

Methods	Generation cost ($/hr.)			No. of hits to minimum solution	Standard Deviation
	Maximum	Minimum	Average		
SSA	623.9170	623.9170	623.9170	50	0
PSO-LRS[47]	626.7210	624.2297	625.3756	27	0.46
APSO[47]	628.3947	624.0145	626.5550	21	0.58
CBPSO-RVM [47]	NA	623.9588	NA	NA	NA

*NA-Not available

Table 5: Optimum power output and fuel cost for SSA and other techniques comparison for 13 unit test system

Unit	Power Output (MW)			
	SSA	SDE[50]	ORCCRO[49]	BSA[57]
P_1	628.3179	628.32	628.32	628.3158
P_2	299.1992	299.20	299.20	299.1947
P_3	297.4468	299.20	299.20	297.4764
P_4	159.7327	159.73	159.73	159.7322
P_5	159.7327	159.73	159.73	159.7330
P_6	159.7328	159.73	159.73	159.7328
P_7	159.7331	159.73	159.73	159.7318
P_8	159.7325	159.73	159.73	159.7329
P_9	159.7328	159.73	159.73	159.7286
P_{10}	77.3995	77.40	77.40	77.3945
P_{11}	114.7993	113.12	112.14	114.7992
P_{12}	92.3997	92.40	92.40	92.3962
P_{13}	92.4000	92.40	92.40	92.3919
Power Generation (MW)	2559.8000	2560.4300	2559.43	2560.3641
Transmission Loss (MW)	39.8000	40.43	39.43	39.8006
Fuel Cost ($/hr.)	24512.6085	24514.88	24513.91	24512.6654

Table 6: Minimum maximum and average cost obtained by SSA and various optimization techniques for 13 generator units (50 trials)

Methods	Generation cost ($/hr.)			No. of hits to minimum solution	Standard Deviation
	Maximum	Minimum	Average		
SSA	24512.61	24512.61	24512.61	50	0
ORCCRO[49]	24518.56	24513.91	24515.72	27	0.46
SDE[50]	24519.74	24514.88	24516.23	21	0.58
BBO[49]	NA	24519.69	NA	NA	NA
DE/BBO[49]	24522.45	NA	24519.58	NA	NA

*NA-Not available

Table 7: Optimum power output and fuel cost for SSA and other techniques comparison for 40 unit test system

Unit	Power Output (MW)		
	SSA	EMA[51]	QPSO[51]
P_1	110.7998	110.7998	111.2000
P_2	110.7998	110.7998	111.7000
P_3	97.3999	97.3999	97.4000

P_4	179.7331	179.7331	179.7300
P_5	87.7998	87.7999	90.1400
P_6	139.9999	140.0000	140.0000
P_7	259.5996	259.5996	259.6000
P_8	284.5996	284.5996	284.8000
P_9	284.5996	284.5996	284.8400
P_{10}	130.0000	130.0000	130.0000
P_{11}	94.0000	94.0000	168.8000
P_{12}	94.0000	94.0000	168.8000
P_{13}	214.7597	214.7598	214.7600
P_{14}	394.2793	394.2793	304.5300
P_{15}	394.2793	394.2793	394.2800
P_{16}	394.2793	394.2793	394.2800
P_{17}	489.2793	489.2793	489.2800
P_{18}	489.2793	489.2793	489.2800
P_{19}	511.2793	511.2793	511.2800
P_{20}	511.2794	511.2793	511.2800
P_{21}	523.2793	523.2793	523.2800
P_{22}	523.2793	523.2793	523.2800
P_{23}	523.2793	523.2793	523.2900
P_{24}	523.2793	523.2793	523.2800
P_{25}	523.2793	523.2793	523.2900
P_{26}	523.2793	523.2793	523.2800
P_{27}	10.0000	10.0000	10.0100
P_{28}	10.0000	10.0000	10.0100
P_{29}	10.0000	10.0000	10.0000
P_{30}	87.7999	87.7999	88.4700
P_{31}	189.9999	190.0000	190.0000
P_{32}	189.9999	190.0000	190.0000
P_{33}	190.0000	190.0000	190.0000
P_{34}	164.7998	164.7998	164.9100
P_{35}	199.9999	200.000	165.3600
P_{36}	194.3976	194.3977	167.1900
P_{37}	109.9999	110.0000	110.0000
P_{38}	109.9999	110.0000	107.0100
P_{39}	109.9999	110.0000	110.0000
P_{40}	511.2794	511.2793	511.3600
Fuel Cost ($/hr.)	121412.5347	121412.5355	121448.2100

Table 8: Minimum maximum and average cost obtained by SSA and various optimization techniques for 40 generator units (50 trials)

Methods	Generation cost ($/hr.)			No. of hits to minimum solution	Standard Deviation
	Maximum	Minimum	Average		
SSA	121415.2584	121412.5347	121413.0794	40	0.20
EMA[51]	121416.2031	121412.5355	121414.6617	21	0.58
QPSO[51]	121455.9510	121448.2100	121453.6287	15	0.70

Table 9: Optimum power output and fuel cost for SSA and other techniques comparison for 40 unit test system

Unit	Power Output (MW)				
	SSA	GAAPI[49]	DE/BBO[49]	SDE[50]	BBO[49]
P_1	113.8585	114.0000	111.0400	110.0600	112.5400
P_2	114.0000	114.0000	113.7100	112.4100	113.2200

P_3	119.3004	120.0000	118.6400	120.0000	119.5100
P_4	183.3369	190.0000	189.4900	188.7200	188.3700
P_5	91.7652	97.0000	86.3200	85.9100	90.4100
P_6	139.9816	140.0000	139.8800	140.0000	139.0500
P_7	299.5148	300.0000	299.8600	250.1900	294.9700
P_8	299.1356	300.0000	285.4200	290.6800	299.1800
P_9	297.6808	300.0000	296.2900	300.0000	296.4600
P_{10}	279.1599	205.2500	285.0700	282.0100	279.8900
P_{11}	171.4666	226.300	164.6900	180.8200	160.1500
P_{12}	94.4916	204.7200	94.0000	168.7400	96.7400
P_{13}	485.0345	346.4800	486.3000	469.9600	484.0400
P_{14}	482.8777	434.3200	480.7000	484.1700	483.3200
P_{15}	484.0869	431.3400	480.6600	487.7300	483.7700
P_{16}	484.9795	440.2200	485.0500	482.3000	483.3000
P_{17}	489.6806	500.0000	487.9400	499.6400	490.8300
P_{18}	488.7718	500.0000	491.0900	411.3200	492.1900
P_{19}	515.9524	550.0000	511.7900	510.4700	511.2800
P_{20}	511.6585	550.0000	544.8900	542.0400	521.5500
P_{21}	532.3453	550.0000	528.9200	544.8100	526.4200
P_{22}	549.9726	550.0000	540.5800	550.0000	538.3000
P_{23}	523.9532	550.0000	524.9800	550.0000	534.7400
P_{24}	527.3965	550.0000	524.1200	528.1600	521.2000
P_{25}	523.3733	550.0000	534.4900	524.1600	526.1400
P_{26}	527.6279	550.0000	529.1500	539.1000	544.4300
P_{27}	10.0009	11.4400	10.5100	10.0000	11.5100
P_{28}	11.1190	11.5600	10.0000	10.3700	10.2100
P_{29}	10.1184	11.4200	10.0000	10.0000	10.7100
P_{30}	86.9830	97.0000	90.0600	96.1000	88.2800
P_{31}	189.9885	190.0000	189.8200	185.3300	189.8400
P_{32}	189.9150	190.0000	187.6900	189.5400	189.9400
P_{33}	189.9535	190.0000	189.9700	189.9600	189.1300
P_{34}	199.9110	200.0000	199.8300	199.9000	198.0700
P_{35}	197.9306	200.0000	199.9300	196.2500	199.9200
P_{36}	165.3294	200.0000	163.0300	185.8500	194.3500
P_{37}	109.4111	110.0000	109.8500	109.7200	109.4300
P_{38}	109.9582	110.0000	109.2600	110.0000	109.5600
P_{39}	109.9271	110.0000	109.6000	95.7100	109.6200
P_{40}	547.6016	550.0000	543.2300	532.4700	527.8200
Fuel Cost ($/hr.)	136653.0219	139864.96	136950.77	138157.46	137026.82
Power Generation (MW)	11459.5499	11545.0600	11457.8300	11474.4300	11470.0000
Transmission Loss (MW)	959.5500	1045.0600	957.8300	974.4300	970.3700

Table 10: Minimum, maximum and average fuel cost obtained by SSA and various optimization techniques for 40 generator units (50 trials)

Methods	Generation cost ($/hr.)			No. of hits to minimum solution	Standard Deviation
	Maximum	Minimum	Average		
SSA	136653.10	136653.02	136653.02	48	0.04
BBO[49]	137587.82	137026.82	137116.58	41	0.18
DE/BBO[49]	137150.77	136950.77	136966.77	45	0.10
ORCCRO[49]	136855.19	136845.35	136848.16	43	0.14

Table 11: Optimum power output and fuel cost for SSA for 140 unit test system

Unit	Power Output (MW)	Unit	Power Output (MW)	Unit	Power Output (MW)	Unit	Power Output (MW)
P_{1}	110.8395	P_{36}	499.9997	P_{71}	140.7389	P_{106}	880.9000
P_{2}	163.9999	P_{37}	240.9999	P_{72}	388.4824	P_{107}	873.6998
P_{3}	189.9518	P_{38}	240.9424	P_{73}	230.9036	P_{108}	877.4000
P_{4}	189.9612	P_{39}	773.9925	P_{74}	271.6243	P_{109}	871.6999
P_{5}	168.3794	P_{40}	768.9999	P_{75}	175.9105	P_{110}	864.7967
P_{6}	186.3858	P_{41}	3.161799	P_{76}	293.5256	P_{111}	881.9998
P_{7}	489.9999	P_{42}	3.072809	P_{77}	306.7155	P_{112}	94.20313
P_{8}	489.9997	P_{43}	239.2171	P_{78}	385.5398	P_{113}	95.06407
P_{9}	496.0000	P_{44}	249.8248	P_{79}	530.9998	P_{114}	94.32693
P_{10}	496.0000	P_{45}	247.436	P_{80}	530.9998	P_{115}	244.0719
P_{11}	495.9984	P_{46}	249.2271	P_{81}	542.0000	P_{116}	245.6768
P_{12}	495.9999	P_{47}	246.1245	P_{82}	56.66217	P_{117}	245.6193
P_{13}	505.9871	P_{48}	247.8030	P_{83}	115.1015	P_{118}	96.84149
P_{14}	508.9965	P_{49}	246.1036	P_{84}	115.0754	P_{119}	95.7353
P_{15}	505.9998	P_{50}	246.5329	P_{85}	115.9195	P_{120}	116.5415
P_{16}	504.9999	P_{51}	165.1967	P_{86}	207.117	P_{121}	175.1441
P_{17}	505.9566	P_{52}	165.8992	P_{87}	207.2333	P_{122}	3.6211
P_{18}	505.9948	P_{53}	185.7631	P_{88}	176.4165	P_{123}	4.0487
P_{19}	505.0000	P_{54}	165.0393	P_{89}	175.7241	P_{124}	15.4299
P_{20}	504.9951	P_{55}	180.1148	P_{90}	177.7537	P_{125}	9.6570
P_{21}	504.9971	P_{56}	180.9737	P_{91}	180.4744	P_{126}	13.0826
P_{22}	504.9874	P_{57}	112.9304	P_{92}	575.3998	P_{127}	10.0005
P_{23}	504.9936	P_{58}	199.5520	P_{93}	547.4997	P_{128}	112.0987
P_{24}	504.9997	P_{59}	311.9997	P_{94}	836.7998	P_{129}	4.7148
P_{25}	537.0000	P_{60}	299.2522	P_{95}	837.4999	P_{130}	5.0210
P_{26}	536.9998	P_{61}	163.5181	P_{96}	681.9973	P_{131}	5.0062
P_{27}	548.9997	P_{62}	99.08827	P_{97}	719.9999	P_{132}	50.1757
P_{28}	548.9996	P_{63}	468.563	P_{98}	717.9918	P_{133}	5.0813
P_{29}	500.9999	P_{64}	510.7641	P_{99}	719.9925	P_{134}	42.0132
P_{30}	498.9999	P_{65}	489.9999	P_{100}	963.9999	P_{135}	42.0579
P_{31}	505.9997	P_{66}	201.0382	P_{101}	957.9999	P_{136}	41.1626
P_{32}	505.9910	P_{67}	488.1348	P_{102}	947.8997	P_{137}	17.0139
P_{33}	505.7959	P_{68}	485.3448	P_{103}	933.9998	P_{138}	7.0044
P_{34}	505.9998	P_{69}	132.4697	P_{104}	934.9996	P_{139}	7.0202
P_{35}	500.0000	P_{70}	338.9781	P_{105}	876.4997	P_{140}	31.3066
Total fuel cost = 1658384.8872 $/hr.							

Table 12: Minimum, maximum and average fuel cost obtained by SSA and various optimization techniques for 140 generator units (50 trials)

Methods	Generation cost ($/hr.)			No. of hits to minimum solution	Standard Deviation
	Maximum	Minimum	Average		
SSA	1658386.57	1658384.88	1658384.25	45	0.10
BBO[49]	1669536.35	1665478.25	1667548.32	NA	NA
DE/BBO[49]	1662349.58	1660215.65	1661257.35	NA	NA
ORCCRO[49]	1659823.97	1659654.83	1659725.96	42	0.16

Table 13: Effect of various parameters on the performance of SSA

c_1	c_2	c_3	Fuel Cost ($/hr.)
0.16	0.41	0.14	1658479.1876
0.68	0.65	0.15	1658455.6489

0.47	0.87	0.62	1658438.3245
0.57	0.54	0.25	1658420.9452
0.55	0.65	0.34	1658397.3249
0.7886	0.4082	0.3452	1658384.8872
0.42	0.26	0.95	1658399.5475
0.94	0.32	0.84	1658456.3225
0.21	0.41	0.25	1658472.2587
0.78	0.52	0.41	1658501.3654

Table 14: Effect of number of search agents on the 140 generator system

Number of Search Agents	No. of hits to best solution	Simulation time (s)	Max. cost ($/hr.)	Min. cost ($/hr.)	Average cost ($/hr.)
20	33	48.213	1658406.547	1658399.254	1658401.879
50	45	50.42	1658386.570	1658384.880	1658384.250
100	28	54.25	1658416.235	1658406.325	1658410.884
150	18	57.247	1658428.625	1658412.658	1658422.558
200	12	62.46	1658468.235	1658435.328	1658460.995

Table 15: Simulation Time Comparison

Algorithm	Time/Iteration (S)	Test Case
SSA	0.046	Test Case 1
TLBO[45]	0.85	
CTLBO[45]	NA*	
AIS[45]	NA*	
SSA	0.051	Test Case 2
PSO-LRS[47]	0.85	
APSO[47]	NA*	
CBPSO-RVM [47]	NA*	
SSA	0.041	Test Case 3
ORCCRO[49]	0.087	
SDE[50]	NA*	
BBO[49]	NA*	
DE/BBO[49]	0.90	
SSA	0.15	Test Case 4(a)
EMA[51]	0.23	
QPSO[51]	0.54	
SSA	0.07	Test Case 4(b)
BBO[49]	0.14	
DE/BBO[49]	0.11	
ORCCRO[49]	0.08	
SSA	50.42	Test Case 5
BBO[49]	126.69	
DE/BBO[49]	83.79	
ORCCRO[49]	71.27	

*NA-Not available

Author's Biography

Dr. Kuntal Bhattacharjee received a BE degree from BIET, Suri Private College (Burdwan University), and M.Tech degree from NIT, Durgapur, India, in 2003 and 2005 respectively all in Electrical Engineering. He is currently in the Electrical Engineering Department, Institute of Technology, Nirma University, India. His research interests include power system optimization, ELD, EELD, and hydrothermal applications.

Nitish Patel received his BE degree from Babaria Institute of Technology under Gujarat Technological University and is currently pursuing his M.Tech in Electrical Power Systems from Institute of Technology, Nirma University, Ahmedabad, India. His research interests include Artificial Intelligence, Power System Optimization, Economic Load Dispatch and Hydro-Thermal applications.