Scientia Iranica D (2022) 29(2), 676–692

Sharif University of Technology
Scientia Iranica
Transactions D: Computer Science & Engineering and Electrical Engineering
http://scientiairanica.sharif.edu

A comparative study of economic load dispatch with complex non-linear constraints using salp swarm algorithm

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Received 2 November 2018; received in revised form 14 September 2019; accepted 11 May 2020

KEYWORDS
Economic load dispatch;
Optimization;
Prohibited operating zone;
Salp swarm algorithm;
Valve-point loading.

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 objective of ELD is to satisfy the entire electric load at a minimum cost. The SSA is a population-based probabilistic method that guides its search agents that are randomly placed in the search space to find an optimal point using their fitness function and also, keeps track of the best solution achieved by each search agent. SSA is 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 solution quality obtained and computational efficiency. The final results also prove that SSA is more robust than other techniques.

1. Introduction

Economic Load Dispatch (ELD) is considered one of the valued optimization problems 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 satisfy the total load demand in the most economical way. The main objective of the ELD is to make the entire system reliable and minimize the total generation cost of the thermal power plant. However, the ELD satisfies all the constraints of each and every generator that is considered for the ELD problem.

There are many classic optimization methods including gradient method [1], Quadratic Programming (QP) [2], Lagrangian relaxation [3], Hopfield modeling framework [4], Linear Programming (LP) [5], and Dynamic Programming (DP) [6] that assume a linear increasing cost function and they have been successfully applied to solve the ELD problem. However, the main problem with the classical approach is that it tends to converge at a local optimum and then, begins to diverge from the global optimal solution. The problem with dynamic programming approach is that it requires very large dimensions and consequently, much programming effort. 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 discontinu-

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doi: 10.24200/sci.2020.52145.2562

ous prohibited operating zones. Moreover, 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 in a local optimum solution. Therefore, it becomes imperative to develop an optimization technique that can overcome these drawbacks of the classical based methods and give the global optimum solution in the least computation time. Many artificial intelligence algorithms like the Hopfield Neural Network (HNN) [7] have been employed to solve the ELD problem. The problem with artificial intelligence algorithms is that they take a large number of iterations to reach the global optimum solution, because the algorithms must converge to the global optimum value and the rate of convergence of these algorithms varies. Due to the difference in the rate of convergence, the time duration taken by different algorithms is different. Hence, a longer time is required to reach the global solution. The computer technology has 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], and Harmony Search Algorithm (HSA) [28] for solving ELD problems. Other optimization algorithms, including the Opposition-based Harmony Search Algorithm (OHSA) introduced by Chatterjee et al., have been proposed to solve the ELD problem [29]. Krill Herd Algorithm (KHA) [30] was successfully applied to solve the ELD problems. The problem of short-term hydrothermal scheduling was solved using the SCA technique in [31]. An enhanced version of Particle Swarm Optimization was proposed in [32] to solve the problem of ELD. A new technique maximum likelihood optima technique was also used to solve the ELD problem in [33]. Group Leader Optimization [34] was proposed because of its special ability to solve the non-linear and non-quadratic equations with greater ease. Even Teaching Learning Based Optimization (TLBO) technique was used in [35] to solve the ELD problem. Some of the above-mentioned algorithms run into difficulty finding a local optimum solution, while others have difficulty finding the global optimum solution. Therefore, to overcome this kind of problem, a new and powerful optimization technique is needed. Even the Simulated Annealing Algorithm (SAA) was employed to solve the economic emission dispatch problem in [36]. Moreover, the enhanced vibrating particles system algorithm was employed to identify the damage to the truss structure in [37]. A new algorithm called ameliorated grey wolf optimization [38] has been recently introduced that could solve the ELD problem. The hybrid artificial algae algorithm was used in [39] to solve the ELD problem. In [40] and [41], the artificial cooperative search algorithm and phasor particle swarm optimization were respectively introduced to solve the ELD problem. Bhattacharjee et al. [42] used the opposition-based krill herd algorithm, while others [43] utilized the adaptive differential evolutionary algorithm to find a solution to 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 properties and it is utilized to reach the global optimal value within the least computation time. Due to its exploration and exploitation properties, SSA avoids local optimum and tends to move directly towards the global optimum value. Lately, some efficient modified and hybrid optimization techniques [45–50] have also been used to solve ELD problems more efficiently. 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, conclusion is drawn in Section 5.

2. Problem formulation

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

The objective function of ELD with quadratic cost function based on Eq. (1) is given below [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 sinusoidal terms of ripple input-output curve with valve point effects. The valve point effect-based cost function of ELD is given below [44]:

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

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 generation of each generator is P_a. Lower and higher limits of power generation are characterized by $P_a^{\min}$ and $P_a^{\max}$, respectively. Power generation of each unit follows the generating capacity constraint:

$$P_a^{\min} \leq P_a \leq P_a^{\max}. \quad (3)$$

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

$$\sum_{a=1}^{N} P_a - P_D - P_{Loss} = 0, \quad (4)$$

where P_D is the total system active power demand; total transmission loss P_{Loss} is calculated by using the B-matrix loss coefficients as expressed below [59]:

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

Ramp rate limit is another constraint that has been considered in solving ELD problems to increase the lifespan of generators as given below:

$$P_a - P_{a0} \leq UR_a \quad \text{(as generation rises)}, \quad (6)$$

$$P_{a0} - P_a \leq DR_a \quad \text{(as generation declines)}, \quad (7)$$

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

where P_{a0} is the power generation of the ath previous interval; UR_a and DR_a are the up-ramp and down-ramp limits, respectively.

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

$$P_a^{\min} \leq P_a \leq P_{a,1}^{l},$$

$$P_{a,j-1}^{u} \leq P_a \leq P_{a,j}^{l},$$

$$P_{a,n}^{u} \leq P_a \leq P_a^{\max},$$

$$j = 1 \quad \text{to} \quad n, \quad (9)$$

where $P_{a,j}^{u}$ and $P_{a,j}^{l}$ represent the upper and lower limits of the jth prohibited operating zone of the ath unit. Total number of prohibited operating zones of the ath unit is n.

For a system with n generators and having n_F fuel options for each unit, the entire cost function is expressed as follows:

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

where $p = 1, 2, \cdots, n_F$. Calculation of slack generator is one of the important parts in ELD problem formulations. If N is the total number of generators, then the $(N-1)$ number of power generations is initially calculated randomly based on Inequalities (3), (6), (7), (8), and (9). The remaining generator (let Nth) called slack generator must be evaluated using Eq. (4). The value of slack generator is given below:

Without transmission losses:

$$P_N = P_D - \sum_{a=1}^{N-1} P_a. \quad (11)$$

With transmission losses:

$$P_N = P_D + P_{Loss} - \sum_{a=1}^{N-1} P_a. \quad (12)$$

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

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

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

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 followers. The leader is the salp and is in front of the chain, while the rest of the salps are considered 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 positions 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 denotes the position of the first salp (leader) in the jth dimension, F_j the position of the food source in the jth dimension, ub_j the upper bound of the jth dimension, and lb_j the lower bound of the 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 parameters c_2 and c_3 are random numbers uniformly generated at the interval of [0,1] and [-1,1], respectively. In fact, they dictate if the next position in the jth dimension should be towards positive infinity or negative infinity as well as the step size. More details of these parameters can be found in [44]. To update the position of the followers, the following equations are 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 the ith follower salp in the jth dimension.

Sequential steps for SSA

i. The lower and upper bounds for all the search agents are initialized. The initialization process for different search agents is assigned randomly at the initial stage within their lower and upper bounds. Moreover, the total number of iterations is decided and then, the number of search agents to be used in the algorithm is decided;

ii. At 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 lower 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 a fixed value and as the iterations increase, the value of these parameters keeps on changing. By using SSA algorithm, the changed value of search agents must check their different constraints. If there is any violation, then their values are fixed in their boundary conditions;

iv. As the iteration changes, the values of these three parameters also change and the search agents collectively move towards the global optimum value (Eq. (14)). Following 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, instead of moving in the entire search space, the search agents will exploit the regions in which the results are promising. In this way, they tend to move towards the global optimum value (Eq. (15)). Once the iteration count is reached or the value of the cost function is obtained within the tolerance limit, the iteration is terminated. The result obtained at that time is considered to be the sub-global value (Eq. (16));

v. Once the final iteration count is reached, the algorithm is terminated and the search agents having the highest fitness are considered to be nearest to the global optimum value.

The flowchart of the SSA algorithm is shown in Figure 1.

In this subsection, the steps to solve the ELD problem through the SSA implementation are explained. The detailed sequential steps for solving the ELD problem are 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 follows:

$$X = X_i = [X_1, X_2, X_3, \cdots, X_{Popsize}],$$

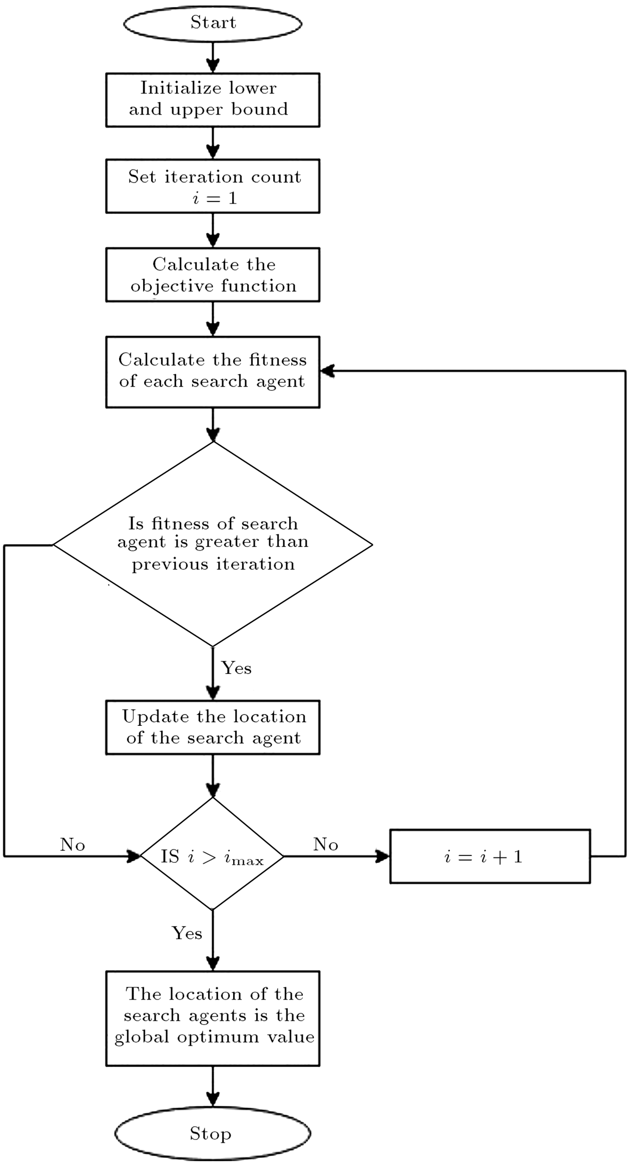

Figure 1. Flowchart of salp swarm algorithm.

where $i = 1, 2, 3, \cdots,$ *Popsize*. For ELD problem, the search agent matrix is assigned as active power generation and represented as follows:

$$[X_{ij}] = [X_{i1}, X_{i2}, X_{i3}, \cdots, X_{im}]$$
$$= [P_{i1}, P_{i2}, P_{i3}, \cdots, P_{im}] = [P_{ij}],$$

where m is the number of generators.

ii. Each of the elements of the search agent should follow Eqs. (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 Inequalities (6)–(9).

iii. For the ELD problem, the objective function is considered the fuel cost of power generation and it can be using Eq. (1) when quadratic fuel cost function is used and Eq. (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 reduce the cost of the power generation in the system. The objective function of fuel cost is calculated based on the power generation (P_{ij}) through step (i).

iv. The main working mechanisms of the algorithm begin from Eq. (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 facilitate the movement of the search agent (X_{ij}) (i.e., power generation (P_{ij})) in the search space. By using Eqs. (13)–(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 Inequalities (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 Inequalities (6)–(9). If any value violates any of these constraints, then its upper or lower value is considered. Moreover, the slack value of power generation can be calculated based on Eqs. (11) and (12). If there are any violations of any Inequality Constraints (3), (6), (7), (8), and (9) which are valid for the slack generator, then repeat step (ii). This process continues until the ultimate set of the 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 those obtained through 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; however, if the current value is not lower than the previous one, 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 at the present iteration is compared to all other values obtained at different iterations and finally, the minimum value is made the global optimum value. This global optimum value is stored in a different memory location.

viii. Go to step (ii) for the next iteration. Terminate the process after reaching a predetermined value of the iteration count.

4. Simulations and results

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

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

Test Case 1: Six generator units have been considered in Test Case 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 were taken from [45] and the system runs for 400 iterations. The number of search agents used is 50 in this case. In Test Case 1, the results of the SSA algorithm are compared with those of TLBO [45], CTLBO [45] and AIS [45] optimization techniques. According to the graph and the table, the minimum cost is first reached using the SSA algorithm and the rest of the optimization techniques take a minimum time compared to others. Table 1 shows that the minimum fuel cost for 6 generator units is 15377.8907 $/hr obtained by the proposed algorithm, which is better than TLBO [45], CTLBO [45], and AIS [45]. The minimum, maximum, and average fuel costs obtained after 50 trials are presented in Table 2. The convergence characteristics of SSA are shown in Figure 2. The net power delivered to the system is calculated as 1274.0128 MW. Hence, the accuracy of the result is 99.99% based on Eq. (4).

Test Case 2: Ten generator units have been considered in Test Case 2, where the transmission losses have been neglected. This test case incorporates multi fuel costs and valve point loading effect. Here, we have not assumed the ram-rate limit or the prohibited operating zone. The total power demand is 2700 MW.

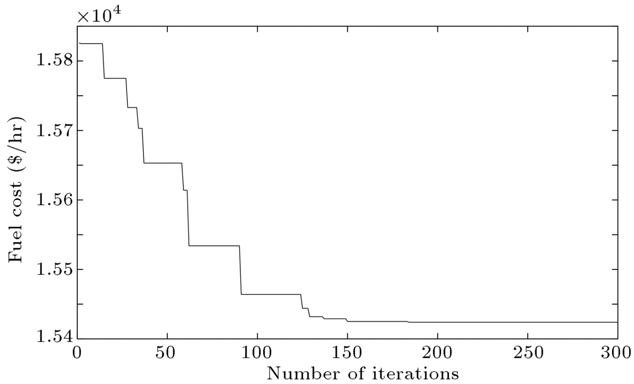

Figure 2. Convergence characteristic of SSA for 6 generator units.

Table 1. Optimum power output and fuel cost for SSA and other techniques comparison for the 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 the 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 generation cost in [47] is 628.8264 $/hr which is much higher than that reported in [47].

Table 4. Minimum, maximum, and average costs 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.

The input data were taken from [46]. The number of search agents used is 50 in this case. In this test case, the results obtained from SSA algorithm are compared with those of 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, which outperforms PSO-LRS [47], APSO [47], CBPSO-RVM [47], and OKHA [47]. The minimum, maximum, and average fuel costs obtained after 50 trials are presented in Table 4. According to Table 4, the minimum cost is first reached by using the SSA algorithm and the rest of the optimization techniques take a minimum time compared to others. The convergence characteristic of SSA is shown in Figure 3. The net power delivered to the system is calculated as 2699.9999 MW. Hence, the accuracy of the result is 99.9999% based on Eq. (4) with transmission losses, which have been neglected. The fuel cost mentioned for OKHA [47] is 605.6449 $/hr; however, based on the mentioned output power generation for each unit with consideration of the input data from [46], the actual fuel cost is calculated as 628.8264 $/hr, which is much higher than that obtained by SSA.

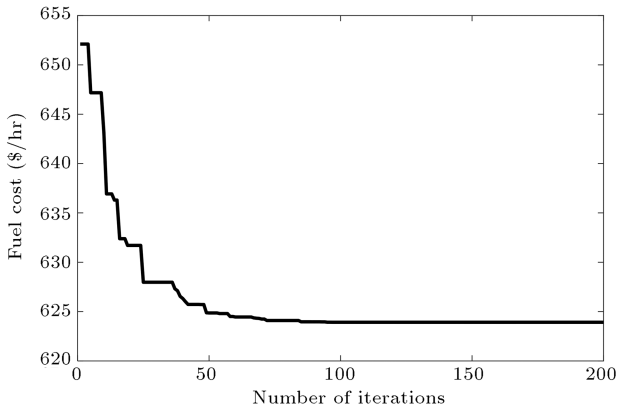

Figure 3. Convergence characteristic of SSA for 10 generator units.

Test Case 3: Thirteen generator units have been considered in Test Case 3, where the transmission losses have been considered. The total power demand is 2520 MW. The input data were taken from [48] and the system runs for 400 iterations. Here, we considered valve point loading and neglected ram-rate limit and prohibited operating zone. The number of search agents used is 50 in this case. In this test case, the results of the SSA algorithm are compared with those obtained by ORCCRO [49], SDE [50], and BSA [57] optimization techniques, as shown in Table 5. The fuel cost obtained using SSA is calculated to be 24512.6085 $/hr. Based on Table 6, the minimum cost is first reached by using the SSA algorithm and the rest of the optimization techniques take minimum time compared to others. The results obtained by the proposed algorithm are better than those of SDE [50], ORCCRO [49], and BSA [57]. The minimum, maximum, and average fuel costs 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 should be 2520 MW. Hence, the accuracy of the result is 100.00% based on Eq. (4).

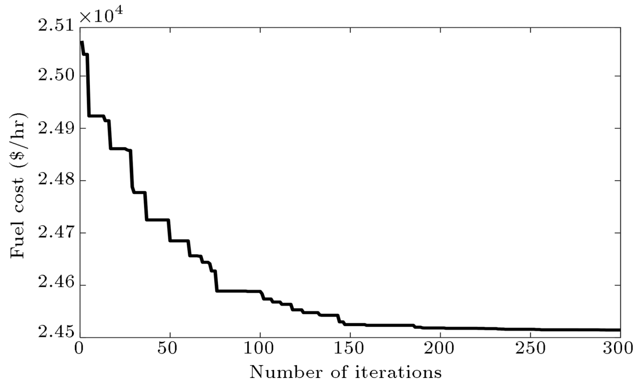

Figure 4. Convergence characteristic of SSA for 13 generator units.

Test Case 4: In this test case, 40 generator units with valve point loading have been considered. The test case has been split into two parts: In Test Case (a), transmission loss has been neglected, while in Test Case (b) it has been considered. For both cases, prohibited operating zone and ram-rate limit have been neglected. The details of these two case studies have been given below. Here, this system can be of two types: that without transmission losses and the one with transmission losses considered.

Table 5. Optimum power output and fuel cost for SSA, and other techniques comparison for the 13-unit test system.

	Power output (MW)			
Unit	**SSA**	**SDE [41]**	**ORCCRO [40]**	**BSA [48]**
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 costs obtained by SSA and various optimization techniques for 13 generator units (50 trials).

	Generation cost ($/hr)			**No. of hits to minimum solution**	**Standard deviation**
Methods	**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 the 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

Test Case 4(a): In this case, 40 generator units with valve point are considered. Transmission losses are neglected. The input data were taken from [51]. The total load demand is 10500 MW. In Test Case 4(a), the results of the SSA algorithm are compared with those of EMA [51] and QPSO [51] optimization techniques. According to Table 7, the minimum cost is first reached by using the SSA algorithm and the rest of the optimization techniques take a longer time to complete. As shown in Table 7, the minimum fuel cost for 40 generator units is 121412.5347 $/hr obtained by the proposed algorithm, which outperforms EMA [51] and QPSO [51]. The minimum, maximum, and average fuel costs obtained after 50 trials are presented

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

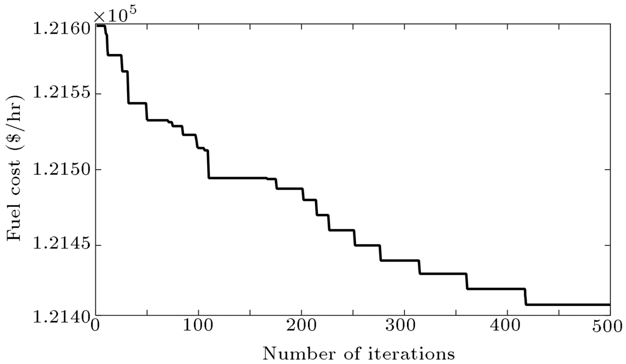

Figure 5. Convergence characteristic of SSA for 40 generator units.

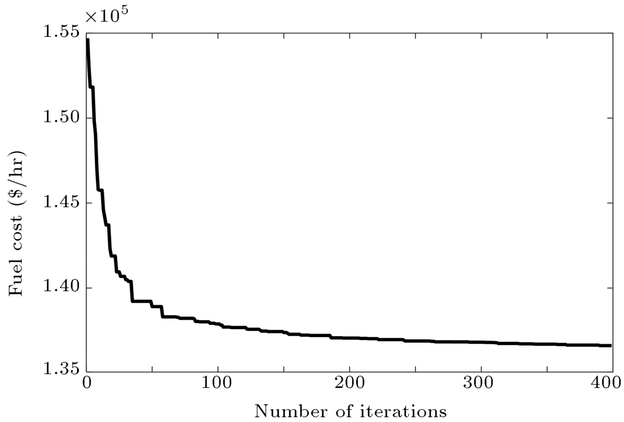

Figure 6. Convergence characteristic of SSA for 40 generating units.

in Table 8. The convergence characteristic of SSA is displayed in Figure 5. The net power delivered to the system is calculated as 10500 MW. Hence, the accuracy of the result is 100.00% based on Eq. (4) with transmission losses neglected.

Test Case 4(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 was taken from [52] and the system runs for 400 iterations. Fifty 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 by different optimization techniques is given in Table 9. Table 10 shows the minimum, maximum, and average fuel costs obtained by various optimization techniques after 50 trials. The convergence characteristic is shown in Figure 6. The minimum fuel cost obtained using SSA is calculated as 136653.0219 $/hr. Based on the tabular data, it is clear that the minimum fuel cost is obtained by SSA which performs better than other techniques like GAAPI [49], DE/BBO [49], SDE [50], and BBO [49]. The net power delivered to the system is calculated as 10500 MW. Hence, the accuracy of the result is 100.00% based on Eq. (4).

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 were taken from [58]. This test system is a fossil fuel-based power system, composed of forty thermal generating units, fifty-one gas units, twenty nuclear units, and twenty-nine oil units. Out of 140 units, 6 thermal units, 4 gas units, and 2 oil units have non-convex fuel cost function addressing valve loading effects. The total load demand is 49342 MW. A large and complicated test system of 140 generating units has been considered here with valve point loading effects, ramp rate limits, and prohibited operating zones. The system is made to run for 1000 iterations. Fifty 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 is calculated as 1658384.8872 $/hr. Table 12 compares the minimum, maximum, and average fuel costs 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 which is much better than other algorithms. The net power delivered to the system is calculated as 49342 MW. Hence, the accuracy of the result is 100.00% based on Eq. (4).

Table 9. Optimum power output and fuel cost for SSA and other techniques comparison for the 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 costs 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 the 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

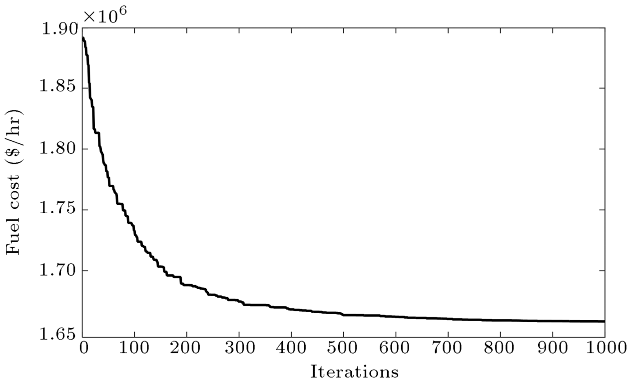

Figure 7. Decreasing cost for 140 generator units using SSA.

4.1. Tuning of parameters for the SSA

To obtain the optimized solution with the use ofSSA, it is imperative to obtain the proper values for parameters c_1, c_2, and c_3. Tuning of these parameters is essential to obtaining an optimized solution. Different values of these parameters give different fuel costs. For one single value of one parameter, other parameters should be changed for all possible combinations. For the single value of c_1, different combinations of c_2 and c_3 have been made to obtain the minimum fuel cost. The optimum fuel cost obtained for the 140-unit test system with all parameters including $c_1 = 0.7886$, $c_2 = 0.4082$, and $c_3 = 0.3452$ is 1658384.8872 $/hr, as shown in Table 13. However, the optimum value of fuel cost obtained for other test systems is also consistent with the same values of all the parameters. Presenting all these results for all test systems in a table takes much space which has made us overlook the details of the tuning procedure. A brief result of the most complex 140-unit generator system out of five test systems is shown in Table 13.

Also, using a large number of search agents or few search agents for screening the search space does not ensure achieving the optimized solution. Therefore, a specific number of search agents only help obtain the optimized solution. For each search agent, trials have been run. The output obtained after using various search agents is shown in Table 14. Out of these trials, 50 search agents achieved the optimized fuel cost. For other search agents, no significant improvement in the fuel cost was observed. Moreover, the simulation time duration is definitely prolonged in the case of more than 50 search agents.

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

Table 14. Effect of the number of search agents on the 140-unit 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

4.2. Simulation Time Comparison

In this section, authors have created a table to compare the simulation time durations of the SSA algorithm with those of all the other algorithms for all the five different test cases. The authors understand that it is not possible to compare the simulation times as different authors have used different computer configurations. However, this table only gives an indication of the superiority of SSA with the same computer configurations. The programs have been written in MATLAB-2017B language and executed using a personal computer featuring 1.7 GHz Intel core i3 and 4 GB RAM. All the systems are re-simulated with the same configuration.

4.3. 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 among other optimization techniques. The cost obtained by SSA is quite affordable compared to the costs obtained by many previously developed algorithms. For example, in Test Case 1, the minimum fuel cost of the SSA is 24512.6085 $/hr which is less than the minimum fuel cost obtained by SDE and ORCCRO. The comparison was made by neglecting the transmission losses as well as 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. A number of trials should be conducted to prove the robustness of any optimisation technique. According to Tables 4 and 6, SSA achieves the optimal solution for all the 50 trials in various test cases. According to 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 SSA is superior to other optimization techniques in terms of performance. This proves that the algorithm performs consistently 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. According to Table 15, the computational time taken for one single iteration is the least for the SSA among other previously developed optimization techniques. Thus, the SSA achieves global optimal results in the least computational time.

5. Conclusion

A new algorithm called Salp Swarm Algorithm was proposed to solve ELD problem. To prove the efficiency of the SSA, five test systems of different kinds of thermal power plants were considered in which the main objective was the net fuel cost reduction. This objective was obtained by SSA, as shown in Tables 1, 3, 5, 7, 9, and 11. The comparison between the proposed technique and other techniques is also shown in these tables. The average, minimum, and maximum values obtained for different optimization techniques in various test systems within a particular number of trials were also considered important and minimized for any optimization technique. The authors managed to prove the effectiveness of SSA compared to other algorithm with consideration of the aforementioned components in Tables 2, 4, 6, 8, 10, and 12. Given that simulation time was also an important object in soft computing techniques, this study considered it for the same test system with the other efficient optimization techniques. The authors considered the simulation time for the above-discussed test systems and successfully proved that SSA took the minimum computational time. This was shown, as given in Table 15. The results proved that SSA was consistent, feasible, and more effective than other algorithms in terms of efficiency and computational time. The numerical results proved that the SSA prevented premature convergence and

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	

had a stable convergence characteristic. Hence, by using the exploration and exploitation properties of SSA, the problem of ELD was successfully solved.

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