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A comparative study of economic load dispatch using sine cosine algorithm

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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 Sine Cosine Algorithm (SCA) 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 SCA 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 functions and keeps a track of the best solution achieved by each search agent. SCA was used to solve the ELD problem due to its favorable exploration and local optima escaping technique. This algorithm confirmed that promising areas of the search space were exploited to have a smooth transition from exploration to exploitation using sine and cosine functions. Simulation results proved that the proposed algorithm surpassed other existing optimization techniques in terms of quality of the solution obtained and computational efficiency. The final results also proved the robustness of the SCA.

1. Introduction

Economic Load Dispatch (ELD) is considered as one of the valuable optimization problems in the field of power system operations. The ELD fulfils the total load demand by economically allocating the load demand to each and every generator while satisfying their operation and physical constraints. 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. Also, it satisfies all the constraints on each and every generator that is considered for the ELD problem.

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There are many classical optimization methods, e.g., gradient method [1], Quadratic Programming (QP) [2], Lagrangian relaxation [3], Hopfield modeling framework [4], Linear Programming (LP) [5], and Dynamic Programming (DP) [6], which assume a linear increasing cost function. The application of such methods to solving the ELD problem has generally been successful. However, the main problem with the classical approach is that it tends to converge on a local optimum and then, begins to diverge from the global optimal solution. The problem with the DP approach is that it requires very large dimensions and so many programming efforts. 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 (POZs). Also, due to non-linearity of the ELD problem, many of the classical optimization techniques cannot reach the global optimal solution and tend to diverge at a local optimum. Therefore, it is imperative to develop an optimization technique that can overcome drawbacks of the classical methods and give the global optimum solution in the lowest computational time. Many artificial intelligence algorithms like the Hopfield neural network [7] have been used in solving the ELD problem to overcome the mentioned drawbacks. The problem with the artificial intelligence algorithms is that they take a huge number of iterations to reach the global optimum solution. Hence, more time is required to reach the global solution. The computer technology has helped to develop many population based heuristic optimization techniques, e.g., 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], Backtracking Search Algorithm (BSA) [25], and Teaching Learning Based Optimization (TLBO) [26] for solving ELD problems. Roy and Bhattacharjee [27] and Zarei et al. [28] solved the problem of unit commitment. Also, an optimization technique based on trigonometric functions, called Sine Cosine Algorithm (SCA), was used to solve the problem of unit commitment [29]. Apart from electrical problems, SCA has also been used to solve the engineering design problems [30]. Even the problem of short-term hydrothermal scheduling has been solved using the SCA technique [31]. An enhanced version of the PSO was proposed to solve the problem of ELD [32]. A new maximum likelihood optima technique was presented to solve the ELD problem [33]. Group Leader Optimization (GLO) [34] with special ability to solve the non-linear and the non-quadratic equations with greater ease was proposed. However, some of the above-mentioned algorithms have difficulties in finding the local optimum and some have problems in finding the global optimum solution. Therefore, to overcome such kind of problems, a new powerful optimization technique is needed.

The SCA [35] was proposed based on the trigonometric functions sine and cosine to find the fitness function of a search agent. In this method, the search agent having the maximum fitness is made to move towards the global optimum. The superiority of this method is the exploration and exploitation property it utilizes to reach the global optimal value in the lowest computational time. This characteristic helps the method to avoid the local optima and move directly towards the global optimum value.

To give a better solution to the ELD problem by implementing the trigonometric functions in the algorithm, we applied SCA to solving the problem. ELD is also a problem related to power system optimization in which the fuel cost has to be minimized. These are elaborately described in the following sections.

Section 2 formulates various ELD problems with different feasible constraints. The conception of the SCA is described in Section 3. The performance of the SCA under various test systems and the simulation studies are discussed in Section 4. Finally, the conclusions are presented in Section 5.

2. Problem formulation

The ELD problems are either convex or non-convex with some linear and nonlinear constraints in different applications.

The objective function of ELD with quadratic cost function is given as follows [36]:

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

For more realistic and practical application of ELD problems, the smooth quadratic cost function can be modified by adding sinusoidal terms of ripples input-output curve with valve point effects. The valve point effect based cost function of ELD is given below [36]:

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

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

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

After identifying the inequality constraint of ELD problem, its equality or real power balance constraint can be formulated as:

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

where P_D is total active power demand of the system and total transmission loss P_{Loss} is calculated using the B-matrix loss coefficients, which are expressed as [36]:

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

Ramp rate limit is another constraint considered in ELD problems to increase the life of generators as given below:

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

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

and:

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

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

For different faults in the operation of the machines, boilers, feed pumps, and steam valve as well as the vibration in the bearing, the POZ constraint is considered in the ELD problems. Mathematically, POZ can be expressed as given below:

$$\left.\begin{array}{l} P_a^{\min} \le P_a \le P_{a,1}^{l} \\ P_{a,j-1}^{u} \le P_a \le P_{a,j}^{l} \\ P_{a,n}^{u} \le P_a \le P_a^{\max} \end{array}\right\}; \qquad j = 1, 2, \ldots, n_a \quad (9)$$

where $P_{a,j}^{u}$ and $P_{a,j}^{l}$ are respectively the upper and lower limits of the jth POZ of the ath unit. The total number of generators under POZ is denoted by n_a.

Specifying slack generator is one of the important parts of ELD problem formulation. Let N be the total number of generators. Initially calculate the number of $(N-1)$ power generations randomly based on Eq. (3) and Eqs. (6)–(9). The remaining generator (Nth), which is called slack generator, has to be identified using Eq. (4). The value of slack generator is given below:

$$P_N = P_D - \sum_{a=1}^{N-1} P_a \quad \text{(without transmission losses)}, \quad (10)$$

$$P_N = P_D + P_{Loss} - \sum_{a=1}^{N-1} P_a \quad \text{(with transmission losses)}. \quad (11)$$

Transmission loss (P_{Loss}) is also dependent on power generation based on Eq. (5). Therefore, Eq. (11) is further modified as follows:

$$B_{NN}P_N^2 + P_N\left(2\sum_{a=1}^{N-1} B_{Na}P_a + \sum_{a=1}^{N-1} B_{0N} - 1\right) + \left(P_D + \sum_{a=1}^{N-1}\sum_{b=1}^{N-1} P_a B_{ab} P_b + \sum_{a=1}^{N-1} B_{0a}P_a - \sum_{a=1}^{N-1} P_a + B_{00}\right) = 0. \quad (12)$$

3. Sine Cosine Algorithm (SCA)

SCA [35] is a population-based optimization technique. This technique starts with a random number of search agents. The optimization process is divided into two phases, namely exploration and exploitation. In the phase of exploration, SCA combines all the random numbers of solutions in a set of solutions quickly with a higher rate of randomness so that it can find those regions of search space where there is a higher probability to find the global solution. On the other hand, in the phase of exploitation, there are slow changes in the random solutions and low random variations compared to the exploration phase.

In the SCA, there are four main parameters, namely e_1, e_2, e_3, and e_4. The parameter e_1 indicates the next position, which could be between the solution and the destination or even outside it. The parameter e_2 decides the distance that the search agents have to cover in the direction of the solution. The parameter e_3 helps to decide the weighting factor for the destination. Weighting factors greater than one indicate increased emphasis on a destination and lower than one represent decreased emphasis. The parameter e_4 equally switches between the sine and cosine components. Due to the involving property of switching between the sine and cosine functions, the algorithm is known as the SCA. The sine and the cosine functions have the tendency to re-position themselves around the global solution.

To update the result in every iteration, the following two equations are used:

$$X_a^{t+1} = X_a^t + e_1 * \sin(e_2) * |e_3 * PO_a^t - X_a^t|, \quad (13)$$

$$X_a^{t+1} = X_a^t + e_1 * \cos(e_2) * |e_3 * PO_a^t - X_a^t|, \quad (14)$$

where e_1, e_2, and e_3 are constant variables. The modification is done using variable e_4 given a random value within [0, 1] through the following equation:

$$X_a^{t+1} = \begin{cases} X_a^t + e_1 * \sin(e_2) * |e_3 * PO_a^t - X_a^t|; & e_4 \le 0.5 \\ X_a^t + e_1 * \cos(e_2) * |e_3 * PO_a^t - X_a^t|; & e_4 \ge 0.5 \end{cases} \quad (15)$$

X_a^{t+1} is the position of the search agent in the current $(t+1)$th iteration and ath dimension, and X_a^t is the position of the search agent in the previous tth iteration and ath dimension. PO_a^t is the position of the destination location up to the tth iteration. The main benefits of SCA over other present effective optimization techniques are the following:

1. This algorithm works upon the set of solutions that it has created randomly, so that it can avoid the local optima and benefit from the favourable exploration property. Such feature cannot be found in other classical algorithms;
2. When the sine and cosine functions give a value lower, or greater, than 1, then different regions of the entire search space are explored for finding the global solution;
3. When the sine and cosine functions give a value between 1 and –1, then the search agents will exploit the present regions;
4. The entire range of the sine and cosine functions is utilized to make a smooth transition from the exploration to the exploitation phase;
5. The global solution obtained by the SCA is stored in a variable at a known destination point; thus, the global solution is never lost.

The authors [29–31] have already proved the versatile advantages of SCA algorithm in different domains. The sequential steps of SCA are given below:

3.1. Sequential steps of SCA

(i) In the initialization process, the lower bound and the upper bound values are assigned to each search agent randomly. Also, the total number of iterations is decided and then, the number of search agents to be used in the algorithm is identified;

(ii) The objection function of the system is calculated. This function depends on the independent variables given by the user;

(iii) If the value of the fitness function obtained in the present iteration is lower than that in the previous iteration, then it can be considered as the local best. Then, the sine and cosine functions start processing. Initially, the parameters of SCA are assigned fixed values and as the iterations increase, the values of these four parameters keep on changing. Here, the parameter e_1 decides the direction of movement of the search agent in the search space while the parameter e_2 decides the distance that a particular search agent will move in a particular direction given by parameter e_1. The parameter e_3 assigns a random weighting factor to a particular search agent, which decides its importance among the searching criteria. Finally, the parameter e_4 equally switches between the sine and cosine functions;

(iv) Using SCA algorithm, the changed values of the search agents have to be checked with regard to different constraints. If there is any violation, then their values are fixed with their boundary conditions;

(v) As the iteration changes, the values of the four parameters also change and the search agents move towards the global optimum value together. After every iteration, the fitness values of the search agents also change. The nearest search agent to the global optimum value has the highest fitness. In this way, the search agents will move in the search space and explore it entirely for the optimized value. Once the location of the optimized value is known to the search agent, the exploitation phase will be started. 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. Once the identified number of iterations is reached or the value of the cost function is obtained within the tolerance limit, the iteration is terminated. The result obtained is considered as the sub-global value;

(vi) Once the final iteration is performed, the algorithm is terminated and the search agents having the highest fitness are considered as the nearest to the global optimum value.

3.1.1. Consecutive steps of SCA algorithm for the ELD problem

In this subsection, the steps to solve the ELD problem by the implementation of SCA are explained. The flowchart for the implementation is shown in Figure 1. The steps for solving the ELD problem are the following:

(i) Initialization of various parameters takes place in the first step. Different variables such as *lower bound, upper bound, total power demand* P_D, etc. are initialized. The total number of generators is denoted by N and total number of search agents is denoted by $Popsize$.

The search agent matrix is represented as:

$$X_{ij} = X_i = [X_1, X_2, X_3, ..., X_{Popsize}],$$

where $i = 1, 2, 3, ..., Popsize$. In the ELD problem, the search agent matrix is considered for active power generation and represented as follows:

$$[X_{ij}] = [X_{i1}, X_{i2}, X_{i3}, ..., X_{iN}]$$
$$= [P_{i1}, P_{i2}, P_{i3}, ..., P_{iN}] = [P_{ij}],$$

where N is the number of generators;

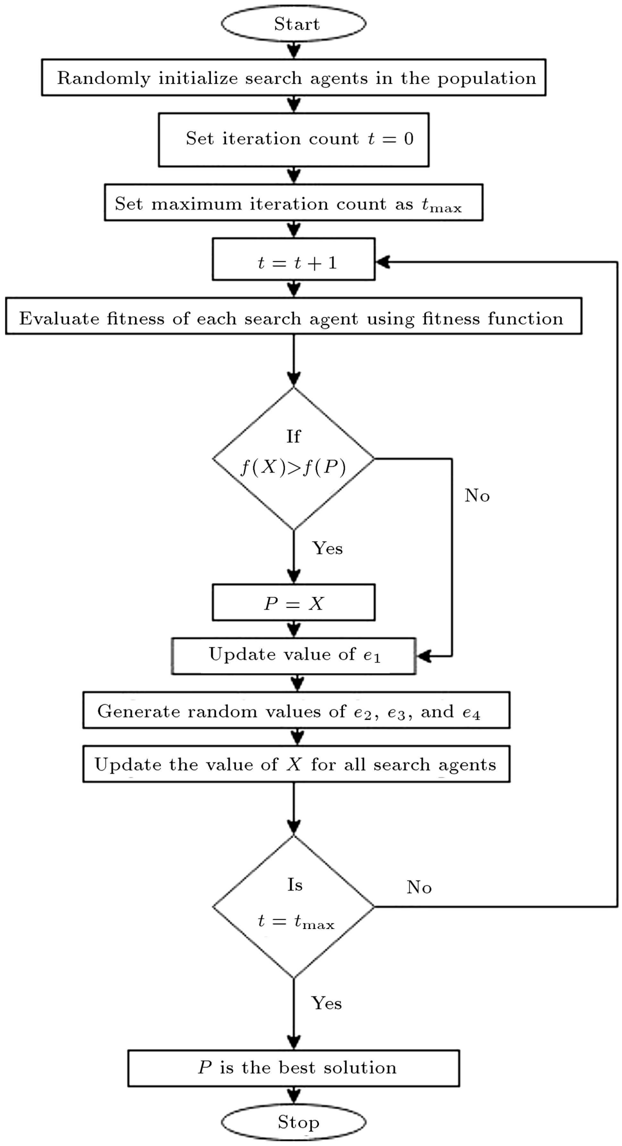

Figure 1. Sine Cosine Algorithm (SCA) Flowchart.

(ii) Each of the elements of the search agent should follow Eq. (3) and Eqs. (6)–(9). If various effects like the ramp rate limit and the POZ are considered, then the equation should be satisfied based on Eqs. (6)–(9), respectively;

(iii) The objective function is the fuel cost of power generation and it is calculated through 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. It should be minimized to minimize the cost of power generation in the system. The objective function of fuel cost is calculated based on the power generation (P_{ij}) in step (i);

(iv) The main working mechanisms of the algorithm begin at this point. The values for the main four parameters of the algorithm are assigned to the concerned variables, i.e., e_1 to e_4. These values help the movement of the search agent (X_{ij}) (i.e., power generation (P_{ij})) in the search space. Using Eqs. (13)–(15), the movement of search agents takes place in the search space;

(v) If the value of parameter e_1 is greater than 1, then the search agent has to move in the direction opposite to its current one; but if the value of e_1 is less than 1, then the search agent has to move in the same specified direction. Similarly, the parameter e_2 will determine how much distance a particular search agent has to move in the specified direction. Also, the parameter e_3 will give the weighting factor to the search agent based upon its proximity to the optimized value;

(vi) Now, the new values of power generation are obtained. These new values are checked for the constraints given in Eq. (3) and Eqs. (6)–(9). If various effects, like the ramp rate limit and the POZ, are considered, then the equation should be satisfied based on Eqs. (6)–(9), respectively. If any variable violates any of these constraints, then its upper or lower value is considered. The slack value of power generation can be calculated based on Eqs. (11) and (12). If there are any violations of any inequality constraint among Eq. (3) and Eqs. (6)–(9) that are valid for the slack generator, then step (ii) onward is repeated. This process will continue until the ultimate set of power generation matrix is formed;

(vii) The new objective function of fuel cost can be calculated based on the newly generated power generation matrix;

(viii) Now, the current objective values are compared with the values obtained in the previous iterations. If the present objective value is lower than the previous one, it is treated as the best local optimal value. Otherwise, i.e., if it is not lower than the previous value, then the previous value takes the position of the newly generated value in the power generation matrix. Now, the objective function value obtained in the present iteration will be compared with 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;

(ix) In the next iteration, step (ii) and the following ones are repeated. When a predetermined

Table 1. Comparison of the optimum power output and fuel costs obtained by Sine Cosine Algorithm (SCA) and other techniques for 13-unit test system.

Unit	Power output (MW)					
	SCA	**BSA [25]**	**SDE [37]**	**ORCCRO [39]**	**OIWO [40]**	**FPSOGSA [41]**
P_1	628.3179	628.3158	628.32	628.32	628.3185	628.3185
P_2	299.1992	299.1947	299.20	299.20	299.1989	299.1993
P_3	297.4468	297.4764	299.20	299.20	299.1991	299.1993
P_4	159.7327	159.7322	159.73	159.73	159.7331	159.7331
P_5	159.7327	159.7330	159.73	159.73	159.7331	159.7331
P_6	159.7328	159.7328	159.73	159.73	159.7331	159.7331
P_7	159.7331	159.7318	159.73	159.73	159.7330	159.7331
P_8	159.7325	159.7329	159.73	159.73	159.7331	159.7331
P_9	159.7328	159.7286	159.73	159.73	159.7330	159.7331
P_{10}	77.3995	77.3945	77.40	77.40	77.3953	76.9368
P_{11}	114.7993	114.7992	113.12	112.14	113.1079	114.2795
P_{12}	92.3997	92.3962	92.40	92.40	92.3594	92.2438
P_{13}	92.4000	92.3919	92.40	92.40	92.3911	92.2007
Power generation (MW)	**2559.8000**	2560.3641	2560.4300	2559.43	2560.3686	2560.7765
Transmission loss (MW)	**39.8000**	39.8006	40.43	39.43	40.3686	40.7765
Fuel cost ($/hr.)	**24512.6085**	24512.6654	24514.88	24513.91	24514.83	24515.35543

number of iterations is reached, the process is terminated.

The algorithm of SCA is presented in Figure 1.

4. Simulations and results

To prove the effectiveness of the SCA, four sets of experiments have been conducted and the final results are compared with the results of various existing methods in tabular and graphical forms.

The SCA algorithm has been applied to four different test systems with varying degrees of complexity to verify its effectiveness and feasibility. The program is written in MATLAB-2017B language and executed on a 1.7 GHz Intel core i3 personal computer with 4-GB RAM.

Test case 1: 13 generator units have been considered in test system 1 with transmission losses. The input data for the transmission loss is taken from the study by Srinivasa and Vaisakh [37]. The total power demand is 2520 MW. The input data is taken from Sinha et al. [38] 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 SCA algorithm are compared with those of the Oppositional Real Coded Chemical Reaction Optimization (ORCCRO) [39] and Stochastic Differential Equation (SDE) [37] optimization techniques. It can be seen from the graph and the table that the minimum cost is first reached by using SCA algorithm and the rest of the algorithms take more time as compared to SCA. According to Table 1, the minimum fuel cost for 13 generator units in the proposed algorithm is 24512.6085 $/hr, which is better than the those in SDE [37] and ORCCRO [39]. The minimum, maximum, and average fuel costs obtained after 50 trials are presented in Table 2. The comparison of the convergence characteristics of the SCA with those of SDE and ORCCRO is presented in Figure 2. The net power delivered to the system is 2520 MW. Hence, the accuracy of the results is 100% based on Eq. (4).

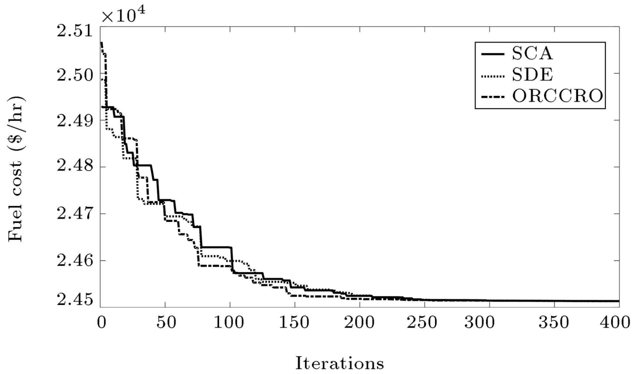

Figure 2. Graphical comparison of SCA, Stochastic Differential Equation (SDE), and Oppositional Real Coded Chemical Reaction Optimization (ORCCRO) for 13 generator units.

Table 2. Minimum, maximum, and average costs obtained by Sine Cosine Algorithm (SCA) and various optimization techniques for 13 generator units (50 trials).

Method	Generation cost ($/hr.)			Time/iteration (s)	Number of hits to minimum solution
	Maximum	Minimum	Average		
SCA	**24512.6085**	**24512.6085**	**24512.6085**	**0.041**	**50**
BSA [25]	24512.6654	24512.6654	24512.6654	0.035	50
ORCCRO [39]	24513.91	24513.91	24513.91	0.04	50
SDE [37]	24519.74	24514.88	24516.23	NA*	21
BBO [39]	24516.09	24515.21	24515.32	0.15	44
DE/BBO [39]	24515.98	24514.97	24515.05	0.11	46

*NA: Not Available.

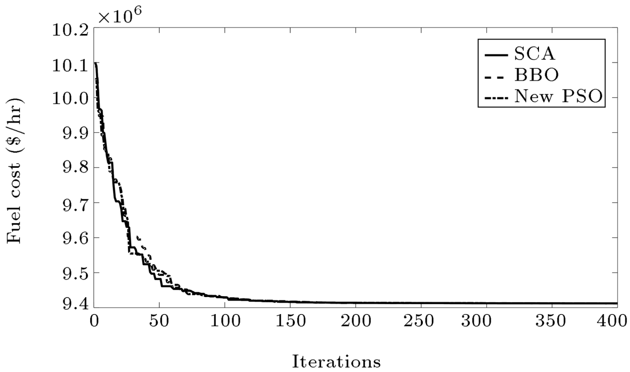

Figure 3. Comparison of SCA, BBO, and NEW PSO for 38 generating units.

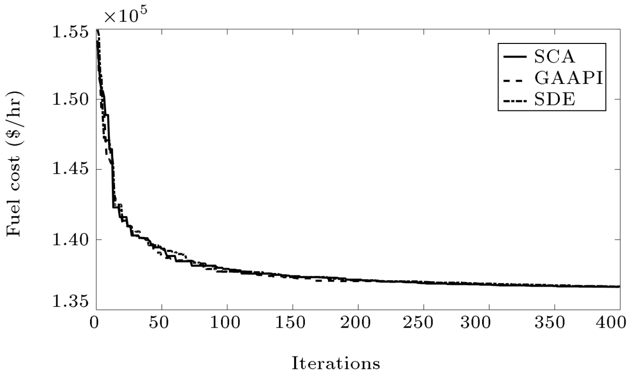

Figure 4. Comparison of Sine Cosine Algorithm (SCA), GAAPI, and Stochastic Differential Equation (SDE) for 40 generating units.

Test case 2: In this system, 38 units of generators are considered and transmission loss is neglected. The total load demand is 6000 MW. The minimum fuel cost has been calculated using SCA. The input data is taken from Sydulu [42] and the system is run in 400 iterations. Fifty search agents are used in this case. The final results obtained by SCA are compared with those by Biogeography Based Optimization (BBO) [43], DE/BBO [43], New PSO [43], and PSO Time Varying Acceleration Coefficients (TVAC) [43]. It is clear from the tabular and graphical data that the best result is obtained by SCA in the minimum computational time. The best solutions obtained by various optimization techniques are presented in Table 3. The minimum, maximum, and average fuel costs by other optimization techniques after 50 trials are stated in Table 4. The comparison of the convergence characteristics of SCA with those of BBO and NEW PSO is given in Figure 3. The net power delivered to the system is 5999.9999 MW. Hence, the accuracy of the result is 99.9999% based on Eq. (4) when transmission lost is neglected.

Test case 3: In this case, 40 generator units are considered and their transmission losses have been taken into consideration. The total power demand is 10500 MW. The input data is taken from Sinha et al. [38] and the system is run in 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 B-coefficients for the transmission losses in this system have been taken from the B-coefficients of the 6-generator test system [44] by multiplication of rows and columns up to 40 units. The comparison of the optimum fuel costs obtained using various optimization techniques is given in Table 5. Table 6 illustrates the minimum, maximum, and average fuel costs of various optimization techniques after 50 trials. The comparison of the convergence characteristics of the SCA with those of GAAPI [39] and SDE [37] is illustrated in Figure 4. Looking at the tabular and graphical data, it is clear that the minimum fuel cost obtained by the SCA is better that those by other techniques like GAAPI [39], DE/BBO[43], SDE [37], and BBO[43]. The net power delivered to the system is 10499.9999 MW. Hence, the accuracy of the result is 99.9999% based on Eq. (4).

Table 3. Comparison of the optimum power output and fuel costs obtained by Sine Cosine Algorithm (SCA) and other techniques for 38-unit test system.

Unit	Power output (MW)				
	SCA	**BBO [43]**	**DE/BBO [43]**	**NEW PSO [43]**	**PSO TVAC [43]**
P_1	426.609880	422.2305	426.6060	550.000	443.659
P_2	426.630334	422.1179	426.6060	512.263	342.956
P_3	429.671911	435.7794	429.6631	485.733	433.117
P_4	429.649739	445.4819	429.6631	391.083	500.00
P_5	429.674382	428.4757	429.6631	443.846	410.539
P_6	429.667300	428.6492	429.6631	358.398	492.864
P_7	429.668089	428.1192	429.6631	415.729	409.483
P_8	429.646541	429.9006	429.6631	320.816	446.079
P_9	114.000000	115.9049	114.0000	115.347	119.566
P_{10}	114.000000	114.1153	114.0000	204.422	137.274
P_{11}	119.769633	115.4186	119.7680	114.000	138.933
P_{12}	127.048847	127.5114	127.0728	249.197	155.401
P_{13}	110.000000	110.0009	110.0000	118.886	121.719
P_{14}	90.000000	90.0217	90.0000	102.802	90.924
P_{15}	82.000000	82.0000	82.0000	89.0390	97.941
P_{16}	120.000000	120.0384	120.0000	120.000	128.106
P_{17}	159.601791	160.3038	159.5980	156.562	189.108
P_{18}	65.000000	65.0001	65.0000	84.265	65.0000
P_{19}	65.000000	65.0001	65.0000	65.041	65.0000
P_{20}	271.999999	271.9995	272.0000	151.104	267.422
P_{21}	271.999998	271.8726	272.0000	226.344	221.383
P_{22}	259.999994	259.7320	260.0000	209.298	130.804
P_{23}	130.632251	125.9930	130.6486	85.719	124.269
P_{24}	10.000098	10.4143	10.0000	10.000	11.535
P_{25}	113.278756	109.4177	113.3050	60.000	77.103
P_{26}	88.092495	89.3772	88.0669	90.489	55.018
P_{27}	37.511273	36.4110	37.5051	39.670	75.000
P_{28}	20.000000	20.0098	20.0000	20.000	21.628
P_{29}	20.000000	20.0089	20.0000	20.995	29.829
P_{30}	20.000000	20.0000	20.0000	22.810	20.326
P_{31}	20.000000	20.0000	20.0000	20.000	20.000
P_{32}	20.000000	20.0033	20.0000	20.416	21.840
P_{33}	25.000000	25.0066	25.0000	25.000	25.620
P_{34}	18.000000	18.0222	18.0000	21.319	24.261
P_{35}	8.000000	8.0000	8.0000	9.1220	9.6670
P_{36}	25.000000	25.0060	25.0000	25.184	25.000
P_{37}	21.787463	22.0005	21.7820	20.000	31.642
P_{38}	21.059227	20.6076	21.0621	25.104	29.935
Fuel cost ($/hr.)	**9417235.7919**	9417633.6376	9417235.7863	9516448.312	9500448.307

Table 4. Minimum, maximum, and average, fuel costs obtained by SCA and various optimization techniques for test system 2 (50 trials).

Method	Generation cost ($/hr.)			Time/iteration (s)	Number of hits to minimum solution
	Maximum	Minimum	Average		
SCA	**9417235.7919**	**9417235.7919**	**9417235.7919**	**5.24**	**50**
BBO [43]	9417658.75	9417633.63	9417638.15	12.21	41
DE/BBO [43]	9417250.83	9417235.78	9417237.29	17.75	45
ORCCRO [39]	9412404.27	9412445.45	9412423.45	9.35	37

Table 5. Comparison of the optimum power output and fuel costs obtained by Sine Cosine Algorithm (SCA) and other techniques for 40-unit test system.

Unit	Power output (MW)				
	SCA	**GAAPI [37]**	**DE/BBO [43]**	**SDE [37]**	**BBO [43]**
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 6. Minimum, maximum, and average fuel costs obtained by Sine Cosine Algorithm (SCA) and various optimization techniques for 40 generator units (50 trials).

Method	Generation cost ($/hr) Maximum	Minimum	Average	Time/iteration (s)	Number of hits to minimum solution
SCA	**136653.10**	**136653.02**	**136653.02**	**0.07**	**48**
BBO [43]	137587.82	137026.82	137116.58	0.2	41
DE/BBO [43]	137150.77	136950.77	136966.77	0.16	45
ORCCRO [39]	136855.19	136855.19	136855.19	0.07	50

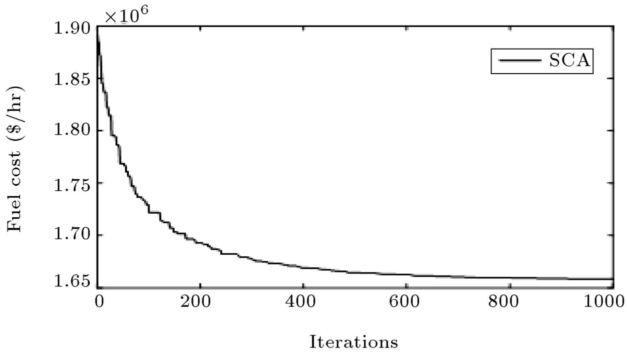

Figure 5. Decreasing cost for 140 generator units using Sine Cosine Algorithm (SCA).

Test case 4: In this case, 140 generator units have been considered. The transmission losses have been neglected in this test system. The total load demand is 49342 MW and the input data is taken from Jong-Bae et al. [45]. The large and complicated test system of 140 generating units is considered with valve point loading effects, ramp rate limits, and POZs. The system is made to run for 1000 iterations. Fifty search agents are used in this case. Table 7 shows the power generation of each of the 140 generators using the SCA. Table 8 compares the minimum, maximum, and average fuel costs obtained using various optimization techniques after 50 trials. The results in Table 8 prove that the minimum fuel cost obtained by SCA is much better than those by other algorithms. The net power delivered to the system is 49342.0006 MW. Hence, the accuracy of the result is 99.9999% based on Eq. (4) when transmission loss is neglected. The convergence characteristics for the SCA are shown in Figure 5.

4.1. Tuning of parameters for the SCA

To obtain the optimized solution by the use of SCA, it is imperative to obtain the proper values of parameters e_1, e_2, and e_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 in all possible combinations. For a single value of e_1, different combinations of e_2 and e_3 have been tried to obtain the minimum fuel cost. A summary of the results for the 140-generator system is provided in Table 9.

Also, using a too large or too small number of search agents for screening the search space does not lead to the optimized solution. Thus, only a specific number of search agents will help to obtain the optimized solution. For each number of search agents, 50 trials have been run. The trials show that the number of 50 search agents end in achieving the optimized fuel cost. For other numbers of search agents, no significant improvement in the fuel cost is observed. Moreover, beyond the number of 50 search agents, the simulation time also increases. The best output obtained by SCA for each number of search agents in the 140-generator system is presented in Table 10.

The optimum values of the tuned parameters are $P_{size} = 50$, $e_1 = 0.55$, $e_2 = 0.15$, $e_3 = 0.72$, and $e_4 = 0.5$.

5. Comparative study

5.1. Quality of solution

Tables 1, 3, 5, and 7 show that the fuel costs obtained by the SCA are the lowest among all optimization techniques. Also, the cost obtained by the SCA is better than the cost obtained by many previously developed algorithms. For example, in test case 1, the minimum fuel cost obtained by the SCA is 24512.6085 $/hr, which is lower than those obtained by SDE and ORCCRO. The comparison has been made in both cases of taking the transmission losses into account and neglecting them. Thus, it is clear that the quality of the solution is the best when SCA is applied.

5.2. Robustness

The robustness of any optimization algorithm cannot be judged by only running in for a single time. A number of trials should be carried out in order to prove the robustness of any optimisation technique. It is evident form Tables 2 and 4 that SCA achieves the global optimal solution for all the 50 trials in various

Table 7. Optimum power output and fuel cost obtained by Sine Cosine Algorithm (SCA) 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}	247.803	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 8. Minimum, maximum, and average fuel costs obtained by Sine Cosine Algorithm (SCA) and various optimization techniques for 140 generator units (50 trials).

Method	Generation cost ($/hr)			Time/iteration (s)	Number of hits to minimum solution
	Maximum	Minimum	Average		
SCA	**1658386.57**	**1658384.88**	**1658385.04**	**50.47**	**45**
BBO [43]	1657809.57	1657724.38	1657739.72	142.5	41
DE/BBO [43]	1657781.72	1657716.84	1657725.92	125.4	43
RCCRO [36]	1657742.97	1657690.83	1657693.96	75.8	47

Table 9. Effect of various parameters on the performance of Sine Cosine Algorithm (SCA).

e_1	e_2	e_3	e_4	**Fuel cost ($/hr)**
0.16	0.41	0.14	0.5	1658479.1876
0.68	0.65	0.15	0.5	1658455.6489
0.47	0.87	0.62	0.5	1658438.3245
0.57	0.54	0.25	0.5	1658420.9452
0.55	0.65	0.34	0.5	1658397.3249
0.55	**0.15**	**0.72**	**0.5**	**1658384.8872**
0.42	0.26	0.95	0.5	1658399.5475
0.94	0.32	0.84	0.5	1658456.3225
0.21	0.41	0.25	0.5	1658472.2587
0.78	0.52	0.41	0.5	1658501.3654

Table 10. Effect of the number of search agents on the 140-generator system.

No. of search agents	**Number of hits to best solution**	**Simulation time (sec)**	**Max. cost ($/hr)**	**Min. cost ($/hr)**	**Average cost ($/hr)**
20	32	48.25	1658406.547	1658399.254	1658401.879
50	**45**	**50.47**	**1658386.570**	**1658384.880**	**1658385.0 4**
100	27	54.36	1658416.235	1658406.325	1658410.884
150	19	57.25	1658428.625	1658412.658	1658422.558
200	11	62.33	1658468.235	1658435.328	1658460.995

test cases and from Tables 6 and 8 that SCA gives the minimum fuel cost for the maximum number of trials in comparison with other optimization techniques. This proves that the efficiency of the SCA is very high and its performance is superior to other optimization techniques, which in turn confirms the robustness of the algorithm.

5.3. Computational efficiency

The efficiency of any optimization technique is determined by the time the technique takes to the reach the global optimal solution. It is clear form Tables 2, 4, 6, and 8 that the computational time taken for one single iteration is the minimum in the SCA as compared to other previously developed optimization techniques. Thus, the SCA gives the global optimal results in the lowest computational time.

6. Conclusion

In this paper, a new algorithm, named Sine Cosine Algorithm (SCA), was proposed to solve Economic Load Dispatch (ELD) problem. To prove the efficiency of the SCA, four test cases were considered and the net fuel cost obtained by SCA was compared with those by other optimization techniques. The results were presented in tabular and graphical forms. They proved that SCA was robust, feasible, and effective as compared to other algorithms in terms of efficiency and computational time. The numerical results also proved that the SCA prevented premature convergence and had a stable convergence characteristic. Hence, by using the exploration and exploitation ability of SCA, the problem of ELD was successfully solved.

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