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Sine-Cosine Algorithm for the Dynamic Economic Dispatch Problem With the Valve-Point Loading Effect

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ABSTRACT

Dynamic economic dispatch (DED) deals with the allocation of predicted load demand over a certain period of time among the thermal generating units at minimum fuel cost. The objective function of DED becomes highly complex and nonlinear after considering various operating constraints like valve point loading, ramp rate limit, transmission loss, and generation limits. In this study, the sine-cosine algorithm has been presented to solve the DED problem with various constraints. The randomly placed swarm finds an optimum solution according to their fitness values and keeps the path towards the best solution attained by each swarm. The swarm avoid local optima in the exploration stage and move towards the solution exploitation stage using sine and cosine functions. The proposed technique has been tested in several test systems. The results obtained by the proposed technique have been compared with those obtained by other published methods employing the same test systems. The results validate the superiority and the effectiveness of the proposed technique over other well-known techniques.

KEYWORDS

Dynamic Economic Dispatch, Ramp- Rate Limit, Sine-Cosine Algorithm, Transmission Loss, Valve Point Loading Effect

1. INTRODUCTION

The operation of a power system depends upon the system's security, reliability, and economy (Bhattacharjee, Bhattacharya, & Nee Dey 2014). The Economic Dispatch (ED) is the main function of power system operation to reduce the cost of different fuel types. The main aim of the ED is to allocate load demand among committed thermal generators at a minimum price while satisfying power balance and other system constraints (Nourianfar & Abdi 2021). Thus, the ED problem is a highly complex and nonlinear optimization problem. The ED can be classified into Static Economic Dispatch (SED) and Dynamic Economic Dispatch (DED) (Verma et al. 1AD). In SED, the thermal generating units have been allocated economically to satisfy load demand for a specific time interval.

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The SED does not consider the fundamental relation of the system between the different periods (Soni et al., 2020). The DED, an extension of SED, issues time-varying load demand among the generators by satisfying various operating constraints. The DED considers the relation of different operating times to meet multiple constraints (Bhattacharjee, Shah, & Soni 2022a). Traditionally, the valve point loading effect (VPLE) has been ignored in DED to make the problem tractable (Bhattacharjee & Patel 2020). The solution becomes inaccurate and imprecise. The DED problem with VPLE has been considered to make the system more (Soni & Pandya, 2018).

DED problem was introduced in 1971 to obtain optimal operation of thermal units for a certain pe with satisfying physical and operational constraints such as ramp-rate limits, power generation limits, and power balance constraints. The transmission loss should not be ignored due to the large-scale power systems. The DED problem becomes more complicated after considering transmission loss and VPLE. The different optimization methods have been used to get the solutions of the DED problem (Bhattacharjee, Shah, & Soni, 2022b). These optimization methods have been classified into traditional methods and artificial intelligence methods. Conventional methods like linear programming, nonlinear programming, quadratic programming, Lagrange relaxation, and dynamic programming have been used to DED problems. These traditional methods suffer from the curse of dimensionality and fail to get an in large-scale DED problems (Bhattacharjee & Patel, 2018). With the massive development of artificial intelligence methods, their use for DED problems increases due to their effectiveness and feasibility. Stochastic search techniques like simulated annealing (SA) (Soni & Bhattacharjee, 2022), artificial immune system (AIS) (Bhattacharjee & Patel, 2018), differential evolution (DE) (Barisal, 2013), and genetic algorithm (GA) (Mohajeri, Seyedi, & Sabahi, 2015) have been successfully applied to solve DED problems due to their ability to find near an optimal global solution. The meta-heuristics methods have been developed by the behavior of insects. The swarm intelligence techniques like harmony search (HS) (Sivasubramani & Swarup, 2011), particle swarm optimization (PSO) (Abarghooee & Aghaei, 2011), cuckoo search (CS) (Chandrasekaran, Simon, & Padhy, 2014), artificial bee colony (ABC) (Barisal, 2013), Symbiotic organisms search algorithm (SOC) (Guvenc et al., 2018), and imperialist competitive algorithm (ICA) (Morshed and Asgharpour 2014) have been successfully applied to the DE problem. These techniques use the probabilistic rule to get a solution. Thus, these methods do not guarantee finding the global optimum solution. Many researchers have recently combined probabilistic and deterministic approaches to solve DED problems. Hybrid methods like hybrid bee colony optimization and sequential quadratic programming (BCO-SQP) (Balamurugan & Subramanian, 2008), hybrid PSO and sequential quadratic programming (PSO-SQP) (dos Santos Coelho & Mariani, 2006), Enhanced adaptive particle swarm optimization algorithm (EAPSO) (Niknam and Golestaneh 2012), hybrid bacterial foraging and simplified swarm optimization algorithm (MBF-SSO) (Balamurugan and Subramanian 2008), Time-varying acceleration coefficients IPSO (TVAC-IPSO) (Ghasemi et al., 2020), Covariance matrix adapted evolution strategy algorithm (CMAES) (Manoharan et al. 2009), and hybrid Hopfield neural network and quadratic programming (HNN-QP) (Jayabarathi & Sadasivam, 2000) have been applied to get solutions of DED problems. These above-mentioned methods take more computation time to get the optimum solution (Bhattacharjee et al., 2021). Thus, a strong and effective optimization technique is required to solve highly complex and nonlinear DED problems (Kaluri and CH 2018).

Recently, the population-based Sine Cosine Algorithm (SCA) has been proposed by Mirjalili et al. (Mirjalili, 2016). The nineteen unimodal, multimodal, and composite benchmark functions have been solved by Mirjalili et al. (Mirjalili, 2016).In SCA, the multiple initial random populations are generated and moved outward or toward the best solution. The trigonometric sine and cosine function of SCA is used to find the fitness value of populations. SCA has the exploration and exploitation property. The randomly generated solution by SCA gets to benefit from higher exploration and avoids local optima value. Such a feature is not available in other algorithms. These properties help to prevent local optima and move directly to global optima in significantly less computational time.

The advantages of SCA have encouraged present authors to use this newly developed algorithm to resolve highly nonlinear and complex DED problems (Kaluri & Reddy, 2017).

Key contributions to this work have been mentioned below:

- Recently an efficient soft computing technique called SCA has been proposed by Mirjalili et al. The 15 benchmark functions have been optimized by Mirjalili et al. to prove the robustness of the above-said algorithm. It has been seen that SCA is giving much better results than most of the recently developed algorithms. For this reason, the SCA has been adopted in this paper, for the first time, to solve highly complex and non-linear dynamic economic load dispatch problems.
- The various operating constraints like valve point loading effect, ramp-rate, transmission loss, generation limit, and generation balance have been considered to make the system more realistic
- The proposed work has been verified with various test systems.
- The comparative assessment for the proposed algorithm with some of the recent techniques shows the effectiveness and superiority of the proposed SCA algorithm

The problem formulation of the DED problem is given in Section 2. Section 3 provides information on the original SCA method. The steps involved in solving the DED problem using SCA are discussed in Section 4. Section 5 shows the simulation results of various test cases. Finally, the conclusion of the manuscript is pointed out in Section 6.

2. PROBLEM FORMULATION

The main aim of DED is to operate thermal generating units at minimum cost during a specified period (Sivasubramani & Swarup, 2011). The time period can be divided into 24 intervals for a day. The VPLE, transmission loss, and other various operating constraints have been considered in this research work. The mathematical formulation of DED is expressed in detail:

2.1. Objective Function

The objective function of the DED problem is to minimize total fuel cost over the operating time. It can be expressed as:

$$Total\,fuel\,cost = min\sum_{t=1}^{\mathrm{T}}\sum_{i=1}^{N} f\left(p_{t,i}\right) \tag{1}$$

Where f(Pi) is the total fuel cost of the ith thermal generating unit; Pi is the output of the ith thermal generating unit; T is the number of hours during overall time period; N is the number of thermal generating units.

2.1.1 The Total Cost Function of DED Without VPLE

The objective function of cost for the thermal unit is a second-order polynomial equation (Bhattacharjee, Bhattacharya, & nee Dey, 2014). The objective function of cost for DED without VPLE is shown as below:

$$Fuel\,cost\,of\,ith\,thermal\,generating\,unit\,f\left(p_{t,i}\right) = a_{iT} + b_{iT}T_{iT} + c_{iT}T_{iT}^{2} \tag{2}$$

where aiT, biT and ciT are thermal cost co-efficient of ith unit.

2.1.2 The Total Cost Function of DED With VPLE

To consider the realistic and practical application of the DED problem, the sinusoidal phase of VLPE is added in the objective function (Azizivahed et al., 2020). The cost function of DED with VPLE is stated as

$$Fuel\,cost\,of\,ith\,thermal\,generating\,unit\,f\left(p_{t,i}\right) = a_{iT} + b_{iT}T_{iT} + c_{iT}T_{iT}^{2} + \left|e_{iT}sin\left\{f_{iT} \times \left(T_{iT}^{min} - T_{iT}\right)\right\}\right| \tag{3}$$

where eiT and fiT are co-efficient of thermal ith unit representing VPLE. The objective function (2) and (3) are minimized subject to subsequent constraints:

2.2. Constraints

The multiple inequality and equality constraints like ramp rate limit constraints, unit capacity constraints, and power balance constraints can be considered in the DED problem (Nazari-Heris, Mohammadi-Ivatloo, & Nazarpour, 2019). These constraints are for quality of the grid and safety of the thermal units and are discussed as follows:

2.2.1 Thermal generator operating limit

The power generated by each generator has a minimum and maximum permissible power limit for efficient operation.

$$T_{iT}^{\min} \le T_{iT} \le T_{iT}^{\max}; iT = 1,2,3,\ldots,N \tag{4}$$

Where T_i^{min}, T_i^{max} are the minimum and maximum power limit of each unit

2.2.2 Ramp rate limit

The change in output power of any thermal generating unit must be in an acceptable range to avoid undue stresses on the combustion equipment and boiler (Bhattacharya & Chattopadhyay, 2010). The ramp rate limit of each generating unit can be expressed as follows:

$$\max\left(T_{i}^{\min}, T_{i0} - DR\right) \le T_{i} \le \min\left(T_{i}^{\max}, T_{i0} - UR\right) \tag{5}$$

Where UR and DR are the ramp-up and ramp-down limit of the ith thermal generating unit respectively.

2.2.3 Power balance

The total real power generated must balance the total load demand.

$$\sum_{iT=1}^{N} T_{iT} = \left(T_{D} + T_{L}\right) \tag{6}$$

where T_D is total load demand and T_L is total transmission loss.

3. SINE COSINE ALGORITHM

SCA starts the optimization using a random search agent because it is a population-based technique (Mirjalili, 2016). The random search population is evaluated repetitively and upgraded using a set of rules. SCA has an exploration and exploitation stage. In the exploration stage, all the random solutions are combined at a higher randomness rate to get a search space area where there is a higher possibility of getting the global solution. In the exploitation stage, the random solutions are changed slowly and that variation is significantly less than the exploration stage.

The four parameters g_1, g_2, g_3 and g_4 are the main in SCA. The g_1 parameter represents the next position that can be in space between the solution and destination or exterior of it. The g_2 parameter represents distance that population have to go in the direction of the solution. The g_3 parameter helps to find weights for the destination. The weights greater than one and less than one represent emphasize and deemphasize on a solution. The g_4 parameter switches between sine and cosine terms in (9). The trigonometric sine and cosine function is involved in this formulation. Thus, it is called SCA. The following equations of SCA are used to update results in every iteration:

$$P_h^{t+1} = P_i^t + g_1 \times \sin\left(g_2\right) \times \left|g_3 PO_h^t - P_h^t\right| \tag{7}$$

$$P_h^{t+1} = P_h^t + g_1 \times \cos\left(g_2\right) \times \left|g_3 PO_h^t - P_h^t\right| \tag{8}$$

where g_1, g_2 and g_3 are constant variables. The g_4 variable is given a random variable between 0 and 1. The equations (7) and (8) are modified as below:

$$P_h^{t+1} = \begin{cases} P_h^t + g_1 \times \sin\left(g_2\right) \times \left|g_3 PO_h^t - P_h^t\right|; & g_4 < 0.5 \\ P_h^t + g_1 \times \cos\left(g_2\right) \times \left|g_3 PO_h^t - P_h^t\right|; & g_4 \geq 0.5 \end{cases}$$

where P_h^{t+1} is the position of the population at current $(t+1)^{th}$ iteration and h^{th} dimension; P_h^t is position of population at previous t^{th} iteration and h^{th} dimension; PO_h^t is the position of destination point at previous t^{th} iteration and h^{th} dimension. The sequential steps of SCA are given below:

3.1. Sequential Steps of SCA

1. Initialization of lower and upper bound limit of each search agent. Decide the total number of iteration and population size.
2. The objective is computed by considering input variables.
3. Evaluate the fitness function value of each population using an objective function.
4. If the fitness function value is lower than the previous one, it is considered as local minima. The parameters g_1, g_2 and g_3 are initially assigned. After each iteration, the value of parameters will change. The parameter g_4 switches between sine and cosine function.
5. The changed values of the population is checked if it violated or not. If yes, fix their boundary limits.
6. The search agents will move in the whole search space to find global optima in the exploration stage.
7. Once the destination point is found, the population will move in that direction in the exploitation stage.
8. Repeat steps 3 to 7 until termination criteria are reached.

4. SCA USED IN DED PROBLEM

The steps for solving the DED problem by using SCA are discussed in this section. The flowchart of the SCA used in solving the DED problem is given in Figure 1. The steps to solve the problem as shown below:

Step 1 Initialize the number of generators, population size, lower bound, and upper bound of thermal generators.
Step 2 Each search agent randomly initializes the population matrix for thermal power plants and evaluates the fitness function. Select best swarm based on fitness value
The main working of SCA algorithm begins at this point. Randomly generate g_2, g_3 and g_4 parameters and determine the value of g_1.
Step 3 If the value of parameter g_1 is greater than 1, the swarm moves in opposite direction. And if the value of parameter g_1 is less than 1, the swarm moves in the same specified direction. The value of parameter g_2 show distance to swarm for moving in the specified direction. the parameter g_3 is weighting factor of swarms.
Step 4 Update the position of each search agents using equation (9).
Step 5 Check for constraint limits of each generator based on equations (4) to (6).
Step 6 Compute the fitness function and update the local best position of each search agent. Update best mean cost and SD.
Step 7 Repeat step (3) until the termination criterion is reached.

5. RESULTS AND DISCUSSION

In this section, the SCA technique is tested by applying it on two test systems with different number of generating units. The 24 intervals for a day have been considered in all cases. MATLAB 2021a software is used to simulate the problem and validated in 1.7GHz intel core, 4GB RAM personal computer.
Case 1: The first case consists of five thermal generating units with considering VPLE, RRL, transmission loss, and generation limits.
Case 2: The second case consists of ten thermal generating units with considering VPLE, RRL, transmission loss, and generation limits.

The 50 independent trails have been conducted with random initial solution for each run and results (Min, Max, and Mean) have been calculated. The value of each parameter has been selected from empirical tests by running the algorithm several times with different parameter combination.

5.1. Test Case 1

The input data of five thermal units is given in (Panigrahi et al., 2007). The B-matrix coefficients to calculate the transmission loss are given in (Basu, 2011). The various operating constraints like VPLE, RRL and generation limits have been considered in this test system. The DED problem has been solved by different values of parameters. The optimal values of the parameters are listed as g_1=0.4, g_2=0.5, g_3=0.4, g_4=0.3. The best generation schedule of five thermal units obtained by SCA technique is shown in Table 1. The results obtained by SCA algorithm has been compared with various algorithms as shown in Table 2. To examine the quality of the solution, the standard deviation from 100 independent runs using the SCA approach is calculated. The standard deviation is equal to $23.85. Thus, there is very small variation in the total cost obtained by SCA technique. The results show that the SCA method yields improved results over other published methods. The convergence characteristic by SCA is shown in Figure 2.

5.2. Test Case 2

The input data of ten thermal units is given in (Basu, 2008). The B-matrix coefficients to calculate the transmission loss are given in (Basu, 2011). The various operating constraints like VPLE, RRL and generation limits have been considered in this test system. The best generation schedule of each thermal units obtained by SCA technique is shown in Table 3. The results obtained by SCA algorithm has been compared with various algorithms as shown in Table 4. To examine the quality of the solution, the standard deviation from 100 independent runs using the SCA approach is calculated. The standard deviation is equal to $81.52. Thus, there is very small variation in the total cost obtained by SCA

Figure 1. Flowchart of SCA used in solving DED problem

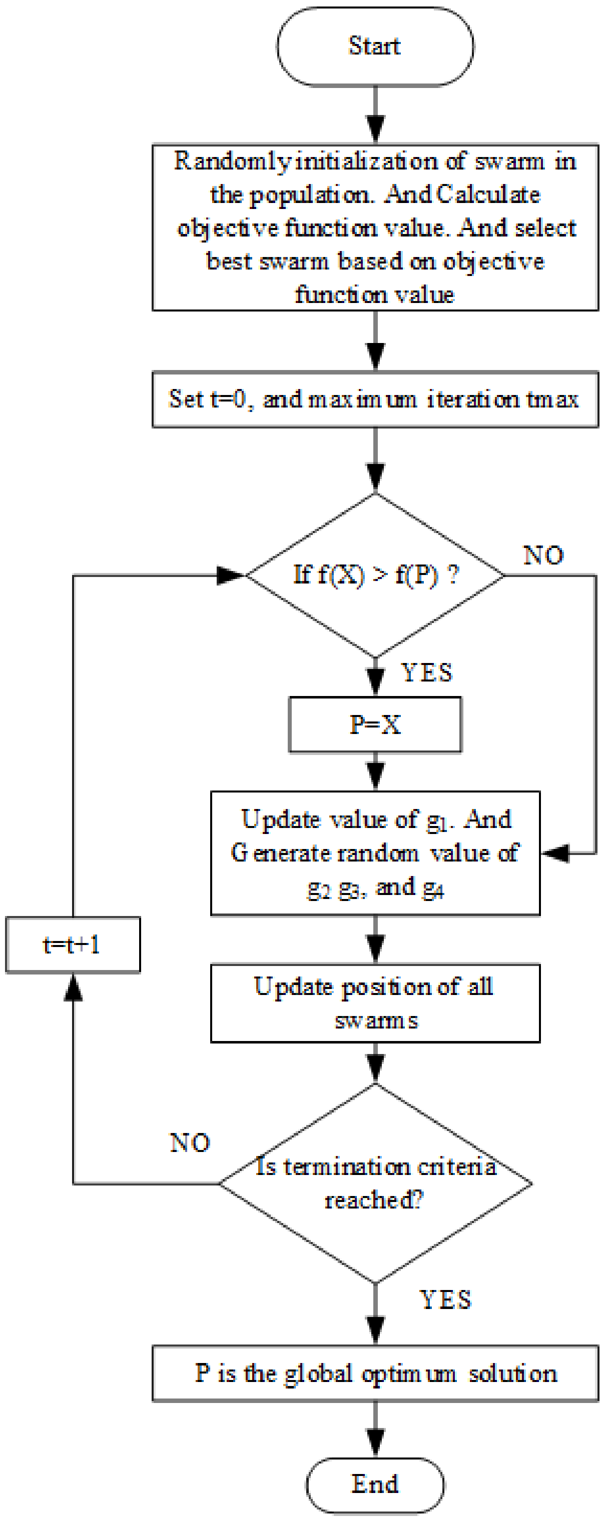

Table 1. The best generation schedule for five unit test system using SCA technique

Time	T1	T2	T3	T4	T5	Load Demand	Fuel Cost
1	18.326012	98.474924	30.427595	124.09328	138.67819	410	1247.9664
2	42.744966	99.709663	112.43856	42.058983	138.04783	435	1400.4093
3	9.235536	98.108698	102.67908	125.54763	139.42905	475	1416.4085
4	23.639082	29.180815	116.46335	125.70067	235.01609	530	1656.7053
5	10.01392	88.73643	111.9119	124.7604	229.264	558	1616
6	42.53676	103.48262	199.16443	123.35585	139.46035	608	1831.8958
7	75.436075	99.745833	184.22942	125.0195	141.56917	626	1853.0288
8	12.60176	98.55414	112.8777	209.6984	229.5249	654	1798
9	40.180668	101.86111	108.7567	209.29952	229.90201	690	1994.6727
10	64.14043	98.45003	112.6611	209.812	229.4956	704	1997
11	79.597286	98.870156	187.65208	125.27523	228.60525	720	2033.116
12	16.469789	98.023017	194.37315	208.02238	223.11166	740	2066.5538
13	64.28194	98.47242	112.5991	209.7461	229.4596	704	1997
14	31.306577	102.21481	112.75404	213.48848	230.23608	690	1977.7247
15	11.956639	14.378254	112.96724	285.89449	228.80338	654	1896.9873
16	22.045405	97.493032	112.03346	209.92609	138.50202	580	1657.0593
17	10.136708	90.381877	112.25386	208.50809	136.71946	558	1616.7205
18	53.874246	95.047479	110.34173	208.23809	140.49846	608	1808.4793
19	11.55225	99.35399	112.815	209.8138	229.7294	654	1799
20	57.340426	98.637468	192.06793	126.48632	229.46785	704	2024.0381
21	31.973963	99.105121	111.21418	207.67924	230.0275	680	1934.8204
22	36.515257	101.33853	113.87112	213.92607	139.34902	605	1792.971
23	37.019145	15.714886	36.604197	208.12626	229.53551	527	1654.8832
24	66.261275	98.601233	29.311384	41.191828	227.63428	463	1449.3114
						Total	**42520.752**

technique. The results show that the SCA method show superiority over other published methods. The convergence characteristic by SCA is shown in Figure 3.

5.2.1. Tuning the Parameter of the SCA

The parameters of the SCA algorithm should be tuned to obtain optimum solution in less computational time. The different values of the parameters 'g_1, g_2, g_3, and g_4' give different minimum fuel costs. For single values of g_1 parameter, the values of other parameters 'g_2, g_3 and g_4' have to be varied in all possible combinations. It takes very large space to show here. Thus, the summarized results of minimum fuel costs, after 100 trails run, for all possible combinations have been shown in Table 5. The optimal values of the parameters are listed as g_1=0.5, g_2=0.6, g_3=0.3, g_4=0.5.

6. CONCLUSION

The SCA optimization technique has been used in this study to get optimal solution of DED problem. The various operating constraints like VPLE, transmission loss, RRL, and generation limit have been considered to make system more realistic. The proposed technique has been demonstrated using the

Table 2. Total fuel cost comparison for five unit test system

Method	Min ($)	Max ($)	Mean ($)	Std. dev.
EAPSO (Niknam and Golestaneh 2012)	43820	44982	44082	NA
MBF-SSO (Abarghooee and Aghaei 2011)	43048	43093	43068	NA
DE (Barisal 2013)	43213	44247	43813	NA
TVAC-IPSO (Barisal 2013)	43136.561	43302.233	43185.664	NA
ABC (Aydin et al. 2014)	44046.83	44218.64	44064.73	NA
ICA (Morshed and Asgharpour 2014)	43117.055	43209.533	43144.472	NA
CMAES (Faramarzi et al. 2020)	43526	44191	43915	10.2351
Lbest-PSO (Huang et al. 2013)	43738	NA	NA	NA
LPSO-DVS (P. Verma and Parouha 2021)	43125.5166	NA	NA	NA
SOC (Fang et al. 2019)	43090.5925	43162.2146	43103.0828	NA
LDISS (Bakirtzis 1994)	43213	NA	NA	NA
BBPSO (Kamboj, Bath, and Dhillon 2016)	43233	44252	43732	274.95
BBO (Bhattacharya and Chattopadhyay 2010)	44433.8165	45276.3973	44763.6307	219.2459
BSO (Barisal 2013)	43376.9956	45234.3971	44194.2096	445.4947
BLPSO (Yadav 2019)	43322.4764	43875.7363	43542.3052	158.6055
CSO (Balamurugan and Subramanian 2008)	43161.843	43956.4777	43450.9566	184.3599
DE/BBO (Sayah and Hamouda 2013)	43047.4645	43683.7981	43292.7217	177.7068
DE/eig (Kaur, Singh, and Dhillon 2021)	43112.8236	43826.9965	43361.4475	190.2852
LETLBO (Nandi and Kamboj 2021)	43304.3385	46205.608	44249.3421	656.9117
LWOA (Maity, Banerjee, and Chanda 2018)	44663.3334	47200.0106	46021.1086	649.404
SATLBO (Hu et al. 2016)	43385.1333	44536.3469	43698.1971	270.6494
SLPSO (Shaw, Ghoshal, and Mukherjee 2011)	43125.0913	44237.2007	43681.8656	245.1994
BBOSB (Xiong and Shi 2018)	43017.9597	43197.0128	43066.4046	83.4913
SCA	**42520.752**	**42854.854**	**42658.211**	23.8541

Figure 2. Convergence characteristics of SCA technique for five unit test system

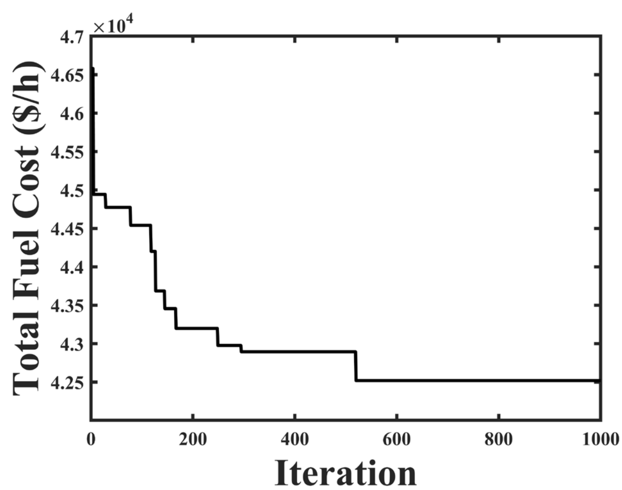

Table 3. The best generation schedule for ten unit test system using SCA technique

Hour	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	Load (MW)	Fuel Cost
1	120.45	103.75	77.48	72.77	243.60	123.87	37.18	121.92	81.22	53.76	1036.00	61225.00
2	145.06	94.74	126.69	125.80	116.30	136.43	127.31	147.03	44.84	45.79	1110.00	64117.01
3	98.02	94.17	194.17	228.49	259.71	110.83	88.20	116.54	15.96	51.90	1258.00	70828.00
4	122.91	119.37	336.60	156.77	258.46	57.62	98.33	136.70	76.27	42.96	1406.00	79802.07
5	132.21	142.30	364.62	94.62	235.15	183.39	84.99	127.31	69.44	45.98	1480.00	83932.65
6	193.88	170.90	269.10	135.59	319.06	178.54	133.29	124.38	58.67	44.59	1628.00	92941.64
7	206.59	185.14	384.91	202.32	168.14	204.45	139.15	147.76	12.81	50.73	1702.00	99663.29
8	165.95	131.62	342.93	345.06	258.19	173.41	153.48	108.29	55.29	41.79	1776.00	99833.04
9	276.00	233.98	325.77	404.80	343.50	149.05	69.69	78.86	26.85	15.48	1924.00	119522.83
10	317.59	233.44	364.58	385.80	199.44	217.64	148.98	77.26	73.20	54.08	2072.00	129610.47
11	295.68	363.84	343.13	294.80	304.90	182.14	138.59	116.47	83.37	23.08	2146.00	136984.13
12	332.66	278.02	436.65	354.69	277.76	167.75	138.96	86.13	96.06	51.32	2220.00	140862.36
13	311.91	305.02	315.66	336.16	233.64	203.16	129.16	108.21	101.42	27.68	2072.00	131103.97
14	274.52	274.25	327.88	395.79	195.94	192.17	74.53	107.41	36.08	45.42	1924.00	121278.55
15	156.39	228.55	372.73	261.57	309.33	126.55	125.72	74.98	77.49	42.69	1776.00	102803.14
16	140.88	151.76	283.12	309.60	149.47	188.06	112.92	147.30	58.02	12.88	1554.00	87930.21
17	135.12	122.42	385.35	175.52	275.23	117.66	88.02	98.97	49.60	32.12	1480.00	83921.18
18	150.49	135.04	312.82	299.98	243.00	160.00	129.64	119.70	79.97	45.36	1628.00	92956.00
19	248.47	163.90	406.02	365.21	227.04	127.53	78.45	77.63	33.17	48.58	1776.00	107561.82
20	309.70	309.53	339.93	300.00	242.83	160.00	129.93	119.99	80.00	54.97	2072.00	129178.00
21	212.90	260.07	359.96	276.82	278.66	183.24	118.66	157.98	36.95	38.76	1924.00	113795.34
22	227.74	168.11	265.17	158.15	323.45	186.09	110.25	62.64	74.48	51.91	1628.00	95866.16
23	154.65	150.49	80.99	222.48	327.27	51.87	163.94	81.85	88.22	10.26	1332.00	76496.29
24	145.28	138.86	74.13	94.02	307.34	105.63	84.08	164.14	30.60	39.92	1184.00	68223.36
											Total	**2390436.53**

Table 4. Total fuel cost comparison for ten-unit test system

Algorithms	Min costs ($)	Max cost	Mean Cost	SD
AIS (Naderi, Khalili, and Tavakkoli-Moghaddam 2009)	2519700	2519800	2519732	NA
EP (Venkatesh, Gnanadass, and Padhy 2003)	2585000	2585252	2585132	NA
PSO (Gaing 2003)	2571800	2571963	2571841	NA
DE-SQP (dos Santos Coelho and Mariani 2006)	2465900	2466211	2466200	NA
PSO-SQP (Zhang et al. 2013)	2466800	2466850	2466832	NA
IBFA (Pandit et al. 2012)	2484700	2484854	2484798	NA
CRO (Roy, Bhui, and Paul 2014)	2482600	2482808	2482785	NA
HCRO (Roy, Bhui, and Paul 2014)	2480000	2480465	2480451	NA
SPS-DE (Sayah and Hamouda 2013)	2470000	2471220	2470112	NA
MBDE (Liang et al. 2018)	2602000	2602250	2602201	NA
WOA (Yang et al. 2021)	2470300	2470480	2470415	NA
EEWOA (Yang et al. 2021)	2465200	2465620	2465320	NA
SCA	**2390436.53**	**2390512.41**	**2390444.62**	81.52

Figure 3.Convergence characteristics of SCA technique for ten-unit test system

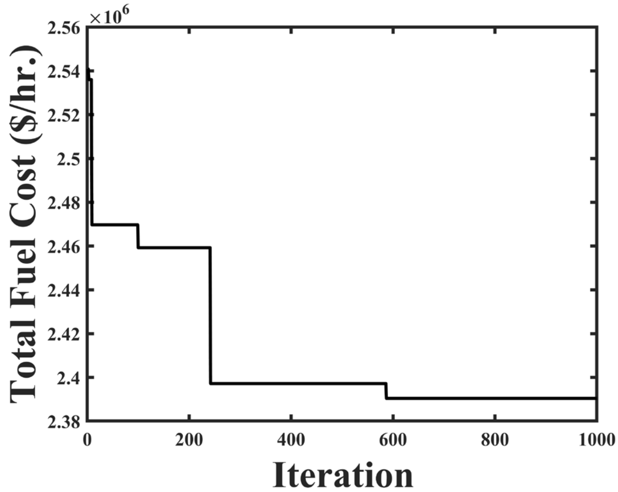

Table 5. The minimum fuel cost for different values of SCA parameters

g_1	g_2	g_3	g_4	Minimum fuel cost ($ / hr.)
0.1	0.40	0.10	0.1	2390498.33
0.2	0.45	0.15	0.2	2390511.96
0.3	0.50	0.2	0.3	2390441.21
0.4	0.55	0.25	0.4	2390474.63
0.5	0.60	0.30	0.5	**2390436.53**
0.6	0.65	0.35	0.6	2390452.78
0.7	0.70	0.40	0.7	2390462.88
0.8	0.75	0.45	0.5	2390489.12

commonly used test systems. These test systems are 5- and 10-unit test systems. The results obtained by SCA technique have been compared with other recently reported techniques. The results show that the total cost obtained by SCA technique is smaller than those found by other methods. The proposed technique is a effective and promising method for solving DED problem and other optimization problems. The proposed optimization technique can be used to solve many other complex engineering problems like in electric vehicles, mechanical vibration, and battery management system.

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