Economic Load Dispatch using Sine Cosine Algorithm

Major Project Report

Submitted in Partial Fulfillment of the Requirements for the Degree of

MASTER OF TECHNOLOGY

IN

ELECTRICAL ENGINEERING
(Electrical Power Systems)

By

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Undertaking for originality of the work

I **Nitish Patel** roll no. **(16MEEE18)**, give undertaking that the major project entitled **"Economic Load Dispatch using Sine Cosine Algorithm"** submitted by me, towards the partial fulfillment of the requirement for the degree of Master of technology in Electrical Power Systems of Nirma University, Ahmedabad, is the original work carried out by me and I give assurance that no attempt of plagiarism has been made. I understand that in the event of any similarity found subsequently with any published work or any dissertation work elsewhere; it will result in serve disciplinary action.

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CERTIFICATE

This is to certify that the Major Project Report entitled **"Economic Load Dispatch using Sine Cosine Algorithm"** submitted by **Mr. Nitish Patel (16MEEE8)**, towards the partial fulfillment of the requirements for the award of degree in Master of Technology (Electrical Engineering) in the field of Electrical Power Systems of Nirma University is the record of work carried out by him under our supervision and guidance. The work submitted has in our opinion reached a level required for being accepted for examination. The results embodied in this major project work to the best of our knowledge have not been submitted to any other University or Institution for award of any degree or diploma.

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Abstract

This project proposes a powerful Sine Cosine Algorithm (SCA) to explain the Economic Load Dispatch (ELD) problem including equality and inequality constraints. The Economic Load Dispatch accomplishes the most reliable and nominal dispatching among the accessible thermal generators. The main aim of ELD is to satisfy the entire electric load at minimum cost. The SCA is a population based optimization technique which guides its search agents, that are randomly place in the search space, towards an optimal point using their fitness function and also keeps a track of the best solution achieved by each search agent. The Sine Cosine Algorithm is being used for the Economic Load Dispatch problem due to its high exploration and local optima avoidance technique compared to other individual based algorithms. This algorithm confirms that the promising areas of the search space are exploited to have a smooth transition from exploration to exploitation using adaptive range in the sine and cosine functions.

Abbreviations

ELD	Economic Load Dispatch
SCA	Sine Cosine Algorithm
TLBO	Teaching Learning Based Optimization
EP	Evolutionary Programming
PSO	Particle Swarm Optimization
GLOT	Group Leader Optimization Technique
ORCCRO	Oppositional Real Coded Chemical Reaction Optimization
SDE	Shuffled Differential Evolution
BBO	Biogeography Based Optimization
DE	Differential Evolution

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Chapter 1

Introduction

1.1 Introduction to Economic Load Dispatch

The Economic Load Dispatch helps to achieve the most reliable and low cost dispatching among the available thermal generators. The main aim is to satisfy the entire load at minimum cost. It ensures that the real and reactive power of the generators vary within a certain limit and the load demand is fulfilled with less fuel cost. In a power system, it is not always necessary to run all the generators at full load. Hence the concept of Economic Load Dispatch was introduced to ensure that the most economic combination of generators is used to supply the load in order to get the least generation cost.

1.2 Requirement of Optimization Techniques in solving Economic Load Dispatch problem

In recent years, evolutionary algorithms have been widely used due to their natural selection process, flexibility, versatility, and robustness in searching a globally optimal solution. Optimization is defined as the art of finding the optimal value for a given parameter of a given system from all the possible values. In an optimization technique, the mathematical modelling is not required as it monitors the change in the output based on the change in the input. The algorithm used utilises the functions sine and cosine to explore and exploit the space between two solutions in the search space to find the best output.

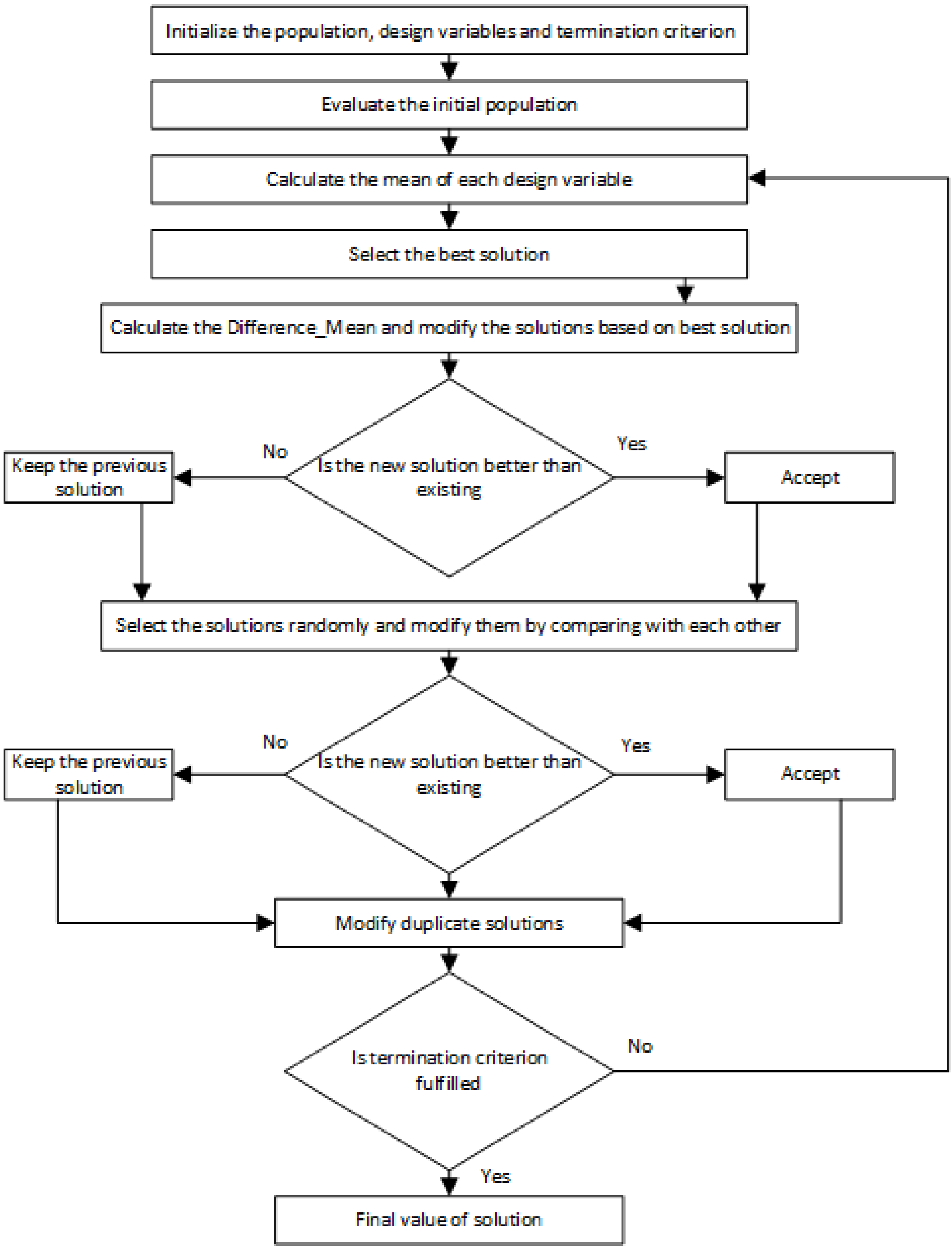
Chapter 2

Literature review

M. Basu, "Teaching e learning-based optimization algorithm for multi-area economic dispatch" Energy, vol. 68, pp. 21-28, 2014.

TLBO is also a population-based method and uses a population of solutions to proceed to the global solution. The population is considered as a group of learners or a class of learners. The process of TLBO is divided into two parts: the first part consists of the Teacher Phase and the second part consists of the Learner Phase. Teacher Phase means learning from the teacher and Learner Phase means learning by the interaction between learners.

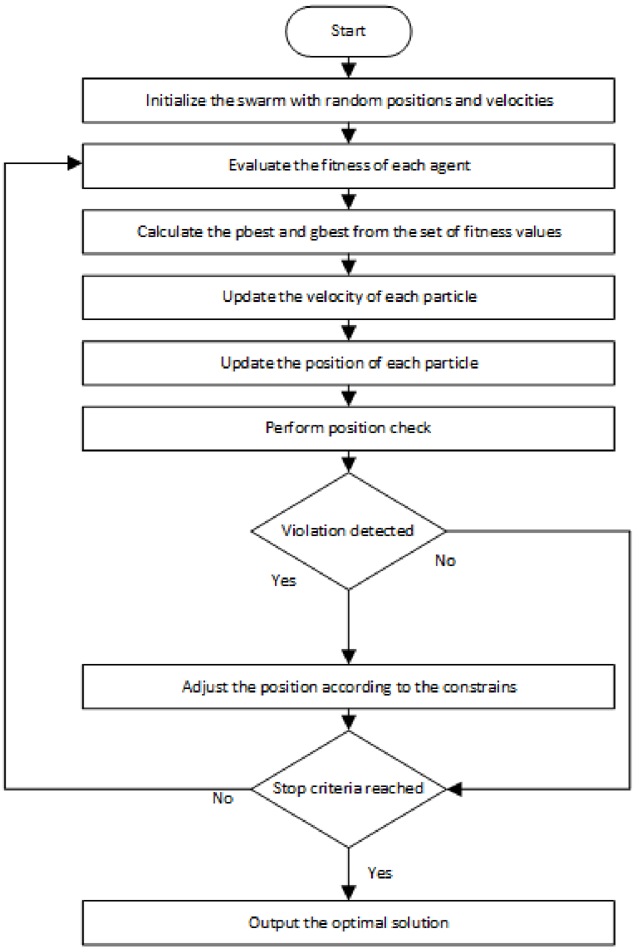
In this optimization algorithm, a group of learners is considered a population, and different subjects offered to the learners are considered design variables of the optimization problem. A learners result is analogous to the fitness value of the optimization problem. The best solution in the entire population is considered the teacher. The design variables are the parameters involved in the objective function of the given optimization problem, and the best solution is the best value of the objective function.


Initialize the population, design variables and termination criterion
Evaluate the initial population
Calculate the mean of each design variable
Select the best solution
Calculate the Difference_Mean and modify the solutions based on best solution
Is the new solution better than existing
No
Yes
Keep the previous solution
Accept
Select the solutions randomly and modify them by comparing with each other
Is the new solution better than existing
No
Yes
Keep the previous solution
Accept
Modify duplicate solutions
Is termination criterion fulfilled
No
Yes
Final value of solution

M. N. Alarn, A. Mathur, and K. Kurnar, "Economic Load Dispatch using a Differential Particle Swarm Optimization," no. 2, pp. 1-5, 2016

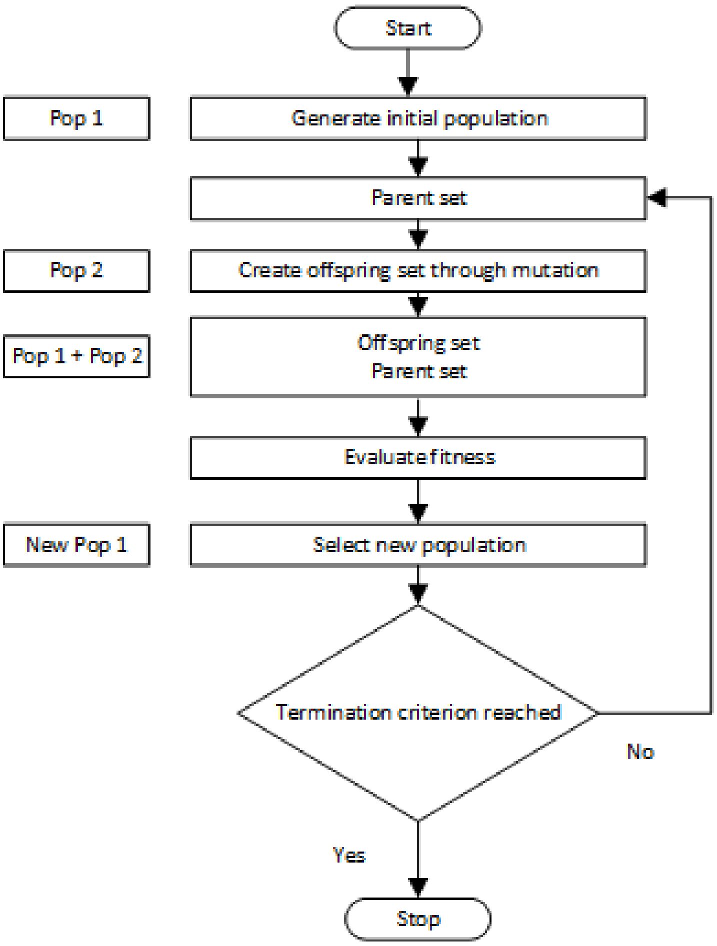
Particle swarm optimization is a population based stochastic optimization technique. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles.

Each particle keeps track of its coordinates in the problem space which are associated with the best solution it has achieved so far. This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbours of the particle. This location is called lbest. when a particle takes all the population as its topological neighbours, the best value is a global best and is called gbest. The particle swarm optimization concept consists of, at each time step, changing the velocity of each particle toward its pbest and lbest locations. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and lbest locations.



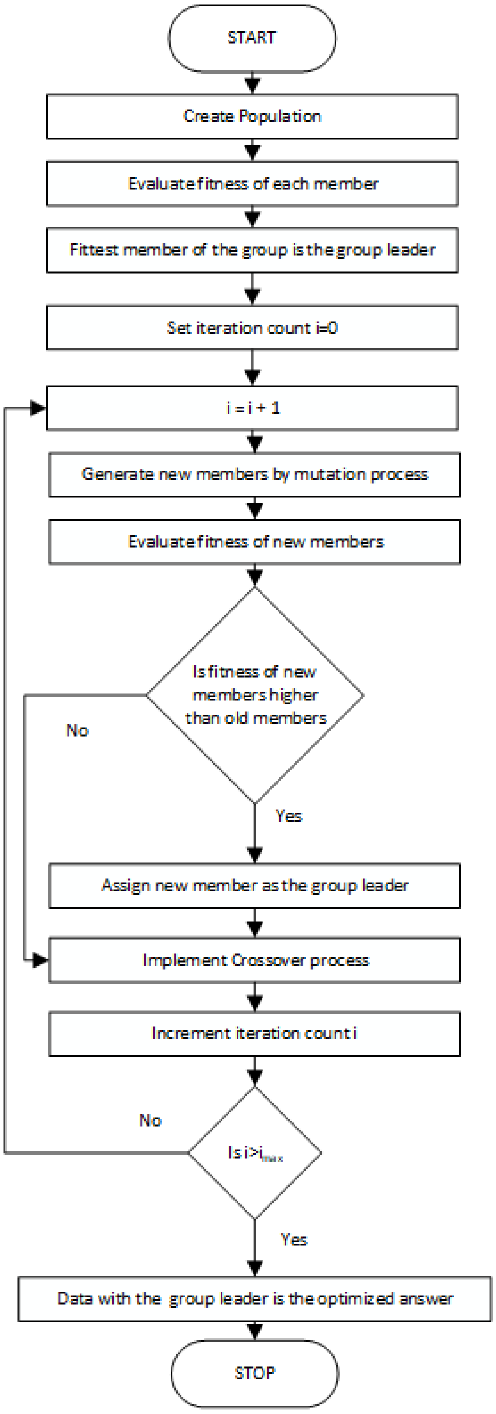
N. Sinha, R. Chakrabarti, and P. K. Chattopadhyay, "Evolutionary Programming Techniques for Economic Load Dispatch," vol. 7, no. 1, pp. 83-94, 2003.

It is a heuristic search algorithms based on population and Evolutionary process of natural selection. It generally provides a fast and reasonable solution. It uses the control parameters in real values. Population is initialized in terms of real values. Mutation of all the solutions in the current population is done. Selection of the next generation among mutated and current solutions is also done.



A. Daskin, “Group leader optimization algorithm,” 2011.

At the initial stage of this algorithm creating a number of groups by the members based on random selection. Each group tries to find a global solution which is to be taken as the group leaders which are the closest members of the groups to local or global minima. In each group the leaders are those whose fitness value is the best in their groups, after an iteration if another member in the same group then has a better fitness value to leader, then leader can lose its position.



Chapter 3

Mathematical problem formulation for Economic Load Dispatch problem

3.1 Problem Formulation

The ELD problems are expressed as convex or non-convex problems with some linear and nonlinear constrains for different applications. The objective function of ELD with quadratic cost function based on (3.1) as follows:

$$F_{cost} = min \sum_{a=1}^{N} (\alpha_a + \beta_a P_a + \gamma_a P_a^2) \tag{3.1}$$

For more realistic and practical application of ELD problems the smooth quadratic cost function have been 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:

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

Where α, β, γ, δ and ϵ are the constant values of fuel cost function. N is the total number of thermal generators. Power generations from each generators is Pa. Lower limit and higher limit of power generation is characterized by and . Power generations from each unit are followed by following generating capacity constraint:

$$P_a^{min} \leq P_a \leq P_a^{max} \tag{3.2}$$

This is inequality constraints of ELD problems. The equality constraints or real power balance constraint of ELD is based on (3.3).

$$\sum_{a=1}^{N} P_a - P_D - P_{loss} = 0 \tag{3.3}$$

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

$$P_{loss} = \sum_{a=1}^{N}\sum_{b=1}^{N} P_a B_{ab} P_b + \sum_{a=1}^{N} B_{0a} P_a + B_{00} \tag{3.4}$$

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

$$P_a - P_{a0} \leq UR_a \tag{3.5}$$

$$P_{a0} - P_a \leq DR_a \tag{3.6}$$

$$\max\left(P_a^{\min}, P_{a0} - DR_a\right) \leq \min\left(P_a^{\max}, P_{a0} + UR_a\right) \tag{3.7}$$

Where P_{ao} is the power generations of a^{th} previous interval; and are the up-ramp limit and down ramp limit.

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

$$\left.\begin{array}{l} P_a^{\min} \leq P_a \leq P_{a,1}^{l} \\ P_{a,j-1}^{u} \leq P_a \leq P_{a,j}^{l} \\ P_{a,n}^{u} \leq P_a \leq P_a^{\max} \end{array}\right\} ; j = 1, 2, \ldots, n \tag{3.8}$$

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

Calculation of slack generator is one of the important part in ELD problem formulations. If N is the total number of generators then initially calculate (N-1) number of power generations randomly based on (3.2), (3.5), (3.6), (3.7) and (3.8). The remaining generator (let N^{th}) which is called slack generator have to be calculated using (3.3). The value of slack generator is given below:

$$P_N = P_D - \sum_{a=1}^{N-1} P_a \qquad Without\ transmission\, losses \tag{3.9}$$

$$P_N = P_D + P_{Loss} - \sum_{a=1}^{N-1} P_a \qquad With\, transmission\, losses \tag{3.10}$$

Transmission loss (P_{loss}) is also related to power generations based on (3.4), therefore (3.10) is further modified and is given below:

$$\begin{aligned} & B_{NN}P_N^2 + P_N\left(2\sum_{a=1}^{N-1} B_{Na}P_a + \sum_{a==1}^{N-1} B_{0N} - 1\right) \\ & + \left(P_D + \sum_{a=1}^{N-1}\sum_{b=1}^{N-1} P_a B_{ab} P_b + \sum_{a=1}^{N-1} B_{0a}P_a - \sum_{a=1}^{N-1} P_a + B_{00}\right) = 0 \end{aligned} \tag{3.11}$$

Chapter 4

Sine Cosine Algorithm

4.1 Introduction to Sine Cosine Algorithm

The sine cosine algorithm 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 exploration phase the optimization algorithm combines all the random solutions in a set of solutions quickly with a high rate of randomness so that it can find promising regions of the search space. While in the exploitation phase there are slow changes in the random solutions and the random variations are less as compared to those in the exploration phase.

In the sine cosine algorithm there are four main parameters: e_1, e_2, e_3 and e_4. The parameter e1 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 weightage factor for the destination. For example, if a destination is given a weightage factor of greater than one then its emphasis is being increased and if the weightage factor is less that one, then its emphasis is being decreased. The parameter e_4 equally switches between the sine and cosine components. Due to the switching between the sine and cosine functions, the algorithm is known as Sine Cosine Algorithm. The cyclic pattern of sine and cosine functions allows a solution to be re-positioned around its solution. The number of iterations is selected by the user and when the iteration count exceeds the pre-set value, the optimization process terminates by itself and the best solution obtained so far is the final solution to the optimization problem.

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

$$X_i^{t+1} = X_i^t + e_1 * sin(e_2) * |e_3 P_i^t - X_i^t| \tag{4.1}$$

$$X_i^{t+1} = X_i^t + e_1 * cos(e_2) * |e_3 P_i^t - X_i^t| \tag{4.2}$$

Note the use of the variables e_1, e_2 and e_3 in the above equations. The above two equations are combined by using the e_4 variable.

$$X_i^{t+1} = X_i^t + e_1 * sin(e_2) * |e_3 P_i^t - X_i^t|; e_4 \leq 0.5 \tag{4.3}$$

$$X_i^{t+1} = X_i^t + e_1 * cos(e_2) * |e_3 P_i^t - X_i^t|; e_4 \geq 0.5 \tag{4.4}$$

4.2 Algorithm

- Define the number of search agents
- Define the maximum number of search agents
- Get details of the function
- Accept the total number of generators
- Get the maximum and the minimum generation limit of each generator
- Get the total power demand from the user
- Calculate the objective function
- The sine cosine algorithm begins with initialization where various parameters like lower bound, upper bound, limits, etc. are initialized
- Then the fitness of the first set is calculated and is assigned the best value
- In the second iteration update the value of e_1 to e_4 parameters

- If the solution of the second iteration is better, then the destination needs to be updated
- Finally display the optimum value obtained after all the iterations

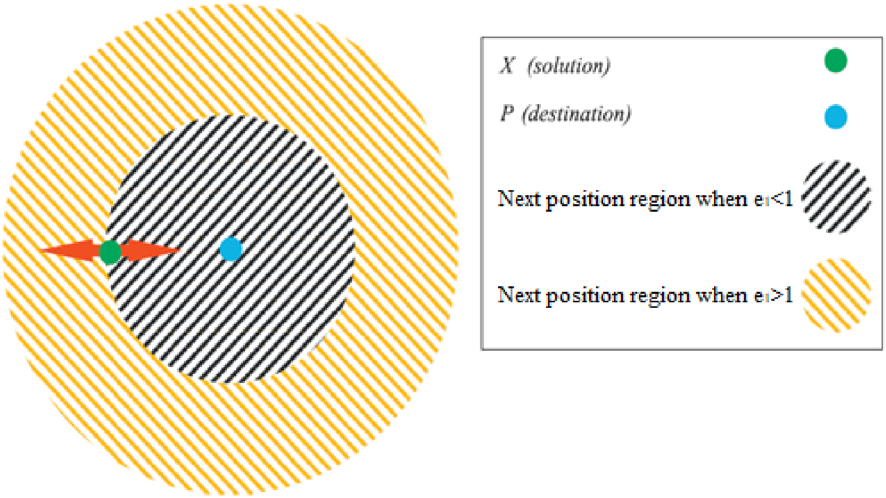


Figure 4.1: Effect of parameters on next position

This figure shows that how the equations define a space between two solutions in the search space. It should be noted that this equation can be extended to higher dimensions although a two- dimensional model is illustrated. The cyclic pattern of sine and cosine function allows a solution to be re-positioned around another solution. This can guarantee exploitation of the space defined between two solutions. For exploring the search space, the solutions should be able to search outside the space between their corresponding destinations as well.

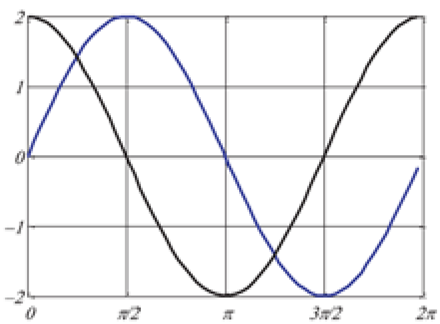


Figure 4.2: Sine and cosine with range of [-2,2]

For searching outside the search space, the range of the sine cosine function can be varied according to the requirement.

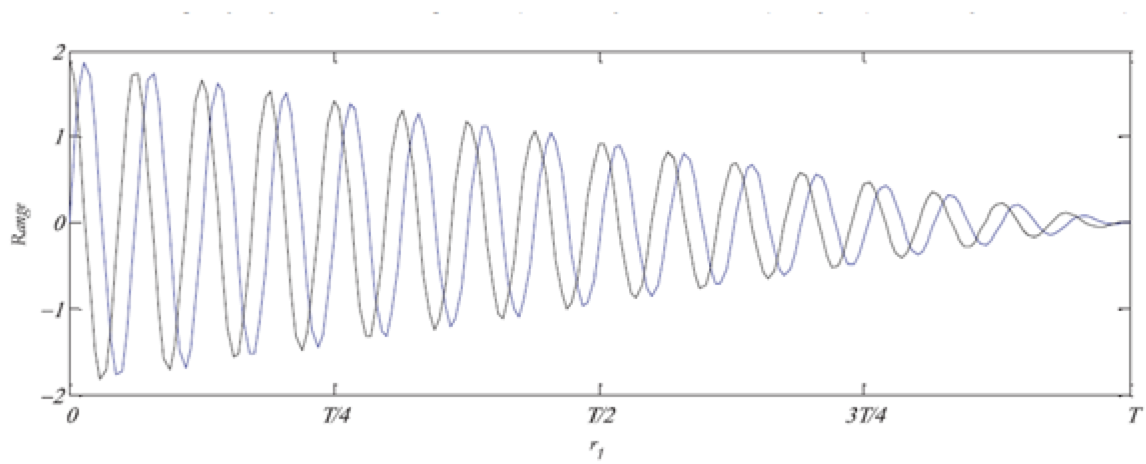


Figure 4.3: Decreasing pattern of sine and cosine

The above figure shows the decreasing pattern of the sine cosine algorithm. As the iteration count increases, the range of the algorithm will decrease as the algorithm will tend to move towards the optimal answer.

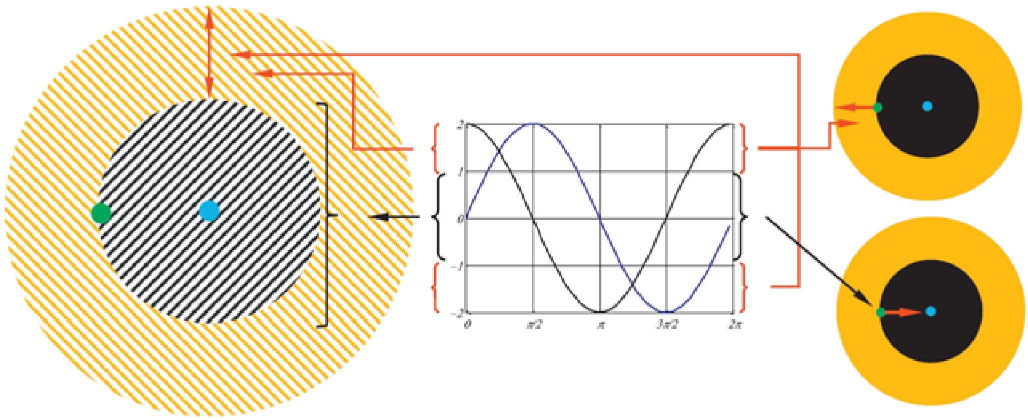


Figure 4.4: Tracking of global values

The above figure shows that the search agents will move from the range of -2 to 2 in the search space. It is quite evident that how the range of the sine cosine algorithm changes so that the position of the search agents is inside or outside the search space. The initial random location is fixed by giving a random value to e_2. Therefore, this mechanism guarantees exploration and exploitation of the search space.

An algorithm should be able to balance exploration and exploitation to find the promising regions of the search space and eventually converge to the global optimum. Thus to ensure this the range of the sine cosine function is changed using the equation.

$$el = a - (t * a)/T$$

Where t is the current iteration, T is the maximum number of iterations and a is a constant. The algorithm saves the best solutions obtained so far, assigns it as the destination point, and updates other solutions with respect to it. Meanwhile, the ranges of sine and cosine functions are updated to emphasize exploitation of the search space as the iteration counter increases.

The sine cosine algorithm terminates the optimization process when the iteration counter goes higher than the maximum number of iterations by default. However, any other termination condition can be considered such as maximum number of function evaluation or the accuracy of the global optimum obtained.

4.3 Consecutive steps of SCA algorithm integrated in ELD problem

- Initially choose all the predefined values like total number of iteration *Imax*, total number of thermal unit N and the total number of population set *Psize*, upper and lower limit of each generator, load demand, B-coefficients matrix for transmission loss and e_1, e_2, e_3 and e_4 constant variables for SCA algorithm
- Active power generations for ELD problems *Pgen* is consider as population set of searching dimension X in SCA algorithm and the matrix can be formed based on (3.2)
- Calculate the objective function for each power generating units based on (3.1)
- Change all the values of power generations using (4.3) and (4.4). All the values of power generations should satisfy the inequality constants (3.2). If any value of the matrix violates any constraints like (3.2) and (3.3), then the matrix is regenerated until all the constraints are satisfied
- Calculate the objective function for newly generated matrix. Compare them on the basis of objective function of newly and old generated population set. The better fitness value should be assigned into the positional matrix of power generation (P)

4.4 Flowchart

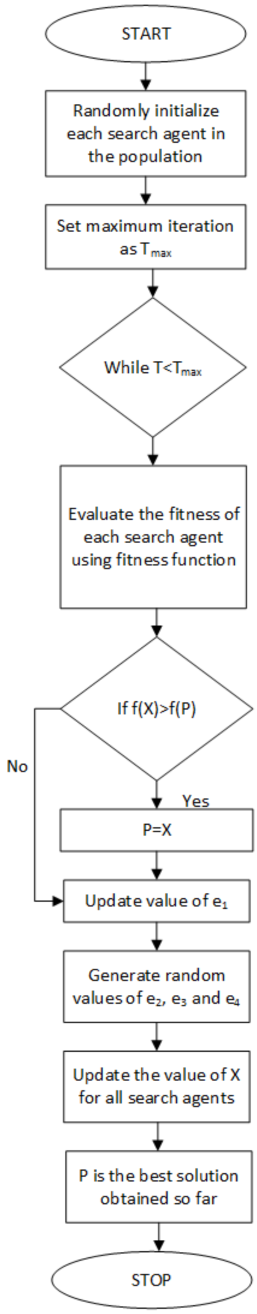


Figure 4.5: Flowchart of Sine Cosine Algorithm

4.5 Advantages of Sine Cosine Algorithm

- Sine Cosine Algorithm creates and improves upon a set of random solutions for a given problem, so it intrinsically benefits from the high exploration and local optima avoidance compared to individual based algorithms
- Different regions of the search space are explored by the algorithm when the sine and cosine functions return a value greater than 1 or less than 1
- Promising regions of the search space is exploited when sine and cosine return value between 1 and 1
- The SCA algorithm smoothly transits from exploration to exploitation using adaptive range in the sine and cosine functions
- The best approximation of the global optimum is stored in a variable as the destination point and never get lost during optimization
- Since the solutions always update their positions around the best solution obtained so far, there is a tendency of the algorithm to move towards the best regions of the search spaces during optimization
- Since the proposed algorithm considers optimization problem as black boxes, it is readily incorporable to problems in different fields subject to proper problem formulation

Chapter 5

Results and Simulations

To prove the effectiveness of the SCA, two test cases have been considered. The ELD problem has been solved for both the test systems and then their output results have been compared with the output results using other optimization techniques.

5.1 Test case: 1

13 generator units have been considered in test system 1, where the transmission losses have been considered. The total power demand is 2520 MW. In the test case 1, the results of the SCA. are compared with SDE [7] and ORCCRO [8] optimization techniques. The input data is taken from [9]. It can be seen from the graph and the table that the minimum cost is first reached by using the SCA. The rest of the optimization techniques take more time as compared to SCA. In table 4.2, the minimum fuel cost for 13 generator units is 24512.6085 $/hr. obtained by the proposed algorithm, is better than SDE [7], ORCCRO [8]. The convergence characteristics compares the SCA with SDE[7] and ORCCRO[8] shown in Figure 4.1.

The input data for 13 thermal units is given in the table below:

Table 5.1: Input data of 13 generators : Maximum power, Minimum power and coefficients of active power

Generator	Pmin (MW)	Pmax (MW)	a ($)	b ($/MW)	c ($/MW^2)	e ($)	f (MW^{-1})
1	0	680	0.00028	8.10	550	300	0.035
2	0	360	0.00056	8.10	309	200	0.042
3	0	360	0.00056	8.10	307	150	0.042
4	60	180	0.00324	7.74	240	150	0.063
5	60	180	0.00324	7.74	240	150	0.063
6	60	180	0.00324	7.74	240	150	0.063
7	60	180	0.00324	7.74	240	150	0.063
8	60	180	0.00324	7.74	240	150	0.063
9	60	180	0.00324	7.74	240	150	0.063
10	40	120	0.00284	8.60	126	100	0.084
11	40	120	0.00284	8.60	126	100	0.084
12	55	120	0.00284	8.60	126	100	0.084
13	55	120	0.00284	8.60	126	100	0.084

Based on the input data available, the SCA was applied to solve the ELD problem. The results are compared with SDE[7] and ORCCRO[8] in tabular form as well as graphically.

Table 5.2: Power generation comparison for 13 genetarors

Unit	**Output power generations (MW)**		
	SCA	**SDE[7]**	**ORCCRO[8]**
P_1	628.3179	628.32	628.32
P_2	299.1992	299.2	299.2
P_3	297.4468	299.2	299.2
P_4	159.7327	159.73	159.73
P_5	159.7327	159.73	159.73
P_6	159.7328	159.73	159.73
P_7	159.7331	159.73	159.73
P_8	159.7325	159.73	159.73
P_9	159.7328	159.73	159.73
P_{10}	77.3995	77.4	77.4
P_{11}	114.7993	113.12	112.14
P_{12}	92.3997	92.4	92.4
P_{13}	92.4	92.4	92.4
Fuel Cost ($/hr.)	**24512.6085**	**24514.88**	**24513.91**

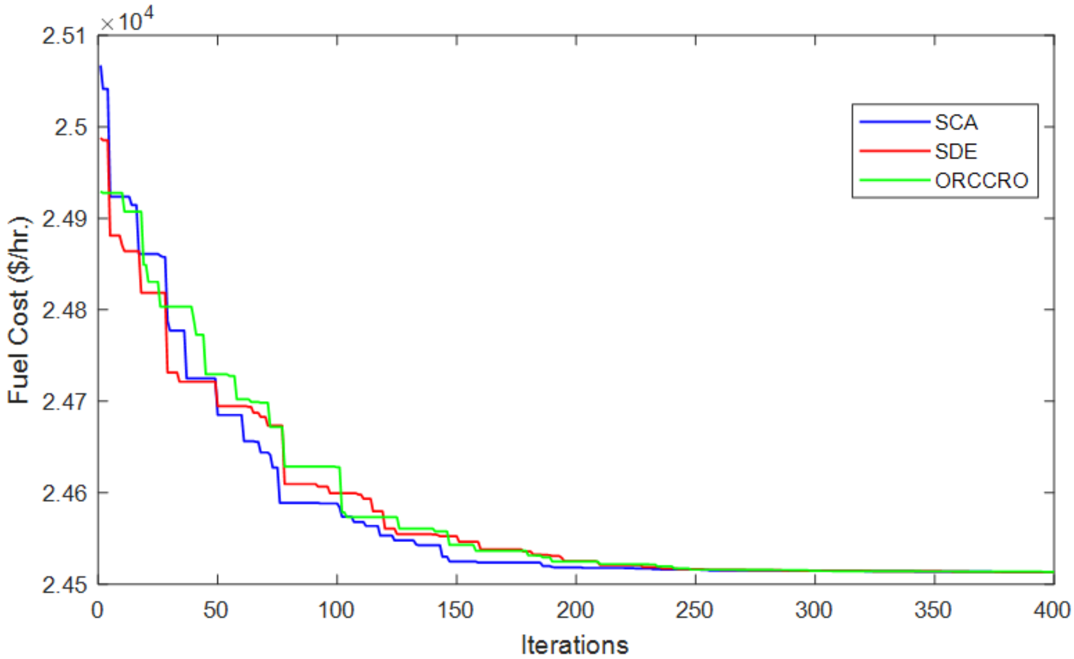


Figure 5.1: Comparision of SCA, SDE and ORCCRO

Table 5.3: Minimum maximum and average cost obtained by SCA and various optimization techniques for 13 generator units

Methods	Generation cost ($/hr.)			Time/iteration (s)	No. of hits to minimum solution
	Maximum	Minimum	Average		
SCA	24512.61	24512.61	24512.61	0.0361	50
ORCCRO[8]	24518.56	24513.91	24515.72	0.0533	27
SDE[7]	24519.74	24514.88	24516.23	NA*	21

*NA-Not Available

The fuel cost obtained using SCA is compared to other two optimization techniques, SDE[7] and ORCCRO[8]. It is clear from the graph that the best results are obtained using the SCA. The SCA gives the minimized fuel cost for operating the 13 generator units in the least computational time.

5.2 Test case: 2

In this system 38 units of generators are considered and transmission loss is neglected here. The total load demand is 6000 MW. The minimum fuel cost has been calculated using SCA. The input data is taken from [10]. The final results obtained by using SCA have been compared with the results obtained by BBO [11], DE/BBO [11], New PSO [11] and PSO TVAC [11]. It is clear from the tabular and the graphical data that the best result is obtained by using SCA and that too in minimum computational time. The best solutions obtained by various optimization techniques are presented in table 4.4. The convergence characteristics compares the SCA with BBO and NEW PSO shown in Figure 4.2.

The input data for 38 thermal units is given in the table below:

Table 5.4: Input data for 38 generators:Maximum power, Minimum power and coefficients of active power

Generator	**Pmin (MW)**	**Pmax (MW)**	**a($)**	**b($/MW)**	**c** ($/MW^2)
1	220	550	64782	796.9	0.3133
2	220	550	64782	796.9	0.3133
3	200	500	64670	795.5	0.3127
4	200	500	64670	795.5	0.3127
5	200	500	64670	795.5	0.3127
6	200	500	64670	795.5	0.3127
7	200	500	64670	795.5	0.3127
8	200	500	64670	795.5	0.3127
9	114	500	172832	915.7	0.7075
10	114	500	172832	915.7	0.7075
11	114	500	176003	884.2	0.7515
12	114	500	173028	884.2	0.7083
13	110	500	91340	1250.1	0.4211
14	90	365	63440	1298.6	0.5145
15	82	365	65468	1298.6	0.5691
16	120	325	72282	1290.8	0.5691
17	65	315	190928	238.1	2.5881
18	65	315	285372	1149.5	3.8734
19	65	315	271376	1269.1	3.6842
20	120	272	39197	696.1	0.4921
21	120	272	45576	660.2	0.5728
22	110	260	28770	803.2	0.3572
23	80	190	36902	818.2	0.9415
24	10	150	105510	33.5	52.123
25	60	125	22233	805.4	1.1421
26	55	110	30953	707.1	2.0275
27	35	75	17044	833.6	3.0744
28	20	70	81079	2188.7	16.765

Generator	**Pmin (MW)**	**Pmax (MW)**	**a($)**	**b($/MW)**	**c** ($/MW^2)
29	20	70	124767	1024.4	26.355
30	20	70	121915	837.1	30.575
31	20	70	120780	1305.2	25.098
32	20	60	104441	716.6	33.722
33	25	60	83224	1633.9	23.915
34	18	60	111281	969.6	32.562
35	8	60	64142	2625.8	18.362
36	25	60	103519	1633.9	23.915
37	20	38	13547	694.7	8.482
38	20	38	13518	655.9	9.693

Based on the input data available, the SCA was applied to solve the ELD problem. The results are compared with BBO[11], DE/BBO[11], NEW PSO[11] and PSO TVAC[11] in tabular form as well as graphically.

Table 5.5: Power generation comparison for 38 generators

Unit	Power generated (MW)				
	SCA	BBO[11]	DE/BBO[11]	NEW PSO [11]	PSO TVAC [11]
P_1	408.1903	422.2305	426.6060	550.0000	443.6590
P_2	432.9113	422.1179	426.6060	512.2630	342.9560
P_3	430.3353	435.7794	429.6631	485.7330	433.1170
P_4	432.8785	445.4819	429.6631	391.0830	500.0000
P_5	433.0516	428.4757	429.6631	443.8460	410.5390
P_6	425.5081	428.6492	429.6631	358.398	492.8640
P_7	434.6013	428.1192	429.6631	415.729	409.483
P_8	428.3625	429.9006	429.6631	320.8160	446.0790
P_9	115.6028	115.9049	114.0000	115.3470	119.5660
P_{10}	114.0958	114.1153	114.0000	204.4220	137.2740

Unit	SCA	BBO[11]	DE/BBO[11]	NEW PSO[11]	PSO TVAC
P_{11}	115.6772	115.4186	119.7680	114.000	138.933
P_{12}	132.0374	127.5114	127.0728	249.197	155.401
P_{13}	110.0000	110.0009	110.0000	118.886	121.719
P_{14}	90.0000	90.0217	90.0000	102.802	90.924
P_{15}	82.0000	82.0000	82.0000	89.0390	97.941
P_{16}	120.0000	120.0384	120.0000	120.000	128.106
P_{17}	160.7668	160.3038	159.5980	156.562	189.108
P_{18}	65.0000	65.0001	65.0000	84.265	65.0000
P_{19}	65.0000	65.0001	65.0000	65.041	65.0000
P_{20}	271.2393	271.9995	272.0000	151.104	267.422
P_{21}	271.7550	271.8726	272.0000	226.344	221.383
P_{22}	259.8894	259.7320	260.0000	209.298	130.804
P_{23}	130.9003	125.9930	130.6486	85.719	124.269
P_{24}	10.4982	10.4143	10.0000	10.000	11.535
P_{25}	118.1671	109.4177	113.3050	60.000	77.103
P_{26}	87.4068	89.3772	88.0669	90.489	55.018
P_{27}	36.4419	36.4110	37.5051	39.670	75.000
P_{28}	20.0000	20.0098	20.0000	20.000	21.628
P_{29}	20.0000	20.0089	20.0000	20.995	29.829
P_{30}	20.0000	20.0000	20.0000	22.810	20.326
P_{31}	20.0000	20.0000	20.0000	20.000	20.000
P_{32}	20.0000	20.0033	20.0000	20.416	21.840
P_{33}	25.0000	25.0066	25.0000	25.000	25.620
P_{34}	18.0000	18.0222	18.0000	21.319	24.261
P_{35}	8.0000	8.0000	8.0000	9.1220	9.6670
P_{36}	25.0000	25.0060	25.0000	25.184	25.000
P_{37}	20.2437	22.0005	21.7820	20.000	31.642
P_{38}	21.4383	20.6076	21.0621	25.104	29.935
Fuel Cost $/hr	**9412311.45**	**9417633.63**	**9417235.78**	**9516448.31**	**9500448.30**

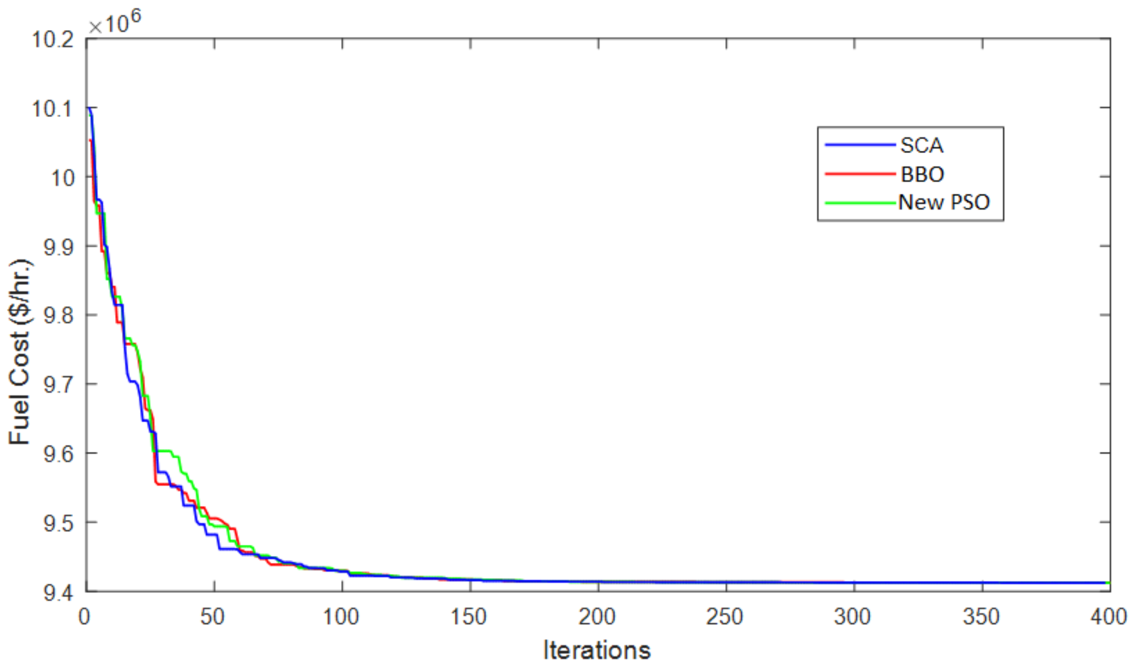


Figure 5.2: Comparision of SCA, BBO and New PSO

Table 5.6: Minimum maximum and average fuel cost for SCA and various optimization techniques for 38 generator units (50 trials)

Methods	**Generation cost ($/hr.)**			**Time/iteration (S)**	**No. of hits to minimum solution**
	Maximum	Minimum	Average		
SCA	9412311.45	9412311.45	9412311.45	0.1149	50
BBO[11]	9417658.75	9417633.63	9417638.15	24.42	41
DE/BBO [11]	9417250.83	9417235.78	9417237.29	35.50	45

It is evident from the results that the minimum fuel cost is obtained using the SCA. The fuel cost obtained using SCA is compared to the cost obtained using various other optimization techniques and the results prove the effectiveness of SCA.

5.3 Test case: 3

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 system runs for 400 iterations. 50 search agents are used in this case. Only valve-point loading effect is considered as a constraint for this test case.The comparison of the optimum fuel cost obtained using various optimization techniques is given in Table 5.8. Table 5.9 illustrates the minimum, maximum and the average fuel cost of various optimization techniques after 50 trials. The convergence characteristics compares the SCA with GAAPI [8] and SDE [7] shown in Figure 5.3. Looking at the tabular data and the graphical data, it is clear that the minimum fuel cost is obtained by using the SCA is better with other techniques like GAAPI [8], DE/BBO[11], SDE [7] and BBO[11].

Table 5.7: Input data for 40 generator system

Generator	**Pmin (MW)**	**Pmax (MW)**	**a ($)**	**b ($/MW)**	**c ($/MW^2)**	**e ($)**	**f (MW^{-1})**
1	36	114	0.0069	6.73	94.705	100	0.084
2	36	114	0.0069	6.73	94.705	100	0.084
3	60	120	0.02028	7.07	309.54	100	0.084
4	80	190	0.00942	8.18	369.03	150	0.063
5	47	97	0.0114	5.35	148.89	120	0.077
6	68	140	0.01142	8.05	222.33	100	0.084
7	110	300	0.00357	8.03	287.71	200	0.042
8	135	300	0.00492	6.99	391.98	200	0.042
9	135	300	0.00573	6.6	455.76	200	0.042
10	130	300	0.00605	12.9	722.82	200	0.042
11	94	375	0.00515	12.9	635.2	200	0.042
12	94	375	0.00569	12.8	654.69	200	0.042
13	125	500	0.00421	12.5	913.4	300	0.035
14	125	500	0.00752	8.84	1760.4	300	0.035
15	125	500	0.00708	9.15	1728.3	300	0.035
16	125	500	0.00708	9.15	1728.3	300	0.035
17	220	500	0.00313	7.97	647.85	300	0.035
18	220	500	0.00313	7.95	649.69	300	0.035
19	242	550	0.00313	7.97	647.83	300	0.035
20	242	550	0.00313	7.97	647.81	300	0.035
21	254	550	0.00298	6.63	785.96	300	0.035
22	254	550	0.00298	6.63	785.96	300	0.035
23	254	550	0.00284	6.66	794.53	300	0.035
24	254	550	0.00284	6.66	794.53	300	0.035
25	254	550	0.00277	7.1	801.32	300	0.035
26	254	550	0.00277	7.1	801.32	300	0.035
27	10	150	0.52124	3.33	1055.1	120	0.077
28	10	150	0.52124	3.33	1055.1	120	0.077
29	10	150	0.52124	3.33	1055.1	120	0.077
30	47	97	0.0114	5.35	148.89	120	0.077
31	60	190	0.0016	6.43	222.92	150	0.063
32	60	190	0.0016	6.43	222.92	150	0.063
33	60	190	0.0016	6.43	222.92	150	0.063
34	90	200	0.0001	8.95	107.87	200	0.042
35	90	200	0.0001	8.62	116.58	200	0.042
36	90	200	0.0001	8.62	116.58	200	0.042
37	25	110	0.0161	5.88	307.45	80	0.098
38	25	110	0.0161	5.88	307.45	80	0.098
39	25	110	0.0161	5.88	307.45	80	0.098
40	242	550	0.00313	7.97	647.83	300	0.035

Table 5.8: Optimum power output and fuel cost for SCA and other techniques comparison for 40 unit test system

Unit	Power Output (MW)				
	SCA	**GAAPI[8]**	**DE/BBO[11]**	**SDE[7]**	**BBO[11]**
P_1	113.8585	114	111.04	110.06	112.54
P_2	114	114	113.71	112.41	113.22
P_3	119.3004	120	118.64	120	119.51
P_4	183.3369	190	189.49	188.72	188.37
P_5	91.7652	97	86.32	85.91	90.41
P_6	139.9816	140	139.88	140	139.05
P_7	299.5148	300	299.86	250.19	294.97
P_8	299.1356	300	285.42	290.68	299.18
P_9	297.6808	300	296.29	300	296.46
P_{10}	279.1599	205.25	285.07	282.01	279.89
P_{11}	171.4666	226.3	164.69	180.82	160.15
P_{12}	94.4916	204.72	94	168.74	96.74
P_{13}	485.0345	346.48	486.3	469.96	484.04
P_{14}	482.8777	434.32	480.7	484.17	483.32
P_{15}	484.0869	431.34	480.66	487.73	483.77
P_{16}	484.9795	440.22	485.05	482.3	483.3
P_{17}	489.6806	500	487.94	499.64	490.83
P_{18}	488.7718	500	491.09	411.32	492.19
P_{19}	515.9524	550	511.79	510.47	511.28
P_{20}	511.6585	550	544.89	542.04	521.55
P_{21}	532.3453	550	528.92	544.81	526.42
P_{22}	549.9726	550	540.58	550	538.3
P_{23}	523.9532	550	524.98	550	534.74
P_{24}	527.3965	550	524.12	528.16	521.2
P_{25}	523.3733	550	534.49	524.16	526.14
P_{26}	527.6279	550	529.15	539.1	544.43
P_{27}	10.0009	11.44	10.51	10	11.51
P_{28}	11.119	11.56	10	10.37	10.21
P_{29}	10.1184	11.42	10	10	10.71
P_{30}	86.983	97	90.06	96.1	88.28
P_{31}	189.9885	190	189.82	185.33	189.84
P_{32}	189.915	190	187.69	189.54	189.94
P_{33}	189.9535	190	189.97	189.96	189.13
P_{34}	199.911	200	199.83	199.9	198.07
P_{35}	197.9306	200	199.93	196.25	199.92
P_{36}	165.3294	200	163.03	185.85	194.35
P_{37}	109.4111	110	109.85	109.72	109.43
P_{38}	109.9582	110	109.26	110	109.56
P_{39}	109.9271	110	109.6	95.71	109.62
P_{40}	547.6016	550	543.23	532.47	527.82
Fuel Cost ($/hr.)	136653.0219	139864.96	136950.77	138157.46	137026.82
Power Generation (MW)	11459.5499	11545.06	11457.83	11474.43	11470
Transmission Loss (MW)	959.55	1045.06	957.83	974.43	970.37

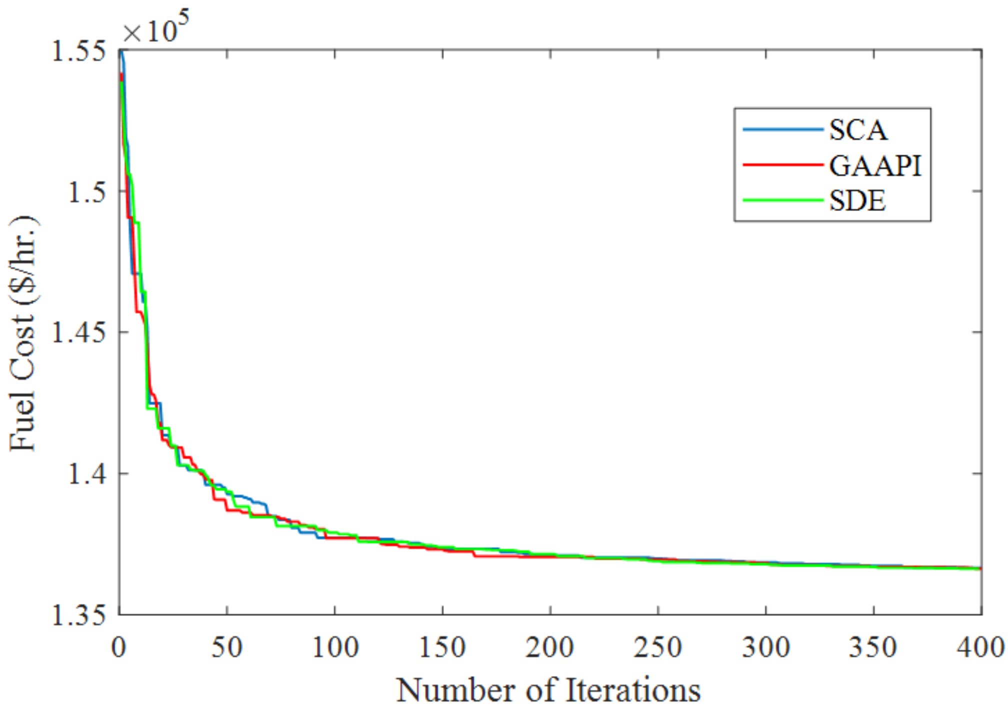


Figure 5.3: Comparision of SCA, GAAPI and SDE

Table 5.9: Minimum, maximum and average fuel cost obtained by SCA and various optimization techniques for 40 generator units (50 trials)

Methods	**Generation cost ($/hr.)**			**Time/iteration (S)**	**No. of hits to minimum solution**
	Maximum	**Minimum**	**Average**		
SCA	136653.1	136653.02	136653.02	0.0199	48
BBO[11]	137587.82	137026.82	137116.58	0.4000	41
DE/BBO[11]	137150.77	136950.77	136966.77	0.3200	45
ORCCRO[8]	136855.19	136845.35	136848.16	0.1400	43

It is evident from the results that the minimum fuel cost is obtained using the SCA. The fuel cost obtained using SCA is compared to the cost obtained using various other optimization techniques and the results prove the effectiveness of SCA.

5.4 Test case: 4

To investigate the efficiency of SCA in a large power system, experiments are conducted on the Korean power system. This test system is fossil fuel based power system, comprising of forty thermal generating units, fifty-one gas units, twenty nuclear unit and twenty-nine oil units. Out of 140-units, 6 thermal units, four gas units and two oil units have non-convex fuel cost function addressing valve loading effects. The total load demand is 49342 MW. The large and complicated test system of 140 generating units have been considered here with valve point loading effects, ramp rate limits and prohibited operating zones. The input data is taken from [17]. The system is made to run for 1000 iterations. 50 search agents are used in this case. Since the cost function of each generating unit is considered as the second-order polynomial, the global optimum solution can be obtained using the mathematical programming techniques. Table 5.11 shows the power generation of each of the 140 generators using the SSA. Table 5.12 compares the minimum, maximum and the average fuel cost obtained using various optimization techniques after 50 trials. The results in Table 5.12 prove that the minimum fuel cost is obtained using SSA is much better than other algorithms. Figure 5.4 shows the convergence characteristic of the SCA.

Table 5.10: Input Data for 140 generator units

Unit	a_i($)	b_i($/MW)	c_i($/MW^2)	P_i^{min}(MW)	P_i^{max}(MW)	UR_i(MW/hr.)	DR_i(MW/hr.)	P_io(MW)
Coal#01	122.0645	61.242	0.03288	71	119	30	120	98.4
Coal#02	1315.118	41.095	0.00828	120	189	30	120	134
Coal#03	874.288	46.31	0.00384	125	90	60	60	141.5
Coal#04	874.288	46.31	0.00384	125	90	60	60	183.3
Coal#05	1976.469	54.242	0.04246	90	190	150	150	125
Coal#06	1338.087	61.215	0.01499	90	190	150	150	91.3
Coal#07	1818.299	11.791	0.00703	280	490	180	300	401.1
Coal#08	1133.978	15.055	0.003079	280	490	180	300	329.5
Coal#09	1320.636	13.226	0.00506	260	496	300	510	386.1
Coal#10	1320.636	13.226	0.00506	260	496	300	510	386.1
Coal#11	1320.636	13.226	0.00506	260	496	300	510	412.2
Coal#12	1106.539	14.498	0.00355	260	496	300	510	370.1
Coal#13	1176.504	14.651	0.0039	260	506	600	600	301.8
Coal#14	1176.504	14.651	0.0039	26	509	600	600	368
Coal#15	1176.504	14.651	0.0039	260	506	600	600	301.9
Coal#16	1176.504	14.651	0.0039	260	506	600	600	476.4
Coal#17	1017.406	15.669	0.00239	260	506	600	600	283.1
Coal#18	1017.406	15.669	0.00239	260	506	600	600	414.1
Coal#19	1229.131	14.656	0.00368	260	505	600	600	328
Coal#20	1229.131	14.656	0.00368	260	505	600	600	389.4
Coal#21	1229.131	14.656	0.00368	260	505	600	600	354.7
Coal#22	1229.131	14.656	0.00368	260	505	600	600	262
Coal#23	1267.894	14.378	0.004	260	505	600	600	461.5
Coal#24	1229.131	14.656	0.00368	260	505	600	600	371.6
Coal#25	975.926	16.261	0.001619	280	537	300	300	462.6
Coal#26	1532.093	13.362	0.005093	280	537	300	300	379.2
Coal#27	641.989	17.203	0.00099	290	549	360	360	530.8
Coal#28	641.989	17.203	0.00099	290	549	360	360	391.9
Coal#29	911.533	15.274	0.00247	260	501	180	180	480.1
Coal#30	910.533	15.212	0.00254	260	501	180	180	319
Coal#31	1074.81	15.033	0.003542	260	506	600	600	329.5
Coal#32	1074.81	15.033	0.003542	260	506	600	600	333.8
Coal#33	1074.81	15.033	0.003542	260	506	600	600	390
Coal#34	1074.81	15.033	0.003542	260	506	600	600	432
Coal#35	1278.46	13.992	0.00313	260	500	660	660	402
Coal#36	861.742	15.679	0.00132	260	500	900	900	428
Coal#37	408.834	16.542	0.00295	120	241	180	180	178.4
Coal#38	408.834	16.542	0.00295	120	241	180	180	194.1
Coal#39	1288.815	16.518	0.00099	423	774	600	600	474
Coal#40	1436.251	15.815	0.001581	423	769	600	600	609.8
LNG#1	669.988	75.464	0.9023	3	19	210	210	17.8
LNG#2	134.544	129.544	0.1102	3	28	366	366	6.9

Unit	a_i(\$)	b_i(\$/MW)	c_i(\$/MW^2)	P_i^{min}(MW)	P_i^{max}(MW)	UR_i(MW/hr.)	DR_i(MW/hr.)	P_io(MW)
LNG_CC#01	3427.912	56.613	0.0244	160	250	702	702	224.3
LNG_CC#02	3751.772	54.451	0.0244	160	250	702	702	210
LNG_CC#03	3918.78	54.736	0.0244	160	250	702	702	212
LNG_CC#04	3379.58	58.034	0.01651	160	250	702	702	220
LNG_CC#05	3345.296	55.981	0.02658	160	250	702	702	220
LNG_CC#06	3138.754	61.52	0.00754	160	250	702	702	232.9
LNG_CC#07	3453.05	58.635	0.01643	160	250	702	702	168
LNG_CC#08	5119.3	44.647	0.04593	160	250	702	702	208.4
LNG_CC#09	1898.415	71.584	0.000044	165	504	1350	1350	443.9
LNG_CC#10	1898.415	71.584	0.00004	165	504	1350	1350	426
LNG_CC#11	1898.415	71.584	0.00004	165	504	1350	1350	434.1
LNG_CC#12	1898.415	71.584	0.00004	165	504	1350	1350	402.5
LNG_CC#13	2473.39	85.12	0.002528	180	471	1350	1350	357.4
LNG_CC#14	2781.705	87.682	0.000131	180	561	720	720	423
LNG_CC#15	5515.508	69.532	0.01037	103	341	720	720	220
LNG_CC#16	3478.3	78.339	0.00762	198	617	2700	2700	369.4
LNG_CC#17	6240.909	58.172	0.01246	100	312	1500	1500	273.5
LNG_CC#18	9960.11	46.636	0.03944	153	471	1656	1656	336
LNG_CC#19	3671.997	76.947	0.007278	163	500	2160	2610	432
LNG_CC#20	1837.383	80.761	0.000044	95	302	900	900	220
LNG_CC#21	3108.395	70.136	0.000044	160	511	1200	1200	410.6
LNG_CC#22	3108.395	70.136	0.000044	160	511	1200	1200	422.7
LNG_CC#23	7095.484	49.84	0.01882	196	490	1014	1014	351
LNG_CC#24	3392.732	65.404	0.010852	196	490	1014	1014	296
LNG_CC#25	7095.484	49.84	0.018827	196	490	1014	1014	411.1
LNG_CC#26	7095.484	49.84	0.018827	196	490	1014	1014	263.2
LNG_CC#27	4288.32	66.465	0.03456	130	432	1350	1350	370.3
LNG_CC#28	13813.001	22.941	0.08154	130	432	1350	1350	418.7
LNG_CC#29	4435.493	64.314	0.02353	137	455	1350	1350	409.6
LNG_CC#30	9750.75	45.017	0.03547	137	455	1350	1350	412
LNG_CC#31	1042.366	70.644	0.000915	195	541	780	780	423.2
LNG_CC#32	1159.895	70.959	0.000044	175	536	1650	1650	428
LNG_CC#33	1159.895	70.959	0.000044	175	540	1650	1650	436
LNG_CC#34	1303.99	70.302	0.001307	175	538	1650	1650	428
LNG_CC#35	1156.193	70.662	0.000392	175	540	1650	1650	425
LNG_CC#36	2118.968	71.101	0.000087	330	574	1620	1620	497.2
LNG_CC#37	779.519	37.854	0.000521	160	531	1482	1482	510
LNG_CC#38	829.888	37.768	0.000498	160	531	1482	1482	470
LNG_CC#39	2333.69	67.983	0.001046	200	542	1688	1688	464.1
LNG_CC#40	2028.954	77.838	0.13205	56	132	120	120	118.1
LNG_CC#41	4412.017	63.671	0.09696	115	245	180	180	141.3
LNG_CC#42	2982.219	79.458	0.05486	115	245	120	180	132
LNG_CC#43	2982.219	79.458	0.05486	115	245	120	180	135
LNG_CC#44	3174.939	93.966	0.01438	207	307	120	180	252
LNG_CC#45	3218.359	94.723	0.01316	207	307	120	180	221

Unit	a_i(\$)	b_i(\$/MW)	c_i(\$/MW^2)	P_i^{min}(MW)	P_i^{max}(MW)	UR_i(MW/hr.)	DR_i(MW/hr.)	P_io(MW)
LNG_CC#46	3723.822	66.919	0.016033	175	345	318	318	245.9
LNG_CC#47	3551.405	68.185	0.01365	175	345	318	318	247.9
LNG_CC#48	4322.615	60.821	0.02814	175	345	318	318	183.6
LNG_CC#49	3493.739	68.551	0.01347	175	345	318	318	288
Nuclear#01	226.799	2.842	0.000064	360	580	18	18	55704
Nuclear#02	382.932	2.946	0.0000252	415	645	18	18	529.5
Nuclear#03	156.987	3.096	0.000022	795	984	36	36	800.8
Nuclear#04	154.484	3.04	0.000022	795	978	36	36	801.5
Nuclear#05	332.834	1.709	0.0000203	578	682	138	204	582.7
Nuclear#06	326.599	1.668	0.000198	615	720	144	216	680.7
Nuclear#07	345.306	1.789	0.000215	612	718	144	216	670.7
Nuclear#08	350.372	1.815	0.000218	612	720	144	216	651.7
Nuclear#09	370.377	2.726	0.000193	758	964	48	48	921
Nuclear#10	367.067	2.732	0.000197	755	958	48	48	916.8
Nuclear#11	124.875	2.651	0.000324	750	1007	36	54	911.9
Nuclear#12	130.785	2.798	0.000344	750	1006	36	54	898
Nuclear#13	878.746	1.595	0.00069	713	1013	30	30	905
Nuclear#14	827.959	1.0503	0.00065	718	1020	30	30	846.5
Nuclear#15	432.007	2.425	0.000233	791	954	30	30	850.9
Nuclear#16	445.606	2.499	0.000239	786	952	30	30	843.7
Nuclear#17	467.223	2.674	0.000261	795	1006	36	36	841.4
Nuclear#18	475.94	2.692	0.000259	795	1013	36	36	835.7
Nuclear#19	899.367	1.633	0.000707	795	1021	36	36	828.8
Nuclear#20	1000.367	10816	0.000786	795	1015	36	36	846
Oil#01	1296.132	89.83	0.014355	94	203	120	120	179
Oil#02	1296.132	89.83	0.014355	94	203	120	120	120.8
Oil#03	1296.132	89.83	0.014355	94	203	120	120	121
Oil#04	4965.124	64.125	0.0302	244	379	480	480	317.4
Oil#05	4965.124	64.125	0.0302	244	379	480	480	318.4
Oil#06	4965.124	64.125	0.0302	244	379	480	480	335.8
Oil#07	2243.185	76.129	0.024	95	190	240	240	151
Oil#08	2290.381	81.805	0.00158	95	189	240	240	129.5
Oil#09	1681.533	81.14	0.022095	116	194	120	120	130
Oil#10	6743.302	46.665	0.0768	175	321	180	180	218.9
Oil#11	394.398	78.412	0.9534	2	19	90	90	5.4
Oil#12	1243.165	112.088	0.000044	4	59	90	90	45
Oil#13	1454.74	90.871	0.072468	15	83	300	300	20
Oil#14	1011.051	97.116	0.000448	9	53	162	162	16.3
Oil#15	909.269	83.244	0.599112	12	37	114	114	20
Oil#16	689.378	95.665	0.2447	10	34	120	120	22.1
Oil#17	1443.792	91.202	0.000042	112	373	1080	1080	125
Oil#18	535.553	104.501	0.0851	4	20	60	60	10
Oil#19	617.734	83.015	0.524718	5	38	66	66	13
Oil#20	90.966	127.795	0.1765	5	19	12	6	7.5

Unit	$\mathbf{a}_i$**(\$)**	$\mathbf{b}_i$**(\$/MW)**	$\mathbf{c}_i$**(\$/MW^2)**	$\mathbf{P}_i^{min}$**(MW)**	$\mathbf{P}_i^{max}$**(MW)**	$\mathbf{UR}_i$**(MW/hr.)**	$\mathbf{DR}_i$**(MW/hr.)**	$\mathbf{P}_i o$**(MW)**
Oil#21	974.447	77.929	0.06341	50	98	300	300	53.2
Oil#22	263.81	92.779	2.7404	5	10	6	6	6.4
Oil#23	1335.594	80.95	0.112438	42	74	60	60	69.1
Oil#24	1033.871	89.073	0.041529	42	74	60	60	49.9
Oil#25	1391.325	161.288	0.000911	41	105	528	528	91
Oil#26	4477.11	161.829	0.005245	17	51	300	300	41
Oil#27	57.794	84.972	0.23478	7	19	18	30	13.7
Oil#28	57.794	84.972	0.23478	7	19	18	30	7.4
Oil#29	1258.437	16.087	1.111878	26	40	72	120	28.6

Table 5.11: Power generation for 140 generator units

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}	880.9
P_2	163.9999	P_{37}	240.9999	$_{72}$	388.4824	P_{107}	873.6998
P_3	189.9518	P_{38}	240.9424	P_{73}	230.9036	P_{108}	877.4
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	P_{44}	249.8248	P_{79}	530.9998	P_{114}	94.32693
P_{10}	496	P_{45}	247.436	P_{80}	530.9998	P_{115}	244.0719
P_{11}	495.9984	P_{46}	249.2271	P_{81}	542	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	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}	9.657
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}	199.552	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	P_{60}	299.2522	P_{95}	837.4999	P_{130}	5.021
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}	505.991	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	P_{70}	338.9781	P_{105}	876.4997	P_{140}	31.3066
Total fuel cost = 1658384.8872 $/hr.							

Table 5.12: Comparison of outputs of SCA with other optimization techniques

Methods	**Generation cost (\$/hr.)**			**Time/iteration (s)**	**No. of hits to minimum solution**
	Maximum	Minimum	Average		
SCA	**1658386.57**	**1658384.88**	**1658384.25**	**0.7854**	**45**
BBO[11]	1669536.35	1665478.25	1667548.32	0.9245	NA
DE/BBO[11]	1662349.58	1660215.65	1661257.35	0.9833	NA
ORCCRO[8]	1659823.97	1659654.83	1659725.96	1.1257	42

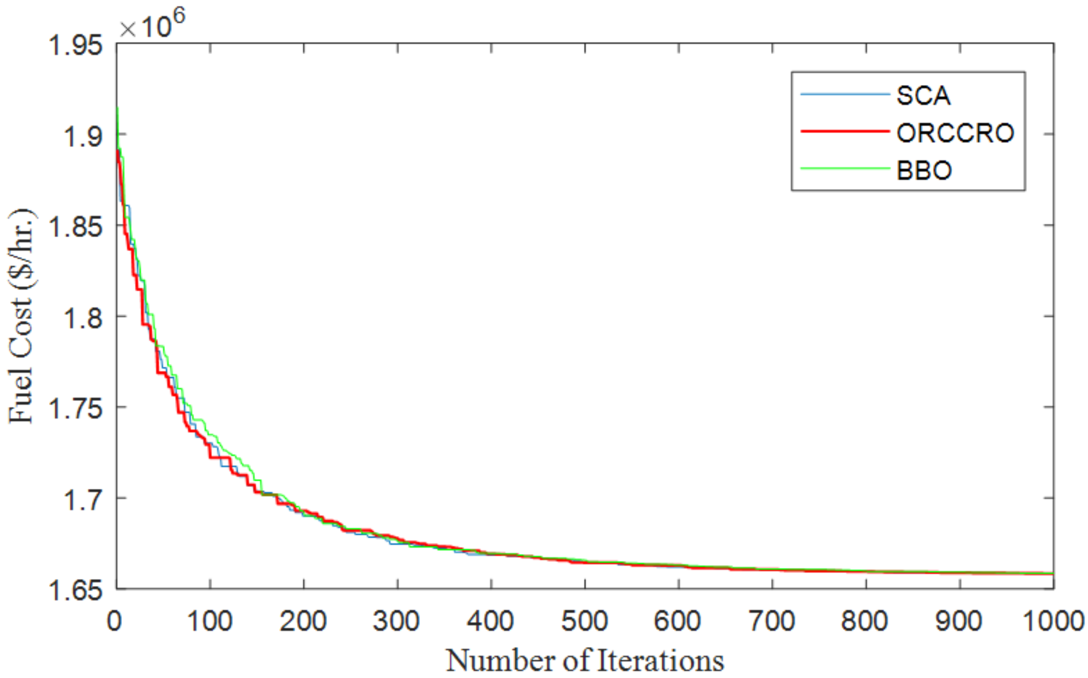


Figure 5.4: Comparison of SCA, ORCCRO and BBO

Tuning of parameters for the SCA

To obtain the optimized solution with 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 for all possible combinations. For single value of e_1 different combinations of e_2 and e_3 have been tried to obtain the minimum fuel cost. A brief summarized result for the 140 generator system is shown in Table 5.13.

Table 5.13: Effect of various parameters on the performance of SCA

e_1	e_2	e_3	e_4	**Fuel Cost ($/hr.)**
0.16	0.41	0.14	0.5	1658479.188
0.68	0.65	0.15	0.5	1658455.649
0.47	0.87	0.62	0.5	1658438.325
0.57	0.54	0.25	0.5	1658420.945
0.55	0.65	0.34	0.5	1658397.325
0.55	**0.15**	**0.72**	**0.5**	**1658384.887**
0.42	0.26	0.95	0.5	1658399.548
0.94	0.32	0.84	0.5	1658456.323
0.21	0.41	0.25	0.5	1658472.259
0.78	0.52	0.41	0.5	1658501.365

Also, using large number of search agents or using too less search agents for screening the search space does not give the optimized solution. So a specific number of search agents will only help to obtain the optimized solution. For each number of search agent trials have been run. Out of these trials, 50 number of search agents achieves the optimized fuel cost. For other number of search agents, no significant improvement in the fuel cost is observed. Moreover, beyond 50 number of search agents, the simulation time also increases. The best output obtained by SCA for each number of search agent in the 140 generator system is presented in Table 5.14.

Table 5.14: Effect of number of search agents on the 140 generator system

Number of Search Agents	**No. of hits to best solution**	**Simulation time (s)**	**Max. cost ($/hr.)**	**Min. cost ($/hr.)**	**Average cost ($/hr.)**
20	32	48.25	1658406.547	1658399.254	1658401.879
50	**45**	**50.47**	**1658386.57**	**1658384.88**	**1658384.25**
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

Comparative study

Quality of Solution: Tables 5.3, 5.6, 5.9 and 5.12 that the fuel cost obtained by the SCA is the least as compared to other optimization techniques. The cost obtained by SCA is better than the cost obtained by many previously developed algorithms. Like for example, in test case 1, the minimum fuel cost using the SCA is 24512.6085. which is less as compared to the minimum cot obtained by using SDE and ORC-CRO. The comparison has been made by neglecting the transmission losses as well as by taking the transmission losses into account. Thus, it is clear that the quality of the solution is the best when SCA is applied.

Robustness: The robustness of any optimization algorithm cannot be judged by only running the algorithm for a single time. Number of trials should be conducted in order to prove the robustness of any optimisation technique. It is evident form tables 5.3 and 5.6 that SCA achieves the global optimal solution for all the 50 trials for various test cases and from tables 5.9 and 5.12 it can be said that SCA gives the minimum fuel cost for the maximum number of trials as compared to other optimization techniques. This proves that the efficiency of the SCA is very high and so the performance of SCA is superior as compared to other optimization techniques. This proves the robustness of the algorithm.

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 5.3, 5.6, 5.9 and 5.12 that the computational time taken for one single iteration is the least for the SCA as compared t other previously developed optimization techniques. Thus, the SCA gives the global optimal results in the least computational time.

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

In this project, a new algorithm named Sine Cosine Algorithm has been proposed to solve ELD problem. To prove the efficiency of the SCA, four test cases have been taken in which the net fuel cost obtained by SCA is compared with other optimization techniques in a tabular form as well as graphically. The results prove that SCA is robust, feasible, and more effective as compared to other algorithms in terms of efficiency and computational time. The numerical results also prove that the SCA prevents premature convergence and has a stable convergence characteristic. Hence, by using the exploration and exploitation ability of SCA, the problem of ELD has successfully been solved.

6.2 Future Scope

The SCA has been implemented to solve the ELD problem for various number of generators in different test systems. This algorithm can be used to solve various problems in the electrical domain as well as other problems that require optimization. This algorithm can also be used to solve the unit commitment problem which is similar to the ELD problem. The results that are obtained by the SCA can again be compared with other optimization techniques.

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