Solution of Non-Convex Economic Load Dispatch Problem for Small Scale Power

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***Abstract*— Sine Cosine Algorithm (SCA) is a novel population based optimization algorithm used for solving constrained optimization problems and based on the concept of a mathematical model of sine and cosine functions. This paper presents the application of SCA algorithm for the solution of non-convex and dynamic economic load dispatch problem of electric power system. The performance of SCA algorithm is tested for economic load dispatch problem of Three IEEE benchmarks of small scale power systems and the results are verified by a comparative study with Lambda Iteration Method, Particle Swarm Optimization (PSO) algorithm, Genetic algorithm(GA), Artificial Bee Colony(ABC). Comparative results show that the performance Sine Cosine Optimizer Algorithm is better than Particle Swarm Optimization (PSO) algorithm, Genetic algorithm (GA), Artificial Bee Colony (ABC) search algorithms.**

Keywords— Economic Load Dispatch Problem (ELDP), Sine Cosine Optimizer (SCA)

I. INTRODUCTION

Electrical power utilities are needed to guarantee that electrical power necessity from the consumer end is fulfilled in accordance with the reliable power quality and minimum cost. Due to increasing technological research, industrial development and population, the power demand increases. With increasing electrical power demand worldwide, the non-renewable energy sources are reducing day after day. In the recent power system networks, there are various generating resources like thermal, hydro, nuclear etc. Also, the load demand varies during a day and attains different peak values. Thus, it is required to decide which generating unit to turn on and at what time it is needed in the power system network and also the sequence in which the units must be shut down keeping in mind the cost effectiveness of turning on and shutting down of respective units. The entire process of computing and making these decisions is known as unit commitment (UC). The unit which is decided or scheduled to be connected to the power system network, as and when required, is known to be committed unit. Unit commitment in power systems refers to the problem of determining the on/off states of generating units that minimize the operating cost for a given time horizon. Electrical power plays a pivotal role in the modern world to satisfy various needs. It is therefore very important that the electrical power generated is transmitted and distributed efficiently in order to satisfy the power requirement. Electrical power is generated in several ways. The most significant crisis in the planning and operation of electric power generation system is the effective scheduling of all generators in a system to meet the required demand. The Economic Load Dispatch (ELD) problem is the most important optimization problem in scheduling the generation among thermal generating units in power system.

Economic dispatch in electric power system refers to the short-term discernment of the optimal generation output of various electric utilities, to meet the system load demand, at the minimum possible cost, subject to various system and operating constraints viz. operational and transmission constraints. The Economic Load Dispatch Problem (ELDP) means that the electric utilities (i.e. generator's) real and reactive power are allowed to vary within certain limits so as to meet a particular load demand within lowest fuel cost. The ultimate aim of the ELD problem is to minimize the operation cost of the power generation system, while supplying the required power demanded. In addition to this, the various operational constraints of the system should also be satisfied. The problem of ELD is usually multimodal, discontinuous and highly nonlinear. Although the cost curve of thermal generating units are generally modelled as a smooth curve, the input-output characteristics are nonlinear by nature because of valve-point loading effects, Prohibited Operating Zones (POZ), ramp rate limits etc.

In recent years, various evolutionary, heuristic and meta-heuristics optimization algorithms have been developed simulating natural phenomena such as: Genetic Algorithm(GA) [1], Ant Colony Optimization (ACO) [2], Particle Swarm Optimization[3], Simulating Annealing(SA)[4], Gravitational Local Search (GLSA) [5], Big-Bang Big-Crunch (BBBC) [6], Gravitational Search Algorithm (GSA) [7], Curved Space Optimization (CSO) [8], Charged System Search (CSS) [9], Central Force

Optimization (CFO) [10], Artificial Chemical Reaction Optimization Algorithm (ACROA) [11], Black Hole (BH) [12] algorithm, Ray Optimization algorithm(ROA) [13], Small-World Optimization Algorithm (SWOA) [14], Galaxy-based Search Algorithm (GbSA) [15], Shuffled Frog Leaping Algorithm(SFLA)[16], Snake Algorithm[17], Biogeography Based Optimization[18], Marriage in Honey Bees Optimization Algorithm (MBO) [19] ,Artificial Fish-Swarm Algorithm (AFSA) [20] , Termite Algorithm (TA)[21] , Wasp Swarm Algorithm(WSA) [22] , Monkey Search Algorithm(MSA) [23] , Bee Collecting Pollen Algorithm (BCPA) [24] , Cuckoo Search Algorithm (CSA) [25], Dolphin Partner Optimization (DPO)[26] , Firefly Algorithm[27], Krill Herd (KH) algorithm [28] , Fruit fly Optimization Algorithm (FOA) [29], Distributed BBO[30]. Out of these heuristics evolutionary search algorithm, some of these are used to solve Economic Load Dispatch Problem(ELDP), Combined Economic Load Dispatch Problem(CELDP), Dynamic Economic Dispatch Problem(DEDP) and Combined Economic Emission Dispatch (CEED) and are reported in numerous literatures as: Evolutionary Programming [31], Particle Swarm Optimization[32], Genetic Algorithm[32,33], Improved Genetic Algorithm[34], Adaptive PSO and Chaotic PSO[35], cardinal Priority ranking based Decision making[36], Gravitational Search Algorithm[37, 42, 45], Biogeography Based Optimization[38, 39, 44], Intelligent Water Drop Algorithm[40], Hybrid Harmony Search Algorithm[41], Firefly Algorithm[43], Cuckoo Search Algorithm[46, 54], Biogeography Based Optimization[44], Differential harmony Search[47], Hybrid Particle Swarm Optimization and Gravitational Search Algorithm[48], Differential Evolution[49], Modified Ant Colony Optimization[50], Modified Harmony Search[51], Hybrid GA-MGA[52], Artificial Bee Colony[53]. Although no optimization algorithm can perform general enough to solve all optimizations problems, each optimization algorithm have their own advantages and disadvantages. The limitations of some of these well known optimization algorithms are listed below:

The major limitations of the numerical techniques and dynamic programming method are the size or dimensions of the problem, large computational time and complexity in programming. The mixed integer programming methods for solving the economic load dispatch problem fails when the participation of number of units increases because they require a large memory and suffer from great computational delay. Gradient Descent method is distracted for Non-Differentiable search spaces. The Lagrangian Relaxation (LR) approach fails to obtain solution feasibility and solution quality of problems and becomes complex if the number of units are more. The Branch and Bound (BB) method employs a linear function to represent fuel cost, start-up cost and obtains a lower and upper bounds. The difficulty of this method is the exponential growth in the execution time for systems of a large practical size. An Expert System (ES) algorithm rectifies the complexity in calculations and saving in computation time. But it faces the problem if the new schedule is differing from schedule in database. The fuzzy theory method using fuzzy set solves the forecasted load schedules error but it suffers from complexity. The Hopfield neural network technique considers more constraints but it may suffer from numerical convergence due to its training process. The Simulated Annealing (SA) and Tabu Search (TS) are powerful, general-purpose stochastic optimization technique, which can theoretically converge asymptotically to a global optimum solution with probability one. But it takes much time to reach the near-global minimum. Particle swarm optimization (PSO) has simple concept, easy implementation, relative robustness to control parameters and computational efficiency[55], although it has numerous advantages, it get trapped in a local minimum, when handling heavily constrained problems due to the limited local/global searching capabilities [56, 57]. Differential Evolution (DE) algorithm has the ability to find the true global minimum regardless of the initial parameters values and requires few control parameters. It has parallel processing nature and fast convergence as compared to conventional optimization algorithm. Although, it does not always give an exact global optimum due to premature convergence and may require tremendously high computation time because of a large number of fitness evaluations. The Biogeography Based Optimization (BBO) is an efficient algorithm for Power System optimization, which does not take unnecessary computational time and is good for exploiting the solutions. The solutions obtained by BBO algorithm does not die at the end of each generation like the other optimization algorithm, but the convergence becomes slow for medium and large scale systems. Gravitational Search algorithm has the advantages to explore better optimized results, but due to the cumulative effect of the fitness function on mass, masses get heavier and heavier over the course of iteration. This causes masses to remain in close proximity and neutralise the gravitational forces of each other in later iterations, preventing them from rapidly exploiting the optimum [55]. Therefore, increasing effect of the cost function on mass, masses get greater over the course of iteration and search process and convergence becomes slow. To overcome the limitation of GSA, Seyedali Mirjalili[55] proposed an Adaptive gbest-Guided Gravitational Search algorithm (AgGGSA), in which the best mass is archived and utilised to accelerate the exploitation phase, enriching the weakness of GSA. Grey wolf Optimizer (GWO) is a recently developed powerful evolutionary algorithm proposed by Seyedali Mirjalili [57] and has the ability to converge to a better quality near-optimal solution and possesses better convergence characteristics than other prevailing techniques reported in the recent literatures. Also, GWO has a good balance between exploration and exploitation that result in high local optima avoidance, but the computation of GWO algorithm becomes slow, when applied to economic dispatch problem of medium and large scale power system. To overcome the drawbacks of Particle Swarm Optimization (PSO) algorithm, Genetic algorithm(GA), Artificial Bee Colony(ABC) search algorithms, newly developed Sine Cosine Optimizer algorithm developed by Seyedali Mirjalili [59] is tested for the solution of non-convex and dynamic economic load dispatch problem of electric power system in the proposed research.

II. ECONOMIC LOAD DISPATCH PROBLEM FORMULATION

The scheduling of electric utilities along with the distribution of the generation power which must be planned to meet the load demand for a specific time period represents the Unit Commitment Problem (UCP). Economic Load Dispatch Problem (ELDP) refers the optimal generation schedule for the generation system to deliver the required load demand plus transmission loss with the optimal generation fuel cost. Noteworthy economical benefits can be achieved by searching a better solution to the Economic Load Dispatch Problem (ELDP). The economic dispatch problem is defined so as to optimize the total operational cost of an electric power system while meeting the total load demand plus transmission losses within utilities generating limits[56]. The overall objective of Economic Load Dispatch Problem (ELDP) of electric power system is to plan the devoted (Committed) electric utilities outputs so as to congregate the load demand at optimal operating cost while satisfying all generating utilities constraints and various operational constraints of the electric utilities. The economic load dispatch problem (ELDP) is a constrained optimization problem and it can be mathematically expressed as follows [56]:

$$\min[FC(P_n)] = \sum_{n=1}^{U}(\alpha_n P_n^2 + \beta_n P_n + \gamma_n) \text{ \$/hour} \qquad (1)$$

subject to:

(i) The energy balance equation:

$$\sum_{n=1}^{U} P_n = P_{Demand} + P_{Loss}. \qquad (2)$$

(ii) The inequality constraints:

$$P_n^{\min} \le P_n \le P_n^{\max} \qquad (\mathrm{n} = 1, 2, 3, \ldots, \mathrm{U}). \qquad (3)$$

where, α_n, β_n and γ_n are cost coefficients.

P_{Demand} is Load Demand.

P_{Loss} is power transmission Loss.

U is the number of generating units.

P_n is real power generation and will act as decision variable.

The most simple and approximate method of expressing power transmission loss, P_{Loss} as a function of generator powers is through George's Formula using B-coefficients and mathematically can be expressed as [56]:

$$P_{Loss} = \sum_{n=1}^{U}\sum_{m=1}^{U} P_{g_n} B_{nm} P_{g_m} \text{ MW.} \qquad (4)$$

where, P_{g_n} and P_{g_m} are the real power generations at the nth and mth buses respectively.

B_{nm} is the loss coefficients which are constant under certain assumed conditions and U is the number of generating units.

The constrained Economic Load Dispatch Problem can be converted to unconstrained ELD Problem using Penalty of definite value, which can be mathematically expressed as:

$$\min[FC(P_n)] = \sum_{n=1}^{U} F_n(P_n) + 1000 * \left|\left(\sum_{n=1}^{U} P_n - P_{Demand} - \sum_{n=1}^{U}\sum_{m=1}^{U} B_{nm} P_n P_m\right)\right| \qquad (5)$$

The equation (5) represent the unconstrained economic load dispatch problem including penalty factor of $\sum_{n=1}^{U}\sum_{m=1}^{U} B_{nm} P_n P_m$. The complete unconstrained economic load dispatch problem having (U-1) variables can be represented as:

$$\min[FC(P_n)] = \sum_{n=1}^{U}(\alpha_n P_n^2 + \beta_n P_n + \gamma_n) + 1000 * \left|\mathrm{abs}\left(\sum_{n=1}^{U} P_n - P_{Demand} - \sum_{n=1}^{U}\sum_{m=1}^{U} B_{nm} P_n P_m\right)\right| \qquad (6)$$

The complete unconstrained economic load dispatch problem with valve point effect having (U-1) variables can be represented as:

$$\min[FC(P_n)] = \sum_{n=1}^{U}(\alpha_n P_n^2 + \beta_n P_n + \gamma_n + |(\delta_n \times \sin(\varepsilon_n \times (P_n^{\min} - P_n))|) + 1000 * \mathrm{abs}\left(\sum_{n=1}^{U} P_n - P_{Demand} - \sum_{n=1}^{U}\sum_{m=1}^{U} B_{nm} P_n P_m\right) \qquad (7)$$

III. SINE COSINE OPTIMIZER AND MATHEMATICAL FORMULATION

Sine Cosine Algorithm (SCA) is a novel population based optimization algorithm used for solving optimization problems. The SCA creates multiple initial random candidate solutions and requires them to fluctuate out wards or towards the best solution using a mathematical model based on sine and cosine functions [59]. The performance of SCA is benchmarked in three test phases:

1) First, asset of well-known test cases including unimodal, multimodal, and composite functions are employed to test exploration, exploitation, local optima avoidance, and convergence of SCA.
2) Second, several performance metrics (search history, trajectory, average fitness of solutions, and the best solution during optimization) are used to qualitatively observe.
3) Third, confirm the performance of SCA on shifted two-dimensional test functions [59].

The following position updating equations are proposed for both phases:

$$X_i^{t+1} = X_i^t + r_1 \times \mathrm{Sin}(r_2) \times \left|r_3 P_i^t - X_i^t\right| \qquad (8)$$

$$X_i^{t+1} = X_i^t + r_1 \times \mathrm{Cos}(r_2) \times \left|r_3 P_i^t - X_i^t\right| \qquad (9)$$

Where X_i^t is show the position of the current solution in i^{th} dimension at t^{th} iteration, $r_1/r_2/r_3$ are shows the random numbers, P_i is shows the position of the destination point in i^{th} dimension, and || is indicates the absolute value.

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 \times \mathrm{Sin}(r_2) \times \left|r_3 P_i^t - X_i^t\right|, r_1 \le 0.5 \\ X_i^t + r_1 \times \mathrm{Cos}(r_2) \times \left|r_3 P_i^t - X_i^t\right|, r_1 \ge 0.5 \end{cases} \qquad (10)$$

Where r_4 is shows random number in [0, 1] side or outside is achieved by defining a random number for r_2 in [0,2π] in Eq.(3.3SS) .Therefore, this mechanism guarantees exploration and exploitation of the search space respectively [59].

$$r_1 = a - t\frac{a}{T} \qquad (11)$$

IV. TEST SYSTEMS, RESULTS AND DISCUSSION

In order to show the effectiveness of the SCA Algorithm for Economic Load Dispatch Problem, three benchmark test system of small scale power systems having standard IEEE bus systems have been taken into consideration. The performance of the proposed SCA algorithm is tested in MATLAB 2013a (8.1.0.604) software on Intel® core™ i-5-3470S CPU@ 2.90 GHz, 4.00 GB RAM system.

A. *Test system-I: 3-generating unit system considering transmission losses*

The first test system consists of 3-Generating units with a load demand of 150 MW [60]. Test data of 3-Generating Unit System are taken from [60]; Loss Coefficients Matrices are used to calculate the corresponding Transmission losses. The algorithm is tested for 250 iterations and the corresponding results are compared with lambda iteration method [60] and Particle Swarm Optimization (PSO) [60]. Table-I shows that optimal fuel cost for 3-unit generating model for 150MW load demand using SCA algorithm is **1597.4817** Rs./hour, power loss using SCA is **2.2202622 MW** and Iteration time for SCA algorithm is **0.967814 seconds,** which shows the superiority of SCA algorithm over population based PSO algorithm. The convergence curve of test case-I is shown in Fig.1.

B. *Test system-II: 3-generating unit system without transmission losses*

The second test system also consisting of 3-Generating Unit System [58] is tested for two different load demands of 850 MW and 1050 MW including transmission losses. The corresponding results are compared with lambda iteration method [58], Genetic Algorithm (GA) [58], Particle Swarm Optimization (PSO)[58,60], and Artificial Bee Colony(ABC)[58]. Table-II and III shows the comparison of results with different methodologies and it is found that optimal value of fuel cost obtained by SCA algorithm is much less that lambda iteration, GA, PSO, and ABC. The convergence curve of test case-II is shown in Fig.2 and Fig.3.

C. *Test system-III: 5-generating unit system considering valve point effect.*

The third test system consists of 5-Generating Unit System [58] is tested for load demand of 730 MW. Valve point effect is taken into consideration, but transmission losses are neglected while calculating optimal fuel cost. The results obtained by SCA algorithm are compared with lambda iteration method [58], Genetic Algorithm (GA) [58], Particle Swarm Optimization (PSO) [58], and APSO [58]. Table-IV shows the comparison of results with different methodologies and it is found that optimal value of fuel cost obtained by SCA algorithm is much less that lambda iteration, GA, PSO, and APSO. The convergence curve of test case-II is shown in Fig.4.

V. CONCLUSION

In this research paper, application of SCA algorithm is presented for the solution of non-convex and dynamic economic load dispatch problem of electric power system. Performance of SCA algorithm is tested for small scale power plants. The effectiveness of proposed SCA algorithm is tested with the standard IEEE bus system consisting of 3 and 5-generating units model considering transmission losses (Power Loss) and valve point effect.

The simulation results show that SCA have been successfully implemented to solve different ELD problems moreover, SCA is able to provide very spirited results in terms of minimizing total fuel cost and lower transmission loss. Also, convergence of SCA is very fast as compared to Lambda Iteration Method, Particle Swarm Optimization (PSO) algorithm, Genetic algorithm (GA), APSO, Artificial Bee Colony (ABC) for small scale power systems.

Also, it has been observed that the SCA has the ability to converge to a better quality near-optimal solution and possesses better convergence characteristics than other widespread techniques reported in the recent literatures.

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Table-1: Economic load dispatch for 3-generating units system (load demand=150mw)

Method	**Load Demand**	**P1 (MW)**	**P2(MW)**	**P3(MW)**	**Fuel Cost(Rs./h)**	**P_{loss} (MW)**	**No. of Iteration**	**Elapsed Time(Seconds)**
Lambda Iteration [60]	150 MW	33.4401	64.0974	55.1011	1599.9	2.66	250	NA
PSO [60]	150 MW	33.0858	64.4545	54.8325	1598.79	2.37	250	NA
SCA	150 MW	48.3112	37.66128	66.2476	1597.4817	2.2202622	250	**0.967814**

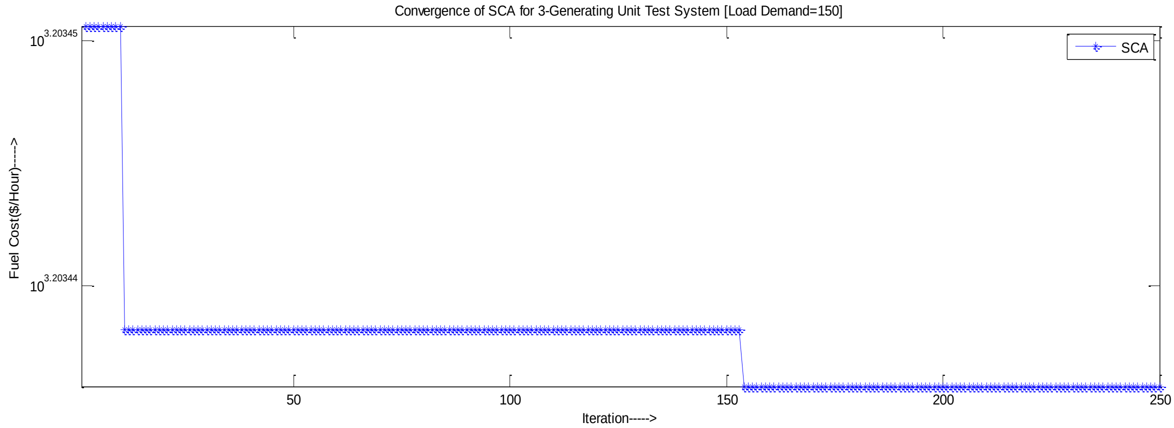

Fig.1: The convergence curve of test case-I for Load demand of 150 MW

Table-II: Economic load dispatch for 3-generating units system (load demand=850mw)

Method	Load Demand	Generation Scheduling			Fuel Cost(Rs./h)	Best Cost	Average Cost	Worst Cost	Iteration Time(sec.)
		U1	U2	U3					
Lambda Iteration	850 MW	382.258	127.419	340.323	8575.68	---	---	---	---
GA	850 MW	382.2552	127.4184	340.3202	8575.64	---	---	---	---
PSO	850 MW	394.5243	200	255.4756	8280.81	---	---	---	---
ABC	850 MW	300.266	149.733	400	8253.1	---	---	---	---
SCA	850MW	531.318	199.153	119.52	8253.108	8253.108	8253.1850	8253.2673	0.293775

Table-III: Economic load dispatch for 3-generating units system (load demand=1050mw)

Method	Load Demand (MW)	Generation Scheduling			Cost (Rs./Hour)	Best Cost	Average Cost	Worst Cost	Iteration Time(sec.)
		U1	U2	U3					
Lambda Iteration	1050	487.5	162.5	400	10212.459	---	---	---	---
GA	1050	487.498	162.499	400	10212.44	---	---	---	---
PSO	1050	492.699	157.3	400	10123.73	---	---	---	---
ABC	1050	492.6991	157.301	400	10123.73	---	---	---	---
SCA	1050	228.78	121.17	100.04	10123.7358	10123.735	10123.97	10124.51	0.298570

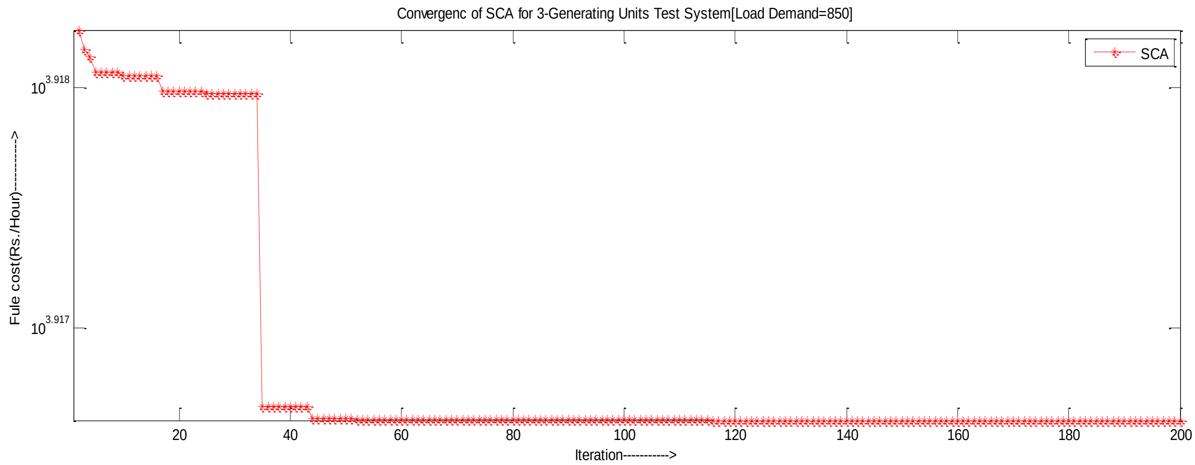

Fig.2: The convergence curve of test case-II for Load demand of 850 MW.

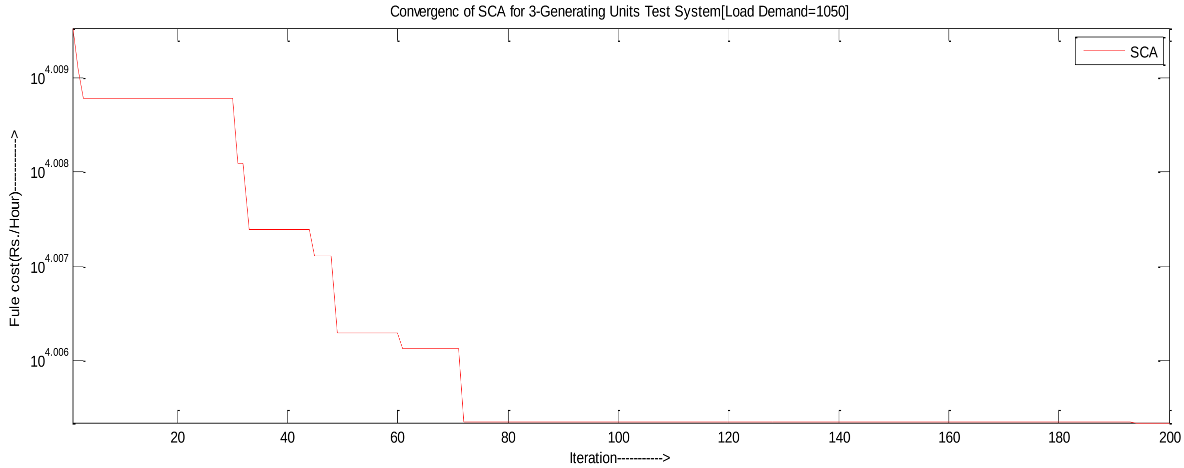

Fig.3: The convergence curve of test case-II for Load demand of 1050 MW

Table-IV: Economic load dispatch for 5-generating units (load demand=730 mw)

Method	Load Demand	U1	U2	U3	U4	U5	Cost (Rs./Hour)	Best Cost	Average Cost	Worst Cost
Lambda Iteration	730 MW	218.028	109.014	147.535	28.38	272.042	2412.709	---	---	---
GA	730 MW	218.0184	109.0092	147.5229	28.37844	227.0275	2412.538	---	---	---
PSO	730 MW	229.5195	125	175	75	125.4804	2252.572	---	---	---
APSO	730 MW	225.3845	113.02	109.4146	73.11176	209.0692	2140.97	---	---	---
SCA	730MW	215.20	78.9184	141.8524	49.21	244.8096	2048.5303	2048.53	2091.89	2102.99

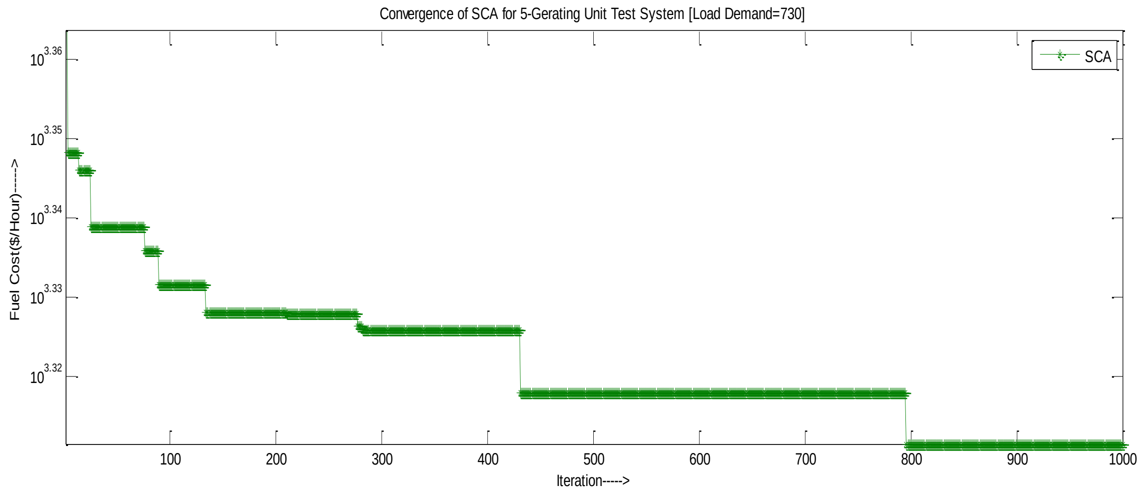

Fig.4: The convergence curve of test case- III for Load demand of 730 MW