Comparative Analysis on Economic Load Dispatch Problem Optimization using Moth Flame Optimization and Sine Cosine Algorithms

Pawan Preet Singh [1], Rohit Bains [2], Gurjit Singh [3], Neha Kapila [4], Vikram Kumar Kamboj [5]

[1] *Pawan Preet Singh, Assistant Prof., Department of Electrical Engg., GNIEM, Naushehra, Punjab ,India*
[2] *Rohit Bains, Assistant Prof., Department of Electrical Engg., GNIEM, Naushehra, Punjab ,India*
[3] *Gurjit Singh, Assistant Prof., Department of Electrical Engg., Formerly Dr. B. R. Ambedkar N.I.T , Jalandhar, Presently GNIEM, Naushehra, Punjab ,India*
[4] *Neha Kapila, Assistant Prof., Department of Electrical Engg., GNIEM, Naushehra, Punjab ,India*
[5] *Vikram Kumar Kamboj, Assistant Prof., Department of Electrical Engg., DAV University, Jalandhar, Punjab ,India*
[6]*Ashutosh Bhadoria, Assistant Prof., Department of Electrical Engg., DAV University, Jalandhar, Punjab, India*

ABSTRACT

This paper proposes a heuristic approach for Economic Load Dispatch Problem Optimization (ELDPO) in Power Management System (PMS) using Sine Cosine Algorithm (SCA) and Moth Flame Optimizer Algorithm (MFO), erstwhile performing a combinatorial analysis among them. ELDPO is a remedy to real time onsite problem incurred in PMS of Electrical Power Generation Systems (EPGS) (Both Conventional & Non-Conventional) which paves way to transmission and operation constraints. SCA is used for constrained optimization problems and based on the concept of a correlation mathematical model of sine and cosine functions. Also, MFO is a heuristic algorithm which utilizes the concept that the moth eventually converges towards the light. Both SCA algorithm and MFO algorithm are utilized for ELDPO of Three IEEE benchmarks of small scale power systems and are verified by a comparative study with Lambda Iteration. Combinatorial results show that the performance of MFO is better than SCA algorithm in view of various parameters viz. Exploration, local optima avoidance, exploitation and convergence.

Keyword: - *Economic Load Dispatch Problem Optimization (ELDPO), Power Management System (PMS), Moth Flame Optimization (MFO), Sine Cosine Algorithm (SCA)*

1. INTRODUCTION

Electrical energy pays a vital role in modern power systems grid of energy management systems (EMS). In the modern power system grids, there are numerous energy resources both conventional & non-conventional. The peak values of the load varies at different instant of time, giving rise to Economic Load dispatch problem. Therefore, it is paves way to decide which generating division to turn on and at what time it is needed in the power system network with respect to the sequence in which the units must be shut down redefining the cost-effectiveness of switching on &off of respective divisions.

The complete process of computing, deciding & executing the same is known as Economic Load Dispatch Problem. The unit which is live in the power system network of energy management system, is known to be committed unit.

The economic load dispatch problem Optimization (ELDPO) is the most important in scheduling the Generation among generating divisions (Conventional or non-conventional). It is a real onsite problem in power management system (PMS) of electrical power generation 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 h creates system and operating constraints viz. operational and transmission constraints. The economic load dispatch problem (ELDP) means that the electric utilities (i.e. Generators) real and reactive power are tolerable to vary within certain limits so as to meet a particular load demand within lowest fuel cost. The ultimate aim of the ELDPO 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 ELDP is usually multimodal, discontinuous and extremely nonlinear [1][4][5].

Moth-Flame Optimization Algorithm (MFO) is a nature inspired prototype. The fancy insects are known as moths and has similarity with the butterflies family. The special feature in the Moths is their traversing nature at night. The MFO algorithm mathematically models the behavior of the flies for optimization problem. The inspiration of this optimizer is the navigation method in the moths in the nature termed transverse orientation. The moth flies by keeping fixed angle with respect to moon, it’s very effective mode for travelling long distances in straight path. In the moth flame optimization algorithm it is assumed that the candidate solutions are the moths and the problem’s variables are the position of the moths in the space [9].

The SCA (Sine Cosine Algorithm) is a proposed novel population based algorithm which creates multiple initial random candidate solution and involves them to vary in the direction of the best solution with the help of mathematical algorithm i.e. (SCA). It is a population based optimization technique that starts the optimization with the set of random solutions. This random function set is evaluated continually by an objective function and is improved by implementing set of rules to attain an optimized solution [10].

2. ECONOMIC LOAD DISPATCH PROBLEM FORMULATION

Forecasting of the electric utilities sideways through the distribution of the generation power (conventional and non-conventional) which need to be calculated to satisfy the load demand requirement for a definite time span signifies the (UCP) Unit Commitment Problem. Economic Load Dispatch Problem Optimization (ELDPO) refers the optimum generation plan for the generation system for delivering the entailed load demand in addition of transmission loss by means of generation fuel cost to be optimum. Significant cost-effective benefits can be achieved by examining an enhanced ELDPO for Power Management System (PMS). The optimization of the total operating cost for an electric power system however congregating the total load demand in addition to the transmission losses inside the utilities generation boundaries is defined as Economic Load Dispatch Problem (ELDP). In general, the intent of ELDPO for electric power system is towards planning a fanatical electric utilities outputs while satisfying the load requirement at optimum operating cost while satisfying several operative constraints & generating utilities constraints for every electrical utility. Mathematically, the ELDP is an optimization problem with some constraints, which can be put across by the following expressions [1][2][3]:

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

Subjected to the:

(i) Equation for Energy Balance:

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

(ii) Equation for Inequality Constraints:

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

Here, the cost coefficients are expressed by α_n, β_n & γ_n,

Load Demand for 'P_{Demand}'.

Power Transmission Loss for 'P_{Loss}'.

The Number of Generating Units for 'U'.

Real Power Generation for 'P_n', which will operate as a decision variable.

The power transmission loss P_{Loss} can be expressed by the utmost easy & estimated technique by means of George's Formula employing B-coefficients, [1][4] i.e.

$$P_{Loss} = \sum_{n=1}^{U}\sum_{m=1}^{U} P_{g_n} B_{nm} P_{g_m} \quad \mathrm{MW} \tag{4}$$

Here, the n^{th} & m^{th} buses real power generations are represented by P_{g_n} and P_{g_m} respectively. Also, B_{nm} is the constant loss coefficients beneath specific presumed circumstances.
The conversion of constrained (ELDP) into unconstrained (ELDP) by means of Penalty of definite value, mathematically expressed as follows:

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

Here, equation (5) exemplify the unconstrained (ELDP) comprising of penalty factor, i.e. $\sum_{n=1}^{U}\sum_{m=1}^{U} \mathrm{B_{nm} P_n P_m}$.
Therefore, the whole unconstrained (ELDP) including (U-1) variables can be exemplified as follows:

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

The whole unconstrained (ELDP) incorporating valve point effect including (U-1) variables can be exemplified as follows [1][5][7]:

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

3. SINE COSINE OPTIMIZER MATHEMATICAL FORMULATION

For solving optimization problems, a noval population centered optimization algorithm i.e. Sine Cosine Algorithm (SCA) is proposed. Initial random candidate solutions are created by the SCA & for obtaining best solutions a mathematical model centered on the Sine & Cosine Functions entails these random candidate solutions to oscillate away from or near the best solution [10]. In three test phases, the functioning of SCA is benchmarked, which are given as:

1) An asset of renowned test cases comprising composite, unimodal & multimodal functions are exercised to examine exploitation, exploration, convergence & avoidance of local optima of SCA.

2) For superior observation, numerous performance metrics are used such as trajectory, the best solution throughout optimization, average fitness of the solutions, search history.
3) SCA performance is confirmed on shifted two-dimensional test functions [10].

In SCA, the position is updated by means of two equations one for each phase:

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

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

Here, the position of the current solution is depicted by X_i^t at t^{th} iteration in i^{th} dimension, the random numbers are represented as $r_1/r_2/r_3$, the destination point position is depicted by P_i in i^{th} dimension & the absolute value is indicated by || .

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

Here, 'r_3'presents a random number in the range [0,1] inwards or outwards is attained by specifying 'r_2' a random number in the range [0,2π]. The exploitation & exploration of the search space is assured by this method respectively [10].

$$r_1 = a - t\frac{a}{T} \tag{11}$$

Here, 't' shows the current iteration, 'T' shows the maximum number of iteration & 'a' is a constant value.

4. MOTH-FLAME OPTIMIZER AND MATHEMATICAL FORMULATION

A novel nature motivated heuristic pattern i.e. Moth-Flame Optimization algorithm is suggested by Seyedali Mirjalili [9], enthused from the course plotting technique or transverse orientation of moths centered on the perception that they will ultimately congregates towards the light as seen in nature. In the night, Moths fly continuously acquiring a certain angle in accordance with the moon for voyaging in straight forward path for covering wide spaces. Although, these insects are enchanted in decisive spiral path nearby mock lights. The Fig.1 (a)-(c) depicts the convergence stages of moth in the direction of light as shown below:

(a) **(b)** **(c)**

Fig -1(a)-(c) Convergence of moth towards light.

The mathematical model of MFO can be described with the aid of succeeding steps:

For resolving ELDP, an assumption is made in which the moths represents the optimum values of fuel cost &in the space the position of moths represents the generation scheduling are. The following set represents the matrix of moths:

$$M = \begin{bmatrix} m_{11} & m_{12} & \ldots\ldots & m_{1d} \\ m_{21} & m_{22} & \ldots\ldots & m_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ m_{n1} & m_{n2} & \ldots\ldots & m_{nd} \end{bmatrix} \tag{8}$$

Here, 'd' shows the number of population or dimension & 'n' shows the number of generating units (i.e. moths). The optimal cost (i.e. corresponding fitness values) for all generating units (i.e. moths) can be stockpiled in an array shown as:

$$OM = \begin{bmatrix} OM_1 \\ OM_2 \\ \vdots \\ OM_n \end{bmatrix} \tag{9}$$

The following matrix represents the set of flames similar to moths as shown below:

$$F = \begin{bmatrix} F_{11} & F_{12} & \ldots & F_{1d} \\ F_{21} & F_{22} & \ldots & F_{2d} \\ \ldots & \ldots & \ldots & \\ F_{n1} & F_{n2} & \ldots & F_{nd} \end{bmatrix}_{n\times d} \tag{10}$$

The optimal values for every flame can be stockpiled in an array shown as:

$$OF = \begin{bmatrix} OF_1 \\ OF_2 \\ \vdots \\ OF_n \end{bmatrix} \tag{11}$$

Moth Flame Optimization (MFO) algorithm is a three stage algorithm that approaches the optimization problem global optimum represented as:

$$MFO = (I, P, T)$$

(12)

Here, ‘I’, ‘P’ and ‘T’ are three functions.

‘I’ generates random population of moths & mathematical corresponding fitness values can be characterized as:

$$\mathrm{I} : \Phi = \{M, OM\}$$

(13)

‘P’ controls the movement of moths throughout the search space. It updates the received matrix M which can be mathematical denoted as:

$$\mathrm{P} : \mathrm{M} \rightarrow \mathrm{M}$$

(14)

‘T’ performs the logical operation, if the termination condition is fulfilled it gives back **true** & if the termination condition is fulfilled it returns **false**. The mathematical representation is shown below:

$$\mathrm{T} : \mathrm{M} \rightarrow \{\mathrm{True}, \mathrm{False}\}$$

(15)

The framework of MFO algorithm among I, P & T can be updated as:

```
M=I ();
While T (M) is equal to false
        M=P(M);
end
```

```
for i=1:n
  for j=1:d
    M(i,j)=Pmin(i)+rand()*[Pmax(i)-Pmin(i)]
  end
end
    OM=CostFunction(M);
```

Fig -2 Framework of MFO algorithm

The generating unit’s maximum & minimum generation capacity can be specified as:

$$\mathrm{Pmax} = [\mathrm{P}\max_1 \quad \mathrm{P}\max_2 \quad \cdots \quad \mathrm{P}\max_{n-1} \quad \mathrm{P}\max_n]$$

(16)

Here, $Pmax_i$ shows the maximum capacity for i^{th} unit.

$$Pmin = [Pmin_1 \quad Pmin_2 \quad \cdots \quad Pmin_{n-1} \quad Pmin_n] \tag{17}$$

Here, $Pmin_i$ shows the minimum capacity of i^{th} unit. Until the function T returns true, the function P is iteratively run after the initialization. This transverse orientation can be mathematically modeled as the location of every moth with respect to a flame is updated by means of the succeeding equation:

$$\mathbf{M}_i = \mathbf{S}(\mathbf{M}_i, \mathbf{F}_j) \tag{18}$$

Here, 'S' specifies the spiral function, 'F_j' specifies the j^{th} flame &'M_i' specifies the i^{th} moth.

The logarithmic spiral equation for MFO algorithm, centered on logarithmic spiral mechanism of moths can be denoted as:

$$S(M_i, S_j) = D_i . e^{bt} . \cos(2\pi t) + F_j \tag{19}$$

Here, 'D_i' shows the space of i^{th} moth for j^{th} flame, 'b' is a constant which defines the logarithmic spiral shape and 't' is an arbitrary number in [-1,1]. The value of 'D_i' can be evaluated as:

$$D_i = \left| F_j - M_i \right| \tag{20}$$

The exploitation of the best optimum solutions may be ruined by the location updating of moths with respect to 'n' diverse locations in the search area. The following mathematical mechanism is opted to resolve this issue, shown as:

$$flameNo. = round(N - l * \frac{N-1}{T}) \tag{21}$$

```
Update flame no using eqn. (21)
    OM=CostFunction(M)
If iteration==1
    F=sort(M)
    OF=sort(OM);
else
    F=sort(Mt-1, Mt);
    OF=sort(Mt-1, Mt)
end;
 for i=1:n
    for j=1:d
        Update r and t
        Calculate D using eqn.(20) w.r.t. corresponding moth
        Update M(I,j)using eqn.(18) and (19) w.r.t corresponding moth
    end
end
```

Fig -3 Pseudo code of MFO algorithm

5. TEST SYSTEM, RESULTS AND DISCUSSION

The efficacy of the SCA & MFO Algorithm for Economic Load Dispatch Problem is shown by three benchmark test systems of small scale power systems enclosing standard IEEE bus systems. The operation of the suggested SCA & MFO algorithm is verified in MATLAB 2013a (8.1.0.604) software on Intel® core™ i-5-3470S CPU@2.90 GHz, 4.00 GB RAM system.

5.1 TEST SYSTEM-1: 3-GENERATING UNIT SYSTEM CONSIDERING TRANSMISSION LOSSES

The first test system consists of 3-Generating units with a load demand of 850 MW [1][7]. Test data of 3-Generating Unit System are taken from [1][7]. The algorithm is tested for 200 iterations & The corresponding results are compared with lambda iteration method [1][7], Particle Swarm Optimization (PSO) [1][7] and Genetic Algorithm (GA) [1][7]. Table-1 shows that optimal fuel cost for 3-unit generating model for 850MW load demand using MFO algorithm is **8253.105** Rs./hour, Iteration time for MFO algorithm is **2.468 seconds,** which shows the superiority of MFO algorithm over population based PSO, SCA and GA. MFO algorithm completely converges in **58** iterations, while SCA algorithm takes **92** iterations for convergence**.** Showing the optimal fuel cost for 3-unit generating model for 850MW load demand using MFO algorithm of **8253.105** Rs./hour. The convergence curve of test case-1 is shown in Fig- 4.

5.2 TEST SYSTEM-2: 3-GENERATING UNIT SYSTEM WITHOUT TRANSMISSION LOSSES

The second test system consists of 3-Generating units with a load demand of 150 MW incorporating transmission losses [1][7]. The algorithm is tested for 200 iterations & the analogous results are equated with lambda iteration method [1] [7], Particle Swarm Optimization (PSO) [1] [7] and Sine Cosine Algorithm (SCA). Table-2 shows that optimal fuel cost for 3-unit generating model for 150MW load demand using MFO algorithm is **1597.4815** Rs./hour, transmission losses occurring is **2.3420 MW**, Iteration time for MFO algorithm is **2.468 seconds.** Whereas, optimal fuel cost for 3-unit generating model for 150MW load demand using SCA is **1597.4829** Rs./hour, transmission losses occurring is **2.2202622**, Iteration time for MFO algorithm is **4.761541 seconds,** which shows the superiority of MFO algorithm over population based lambda iteration method, PSO and SCA. MFO algorithm completely converges in **8** iterations, while SCA algorithm takes **54** iterations for convergence**.** The convergence curve of test case-2 is shown in Fig- 5.

5.3 TEST SYSTEM-3: 5-GENERATING UNIT SYSTEM CONSIDERING VALVE POINT EFFECT

The third test system comprises of 5-Generating Unit System [7] which is examined for a load demand of 730 MW. Also, incorporating the Valve point effect, while the transmission losses are deserted while calculating the optimum fuel cost. The optimum results attained by MFO algorithm are equated with lambda iteration method [7], Genetic Algorithm (GA) [7], Particle Swarm Optimization (PSO) [7], APSO [7] and Sine Cosine Algorithm (SCA). Table-3 displays the comparative results amongst diverse methodologies & it is found that optimum value of fuel cost attained by MFO algorithm is much less that lambda iteration, GA, PSO, APSO and SCA. The optimal fuel cost for 5-unit generating model for 730 MW load demand using MFO algorithm is **2032.6748** Rs./hour. Whereas, optimal fuel cost for 5-unit generating model for 730 MW load demand using SCA is **2127.5502** Rs./hour. Which illustrates the dominance of MFO algorithm over population based PSO, SCA & GA. The convergence curve of test case-3 is shown in Fig- 6.

6. CONCLUSION

The efficacy of suggested algorithm is tested with the standard IEEE bus system containing 3 & 5-Generating units model taking into account transmission losses & valve point effect. The simulation outcomes shows that MFO have been effectively employed to resolve diverse ELD problems likewise, SCA is capable to deliver very spirited outcomes in terms of reducing total fuel cost & reduce the transmission loss. Moreover, the convergence of MFO is very swift in comparison to the Lambda Iteration Method, Genetic algorithm (GA), Particle Swarm Optimization

(PSO) algorithm for the small scale power systems. It has been examined that the MFO has the capability to congregate to a superior quality near optimum solution & owns superior convergence attributes than another well-known methods stated in the literature recently.

7. REFERENCES

[1]. A. J. Wood and B. F. Wollenberg, "*Power Generation, Operation and Control*", 2nd ed. New York, NY, USA: Wiley, 1996.
[2]. Gaing, Zwe-Lee. "*Particle Swarm Optimization to Solving the Economic Dispatch Considering the Generator Constraints*" Power Systems, IEEE Transactions on 18, no. 3 (2003): 1187-1195.
[3]. Chiang, Chao-Lung. "*Improved Genetic Algorithm for Power Economic Dispatch of Units with Valve-Point Effects and Multiple Fuels.*" Power Systems, IEEE Transactions on 20, no. 4 (2005): 1690-1699.
[4]. Devi, A. Lakshmi, and O. Vamsi Krishna. "*Combined Economic and Emission Dispatch Using Evolutionary Algorithms-A Case Study.*" ARPN Journal of engineering and applied sciences 3, no. 6 (2008): 28-35.
[5]. Kumar, K. Sathish, R. Rajaram, V. Tamilselvan, V. Shanmugasundaram, S. Naveen, and IG Mohamed Nowfal Hariharan T. Jayabarathi. "*Economic Dispatch with Valve Point Effect Using Various PSO Techniques.*" Vol 2, No. 6, (2009):130-135
[6]. V.Selvi , Dr.R.Umarani. "*Comparative Analysis of Ant Colony and Particle Swarm Optimization Techniques.*" International Journal of Computer Applications (0975 – 8887) Volume 5– No.4, August 2010.
[7]. Bestha Mallikarjuna, K Harinath Reddy, O Hemakeshavulu, "*Economic Load Dispatch with Valve-Point Result Employing a Binary Bat Formula*", International Journal of Electrical and Computer Engineering (IJECE), Vol. 4, No. 1, pp. 101-107, Feburary 2014.
[8]. Vikram Kumar Kamboj, S. K. Bath, J. S. Dhillon, "*Solution of Non-Convex Economic Load Dispatch Problem Using Grey Wolf Optimizer.*" Neural Comput & Applic Doi 10.1007/S00521-015-1934-8. 3 June 2015.
[9]. S. Mirjalili "*The Moth-Flame Optimization*" Adv Eng Softw (2015), Dx. Doi. Org/10.1016/J.Advengsoft. 2015.01.010., November 2015
[10].S. Mirjalili, "*SCA: A Sine Cosine Algorithm for Solving Optimization Problems*", Knowledge-Based Systems, in press, 2015, DOI: http://dx.doi.org/10.1016/j.knosys.2015.12.022

TABLE-1: ECONOMIC LOAD DISPATCH FOR 3-GENERATING UNITS SYSTEM (LOAD DEMAND=850MW)

Method	**Load Demand**	**Generation Scheduling (MW)**			**Fuel Cost (Rs./h)**	**Best Cost**	**Average Cost**	**Worst Cost**	**Iteration Time(sec.)**
		U1	**U2**	**U3**					
Lambda Iteration [1]	850 MW	382.258	127.419	340.323	8575.68	---	---	---	---
GA [1]	850 MW	382.2552	127.4184	340.3202	8575.64	---	---	---	---
PSO[1]	850 MW	394.5243	200	255.4756	8280.81	---	---	---	---
SCA	850 MW	**531.318**	**199.153**	**119.52**	**8253.1227**	---	---	---	---
MFO	850MW	**300.266**	**149.733**	**400**	**8253.105**	**8253.1052**	**8253.1052**	**8253.1052**	**2.468**

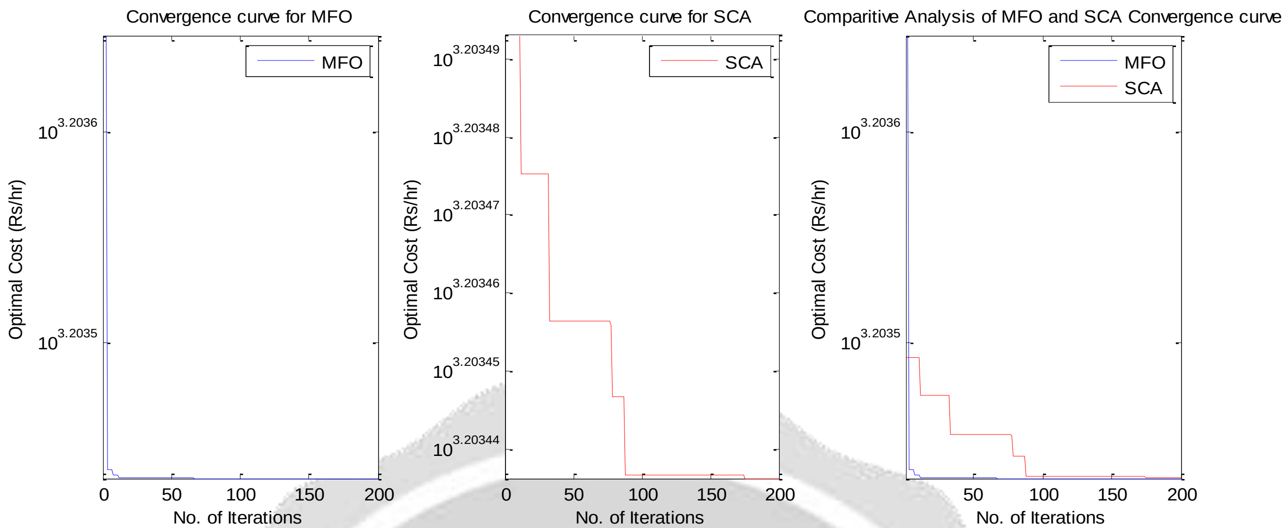

Fig- 4 The convergence curve of test case-I for Load demand of 150 MW

TABLE-2: ECONOMIC LOAD DISPATCH FOR 3-GENERATING UNITS SYSTEM INCORPORATING TRANSMISSION LOSSES (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 [1][7]	150 MW	33.4401	64.0974	55.1011	1599.9	2.66	200	NA
PSO [1][7]	150 MW	33.0858	64.4545	54.8325	1598.79	2.37	200	NA
SCA	150 MW	**48.3112**	**37.66128**	**66.2476**	**1597.4829**	**2.2202622**	200	**4.761541**
MFO	150 MW	**32.8101**	**64.595**	**54.9369**	**1597.4815**	**2.3420**	200	**2.252332**

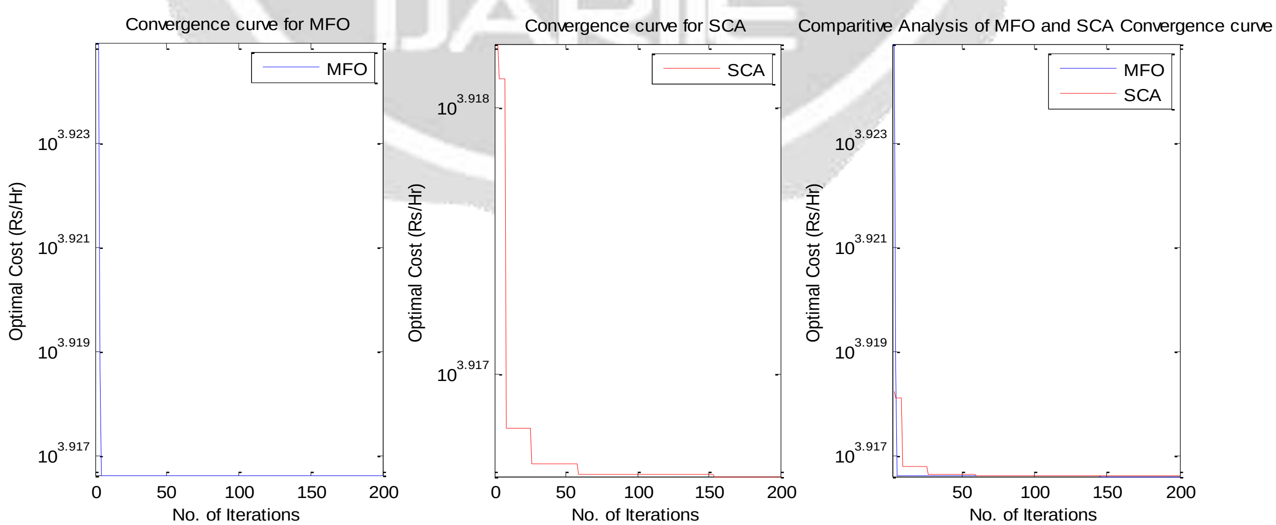

Fig- 2 The convergence curve of test case-II for Load demand of 150 MW

TABLE-3: ECONOMIC LOAD DISPATCH FOR 5-GENERATING UNITS (LOAD DEMAND=730 MW)

Method	Load Demand	U1 MW	U2 MW	U3 MW	U4 MW	U5 MW	Fuel Cost (Rs./Hour)	Best Cost	Average Cost	Worst Cost
Lambda Iteration [1][7]	730 MW	218.028	109.014	147.535	28.38	272.042	2412.709	---	---	---
GA [1][7]	730 MW	218.0184	109.0092	147.5229	28.37844	227.0275	2412.538	---	---	---
PSO [1][7]	730 MW	229.5195	125	175	75	125.4804	2252.572	---	---	---
APSO [1][7]	730 MW	225.3845	113.02	109.4146	73.11176	209.0692	2140.97	---	---	---
SCA	730 MW	**215.20**	**78.9184**	**141.8524**	**49.21**	**244.8096**	**2127.5502**	---	---	---
MFO	730MW	**229.5196**	**102.9911**	**112.673503**	**75**	**209.815819**	**2032.6748**	**2029.665**	**2050.304**	**2161.316**

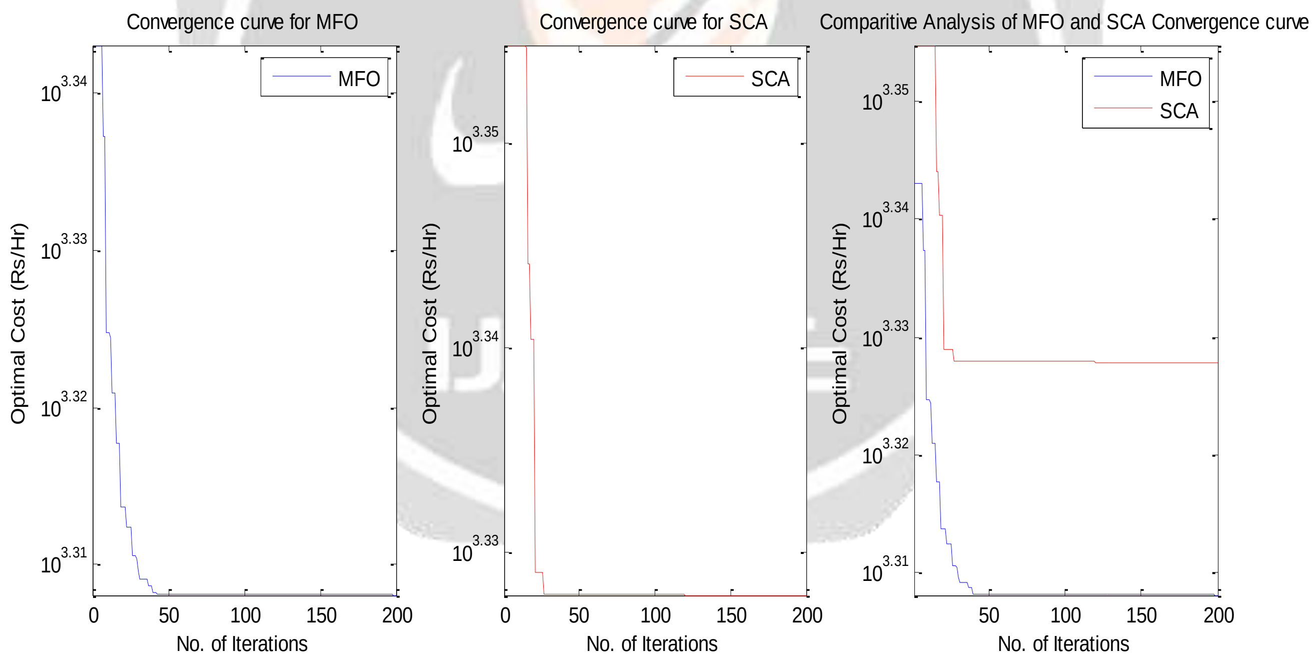

Fig- 6 The convergence curve of test case- 3 for Load demand of 730 MW