Research Article

An Intelligent Soft Computing Technique based Solution to Economic Load Dispatch Problem in Power System

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Abstract: The economic load dispatch plays an important role in the operation of power system, and several models by using different techniques have been used to solve these problems. Several traditional approaches, like lambda-iteration and gradient method are utilized to find out the optimal solution of non-linear problem. More recently, the soft computing techniques have received more attention and were used in a number of successful and practical applications. This paper an interesting new optimization algorithm of Rao algorithm is proposed to solve the economic dispatch problem. Here, an attempt has been made to find out the minimum cost by using Rao algorithm. Numerical example with three and six generating units is considered to illustrate the performance of the proposed method. In this work, data has been taken from the published work and given with the max-min power limit and cost function. The proposed Rao algorithm is implemented in MATLAB environment and applied to find out the minimum cost for different power demand which is finally compared with other available methods of lambda- iteration method and GA, PSO and ALO technique. From the results the proposed method gives a better result with less computational effect.

Keywords: Economic load dispatch, Thermal power generation, Fuel cost minimization, Rao algorithm

1. Introduction

Since an engineer is always concerned with the cost of products and services, the efficient optimum economic operation and planning of electric power generation system have always occupied an important position in the electric power industry. With large interconnection of the electric networks, the energy crisis in the world and continuous rise in prices, it is very essential to reduce the running charges of the electric energy. A saving in the operation of the system of a small percent represents a significant reduction in operating cost as well as in the quantities of fuel consumed. The classic problem is the economic load dispatch of generating systems to achieve minimum operating cost [1].

This problem area has taken a subtle twist as the public has become increasingly concerned with environmental matters, so that economic dispatch now includes the dispatch of systems to minimize pollutants and conserve various forms of fuel, as well as achieve minimum cost. In addition there is a need to expand the limited economic optimization problem to incorporate constraints on system operation to ensure the security of the system, thereby preventing the collapse of the system due to unforeseen conditions [2]. However closely associated with this economic dispatch problem is the problem of the proper commitment of any array of units out of a total array of units to serve the expected load demands in an 'optimal' manner. For the purpose of optimum economic operation of this large scale system, modern system theory and optimization techniques are being applied with the expectation of considerable cost savings.

The ELD is solved traditionally using mathematical programming based on optimization techniques such as lambda iteration, gradient method and so on [2],[3],[4],[5] and [6]. Economic load dispatch with piecewise linear cost functions is a highly heuristic, approximate and extremely fast form of economic dispatch [2].

Complex constrained ELD is addressed by intelligent methods. Among these methods, some of them are genetic algorithm (GA) [7]and [8], evolutionary programming (EP) [9] and [10], dynamic programming (DP)[11], tabu search [12], hybrid EP [13], neural network (NN) [14], adaptive Hopfield neural network (AHNN)[15], particle swarm optimization (PSO)[16], [17], [18], and [19], etc. For calculation simplicity, existing methods use second order fuel cost functions which involve approximation and constraints are handled separately, although sometimes valve-point effects are considered. However, the authors propose higher order cost functions for (a) better curve fitting of running cost, (b) less approximation, (c) more practical, accurate and reliable results, and modified particle swarm optimization (MPSO) is introduced to calculate the optimum dispatch of the proposed higher order cost polynomials. Constraint management is incorporated in the MPSO and no extra concentration is needed for the higher order cost functions of single or multiple fuel units in the proposed method.

Lambda iteration, gradient method [2], [3] and [4] can solve simple ELD calculations and they are not sufficient for real applications in deregulated market. However, they are fast. There are several Intelligent methods among them genetic algorithm applied to solve the real time problem of solving the economic load dispatch problem [7],[8].where as some of the works are done by Evolutionary algorithm [9],[10],[13].Few other methods like tabu search are applied to solve to solve the problem [12].

Artificial neural network are also used to solve the optimization problem [14],[15].However many people applied the swarm behavior to the problem of optimum dispatch as well as unit commitment problem [16],[17],[18],[19],[20] and [21] are general purpose; however, they have randomness. For a practical problem, like ELD, the intelligent methods should be modified accordingly so that they are suitable to solve economic dispatch with more accurate multiple fuel cost functions and constraints, and they can reduce randomness.

Intelligent methods are iterative techniques that can search not only local optimal solutions but also a global optimal solution depending on problem domain and execution time limit. They are general-purpose searching techniques based on principles inspired from the genetic and evolution mechanisms observed in natural systems and populations of living beings. These methods have the advantage of searching the solution space more thoroughly. The main difficulty is their sensitivity to the choice of parameters. Among intelligent methods, PSO is simple and promising. It requires less computation time and memory. It has also standard values for its parameters.

J.H.Park, I.K.Eong, Y.S. Kin, and K.Y.Lee [22] proposed Hopfield (neural network) method. Hopfield method solved the ELD problem with the cost function represented as a piecewise quadratic function instead of convex function. It is suitable for large number of generators. The advantage of real time response favours application of hardware. Po-Hung and Hong-Chan Chang [23] applied genetic algorithms to solve the economic load dispatch problem. In case of dispatch on a large scale GA solution time increases with the increase in generator units. This algorithm can be used worldwide. Owing to its flexibility it can deal with ramp-rate limits, restricted zones of operation and losses in the network.

Zee-Lee Gaing [24] used PSO to solve ELD. It considers the non-linear characteristics of the generators. The feasibility of PSO was checked and it was found to be superior to Genetic Algorithms. PSO gives high quality solutions, computational efficiency and better characteristics of convergence. T. A. Albert Victoire, A. E. Jeyakumar [25] combined PSO (particle swarm optimization) and SQP (sequential quadratic programming) to solve the economic load dispatch (ELD) problem. PSO acts as the main optimizer and SQP adjusts the refinement in every solution of the PSO. SQP is a non-linear programming technique used to solve constrained optimization problem. It showed high efficiency and accuracy. The property of convergence is not strained; it depends on incremental-cost-function. The combination PSO-SQP offers fast convergence characteristics and high quality solutions. This method is more practical as it can be employed in prohibited zone and with the consideration of network losses and valve-point effects.

Authors Yi Da, and G. Xiurun [26] proposed SA (simulated annealing) to improve PSO. They introduced the idea of SAPSO-based-ANN. Three-layer feed-forward neural network was employed. It consists of one hidden, one input and one output layer. SAPSO-based ANN proved to be superior to PSO-based ANN. Owing to its flexibility it was employed to solve many other problems.

In the present work, the Rao algorithm is proposed as a methodology for economic load dispatch. The numerical example of three generating units and six generating units has taken to solve the ELD problem. The simulation results are compared with the conventional and other optimization algorithms available in the literature.

2. Problem Formulation

2.1 Objective Function

The objective function of the ELD problem is to minimize the total generation cost while satisfying the different constraints, when the necessary load demand of a power system is being supplied. The objective function to be minimized is given by the following equation:

$$F(P_g) = \sum_{i=1}^{n} (a_i P_{gi}^2 + b_i P_{gi} + c_i) \tag{1}$$

2.2 Constrains

1) Power balance constraint

The total generation by all the generators must be equal to the total power demand and system's real power loss.

$$\sum_{i=1}^{n} P_{gi} - P_d - P_l \tag{2}$$

2) Generator limit constraint

The real power generation of each generator is to be controlled within its particular lower and upper operating limits.

$$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max} \text{ I } =1,2,\dots,\text{ng} \tag{3}$$

3. SOLUTION METHODOLOGY

3.1 Overview of RAO algorithm

In recent years the field of population based meta-heuristic algorithms is flooded with a number of 'new' algorithms based on metaphor of some natural phenomena or behavior of animals, fishes, insects, societies, cultures, planets, musical instruments, etc. Many new optimization algorithms are coming up every month and the authors claim that the proposed algorithms are 'better' than the other algorithms. Some of these newly proposed algorithms are dying naturally as there are no takers and some have received success to some extent. However, this type of research may be considered as a threat and may not contribute to advance the field of optimization (Sorensen, 2015). It would be better if the researchers focus on developing simple optimization techniques that can provide effective solutions to the complex problems instead of looking for developing metaphor based algorithms. Keeping this point in view, three simple metaphors-less and algorithm-specific parameter-less optimization algorithms are developed in this paper. The next section describes the proposed algorithms.

Let $f(x)$ is the objective function to be minimized (or maximized). At any iteration i, assume that there are 'm' number of design variables, 'n' number of candidate solutions (i.e. population size, k=1,2,…,n). Let the best candidate best obtains the best value of $f(x)$ (i.e. $f(x)$best) in the entire candidate solutions and the worst candidate worst obtains the worst value of $f(x)$ (i.e. $f(x)$worst) in the entire candidate solutions. If $X_{j,k,i}$ is the value of the j^{th} variable for the k^{th} candidate during the i^{th} iteration, then this value is modified as per the following equations.

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i}\,(X_{j,best,i} - X_{j,worst,i}), \tag{4}$$

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i}\,(X_{j,best,i} - X_{j,worst,i}) + r_{2,j,i}\,(\,|X_{j,k,i} \text{ or } X_{j,l,i}| - |X_{j,l,i} \text{ or } X_{j,k,i}|\,), \tag{5}$$

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i}\,(X_{j,best,i} - |X_{j,worst,i}|) + r_{2,j,i}\,(\,|X_{j,k,i} \text{ or } X_{j,l,i}| - (X_{j,l,i} \text{ or } X_{j,k,i})), \tag{6}$$

Where, $X_{j,best,i}$ is the value of the variable j for the best candidate and $X_{j,worst,i}$ is the value of the variable j for the worst candidate during the ith iteration. $X'_{j,k,i}$ is the updated value of $X_{j,k,i}$ and $r_{1,j,i}$ and $r_{2,j,i}$ are the two random numbers for the j^{th} variable during the ith iteration in the range [0, 1].

In Eqns. (5) and (6), the term $X_{j,k,i}$ or $X_{j,l,i}$ indicates that the candidate solution k is compared with any randomly picked candidate solution and the information is exchanged based on their fitness values. If the fitness value of kth solution is better than the fitness value of l^{th} solution then the term "$X_{j,k,i}$ or $X_{j,l,i}$" becomes $X_{j,k,i}$. On the other hand, if the fitness value of l^{th} solution is better than the fitness value of kth solution then the term "$X_{j,k,i}$ or $X_{j,l,i}$" becomes $X_{j,l,i}$. Similarly, if the fitness value of kth solution is better than the fitness value of l^{th} solution then the term "$X_{j,l,i}$ or $X_{j,k,i}$" becomes $X_{j,l,i}$. If the fitness value of lth solution is better than the fitness value of kth solution then the term "$X_{j,l,i}$ or $X_{j,k,i}$" becomes $X_{j,k,i}$.

3.2 Implementation of RAO Algorithm for ELD Problem

When any optimization process is applied to the ELD problem some constraints are considered. In this work two different constraints are considered. Among them the equality constraint is summation of all the generating power must be equal to the load demand and the inequality constraint is the powers generated must be within the limit of maximum and minimum active power of each unit. The flow chart of the ELD problem by proposed method is shown in fig. 1.The sequential steps of the proposed Rao method are given below.

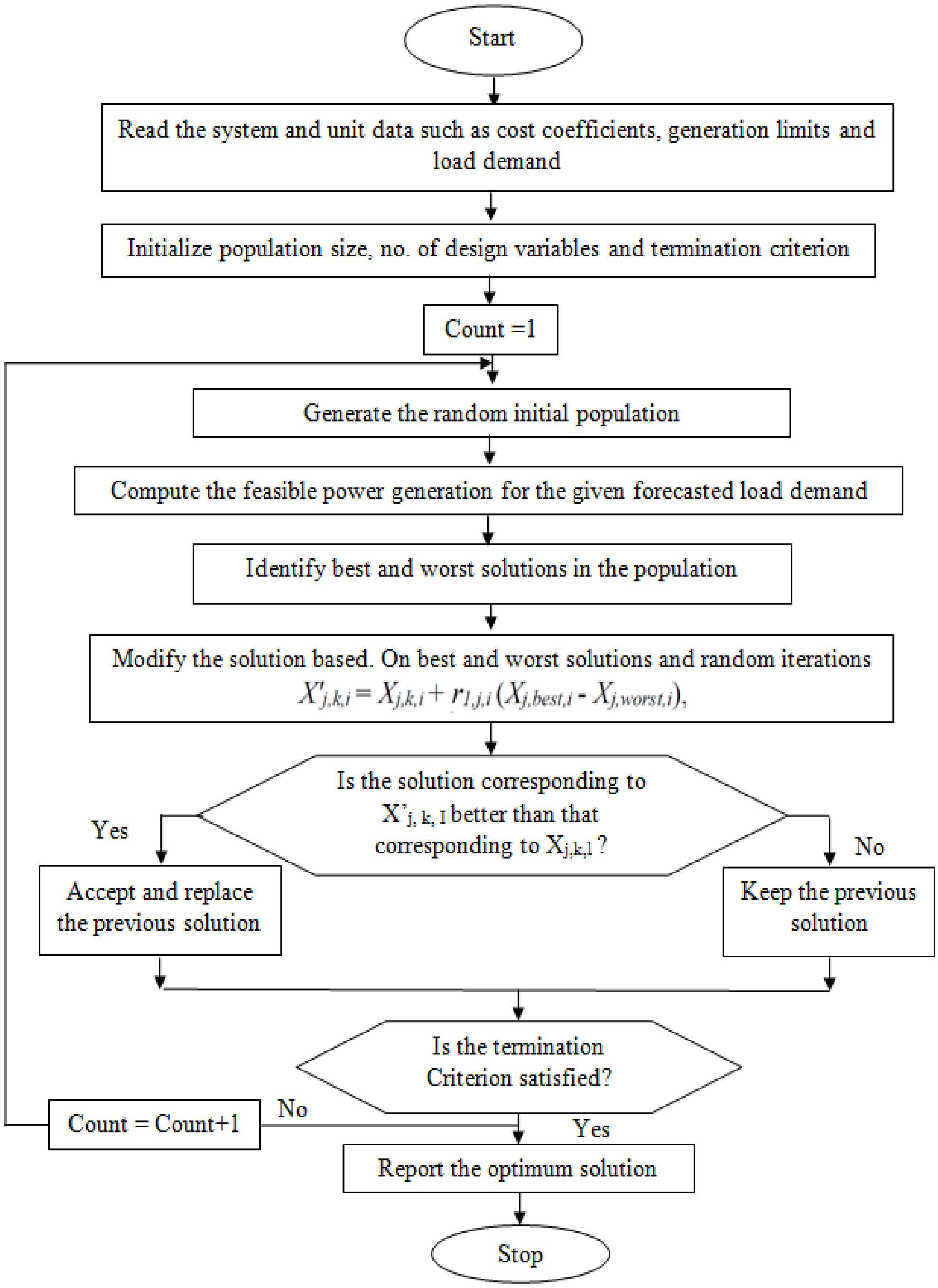

Figure.1 Flowchart for ED problem using Rao-1 algorithm

Step 1: Read the system and unit data of proposed test system such as cost coefficients, generator limits and load demand.

Step 2: The individuals of the population are randomly initialized according to the limit of each unit including individual dimensions. These initial individuals must be feasible candidate solutions that satisfy the practical operation constraint

Step 3: Each set of solution in the space should satisfy the equality constraints .So equality constraints are checked. If any combination doesn't satisfy the constraints then they are set according to the power balance equation.

Step 4: The evaluation function of each individual Pgi, is calculated in the population using the evaluation function F in equation (1). Here F is

$$F = a \times (P_{gi})^2 + b \times P_{gi} + c$$

Where a, b, c are constants.

Step 5: Each value is compared with the other values in the population and store the best evaluation value.

Step 6: Update the optimal solution of the system variable (power generation) using the equation (6)

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i}\left(X_{j,best,i} - \left|X_{j,worst,i}\right|\right) + r_{2,j,i}\left(\left|X_{j,k,i} \text{ or } X_{j,l,i}\right| - \left(X_{j,l,i} \text{ or } X_{j,k,i}\right)\right),$$

Step 7: Check weather all constraints of thermal units and meet the system load demand are satisfied no means go to next step otherwise got to step 9.

Step 8: Call Rao algorithm and determine optimal solution of thermal power generation and Total operating cost of the system.

Step 9: Step 8: Check whether the optimal solution is reached yes means go to next step else go to step 3.

Step 10: Save the best solution & Print the results and STOP.

4. Results and Discussion

Rao algorithm has been used to solve the ELD problems in three different test cases for exploring its optimization potential, where the objective function was limited within power ranges of the generating units. The iterations performed for each test case are 500 and number of search agents (population) taken in both test cases is 30.

4.1 Test System I: Three Unit test system

The input data for three generators is derived from reference [19] and is given in Table 1. This table includes cost coefficients and generator limits of three unit test system. According to the constraints considered in this work among inequality constraints only active power constraints are constraints are considered. There operating limit of maximum and minimum power are also different.

Table.1. Generating Unit Data for three unit test system

Unit	a_i	b_i	c_i	P_{gi}^{min}	P_{gi}^{max}
1	0.03546	38.30553	1243.531	35	210
2	0.02111	36.32782	1658.5696	130	325
3	0.01799	38.27041	1356.6592	125	315

Table. 2. Simulation results of proposed three unit test system

Sl. No	Power Demand (MW)	P1 (MW)	P2 (MW)	P3 (MW)	Fuel Cost (Rs/hr)	Time in sec
1	400	126.4884	130.0000	142.3071	20479.82037	2.5
2	500	101.1910	187.6933	211.2065	24923.61614	3.00
3	600	135.1889	207.0749	259.1532	29519.89759	3.50

Table. 3. Comparison of fuel cost of proposed three unit test system

Sl.	Power	Fuel Cost (Rs/hr)

No	Demand (MW)	Lambda Iteration [19]	FFA [19]	ALO [27]	RAO (Proposed)
1	400	20817.4	20812.3	20812.2936	20479.82037
2	500	25495.2	25465.5	25465.46914	24923.61614
3	600	30359.3	30334.0	30333.9858	29519.89759

The proposed RAO algorithm is effectively optimized and determines the optimal generation scheduling of three thermal units. The simulation results proposed three unit test system is given in Table 2. This table explains the optimal power schedule, minimum fuel cost and computational time for various power demands of 400 MW, 500 MW and 600 MW respectively.

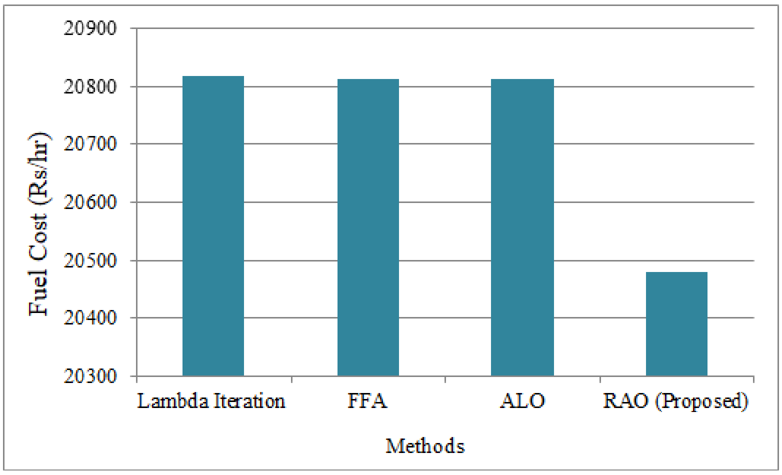

Figure.2 Comparison of fuel cost of proposed with existing methods

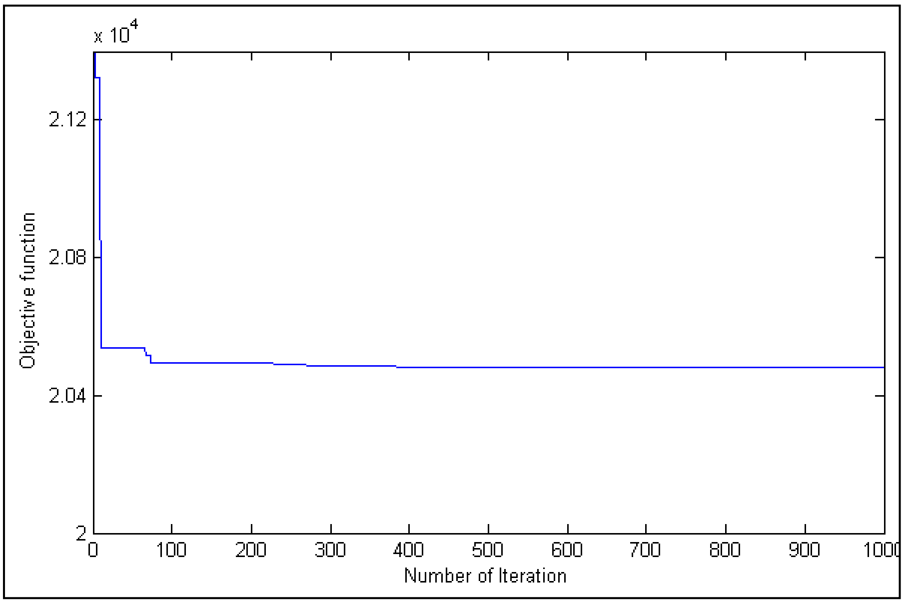

Figure.3 Convergence curve of proposed 3 unit test system

After, the simulation results are compared with the other available methods of Lambda Iteration [19], FFA [19] and ALO [27] and given in Table 3. From the results the proposed method provides minimum cost with less computational time compared with existing methods.

4.2 Test System 2: IEEE-30 bus test system (Six Generating Units)

The input data for six generators is derived from reference [19] and is given in table 3 .this table includes cost coefficients and generator limits. According to the constraints considered in this work among inequality constraints only active power constraints are constraints are considered. There operating limit of maximum and minimum power are also different.

Table. 4. Generating Unit Data for IEEE-30 bus test system (6 Generating Units)

Unit	a_i	b_i	c_i	P_{gi}^{min}	P_{gi}^{max}
1	0.15240	38.53973	756.79886	10	125
2	0.10587	46.15916	451.32513	10	150
3	0.02803	40.39655	1049.9977	35	225
4	0.03546	38.30553	1243.5311	35	210
5	0.02111	36.32782	1658.5596	130	325
6	0.01799	38.27041	1356.6592	125	315

Table. 5. Simulation results of proposed IEEE-30 bus test system

Sl. No	Power Demand (MW)	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)	Fuel Cost (Rs/hr)	Time in sec
1	600	45.9257	22.6266	189.8635	35.0000	136.4747	166.7282	31445.14784	5.00
2	700	10.0000	39.6412	43.3142	114.7405	325.0000	167.3121	36002.90575	5.25
3	800	46.6824	76.4170	162.2427	73.1301	262.2235	181.9774	40675.61407	5.5.
4	850	43.6825	125.4858	175.7687	163.1786	189.3567	154.5693	43055.65843	5.80
5	900	55.9135	107.3197	138.1643	81.4086	310.9411	187.9870	45463.53897	6.00

Table. 6. Comparison of fuel cost of proposed IEEE-30 bus test system

Sl. No	Power Demand (MW)	Fuel Cost (Rs/hr)					
		GA [2]	PSO [2]	Lambda Iteration [19]	FFA [19]	ALO [27]	RAO (proposed)
1	600	32091.68	32091.68	32132.1	32094.7	32094.6783	31445.14784
2	700	36913.7	36912.2	36914.1	36912.2	36912.20	36002.90575
3	800	41926.6	41896.2	41927.1	41896.9	41896.6286	40675.61407
4	850	44456.28	44452.08	44452.1	-	-	43055.65843
5	900	49682.7	49681.38	49683.1	-	-	45463.53897

The validity proposed RAO algorithm is tested on six unit test system. The control parameters of effectively optimized and determines the optimal generation scheduling of six thermal units. The simulation results proposed three unit test system is given in Table 4.

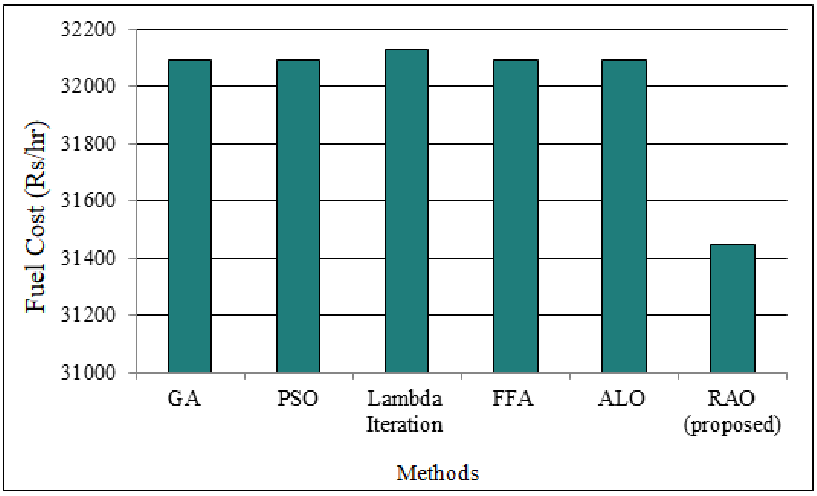

Figure. 4. Comparison of fuel cost of proposed with existing methods

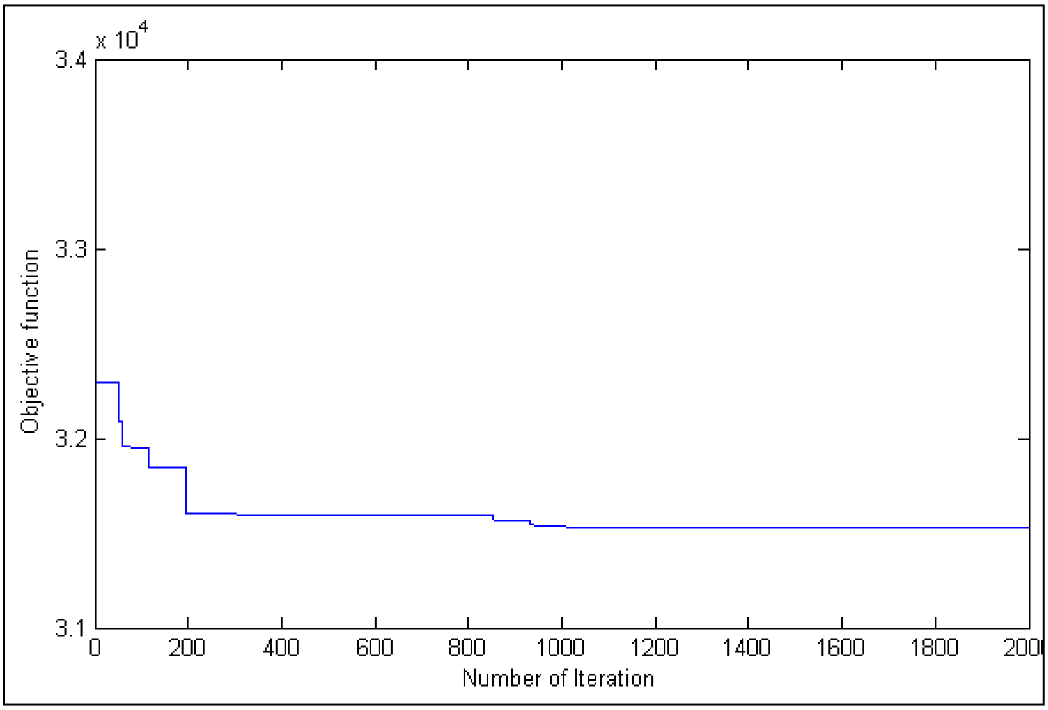

Figure. 5. Convergence curve of proposed IEEE-30 bus test system

This table explains the optimal power schedule, minimum fuel cost and computational time for various power demands of 600 MW, 700 MW, 800 MW, 850 MW and 900 MW respectively. After, the simulation results are compared with the other available methods of Lambda Iteration [2], GA [2], PSO [19], FFA [19] and ALO [27] and given in Table.6. From the results the proposed method provides minimum cost with less computational time compared with existing methods.

5. Conclusion

Economic load dispatch in electric power sector is an important task, as it is required to supply the power at the minimum cost which aids in profit-making. As the efficiency of newly added generating units are more than the previous units the economic load dispatch has to be efficiently solved for minimizing the cost of the generated power.

In this work optimal load dispatch problem has been solved by using Rao algorithm. The results of Rao algorithm are compared for three and six generating unit systems with other techniques. The algorithm is programmed in MATLAB software package. The results display efficacy of Rao algorithm for solving the optimal load dispatch problem. The advantage of Rao algorithm is its simplicity, reliability and efficiency for practical applications.

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