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Economic Load Dispatch in Power System Networks Using Optimization Techniques

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Abstract- Practical economic dispatch (ED) problems have highly non-linear objective function with rigid equality and inequality constraints. Particle swarm optimization (PSO) is applied to allot the active power among the generating stations satisfying the system constraints and minimizing the cost of power generated. The viability of the method is analyzed for its accuracy and rate of convergence. The economic load dispatch problem is solved for two, three and six-unit system using PSO and conventional method for both cases of neglecting and including transmission losses. The results of PSO method were compared with conventional method and were found to be superior. The conventional optimization methods are unable to solve such problems due to local optimum solution convergence. The optimization technique is constantly evolving to provide better and faster results.

Key Words: Economic Dispatch (ED), Particle Swarm Optimization (PSO).

1.INTRODUCTION:

The Economic Load Dispatch (ELD) problem is one of the fundamental issues in power system operation. The main objective is to reduce the cost of energy production considering the transmission losses. In the past decade, conventional optimization techniques such as lambda iterative method, linear programming and quadratic programming have been successfully used to solve power system optimization problems such as Unit commitment, Economic load dispatch, Feeder reconfiguration and Capacitor placement in a distribution system[1]. The conventional methods are facing difficulties to locate the global optimal solution. Recently there is an upsurge in the use of modern evolutionary computing techniques in the field of power system optimization.

Methods like dynamic programming, genetic algorithm(GI),sine-cosine algorithm(SCA), evolutionary programming, artificial intelligence(AI), and particle swarm optimization(PSO) solve non-convex optimization problems efficiently and often achieve a fast and near global optimal solution. Among them PSO was developed through simulation of a simplified social system, and has been found to be robust in solving continuous non-linear optimization problems. The PSO technique can generate high-quality solutions within shorter calculation time and stable convergence characteristics.

Particle Swarm Optimization (PSO), first introduced by Kennedy and Eberhart, is one of the modern heuristic algorithms. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous non-linear optimization problems[3,4].The PSO technique can generate high-quality solutions within shorter calculation time and stable convergence characteristics than other stochastic methods. Unlike in GA method, in PSO the selection operation is not performed. All the particles in PSO are kept as members of the population through the course of a run (a run is defined as the total number of generations of the evolutionary algorithms prior to termination). It is the velocity of the particle which is updated according to its previous best position of its companions. The particles fly with the updated velocities. This paper proposes the application of PSO method for solving the economic load dispatch of three example problems, that is,

Two-unit, Three-unit & six-unit thermal plant systems and the results of conventional method with particle swarm optimization method and

2.PROBLEM FORMULATION:

Power stations or power plants are the industrial facilities for the generation of electric power. The type of the power station is determined according to the type of energy source utilized to turn the generator which differs vastly. Most power plants all over the world burn fossil fuels as coal, natural gas and oil to generate electricity. While nowadays there is an increase in the usage of clean energy sources as nuclear power and renewables as wind, solar, hydroelectric and geothermal. For example, the nuclear power plants operate at constant output levels. While at hydro-stations, storing energy is apparently free so the operating costs do not carry any meaning. Therefore, only the fuel burnt cost in fossil plants shares to the dispatching process. The generator’s operational costs include fuel, labor and maintenance. Costs of supplies, labor and maintenance are excluded since these are a fixed proportion of incoming fuel cost. Then only the fuel cost has to be considered[5].

The thermal power plant input is expressed in Btu/h. Active power output can be expressed in MW. In fossil fuel plants the output power is increased sequentially at the inlet of a steam-turbine by opening the valves. When a valve is just open, the throttling losses become large and when it is fully opened, throttling losses become smaller. The objective economic dispatch (ED) problem is to minimize the fuel cost level of a power system over some appropriate period, while satisfying various constraints.

2.1 OBJECTIVE FUNCTION:

The objective function for the ELD reflects the costs associated with generating power in the system. The quadratic cost model is used. The objective function for the entire power system can then be written as the sum of the quadratic cost model for each generator[1].

The fuel cost curve may be modelled as a quadratic function of active power as shown below,

$$\text{Minimize } F_t = \sum_{i=1}^{n} F_i(P_i) \quad \ldots\ldots\ldots (1)$$

$$\text{Where } F_t = \sum_{i=1}^{n} A_i P_i^2 + B_i P_i + C_i \quad \ldots\ldots. (2)$$

2.2 SYSTEM CONSTRAINTS: Generally, there are two types of constraints:

1. Equality constraints
2. Inequality constraints

2.2.1 EQUALITY CONSTRAINTS:

The equality constraints are the basic load flow equations of active and reactive power.

$$\sum_{i=1}^{n} P_i - P_D - P_L = 0 \quad \ldots\ldots.. (3)$$

2.2.2 INEQUALITY CONSTRAINTS:

(a). Generator Constraints: The KVA loading of a generator can be represented as $\sqrt{P^2 + Q^2}$. The KVA loading should not exceed a pre-specified value to limit the temperature rise. The maximum active power generated 'P' from a source is also limited by thermal consideration to keep the temperature rise within limits. The minimum power generated is limited by the flame instability of the boiler. If the power generated out of a generator falls below a pre-specified value P min, the unit is not put on the bus bar.

$$P\ min \le P \le P\ max \quad \ldots\ldots\ldots (4)$$

The maximum reactive power is limited by overheating of rotor and minimum reactive power is limited by the stability limit of machine. Hence the generator reactive powers Q should not be outside the range stated by inequality for its stable operation.

$$Q\ min \le Q \le Q\ max \quad \ldots\ldots\ldots (5)$$

(b) Voltage Constraints:

The voltage magnitudes and phase angles at various nodes should vary within certain limits. The normal operating angle of transmission should lie between 30 to 45 degrees for transient stability reasons.

$$V\ min \le V \le V\ max \quad \ldots\ldots\ldots. (6)$$

A higher operating angle reduces the stability during faults and lower limit of delta assures proper utilization of the available transmission capacity.

3.PARTICLE SWARM OPTIMIZATION:

PSO, as an optimization tool, provides a population-based search procedure in which individuals called particles change their position (states) with time. In a PSO system particles fly around in a multi-dimensional search space[3,7]. During flight, each particle adjusts its position according to its own experience and the experience of neighboring particles, making use of the best position encountered by it and neighbors. The swarm direction of a particle is defined by the set of particles neighboring the particle and its history experience[4]. Instead of using evolutionary operation to manipulate the individuals, like in other evolutionary computational algorithms, each individual in PSO flies in the search space with a velocity which is dynamically adjusted according to its own flying experience and its companions flying experience.

Let x and v denote a particle co-ordinate (position) and its corresponding flight speed (velocity) in a search space respectively. Therefore, each i^{th} particle is treated as a volume less particle, represented as x_i= (x_{i1}, x_{i2} …x_{id}) in the d - dimensional space. The best previous position of the ith particle is recorded and represented as p$best_i$= (p$best_{i1}$, p$best_{i2}$,…. p$best_{id}$). The index of the best particle among all the particles is treated as global best particle, is represented as $gbest_d$. The rate of velocity for particle 'i' is represented as v_i= (v_{i1}, v_{i2} …v_{id}). The modified velocity and position of each particle can be calculated using the current velocity and the distance from p$best_{id}$ to g$best_{id}$ as shown in the following formulas,

$$V_{id}^{(t+1)} = \omega V_i^{(t)} + C_1 \text{rand( )}(pbest_{id} - P_{gid}^{(t)}) + C_2 \text{Rand( )}(gbest_{id} - P_{gid}^{(t)}) \quad \ldots\ldots\ldots\ldots (7)$$

$$P_{gid}^{(t+1)} = P_{gid}^{(t)} + V_{id}^{(t+1)} \quad \ldots\ldots\ldots\ldots. (8)$$

In the above equation, C1 has a range (1.5, 2), which is called self-confidence range; C2 has a range (2, 2.5), which is called swarm range.

The term rand ( )*($pbest_{id}$- $P_{gid}^{(t)}$) is called particle memory influence.

The term Rand ( )*($gbest_{id}$- $P_{gid}^{(t)}$) is called swarm influence. $v_i^{(t)}$ which is the velocity of ith particle at iteration 't' must lie in the range $V_d^{(min)} \leq v_i^{(t)} \leq V_d^{(max)}$. The parameter $V_d^{(max)}$ determines the resolution, or fitness, with which regions are to be searched between the present position and the target position. If $V_d^{(max)}$. is too high, particles may fly past good solutions. If $V_d^{(max)}$. is too small, particles may not explore sufficiently beyond local solutions. In many experiences with PSO, $V_d^{(max)}$. was often set at 10-20% of the dynamic range on each dimension[3].

The constants C1 and C2 pull each particle towards Pbest and Gbest positions. Low values allow particles to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement towards, or past, target regions[4]. Hence, the acceleration constants C1 and C2 are often set to be 2.0 according to past experiences. Suitable selection of inertia weight 'ω' provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. As originally developed, ω often decreases linearly from about 0.9 to 0.4 during a run. In general, the inertia weight w is set according to the following equation,

$$\omega = \omega_{max} - [\frac{\omega_{max} - \omega_{min}}{iter_{max}}]*iter \quad ....(9)$$

where ω – inertia weight factor
ω_{max} – maximum value of weighting factor
ω_{min} – minimum value of weighting factor
$iter_{max}$ – maximum number of iterations
iter – current number of iteration

3.1 APPLICATION OF PSO METHOD TO ECONOMIC LOAD DISPATCH:

STEPS OF IMPLEMENTATION:

1. Initialize the Fitness Function i.e., Total cost function from the individual cost function of the various generating stations.
2. Initialize the PSO parameters Population size, C1, C2, ω_{max}, ω_{min}, error gradient etc.
3. Input the Fuel cost Functions, MW limits of the generating stations along with the B-coefficient matrix and the total power demand.
4. At the first step of the execution of the program a large no (equal to the population size) of vectors of active power satisfying the MW limits are randomly allocated.
5. For each vector of active power the value of the fitness function is calculated. All values obtained in an iteration are compared to obtain Pbest. At each iteration all values of the whole population till then are compared to obtain the Gbest. At each step these values are updated.
6. At each step error gradient is checked and the value of Gbest is plotted till it comes within the pre-specified range.
7. This final value of Gbest is the minimum cost and the active power vector represents the economic load dispatch solution.

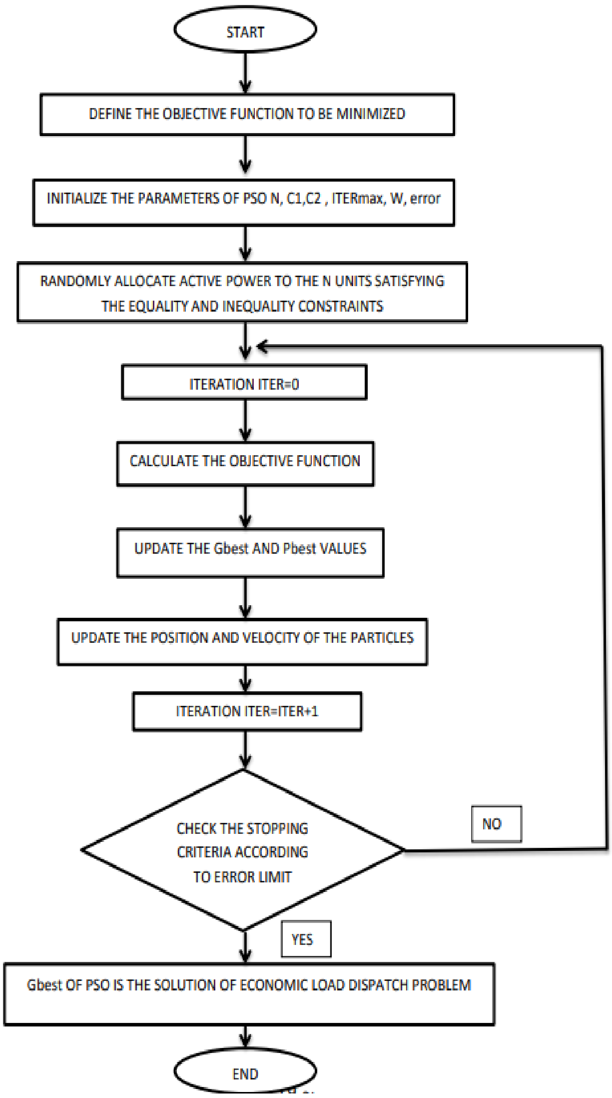

Fig -1: Flowchart of PSO Algorithm

4.EXAMPLE PROBLEM AND SIMULATION RESULTS:.

To verify the feasibility of the proposed PSO method, three different power systems were tested. At each sample system, under the same evaluation function and individual definition, we performed 50 trials to observe the evolutionary process and to compare their solution quality, convergence characteristic, and computation efficiency.

A reasonable Bmn loss coefficients matrix of power system network was employed to draw the transmission line loss and satisfy the transmission capacity constraints. The software is developed in MATLAB. Although the PSO method seems to be sensitive to the tuning of some weights or parameters, according to the experiences of many experiments, the following PSO parameters can be used [3, 7 and 8].

PSO Method Parameters: Population size = 100

Inertia weight factor w is set by (9),

where ω_{max} = 0.9 and ω_{min} = 0.4 ;

The limit of change in velocity of each member in an individual was as $V_d^{(max)}$=0.5 Pd max, $V_d^{(min)}$ =-0.5 Pd min; Acceleration constant C1 = 2 and C2 = 2;

4.1. Case study-1: TWO UNIT THERMAL SYSTEM:

The cost characteristics of the two units are given as

F1 = $0.00156P_1^2 + 7.92P_1 + 561$ Rs/Hr

F2 = $0.00194P_2^2 + 7.85\,P_2 + 310$ Rs/Hr

The unit operating ranges are:

100 MW $\le P_1 \le$ 600 MW

100 MW $\le P_2 \le$ 400 MW

Bmn Coefficient matrix:

$$Bmn=\begin{matrix} 0.000075 & 0 \\ 0 & 0 \end{matrix}$$

For the system loads of 585 MW, 600 MW,700 MW and 800 MW, the proposed PSO method is applied and the results obtained for loss neglected case are shown in Table 1. The results obtained by the proposed method is compared with the solution obtained from conventional method and is shown in Table 2. The comparison of results shows that the proposed algorithm is very reliable in the aspect of solution quality.

Table 1: Optimal Scheduling of Generators of a Two-unit system by PSO Method (Loss neglected case)

S.NO	POWER DEMAND (MW)	P1(MW)	P2(MW)	TOTAL FUEL COST(Rs/hr)
1	585	314.2571	270.7429	5771.5151
2	600	322.5714	277.4286	5913.2169
3	700	378.000	322.000	6813.506
4	800	433.4286	366.5714	7725.0889

Table 2: Comparison of results between Conventional method and PSO method for Two-unit system (Loss Neglected Case).

S.NO	POWER DEMAND (MW)	Conventional Method (Rs/Hr)	PSO Method (Rs/Hr)
1	585	5779.0	5771.5151
2	600	5914.60	5913.2169
3	700	6814.90	6813.506
4	800	7726.10	7725.0889

By using the loss formula co-efficients the transmission loss has been calculated and the above problem is solved for power demands of 400MW,585MW,600MW and 700 MW. The optimal scheduling of generators obtained by the proposed PSO algorithm for two-unit system is shown in Table3.

Table 3: Optimal Scheduling of Generators of a Two-unit system by PSO Method (Loss included case)

S.NO	POWER DEMAND (MW)	P1(MW)	P2(MW)	PL(MW)	TOTAL FUEL COST(Rs/hr)
1	400	179.5260	222.8912	2.4172	4181.2003
2	585	265.3757	324.9061	5.2818	5828.9446
3	600	272.3036	333.2576	5.5612	5965.8471
4	700	318.3760	389.2263	7.6022	6889.995

Table 4: Comparison of results between Classical Method and PSO method of a Two- unit system (Loss included Case)

S.NO	POWER DEMAND (MW)	Conventional Method (Rs/Hr)	PSO Method (Rs/Hr)
1	400	4182.3	4181.2003
2	585	5829.5	5828.9446
3	600	5966.8	5965.8471
4	700	6890.9	6889.995

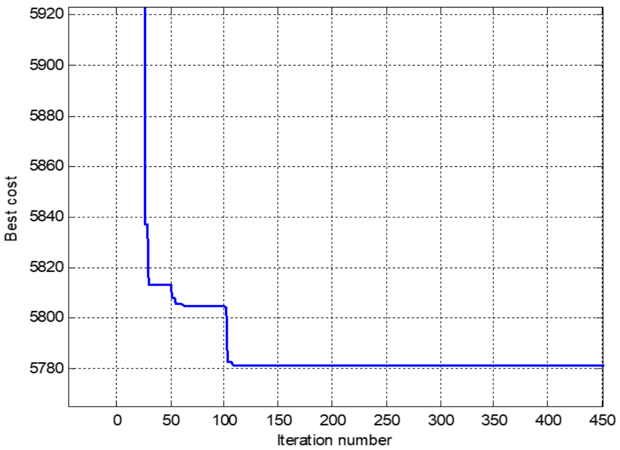

Fig.2 Convergence Characteristics for Two-unit System

4.2. Case study-2: THREE UNIT THERMAL SYSTEM:

The cost characteristics of the three units are given as

F1 = $0.00156P_1^2 + 7.92P_1 + 561$ Rs/Hr

F2 = $0.00194P_2^2 + 7.85\,P_2 + 310$ Rs/Hr

F3= $0.00482P_3^2 + 7.97\,P_3 + 78$ Rs/Hr

The unit operating ranges are:

100 MW $\le P_1 \le$ 600 MW

100 MW $\le P_2 \le$ 400 MW

50 MW $\le P_3 \le$ 200 MW

Bmn Coefficient matrix:

$$Bmn=\begin{matrix} 0.000075 & 0.000005 & 0.0000075 \\ 0.001940 & 0.000015 & 0.0000100 \\ 0.004820 & 0.000100 & 0.0000450 \end{matrix}$$

For the system loads of 585 MW, 700 MW and 800 MW, the proposed PSO method is applied and the results obtained for loss neglected case are shown in Table 5. The results obtained by the proposed method is compared with the solution obtained from conventional method is shown in Table 6. The comparison of results shows that the proposed algorithm is very reliable in the aspect of solution quality.

Table 5: Optimal Scheduling of Generators of a Three-unit system by PSO Method (Loss neglected case)

S.NO	POWER DEMAND (MW)	P1(MW)	P2(MW)	P3(MW)	TOTAL FUEL COST(Rs/hr)
1	585	268.8938	234.2651	81.8411	5821.4392
2	700	322.9408	277.7256	99.3336	6838.4143
3	800	369.9383	315.5174	114.5443	7738.5035

Table 6: Comparison of results between Conventional method and PSO method for Three-unit system (Loss Neglected Case).

S.NO	POWER DEMAND (MW)	Conventional Method (Rs/Hr)	PSO Method (Rs/Hr)
1	585	5821.80	5821.4392
2	700	6838.480	6838.4143
3	800	7738.60	7738.5035

By using the loss formula co-efficients the transmission loss has been calculated and the above problem is solved for power demands of 585.33 MW and 812.57 MW. The optimal scheduling of generators obtained by the proposed PSO algorithm for three-unit system is shown in Table 7. The comparisons of results obtained by optimization techniques have been shown in Table-8. From Table 8, it was found that the proposed method is capable of giving improved solution for the above problem compared with other method.

Table 7: Optimal Scheduling of Generators of a Three-unit system by PSO Method (Loss included case)

S.NO	POWER DEMAND (MW)	P1(MW)	P2(MW)	P3(MW)	PL(MW)	TOTAL FUEL COST(Rs/hr)
1	585.33	244.0666	256.1469	92.3891	7.2726	5890.457
2	812.57	323.2987	367.5329	135.2656	13.5272	7977.0268

Table 8: Comparison of results between Classical Method and PSO method of a Three- unit system (Loss included Case)

S.NO	Power Demand(MW)	Conventional Method (Rs/Hr)	PSO Method (Rs/Hr)
1	585.33	5891.2	5890.457
2	812.57	7977.7	7977.0268

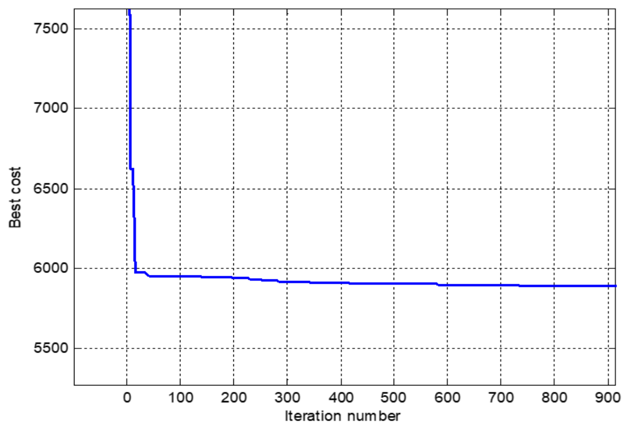

Fig.3 Convergence Characteristics for Three-unit System

4.3. Case study-3: SIX UNIT THERMAL SYSTEM:

The cost characteristics of the six units are given as follows:

$F1 = 0.15240P_1^2 + 38.53973 P_1 + 756.79886$ Rs/Hr

$F2 = 0.10587P_2^2 + 46.15916P_2 + 451.32513$ Rs/Hr

$F3= 0.02803P_3^2 + 40.39655P_3 + 1049.9977$ Rs/Hr

$F4 = 0.03546P_4^2 + 38.30553P_4 + 1243.5311$ Rs/Hr

$F5 = 0.02111P_5^2 + 36.32782P_5 + 1658.5596$ Rs/Hr

$F6= 0.01799P_6^2 + 38.27041P_6 + 1356.6592$ Rs/Hr

The unit operating ranges are

$10 \text{ MW} \le P_1 \le 125$ MW; $10 \text{ MW} \le P_2 \le 150$ MW;
$35 \text{ MW} \le P_3 \le 225$ MW; $35 \text{ MW} \le P_4 \le 210$ MW;
$130 \text{ MW} \le P_5 \le 325$ MW; $125 \text{ MW} \le P_6 \le 315$ MW

Bmn Coefficient matrix:

Bmn=

0.000140	0.000017	0.000015	0.000019	0.000026	0.000022
0.000017	0.000060	0.000013	0.000016	0.000015	0.000020
0.000015	0.000013	0.000065	0.000017	0.000024	0.000019
0.000019	0.000016	0.000017	0.000071	0.000030	0.000025
0.000026	0.000015	0.000024	0.000030	0.000069	0.000032
0.000022	0.000020	0.000019	0.000025	0.000032	0.000085

The above test case was solved by the proposed PSO method and the optimal scheduling of generators for the power demands of 800 MW,900 MW & 1000 MW is tabulated in Table 9. The results obtained by the proposed algorithm are compared with other optimization technique as shown in Table 10. From the above comparison it is found that the results obtained by the proposed algorithm is less and the computation time also reasonable.

Table 9: Optimal Scheduling of Generators of a six-unit system by PSO Method (Loss neglected case)

POWER DEMAND (MW)	P1(MW)	P2(MW)	P3(MW)	P4(MW)	P5(MW)	P6(MW)	TOTAL FUEL COST(Rs/hr)
800	29.5435	10.0000	121.0306	128.5244	255.8622	255.0391	40676.9326
900	34.6974	10.0000	132.6364	134.9847	289.1097	298.5718	45464.0734
1000	36.1950	16.4321	162.6086	158.1843	320.5402	306.0397	50365.8715

Table 10: Comparison of results between Conventional method and PSO method for six-unit system (Loss Neglected Case).

S.NO	Power Demand(MW)	Conventional Method (Rs/Hr)	PSO Method (Rs/Hr)
1	800	40681	40676.9326
2	900	45465	45464.0734
3	1000	50370	50365.8715

Table 11: Optimal Scheduling of Generators of a six-unit system by PSO Method (Loss included case)

POWER DEMAND (MW)	P1(MW)	P2(MW)	P3(MW)	P4(MW)	P5(MW)	P6(MW)	PL(MW)	TOTAL FUEL COST(Rs/hr)
800	32.7647	20.5009	144.5165	155.7834	251.3302	219.7529	24.6486	41897.8437
900	35.3787	21.8020	162.5203	155.8363	293.5142	262.8978	31.9493	47047.9020
1000	43.0419	25.1588	183.1036	174.2645	309.0934	304.9389	39.6011	52363.5104

Table 12: Comparison of results between Classical Method and PSO method of a six- unit system (Loss included Case)

S.NO	Power Demand(MW)	Conventional Method (Rs/Hr)	PSO Method (Rs/Hr)
1	800	41899	41897.8437
2	900	47048	47047.9020
3	1000	52364	52363.5104

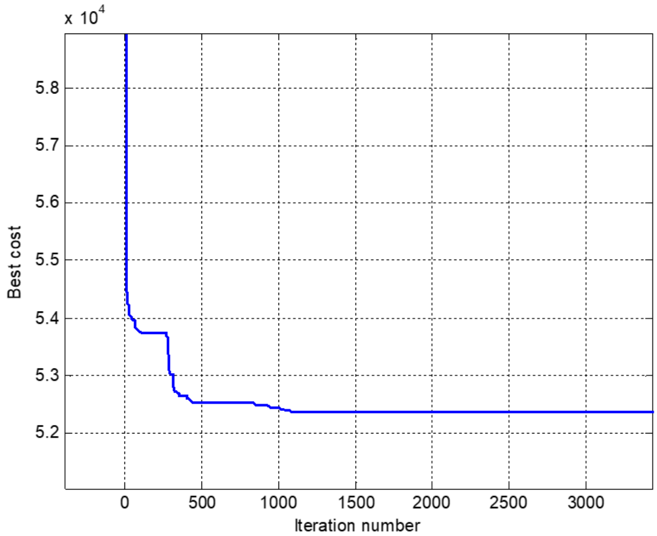

Fig.4 Convergence Characteristics for six-unit System

5.CONCLUSION:

In this paper, the PSO method was successfully employed to solve the ELD problem with all the constraints. The PSO algorithm has been demonstrated to have superior features including high quality solution, stable convergence characteristics, and less computation time. Many non-linear characteristics of the generators can be handled efficiently by the proposed method. The comparison of results for the test cases clearly shows that the proposed method was indeed capable of obtaining higher quality solution efficiently for ELD problems. Figure 4. Shows the convergence characteristics of the proposed algorithm for the six-unit system. In addition, in order to verify it being superior to conventional method.

It is clear from the results that the proposed PSO method can avoid the disadvantage of Conventional method and can obtain higher quality solution with better computation efficiency.

Advantages of PSO:

1. It only requires a fitness function to measure the 'quality' of a solution instead of complex mathematical operation like gradient or matrix inversion. This reduces the computational complexity and relieves some of the restrictions that are usually imposed on the objective function like differentiability, continuity or convexity.
2. It is less sensitive to a good initial solution since it is a population-based method.
3. It can be easily incorporated with other optimization tools to form hybrid ones.
4. It has the ability to escape local minima since it follows probabilistic transition rules.
5. It can be easily programmed and modified with basic mathematical and logical operations.
6. It is in-expensive in terms of computation time and memory.
7. It requires less parameter tuning.

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