ISSN: 2321-8169
3878 - 3885

Particle Swarm Optimization Technique with Time Varying Acceleration Coefficients for Load Dispatch Problem

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***Abstract*—** Economic load dispatch is a non linear optimization problem which is of great importance in power systems . While analytical methods suffer from slow conversion and curse of dimensionality particle swarm optimization can be an efficient alternative to solve large scale non linear optimization problem.A lot of advancements have been done to modify this algorithm. This paper presents an overview of Classical PSO and then PSO with TVAC. Results are compared first with GA then CPSO and PSO with TVAC.

***Keywords*—** Classical particle swarm optimization (CPSO), Particle swarm optimization with time varying coefficients(PSOTVAC),Swarm intelligence, non smooth cost functions.

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I. Introduction

Economic load dispatch (ELD) is a constrained optimization problem in power systems that have the objective off dividing the total power demand among the online participating generators economically while satisfying the equality constraints. The conventional methods include the lambda iteration methods [1, 2], base point and participation factors, etc. Among these methods lambda iteration is the most common method because of ease of implementation. The ELD is a non-convex optimization problem required rigours to solve by traditional methods.

Moreover, evolutionary and behavioural random search algorithms such as genetic algorithm (GA) [3], particle swarm optimization (PSO) [4] have been implemented on the ELD problem. Gas does possess some weaknesses leading to larger computation time premature convergence [5].

This paper proposes CPSO as an optimization technique to solve constrained quadratic cost function with generator constrained and power loss. Both algorithm are tested for three generator units and then for six generator. Results are compared with GA and lambda iteration method. The proposed methodology emerges as robust optimization techniques for solving the ELD problem for different size power system.

II. Problem Formulation

The classic ELD problem minimizes the following incremental fuel cost function associated to dispatch able units [6];

$$F_T = \sum_{i=1}^{N} F_i(P_i) \quad (1)$$

The inclusion of valve-point loading effects makes the modelling of the incremental fuel cost function of the generators more practical. This increases the non-linearity as well as number of local optima in the solution space. Also the solution procedure can easily trap in the local optima in the vicinity of optimal value. The incremental fuel cost function of the generating units with valve-point loadings are represented as follows [7]:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \quad (2)$$

Where a_i, b_i, c_i are coefficients

(a) real power balance;

$$\sum_{i=1}^{N} P_i = P_{Loss} + P_D$$

Where P_{Loss} calculated using the B-Matrix loss coefficients and expressed in the quadratic form as given below:

$$P_{loss} = \sum_{m=1}^{N} \sum_{n=1}^{N} P_m B_{mn} P_n \quad (3)$$

(b) Real power generation limit:

$$P_{imin} \le P_i \le P_{imax} \quad (4)$$

Where F_T total production cost (R/h); $F_i(P_i)$, incremental fuel cost function (R/h); P_i, real power output of the *i*th unit (MW); *N*, number of generating units; P_D, power demand (MW); P_{Loss}, power loss (MW); B_{mn}, transmission loss coefficients;

$P_{i\,min}$, minimum limit of the real power of the ith unit (MW);
$P_{i\,max}$, maximum limit of the real power of the ith unit (MW).

The problem of economic dispatch generation of real power is to be done to the required load demand by satisfying the above constrains.

III. Classical Particle Swarm Optimization (CPSO)

Particle swarm optimization was first introduced by Kennedy and Eberhart in the year 1995. It is an exciting new methodology in evolutionary computation and a population-based optimization tool like GA. PSO is motivated from the simulation of the behaviour of social systems such as fish schooling and birds flocking.

The PSO algorithm requires less memory because of its inherent simplicity. PSO is similar to the other evolutionary algorithms in that the system is initialized with a population of random solutions, call particle (swarm), flies in the d-dimension problem space with a velocity, which is dynamically adjusted according to the flying experiences of its own and colleagues. Swarms collect information from each other through an array constructed by their positions using the velocity of particles. Position and velocity are both updated by using guidance from particles' own experience and experience of neighbours.

The position and velocity vectors of the ith particle of a d-dimensional search space can be represented as $X_i = (x_{i1},x_{i2},\ldots..x_{id})$ and $V_i = (v_{i1},v_{i2},\ldots\ldots.v_{id})$, respectively. On the basis of the value of the evaluation function, the best previous position of a particle is recorded and represented as $p_{besti}= (p_{i1},p_{i2},\ldots\ldots.p_{id})$.If the gth particle is the best among all particles in the group so far, it is represented as P_{bestg} = G-best= $(p_{g1},p_{g2},\ldots\ldots.p_{gd})$.The particle tries to modify its position using the current velocity and the distance from pbest and gbest. The modified velocity and position of each particle for fitness evaluation in the next, that is, (k +1)th iteration, are calculated using following equations:

$$v_{id}^{(k+1)} = [W*v_{id}^{k} + c_1 *Rand_1()*(P_{bestid}- x_{id}^{k}) + c_2 *Rand_2()*(G_{best\,gd} - x_{id}^{k})] \quad (5)$$

$$x_{id}^{(k+1)} = x_{id}^{k} + v_{id}^{k+1} \quad (6)$$

Here W is the inertia weight parameter which controls the global and local exploration capabilities of the particle. c_1 and c_2 are cognitive and social coefficients, respectively, and $Rand_1(),Rand_2()$ are random numbers between 0 and 1. c_1 pulls the particles towards local best position and c_2 pulls towards the global best position. Usually these parameters are selected in the range of 0 to 4.

In the procedure of the particle swarm paradigm, the value of maximum allowed particle velocity V_{max} determines the resolution, or fitness, with which regions are to be searched between the present position and the target position. If V_{max} is too high, particles may fly past good solutions. If V_{max} is too small, particles may not explore sufficiently beyond local solutions. Thus, the system parameter V_{max} has the beneficial effect of preventing explosion and scales the exploration of the particle search.

Suitable selection of inertia weight W provides a balance between global and local explorations, thus requiring less iteration on an average to find a sufficiently optimal solution. Since W decreases linearly from about 0.9 to 0.4 quite often during a run, the following weighing function [27] is used in equation (5)

$$W = W_{max} - \frac{W_{max} - W_{min}}{iter_{max}} x\ iter \quad (7)$$

Where,

W_{max} is the initial weight,

W_{min} is the final weight,

$iter_{max}$ is the maximum iteration number, iter is the current iteration number.

The equation (5) is used to calculate the particle's new velocity according to its previous velocity and the distances of its current position from its own best experience (position) and the group's best experience. Then the particle flies towards a new position according to equation (6). The performance of each particle is measured according to a predefined fitness function, which is related to the problem to be solved.

A. Basic PSO Algorithm

The step by step procedure of PSO algorithm is given as follows:

1. Initialize a population of particles as
   $$P_i = (P_{i1}, P_{i2}, P_{i3}\ldots\ldots\ldots\ldots P_{iN}) \quad (8)$$
   ' N' is number of generating units.
   Population is initialized with random values and velocities within the d-dimensional search space. Initialize the maximum allowable velocity magnitude of any particle V_{max}. Evaluate the fitness of each particle and assign the particle's position to P-best position and fitness to P-best fitness. Identify the best among the P-best as G-best and store the fitness value of G-best.
2. Change the velocity and position of the particle according to equations (5) and (6), respectively.
3. For each particle, evaluate the fitness, if all decisions variable are within the search ranges.
4. Compare the particle's fitness evaluation with its previous P-best. If the current value is better than the previous P-best, then set the P-best value equal to the current value and the P-best location equal to the current location in the d-dimensional search space.
5. Compare the best current fitness evaluation with the population G-best. If the current value is better than the population G-best, then reset the G-best to the current best position and the fitness value to current fitness value.

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6. Repeat steps 2-5 until a stopping criterion, such as sufficiently good G-best fitness or a maximum number of iterations/function evaluations is met.

The general flowchart of Classical PSO is illustrated as follows:

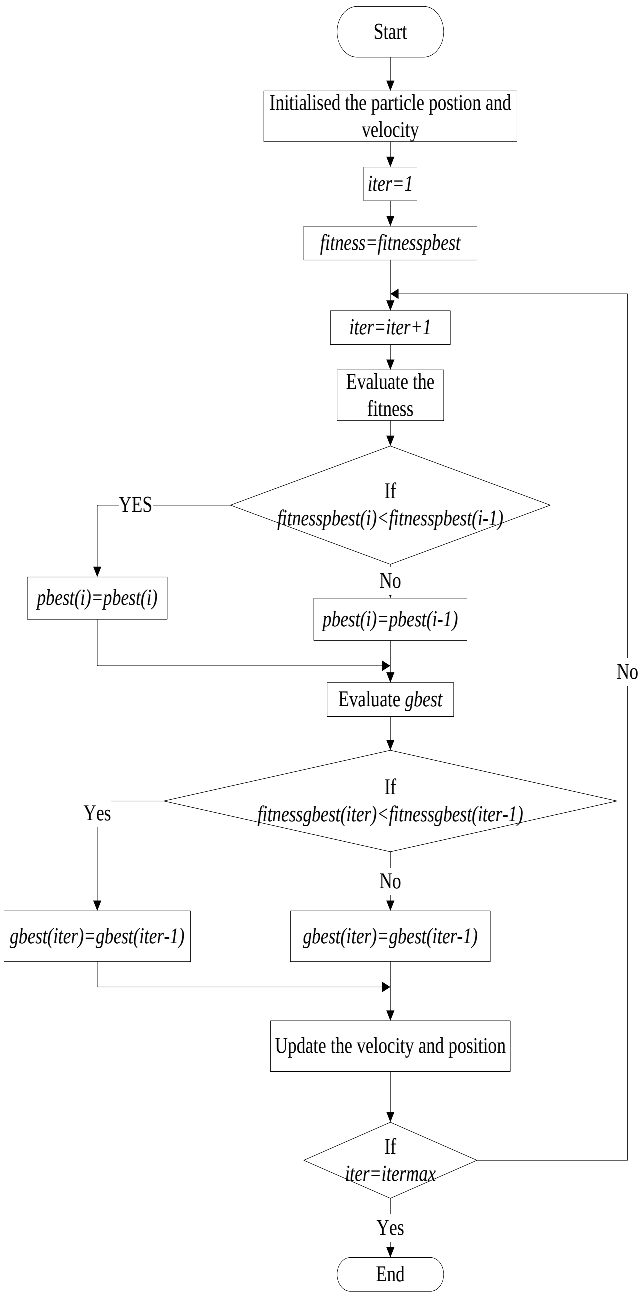

Figure - 1: Flow Chart of Classical PSO

B. Implementation of Classical PSO for ELD solution

The main objective of ELD is to obtain the amount of real power to be generated by each committed generator, while achieving a minimum generation cost within the constraints. The details of the implementation of PSO components are summarized in the following subsections.

The search procedure for calculating the optimal generation quantity of each unit is summarized as follows:

1. Initialization of the swarm: For a population size P, the particles are randomly generated in the range 0-1 and located between the maximum and the minimum operating limits of the generators. If there are N generating units, the ith particle is represented as
$P_i = (P_{i1}, P_{i2}, P_{i3} \ldots\ldots\ldots\ldots P_{iN})$.
The jth dimension of the ith particle is allocated a value of P_{ij} as given below to satisfy the constraints.

$$P_{ij} = P_{jmin} + r\,(P_{jmax} - P_{jmin}) \quad (9)$$

Here r∈ [0,1]

2. Defining the evaluation function: The merit of each individual particle in the swarm is found using a fitness function called evaluation function. The popular penalty function method employs functions to reduce the fitness of the particle in proportion to the magnitude of the equality constraint violation.
The evaluation function is defined to minimize the non-smooth cost function given by equation (2).
3. Initialization of P-best and G-best: The fitness values obtained above for the initial particles of the swarm are set as the initial Pbest values of the particle.
The best value among all the Pbest values is identified as G-Best .
4. Evaluation of velocity: The update in velocity is Done by equation (5).
5. Check the velocity constraints of the members of each individual from the following conditions [25]:

If, $V_{id}^{(k+1)} > V_d^{max}$, then $V_{id}^{(k+1)} = v_d^{max}$,
$V_{id}^{(k+1)} < V_d^{min}$
then, $V_{id}^{(k+1)} = v_d^{min}$ (10)
Where, $V_{dmin} = -0.5\, P_g^{min}$, $V_{dmax} = +0.5\, P_g^{max}$

6. Modify the member position of each individual Pg [25] according to the equation

$$P_{gid}^{(k+1)} = P_{gid}^{(i)} + V_{id}^{(k+1)} \quad (11)$$

$P_{gid}^{(k+1)}$ must satisfy the constraints, namely the generating limits. If $P_{gid}^{(k+1)}$ violates the constraints, then $P_{gid}^{(k+1)}$ must be modified towards the nearest margin of the feasible solution.
7. If the evaluation value of each individual is better than previous P-best, the current value is set to be P-best. If the best P-best is better than G-best, the best P-best is set to be G-best. The corresponding value of fitness function is saved.
8. If the number of iterations reaches the maximum, then go to step 10. Otherwise, go to step-2.
9. The individual that generates the latest G-best is the optimal generation power of each unit with the minimum total generation cost.

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The flowchart of implementation of PSO for ELD problem is illustrated as:

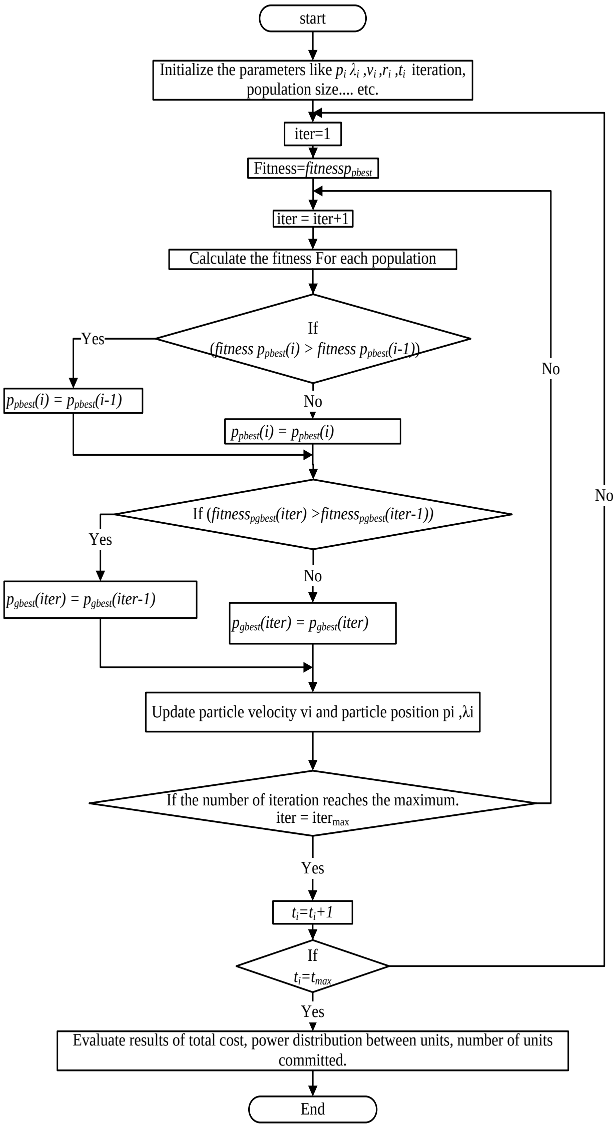

Figure - 2: Flow Chart of Implementation of Classical PSO for ELD problem

IV. .IV.NUMERICAL EXAMPLES AND RESULTS

To verify the feasibility of the proposed classical PSO method three unit test system is taken for without transmission loss and with transmission loss cases.

A. Case-1 3-unit system

The system contains 3 thermal units[1]. The data is given below

$$F_1 = 0.00156\ P_1^2 + 7.92\ P_1 + 561\ R/h$$
$$F_2 = 0.00194\ P_2^2 + 7.85\ P_2 + 310\ R/h$$
$$F_3 = 0.00482\ P_3^2 + 7.97\ P_3 + 78\ \ R/h$$

where 'R' is any arbitrary money value.

The unit operating ranges are

$$100\ MW \le P_1 \le 600\ MW;$$
$$100\ MW \le P_2 \le 400\ MW;$$
$$50\ MW \le P_3 \le 200\ MW;$$

The economic load dispatch for the first test case with the corresponding loads is given as 585 MW, 700 MW and 800 MW, respectively [25]. The proposed PSO method is applied to obtain the minimum generation cost. Table 4.2 provides the results of optimal scheduling of generators obtained by Classical PSO method for three thermal unit system losses are neglected.

Table-1 Optimal scheduling of generators for 3-unit system neglecting losses Classical PSO

S. No.	Load Demand P_D (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	F_t (R/h)	Execution Time (Sec)
1.	585	268.8916	234.2665	81.8409	5821.4	0.6
2.	700	322.9451	277.7309	99.3354	6838.4	0.6
3.	800	369.9355	315.5187	114.5438	7738.51	0.6

(i). Simulation Results for Different Loads for 3 Unit Loss Neglected Case

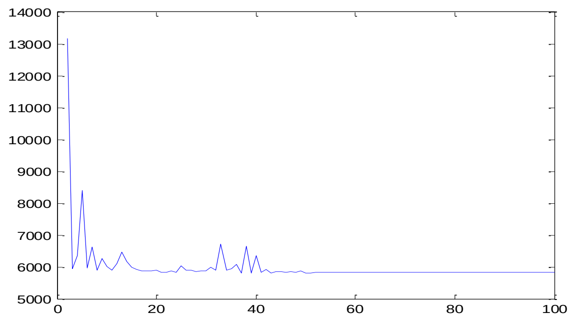

Figure 3-Graph between No. of Iterations and Cost in R/hr for load of 585 MW

The below graph shown in Fig.4 shows the behaviour of P-best solutions for a load of 585 MW for a three unit thermal system without considering transmission losses.This plot is for one iteration.

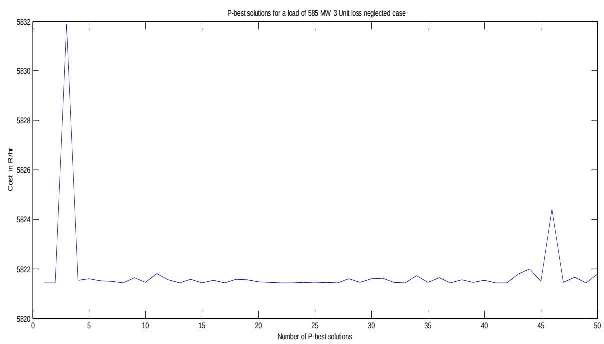

Figure 4-Graph between P-best solutions and Cost in R/hr

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for a load of 585 MW

The above figure shows the behaviour of 50 P-best solutions with respect to the cost.

The below figure 5 shows the G-best solutions for a load of 585 MW for a three unit thermal system without considering transmission line losses.

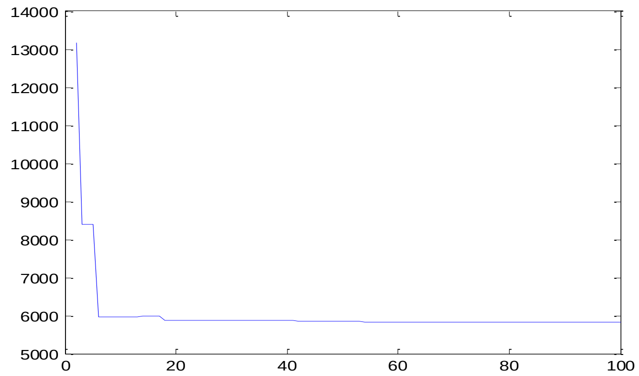

Figure 5-Graph between G-best solutions and Cost in R/hr for a load of 585 MW

The above graph shown in Fig.5 is plotted between G-best solutions and cost in R/hr.We can see from the above graph that cost is monotonically decreasing untill the convergence is achieved.

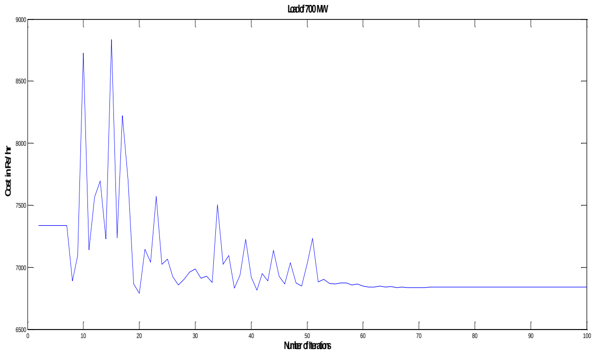

Figure 6-Graph between No. of Iterations and Cost in R/hr for load of 700 MW

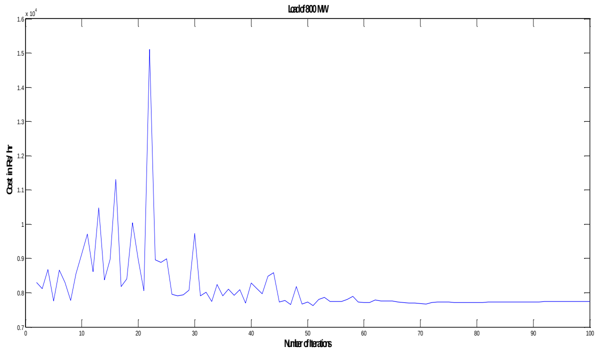

Figure 7-Graph between No. of Iterations and Cost in R/hr for load of 800 MW

These graphs shown in Fig.5, Fig.6, and Fig.7 are plotted between number of iterations against cost in R/hour.We can compare these results obtained from PSO method with conventional method and GA method[25].This comparison is shown in the below Table .

Table 2-Comparison of different methods for 3-unit system loss neglected

S. No.	Load Demand P_D (MW)	Conventional Method [25] (R/h)	GA Method [25] (R/h)	PSO Method (R/h)
1.	585	5821.4000	5827.5	5821.4
2.	700	6838.4056	6877.2	6838.4
3.	800	7738.5189	7756.8	7738.5

From the above table we can see that PSO method is providing better results.

(ii) Three-Unit Thermal System with Transmission Losses

When the above system is tested for a load demand of 585.33 MW and 812.57 MW [25] using the proposed PSO method including transmission losses which can be calculated with the help of loss matrix B_{mn} provided in section then the results.

Table 3- Optimal Scheduling of Generators for 3-Unit System including Losses for Classical PSO

S. No.	Load Demand P_D (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	F_T (Rs/h)	Loss P_L (MW)	Execution Time (Sec.)
1.	585.33	233.3804	268.0099	90.8911	5889.9	6.9661	1.2
2.	812.57	325.2956	370.8859	129.9525	7985.9	13.5642	1.2

B. Simulation Results for Different Loads- 3 unit Loss included case

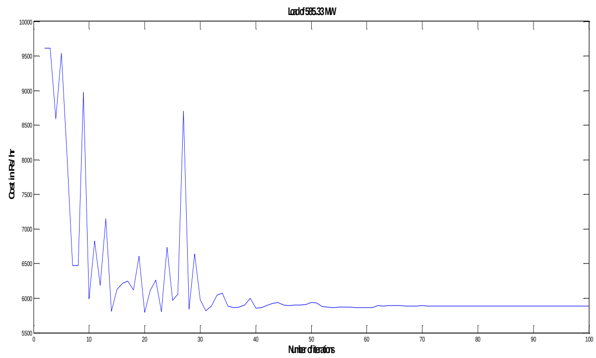

Figure 8-Graph between No. of Iterations and Cost in R/hr for load of 585.33 MW

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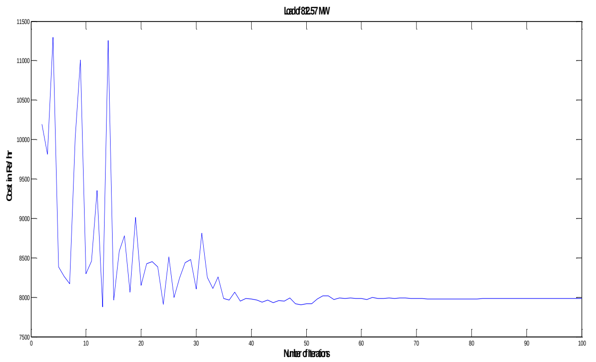

Figure 9-Graph between No. of Iterations and Cost in R/hr for load of 812.57 MW

From the above simulation results we can compare the results with Conventional Method and GA Method the results are shown in the below Table 4.

Table 4- Solution of different methods including losses – 3-unit system

S. No.	Load Demand P_D (MW)	Conventional Method [25] (R/h)	GA Method [25] (R/h)	Classical PSO Method (R/h)
1.	585.33	5890.06	5890.09	5889.9
2.	812.57	7986.09	7986.07	7985.9

Case-2 : Six Unit Thermal System

The system tested consists of six-thermal units [25]. The cost coefficients of the system are given below in R/h.

$F_1 = 0.15240P_1^2 + 38.53973\ P_1 + 756.79886$ R/h

$F_2 = 0.10587P_2^2 + 46.15916\ P_2 + 451.32513$ R/h

$F_3 = 0.02803P_3 ++ 40.39655\ P_3 + 1049.9977$ R/h

$F_4 = 0.03546P_4^2 + 38.30553\ P_4 + 1243.5311$ R/h

$F_5 = 0.02111P_5^2 + 36.32782\ P_5 + 1658.5596$ R/h

$F_6 = 0.01799P_6^2 + 38.27041\ P_6 + 1356.6592$ R/h

The unit operating ranges are

$10\ MW \leq P1 \leq 125\ MW;$

$10\ MW \leq P_2 \leq 150\ MW;$

$35\ MW \leq P3 \leq 225\ MW;$

$35\ MW \leq P_4 \leq 210\ MW;$

$130\ MW \leq P_5 \leq 325\ MW;$

$125\ MW \leq P_6 \leq 315\ MW;$

B_{mn} Coefficient matrix:

$$B_{mn} = \begin{bmatrix} 0.000140 & 0.000017 & 0.000015 & 0.000019 & 0.000026 & 0.000022 \\ 0.000017 & 0.000060 & 0.000013 & 0.000016 & 0.000015 & 0.000022 \\ 0.000015 & 0.000013 & 0.000065 & 0.000017 & 0.000024 & 0.000019 \\ 0.000019 & 0.000016 & 0.000017 & 0.000071 & 0.000030 & 0.000025 \\ 0.000026 & 0.000016 & 0.000024 & 0.000030 & 0.000069 & 0.000032 \\ 0.000022 & 0.000020 & 0.000019 & 0.000025 & 0.000032 & 0.000085 \end{bmatrix}$$

C. Six-Unit Thermal System with Loss

The economic load dispatch for the second test case is solved for the corresponding loads given as 700 MW and 800 MW, respectively [25]. The proposed PSO method is applied to obtain the minimum generation cost. Table 4.6 provides the result of optimal scheduling of generators obtained by proposed PSO method for six thermal unit system when losses are included.

Table 5- Optimal Scheduling of Generators for 6-Unit System including losses for Classical PSO

SL No	Load MW	P_1 MW	P_2 MW	P_3 MW	P_4 MW	P_5 MW	P_6 MW	Cost (R/hr)	Loss (MW)	Time (Sec.)
1.	700	36.536	17.698	41.706	136.899	250.852	236.535	37288.7	20.11	18
2.	800	37.203	26.430	41.235	156.735	288.588	276.269	42459	26.15	18

Simulation results for the load of 700 MW and 800 MW are shown.

D. Simulation Results for Different Loads- 6 unit Loss Included Case-

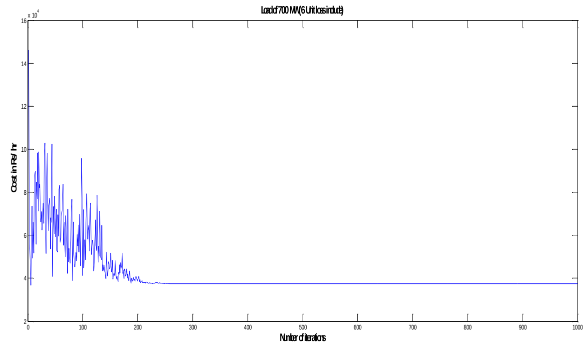

Figure 10- Graph between No. of Iterations and Cost in R/hr for load of 700 MW

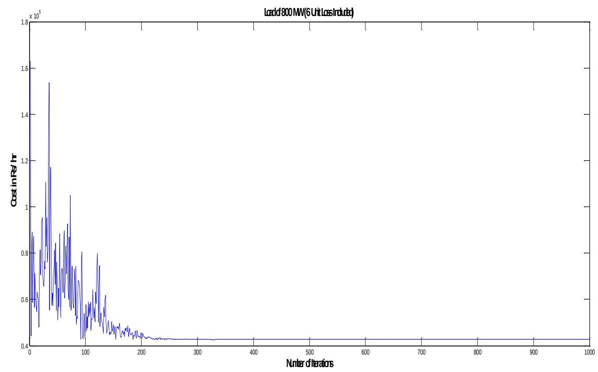

Figure 11-Graph between No. of Iterations and Cost in R/hr for load of 800 MW

Table 6 provides a comparison of economic load dispatch results obtained by various optimization methods for a six unit thermal system with losses included.

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Table 6 - Solution of different methods including losses 6 -units system

Sl. No.	Load Demand P_D (MW)	Conventional Method [25] (R/h)	GA Method [25] (R/h)	Classical PSO Method (R/h)
1.	700	37288.7	37288.9	37288.7

V. PSO WITH TIME VARYING ACCELERATION COEFFICIENTS (PSO_TVAC)

It has been observed by most researchers that in PSO, problem-based tuning of parameters is a key factor to find the optimum solution accurately and efficiently. Relatively higher value of the cognitive component (c_1), compared with the social component (c_2), results in roaming of individuals through a wide search space. On the other hand, a relatively high value of the social component leads particles to local optima prematurely. Normally acceleration coefficients c_1 and c_2 are kept as 2, in order to make the mean of both stochastic factors equal to one, so that the particles would over fly only half the time of search.

In population based optimization methods, the policy is to encourage the individuals to roam through the entire search space, during the initial part of the search without clustering around the local optima. During the latter stages, however convergence towards the global optima should be encouraged, to find the optimum solution efficiently. In TVAC [30], this is achieved by changing the coefficients c_1 and c_2 with time in such a manner that the cognitive component is reduced while the social component is increased as the search proceeds. A large cognitive component and small social component at the beginning allows particles to move around the search space, instead of moving towards the population based prematurely. During the latter stage in optimization, a small cognitive component and a large social component allow particles to converge to the global optima. The acceleration coefficients are expressed as in equation (3.7) and (3.8).

$$c_1 = \left(c_{1f} - c_{1i}\right) \frac{iter}{iter_{max}} + c_{1i} \quad \ldots\ldots\ldots\ldots (3.7)$$

$$c_2 = \left(c_{2f} - c_{2i}\right) \frac{iter}{iter_{max}} + c_{2i} \quad \ldots\ldots\ldots\ldots (3.8)$$

Where c_{1i}, c_{1f}, c_{2i}, c_{2f} are initial and final values of cognitive and social acceleration factors respectively. The values considered for acceleration coefficients are c_{1f} =0.5, c_{1i} =2.5 and c_{2f} =2.5, c_{2i} =0.5.

Table7-Optimal Scheduling of Generators for 6 unit system including losses using PSO with TVAC

S. No	P_d MW	P_1 MW	P_2 MW	P_3 MW	P_4 MW	P_5 MW	P_6 MW	F_T (R/hr)	Loss MW	Time (sec.)
1.	700	69.013	47.950	55.626	143.924	191.220	211.704	37288.6	19.43	16.00
2.	800	60.462	41.087	40.726	179.107	261.276	243.123	42443	24.76	16.00

VI. .RESULT

PSO proves better than GA.
We can see from the above table that after applying Time Varying Acceleration Coefficients(TVAC) in PSO algorithm the results got improved (Table 7).

VII. CONCLUSIONS

We can draw important conclusions on the basis of the work done. Some important conclusions are given below

Three Unit Systems:

In PSO method selection of parameters c1, c2 and W is very much important. It is stated in various research papers that the good results are obtained when c1 = 2.0 and c2= 2.0 and W value is varied from 0.9 to 0.4 for both cases loss neglected and loss included. We can see from Table 4 and Table 5 that Classical PSO gives better result than GA.

In PSO method numbers of iterations are not much affected when the transmission line losses are considered. In both cases for loss included and loss neglected it is approximately 50 iterations for Classical PSO method.

Six Unit Systems:

The selection of parameters is same as c_1=2,c_2=2,W is varying from 0.9 to 0.4.We can see from the Table 4 that Classical PSO method gives better result than the Genetic Algorithm method as the cost is reduced. When transmission losses are considered.

We can also see that after applying TVAC concept the results of PSO got improved.

Overall we can conclude that today when there is competition amongst power generating companies, fast emerging difference between demand and supply then we need to develop a requisite for proper operation policies for power generating companies. It can be accomplished only when a proper mathematical formulation of ELD problem is there and all practical constraints are taken into account.PSO has paid a lot of attention for solution of such problems, as it does not suffers from sticking into local optimal solution, dependability on initial variables and curse of dimensionality.

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