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Exponential Decreasing Inertia Weight Particle Swarm Optimization In Economic Load Dispatch

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***Abstract*- Economic load dispatch (ELD) is one of the important task which provides cost effective generation in power system. It is an optimization problem and the main objective is to minimize the total generation cost of all committed generating units, while satisfying various physical and operational constraints. In the development of artificial intelligence(AI) technique Eberhart and kennedy suggested Particle Swarm Optimization (PSO) used to solve NonConvex Economic Dispatch (NCED) problem. PSO has performance parameters such as inertia weight, acceleration coefficient, random numbers which can enhance the performance of PSO. Among these parameter, inertia weight is very important, which can approaches in fuzzy or linear way. In this paper Exponential Decreasing Inertia Weight (EDIW) has been proposed. The effectiveness of proposed algorithm tested on case system & shown superior result in terms of convergence and solution quality.**

***Keywords* - Economic load dispatch, Problem formulation, Exponential decreasing inertia weight particle swarm optimization.**

I. Introduction

The main aim of electric supply utility has been identified as to provide the smooth electrical energy to the consumers. While doing so, it should be ensured that the electrical power is generated with minimum cost. Hence in order to achieve an economic operation of the system, the total demand must be appropriately shared among the units. This will minimize the total generation cost for the system with the voltage level maintained at the safe operating limits. Major considerations to fulfilling the objectives are loss minimization. fuel cost minimization and profit maximization (fuel costs/load tariffs).The main factor controlling the most desirable load allocation between various generating units is the total running cost. In electrical power system, there are many optimization problems such as optimal power flow, economic dispatch, generation and transmission planning, unit commitment, and forecasting & control. Economic dispatch is one of the major optimization issue in power system. Its objective is to allocate the demand among committed generator in the most economical manner, while all physical & operational constraints are satisfied. Many conventional & nonconventional optimization techniques available in literature are applied to solve such problems. Quadratic linear programming [1], Mathematical linear programming [2], Non linear programming[3], dynamic programming [4,5] are the conventional methods. Conventional methods have simple mathematical model and high search speed but they are failed to solve such problem because they have the drawbacks of Multiple local minimum points in the cost function, Algorithms require that characteristics be approximated, however, such approximations are not desirable as they may lead to suboptimal operation and hence huge revenue loss over time, restrictions on the shape of the fuel-cost curves.

Other methods based on artificial intelligence have been proposed to solve the economic dispatch problem, these are Genetic algorithm [6,7], Tabu search[8], Particle swarm optimization [9]. The PSO first introduced by kennedy and eberhart is a flexible, robust, population based algorithm. This method solve variety of power systems problems due to its simplicity, superior convergence characteristics and high solution quality. Classical PSO approach suffers from premature convergence, particularly for complex functions having multiple minima.

Shi & Eberhart [20] had introduced a parameter inertia weight into the original particle swarm optimizer. It was concluded that the PSO with the inertia weight in the range(0.9,1.2) on average had a better performance wit respect to find the global optimum point with a reasonable no. of iterations. Z.L.Gaing et. al [21]presented an approach in which a fuzzy system was implemented to dynamically adapt the inertia weight of the PSO algorithm. New hybrid PSO is proposed [22] that incorporating a wavelet theory based mutation operation for solving economic load dispatch. Gumin Chen. et. al.[17] gave new idea of decreasing inertia weight in which two strategies of natural exponential function were proposed. in this paper exponential decreasing inertia weight PSO has been applied. The result of the experiments showed that these two new strategies converge faster than the linear one during the early stage of the search process.

II. Problem Formulation

The Economic Dispatch problem may be formulated as single objective & multi objective problem, here in present work optimization problem has been formulated as single objective optimization problem without valve point loading effect subject to various equality & inequality constraints.

2.1 Objective Function

The primary objective of any ED problem is to reduce the operational cost of system fulfilling the load demand within limits of constraints. However due to growing concern of environment, there are various kinds of objective function can be done as given in subsequent sections.

2.1.1 Simplified Economic Cost Function

Let F_i mean the cost, expressed for example in dollars pr hour, of producing energy in the generator unit i .The total controllable system production cost such an approach will not be workable for nonlinear functions in practical systems. Therefore will be

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

The fuel input-power output cost function of the i^{th} unit is given as

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

where F total generating cost, Fi cost function of i^{th} generating unit, P_i power of generator N no. of generators, a_i, b_i, c_i cost coefficients of generator i.

2.2 System Constraints

Broadly speaking there are two types of constraints-equality constraint and inequality constraints. The inequality constraints are of two types(i) Hard type,(ii) Soft type. The harad type are those which are definite and specific like the tapping range of an on-load tap changing transformer whereas soft type are those which have flexibility associated with them like the nodal voltage and phase angles between the nodal voltages, etc. soft inequality constraints have been very efficiently handled by penalty function methods.

2.2.1 Equality and inequality constraint

From observation we can conclude that cost function is not affected by the reactive power demand. So the full attention is given to the real power balance in the system. Different types of constraints are as under

2.2.1.1 *Active power balance equation*

For power balance equation, equality constraints should be satisfied. The total generated power should be the same as total load demand plus the total line loss,

$$\sum_{i=1}^{N} P_i = P_D + P_{loss} \quad \textbf{(3)}$$

Where P_D is the total system demand and P_{loss} is the total line loss. To calculate system losses , Method based on constant loss formula coefficient or B coefficient are used. The transmission loss equation expressed as:

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{oi} P_i + B_{oo} \quad \textbf{(4)}$$

2.2.1.2 *Minimum and maximum power limits:*

Generator output of each generator should be laid between maximum and minimum limits .the corresponding inequality constraints for each generator are

$$P_{i\,min} \le P_i \le P_{i\,max} \quad \textbf{(5)}$$

where P_{imin} and P_{imax} are minimum and maximum output of generator i.

III. Overview of Some PSO Strategies

3.1 *Classical PSO*

Kennedy and Eberhart [15] developed a particle swarm optimization (PSO) algorithm based on the behavior of individuals (i.e., particles or agents) of a swarm. Its roots are in zoologist's modeling of the movement of individuals (i.e., fishes, birds and insects) within a group. It has been noticed that members of the group seem to share information among them, a fact that leads to increased efficiency of the group. The PSO algorithm searches in parallel using a group of particles. Each particle corresponds to a candidate solution to the problem. A particle moves towards the optimum based on its present velocity, its previous experience and the experience of its neighbors.

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 $x_i = (x_{i1}, x_{i2} \ldots x_{id})$ in the d - dimensional space. The best previous position of the i^{th} particle is recorded and represented as $pbest_i = (pbest_{i1}, pbest_{i2}, \ldots\ldots\ldots pbest_{id})$.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 $v_i = (v_{i1}, v_{i2} \ldots\ldots\ldots v_{id})$.The modified velocity and position of each particle can be calculated using the current velocity and the distance from $pbest_{id}$ to $gbest_{id}$ as shown in the following formulas,

$$V_{id} = \omega \times V_i(t) + C_1 \times Rand() \times (pbest_{id} - P_{gid}^{(t)})$$
$$+ C_2 \times Rand() \times (gbest_{id} - P_{gid}^{(t)}) \quad \textbf{(6)}$$

the acceleration constants C_1 and C_2 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 ω is set according to the following equation.

$$\omega = \omega_{max} - [(\omega_{max} - \omega_{min}) \div iter_{max}] \times iter \quad \textbf{(7)}$$

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. Each individual moves from the current position to the next one by the modified velocity using the following eq.(8)

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

3.2 *Self organizing hierarchical PSO with TVAC(SOH_PSO)*

This strategy handles the problem of premature convergence for nonconvex economic dispatch (NCED). The performance of this method is also improves when time varying acceleration coefficient are included. This PSO strategy provide the required momentum for particles to find the global optimum solution in the absence of the previous velocity term in eq.(13). In this method the previous velocity term has been considered zero. When a particle stagnates, its associated pbest remains unchanged for a number of iterations. When more particles stagnate, the gbest also undergoes the same fate and the PSO algorithm converges prematurely to a local optima and V_{id} becomes zero. A necessary push to the PSO algorithm is imparted by reinitializing V_{id} by a random velocity term. The method works as follows [16].

$$V_{id}^{k+1} = \left(\left\{ c_{1f} - c_{1i} \right\} \frac{iter}{iter_{\max}} + c_{1i} \right) \times Rand() \times (pbest_{id} - P_{gid}^{(t)})$$

$$+ \left(\left\{ c_{2f} - c_{2i} \right\} \frac{iter}{iter_{\max}} + c_{2i} \right) \times Rand() \times (gbest_{id} - P_{gid}^{(t)}) \quad \textbf{(9)}$$

where c_{1f},c_{1i},c_{2f} & c_{2i} are constants, iter is the current iteration no., $iter_{max}$ is the maximum allowable iteration number.

3.3 *Natural exponential inertia weight strategy*:

Guimin[17] proposed two natural exponential (base e) inertia weight strategies. In this strategies. The first strategy is expressed as:

$$\omega(t) = \omega_{\min} + (\omega_{\max} - \omega_{\min}).e^{t/\left(\max iter/10\right)} \quad \textbf{(10)}$$

The PSO algorithm adopting this strategy is called e_1-PSO for short. The second one is expressed as:

$$\omega(t) = \omega_{\min} + (\omega_{\max} - \omega_{\min}).e^{-\left[t/\left(\frac{\max iter}{4}\right)\right]^2} \quad \textbf{(11)}$$

the PSO algorithm adopting this strategy is called e_2-PSO. It is assumed that ω_{start}=0.9,ω_{end}=0.4,

IV. Solution of ED Problem Using E_1-PSO and E_2-PSO.

The paper presents solution of ED problem without complexity such as valve point loading, prohibited operating zones & ramp rate limit employing exponential decreasing inertia weight PSO for test system [18]. The implementation steps are as follows:

Step 1: Choose the population size , no. of generation, ω_{min}, ω_{max}.

Step 2: Initialize position of all particles are randomly set to within their prespecified range following the eq(12).

Pij = Pjmin + r (Pjmax - Pjmin) **(12)**

Step 3: Velocity is made to lie between –Vjmax & Vjmax. The maximum velocity limit for the K^{th} generating unit is computed as follows.

$$V_j^{\max} = \frac{Pj\max - Pj\min}{R} \quad \textbf{(13)}$$

Step 4: Evaluate the fitness of each particle according to the objective function. Objective function is calculated by eq.(20)

$$f(P_i) = \sum_{i=1}^{N} F_i(P_i) + \alpha \left[\sum_{i=1}^{N} P_i - (P_D + P_L) \right] + \beta \left[\sum_{k=1}^{ni} P_i(violation)_k \right]^2 \quad \textbf{(14)}$$

Where α is the penalty parameters for not satisfying load demand & β represents the penalty for a unit loading falling, P_D load demand, P_L power loss. In this paper we consider P_L & β=0

Step 5: The minimum value of evaluation function obtained above equation (14) for the initial particles are set as the initial pbest values of the particles. The best value among all the pbest values is identified as gbest.

Step 6: Update Velocity of each particles by using global best & individual best according to equation (6).

Step 7: Update position by using the updated velocity. The particle position vector is updated by eq.(8) and check position limits and then pbest & gbest values are updated.

Step 8: check for maximum number of iteration, if number of iteration is less then maximum number of iteration then go to step 4 & if number of iteration is greter then maximum number of iteration then latest gbest value will be the final solution.

V. Numerical Results and Analysis

A. Testing Strategies

The ED problem was solved using exponential decreasing inertia weights PSO and its performance is compared with best reported cost in literature [19] for 6 unit system is $ 15275.93/h using SOH_PSO. To evaluate the performance of both optimization algorithms i.e. e1-PSO & e2-PSO No. of Trials 50, population size= 500 and no. of iterations= 500 have been taken. The software program has been coded in MATLAB 7.3 language on a Intel(R) core(TM)2 DUO CPU, 2.99GHz, 1.95GB RAM.

B. Effectiveness of on Different Benchmarks

The proposed exponential decreasing inertia weight PSO technique applied to the test system consists of six generating unit [18], a total load of 1263 MW, without complexity i.e. losses, POZ & ramp limits. the global best cost of $15275.565/h by e_1-PSO method & $15275.566/h e_2-PSO method was achieved. Best results amongst all trails have been considered as mentioned in Table-I given below.

TABLE I
RESULT OF 6 UNITS SYSTEM WITH OUT COMPLEXITY

Unit power o/p	SOH_PSO	e1 PSO	e2 PSO
P1(MW)	446.68	446.72	446.62
P2(MW)	171.25	171.35	171.18
P3(MW)	264.13	264.05	264.00
P4(MW)	125.18	124.95	125.04
P5(MW)	172.15	172.11	171.86
P6(MW)	83.62	83.74	83.90
Total cost($/h)	15275.93	15275.565	15275.566
Total power O/P(MW)	1263.00	1263.00	1263.00

C. Selection of parameters for e_1-PSO & e_2-PSO

It is accepted that proper control of global exploration and local exploitation is crucial in finding the optimum solution efficiently in population based optimization methods. We can choose an appropriate constants for ω to compromise between global exploration and local

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exploitation. It has been observed that the optimal solution can be improved by varying the value of inertia weight from 0.9 at the beginning of the search to 0.4 at the end of the search for most problems. The following PSO parameters have been used for simulation of results.

1. C1=C2=2
2. ω end=0.4
3. ω start=0.9
4. No. of iterations=100,200,300,400,500

Six generating unit characteristic data are given in Table II

TABLE II
COST CURVES AND OPERATING LIMITS OF 6 UNITS SYSTEM

Unit	Pi(min)	Pi(max)	Pi	ai	bi	ci
1	100	500	440	0.0070	7	240
2	50	170	170	0.0095	10	200
3	80	200	200	0.0090	8.5	220
4	50	150	150	0.0090	11	200
5	50	190	190	0.0080	10.5	220
6	50	120	110	0.0075	12	190

D. Effect of Population Size

The optimum population size is found to be related to the problem dimension & complexity. Large dimension or complex problem requires big popsize to achieve optimal results. Table-III & Table-IV shows the performance of the e_1-PSO. & e_2-PSO with different population size and iterations. Test were carried out for a population of 15,20,25,30 &500 for the six unit system. A population of 500 resulted in achieving global solution. Maximum number of iteration used were 500 for both e_1-PSO. & e_2-PSO. Table-V shows the results of e_1-PSO. & e_2-PSO for different iteration at popsize 500.

TABLE III
RESULT OF e1- PSO FOR DIFFERENT POPULATION SIZES.

S.NO.	POP SIZE	ITERATION 100	200	300	400	500
1.	15	15282.49	15281.00	15282.21	15280.24	15279.13
2.	20	15282.35	15282.37	15280.97	15280.28	15279.38
4.	25	15281.17	15280.83	15279.26	15279.27	15279.99
	30	15278.91	15278.34	15277.45	15278.34	15278.36

TABLE IV
RESULT OF e2- PSO FOR DIFFERENT POPULATION SIZES

S. NO.	POP SIZE	ITERATION 100	200	300	400	500
1.	15	15285.91	15286.37	15282.97	15284.08	15281.49
2.	20	15283.79	15282.37	15283.10	15280.04	15278.98
3.	25	15282.76	15283.21	15280.55	15281.69	15278.78
4.	30	15282.42	15280.91	15279.25	15278.40	15276.19

TABLE V
RESULT OF e_1-PSO & e_2-PSO FOR DIFFERENT ITERATION &POPSIZE 500

	ITERATIONS 100	200	300	400	500
e_1-PSO	15275.88	15275.64	15275.60	15275.67	15275.56
e_2-PSO	15275.80	15275.64	15275.62	15275.58	15275.56

E. Comparison of e1-PSO & e2-PSO with SOH_PSO

1. Convergence Characteristics

The Fig.(4) show the convergence characteristic of e_1-PSO. & e_2-PSO

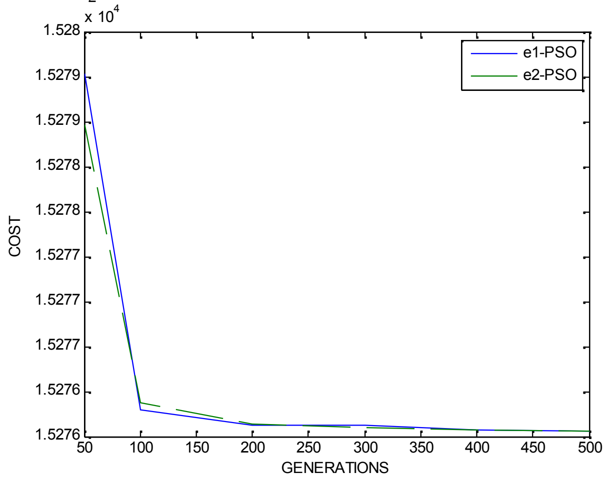

Fig.4. convergence characteristic of e_1-PSO. & e_2-PSO

2. Solution Quality

The dynamic convergence behavior of the method was also studied by calculating the mean μ and standard deviation σ of the swarm at each iteration as

$$\mu = \frac{\sum_{i=1}^{PS} f(P_i)}{PS} \qquad \textbf{(15)}$$

$$\sigma = \sqrt{\frac{1}{PS}\sum_{i=1}^{PS}(f(P_i)-\mu)^2} \qquad \textbf{(16)}$$

PS- Population size
$f(P_i)$- Evaluation function.

Fig. (5) and (6) plot the mean and standard deviation with respect to iteration for the test system. The mean as well as standard deviation of the members of the swarm reduces continuously.

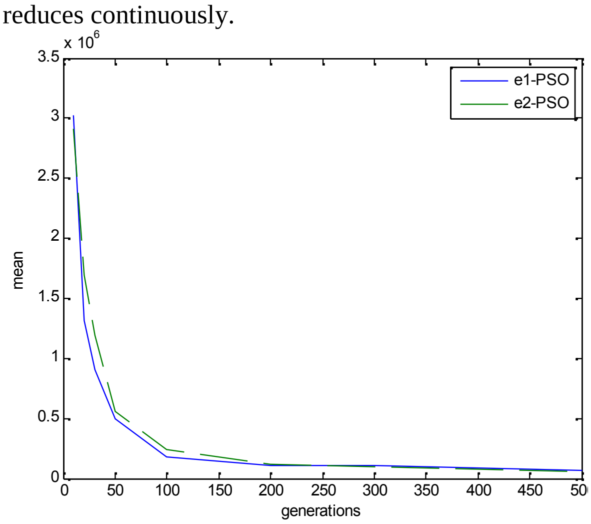

Fig.5. Mean value of e_1-PSO. &e_2-PSO with popsize 500

International Journal of Engineering Innovation & Research
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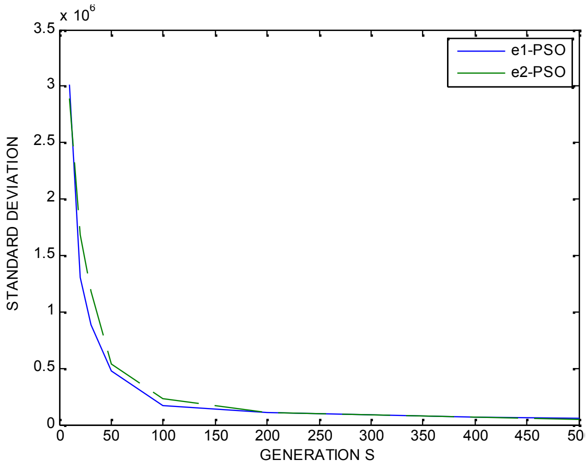

Fig.6. Standard deviation value of e_1-PSO. &e_2-PSO with popsize 500

3. Comparison of best solution

The best solution obtained by e1 PSO & e2-PSO for the six unit system is compared with SOH_PSO[19] in Table-I which clearly shows that proposed algorithm i.e. e_1-PSO. &e_2-PSO gives superior results in terms of quality solution.

VI. Conclusions

Two strategies of exponential decreasing inertia weight i.e. e_1-PSO. &e_2-PSO have been successfully applied to determine the optimal generation schedule of the six unit test system[18]. Results are taken at 15,20,25,30 & 500 population sizes & it has been observed that 500 popsize is giving optimal value of objective function i.e. 15275.565$/h and 15275.566 $/h for e_1-PSO & e_2-PSO respectively in comparison to SOH_PSO at reported in literature[19]. Apart from solution quality e_1-PSO. & e_2-PSO are giving better dynamic convergence.

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