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NEW PSO USED FOR OPTIMIZATION OF ECONOMIC LOAD DISPATCH

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***Abstract*—this text used PSO and a new PSO based time varying of acceleration coefficients. This new PSO has the capability to discover the particles by means of varying the acceleration coefficient within the seek areas greater correctly and will increase their convergence charges. Economic load dispatch is the method of allocating present generating units in such a way to include the load demand and fulfills the limitations in order that the overall technology price at the thermal power plant is minimized. Particle swarm optimization is an optimization method primarily based at the population of social conduct is carried out to numerous nonlinear optimization problems. Usefulness of the PSO and TVACPSO algorithm is validated for 13 and 15 generating unit IEEE check facts systems.**

Keywords-Economic Load Dispatch (ELD), Particle swarm optimization (PSO), Time varying acceleration coefficients Particle Swarm Optimization (TVAC-PSO).

1.INTRODUCTION

Electric utility system is interconnected to achieve the benefits of minimum production cost, maximum reliability and better operating conditions. The economic scheduling is the on-line economic load dispatch, wherein it is required to distribute the load among the generating units which are actually paralleled with the system, in such a way as to minimize the total operating cost of generating units while satisfying system equality and inequality constraints. For any specified load condition, ELD determines the power output of each plant (and each generating unit within the plant) which will minimize the overall cost of fuel needed to serve the system load [1]. ELD is used in real-time energy management power system control by most programs to allocate the total generation among the available units. ELD focuses upon coordinating the production cost at all power plants operating on the system.

Conventional as well as modern methods have been used for solving economic load dispatch problem employing different objective functions. Various conventional methods like lambda iteration method, gradient-based method, Bundle method [2], nonlinear programming [3], mixed integer linear programming [4], [5], dynamic programming [8], linear programming [7], quadratic programming [9], Lagrange relaxation method [10], direct search method [12], Newton-based techniques [11], [12] and interior point methods [6], [13] reported in the literature are used to solve such problems.

Conventional methods have many draw back such as nonlinear programming has algorithmic complexity. Linear programming methods are fast and reliable but require linearization of objective function as well as constraints with non-negative variables. Quadratic programming is a special form of nonlinear programming which has some disadvantages associated with piecewise quadratic cost approximation. Newton-based method has a drawback of the convergence characteristics that are sensitive to initial conditions. The interior point method is computationally efficient but suffers from bad initial termination and optimality criteria.

Recently, different heuristic approaches have been proved to be effective with promising performance, such as evolutionary programming (EP) [16], [17], simulated annealing (SA) [18], Tabu search (TS) [19], pattern search (PS) [20], Genetic algorithm (GA) [21], [22], Differential evolution (DE) [23], Ant colony optimization [24], Neural network [25] and particle swarm optimization (PSO) [26]. Although the heuristic methods do not always guarantee discovering globally optimal solutions in finite time, they often provide a fast and reasonable solution. EP is rather slow converging to a near optimum for some problems. SA is very time consuming, and cannot be utilized easily to tune the control parameters of the annealing schedule. TS is difficult in defining effective memory structures and strategies which are problem dependent. GA sometimes lacks a strong capacity of producing better offspring and causes slow convergence near global optimum, sometimes may be trapped into local optimum. DE greedy updating principle and intrinsic differential property usually lead the computing process to be trapped at local optima.

Particle-swarm-optimization (PSO) method is a population-based Evolutionary technique first introduced in [26], and it is inspired by the emergent motion of a flock of birds searching for food. In comparison with other EAs such as GAs and evolutionary programming, the PSO has comparable or even superior search performance with faster and more stable convergence rates. Now, the PSO has been extended to power systems, artificial neural network training, fuzzy system control, image processing and so on.

The main objective of this study is to use of PSO with inertia weight improved to solve the power system economic load dispatch to enhance its global search ability. This new development gives particles more opportunity to explore the solution space than in a standard PSO. The proposed method focuses on solving the economic load dispatch with constraint. The feasibility of the proposed method was demonstrated for three and six generating unit system.

2. PROBLEM FORMULATION

ELD is one of the most important problems to be solved in the operation and planning of a power system the primary concern of an ED problem is the minimization of its objective function. The total cost generated that meets the demand and satisfies all other constraints associated is selected as the objective function.

The ED problem objective function is formulated mathematically in (1) and (2),

$$F_T = \text{Min } f(FC) \qquad (1)$$

$$FC = \sum_{i=1}^{n} a_i \times P_i^2 + b_i \times P_i + c_i \qquad (2)$$

Where, F_T is the main objective function,
a_i, b_i and c_i are the cost coefficients.

2.1 CONSTRAINTS

This model is subjected to the following constraints,

1) Power Balance Equation

For power balance, an equality constraint should be satisfied. The total generated power should be equal to total load demand plus the total losses,

$$\sum_{i=1}^{n} P_i = P_D + P_L \qquad (3)$$

Where, P_D is the total system demand and P_L is the total line loss.

2) Limits of Power Generation

There is a limit on the amount of power which a unit can deliver. The power output of any unit should not exceed its rating nor should it be below that necessary for stable operation. Generation output of each unit should lie between maximum and minimum limits.

$$P_i^{min} \le P_i \le P_i^{max} \qquad (4)$$

Where, Pi is the output power of i_{th} generator ,
$P_{i,min}$ and $P_{i,max}$ are the minimum and maximum power outputs of generator i respectively.

3. Particle swarm optimization (PSO)

Particle swarm optimization was first introduced by Kennedy and Eberhart in the year 1995 [26]. It is an exciting new methodology in evolutionary computation and a population-based optimization tool. PSO is motivated from the simulation of the behavior of social systems such as fish schooling and birds flocking. It is a simple and powerful optimization tool which scatters random particles, i.e., solutions into the problem space. These particles, called swarms collect information from each array constructed by their respective positions. The particles update their positions using the velocity of articles. Position and velocity are both updated in a heuristic manner using guidance from particles' own experience and the experience of its neighbors.

The position and velocity vectors of the ith particle of a d-dimensional search space can be represented as $P_i=(p_{i1},p_{i2},\ldots\ldots\ldots p_{id})$ and $V_i=(v_{i1},v_{i2},\ldots\ldots\ldots v_{id},)$ respectively. On the basis of the value of the evaluation function, the best previous position of a particle is recorded and represented as $P_{besti}=(p_{i1},p_{i2},\ldots\ldots\ldots p_{id})$, If the gth particle is the best among all particles in the group so far, it is represented as $P_{gbest}=g_{best}=(p_{g1},p_{g2},\ldots\ldots\ldots p_{gd})$.

The particle updates its velocity and position using (5) and (6).

$$V_i^{(K+1)} = WV_i^K + c_1\text{rand}_1 \times \left(\text{Pbest}_i - S_i^K\right) + c_2\text{rand}_2 \times \left(\text{gbest} - S_i^K\right) \tag{5}$$

$$S_i^{(K+1)} = S_i^K + V_i^{K+1} \tag{6}$$

Where, V_i^k is velocity of individual i at iteration k, W is the weighing factor, C_1, C_2 are the acceleration coefficients, rand_1, rand_2 are the random numbers between 0 & 1, S_i^k is the current position of individual i at iteration k, Pbest- The best position of individual i, and gbest -The best position of the group.

The coefficients c_1 and c_2 pull each particle towards pbest and gbest positions. Low values of acceleration coefficients 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 the target regions. Hence, the acceleration coefficients c_l and c_2 are often set to be 2 according to past experiences.

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. The choice of a value for V^{max} is often set at 10-20% of the dynamic range of the variable for each problem.

W is the inertia weight parameter which 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 is used in (5)

$$W = W_{max} - \frac{W_{max}-W_{min}}{iter_{max}} \times iter \tag{7}$$

Where, W_{max} is the initial weight, W_{min} is the final weight, $Iter_{max}$ is the maximum iteration number and iter is the current iteration position.

3.1 TVAC-PSO

For getting the better global solution, the traditional PSO algorithm is improved by adjusting acceleration coefficients AS SHOWN IN eq. (9) and (10). Based on [15], the velocity of individual I of TVAC PSO algorithm is rewritten as,

$$V_i^{(K+1)} = W * V_i^K + c_1\text{rand}_1 * \left(\text{Pbest}_i - S_i^K\right) + c_2\text{rand}_2 * \left(\text{gbest} - S_i^K\right) \tag{8}$$

Where,

$$c_1 = c_{1max} - \frac{c_{1max}-c_{1min}}{iter_{max}} \times iter \tag{9}$$

$$c_2 = c_{2max} - \frac{c_{2max} - c_{2min}}{iter_{max}} \times iter \quad (10)$$

c1min, c1max: initial and final cognitive factors and c2min, c2max: initial and final social factors.

4. ALGORITHM FOR ELD PROBLEM USING TVAC-PSO

The algorithm for ELD problem with ramp rate generation limits employing TVAC-PSO for practical power system operation is given in following steps:-

Step1:- Initialization of the swarm: For a population size the Particles are randomly generated in the Range 0–1 and located between the maximum and the minimum operating limits of the generators.
Step2:-Initialize velocity and position for all particles by randomly set to within their legal rang.
Step3:-Set generation counter t=1.
Step4:- Evaluate the fitness for each particle according to the objective function.
Step5:-Compare particles fitness evaluation with its Pbest and gbest.
Step6:-Update velocity by using (8)
Step7:- Update position by using (6)
Step8:-Apply stopping criteria.

5. TEST DATA AND RESULTS

TEST CASE 1

The test results are obtained for 15 generating unit system in which all units with their fuel cost coefficients. This system supplies a load demand of 2650 MW. The data for the individual units are given in Table 1. The best result obtained by TVAC-PSO and PSO for different population size is shown in Table 2.

Table 1
Capacity limits and fuel cost coefficients for 15 generating units for the demand load of 2650MW

Units	a_i($)	b_i($/Mw)	c_i($/Mw^2)	Pmin	Pmax
1	671.03	10.07	0.000299	150	455
2	574.54	10.22	0.000183	150	455
3	374.59	8.80	0.001126	20	130
4	374.59	8.80	0.001126	20	130
5	461.37	10.40	0.000205	150	470
6	630.14	10.10	0.000301	135	460
7	548.20	9.87	0.000364	135	465
8	227.09	11.50	0.000338	60	300
9	173.72	11.21	0.000807	25	162
10	175.95	10.72	0.001203	20	160
11	186.86	11.21	0.003586	20	80
12	230.27	9.90	0.005513	20	80
13	225.28	13.12	0.000371	25	85

14	309.03	12.12	0.001929	15	55
15	323.79	12.41	0.004447	15	55

Table 2
Results for 15 generating units after 50 trials

Generating units	PSO	TVAC PSO
P1	352.95	405.345
P2	307.58	415.3405
P3	55.35	102.4841
P4	94.59	127.4206
P5	280.52	354.7904
P6	352.58	460
P7	461	376.5076
P8	275.57	64.3009
P9	43.501	25.4005
P10	164.25	136.7247
P11	72.71	40.7512
P12	66.19	36.6468
P13	25	31.148
P14	45.77	22.4836
P15	31.38	30.656
Total power generation(MW)	2630	2630
Minimum fuel cost($/hr)	32910.43	32608.71
Minimum time(sec)	1.20	1.03

TEST CASE II

In this case considered 13 generating unit systems for the load demand of 1800 MW. The capacity and cost coefficient of 13 generating unit system is shown in table 3. These given data are tested on PSO and TVACPSO algorithm. The result obtained by PSO and TVAC PSO for 50 runs is shown in table 4.

Table 3

Cost coefficient and capacity for 13 generating unit systems for the demand of 1800MW

Gen. Units	a_i	b_i	c_i	P_i^{min}	P_i^{max}
1	0.00028	8.10	550	0	680
2	0.00056	8.10	309	0	360
3	0.00056	8.10	307	0	360
4	0.00324	7.74	240	60	180
5	0.00324	7.74	240	60	180