

Unified Particle Swarm Optimization to Solving Economic Dispatch

I.D.Soubache, P.Ajay-D-Vimal Raj

Abstract: This paper proposes the solution for economic dispatch (ED) problem of thermal plants using unified particle swarm optimization (UPSO) method. The proposed optimization technique can take care of economic dispatch problems involving constraints such as transmission losses, power balance and generation capacity. The feasibility of the proposed method is demonstrated for three units and six units system, and is compared with Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) methods in terms of the solution quality and computation efficiency. Compared with the other existing techniques, the proposed algorithm has been found to perform better in a number of cases. The experimental results show that the proposed UPSO method was indeed capable of obtaining higher quality solutions efficiently in ED problems.

Keywords: Unified Particle Swarm Optimization (UPSO), Economic Dispatch (ED), Particle Swarm Optimization (PSO), Genetic Algorithm (GA).

I. INTRODUCTION

Economic dispatch problem is defined as the method of determining the optimal combination of power outputs for all generating units, which minimizes the total fuel cost of thermal power plants while satisfying load demand and operating constraints of a power system [1]. This makes the a large-scale non-linear optimization problem. In the traditional ED problem, each generator's cost function has been approximately represented by a single quadratic polynomial and can solved by using numerical programming based techniques such as lambda iteration method, gradient-based method [2]. These require incremental fuel cost curves which are piecewise linear and monotonically increasing to determine the global optimal solution. These techniques offer good results but when the search space is non-linear and it has discontinuities they become very complicated with a slow convergence ratio and not always seeking to the feasible solution. This makes the ED problem of finding the global optimum solution challenging. New numerical methods are needed to cope with these difficulties, especially those with high-speed search to the optimal and not being trapped in local minima. Dynamic programming (DP) method [3] is one of the approaches to solve the non-linear and discontinuous ED problem, but it suffers from the problem of curse of dimensionality or local optimality.

Manuscript published on 30 March 2013.

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In order to overcome this problem, the stochastic search algorithms such as genetic algorithm (GA) [4] [5], and simulated annealing (SA) [6] [7], may prove to be very effective in solving nonlinear ED problems without any restriction on the shape of the cost curves. Although these heuristic methods do not always guarantee discovering the globally optimal solution in finite time, they often provide a fast and reasonable solution (suboptimal nearly global optimal). SA is applied in many power system problems. But, the setting of control parameters of the SA algorithm is a difficult task and convergence speed is slow when applied to a real system. Though, the GA method is usually faster than the SA method because the GA has parallel search techniques, which emulate natural genetic operations. The GA methods have been employed successfully to solve complex optimization problems [8] [9], recent research has identified some deficiencies in GA performance. This degradation in efficiency is apparent in applications with highly epistatic objective functions. Moreover the premature convergence of GA degrades its performance and reduces its search capability that leads to a higher probability toward obtaining a local optimum. The PSO has attracted many researchers' sights due to its simplicity and effectiveness. PSO, inspired from bird flocking and fish schooling, is a flexible, robust, population based algorithm [11] that are adopted by many people for solving ED problems and various power system problems [10] [12]. Unified Particle Swarm Optimization (UPSO) is a modified approach of PSO scheme that harnesses the local and global variant of PSO, combining their exploration and exploitation abilities without imposing additional requirements in terms of function evaluations. Preliminary studies have shown that UPSO can tackle efficiently different optimization problems [13]. The performance of UPSO is initially investigated on four constrained engineering optimization problems having the objective function similar to the cost function of the economic load dispatch problem. The systems which are investigated with UPSO are design of a tension/compression spring, design of a welded beam, design of a gear train, and design of a pressure vessel [14]. A penalty function approach is adopted and the obtained results are compared to that of the standard PSO algorithm, providing useful conclusions regarding the efficiency of the unified scheme. In this paper, a unified particle swarm optimization (UPSO) is proposed to solve the ED problems considering the load demand, transmission line losses and generator constraints. Two cases with three units and six units thermal power system are tested and compared with other approaches and found to be promising. After the introduction, a brief description of the ED problem associated with its mathematical formulation is presented in Section II, while in Section III explains the standard PSO and UPSO.

Section IV then details the proposed procedures. Cases study is presented in Section V. Finally, the conclusion is drawn in Section VI.

II. ECONOMIC LOAD DISPATCH PROBLEMS

The ELD may be formulated as a nonlinear constrained problem [2]. The convex ELD problem assumes quadratic cost function along with system power demand and operational limit constraints. As mentioned above, the objective of ED problems is to minimize the fuel cost of committed generators (units) subjected to operating constraints. Practically, the economic power dispatch problem is usually formulated as,

$$F_{T} = \sum_{i=1}^{n} F_{i}(P_{i})$$
Subject to
$$\sum_{i=1}^{n} P_{i} = P_{D} + P_{L}$$
(2)

$$\sum_{i=1}^{n} P_i = P_D + P_L \tag{2}$$

$$P_i^{Min} \le P_i \ge P_i^{Max} \tag{3}$$

where, n is the number of units, F_T is the total fuel cost, F_i and P_i are the cost function and the real power output of i^{th} unit respectively, P_D is the total demand, $\hat{P_L}$ is the transmission loss. P_i^{Min} and P_i^{Max} are the lower and upper bounds of the ith unit respectively. The equality constraint, Eqn.(2) states that the total generated power should be balanced by transmission losses and power consumption while Eqn.(3) denoting unit's operation constraints.

Traditionally, the fuel cost of a generator is usually defined by a single quadratic cost function,

$$F_i(P_i) = \gamma_i P_i^2 + \beta_i P_i + \alpha_i \tag{4}$$

where, α_i , β_i , and γ_i are cost coefficients of the i^{th} unit. Conventionally, transmission loss is calculated using B-matrix loss formula [2], i.e.,

$$P_{T} = P^{T}BP + P^{T}B0 + B00 (5)$$

where, P denotes the real power output of the committed units in vector form, and B, B0 and B00 are loss coefficients in matrix, vector and scalar respectively, which are assumed to be constant, and reasonable accuracy can be achieved when the actual operating conditions are close to the base case where the *B*-coefficients were derived. In the summary, the objective of economic power dispatch optimization is to minimize F_T subject to the constraints Eqn.(2) and (3).

III. PARTICLE SWARM OPTIMIZATION

A. Standard Particle Swarm Optimization

The particle swarm optimization algorithm, first developed by Kennedy and Eberhart [11], is motivated from the simulation of the behavior of social system. PSO searches for optimal solution in the problem domain via collaborating with individuals within a swarm. Each individual is called particle, which is made of two parts, the position and velocity, and follow two major operations, velocity and position updating rules. Position and velocity represent the candidate solution and step size a particle will advance in next iteration, respectively. For a *n*-dimensional problem and a swarm of m particles, the i^{th} particle's position and velocity, is denoted as $x_i = [x_{i1}, x_{i2}, ..., x_{in}]^T$ and $v_i = [v_{i1}, v_{i2}, ..., v_{in}]^T$, for i = 1, 2, ..., m, respectively. PSO stores the best position p_i = $[p_{i1}, p_{i2}, ..., p_{in}]^T$ it has ever visited in the search space. Also, each particle is considered to have a neighborhood that consists of a number of other particles and its movement is influenced by their best experience, i.e., best positions p_g = $[p_{g1}, p_{g2}, ..., p_{gn}]^T$. Here, superscript T denotes transpose of matrix/vector. For the inertia type PSO, the operation on position and velocity are expressed as follow,

$$v_{id}^{t+1} = \omega \cdot v_{id}^{t} + \varphi_1(p_{ed} - x_{id}^{t}) + \varphi_2(p_{id} - x_{id}^{t})$$
 (6)

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \tag{7}$$

where t is the iteration count, ω is the inertia weight, $\varphi_1 = c_1 r_1$ and $\varphi_2 = c_2 r_2$, where c_1 and c_2 are two positive acceleration parameters, called social and cognitive parameter, respectively; r_1 and r_2 both are random numbers uniformly distributed in (0,1), d is the index of dimension.

According to the definition of neighborhoods, there are two variants of PSO with respect to the number of particles that comprise the neighborhood of a particle. If the whole swarm is considered as the neighborhood of each particle, it is called global variant while in local variant, a smaller neighborhood is used. To distinguish the difference between these two variants, p_g is reserved for global variant while in local variant, p_h is used to replace pg for clarify in this paper. Different neighborhood topologies have been proposed with promising results [16] [17] [18]. The most common topology is the ring structure, where the immediate neighbors of the particle x_i are x_{i-1} , x_{i+1} , and x_1 is considered to be the particle that follows immediately after x_m . Another frequently used PSO is the constriction type PSO [16] that uses the constriction coefficient to control the convergence of the particles, in which position updating rule is not change but the velocity updating rule is redefined as,

$$x_{id}^{t+1} = \chi(v_{id}^t + \varphi_1(p_{ed} - x_{id}^t) + \varphi_2(p_{id} - x_{id}^t))$$
 (8)

where, χ is called constriction coefficient.

B. Unified Particle Swarm Optimization

It has been shown that the neighborhood structure affects the performance of PSO. In the global variant, all particles are attracted by the same best position, leading to converge faster toward specific point. In contrast, the local variant, using multiple neighborhood bests, converges slowly with better performance, especially on multimodal functions. Proper balance these two characteristics results in enhanced performance. By extending the concept of PSO, Unified Particle Swarm Optimization (UPSO), developed by Parsopoulos and Vrahatis, is a modified approach of PSO scheme that harnesses the local and global variant of PSO, combining their exploration and exploitation abilities without imposing additional requirements in terms of function evaluations [13] [14].

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To harness both advantages of global and local model, the two variants are used,

$$G_{id}^{t+1} = \chi(v_{id}^t + \varphi_1(p_{ed} - x_{id}^t) + \varphi_2(p_{id} - x_{id}^t))$$
(9)

$$L_{id}^{t+1} = \chi(v_{id}^t + \varphi_1^t(p_{hd} - x_{id}^t) + \varphi_2^t(p_{id} - x_{id}^t))$$
 (10)

where, G_{id}^{t+1} and L_{id}^{t+1} denote the global and local variant of velocity update for each particle respectively, $\varphi_1 = c_3 r_3$ and $\varphi_2 = c_4 r_4$, where c_3 and c_4 are two positive acceleration parameters, called social and cognitive parameter, respectively, r_3 and r_4 both are random numbers uniformly distributed in (0,1), along the d^{th} dimension.

These two search direction is thus combined in a single equation leading to,

$$V_{id}^{t+1} = rG_{id}^{t+1} + (1-r)L_{id}^{t+1}$$
(11)

$$x_{id}^{t+1} = x_{id}^t + V_{id}^{t+1} (12)$$

where, r is a random number in (0, 1), is referred to unification factor that determines the influence of global and local search direction. Obviously, r = 1 and r = 0 correspond to global and local variant of PSO, respectively.

The purpose of this paper is to investigate the capability and effectiveness of UPSO when applying to ED problems that are frequently encountered in power system industry. The implementation is outlined in next section.

IV. IMPLEMENTATION

The candidate solution is encoded in vector form as $x_i = [x_{i1}, x_{i2}, ..., x_{in}]^T$, for i = 1 to m and j = 1 to n, where x_{ij} denotes the output power of the j^{th} committed units for the i^{th} candidate solution, m is the number of candidate solutions and n is the number of units. Now, taking UPSO as kernel, the developed algorithm for ED problems are summarized below. To be simplicity, ring structure of neighborhood is adopted here. Nevertheless, any other topologies of neighborhood will do.

- 1) Set parameters, i.e., *m*, *n*, *nb*, and *tmx*. Here, *nb*, and *tmx* denote the number of particles in the neighborhood and the maximum number of iterations respectively.
- 2) Generate initially a set of *m* particles (feasible candidate solutions) within the problem domain.
- 3) Evaluate each particle, and find the personal best and global best particles.
- 4) For each particle, find neighborhood best and then move to new position using UPSO.
- 5) Check whether the candidate solution out of constraint, if particle violates constraints in Eqn.(2) and (3), making the candidate solution feasible, otherwise proceeds to next step.
- Evaluate each particle and update personal and global best solution.
- 7) Go to (4) if iteration count is less than tmx.
- 8) Output the final result which is equal to the global best found so far.

To verify the effectiveness and capability of the proposed method, case studies for two different units are conducted and the results are reported in the next section.

V. EXPERIMENTAL RESULTS

Proposed UPSO Algorithm has been applied to ED problems in two different thermal unit systems for verifying its feasibility. These are a three units system and a six units system [4] [10]. The transmission losses will not take into account in all the case studies here for the sake of comparison with other algorithms presented in literature [5] [10] [15]. The stopping criterion, maximum number of iteration, varies for each case in considering the problem scale. The software has been written in MATLAB language and executed in Pentium ® Dual-Core personal computer with 1GB RAM.

Although the UPSO method seems to be sensitive to the tuning of some weights or parameters, according to the experiences of many experiments, the following UPSO [14] and real-coded GA parameters can be used [4].

(i) UPSO Method

- Population size = 100
- Generations = 200
- Inertia weight factor ω is set by a value between 0.9 and 0.4
- The limit of change in velocity of each member in an individual was as $V_{Pd}^{Max} = 0.5 P_d^{Max}$ and $V_{Pd}^{Min} = -0.5 P_d^{Min}$
- Acceleration constant $c_1=2$, $c_2=2$, $c_3=2$ and $c_4=2$.

(ii) GA Method

- Population size = 100
- Generations = 200
- Crossover rate $P_c = 0.8$
- Mutation rate $P_m = 0.01$
- Crossover parameter a = 0.5.

A. Case study 1- Three units system

In this example, a simple system with three thermal units is used to demonstrate how the proposed approach works. The unit characteristics are given in Table 1. In this case, each individual P_g contains three generator power outputs, such as P_1 , P_2 , and P_3 , which are generated randomly. The dimension of the population is equal to 3 X 100. Now, Table 2 provides the statistic results that involved the generation cost, evaluation value, and average CPU time. Figure 1 showed the distribution outline of the best solution for 500 iterations.

TABLE 1 GENERATING UNIT'S CAPACITY AND COEFFICIENTS

Unit	P _{min} MW	P _{max} MW	α \$	β \$/MW	γ \$/ MW ²
1	50	250	328.13	8.663	0.00525
2	5	150	136.91	10.040	0.00609
3	15	100	59.16	9.760	0.00592

In normal operation of the system, the loss coefficients with the 100-MVA base capacity are as follows,



	0.000136	0.0000175	0.000184
$B_{ij} =$	0.0000175	0.000154	0.000283
	0.000184	0.000283	0.00161

Load = 300 MW

TABLE 2

REST POWER	OUTPUT FOR	3-GENERATOR	SYSTEM
DESTRUMEN	OUTFULFOR	. 3-GENERATOR	DIDIEM

Unit Output	GA	PSO	UPSO
P1 (MW)	208.99	209.001	206.28
P2 (MW)	86.0041	85.92	90.68
P3 (MW)	15.4163	15	12.60
Total Power Output (MW)	310.4099	309.9211	309.5659
Total Generation Cost (\$/h)	3624.28	3621.75	3621.59
Power Loss (MW)	10.4099	9.9833	9.5672
Average CPU time (sec)	14.24	32.065	4.81

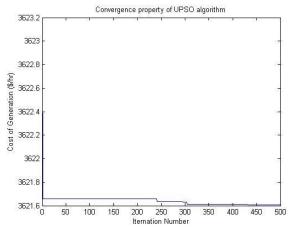


Figure 1 Convergence characteristic of Three-generator system

B. Case study 2- Six units system

The system contains six thermal units, 26 buses, and 46 transmission lines [10]. The load demand is 1263MW. The characteristics of the six thermal units are given in Tables 3. In this case, each individual P_g contains six generator power outputs, such as P_1 , P_2 , P_3 , P_4 , P_5 and P_6 , which are generated randomly. The dimension of the population is equal to 6 X 100. Now, Table 4 provides the statistic results that involved the generation cost, evaluation value, and average CPU time. Figure 2 showed the distribution outline of the best solution for 500 iterations.

In normal operation of the system, the loss coefficients with the 100-MVA base capacity are as follows,

$$B_{ij} = \begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0 & -0.001 & -0.0006 \\ -0.0001 & 0.0001 & 0 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.001 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.015 \end{bmatrix}$$

 $B0 = 10^{-3} [-0.3908 - 0.1297 \ 0.7047 \ 0.0591 \ 0.2161 - 0.6635]$

B00 = 0.056

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TABLE 3 GENERATING UNIT'S CAPACITY AND COEFFICIENTS

Unit	P _{min} MW	P _{max} MW	α \$	β \$/MW	γ \$/ MW ²
1	100	500	240	7.0	0.0070
2	50	200	200	10.0	0.0095
3	80	300	220	38.5	0.0090
4	50	150	200	11.0	0.0090
5	50	200	220	10.5	0.0080
6	50	120	190	12.0	0.0075

Load = 1263 MW

TABLE 4

BEST POWER OUTPUT FOR 6-GENERATOR SYSTEM

Unit Output	GA	PSO	UPSO
P1 (MW)	474.8066	447.497	445.19
P2 (MW)	178.6363	173.3221	172.98
P3 (MW)	262.2089	263.4745	263.91
P4 (MW)	134.2826	139.0594	139.72
P5 (MW)	151.9039	165.4761	164.81
P6 (MW)	74.1812	87.128	89.14
Total Power	1276.03	1276.01	1275.73
Output (MW)			
Total	15,459	15,450	15,447.3
Generation			
Cost (\$/h)			
Power Loss	13.0217	12.9584	12.7325
(MW)			
Average CPU	41.58	14.89	6.0624
time (sec)			

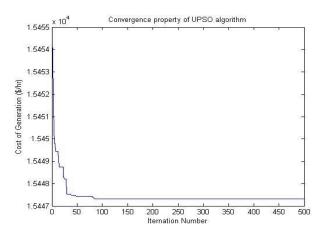


Figure 2 Convergence characteristic of Six-generator system

VI. CONCLUSION

In this paper, we have successfully employed the UPSO method to solve the ED problem with the generator constraints. The UPSO algorithm has been demonstrated to have superior features, including high-quality solution, stable convergence characteristic, and good computation efficiency. The algorithm is implemented for three units and six units system. From the result, it is clear that the proposed algorithm has the ability to find the better quality solution and has better convergence characteristics, computational efficiency and less average CPU time when compared to other methods such as PSO and GA.

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ACKNOWLEDGMENT

The authors wish to thank the authorities of PRIST University, Vallam, Thanjavur, Tamil Nadu, India for the facilities provided to prepare this paper.

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