Economic Dispatch Resolution using Adaptive Acceleration Coefficients based PSO considering Generator Constraints

Salhi Ahmed*, IEEE member, Bouktir Tarek** and Naimi Djemai*
*Laboratory of Electrical Engineering (LGEB), BP 145, 07000 Biskra University, Algeria
**Department of Electrical Engineering, Faculty of Technology, University of Setif1, Algeria
*Email: a_salhi_m@yahoo.fr, **Email: tarek.bouktir@esrgroups.org

Abstract— **The Economic Dispatch (ED) is one of the main concerns for the operation of power systems. Several methods have been applied to solve such problem. Unfortunately, the conventional methods are not suitable to deal with this optimization issue because of the practical operating constraints of generators. This paper present an improved Particle Swarm Optimization (PSO) method based on a variation of acceleration coefficients according to iteration number and adaptively with cognitive and social best positions of the swarm.**
The new approach is founded on Adaptive Acceleration Coefficients (AAC) based PSO and tested on two power systems contain 6 and 15 generating units. The algorithm is compared with other heuristic optimization techniques as demonstrating improved performance and effectiveness over them.

Keywords— Adaptive Acceleration Coefficients; Economic Dispatch; Generator Constraints; Particle Swarm Optimization; Prohibited Zone; Ramp Rate Limit.

I. INTRODUCTION

The main objective of the ED of generation in power systems is to determine the output of each generating unit based on the committed generation mix for the next dispatch interval such that the total generation cost is minimized, while continuously respecting system constraints.
The ED is considered as the most important optimization problem for both the generating companies competing in a free electricity market and the Systems Operator (SO) in charge with a fair handling of transactions between electricity suppliers and their customers [1].

Previous efforts to solve the ED are devoted to classical optimization techniques as deterministic methods based on Lagrange multipliers [2], Gradient method [3], linear programming [4] and quadratic programming [5]. These algorithms require monotonically increasing incremental cost curves, in other words, the existence of the first and second order derivatives of the cost functions. Thus, the problem is resumed to optimizing a convex function over a convex set which is guaranteed to have a unique minimum.

Unfortunately, this assumption may render these algorithms infeasible because of the nonlinear characteristics of input – output of generators in practical systems with the inclusion of prohibited zones and ramp rate limit constraints. Several studies to overcome the problems, cited above are based on modern heuristic optimization techniques such as Genetic Algorithm (GA) [6], Particle Swarm Optimization (PSO) [7], Differential Evolution (DE) [8], Ant Colony Optimization (ACO) [9] and artificial neural networks [10] have been applied by many researchers due to ability of these techniques to find an almost global optimal solution for ED problem with practical operating constraints.

Particle Swarm Optimization (PSO) is one of the most powerful stochastic optimization techniques developed by Eberhart and Kennedy in 1995 [11]. It has recently attracted more attention due to its rapid convergence and algorithmic accuracy compared to other optimization methods. PSO is inspired by social behavior of bird flocking or fish schooling and shares many similarities with evolutionary computation techniques such as GA [12].

In references [13] and [14], Zwe-Lee Gaing and Jong-Bae Park have implanted PSO to solving ED problem considering practical constraints where classical optimization algorithms are not able to deal with such issues. However PSO as other stochastic optimization techniques fails to locate a global solution for large systems and complex situation with multiminima functions, it fails also to exploit the promising research space to get good quality solution. Several improved Algorithms of PSO have been developed in recent years by many researchers to find the best approximate solution of global minimum for ED problems. Among recent algorithms, Adaptive PSO (APSO) [15] presents a novel heuristic optimization approach to constrained ED problems using the adaptive variable population based PSO technique. Chaotic and Gaussian approaches (PSO-CG) with Gaussian probability distribution and chaotic sequences to generate random numbers into the velocity update equation are presented in [16].

In this paper, a new approach is proposed; rely on the variation of acceleration factors in the velocity equation with adaptive manner and best management of exploration and exploitation in space search. This method is called Adaptive Acceleration Factors (AAC) based PSO and applied on ED considering practical generator constraints. Results are obtained and compared to previous works in respect to the same models of studies.

This paper is organized as follows: Section II formulates the ED problem with practical operating constraints. Section III is addressed to conventional PSO as introduction to the proposed approach. Section IV is devoted to our approach AAC descriptions, with its application in section V on two test systems by releasing interpretations about simulation results. Lastly, the conclusion is given.

II. Formulation of Economic Dispatch Problem with Generator Constraints

The objective of the ED problem is to minimize the total fuel cost at thermal power plants subjected to the operating constraints of a power system. Therefore, it can be formulated mathematically with an objective function and two constraints (equality and inequality) considering practical generator constraints.

A. Objective Function

The objective function corresponding to the production cost can be approximated as a quadratic function of the active power outputs from the generating units.

$$min\ F_t^{\cos t} = \sum_{i=1}^{Ng}(a_i + b_i P_{gi} + c_i P_{gi}^2)\ \ (\$/h) \tag{1}$$

$F_t^{\cos t}$: Total fuel cost function.
P_{gi}: Active power output of unit *i.*
a_i , b_i and c_i : cost coefficients of generator *i.*
N_g: number of generating units.

B. Equality Constraints

In the power balance criterion, the equality constraint should be satisfied as:

$$\sum_{i=1}^{m} P_{gi} - P_D - P_L = 0 \tag{2}$$

The total generated real power should be the same with the total load demand plus transmission losses of the system.
P_D is the system's total demand (in MW); P_L represents the total line losses (in MW) and can be calculated using power flows coefficients B_{ij} by the following formula:

$$P_L = \sum_{i=1}^{Ng}\sum_{j=1}^{Ng} P_{gi} B_{ij} P_{gj} + \sum_{i=1}^{Ng} B_{oi} P_{gi} + B_{oo} \tag{3}$$

C. Inequality Constraints

Inequality constraints for each generator must be also satisfied. Generation power of each generator should be laid between maximum and minimum limits.

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \tag{4}$$

Under practical circumstances, ramp rate limits restrict the operating range of all the on-line units for adjusting the generator operation between two operating periods [17].

$$\max(P_{gi}^{\min}, P_{gi}^{o} - DR_i) \le P_{gi} \le \min(P_{gi}^{\max}, P_{gi}^{o} + UR_i) \tag{5}$$

Generating units may have certain restricted operation zone due to limitations of machine components or instability concerns. The allowable operation zones can be defined as [17]:

$$P_{gi} \in \begin{cases} P_{gi}^{\min} \le P_{gi} \le P_{gi,1}^{l} \\ P_{gi,k-1}^{u} \le P_{gi} \le P_{gi,k}^{l} & k = 2,......npz \\ P_{gi,zi}^{u} \le P_{gi} \le P_{gi}^{\max} \end{cases} \tag{6}$$

where: Pgi^{min} and Pgi^{max} are the minimum and maximum outputs of the i[th] generation unit respectively.
DRi and *URi* are the down and up ramp rate limits respectively. Pgi^{o} is the output power of previous time period.
$Pgi_m^{u/l}$ is the upper / lower bounds of the m[th] prohibited zone of unit *i*, *npz* is the number of prohibited zones of unit *i*.

D. Evaluation Function

Evaluation function is an important issue to define the ability measure of each solution, it is called fitness function. In order to speed up the convergence of iteration procedure, the evaluation value is normalized into the range between 0 and 1. Specifically, the evaluation function is adopted in [13] and as bellow:

$$fitness = \frac{1}{F_N + P_{pbc}} \tag{7}$$

where:

$$F_N = 1 + abs\frac{(\sum_{i=1}^{Ng} F_i(Pgi) - F\min)}{(F\max - F\min)} \tag{8}$$

$$P_{pbc} = 1 + (\sum_{i=1}^{Ng} Pgi - P_D - P_L)^2 \tag{9}$$

Here, F_N is the normalized total fuel cost function. Fmax and Fmin are the total fuel cost of generating units at their maximum and minimum limits respectively, calculated at the initial population. P_{pbc} is the power balance constraint, added to the total fuel cost as penalty function.

III. Conventional Particle Swarm Optimization

The PSO can be best understood through an analogy of a swarm of birds in a field. Without any prior knowledge of the field, the birds move in random locations with random velocities looking for foods.

In conventional PSO, particles change their positions (states) with time. Let 'X' and 'V' denote a particle coordinates (position) and its corresponding flight speed (velocity) in a search space respectively. The position vector *Xi* and the velocity vector *Vi* of the *i*[th] particle in the *n*-dimensional search space can be represented as $X_i = (x_{i1}, x_{i2}, ..., x_{in})$ and $V_i = (v_{i1}, v_{i2}, ..., v_{in})$ respectively.

The best previous position of the *i*[th] particle is recorded and represented as $Pbest = (x_{i1}^{pbest}, x_{i2}^{pbest}, ..., x_{in}^{pbest})$. The index of the best particle among all the particles in the group is represented by the $Gbest = (x_1^{Gbest}, x_2^{Gbest}, ..., x_n^{Gbest})$. The modified velocity and position of each particle can be calculated as per following formulas [7]:

$$V_i^{(t+1)} = \underbrace{\omega V_i^{(t)}}_{Previous\ Velocity} + \underbrace{c_1 r_1 \times (Pbest_i^{(t)} - X_i^{(t)})}_{Cognitive\ Component} + \underbrace{c_2 r_2 \times (Gbest^{(t)} - X_i^{(t)})}_{Social\ Component} \quad (10)$$

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)} \quad (11)$$

where ω, c_1, $c_2 \geq 0$,
ω : is the inertia weight factor.
c_1 and c_2 : are the acceleration coefficients.
r_1 and r_2 : are two random numbers within the range [0,1].
$V_i^{(t)}$, $X_i^{(t)}$: are the velocity and the current position of particle *i* in the search space at iteration *t*, respectively.
In general, the inertia weight ω provides a balance between global and local explorations (control the influence of the previous history of the velocities on the current one). It is set according to the following equation:

$$\omega = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min})}{t_{\max}} \times t \quad (12)$$

$\omega_{\min}$, $\omega_{\max}$: initial and final inertia factor weights.
t_{max} : maximum iteration number.
t: current iteration number.
The constants c_1 and c_2 pulls each particle toward *Pbest* positions (cognitive component of velocity) and *Gbest* positions (social component of velocity).
The position is updated with respect to (11).

IV. ADAPTIVE ACCELERATION COEFFICIENTS CONCEPT

The time-varying inertia weight (TVIW) relied on (12) can locate a good solution at a significantly faster rate but its ability to fine tune the optimum solution is weak, due to the lack of diversity at the end of the search. 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 [18]. New researches have emerged to improve PSO Algorithms, as Time-Varying Acceleration Coefficients (TVAC) [19], where c_1 and c_2 in (10) change linearly with time, in the way that the cognitive component is reduced while the social component is increased as the search proceeds [14].

In this section, a new approach called AAC to implement the PSO algorithm will be described in solving the ED problems. Especially, a suggestion will be given on how to deal with inertia weight and acceleration factors. The new approach is destined to change acceleration coefficients exponentially (with inertia weight) in the time, with respect to their minimal and maximal values. The choice of the exponential function is justified by the increasing or decreasing speed of such a function to accelerate the convergence process of the algorithm and to get better search in the exploration space. Furthermore, c_1 and c_2 vary adaptively according to the fitness value of Gbest and Pbest, (10) becomes:

$$V_i^{(t+1)} = \omega^{(t)} V_i^{(t)} + c_1^{(t)} r_1 \times (Pbest_i^{(t)} - X_i^{(t)}) + c_2^{(t)} r_2 \times (Gbest^{(t)} - X_i^{(t)}) \quad (13)$$

where:

$$\omega^{(t)} = \omega_o . \exp(-\alpha_w \times t) \quad (14)$$

$$c_1^{(t)} = c_{1o} . \exp(-\alpha_c \times t \times k_c^{(t)}) \quad (15)$$

$$c_2^{(t)} = c_{2o} . \exp(\alpha_c \times t \times k_c^{(t)}) \quad (16)$$

$$\alpha_c = -\frac{1}{t_{max}} . ln\left(\frac{c_{2o}}{c_{1o}}\right) \quad (17)$$

$$k_c^{(t)} = \frac{(F_m^{(t)} - Gbest^{(t)})}{F_m^{(t)}} \quad (18)$$

$\omega^{(t)}$, $c_i^{(t)}$ are the inertia weight factor and acceleration coefficient respectively at iteration *t*, with *i=1 or 2*. *t* is the iteration number, *ln* is the neperian logarithm.

α_w is determined with respect to initial and final values of ω with the same manner as α_c described in (17).

$k_c^{(t)}$ is determined based on the fitness value of Gbest and Pbest at iteration *t*.

ω_o, c_{oi} initial values of inertia weight factor and acceleration coefficients respectively with *i=1or 2*.

$F_m^{(t)}$ is the mean value of the best positions related to all particles at iteration *t*.

The procedure of AAC based PSO is described as bellow:

Step1: Initialization: Generate N-particles randomly with initial position vector (initial vector of generators' real power outputs, within their minimum and maximum power outputs). Initial velocities are generated randomly in their predetermined permissible range. Fmax and Fmin are specified in the initial population with initial values of weight factor and acceleration coefficients ω_o and c_{oi}.

Step2: Evaluate the fitness function of all particles in the population using (7), (8) and (9). Find best position Pbest of each particle and update its objective value. Similarly, find the global best position Gbest among all the particles and update its objective value.

Step3: If stopping criterion is met, output the Gbest particle and its objective value. Otherwise continue.

Step4: Calculate k_c coefficient, evaluate the inertia factor and acceleration coefficients according to (14), (15) and (16); so that each particles movement is directly controlled by Gbest and Pbest fitness values.

Step5: Update the velocity using (13) and if its new value goes out of range, set it to the boundary value.

Step6: Update the position of each particle according to (11). Check if the limits of particle's positions (ramp rate limits and generators prohibited operating zones) are enforced using (5) and (6). If any of the limits are violated then the particle's position must be modified toward the near margin of the feasible solution. Go to step 2.

V. SIMULATION AND RESULTS

For assessment of the efficiency of the proposed AAC-PSO two case studies are applied for ED with losses considering ramp rate limits and prohibited operating zones. PSO approach was implemented in MATLAB (Math-Works). The programs were run on a 3 GHz Pentium IV Dual-Core, processor with 1 GB of RAM (Random Access Memory). In each case study, 50 independent runs were made for the optimization algorithm involving 50 different initial trial solutions.

A. *Case study 1: Six Unit System*

For this case, the system contains six thermal units, 26 buses, and 46 transmission lines [20]. The load demand is 1263MW. The characteristics of the six thermal units are given in [13]. The network losses are calculated by B-matrix loss formula. Each thermal unit contains two prohibited zones. Ramp rate limits, cost coefficients and B-coefficients are illustrated in [13].

The parameters of AAC-PSO are selected as following:

- The population size=100.
- Number of iterations=200.
- Limitation of velocity of each individual $V_{i(max)}=0.5.P_{gi}^{(max)}$ and $V_{i(min)}=-0.5.P_{gi}^{(min)}$.
- Initial inertia factor $\omega_o=0.9$, Initial acceleration factors are $c_{1o}=2.05$ and $c_{2o}=0.5$.

The results of simulation are reported in Table I, minimum and mean values for 50 trials of execution are considered to verify the efficiency of the algorithm. The previous table shows the comparison of results from AAC-PSO, Genetic Algorithms GA [13], conventional PSO [13], NPSO-LRS [15], APSO [15], ICA-PSO [18], SOH-PSO [19] and CPSO1 [20] methods for the current test system.

Figure.1 represents the convergence characteristics of AAC-PSO compared with conventional PSO for 100 iterations.

It can be evidently seen from results obtained using the proposed AAC-PSO that the new technique provided better results than the other reported evolutionary algorithm techniques like GA, PSO and some modified versions of PSO. It is also observed that simulation results satisfy the system constraints and the mean cost using the proposed approach is less than minimum cost using some of other methods as GA, conventional PSO, CPSO1 and NPSO-LRS. Active power losses P_L are also described.

Referred to Fig.1 with a zoom, the convergence characteristics of AAC-PSO compared with conventional

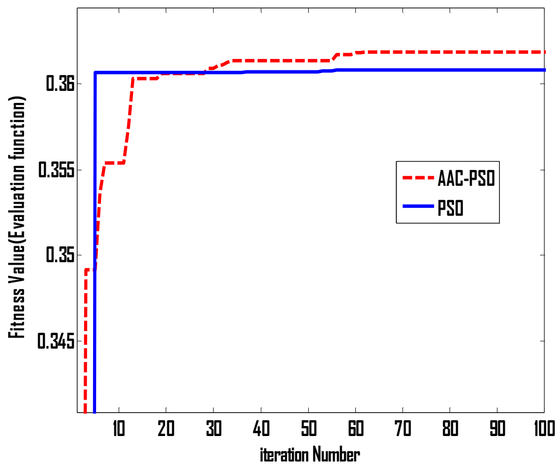

Figure 1. Convergence characteristics of AAC-PSO and conventional PSO (Six-unit system).

PSO shows that the AAC-PSO has good convergence property, thus resulting in good evaluation value of fitness function and low generation cost. After some iteration, the classical PSO characteristics show signs of premature convergence and settle to near optimal results.

B. *Case study 2: Fifteen Unit System*

The system contains 15 thermal units whose characteristics are given in [13]. The load demand of the system is 2630 MW. The loss coefficients matrix was shown in [20].
In this case, the parameters of the PSO-AAC are the same as the previous case, except the population size; which must be changed to 250 because of the size of the electrical network.
The results of numerical simulation of tested AAC-PSO approach are shown in Table II.

Simulation results are compared with other methods; these results also satisfy the inequality constraints of generators including prohibited zones and ramp rate limits. Equality constraint is shown by Power Balance PB displaying best convergence near the optimal solution. Power losses Ploss obtained with the proposed approach are lower than those obtained with other methods.

VI. CONCLUSION

In this paper, a proposed Adaptive Acceleration Factors (AAC) algorithm based PSO is employed for the resolution of Economic Dispatch (ED) problem considering practical generator constraints. The algorithm has been applied in two power systems and has produced results better than those generated by other algorithms. The solutions obtained have superior solution quality and convergence characteristics. It is remarked that the proposed approach is capable of finding the near global solutions of non-linear and non-differentiable objective functions, where classical methods are not able to deal with such functions.

TABLE I. RESULTS RELATED TO SIX UNIT SYSTEM FOR DEMAND OF 1263MW AND COMPARISION WITH OTHER METHODS

Unit Power Output (MW)	**GA [13]**	**PSO [13]**	**APSO [15]**	**SOH-PSO [19]**	**CPSO1 [20]**	**NPSO-LRS [15]**	**ICA-PSO [18]**	**ACC-PSO**
PG1	474.8066	447.4970	446.66857	438.21	434.4236	446.96	447.09	446.6934
PG2	178.6363	173.3221	173.155594	172.58	173.4385	173.3944	173.15	173.3429
PG3	262.2089	263.4745	262.825958	257.42	274.2247	262.3436	263.90	263.9715
PG4	134.2826	139.0594	143.468614	141.09	128.0183	139.5120	139.05	139.5132
PG5	151.9039	165.4761	163.91395	179.37	179.7042	164.7089	165.03	165.2337
PG6	74.1812	87.1280	85.343745	86.88	85.9082	89.0162	86.64	86.6489
Total PG (MW)	1276.03	1276.01	1275.37643	1275.55	1276.0	1275.94	1275.46	**1275.403**
Minimum cost ($/h)	15459	15450	15443.5751	15446.02	15447	15450	15443.24	**15442.656**
Ploss (MW)	13.0217	12.9584	12.421628	12.55	12.9583	12.9361	12.47	**12.404**
Mean cost ($/h)	15469	15454	15449.99	15497.35	15449	15450.5	15443.97	15446.02
Power Balance (MW)	_	_	-0,04522	_	_	_	-0,01	**-0,000685**

TABLE II. RESULTS OF FIFTEEN UNIT AND DEMAND OF 2630 MW

Unit Power Output (MW)	PSO [13]	GA [13]	CPSO1 [20]	CPSO2 [20]	**ACC-PSO**
P_{G1}	439.12	415.31	450.05	450.02	454.999
P_{G2}	407.97	359.72	454.04	454.06	376.028
P_{G3}	119.63	104.42	124.82	124.81	125.409
P_{G4}	129.99	74.98	124.82	124.81	128.127
P_{G5}	151.07	380.28	151.03	151.06	153.315
P_{G6}	459.99	426.79	460	460	459.092
P_{G7}	425.56	341.32	434.53	434.57	427.108
P_{G8}	98.56	124.79	148.41	148.46	67.101
P_{G9}	113.49	133.14	63.61	63.59	123.107
P_{G10}	101.11	89.26	101.13	101.12	88.579
P_{G11}	33.91	60.06	28.656	28.655	77.354
P_{G12}	79.96	50.0	20.912	20.914	76.707
P_{G13}	25.0	38.77	25.001	25.002	39.585
P_{G14}	41.41	41.94	54.418	54.414	38.607
P_{G15}	35.61	22.64	20.625	20.624	24.707
Total PG (MW)	2662.4	2668.4	2662.1	2662.1	**2659.8**
Min. cost ($/h)	32858	33113	32835	32834	**32820**
Ploss (MW)	32.430	38.278	32.1302	32.130	**29.834**
Mean cost ($/h)	–	–	33021	33021	**33015**
PB (MW)	–	–	–	–	**-0,0015**

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