Economic Power Dispatch with Discontinuous Fuel Cost Functions using Improved Parallel PSO

Belkacem Mahdad†, T. Bouktir*, K. Srairi* and M. EL. Benbouzid**

Abstract – This paper presents an improved parallel particle swarm optimization approach (IPPSO) based decomposed network for economic power dispatch with discontinuous fuel cost functions. The range of partial power demand corresponding to the partial output powers near the global optimal solution is determined by a flexible decomposed network strategy and then the final optimal solution is obtained by parallel Particle Swarm Optimization. The proposed approach tested on 6 generating units with smooth cost function, and to 26-bus (6 generating units) with consideration of prohibited zone effect, the simulation results compared with recent global optimization methods (Bee-OPF, GA, MTS, SA, PSO). From the different case studies, it is observed that the proposed approach provides qualitative solution with less computational time compared to various methods available in the literature survey.

Keywords: Parallel Genetic Algorithm, Decomposed Network, PSO, Economic dispatch, Optimal power flow, System security, Planning and control

1. Introduction

The main objective of an economic power dispatch strategy is to determine the optimal operating state of a power system by optimizing a particular objective while satisfying certain specified physical and operating constraints. In its most general formulation, the economic power dispatch (EPD) is a nonlinear, nonconvex, large-scale, static optimization problem with both continuous and discrete control variables. It becomes even more complex when flexible ac transmission systems (FACTS) devices are taken into consideration as control variables [1]-[2].

The global optimization techniques known as genetic algorithms (GA), simulated annealing (SA), tabu search (TS), and evolutionary programming (EP), which are the forms of probabilistic heuristic algorithm have been successfully used to overcome the non-convexity problems of the constrained ED [3].

The literature on the application of the global optimization in the OPF problem is vast and [4] represents the major contributions in this area. In [5] authors present an enhanced genetic algorithm (EGA) for the solution of the OPF problem with both continuous and discrete control variables. The continuous control variables modelled are unit active power outputs and generator-bus voltage magnitudes, while the discrete ones are transformer-tap settings and shunt devices.

Authors in [6] present a Bee optimization algorithm (BeeOA), to solve the economic power dispatch (EPD) with consideration of valve point effects, in [7] authors present a novel string structure for solving the economic dispatch through genetic algorithm (GA). To accelerate the search process authors in [8] proposed a multiple tabu search algorithm (MTS) to solve the dynamic economic dispatch (ED) problem with generator constraints, simulation results prove that this approach is able to reduce the computational time compared to the conventional approaches. Authors in [9] present an algorithm based simulated annealing to solve the optimal power flow.

PSO has parallel search techniques. Due to its high potential for global optimization, PSO has received great attention in solving optimal power flow (OPF) problems with consideration of discontinuous fuel cost functions. Author in [10] present a Particle swarm optimization to solving the economic dispatch considering the generator constraints.

In general to overcome the drawbacks of the conventional methods related to the form of the cost function, and to reduce the computational time related to the large space search required by GA, authors in [11] proposed an efficient decomposed GA for the solution of large-scale OPF with consideration of shunt FACTS devices under severe loading conditions. This paper presents an improved parallel PSO (IPPSO) for the solution of the economic dispatch with consideration of discontinues practical generation constraints. The length of the original particles is reduced successively based on the decomposition level and adapted with the topology of the new partitioned network. Partial decomposed active power demand added as a new dynamic variable and searched within the active power generation variables for the successive decomposed particles. Fig.1 shows the improved parallel swarm optimization (IPPSO) approach combined with FACTS devices to enhance the economic power dispatch (EPD).

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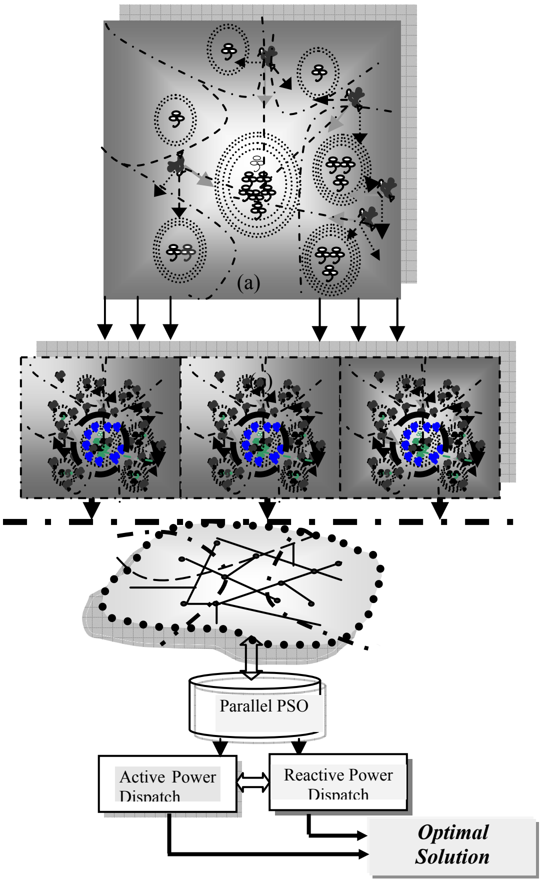

Fig. 1. Global search mechanism based decomposed network using improved parallel PSO.

2. Active Power Dispatch Formulation with Discontinuous Fuel Cost Functions

The main role for economic dispatch is to minimize the total generation cost of the power system but still satisfying specified constraints (generators constraints and security constraints). Fig. 2 shows the economic dispatch strategy.

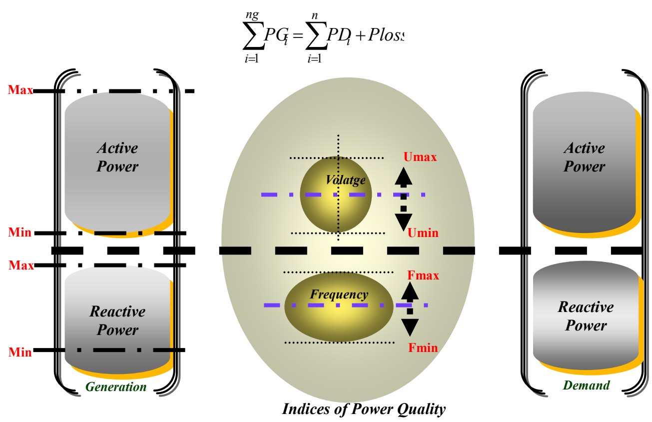

Fig. 2. Economic dispatch strategy.

For optimal active power dispatch, the simple objective function f is the total generation cost as expressed follows:

$$\text{Min} \quad f = \sum_{i=1}^{N_g} \left(a_i + b_i P_{gi} + c_i P_{gi}^2 \right) \tag{1}$$

where N_g is the number of thermal units, P_{gi} is the active power generation at unit i and a_i, b_i and c_i are the cost coefficients of the i^{th} generator.

2.1 The Equality Constraints

In the power balance criterion, the equality constraint should be satisfied as the real and reactive power balance equations, expressed as follows:

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

where NG represents the total number of generators, P_D is the total active power demand, P_{loss} represent the transmission losses, the P_{loss} are calculated using power flow coefficients B_{ij} by the following formula:

$$P_{loss} = \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_{gi} B_{ij} P_{gj} + \sum_{i=1}^{NG} B_{0i} P_{gi} + B_{00} \tag{3}$$

2.2 The inequality Constraints

- Upper and lower limits on the active power generations:

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

- Ramp-rate limits constraints:

$$\begin{aligned} &\max\left(P_{gi}^{\min}, P_{gi}(t-1) - DR_i\right) \le P_{gi}(t) \\ &\le \min\left(P_{gi}^{\max}, P_{gi}(t-1) + UR_i\right) \end{aligned} \tag{5}$$

- Prohibited operating zones constraints:

$$P_{gi} \in \begin{cases} P_{gi}^{\min} \le P_{gi} \le P_{gi,1}^{1} \\ P_{gi,k-1}^{u} \le P_{gi} \le P_{gi,k}^{1}, \quad k = 2,\ldots\ldots, z_i \\ P_{gi,z_i}^{u} \le P_{gi} \le P_{gi}^{\max} \end{cases} \tag{6}$$

where z_i is the number of prohibited zones of unit i;

$P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum outputs of the ith generation unit;

k is the index of prohibited zones of a unit i;

$P_{i,k}^{1/u}$ is the lower/upper bounds of the k^{th} prohibited zone of unit i;

3. Overview of PSO Technique

The PSO can best be understood thought an analogy similar to the one that led to the development of the PSO. Imagine a swarm of bees in a field [12]. Their goal is to find in the field the location with the highest density of flowers without any knowledge of the field a priori, the bees begin in random locations with random velocities looking for flowers each bee can remember the locations that it found the most flowers, and somehow knows the locations where the others bees found an abundance of flowers. The main target is that the bees explore the field: overlying locations of greatest concentration hoping to find the absolute highest concentration of flowers. Soon, all the bees swarm around this point. Unable to find any points of higher flower concentration, they are continually drawn back to the highest flower concentration as indicated in Fig 3 (a, b). Fig. 4.

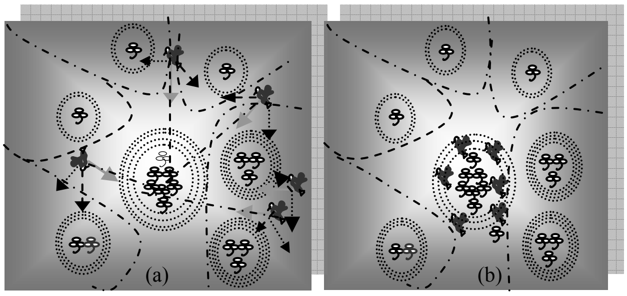

Fig. 3. (a) swarm mechanism search: The particles in PSO are attracted both to the area of highest concentration found by the entire swarm, and the best location personally encountered by the particle.
(b) All the bees swarm around the best location.

3.1 Problem Formulation

Let $X_i = (x_{i1} ......x_{in})$, and $V_i = (v_{i1} ....v_{in})$ denote the coordinates and the corresponding flight speed of the particle i in a search space, respectively. The velocity of the particle is changed according to the relative locations of $Pbest$ and $Gbest$. It is accelerated in the directions of these locations of greatest fitness according to the following equation [13]-[14].

$$V_i^{k+1} = \omega V_i^k + c_1 rand \times \left(Pbest_i^k - X_i^k\right) + c_2 Rand \times \left(Gbest_i^k - X_i^k\right) \quad (7)$$

where

V_i^k velocity of particle i at iteration k;

ω inertia weight factor;

c_1, c_2 acceleration constant;

X_i^k position of particle i at iteration k;

$Pbest_i^k$ best position of particle i until iteration k;

$Gbest_i^k$ best position of group until iteration k;

Once the velocity has been determined it is simple to move the particle to its next location, and a new coordinate X_i^{k+1} is computed for each of the N dimensions according the following equation:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (8)$$

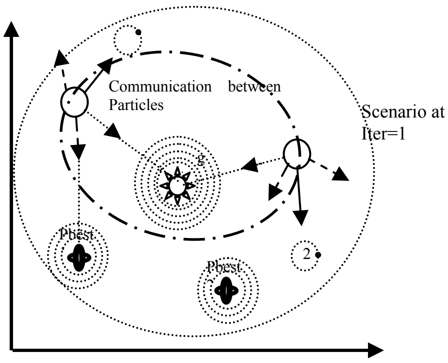

Fig. 4. The search mechanism of the particle swarm optimization.

3.2 Algorithm Steps for Economic Dispatch based Swarm

(1) Chromosome Structure

The active power generations of units are taken as the particles of the PSO. Fig. 5 shows the particles structure

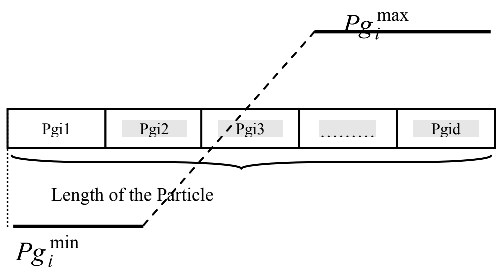

Fig. 5. Particles structure.

where n means population size, d is the number of generator, and Pg_{id} is the generation power output of the dth unit at ith individual.

(2) Evaluation Function

The structure of Evaluation function f or fitness function is important to speed up the convergence of the iteration procedure. The evaluation function [10] is adopted as (9). It is the reciprocal of the generation cost function $F_{cost}(Pg_i)$ and power balance constraint $F_{pbc}(Pg_i)$ as in (2).

$$f = \frac{1}{F_{cost} + F_{pbc}} \quad (9)$$

where

$$F_{\cos t} = 1 + abs\frac{\left(\sum_{i=1}^{n} F_i(Pg_i) - F_{\min}\right)}{\left(F_{\max} - F_{\min}\right)} \quad (10)$$

$$F_{pbc} = 1 + \left(\sum_{i=1}^{n} Pg_i - P_D - P_{loss}\right)^2 \quad (11)$$

$F_{\max}$ maximum generation cost among all individuals in the initial population;

$F_{\min}$ minimum generation cost among all individuals in the initial population.

3.3 Calculation Steps of the Proposed Method

The PSO algorithm is as follows:

Step1: the particles are randomly generated between the maximum and minimum operating limits of units.

Step2: The particle velocities are generated randomly.

Step3: Objective function values of the particles are evaluated. These values are set the best value of the particles.

Step4: the best value among all the pbest values (gbest) is identified.

Step5: new velocities for the particles are calculated using (7). The new velocity is simply the old velocity scaled by ω and increased in the direction of gbest and pbest for that particle dimension. c_1 and c_2 are scaling factors that determine the relative 'pull' of pbest and gbest. c_1 is a factor determining how much the particle is influenced by the memory of his best location, and c_2 is a factor determining how much the particle is influenced by the rest of the Swarm [15].

In this paper, the weighting factor is defined as follows.

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

where

$\omega_{\max}, \omega_{\min}$: initial, final weights;

$Iter_{\max}$: maximum iteration number;

$Iter$:current iteration number.

Step6: the positions for each particle are updated using (8).

The resulting position of a particle is not always guaranteed to satisfy the inequality constraints.

If $v_{i,j} > V_j^{\max}$, then $v_{i,j} = V_j^{\max}$. If $v_{i,j} < V_j^{\min}$, then $v_{i,j} = V_j^{\min}$

Stap7: New objective function values are calculated for the new positions of the particles. If the new value is better than the previous pbest, the new value is set to pbest. If the stopping criterion is met, the positions of particles represent the optimal solution; otherwise the procedure is repeated from step4.

4. Strategy of the Proposed Approach

4.1 Initialization based in Decomposition Procedure

The main idea of the proposed approach is to optimize the active power demand for each partitioned network to minimize the total fuel cost. An initial candidate solution generated for the global N population size.

- For each decomposition level estimate the initial active power demand:

For NP=2 Do

$$Pd1 = \sum_{i=1}^{M1} P_{Gi} \quad (13)$$

$$Pd2 = \sum_{i=1}^{M2} P_{Gi} = PD - Pd1 \quad (14)$$

Where NP the number of partition

$Pd1$: the active power demand for the first initial partition.

$Pd2$: the active power demand for the second initial partition.

PD : the total active power demand for the original network.

The following equilibrium equation should be verified for each decomposed level:

For level 1:

$$Pd1 + Pd2 = PD + Ploss \quad (15)$$

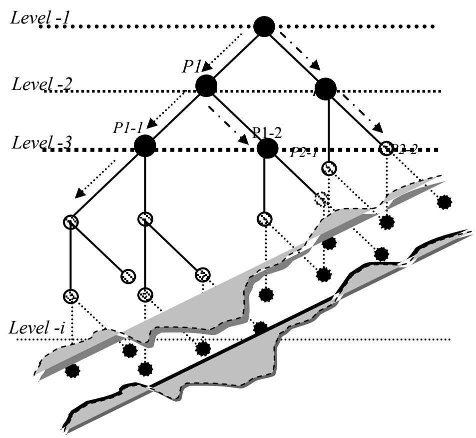

Fig. 6. Sample of network with tree decomposition.

- Fitness Evaluation based Load Flow

For all sub-systems generated perform a load flow calculation to evaluate the proposed fitness function. A candidate solution formed by all sub-systems is better if its fitness is higher.

$$f_i = 1/\left(F_{\cos t} + \omega_l F_{li} + \omega_V F_{Vi}\right) \quad (16)$$

$$F_{Vi} = \sum_{j=1}^{NPQ} \left(\left|V_{PQij} - V_{PQij}^{\lim}\right|\right) / \left(\left|V_{PQij}^{\max} - V_{PQij}^{\min}\right|\right) \quad (17)$$

where f_i is fitness function for sub-systems decomposed at level i.

F_{li} denotes the per unit power loss generated by sub-systems at level i; F_{cost} denotes the total cost of the active power planning related to the decomposition level i; F_{Vi} denotes the sum of the normalized violations of voltages related to the sub-systems at level i.

- Consequently under this concept, the final value of active power demand should satisfy the following equations.

$$\sum_{i=1}^{N_g}(Pg_i)=\sum_{i=1}^{part_i}(Pd_i)+ploss \tag{18}$$

$$Pg_i^{\min} \leq Pg_i \leq Pg_i^{\max} \tag{19}$$

4.2 Final Search Mechanism

- All the sub-systems are collected to form the original network, global data base generated based on the best results U_{best}^{Parti} of partition 'i' found from all sub-populations.
- The final solution U_{best}^{Global} is found out after reactive power planning procedure to adjust the reactive power generation limits, and voltage deviation, the final optimal cost is modified to compensate the reactive constraints violations. Fig. 6 shows an example of tree network decomposition used to search the global database. Fig. 7 illustrates the basic steps of the proposed approach.

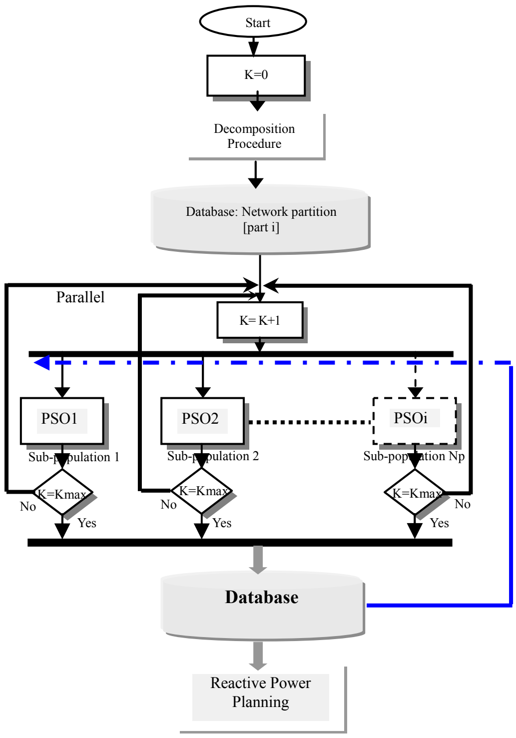

Fig. 7. Procedure of parallel swarm optimization approach for EPD.

5. Application Study

The proposed algorithm is developed in the Matlab programming language using 6.5 version. The proposed approach has been tested on two test network (6 generating units without prohibited zones, and 6 generating units with prohibited zones).

i) IPPSO Parameters

- population size=50-100
- generations=50-100
- inertia weight factor w is set by (12), where $\omega_{\max}=0.9$ and $\omega_{\min}=0.4$;
- acceleration constant c1=1.85 and c2=2.1.

5.1 Test System 1

The first test system has 6 generating units; the characteristics of the six units are given in Table 1. The load demands are 800, 1200 and 1800 MW. In this example the power losses, the ramp rate limits and prohibited zones of the units are not taken into account.

Figs. 8-9-10 show the convergence of the proposed approach for the three partitioned subsystems. The best cost for each partition network obtained with minimum iteration less than 30 iterations. Tables 2-3-4 show the results of the minimum cost obtained by different methods at different loading conditions. The total costs at different loading conditions obtained with the proposed approach are better than the results found from the methods cited in the literature.

Table 1. Technical admissible parameters of generators and the fuel cost Coefficients

Bus Number	*Pmin [MW]*	*Pmax [MW]*	*a [$/hr]*	*b [$/MWhr]*	*c [$/MW²hr]*
1	100	600	561	7.92	0.001562
2	100	400	310	7.85	0.001940
3	50	200	78	7.97	0.004820
4	140	590	500	7.06	00.00139
5	110	440	295	7.46	00.00184
6	110	440	295	7.46	00.00184

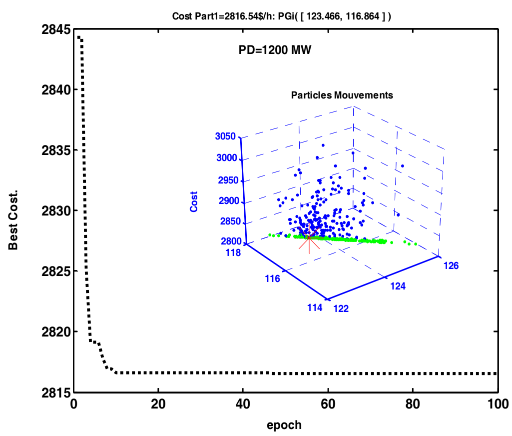

Fig. 8. Convergence of the proposed approach for the first partition: PD=1200MW.

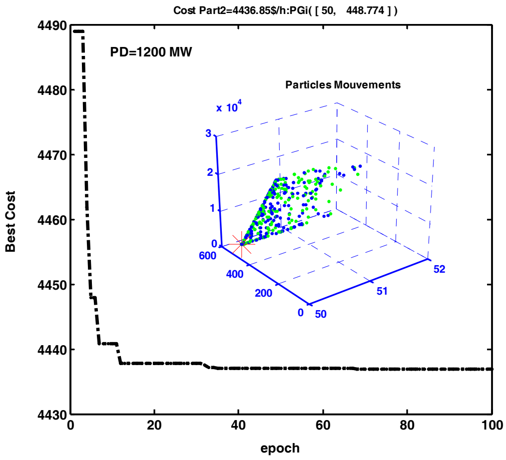

Fig. 9. Convergence of the proposed approach for the second partition: PD=1200MW.

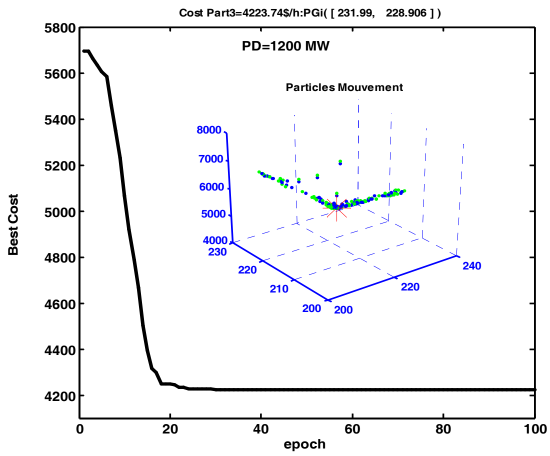

Fig. 10. Convergence of the proposed approach for the third partition: PD=1200MW.

Table 2. Minimum generation cost obtained by different methods on 6-generating units systems: PD=800 MW

Units	CGA [6]	QEGA [6]	BeeOA [6]	Our Approach
P_{g1}	109.17	104.89	100.00	**100.00**
P_{g2}	104.08	105.87	100.00	**100.00**
P_{g3}	52.04	51.74	50.00	**50.00**
P_{g4}	305.05	314.18	305.63	**305.6201**
P_{g5}	114.83	113.16	122.19	**119.7326**
P_{g6}	114.83	113.16	122.19	**124.6471**
Load (MW)	**800**	**800**	**800**	**800**
Total Cost ($/h)	8232.89	8231.03	8227.10	**8227.10**

Table 3. Minimum generation cost obtained by different methods on 6-generating units systems: PD=1200 MW

Units	CGA [6]	QEGA [6]	BeeOA [6]	Our Approach
P_{g1}	142.55	131.50	123.76	**120.2968**
P_{g2}	117.80	129.05	117.68	**120.0325**
P_{g3}	58.90	52.08	50.00	**51.0607**
P_{g4}	515.20	494.08	448.42	**447.7139**
P_{g5}	182.78	200.61	230.06	**231.8129**
P_{g6}	182.78	200.61	230.06	**229.0835**
Load (MW)	**1200**	**1200**	**1200**	**1200**
Total Cost ($/h)	11493.74	11480.03	11477.08	**11477.00**

Table 4. Minimum generation cost obtained by different methods on 6-generating units systems: PD=1800 MW

Units	*CGA [6]*	*QEGA [6]*	*BeeOA [6]*	*Our Approach*
P_{g1}	222.42	250.49	247.99	249.2971
P_{g2}	190.73	215.43	217.719	216.4120
P_{g3}	95.36	109.92	75.18	74.2414
P_{g4}	555.63	572.84	588.04	589.0095
P_{g5}	367.92	325.66	335.52	338.1559
P_{g6}	367.92	335.52	335.53	332.8841
Load (MW)	**1800**	**1800**	**1800**	**1800**
Total Cost ($/h)	16589.05	16585.85	16579.33	**16579.00**

5.2 Test System 2

This case study consisted of six generation units, 26 buses and 46 transmission lines. All thermal units are within the ramp rate limits and prohibited zones. The characteristics of the six units are given in Table 5 and 6. All data of this test system can be retrieved from [10]. In this case, the load demand expected to be determined was PD=1263 MW. The B matrix of the transmission loss coefficient is given by:

$$B_{ij} = 10^{-3}\begin{bmatrix} 1.7 & 1.2 & 0.7 & -0.1 & -0.5 & -0.2 \\ 1.2 & 1.4 & 0.9 & 0.1 & -0.6 & -0.1 \\ 0.7 & 0.9 & 3.1 & 0.0 & -1.0 & -0.6 \\ -0.1 & 0.1 & 0.0 & 0.24 & -0.6 & -0.8 \\ -0.5 & -0.6 & -0.6 & -0.6 & 12.9 & -0.2 \\ -0.2 & -0.1 & -0.6 & -0.8 & -0.2 & 15.0 \end{bmatrix} \tag{20}$$

$$B_{i0} = 10^{-3}[-0.3908 \quad -0.1297 \quad -0.7047 \quad -0.0591 \quad 0.2161 \quad -0.6635] \tag{21}$$

$$B_{00} = 0.056 \tag{22}$$

Table 5. Generating units capacity and cost coefficients: 26-bus test system

Bus Number	*Pmin [MW]*	*Pmax [MW]*	*a [$/hr]*	*b [$/MWhr]*	*c [$/MW²hr]*
1	100	500	240	7.0	0.0070
2	50	200	200	10.0	0.0095
3	80	300	220	8.5	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

Table 6. Ramp Rate limits and prohibited zones of generating units: 26-bus test system

Bus Number	P_i^o	*URi [MW/h]*	*DRi [$/hr]*	*Prohibited zones [MW]*
1	440	80	120	[210 240] [350 380]
2	170	50	90	[90 110] [140 160]
3	200	65	100	[150 170] [210 240]
4	150	50	90	[80 90] [110 120]
5	190	50	90	[90 110] [140 150]
6	110	50	90	[75 85] [100 105]

Table 7 shows the performance comparison among the proposed algorithms, a particle swarm optimization (PSO) approach [10], a novel string based GA [7], standard genetic algorithm (GA) method [10], multiple tabu search algorithm (MTS) [8], and the simulated annealing (SA) method [9]. The simulation results of the proposed approach outperformed recent optimization methods presented in the literature in terms of solution quality and time convergence.

Table 7. Results of the minimum cost and power generation compared with global optimization methods for 26-Bus test system

Generators (MW)		SA[9]	New-string GA [7]	GA [8]	MTS[8]	PSO[10]	**Our Approach**
P_{g1}	**Part1**	478.1258	446.7100	474.8066	448.1277	447.4970	447.8293
P_{g2}		163.0249	173.0100	178.6363	172.8082	173.3221	172.1145
P_{g3}	**Part2**	261.7143	265.0000	262.2089	262.5932	263.4745	263.5932
P_{g4}		125.7665	139.0000	134.2826	136.9605	139.0594	135.9605
P_{g5}	**Part3**	153.7056	165.2300	151.9039	168.2031	165.4761	170.1279
P_{g6}		90.7965	86.7800	74.1812	87.3304	87.1280	85.4056
Total PG		1276.1339	1275.73	1276.03	1276.0232	1276.01	1275.00
Ploss (MW)		13.1317	12.733	13.0217	13.0205	12.9584	12.0310
Cost[$/hr]		15461.10	15447.00	15459.00	15450.06	15450.00	15437.00
CPU time(s)		-	8.36	-	1.29	14.89	1.4120

The performance of the convergence characteristics for the three partitioned network are shown clearly in Figs. 11, 12, 13. The computational time of the proposed approach is reduced significantly in comparison to the other methods.

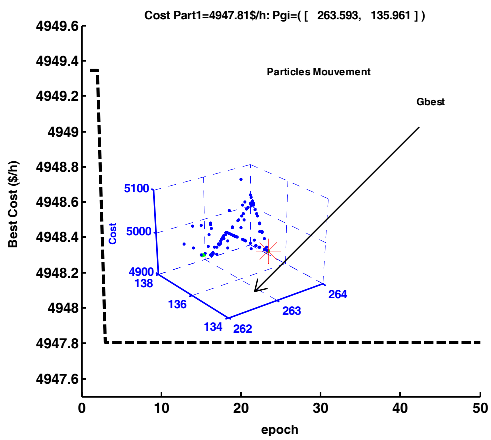

Fig. 11. Convergence of the proposed approach for the first partition: PD=1263MW.

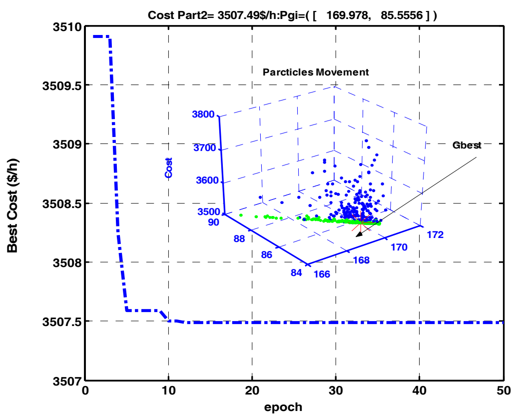

Fig. 12. Convergence of the proposed approach for the second partition: PD=1263MW.

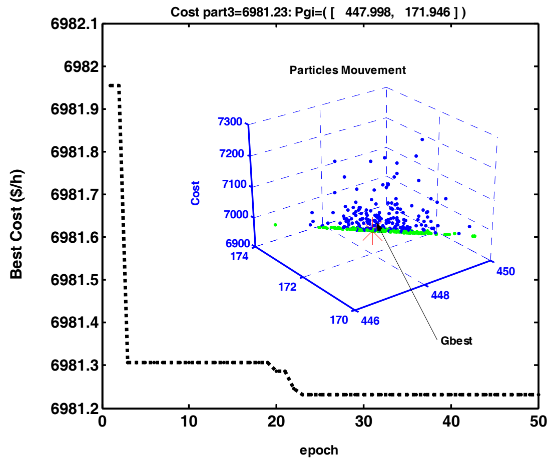

Fig. 13. Convergence of the proposed approach for the third partition: PD=1263MW.

6. Discussions

6.1 Robustness Test

The performance of the proposed approach must be concluded after many trials with different initializations. Table 8, 9, and Table 10 show the best cost solution for 8 trials. From the sample results it is evident that the proposed approach is more consistent.

6.2 Computational Efficiency

Computational efficiency analysis is an important index to test and validate the robustness of an algorithm. The mean CPU time to converge to the best solution have been observed and shown in Table 7. For the proposed approach the IPPSO takes an average CPU time of 1.412s to find the best solution of the second test system. This time is given after identification of the global data base containing the best partitioned network.

Table 8. EP-PSO for 6-generating units: results and convergence characteristics: PD=800MW

Real Power Output and Cost P_G [MW], **PD=800 MW**					
Bus N°		**Run1**	**Run2**	**Run3**	**Run4**
1	**Part1**	100.0000	100.0000	100.0000	100.0000
2		100.0000	100.0000	100.0000	100.0000
3	**Part2**	50.0000	50.0000	50.0000	50.0000
4		305.6201	305.6201	305.6201	305.6201
5	**Part3**	120.0626	122.0641	119.7326	119.3084
6		124.3173	122.3158	124.6471	125.0716
Cost[$/h]		**8227.10**	**8227.10**	**8227.10**	**8227.10**
Ploss (MW)		0	0	0	0
Real Power Output and Cost					
Bus N°		**Run5**	**Run6**	**Run 7**	**Run 8**
1	**Part1**	100.0000	100.0000	100.0000	100.0000
2		100.0000	100.0000	100.0000	100.0000
3	**Part2**	50.0000	50.0000	50.0000	50.0000
4		305.6201	305.6201	305.6201	305.6201
5	**Part3**	121.9559	121.6291	124.2006	123.5904
6		122.4240	122.7509	120.1792	120.7893
Cost[$/h]		**8227.10**	**8227.10**	**8227.10**	**8227.10**
Ploss (MW)		0	0	0	0

Table 9. EP-PSO for 6-generating units: results and convergence characteristics: PD=1200MW

Real Power Output and Cost P_G [MW], PD=1200 MW					
Bus N°		**Run1**	**Run2**	**Run3**	**Run4**
1	**Part1**	122.9447	122.8026	120.2968	121.2401
2		117.3847	117.5268	120.0325	119.0893
3	**Part2**	50.7519	50.0000	51.0607	50.6598
4		448.0230	448.7748	447.7139	448.1150
5	**Part3**	232.0000	231.2201	231.8129	230.8963
6		228.8960	229.6764	229.0835	230.0000
Cost[$/h]		**11477.00**	**11477.00**	**11477.00**	**11477.00**
Ploss (MW)		0	0	0	0
Real Power Output and Cost					
Bus N°		**Run5**	**Run6**	**Run 7**	**Run 8**
1	**Part1**	123.0859	123.0531	125.0111	123.4744
2		17.2435	117.2763	115.3184	116.8549
3	**Part2**	50.0000	51.2571	50.6899	51.2558
4		448.7746	447.5175	448.0850	447.5169
5	**Part3**	231.9073	232.0000	230.8965	232.0000
6		228.9887	228.8967	230.0000	228.8964
Cost[$/h]		**11477.00**	**11477.00**	**11477.00**	**11477.00**
Ploss (MW)		0	0	0	0

Table 10. EP-PSO for six generating units: results and convergence characteristics: PD=1800MW

Real Power Output and Cost P_G [MW], PD=1800 MW					
Bus N°		**Run1**	**Run2**	**Run3**	**Run4**
1	**Part1**	248.2584	247.7467	247.8030	248.3835
2		217.4504	217.9623	217.9060	217.3256
3	**Part2**	76.0276	76.7588	72.5827	75.0705
4		587.2233	586.4921	590.6682	588.1805
5	**Part3**	333.3616	338.6819	337.5439	335.5557
6		337.6785	332.3580	333.4960	335.4843
Cost[$/h]		**16579.00**	**16579.00**	**16579.00**	**16579.00**
Ploss (MW)		0	0	0	0
Real Power Output and Cost					
Bus N°		**Run5**	**Run6**	**Run 7**	**Run 8**
1	**Part1**	245.2436	248.7239	246.2992	249.2971
2		220.4653	216.9850	219.4099	216.4120
3	**Part2**	75.8609	75.2985	75.4824	74.2414
4		587.3900	587.9524	587.7686	589.0095
5	**Part3**	333.5527	335.9037	335.9272	338.1559
6		337.4873	335.1363	335.1127	332.8841
Cost[$/h]		**16579.00**	**16579.00**	**16579.00**	**16579.00**
Ploss (MW)		0	0	0	0

7. Conclusion

Application of an improved parallel PSO to enhance the OPF solution with consideration of practical generation constraints is demonstrated in this paper. In the first stage a decomposition mechanism is proposed to search the efficient partitioned network. A global database generated containing the best technical sub-systems. In the second stage a parallel execution of the adapted PSO associated to each decomposed swarm.

The performance of the proposed approach was tested with 6 generating units with smooth cost function, and with another test system (26 bus test system) with consideration of valve point effect, the results of the proposed algorithm compared with recent global optimization method. It is observed that the proposed approach is capable of finding the near global solutions of non-linear and non-differentiable objective functions and obtain a competitive solution at a reduced time.

References

[1] O. Alsac and B. stott. "Optimal load flow with steady state security," IEEE Trans. Power Appara. Syst., pp.745-751, May-June 1974.

[2] M. Huneault, and F. D. Galiana, "A survey of the optimal power flow literature," IEEE Trans. Power Systems, Vol.6, No.2, pp.762-770, May 1991.

[3] B. Mahdad, T. Bouktir, K. Srairi, "OPF with Environmental Constraints with SVC Controller using Decomposed Parallel GA: Application to the Algerian Network" Journal of Electrical Engineering & Technology, Korea, Vol.4, No.1, pp.55-65, March 2009.

[4] R. C. Bansal, "Otimization methods for electric power systems: an overview," International Journal of Emerging Electric Power Systems, Vol.2, No.1, pp.1-23, 2005.

[5] A. G. Bakistzis, P. N. Biskas, C. E. Zoumas, and V. Petridis, "Optimal power flow by enhanced genetic algorithm, "IEEE Trans. Power Systems, Vol.17, No.2, pp.229-236, May 2002.

[6] R. Kumar, D. Sharma, and A. Kumar, "Economic power dispatch with valave point effects using Bee optimization algorithm" Journal of Electrical Engineering & Technology, Korea, Vol.4, No.1, pp.19-27, March 2009.

[7] C. Chien Kuo, "A novel string structure for economic dispatch problems with practical constraints," Journal of Energy Conversion and management, Elsevier, Vol.49, pp.3571-3577, 2008.

[8] S. Pothiya, I. Nagamroo, and W. Kongprawechnon, "Application of mulyiple tabu search algorithm to solve dynamic economic dispatch considering generator constraints," Journal of Energy Conversion and management, Elsevier, Vol.49, pp.506-516, 2008.

[9] C. A. Roa-Sepulveda, B. J. Pavez-Lazo, " A solution to the optimal power flow using simulated annealing," Electrical Power & Energy Systems (Elsevier), Vol.25, No.1, pp.47-57, 2003.

[10] Z. L. Gaing, "Particle swarm optimization to solving the economic dispatch considering the generator constraints," IEEE Trans. Power Systems, Vol.18, No.3, pp.1187-1195, 2003.

[11] B. Mahdad, T. Bouktir, K. Srairi, "Optimal power flow for large-scale power system with shunt FACTS using fast parallel GA," The 14th IEEE Mediterranean on Electrotechnical Conference, 2008. MELECON 5-7 May 2008. pp.669-676.

[12] Jacob Robinson and yahya Rahmat-Samii, "Particle swarm optimization in electromagnetics," IEEE Trans. Antennas and propagation, Vol.52, No.2, pp.397-407, February 2004.

[13] Ahmed A. A. Esmin, Germano Lambert-Torres, and A. C. Zambroni de souza, "A Hybrid particle swarm optimization applied to loss power minimization," IEEE Trans. Power Systems, Vol.20, No.2, pp.859-866, May 2005.

[14] R. C. Eberhart and Y. Shi, "Particle swarm optimiza-

tion: developments, applications and ressources," in Proc.2001 Congr. Evolutionary Computation, Vol.1, 2001.

[15] B. Mahdad, T. Bouktir, K. Srairi, "Strategy based PSO for Dynamic Control of UPFC to Enhance Power System Security," Accepted at IEEE Powertech Conference 2009.

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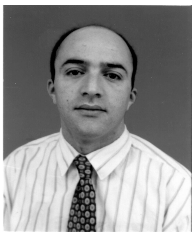

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