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Fuzzy Controlled Parallel PSO to Solving Large Practical Economic Dispatch

Belkacem Mahdad, K. Srairi, T. Bouktir, M. EL. Benbouzid

Abstract—This paper proposes a version of fuzzy controlled parallel particle swarm optimization approach based decomposed network (FCP-PSO) to solve large nonconvex economic dispatch problems. The proposed approach combines practical experience extracted from global database formulated in fuzzy rules to adjust dynamically the three parameters associated to PSO mechanism search. The adaptive PSO executed in parallel based in decomposed network procedure as a local search to explore the search space very effectively. The robustness of the proposed modified PSO tested on 40 generating units with prohibited zones and compared with recent hybrid global optimization methods. The results show that the proposed approach can converge to the near solution and obtain a competitive solution with a reasonable time compared with recent previous approaches.

Key Words—Parallel Genetic Algorithm, Decomposed Network, PSO, economic dispatch, Fuzzy logic, Fuzzy Controlled Planning and control.

I. INTRODUCTION

The economic dispatch problem (EDP) is one of the important problems in modern power system operation and planning. A number of traditional algorithms like lambda iteration, gradient method, and Newton method can solve ED problems effectively; however these methods require that incremental cost curves are monotonically increasing in nature. In practice the input-output curve of modern generating units are highly nonlinear due to many practical constraints, like prohibited zone, valve-loading effect, ramp-rate limits, multi-fuel options, etc. So 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. 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 [1].

The literature on the application of the global optimization in the OPF problem is vast and [1] represents the major contributions in this area. In [2] authors presented an improved coordinated aggregation-based particle swarm optimization (ICA-PSO) algorithm for solving the optimal

economic dispatch, the obtained results are compared to many large recent heuristic optimization techniques (HOT) given in the literature. Authors in [3] present a new fuzzy hybrid particle swarm optimization algorithm for non-linear, non-smooth and non-convex economic dispatch problem. In [4] authors present a novel string structure for solving the economic dispatch through genetic algorithm (GA). To accelerate the search process authors in [5] 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. PSO algorithm is one of the modern heuristic evolutionary techniques widely used in recent years and suitable to solve large-scale nonconvex optimization problem.

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. The main advantages of the PSO algorithm are: simple concept, easy implementation, and computational efficiency. Although the PSO-based approaches have several disadvantages, it may get trapped in a local minimum when handling heavily constrained problems due to the limited local/global searching capabilities. Many hybrid methods have been proposed to enhance the performance of the standard PSO algorithm [7-15].

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 [6-16-17] 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 efficient combined approach based fuzzy rules and PSO based decomposed network to enhance the global solution of large economic dispatch with consideration of practical generator constraints.

II. ACTIVE POWER DISPATCH WITH DISCONTINUOUS FUEL COST FUNCTIONS

The main role for economic dispatch is to minimize the total generation cost of the power system to supply the required demand (equality constraint) and satisfying the specified generators constraints (inequality constraints).

A. ED with smooth cost function

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

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

where;

- f_T : total generation cost;
- P_{gi} : active power generation at unit i ;
- a_i, b_i, c_i : cost coefficients of the i^{th} generator;
- N_g : is the number of generators.

B. ED with non-smooth cost function with valve-point loading effects

The ED with valve-point effect can be represented as a nonsmooth optimization problem having complex and nonconvex features with heavy equality and inequality constraints. The valve-point loading is taken in consideration by adding a sine component to the cost of the generating units. Typically, the fuel cost function of the generating units with valve-point loadings is represented as follows:

$$f_T = \sum_{i=1}^{N_g} (a_i + b_i P_{gi} + c_i P_{gi}^2) + |d_i \sin(e_i (P_i^{\min} - P_i))| \quad (2)$$

d_i and e_i are the cost coefficients of the unit with valve-point effects. The input-output performance curve for a typical thermal unit can be represented as shown in Fig 1.

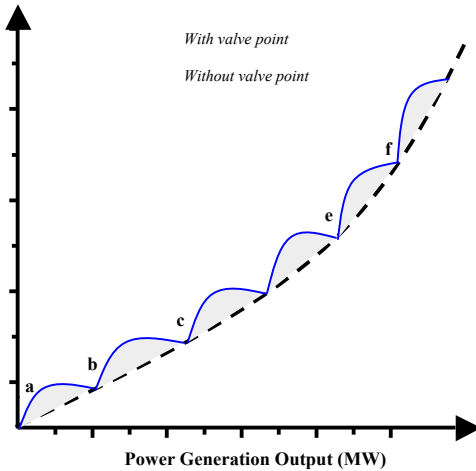


Fig 1 Input-Output curve under valve-point loading

C. The equality constraints:

For active power balance, the total generated power should be the same as the total demand plus the total power loss.

$$\sum_{i=1}^{NG} P_{gi} - P_D - P_{loss} = 0 \quad (3)$$

where P_D is the total active power demand, P_{loss} represent the transmission losses.

D. The inequality constraints:

Power output of generator should be within its minimum and maximum limits. The inequality constraint for each generator expressed as follows:

$$P_{gi}^{\min} \leq P_{gi} \leq P_{gi}^{\max} \quad (4)$$

where P_{gi}^{\min} and P_{gi}^{\max} are the minimum and maximum active power generation limits of generator i , respectively.

III. FUZZY RULES CONTROLLED PSO

A. Overview of PSO Method

Particle swarm optimization (PSO), first introduced by Kennedy and Eberhart in 1995 [11] is one of the modern heuristic algorithms. It was developed through simulation of a simplified social system, and has been found to be robust in solving complex optimization system. The simplified mathematical model for PSO is described as follows.

$$\begin{aligned} V_i^{k+1} = & \omega V_i^k + c_1 \text{rand} \times (P_{best_i}^k - X_i^k) \\ & + c_2 \text{Rand} \times (G_{best}^k - X_i^k) \end{aligned} \quad (5)$$

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 ;
- $P_{best_i}^k$: best position of particle i until iteration k ;
- G_{best}^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 to the following equation:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (6)$$

B. Hybrid-Modified PSO based ED

Many metaheuristic algorithms like GA, EP, SA and PSO performing well for a reduced research space with less complicated objective function. However they fail to locate global solution for large systems and complex situation with multim minima functions, they fail to exploit the promising research space to get good quality solution. With a single method, it is difficult to guarantee the location of the global optimum. For better results and to get faster convergence, conventional PSO methods have been modified. In recent years various combined techniques have been studied to achieve this objective, these include [2]:

- Simulated annealing-PSO (SA-PSO).
- Quantum-Inspired version of the PSO using the harmonic oscillator (HQ-PSO).
- Particle swarm optimization with chaotic and Gaussian approaches (PSO-CG).
- Self-organizing hierarchical particle swarm optimization (QOH-PSO).
- Modified particle swarm optimization (MPSO).
- Hybrid particle swarm optimization with sequential quadratic programming (PSO-SQP).
- Improved coordinated aggregation-based PSO (ICA-PSO).

C. Why Fuzzy Logic Method?

The use of fuzzy logic has received increased attention in recent years because of its usefulness in reducing the need for complex mathematical models in problem solving [1]. Fuzzy logic employs linguistic terms, which deal with the causal relationship between input and output variables. For this reason, the approach makes it easier to manipulate and solve problems. Fig. 2 presents the proposed block diagram of a fuzzy controlled PSO.

This approach proposes a modified PSO Algorithm based on fuzzy logic rules with the ability to adjust dynamically three parameters:

- Inertia weight, w
- The two learning factors c_1 and c_2 .

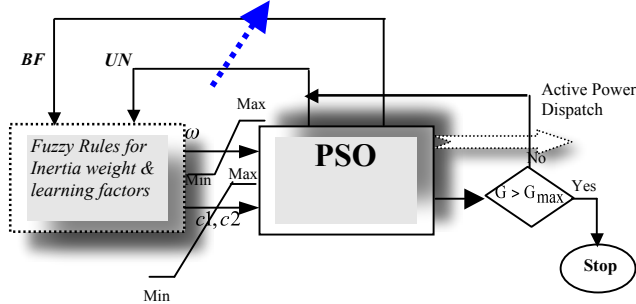


Fig. 2 Block diagram of the PSO parameters adjustment.

Inertia weight (w) and the two learning factors are considered critical for PSO convergence. A suitable value for weighing factor and learning factors provides balance between global and local exploration abilities and consequently results in a reduction of the number of iterations required to locate the optimum solution. Experimental results based in application of PSO to many practical networks at normal and abnormal conditions with load incrementation indicated, that it is better to adjust dynamically the value of the three parameters (w , c_1 and c_2) to assure convergence to the near global solution. c_1 and c_2 are scaling factors that determine the relative ‘pull’ of p_{best} and g_{best} . 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. So if $c_1 > c_2$, the particle has the

tendency to converge to the best position found by itself p_{best} rather than the best position found by the population g_{best} .

The proposed approach employs in the first stage practical rules interpreted in fuzzy logic rules to adjust dynamically the three parameters (inertia weight, and the two learning factors) during execution of the PSO algorithm, in the second stage parallel execution of PSO based decomposed network [6-16].

1) Membership Function Design

The membership function adopted by engineer differs from person to person and depends in problem difficulty therefore they are rarely optimal in terms of reproduced desired output.

2) Inputs and Outputs of Fuzzy Controller.

The main role of this controller is to improve the global searching capability and to increase the probability of escaping from a local minimum. A mechanism search based fuzzy rules designed to adjust dynamically the PSO parameters. The inputs of the proposed search mechanism based fuzzy controller are: changes of the best fitness which reflect the diversity in the cost generation, and the number of generation for unchanged fitness, the output is the variation in weighting factor and the variation in learning (acceleration) factors. Sample fuzzy rules for weight factor and learning factors are presented in Fig. 3.

In this study, the upper and lower value for weighting factor and for the two learning factors, respectively are changed based in membership functions for each variable from 1 to 0.4 and from 1 to 2.2. The final values of inertia weight ‘ w ’ and for the learning factors are calculated using the following equations:

$$w^{(t)} = w^{(t-1)} + \Delta w \quad (7)$$

$$c_1^{(t)} = c_1^{(t-1)} + \Delta c_1 \quad (8)$$

$$c_2^{(t)} = c_2^{(t-1)} + \Delta c_2 \quad (9)$$

where, $w^{(t)}$, $c_1^{(t)}$ and $c_2^{(t)}$ are respectively the inertia factor and learning factors at the iteration ‘ t ’.

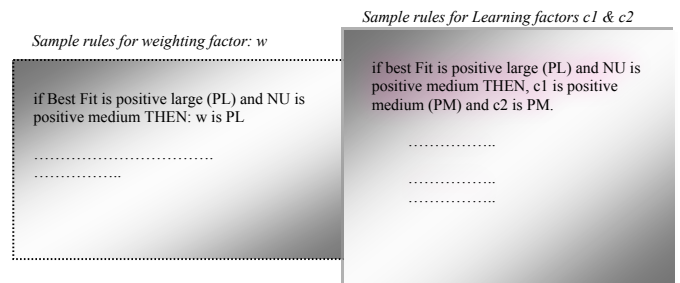


Fig 3 Sample fuzzy rules for PSO parameters tuning.

1. Calculation Steps of the Proposed Method

The modified PSO algorithm formulated as follows:

Step1: the particles are randomly generated between the maximum and minimum operating limits as follows:

$$Pg_{ij}^0 = Pg_j^{\min} + r_{ij} \cdot (Pg_j^{\max} - Pg_j^{\min}) \quad (10)$$

Where r_{ij} is a uniformly distributed random number between [0 1]. The minimum and maximum power outputs should be adjusted using (4).

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.

The structure of Evaluation function f or fitness function is important to speed up the convergence of the iteration procedure. The evaluation function [5] is adopted as (10). It is the reciprocal of the generation cost function $F_{cost}(Pg_i)$ and power balance constraint $F_{pbc}(Pg_i)$ as in (2).

$$f_{it} = \frac{1}{F_{cost} + F_{pbc}} \quad (11)$$

where;

$$F_{cost} = 1 + \frac{\left(\sum_{i=1}^n F_i(Pg_i) - F_{\min} \right)}{(F_{\max} - F_{\min})} \quad (12)$$

$$F_{pbc} = 1 + \left(\sum_{i=1}^n Pg_i - P_D - P_{loss} \right)^2 \quad (13)$$

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

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

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.

In this paper, the weighting factor and the two learning factors are dynamically tuned using fuzzy rules.

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 $v_{i,j} = V_j^{\min}$.

Step7: 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.

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

$$Pd1 = \sum_{i=1}^{M1} P_{Gi} \quad (14)$$

$$Pd2 = \sum_{i=1}^{M2} P_{Gi} = PD - Pd1 \quad (15)$$

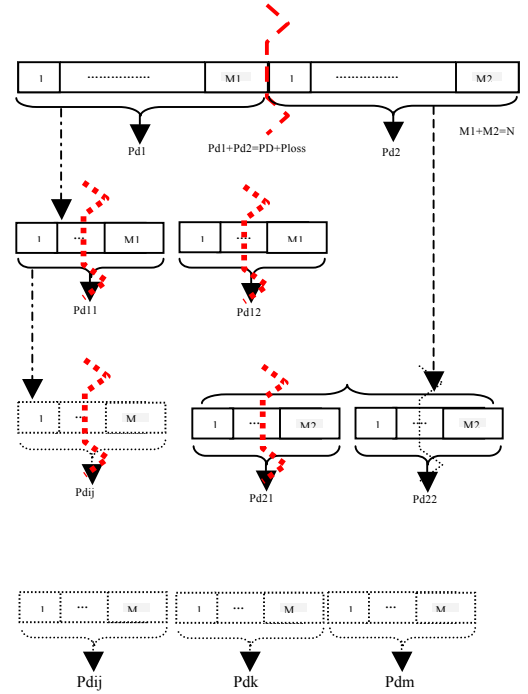


Fig. 4 Mechanism of search partitioning

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:

$$Pd1 + Pd2 = PD + P_{loss} \quad (16)$$

2. Final Search Mechanism

- All the sub-systems are collected to form the original network, global database 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 5 illustrates the basic steps of the proposed approach.

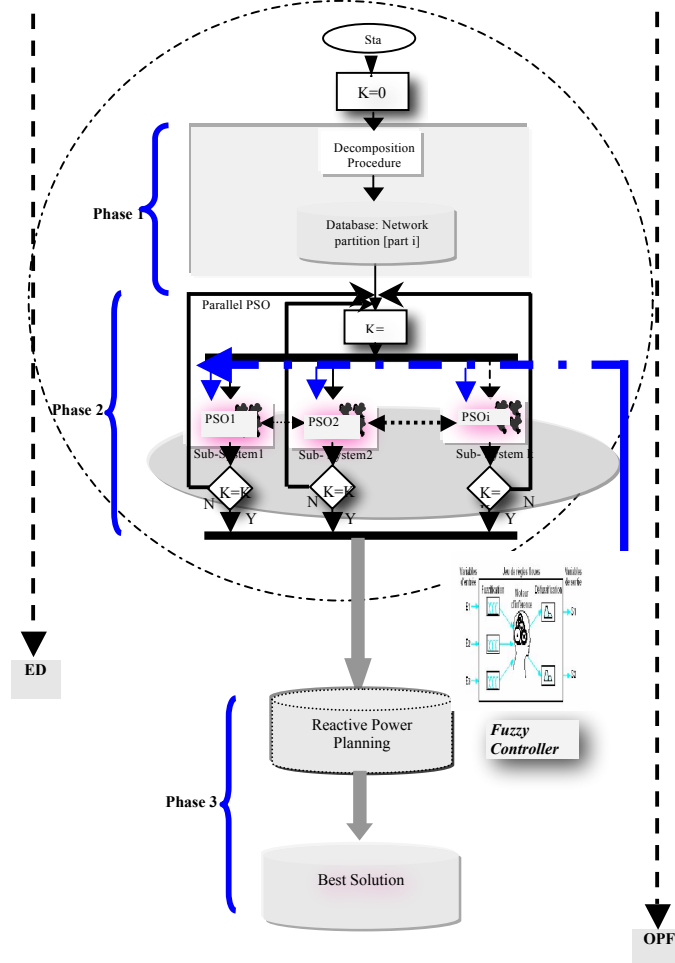


Fig 5 Procedure of parallel swarm optimization approach for EPD.

V. 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).

A. Test System 1

In this application power system has 40-generating units. Total load demand of the system is 10500 MW. This is a larger system, the number of local optima, complexity and nonlinearity to the solution procedure is enormously increased. The system data can be retrieved from [5]. The final fuel cost and output power for all generating units were summarized in Table I.

TABLE I
DISPATCH RESULTS FOR 40-GENERATING units using the PROPOSED
APPROACH: PD =10500 MW

	Pg_i (MW)				Pg_i (MW)		
Unit N°	[QIPSO] [23]	[DEBBO] [22]	Our approach	Unit N°	[QIPSO] [23]	[DEBBO] [22]	Our approach
1	111.2000	110.7998	110.6319	21	523.2800	523.2794	523.2864
2	111.7000	110.7998	110.8083	22	523.2800	523.2794	523.2816
3	97.4000	97.3999	97.4021	23	523.2900	523.2794	523.2881
4	179.7300	179.7331	179.7353	24	523.2800	523.2794	523.2864
5	90.1400	87.9576	87.8080	25	523.2900	523.2794	523.3026
6	140.0000	140.0000	140.0000	26	523.2800	523.2794	523.3026
7	259.6000	259.5997	259.6067	27	10.0100	10.0	10.0000
8	284.8000	284.5997	284.6067	28	10.0100	10.0	10.0000
9	284.8400	284.5997	284.6067	29	10.0000	10.0	10.0000
10	130.0000	130.0000	130.0000	30	88.4700	97.0000	87.8184
11	168.8000	168.7998	94.0032	31	190.000	190.0000	189.9271
12	168.8000	94.0000	94.0000	32	190.000	190.0000	190.0000
13	214.7600	214.7598	214.7620	33	190.000	190.0000	190.0000
14	304.5300	394.2794	394.2864	34	164.910	164.7998	164.8068
15	394.2800	394.2794	394.2816	35	165.3600	200.0000	194.4160
16	394.2800	304.5196	394.2864	36	167.1900	200.0000	200.0000
17	489.2800	489.2794	489.2855	37	110.0000	110.0000	110.0000
18	489.2800	489.2794	489.2864	38	107.0100	110.0000	110.0000
19	511.2800	511.2794	511.3026	39	110.0000	110.0000	110.0000
20	511.2800	511.2794	511.2864	40	511.3600	511.2794	511.2978
TP (MW)					10,500	10,500	10,500
TC (\$/h)					121448.21	121420.89	121417.00
TP: Total Power Generation, TC: Total Cost							

TP: Total Power Generation, TC: Total Cost

VI. DISCUSSIONS

A. Solution Quality

Observing the comparison results depicted in Table II, the proposed hybrid approach is shown to be more efficient than the other global optimization methods. Details results will be given in the next full paper.

B. 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 II. The proposed approach takes an average CPU time of 8.54s to find the best near global solution. Fig 6 shows clearly the performance of the convergence characteristic curve of the fuzzy controlled PSO based decomposed procedure for one partition.

TABLE II
COMPARISON OF EPGA WITH OTHER GLOBAL OPTIMIZATION METHODS
40-GENERATING UNITS PD=10500 MW

Methods	Minimum Cost(\$/h)	Average CPU time (s)
ICA-PSO [2]	121413.200	139.9200
SA-PSO [2]	121430.000	-
SOH-PSO[2]	121501.140	-
MPSO [2]	122252.260	-
PSO-SQP [2]	122094.670	-
CDEMD [9]	121423.4013	44.3
FAPSO-NM[3]	121418.3	40
NPSO[3]	121704.74	-
SOH-PSO[3]	121501.14	-
FAPSO[3]	121712.4	87-
DEC-SQP[3]	121741.97	-
DE-BBO [22]	121420.89	-
QIPSO [23]	121448.21	-
Our Approach	121417.00	8.54

* Exact generation cost from the above schedule is **121422.1684** \$/h which is higher than that reported in [2]

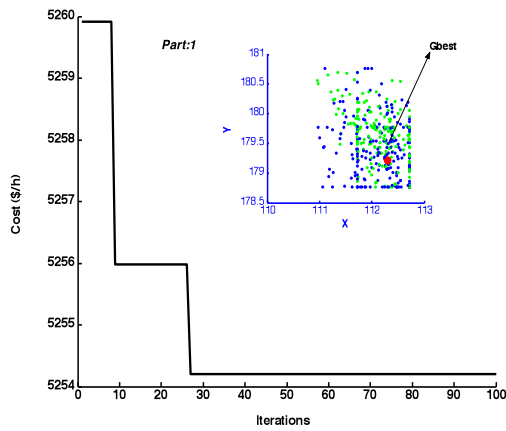


Fig 6 Convergence characteristic curve of the Fuzzy controlled parallel PSO based decomposed procedure for one subsystem (4 generating units).

VII. CONCLUSION

Application of an improved fuzzy controlled parallel PSO based decomposed network to enhance the economic dispatch for large power system with consideration of non-smooth fuel cost functions is demonstrated in this paper. In the first stage a practical rules formulated within fuzzy rules strategy designed to adjust dynamically three PSO parameters. In the second stage a decomposition mechanism is proposed to search the efficient partitioned networks to adjust the first solution found. A parallel execution of the adapted PSO associated to each decomposed search space.

The performance of the proposed approach was tested with large test system (40-generating units) with consideration of valve point effect, the results of the proposed algorithm compared with recent global optimization methods. It is observed that the proposed approach is capable of finding the

near global solution of non-linear and non-differentiable objective functions and obtain a competitive solution at a reduced time.

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