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A Fuzzy Adaptive Hybrid Particle Swarm Optimization Algorithm to Solve Non-Convex Economic Dispatch Problem

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***Abstract*— Economic dispatch (ED) plays an important role in power system operation. ED problem is a non-smooth and non-convex problem when valve-point effects, multi-fuel effects and prohibited operating zones (POZs) have been considered. The main objective of economic dispatch is to minimize the total fuel cost while all operating constraints are satisfied. By involving these three constraints the classical PSO faces premature convergence, performance and the diversity loss in optimization process as well as appropriate tuning of its parameters. To handle the problem of premature convergence this paper presents an efficient hybrid evolutionary approach for solving the economic dispatch problem called FAPSO. The algorithm is tested on two typical systems consisting of 6 and 15 thermal units whose incremental fuel cost functions take into account the prohibited operating zones.**

***Keywords* — Non-Convex Economic Dispatch, Fuzzy Adaptive Particle Swarm Optimization, Prohibited Operating Zones, Ramp Rate Limit.**

I. INTRODUCTION

In power system operation ED problem is an important optimization problem that have the objective to determine the optimal power outputs of all generating units by minimizing the total fuel cost while the total generation should be equal to the total transmission loss plus system demand, the generation output of each unit should be between its minimum and maximum limits [1]. There are different methods to solve ED problems are lambda-iteration method [2], the base point and participation factors method [3], the gradient method [4], and Newton method [2]. These methods can solve the ED problems effectively if and only if the fuel-cost curves of the generating units are piece-wise linear and monotonically increasing and piecewise-linear functions are used [2]. Unfortunately, this assumption may lead to infeasible practical use due to nonlinear characteristics in real generators. A dynamic programming (DP) method had been used for solving the ED problem with valve-point loading effect [5–7]. The DP technique decomposes a multi-stage decision problem into a sequence of single stage decision problems. However, the DP method may cause the dimensions of the ED problem to become extremely large, thus requiring large computational efforts.

So these methods are not suitable when modern power systems are considered with large number of generators. With the development of computer science and technology, evolutionary algorithms have been successfully used to solve the ED problem, such as particle swarm optimization [8,9], genetic algorithm [10,11], simulated annealing and tabu search [12], evolutionary programming (EP) [13], hybrid PSO and sequential quadratic programming (PSO-SQP) [14], evolutionary strategy optimization (ESO) [15-16], self organizing hierarchical PSO (SOHPSO) [17] and new PSO(NPSO) [18]. When compared with conventional techniques, modern heuristic optimization techniques have been paid much more attention by many researchers due to their ability to find an almost global optimal solution for ED problems with operating constraints.

PSO is one of the evolutionary algorithms that have shown great potential and good perspective for the solution of various optimization problems [19-22]. This algorithm was first proposed by Kennedy and Eberhart in 1995. PSO was developed through simulation of a simplified social system, and has been found to be robust in solving continuous non-linear optimization problems [23-25]. This algorithm can produce high-quality solutions within shorter calculation time and more stable convergence characteristics than other stochastic methods [23-25]. Recently, PSO has been successfully used to solve the ED problem while considering generator constraints and non-smooth cost constraints [26-28]. However, the performance of the original PSO greatly depends on its parameters, such as inertia weight, cognitive and the social parameters, and it generally suffers from the problem of being trapped in local optima. Eiben et al. [29] describes two ways of defining the parameter values: adaptive parameter control and self-adaptive parameter control. In the former, the parameter values change according to a heuristic rule that takes feedback from the current search state, while in the latter, the parameters of the meta-heuristic are incorporated into the representation of the solution. Thus, the parameter values evolve together with the solutions of the population and in the SOHPSO approach, the particle velocities are reinitialized whenever the population stagnates at local optima during the search. A relatively high value of the cognitive component results in excessive wandering of particles while a higher value of the social component causes premature convergence of particles [23].

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Hence, time-varying acceleration coefficients (TVAC) [30] are employed to strike a proper balance between the cognitive and social component during the search. Integration of the TVAC with SOH PSO for solving the practical economic dispatch problem has been found to avoid premature convergence during the early stages of the search and promote convergence towards the global optimum solution. Self-Organizing hierarchical particle swarm optimization still having some unsolved problems such as maximum number of iterations is adopted as the stopping criteria comparison with other strategies. In order to avoid these problems in original PSO, this paper presents a new hybrid evolutionary optimization algorithm based on combining the fuzzy adaptive particle swarm optimization (FAPSO).In this paper, an adaptive parameter control is used for inertia weight by using a fuzzy logical controller and the cognitive and the social parameters are self-adaptively evaluated. Also, in order to avoid trapping in local optima, this paper presents a new mutation operator to explore the search space much more efficiently.

This paper considers two types of non-convex ED problems, ED with prohibited operating zones (EDPO) and ramp rate with Prohibited Operating Zone Limits. The presence of prohibited zones for individual generators leads to a disjoint solution space. In addition, power plants usually have multiple valves that are used to control the output power of the unit. When steam admission valves in thermal units are first opened, a sudden increase in power loss is observed. This leads to ripples in the cost function, which is known as the valve point loading. In order to evaluate the performance of the proposed algorithm, two case studies including 6 and 15 generating units are used for ED problem. The results obtained through the improved FAPSO algorithm are analyzed and compared with those reported in the recent literature. The main contribution of the paper is to present a new evolutionary algorithm to solve non-smooth and non-convex economic dispatch problem.

II. NON-CONVEX ECONOMIC DISPATCH

If the practical operating conditions are included then basic ED becomes a non-convex optimization problem.

A. Prohibited Operating Zone

Each generator has its generation capacity limitation, which cannot be exceeded. Moreover, a typical thermal unit may have a steam valve in operation, or a vibration in a shaft bearing, which may result in interference and causes a discontinuity in input–output performance curve, called prohibited zones. Therefore, in practical operation, adjusting the generation output of a unit must be done regarding all capacity limits so that it prevents the unit operation in prohibited zones. The feasible operating zones of a unit can be described as follows:

$$P_j \in \begin{cases} P_j^{min} \le P_j \le P_j^{LB_1} \\ P_j^{UB_{K-1}} \le P_j \le P_j^{LB_K} \\ P_j^{UB_K} \le P_j \le P_j^{max} \end{cases} \quad j=1, 2\ldots Ng \quad (1)$$

Where $P_j^{LB_K}$ and $P_j^{UB_K}$ are lower and upper bounds of the kth prohibited zone of unit j, respectively; k is the index of prohibited zones.

B. Valve Point Loading Effects

The valve-point effects introduce ripples in the heat-rate curves and make the objective function discontinuous, non-convex and with multiple minima. For accurate modeling of valve point loading effects, a rectified sinusoidal function [37] is added in the cost function in this paper. The fuel input- power output cost function of the ith unit is

$$F_j(P_j) = a_j P_j^2 + b_j P_j + C_j + |e_j sin(f_i(P_{j,min} - P_j))| \quad (2)$$

Where e_j and f_j are non-smooth fuel cost coefficients of generator j and $P_{j,min}$ is minimum power generation limit of generator j.

C. The Constraints

The above objective function is to be minimized subject to the following constraints

i) Power balance constraints

The power balance constraint is based on the principle of equilibrium between the total system generation and total system loads (P_{load}) and losses (P_{loss}).

$$\sum_{i=1}^{Ng} P_{gi} = P_{load} + P_{loss} \quad (3)$$

P_{loss} is calculated using B-coefficients and it is described by

$$P_{loss} = \sum_{i=1}^{Ng}\sum_{j=1}^{Ng} P_{gi} \times B_{ij} \times P_{gj} + \sum_{i=1}^{Ng} B_{i0} \times P_{gi} + B_{00} \quad (4)$$

Where B_{ij} is the i, jth element of the loss coefficient square matrix B_{i0} is the ith element of the loss coefficient vector. B_{00} is the loss coefficient constant.

ii) Output generator constraints

The output power of each generating unit has a lower and upper limit. The output generator constraint is defined by a pair of inequality constraints as follows:

$$P_{gi,min} \le P_{gi} \le P_{gi} \quad (5)$$

Where $P_{gi,max}$ is the maximum power output of the ith generating unit.

D. Generator Ramp Rate Limits

If the generator ramp rate limits are considered, the effective real power operating limits are modified as follows:

$$max(P_{imin}, UR_i - P_i) \le P_i \le min(P_{imax}, P_i^{t-1} - DR_i) \quad (6)$$

Where UR_i, DR_i are the upward and downward ramp rate limit of generator.

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III. OVERVIEW OF PSO

A. Simple PSO

PSO is a stochastic optimization algorithm [27–29]. Mathematical modeling and simulation of the food searching activities of a flock of birds is the main idea of the PSO. In the multidimensional space, each particle is moved toward the optimal point by changing its position according to a velocity. The velocity of a particle is calculated by three components; social, cognitive and inertia. The social component models the memory of the bird about the best position among the particles. The cognitive component models the memory of the bird about its previous best position. The inertial component simulates the inertial performance of the bird to fly in the previous direction. The particles move around the multidimensional search space until they find the optimal solution. Based on the above discussion, the modified velocity and position of each particle can be calculated as per following formula:

$$V_i^{t+1} = w * V_i^t + c_1 * rand_1(.) * (Pbest_i - X_i^t) + c_2 * rand_2(.) * (Gbest - X_i^t) \quad (7)$$

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

$$i = 1, 2, 3, \ldots, N_{swarm}$$

where, i is the index of each particle, t is the current iteration number, $rand_1(.)$ and $rand_2(.)$ are random numbers between 0 and 1. $Pbest_i$ is the best previous experience of the ith particle that is recorded. Gbest is the best particle among the entire population. N_{swarm} is the number of the swarms. Constants c_1 and c_2 are the weighting factors of the stochastic acceleration terms, which pull each particle towards the $Pbest_i$ and $Gbest_i$. w is the inertia weight. As indicated in (7), there are three tuning parameters; w, c_1, and c_2 that each of them has a great impact on the algorithm performance. The inertia weight w controls the exploration properties of the algorithm.

The learning factors c_1 and c_2 determines the impact of the personal best $Pbest_i$ and the global best $Gbest_i$ respectively. If $c_1 > c_2$, the particle has the tendency to converge to the best position found by itself $Pbest_i$ rather than the best position found by the population $Gbest_i$, and vice versa.

B. SOH-PSO

The previous velocity term in (7) is made zero in this novel PSO strategy. With this modification the particles rapidly rush towards a local optimum solution and then stagnate because of the absence of momentum. To make this strategy effective whenever it stagnates in the search space, the velocity vector of a particle is reinitialized with a random velocity. When a particle stagnates, it's associated remains unchanged for a number of iterations. When more particles stagnate, the also undergoes the same fate and the PSO algorithm converges prematurely to a local optima and V_i^t becomes zero. The method works as follows [30].

$$V_i^{t+1} = c_1 * rand_1(.) * \left(Pbest_i - X_i^{(t)}\right) + c_2 * rand_2(.) * \left(Gbest - X_i^{(t)}\right) \quad (8)$$

C. FAPSO

From experience, it is known that [25, 33, 34]:

(i) When the best fitness is found at the end of the run, high learning factors and low inertia weight are generally preferred;

(ii) When the best fitness is stagnated at one value for a long time, the number of generations for unchanged best fitness is large. The inertia weight should be increased and learning factors should be decreased. According to this knowledge, a fuzzy system is utilized to tune the inertia weight and learning factors with the best fitness (BF) and the number of generations for the best unchanged fitness (NU) as the input variables, and the inertia weight (w) and learning factors (c1 and c2) as the output variables.

The BF value determines the performance of the best candidate solution found so far. The optimization problems have different ranges of the BF values. To use a FAPSO, which is applicable to a various range of problems, the ranges of the BF and NU values are normalized into [0, 1.0]. The BF values can be normalized using the following formula:

$$NBF = \frac{BF - BF_{min}}{BF_{max} - BF_{min}} \quad (9)$$

Where, BF_{max} and BF_{min} are the maximum and minimum values of BF value. NU values are normalized in a similar way. Other converting methods are possible as well. The bound values for w, c_1 and c_2 and are: $0.2 \leq w \leq 1.2, 1 \leq c_1 and\ c_2 \leq 2$.

IV. PROBLEM FORMULATION

The average convergence time required for convergence in case of FAPSO is lesser than Simple PSO and SOH PSO.

To apply the FAPSO algorithm to solve the ED problem, the following steps should be taken:

Step 1 The initial population and initial velocity for each particle should be generated randomly.

Step 2 The objective function is to be evaluated for each individual.

Step 3 The individual that has the minimum objective function should be selected as the global position.

Step 4 The ith individual is selected

Step 5 The best local position is selected for the ith individual.

Step 6 Update the FAPSO parameters.

Step 7 Calculate the next position for each individual based on the FAPSO parameters and Eq. (7) and then checked with its limit.

Step 8 If all individuals are selected, go to the next step, otherwise i = i + 1 and go to step 4.

Step 9 If the current iteration number reaches the predetermined maximum iteration number, the search procedure is stopped, otherwise go to step 2.

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The last is the solution of the problem.

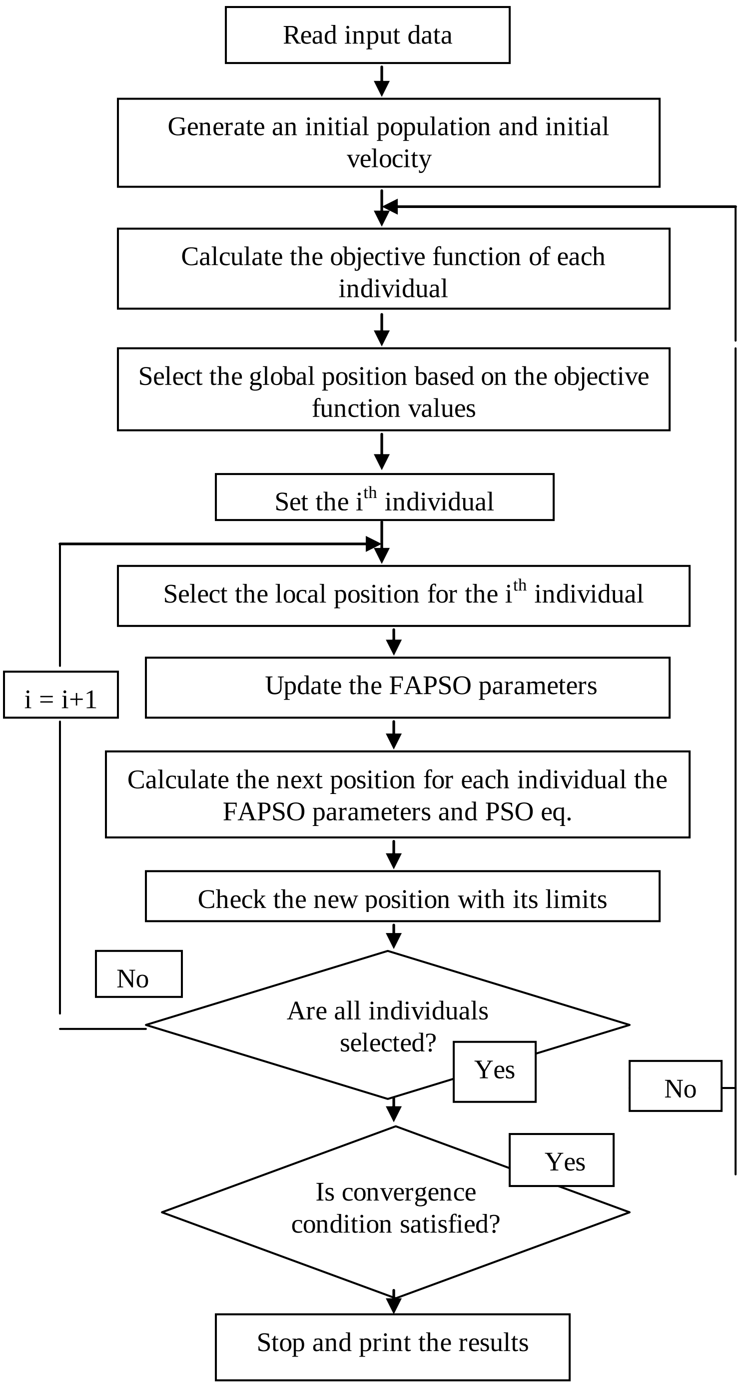

Fig. 1. Flow chart of FAPSO algorithm

V.SIMULATION RESULTS

The NCED problem was solved using the FAPSO and its performance is compared with Simple PSO and Self-organizing hierarchical PSO Algorithms. The proposed FAPSO technique has been applied to six generator power systems (PS).

1) Case study 1

Six-Unit System: The load demand is 1263 MW. The system contains six thermal units, 46 transmission lines, and 26 buses [32]. The characteristics of the six thermal units are given in Tables I and II.

Table I Cost Curves of Six Unit System

UNIT	P_i^{min}	P_i^{max}	a_i	b_i	c_i
1	100	500	0.007	7	240
2	50	200	0.009 5	10	200
3	80	300	0.009 0	8.5	220
4	50	150	0.009 0	11	200
5	50	200	0.008 0	10.5	220
6	50	120	0.007 5	12	190

Table II Ramp Rate and Prohibited Operating Zone Limits for Six Generator System

UNIT	P_i^0	UR_i	DR_i	Prohibited operating zone
1	100	80	120	[210 240] [350 380]
2	50	50	90	[90 110] [140 160]
3	80	65	100	[150 170] [210 240]
4	50	50	90	[80 90] [110 120]
5	50	50	90	[90 110] [140 150]
6	50	50	90	[75 85] [100 105]

Table III Comparison of fuel costs for 6 generators for power demand of 1263MW.

Method	Best Cost ($)	Worst Cost (&)	Average Cost (&)
FAPSO	15,445.24 1	15,451.6 0	15,448.05 0
SOH-PSO	15,446.00	15,451.7	15,450.3
SPSO	15,466.61	15,451.7	15,450.3

The convergence characteristics of 6 units test system with FAPSO, SOH-PSO and PSO algorithms for economic dispatch are shown in Fig. 2. From Fig. 2 it is observed that the cost function value converges smoothly to the optimum value without any abrupt oscillations, thus ensuring convergence reliability of the proposed FAPSO algorithm.

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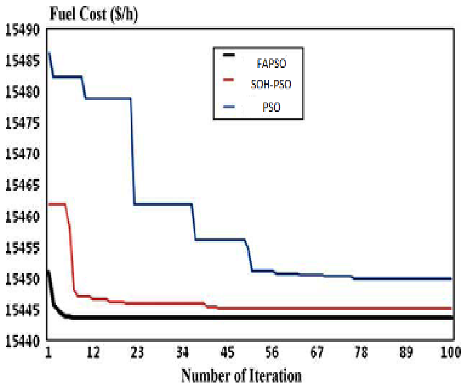

Fig. 2. Convergence characteristics of FAPSO, SOH-PSO and PSO algorithms for a load demand of 1263MW.

2) Case study 2

The load demand is 2630 MW and the system contains 15 thermal units whose characteristics and B matrix loss formula are given in [31], which four units have prohibited operation zones, which, Table 5 lists the prohibited zones of units 2, 5, 6, and 12. These zones result in three disjoint feasible sub-regions for each of units 2, 5, 6, and two for unit 12.

Table IV: Prohibited zones of units for test case study 2.

Generato r	Zone 1 (MW)	Zone 2 (MW)	Zone 3 (MW)
2	[185,225]	[305,335]	[420,450]
5	[180,200]	[305,335]	[390,420]
6	[230,255]	[365,395]	[430,455]
12	[30,40]	[55,65]	–

The load demand is 2630MW and the system contains 15 thermal units. The results of the best, average and the worst fuel costs from this case study are listed in Table V. For validity, these results are also compared with SOH-PSO and PSO. It can be evidently seen from Table V that the proposed technique provides better results than the other reported minimum costs using some of other methods. So, the proposed method is more robust and practically applicable to real systems.

Table V: Comparison of fuel costs for 15 generators for power demand of 2630MW.

Method	Best Cost ($)	Worst Cost (&)	Average Cost (&)
FAPSO	32,547.4848	32,547.4903	32,547.4859
SOH-PSO	32,659.693	32,676.03	32,661.11
PSO	32,857	33,029	32,979

Table VI: Optimum dispatch result of the proposed algorithm for power demand of 2630MW.

Generator	Output power (MW)	Output power (MW)
Pg1	454.9797	455
Pg2	454.9797	455
Pg3	129.99	129.99
Pg4	129.99	129.99
Pg5	134.2003	271.5706
Pg6	460	460
Pg7	463.9999	464
Pg8	60	60
Pg9	25	25
Pg10	30.9937	25
Pg11	76.6914	43.3993
Pg12	79.9799	54.97
Pg13	25	25
Pg14	15	15
Pg15	15	15

By studying the results of Fig. 3, it is clear that the new proposed algorithm is more efficient, faster and giving a cheaper total generating cost than the other algorithms. In other words, the new proposed algorithm is capable of giving a more optimum solution. Since the performance of original PSO depends on its parameters such as inertia weight and two acceleration coefficients (c1 and c2), it is important to determine the suitable values of parameters. To successfully implement the proposed algorithm, some parameters must be determined in advance based on a reasonable framework. In the proposed algorithm, an adaptive parameter control is used for inertia weight by using a fuzzy logical controller and the cognitive and the social parameters are self-adaptively evaluated.

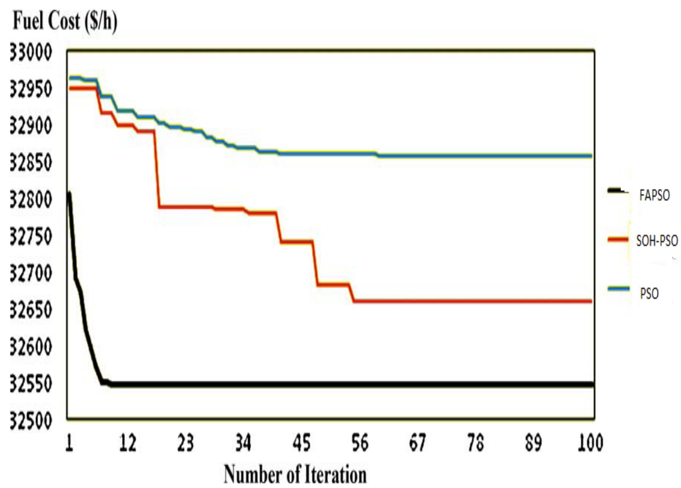

Fig. 3. Convergence Characteristics Of FAPSO, SOH-PSO And PSO Algorithms For Case Study 2 For A Load Demand Of 2630MW.

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VI. CONCLUSION

In this paper, a new hybrid optimization algorithm, called FAPSO, was presented for solving non-convex economic dispatch problem in power system. The results obtained from FA PSO method is compared with Simple PSO and SOH PSO methods. In FAPSO, acceleration factors are coevolved with the particles during optimization process and the inertia weight is tuned based on a fuzzy system. Two case studies have been employed to illustrate the applicability of the proposed method. Numerical results show that the proposed algorithm has advantages over other algorithms in superior robustness, less computational efforts, comparable performance with mathematical programming approach, and applicability to large-scale and practical systems.

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