A Hybrid Particle Swarm Optimization Employing Crossover Operation for Economic Dispatch Problems with Valve-point Effects

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***Abstract*-- This paper presents an efficient approach for solving the economic dispatch (ED) problems with valve-point effects using a hybrid particle swarm optimization (PSO) technique. Although PSO-based algorithms are easy to implement and have been empirically shown to perform well on many power system optimization problems, they may get trapped in a local optimum due to premature convergence when solving heavily constrained optimization problems with multiple local optima. This paper proposes an improved hybrid PSO (HPSO), which combines the conventional PSO framework with the crossover operation of genetic algorithm. By applying the crossover operation in PSO, it not only discourages premature convergence to local optimum but also explores and exploits the promising regions in the search space effectively. To verify the effectiveness of the proposed method, numerical studies have been performed for the large-scale test system of 40 generating units with valve-point effects. The simulation results show that the proposed HPSO outperforms other state-of-the-art algorithms as well as the conventional PSO method in solving ED problems with valve-point effects.**

***Index Terms*-- Economic dispatch problem, valve-point effects, hybrid particle swarm optimization, crossover operation.**

I. INTRODUCTION

MOST of the power system optimization problems have complex and nonlinear characteristics with heavy equality and inequality constraints. Over the past decade, many modern artificial intelligence (AI) based heuristic methods have been successfully applied to the power system optimization problems [1].

Particle swarm optimization (PSO) is one of the modern heuristic algorithms, which can be effectively used to solve nonlinear and non-continuous optimization problems. It is a population-based search algorithm and searches in parallel using a group of particles similar to other AI-based optimization techniques. The original PSO suggested by Kennedy and Eberhart is based on the analogy of swarm of bird and school of fish [2]. In PSO, each particle makes his decision using his own experience together with his neighbor's experiences. The particles are drawn stochastically toward the position of present velocity of each particle, their own previous best performance, and the best previous performance of their neighbors [2], [3]. The main advantages of the PSO algorithm are summarized as; simple concept, easy implementation, relative robustness to control parameters, and computational efficiency when compared with mathematical algorithms and other AI-based heuristic optimization techniques [1].

Economic dispatch (ED) problem is one of the most important ones in power system operation and planning. The main objective of the ED problems is to determine the optimal combination of power outputs of all generating units so as to meet the required demand at minimum cost while satisfying the constraints. Conventionally, the cost function for each unit in ED problems has been approximately represented by a quadratic function and is solved using mathematical programming techniques [4]. Generally, these mathematical methods require some marginal cost information to find the global optimal solution. Unfortunately, the real-world input-output characteristics of generating units are highly nonlinear and non-smooth because of prohibited operating zones, valve-point loadings, and multi-fuel effects, etc. Thus, the practical ED problem is represented as a non-smooth optimization problem with equality and inequality constraints, which directly cannot be solved by the mathematical methods. Dynamic programming approach [5] can deal with such type of problem, but it suffers from the curse of dimensionality. Over the past decade, in order to solve these non-smooth ED problems, many salient methods have been developed such as hierarchical numerical method [6], genetic algorithm [7]-[9], evolutionary programming [10], [11], neural network approaches [12], [13], differential evolution [14], particle swarm optimization [15], [16], and the hybrid method [17].

This paper proposes a new approach for ED problems with non-smooth cost functions due to valve-point effects using a hybrid PSO mechanism. Although PSO has several prominent advantages, it may get trapped in a local optimum when handling heavily constrained optimization problems with multiple local optima. In order to overcome such a drawback, this paper proposes a hybrid PSO (HPSO), which combines the conventional PSO technique with the crossover operation. The crossover operation, which was widely used in the genetic

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algorithm (GA) methods, is adopted to increase the exploration and exploitation capability of the PSO mechanism while not preventing the inherent evolution process of the conventional PSO. The numerical studies have shown the superiority of the suggested HPSO to the existing studies as well as the traditional PSO method.

II. Formulation of Economic Dispatch with Valve-Point Effects

The main objective of ED problem is to minimize the total fuel cost of power plants subjected to the operating constraints of a power system. Generally, it can be formulated with an objective function and two constraints [4]:

$$F_T = \sum_{i=1}^{n} F_i(P_i) \tag{1}$$

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \tag{2}$$

where,

- F_T total generation cost,
- F_i cost function of generator *i*,
- a_i, b_i, c_i cost coefficients of generator *i*,
- P_i power output of generator *i*,
- n number of generators.

1) Active Power Balance Equation: For power balance, an equality constraint should be satisfied. The total generated power should be the same as the total demand plus the total line loss. However, the transmission loss is not considered in this paper for simplicity.

2) *Minimum and Maximum Power Limits:* Generation output of each unit should be laid between its minimum and maximum limits. The corresponding inequality constraints for each generator are

$$P_{i,\min} \le P_i \le P_{i,\max} \tag{3}$$

where $P_{i,\min}$ and $P_{i,\max}$ are the minimum and maximum output of generator *i*, respectively.

The generating units with multi-valve steam turbines exhibit a greater variation in the fuel cost functions. Since the valve point results in the ripples, a cost function contains higher order nonlinearity. Therefore, the cost function (2) should be replaced by the following to consider the valve-point effects:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + \left| e_i \times \sin(f_i \times (P_{i,\min} - P_i)) \right| \tag{4}$$

where e_i and f_i are the cost coefficients of generator *i* reflecting valve-point effects.

III. Overview of Particle Swarm Optimization

Kennedy and Eberhart developed a PSO algorithm based on the behavior of individuals (i.e., particles or agents) of a swarm [2]. The PSO algorithm searches in parallel using a group of particles. Each particle corresponds to a candidate solution to the problem. Particles in a swarm approach to the optimum through its present velocity, its previous experience, and the experience of its neighbors [3]. In a *n*-dimensional search space, the position and velocity of particle *i* are represented as the vectors $X_i = (x_{i1}, \cdots, x_{in})$ and $V_i = (v_{i1}, \cdots v_{in})$ in the PSO algorithm. Let $Pbest_i = (x_{i1}^{Pbest}, \cdots, x_{in}^{Pbest})$ and $Gbest = (x_1^{Gbest}, \cdots, x_n^{Gbest})$ be the best position of particle *i* and its neighbors' best position so far, respectively. The modified velocity and position of each particle can be calculated using the current velocity and the distance from $Pbest_i$ to $Gbest$ as follows:

$$\begin{aligned} V_i^{k+1} = \omega \cdot V_i^k &+ c_1 \cdot rn_1 \cdot (Pbest_i^k - X_i^k) \\ &+ c_2 \cdot rn_2 \cdot (Gbest^k - X_i^k) \end{aligned} \tag{5}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{6}$$

where,

- V_i^k velocity of particle *i* at iteration *k*,
- ω inertia weight factor,
- c_1, c_2 acceleration coefficients,
- rn_1, rn_2 random numbers between 0 and 1,
- X_i^k position of particle *i* at iteration *k*,
- $Pbest_i^k$ best position of particle *i* until iteration *k*,
- $Gbest^k$ best position of the group until iteration *k*.

In the velocity updating process, the values of parameters such as ω, c_1, and c_2 should be determined in advance. The constants c_1 and c_2 represent the weights of the stochastic acceleration terms that pull each particle toward the $Pbest_i$ and $Gbest$ position, respectively. Suitable selection of the inertia weight can provide a balance between global exploration and local exploitation, and can result in less iteration on average to find the optimal solution. In general, the inertia weight ω has a linearly decreasing dynamic parameter framework (i.e., Inertial Weights Approach (IWA) [1], [18], [19]) descending from $\omega_{\max}$ to $\omega_{\min}$ to enhance the convergence characteristics as follows.

$$\omega^k = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} \times k \tag{7}$$

Here, $iter_{\max}$ corresponds to the maximum iteration number and k is the current iteration number.

IV. Solution Procedure of HPSO with Crossover Operation

Since the decision variables in ED problems are real power outputs, the structure of a particle is composed of a set of elements corresponding to the generator outputs. Therefore, particle *i*'s position at iteration *k* can be represented as the vector $X_i^k = (P_{i1}^k, \cdots, P_{in}^k)$ where n is the number of generators in the ED problem. The velocity of particle *i* (i.e., $V_i^k = (v_{i1}^k, \cdots v_{in}^k)$) corresponds to the generation update quantity covering all generators.

The process of the proposed HPSO algorithm can be summarized as the following steps:

Step 1) Initialize the position and velocity of a group at random while satisfying the constraints.

Step 2) Modify the velocity and position of particles considering the constraints.
Step 3) Generate the trial vector through crossover operation process.
Step 4) Update *Pbest* and *Gbest*.
Step 5) Go to Step 2 until satisfying stopping criteria.

1) Creating Initial Position and Velocity of Particles: In the initialization process, a set of particles is created at random as follows to reflect the inequality constraint (3):

$$P_{ij}^0 = P_{j,\min} + r_{ij} \times \left(P_{j,\max} - P_{j,\min}\right) \quad (8)$$

where r_{ij} is a random number between [0,1] for element j in particle i. After creating the initial position of each particle, the velocity of each particle is also created at random. The following strategy is used in creating the initial velocity:

$$\left(P_{j,\min} - \varepsilon\right) - P_{ij}^0 \le v_{ij}^0 \le \left(P_{j,\max} + \varepsilon\right) - P_{ij}^0 \quad (9)$$

where ε is a small positive real number. The velocity element j in particle i is generated at random within the boundary for the inequality constraint treatment. The initial $Pbest_i$ of particle i is set as the initial position of the particle and the initial *Gbest* is determined as the position of the particle with minimum cost of (1).

2) *Modification of Velocity and Position Considering the Constraints:* To modify the position of each particle, it is necessary to calculate the velocity of each particle in the next stage which is obtained from (5). In this process, the inertia weight approach IWA (7) is employed to improve the global searching capability. After updating velocity, the position of each particle is modified by (6). When we create the position of each particle based on the calculated velocity vector, each element of any particle can violate the inequality constraint (3) due to over/under velocity. To deal with the inequality constraint problem, we employed our previous works in [15] where the position of each individual is adjusted to the corresponding minimum or maximum generation output when it violate the inequality constraint. In addition, the equality constraint is considered by specifying a slag generator at random for each individual whose output is determined by the difference of total demand and the summation of all generation outputs except for the slag generator [15]. Based on the constraint treatment strategy, we can always obtain the particles satisfying the constraints in the evolution process.

3) Crossover Operation: In order to increase the diversity of the population, the crossover operation is newly introduced in the PSO framework. This operator is devised to help PSO to prevent the premature convergence and to search the promising regions in the domain space. The suggested crossover operator is a little different from the crossover used in the conventional GA.

It follows the following procedures at certain iteration: 1) The element j of particle i created by (6) is mixed with $Pbest_i$ to generate the trial vector $\hat{X}_i = \left(\hat{P}_{i1}, \cdots, \hat{P}_{in}\right)$ as follows:

$$\hat{P}_{ij}^{k+1} = \begin{cases} P_{ij}^{k+1} & \text{if } r_{ij} \le CR \\ Pbest_{ij}^k & \text{otherwise} \end{cases} \quad (10)$$

for j=1,2,…,n. Here, r_{ij} is the uniformly distributed random number between [0,1], and CR is the pre-determined crossover rate in the range of [0,1]. 2) If the particle i does not satisfy the equality constraint, an element generated at random is assigned as a slag generator to satisfy the constraint. 3) Let i = i + 1, and go to 1) until all the particles are considered.
The benefits of the suggested crossover operation are: 1) All the elements of any trial particle satisfy the inequality constraint. 2) The diversity in a swarm can be obtained by artificially mixing a particle with its best experienced solution, which can potentially prevent the premature convergence. 3) The advantages of PSO and GA can be combined while the main evolution process of PSO is preserved. 4) Not much computation burden is added compared to the conventional PSO. Figure 1 gives an example of the crossover mechanism for an individual i.

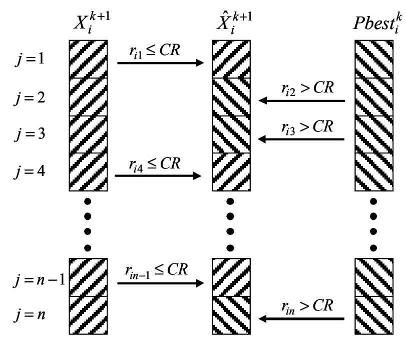

Fig. 1. Illustration of the crossover operation.

4) Update of Pbest and Gbest: The *Pbest* of each particle at iteration k+1 is updated as follows. If vector $\hat{X}_i^{k+1}$ yields better solution than $Pbest_i^k$, then $Pbest_i^{k+1}$ is set to $\hat{X}_i^{k+1}$. Otherwise, the existing $Pbest_i^k$ is retained.

$$Pbest_i^{k+1} = \begin{cases} \hat{X}_i^{k+1} & \text{if } f(\hat{X}_i^{k+1}) < f(Pbest_i^k) \\ Pbest_i^k & \text{otherwise} \end{cases} \quad (11)$$

where f is the value of the object function. Also, *Gbest* at iteration k+1 is set as the best evaluated position among $Pbest_i^{k+1}$.

5) *Stopping Criteria:* The proposed HPSO algorithm is terminated if the iteration reaches a predefined maximum iteration.

V. Numerical Experiments

To verify the effectiveness of the proposed method, the power system of 40 generating units with valve-point effects is tested [11]. The input data for the test system with 40 generating units are provided in Table I and the total demand is considered as 10,500MW.

Since the performance of PSO can depend on its parameters such as inertia weight ω and two acceleration coefficients (i.e., c_1 and c_2), 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 this paper, the inertia weight is set as a linearly decreasing one starting from 0.9 (i.e., $\omega_{\max}$) ending at 0.4 (i.e., $\omega_{\min}$) since these values are widely accepted when solving various power system optimization problems. In addition, when employing the crossover operation, the determination of the crossover rate *CR* can be a key parameter to control the diversity of the population. The value is also determined through the pre-experiments after the suitable parameter values of the acceleration coefficients are determined based on the sensitivity analysis.

In this numerical test, the population size *NP* and maximum iteration number $iter_{\max}$ are set to 50 and 10,000, respectively. In order to find the optimal combination of acceleration coefficients (i.e., c_1 and c_2), nine cases are tested as given in Table II. The acceleration coefficients are determined through the experiments for the system using the conventional PSO, and 100 independent trails are conducted for each case. The optimal values for c_1 and c_2 are selected as 2.0 and 1.0, respectively, based on the results in Table II.

To select the optimal crossover rate, *CR* is also changed from 0.1 to 0.9 with the step size 0.1, and then 100 independent tests are executed for each case. Here, the values of acceleration coefficients are fixed as the pre-determined ones and the conventional PSO mechanism with the constraint treatment strategy is applied. The results are summarized in Table III. According to the experiments the optimal value for *CR* is selected as 0.5. Note that all the cases in Table III showed better performance in terms of minimum cost and average cost than the conventional PSO.

Table IV summarizes the minimum cost, average cost, maximum cost, and standard deviation by the PSO and HPSO for each 100 experiments. The simulation results reveal that HPSO method can provide much better solutions than the PSO due to the adoption of the crossover strategy.

The convergence characteristics of the PSO and the HPSO are compared in Fig. 2. The comparison is made for the best solutions of the PSO and the HPSO among 100 independent trials. In Fig. 2, one can observe the premature convergence of the conventional PSO while HPSO continuously evolves to the better solutions.

TABLE I
GENERATING UNITS DATA FOR 40-UNIT SYSTEM

Gen.	$P_{\min}$	$P_{\max}$	*a*	*b*	*c*	*e*	*f*
1	36	114	94.705	6.73	0.00690	100	0.084
2	36	114	94.705	6.73	0.00690	100	0.084
3	60	120	309.540	7.07	0.02028	100	0.084
4	80	190	369.030	8.18	0.00942	150	0.063
5	47	97	148.890	5.35	0.01140	120	0.077
6	68	140	222.330	8.05	0.01142	100	0.084
7	110	300	278.710	8.03	0.00357	200	0.042
8	135	300	391.980	6.99	0.00492	200	0.042
9	135	300	455.760	6.60	0.00573	200	0.042
10	130	300	722.820	12.90	0.00605	200	0.042
11	94	375	635.200	12.90	0.00515	200	0.042
12	94	375	654.690	12.80	0.00569	200	0.042
13	125	500	913.400	12.50	0.00421	300	0.035
14	125	500	1760.400	8.84	0.00752	300	0.035
15	125	500	1728.300	9.15	0.00708	300	0.035
16	125	500	1728.300	9.15	0.00708	300	0.035
17	220	500	647.850	7.97	0.00313	300	0.035
18	220	500	649.690	7.95	0.00313	300	0.035
19	242	550	647.830	7.97	0.00313	300	0.035
20	242	550	647.810	7.97	0.00313	300	0.035
21	254	550	785.960	6.63	0.00298	300	0.035
22	254	550	785.960	6.63	0.00298	300	0.035
23	254	550	794.530	6.66	0.00284	300	0.035
24	254	550	794.530	6.66	0.00284	300	0.035
25	254	550	801.320	7.10	0.00277	300	0.035
26	254	550	801.320	7.10	0.00277	300	0.035
27	10	150	1055.100	3.33	0.52124	120	0.077
28	10	150	1055.100	3.33	0.52124	120	0.077
29	10	150	1055.100	3.33	0.52124	120	0.077
30	47	97	148.890	5.35	0.01140	120	0.077
31	60	190	222.920	6.43	0.00160	150	0.063
32	60	190	222.920	6.43	0.00160	150	0.063
33	60	190	222.920	6.43	0.00160	150	0.063
34	90	200	107.870	8.95	0.00010	200	0.042
35	90	200	116.580	8.62	0.00010	200	0.042
36	90	200	116.580	8.62	0.00010	200	0.042
37	25	110	307.450	5.88	0.01610	80	0.098
38	25	110	307.450	5.88	0.01610	80	0.098
39	25	110	307.450	5.88	0.01610	80	0.098
40	242	550	647.830	7.97	0.00313	300	0.035

TABLE II
DETERMINATION OF ACCELERATION COEFFICIENTS

Case	c_1	c_2	Min Cost ($)	Average Cost ($)
1	2.0	2.0	121772.9177	122150.2930
2	2.0	1.5	121751.9378	122080.4060
3	**2.0**	**1.0**	**121751.3390**	**121977.6028**
4	1.5	2.0	121754.0167	122167.8336
5	1.5	1.5	121751.3390	122134.5597
6	1.5	1.0	121752.1647	122081.7638
7	1.0	2.0	121753.9811	122344.6859
8	1.0	1.5	121761.0886	122309.8234
9	1.0	1.0	121751.9378	122247.2560

TABLE III
INFLUENCE OF CROSSOVER RATE ON HPSO PERFORMANCE

Case	*CR*	Min. Cost ($)	Average Cost ($)
1	0.1	121454.0992	121658.9017
2	0.2	121453.2000	121605.4304
3	0.3	121452.7265	121572.7435
4	0.4	121452.6741	121555.2500
5	**0.5**	**121452.6741**	**121537.1906**
6	0.6	121452.6741	121560.2108
7	0.7	121452.6741	121596.1496
8	0.8	121452.6741	121662.8050
9	0.9	121452.6741	121717.5510

TABLE IV
COMPARISON OF THE CONVERGENCE RESULTS OF PSO AND HPSO

Methods	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)	Standard Deviation

PSO	121751.3390	121977.6028	122615.7099	209.6960
HPSO	121452.6741	121537.1906	121736.5664	116.7902

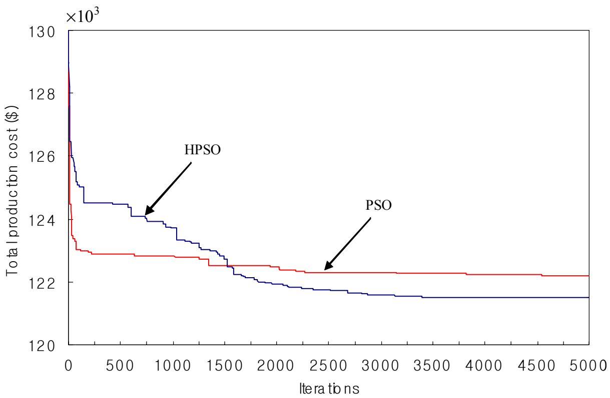

Fig. 2. Convergence characteristics of PSO and HPSO.

In Table V, the results obtained by the PSO and the proposed HPSO are compared with those from evolutionary programming (EP) [11], modified particle swarm optimization (MPSO) [15], PSO-SQP [16], and DEC-SQP [14]. Although the acquired best solution from HPSO is not guaranteed to be the global solution, the proposed algorithm has shown the superiority to the previous researches in terms of minimum cost as well as average cost as described in Table V.

The generation output and the corresponding cost of the obtained best solution from PSO and HPSO are compared with those of the previous researches in Table V. We have also observed that the solutions by the PSO and HPSO always satisfy the equality and inequality constraints due to the employment of the constraint handling strategy.

TABLE V

COMPARISON OF RESULTS OF VARIOUS METHODS

Methods	Minimum Cost ($)	Average Cost ($)
EP [11]	122,624.3500	123,382.0000
MPSO [15]	122,252.2650	N/A
PSO-SQP [16]	122,094.6700	122,245.2500
DEC-SQP [14]	121,741.9793	122,295.1278
PSO	121,751.3390	121,977.6028
HPSO	121,452.6741	121,537.1906

TABLE VI

GENERATION OUTPUT OF EACH GENERATOR AND THE CORRESPONDING COST IN 40-UNIT SYSTEM

Unit	MPSO [15]	DEC-SQP[14]	PSO	HPSO
1	114.000	111.7576	114.0000	110.7998
2	114.000	111.5584	114.0000	110.7998
3	120.000	97.3999	120.0000	97.3999
4	182.222	179.7331	179.7331	179.7331
5	97.000	91.6560	97.0000	87.7999
6	140.000	140.0000	140.0000	140.0000
7	300.000	300.0000	300.0000	300.0000
8	299.021	300.0000	300.0000	284.5997
9	300.000	284.5997	293.3949	284.5997
10	130.000	130.0000	130.0000	130.0000
11	94.000	168.7998	94.0000	94.0000
12	94.000	94.0000	94.0000	94.0000
13	125.000	214.7598	125.0000	214.7598
14	304.485	394.2794	394.2794	394.2794
15	394.607	304.5196	394.2794	304.5196
16	305.323	304.5196	304.5196	394.2794
17	490.272	489.2794	489.2794	489.2794
18	500.000	489.2794	489.2794	489.2794
19	511.404	511.2794	511.2794	511.2794
20	512.174	511.2794	511.2794	511.2794
21	550.000	523.2794	523.2794	523.2794
22	523.655	523.2853	523.2794	523.2794
23	534.661	523.2847	550.0000	523.2794
24	550.000	523.2794	523.2794	523.2794
25	525.057	523.2794	523.2794	523.2794
26	549.155	523.2794	523.2794	523.2794
27	10.000	10.0000	10.0000	10.0000
28	10.000	10.0000	10.0000	10.0000
29	10.000	10.0000	10.0000	10.0000
30	97.000	90.3329	97.0000	96.3569
31	190.000	190.0000	190.0000	190.0000
32	190.000	190.0000	190.0000	190.0000
33	190.000	190.0000	190.0000	190.0000
34	200.000	200.0000	200.0000	200.0000
35	200.000	200.0000	200.0000	200.0000
36	200.000	200.0000	200.0000	200.0000
37	110.000	110.0000	110.0000	110.0000
38	110.000	110.0000	110.0000	110.0000
39	110.000	110.0000	110.0000	110.0000
40	512.964	511.2794	511.2794	511.2794
TP	10500.000	10500.0000	10500.0000	10500.0000
TC	122252.265	121741.9793	121,751.3390	121452.6741

* TP: total power [MW], TC: total generation cost [$].

VI. CONCLUSIONS

This paper proposes a new approach for solving the non-smooth ED problems with valve-point effects. The proposed HPSO employs the crossover operation inspired by the GA to enhance the performance of the conventional PSO. The crossover operator is devised to improve the global searching capability and to enhance the capability of escaping from a local minimum. The advantages of the HPSO are: 1) All the elements of a particle generated from the crossover operation satisfy the inequality constraint. 2) The diversity in a swarm can be obtained by artificially mixing a particle with its best experienced solution. 3) The advantages of PSO and GA can be combined while the main evolution process of PSO is preserved. 4) Not much computation burden is added compared to the conventional PSO. In addition, an efficient constraint treatment strategy is adopted without scarifying the evolution process of the PSO. To verify the performance of the proposed HPSO, the ED problem with 40 generating units are tested. The simulation results clearly show that the proposed HPSO can be used as an optimizer providing satisfactory solutions compared to the PSO and the state-of-art other methods.

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