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Scenario-oriented hybrid particle swarm optimization algorithm for robust economic dispatch of power system with wind power

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Abstract: An economic dispatch problem for power system with wind power is discussed. Using discrete scenario to describe uncertain wind powers, a threshold is given to identify bad scenario set. The bad-scenario-set robust economic dispatch model is established to minimize the total penalties on bad scenarios. A specialized hybrid particle swarm optimization (PSO) algorithm is developed through hybridizing simulated annealing (SA) operators. The SA operators are performed according to a scenario-oriented adaptive search rule in a neighborhood which is constructed based on the unit commitment constraints. Finally, an experiment is conducted. The computational results show that the developed algorithm outperforms the existing algorithms.

Keywords: wind power, robust economic dispatch, scenario, simulated annealing (SA), particle swarm optimization (PSO).

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1. Introduction

Traditional deterministic economic dispatch problem (EDP) does not consider the uncertainties of wind power. However, it is insufficient for real-world power system reliability [1−4]. Robust optimization is becoming a promising alternative method of dealing with uncertain EDP [5−7].

Using scenarios to describe the uncertainty of wind power output, the min-max (regret) criterion is usually used to establish the typical robust optimization model [8−12]. However, the obtained robust solutions are over-conservative because of merely concerning single extreme-point scenarios. In fact, the degradation of performances of power systems could occur under more bad scenarios than the worst-case extreme-point scenario [12]. To hedge against the risk of the degradation of performances under bad scenarios, Wang et al. [13] proposed the bad-scenario-set robust optimization concept for machine scheduling problems [14,15], in which the defect of min-max (regret) robust solutions could be overcome [16].

The bad-scenario-set robust optimization has been applied into uncertain EDP with wind power fluctuations and uncertainties [8−10]. For the robust EDP with complex objective functions, exact algorithms could not be applicable especially for larger-size instances [17]. Various meta-metaheuristic algorithms have been applied [18−22]. Among them, the particle swarm optimization (PSO) algorithm was used frequently because of the advantages of simple implementation and fast convergence [19−21]. Hybrid PSO algorithms of incorporating with local search are usually adopted to deal with the possible premature convergence of PSO [23−26].

This paper discusses the uncertain power system EDP with wind power. The main contributions lie in the following aspects. Firstly, uncertain wind power is modeled by discrete scenarios. A threshold is given to identify bad scenarios. The bad-scenario-set robust economic dispatch model is formulated to hedge against the performance deterioration caused by bad wind power scenarios. The simulated-annealing hybrid PSO (SHPSO) algorithm, which combines PSO with simulated annealing (SA) operators, is developed here to solve the formulated problem. Specifically, the SA operator is designed in a problem-specific way. Finally, the computational results testify that the developed SHPSO algorithm outperforms possible alternative algorithms.

The paper is organized as follows. In Section 2, the bad-scenario-set model is formulated. In Section 3, the SHPSO algorithm is developed to solve the formulated problem. An experiment is conducted to investigate the developed algorithm in Section 4. The conclusions are drawn in Section 5.

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2. Robust EDP with wind power

In order to guarantee the operational security of power system, it is important to handle uncertain wind power for the economic dispatch problem. Robust dispatch methods can hedge against extreme adverse situations. Here the bad-scenario-set robust optimization model is formulated for the dispatch problem of power system with wind power. As the basis, we first provide the description of the deterministic economic dispatch problem.

2.1 Deterministic economic dispatch

In the deterministic economic dispatch problem, only the cost of thermal generators is taken into account as the generation cost of the power system. Here the EDP with wind power does not consider the starting-up and shutting-down states of the units [22], but the valve-point effects are concerned in the total generation cost $F(\boldsymbol{P})$ of all thermal generators as follows:

$$\min\ F(\boldsymbol{P})=\sum_{t=1}^{T}\sum_{i=1}^{I}\Big\{a_iP_{i,t}^2+b_iP_{i,t}+c_i+\big|e_i\cdot\sin\left[f_i\cdot(P_{i,\min}-P_{i,t})\right]\big|\Big\} \tag{1}$$

$$\text{s.t. } \sum_{i=1}^{I}P_{i,t}+P_t^{\mathrm{w}}=P_t^{\mathrm{d}} \tag{2}$$

$$P_{i,\min}\leqslant P_{i,t}\leqslant P_{i,\max} \tag{3}$$

$$P_{i,t}-P_{i,t-1}\leqslant \Delta P_{u,i} \tag{4}$$

$$P_{i,t-1}-P_{i,t}\leqslant \Delta P_{d,i} \tag{5}$$

$$\sum_{i=1}^{I}\min(P_{i,\max}-P_{i,t},\Delta P_{u,i})\geqslant P_{\mathrm{SRt}} \tag{6}$$

$$\sum_{i=1}^{I}\min(P_{i,t}-P_{i,\min},\Delta P_{d,i})\geqslant P_{\mathrm{SRt}} \tag{7}$$

where $\boldsymbol{P}=\{P_{i,t}\mid i=1,2,\cdots,I;\ t=1,2,\cdots,T\}$ is a power output vector representing a set of power output of all generators in all time periods. T is the total number of time periods, t is the index of each time period, I is the total number of thermal generators, and i is the index of each generator. a_i, b_i and c_i are the cost coefficients of generator i. e_i and f_i are the cost coefficients of generator i reflecting valve-point effects. In the constraints (2)−(7), for time period t, $P_{i,\min}$ is the minimum power output of the ith generator, $P_{i,t}$ is the power output of the ith generator, P_t^{w} denotes the forecasted wind power, P_t^{d} denotes the load power, P_{SRt} denotes the rotation reserve capacity of the system. $P_{i,\max}$ denotes the maximum power output of the ith generator. $\Delta P_{u,i}$ and $\Delta P_{d,i}$ respectively represent the ramp-up and ramp-down limits for generator i.

We assume that the wind power P_t^{w} is forecasted to be deterministic input parameters.

2.2 Bad-scenario-set robust economic dispatch model

We discuss the uncertain power system dispatch problem, in which the uncertainty of wind power causes the fluctuation of the power output as well as the generation costs of thermal generators.

Uncertain wind power is described by a set of discrete scenarios. Let Λ be the scenario set of all possible wind power scenarios. For any scenario $\lambda\in\Lambda$, $\lambda=\{\lambda_t\mid t=1,2,\cdots,T\}$, where λ_t is a possible wind power fluctuation deviating from the normal value of wind power P_t^{w} during time period t under scenario λ. We call the uncertain economic dispatch problem with wind power described by scenarios the scenario EDP (SEDP).

Let $F(P|\lambda)$ denote the generation cost of thermal generators with dispatch solution P under wind power scenario λ. Under some scenarios, the values of $F(P|\lambda)$ are getting particularly big. Given a threshold B, those scenarios, under which the generation costs $F(P|\lambda)$ are not lower than B, are called bad scenarios. The set of bad scenarios is identified for dispatch solution P as follows:

$$\Lambda_B(P)=\{\lambda|F(P|\lambda)\geqslant B,\lambda\in\Lambda\}. \tag{8}$$

The bad-scenario-set robust economic dispatch model is formulated by minimizing the total penalties on those bad scenarios. The penalty on individual bad scenario is calculated by the square of deviation between the generation cost $F(P|\lambda)$ and the value of B. For the dispatch solution P, the total penalties with respect to $\Lambda_B(P)$ is the sum of the penalties on all individual scenarios of $\Lambda_B(P)$. The bad-scenario-set robust-optimization (BR) criterion is formulated as follows:

$$\min \mathrm{BR}(P)=\sum_{\lambda\in\Lambda_B(P)}[F(P|\lambda)-B]^2. \tag{9}$$

For the SEDP, the power balance constraint, expressed by (2), should be modified as follows:

$$\sum_{i=1}^{I}P_{i,t}+P_t^{\mathrm{w}}+\lambda_t=P_t^{\mathrm{d}}, \tag{10}$$

$$P_{t,\min}^{\mathrm{w}}\leqslant P_t^{\mathrm{w}}+\lambda_t\leqslant P_{t,\max}^{\mathrm{w}}, \tag{11}$$

where $P_{t,\min}^{\mathrm{w}}$ and $P_{t,\max}^{\mathrm{w}}$ denote the minimum and maximum wind power during time period t, respectively. Constraint (11) expresses the fluctuation range of wind power.

3. SHPSO algorithm

The SEDP is of non-differentiability, high dimensions and multiple constraints. The SHPSO algorithm is developed to solve it.

Basically, the PSO algorithm searches the solution space using a group of particles. Each particle represents a possible solution, and the quality of each particle is evaluated by the fitness function. In each iteration, a particle moves toward the optimum position based on its present velocity, its best previous position and the best previous position of its neighbors. After a number of iterations, the obtained solution is accepted.

To overcome the premature convergence of PSO, the PSO algorithm is incorporated with SA operators. Here we adopt a problem-specific technique to design the SA operator. We utilize the constraints of power output of generators to construct a neighborhood structure, and perform the SA operators according to an elaborately designed scenario-oriented adaptive search rule. In such a local search process, partial constraints are handled while improving the search efficiency of local search.

3.1 Framework of SHPSO algorithm

The SHPSO algorithm adopts the real number encoding scheme [20]. The initial position and velocity of each particle are generated randomly in the way of [19]. We apply the heuristic constraint-handling (HC) technique proposed by Park et al. [19] to satisfy the constraints (2)−(5), and adopt the constraint treatment (CT) method proposed by Elsayed et al. [20] to handle the constraints (6)−(7).

At iteration k, the bad scenario set $\Lambda_B(P_n^k)$ is identified for feasible solution P_n^k, which is expressed by current position of particle n. The objective function expressed by (9) is taken as the fitness function. Let $P_{\text{Pbest},n}^k$ and P_{Gbest}^k be the best previous position of the particle n and the best previous position in the swarm respectively at iteration k. The calculation of $P_{\text{Pbest},n}^k$ and P_{Gbest}^k can be referred to [20]. Based on the positions of $P_{\text{Pbest},n}^k$ and P_{Gbest}^k, the positions of particles are updated as follows:

$$V_n^{k+1} = \omega \cdot V_n^k + c_1 \cdot r_1 \cdot (P_{\text{Pbest},n}^k - P_n^k) + c_2 \cdot r_2 \cdot (P_{\text{Gbest}}^k - P_n^k), \tag{12}$$

$$P_n^{k+1} = P_n^k + V_n^{k+1}, \tag{13}$$

where V_n^k represents the velocity of particle n at iteration k, ω denotes the inertia weight factor, c_1 and c_2 are the acceleration coefficients, r_1 and r_2 are the random numbers between 0 and 1. The inertia weight factor ω decreases linearly [27].

It is shown in (12) that better value of P_{Gbest}^k helps the PSO to converge more rapidly. The scenario-oriented SA operator (SSAO) is performed to obtain a better value of P_{Gbest}^k in the SHPSO algorithm.

The termination criterion of SHPSO is set to be the maximum iteration number K. When the number of iteration $k \geqslant K$, the algorithm is terminated.

In summary, the framework of the SHPSO algorithm is presented in Fig. 1.

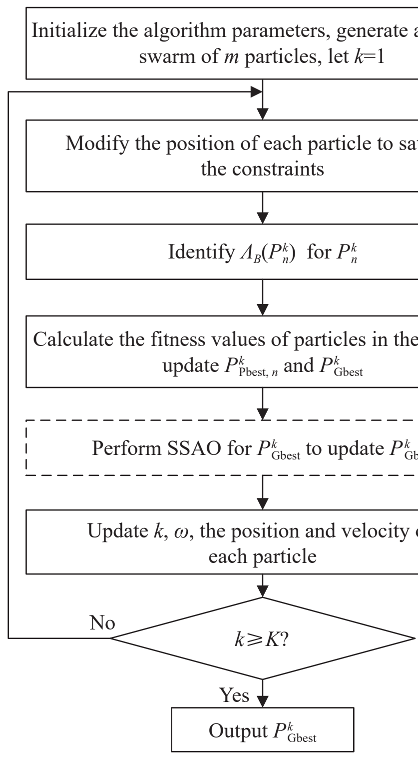


Fig. 1 Framework of SHPSO algorithm

3.2 SSAO

The SA operator searches a constructed neighborhood for current solution and determines whether or not to accept a new solution according to the metropolis criterion. The SA operator usually accepts a better solution than the current solution, but occasionally accepts an inferior solution with a certain probability. Thus the SA operator has the chances to jump out of local minima and furtherly to find the global optimum.

The problem-specific consideration is made for the SSAO through constructing a neighborhood, which is constructed based on the constraint intervals of thermal generators. The cooling function of SSAO adopts the linear cooling method.

3.2.1 Constructing a neighborhood for SSAO

To consider the ramp rate limits and power output limits constraints of conventional generators at the same time, constraints (3)−(5) can be rewritten as an inequality constraint as follows:

$$\max(P_{i,\min}, P_{i,t-1}-\Delta P_{d,i}) \leqslant P_{i,t} \leqslant \min(P_{i,\max}, P_{i,t-1}+\Delta P_{u,i}). \tag{14}$$

For simplification, let $P^-_{i,t}$ denotes the minimum value of $P_{i,t}$, and $P^+_{i,t}$ denotes the maximum value of $P_{i,t}$, then $P_{i,t} \in [P^-_{i,t}, P^+_{i,t}]$. Constraint (14) indicates that any current value of the power output $P_{i,t}$ of generator i could be adjusted to generate new solutions only within the interval $[P^-_{i,t}, P^+_{i,t}]$, otherwise, new solutions will not be able to satisfy the constrains (3)−(5). In fact, the interval $[P^-_{i,t}, P^+_{i,t}]$ can be taken as a neighborhood for current solution $P_{i,t}$. When the SA operator is performed in the neighborhood, all evaluated candidate solutions could satisfy constrains (3)−(5).

Based on the constructed neighborhood, the search rule of SSAO is also a problem-specific consideration because the characteristics of discrete scenarios of uncertain wind power are utilized to design a scenario-oriented adaptive search rule for the SSAO so that the efficiency of the SA operator could be improved.

3.2.2 Designing scenario-oriented adaptive search rule

In the scenario-oriented adaptive search rule, the search direction is guided by the current value of the wind power scenario and the size of search step is dynamically adjusted based on the scenarios and the constraints.

The scenario-oriented adaptive search rule is shown in Fig. 2. The line segment AC represents the neighborhood $[P^-_{i,t}, P^+_{i,t}]$ for current solution $P_{i,t}$. Point B indicates the current solution $P_{i,t}$, point A is the left boundary of the neighborhood, and point C is the right boundary of the neighborhood.

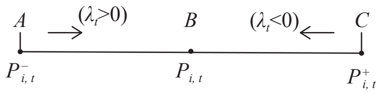


Fig. 2 Scenario-oriented adaptive search rule

According to (10) and (11), if the real-time wind power in time period t is bigger than the forecasted value P^{w}_t, then $\lambda_t > 0$, and the power output of the units should be reduced to maintain the power balance of the system. A better solution should be closer to point A. Therefore, the search direction is from point A to point B. On the contrary, if the real-time wind power in time period t is smaller than the forecasted value P^{w}_t, then $\lambda_t < 0$, and the power output of the units should be increased. A better solution should be closer to point C, thus the search direction is from point C to point B.

Furthermore, for a bigger value of λ_t ($\lambda_t > 0$), a better solution is closer to the point A, and the smaller search step should be set. Let $\Delta P^{\lambda}_{i,t}$ denote the size of search step for current solution $P_{i,t}$ under scenario λ. For a smaller value of $\lambda_t(\lambda_t < 0)$, a better solution is closer to point C, and a smaller value of $\Delta P^{\lambda}_{i,t}$ should be set.

Here the search direction and the step size are adaptively and dynamically adjusted as the wind power scenario changes. Let the maximum search number in the neighborhood be J. Under scenario λ, the value of $\Delta P^{\lambda}_{i,t}$ is set as follows:

$$\Delta P^{\lambda}_{i,t} = \begin{cases} \left(1-\dfrac{\lambda_t}{P^{\mathrm{w}}_{t,\max}-P^{\mathrm{w}}_t}\right)\cdot\dfrac{P_{i,t}-P^-_{i,t}}{J}, & \lambda_t \geqslant 0 \\ \left(1-\dfrac{\lambda_t}{P^{\mathrm{w}}_{t,\min}-P^{\mathrm{w}}_t}\right)\cdot\dfrac{P^+_{i,t}-P_{i,t}}{J}, & \lambda_t < 0 \end{cases}, \tag{15}$$

$$P^{j+1}_{i,t} = \begin{cases} P^-_{i,t} + j\cdot\Delta P^{\lambda}_{i,t}, & \lambda_t \geqslant 0 \\ P^+_{i,t} - j\cdot\Delta P^{\lambda}_{i,t}, & \lambda_t < 0 \end{cases}, \tag{16}$$

where $P^j_{i,t}$ corresponds to the power output of the ith generator in time period t at iteration j, and $P^{j+1}_{i,t}$ is a new candidate solution obtained by the scenario-oriented adaptive search rule.

For the current position of each particle, a neighborhood is constructed in the way that is described in Subsection 3.2.1, and the SSAO is performed according to the scenario-oriented adaptive search rule.

4. Computation results and analysis

An experiment is conducted to verify the effectiveness of the developed algorithm in this section. All the algorithms are coded in Matlab 2014A, and the experiment is conducted on the desktop computer with AMD Ryzen5 1600 3.2G CPU with 12.0G RAM.

The developed SHPSO algorithm is tested on the instances of 10-unit system, 13-unit system and 40-unit system, which are incorporated with wind power. The dispatch of 24 time periods is one cycle, and each time period is 1 h. The 10-unit system and the 13-unit system data are derived from [28]. The relevant data of 40-unit system can be referred to [19]. The forecasted data of wind power comes from [29]. $|\Lambda| = 50$ wind power scenarios are generated by Latin hypercube sampling (LHS) for each instance [30]. The value of B is given in advance. The values of B are given to be 9.539×10^5, 4.268×10^5 and 29.11×10^5 for the BR criterion in the 10-

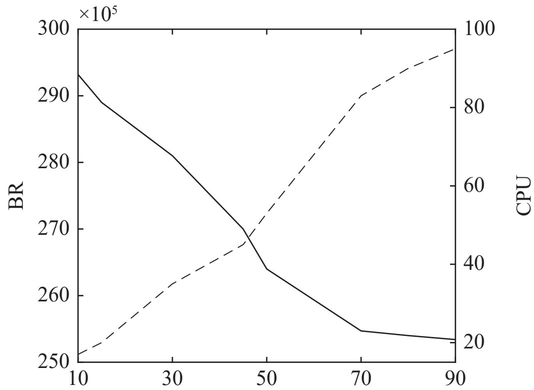
unit, 13-unit and 40-unit instances respectively.

For the SHPSO algorithm, set the population size to be 20. Let the maximum iteration number be 300. Let the maximum and minimum values of inertia weight factor ω be 0.9 and 0.4 respectively. Let $T_0 = 100$, $T_f = 1$, $\xi = 0.8$.

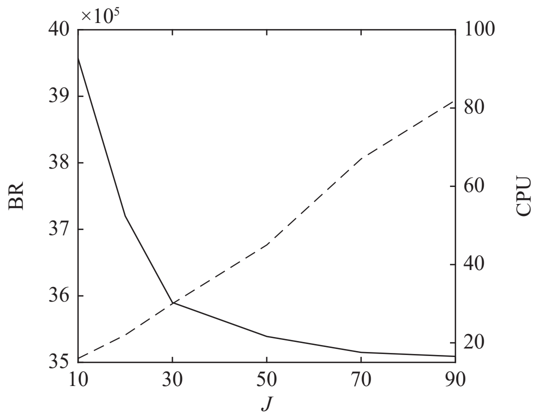
4.1 Tuning the parameter of SHPSO

The maximum search number J used in the SSAO is an important parameter for the developed SHPSO algorithm. In order to set appropriate values of J for different SEDP instances, the tuning test is performed for the instances of 10-unit system, 13-unit system and 40-unit system respectively. The value of J varies from 90 to 10 with the step size of 20. Total 40 runs are executed independently.

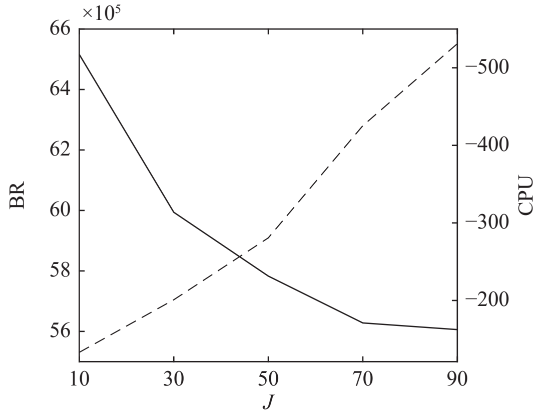
The computational results are presented in Fig.3 for different instances. It is shown that as the value of J gets bigger, the BR performance of solutions obtained by the SHPSO gets better while CPU time spent gets larger for all instances. However, when the value of J increases to a certain extent, the qualities of solutions obtained do not vary again. To take a tradeoff between solution quality and CPU time, the values of J are set to be 50, 30 and 50 respectively for the 10-unit, 13-unit and 40-unit systems.



(a) The 10-unit system



(b) The 13-unit system



(c) The 40-unit system

Fig. 3 Curves of performances obtained by the SHPSO at different *J* values for the systems with 10, 13 and 40 units

4.2 Comparing five algorithms

To test the efficiency of the SHPSO algorithm, we compare the SHPSO with four alternative algorithms. The first algorithm is the general PSO algorithm [19]. The second algorithm is the hybrid PSO algorithm with the conventional neighborhood and the conventional search rule (HPSOCC) [20]. The third algorithm is the hybrid PSO algorithm with the neighborhood based on the constraints but a conventional search rule (HPSONC) [21]. The fourth algorithm is the PSO algorithm with modified inertia weight (MIW-PSO) [23].

The parameters of the compared four algorithms are set according to the SHPSO. Five algorithms are performed respectively to solve the SEDP instances respectively. A total of 40 runs are performed for each instance. The maximum, the minimum and the mean values of BR criterion among 40 runs are recorded for the obtained solutions. The comparisons of solutions obtained are reported in Table 1. It is shown that the advantage of SHPSO over four alternative algorithms is obvious in terms of almost all the maximum, minimum and mean values of BR in all instances. The CPU time consumed by the SHPSO is relatively less. Compared with the PSO, the HPSOCC obtains much better results. It indicates that the efficiency of HPSOCC is improved by cooperating with the SA operators. However, the CPU time consumed by the HPSOCC is greatly bigger. Compared with the HPSONC, the SHPSO obtains better solutions in four test systems. It indicates that the scenario-oriented adaptive search rule could make the local search of SHPSO largely intensified and the CPU time consumed decreased.

Table 1 Comparison of solutions obtained by five algorithms for the SEDP instances

Instance type	Algorithm	BR($\times10^5$)			CPU time/s
		Maximum value	Minimum value	Mean value	
10-unit system	PSO	1031	201.7	357.2	23.00
	HPSOCC	980.6	179.4	296.6	84.00
	HPSONC	784.5	174.5	287.4	71.00
	MIW-PSO	680.4	170.6	273.7	43.00
	SHPSO	631.0	157.1	256.4	55.00
13-unit system	PSO	95.81	16.58	40.25	9.000
	HPSOCC	85.90	13.58	38.26	65.00
	HPSONC	82.84	11.83	37.22	45.00
	MIW-PSO	82.05	10.91	35.95	27.00
	MIW-PSO	79.79	9.819	35.53	30.00
40-unit system	PSO	151.7	35.50	69.54	120.0
	HPSOCC	103.3	29.23	60.05	456.0
	HPSONC	99.64	27.46	58.18	389.0
	MIW-PSO	97.43	24.58	56.95	280.0
	SHPSO	95.93	23.82	56.83	304.0

Specifically, the convergence characteristics of five algorithms in 10-unit system are illustrated in Fig. 4. It is observed that the SHPSO outperforms four alternative algorithms in terms of convergence speed. The convergence of SHPSO is obviously improved due to the synergistic effects of the SSAO.

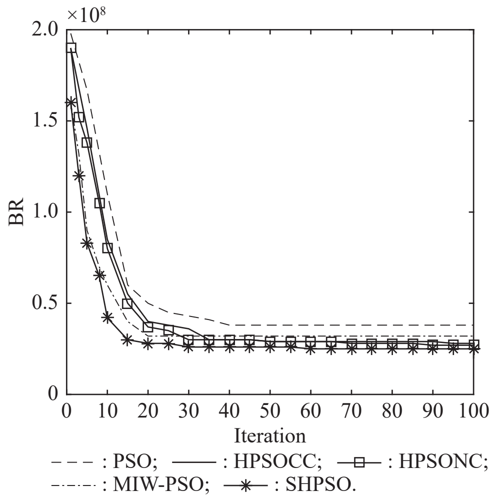


Fig. 4 Comparison of convergence curves of five algorithms in the 10-unit system

5. Conclusions

In the SEDP discussed here, describing uncertain wind power by discrete scenarios, we provide a threshold of performance to identify bad scenarios. The BR criterion based bad-scenario set is used to formulate the EDP with wind power.

To solve the formulated problem, the SHPSO algorithm is developed by combining PSO with SA operators using a problem-specific technique. In the SA operator, the unit commitment constraint of power output of each generator is utilized to construct a neighborhood, in which the SA operator is performed according to a scenario-oriented adaptive search rule. The computational results testify the SHPSO algorithm developed in this paper outperforms other alternative algorithms.

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