Region search evolutionary algorithm with constraint handling for multi-objective short-term wind-solar-hydro-thermal scheduling

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Abstract. Due to the depletion of fossil energy and environmental pollution, renewable clean energy has been paid more and more attention. This paper researches a multi-objective wind-solar-hydro-thermal scheduling model (MOSWS), whose objectives are to minimize the economic cost and minimize the environmental pollution caused by thermal power generation. The region search evolutionary algorithm (RSEA) with constraint handling method is proposed to solve the constrained multi-objective problems and applied to MOSWS model. From the experimental results, we find that RSEA with constraint handling is able to solve the constrained multi-problems and outperforms MODE-ACM in terms of both convergence and diversity. The RSEA is also applied to hydro-thermal system. The results show that wind-solar-hydro-thermal system can not only increase economic benefits, but also reduce the impact of thermal power generation on the atmospheric environment.

1 Introduction

Due to the depletion of fossil energy and environmental pollution, renewable clean energy has been paid more and more attention such as hydro energy, wind energy, solar energy, ocean energy, etc [1-3]. Therefore, traditional thermal power systems will be transformed into multi-energy power systems. Generally, the objectives of a multi-energy power system are to minimize the economic cost and minimize the environmental pollution caused by thermal power generation, which can be formulated as a multi-objective problem.

In the past several decades, multi-objective multi-energy power scheduling model has been developed such as multi-objective optimal hydro-thermal scheduling (MOOHS) problem and multi-objective wind-solar-hydro scheduling (MOWS) problem [4, 5]. From 2000, some constraint and weight approaches such as interactive fuzzy satisfying method (IFSM) [5], e-constraint technique [6], price penalty factor approach [7], were proposed to solve the MOOHS problem. However, these methods can obtain only one optimal solution from a single run, which will consume a lot of time to run the method for many times to obtain the Pareto front.

Multi-objective evolutionary algorithms (MOEAs) can effectively solve the defects existing in weight method and constraint method and get the whole Pareto front through one run. With the development of MOEAs, more and more MOEAs were proposed to solve the multi-energy power scheduling problems. Qin et al. [8]

proposed a multi-objective optimization algorithm based on DE-multi-objective differential evolution with adaptive Cauchy mutation (MODE-ACM) for MOOHS and obtained superior solutions than IFSM. Feng et al. [9] proposed a multi-objective quantum-behaved particle swarm optimization for MOOHS problem and obtained competitive performance compared with several traditional methods. Liu et al. [10] proposed a non-dominated sorting culture differential evolution algorithm for MOWS. Although, these algorithms are successfully applied to the multi-energy power systems, the convergence and diversity of the algorithms are still need to be improved. A region search evolutionary algorithm (RSEA) is proposed in our previous research [11]. The algorithm uses region search strategy to trade off the convergence and diversity of during the process of evolution. The comparison results show that RSEA has better performance in most unconstrained multi-objective problems.

In this paper, the main contributions are summarized as follows: (1) the RSEA with constraint handling method is proposed for constrained multi-objective problems; (2) a multi-objective short-term wind-solar-hydro-thermal scheduling (MOSWS) model is established; (3) RSEA with constraint handling is applied to MOOHS and MOSWS and outperforms other algorithms.

The remainder of this paper is as follows. Section 2 describes the mathematical model of MOSWS. Section 3 give the proposed RSEA with constraint handling method. Section 4 gives the experimental results and discussion. Section 5 concludes this work.

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2 Mathematical model

2.1 Objective function

2.1.1 Economy objective

In the wind-solar-hydro-thermal complementary power generation system, wind, hydro, and solar energy are all renewable energy sources. Therefore, the fuel cost of thermal power plants is the main economic objective in the model. The economic objective can be formulated as follows:

$$\min F_1 = \min \sum_{t=1}^T \sum_{i=1}^{N_T} [\alpha_i + \beta_i \cdot P_{i,t}^T + \gamma_i \cdot (P_{i,t}^T)^2 + |\delta_i \cdot \sin(\varepsilon_i \cdot (P_{i,t}^T - P_{i,t}^{\min}))|] \quad (1)$$

where N_T is the number of thermal generators; T is the length of scheduling period; α_i , β_i , γ_i , δ_i , ε_i are the cost curve coefficients of the i -th thermal generator; $P_{i,t}^T$ denotes the output power of the i -th thermal generator at period t ; $P_{i,t}^{\min}$ is the lower generation limits of i -th thermal generator.

2.1.2 Emission objective

Thermal power stations emit high concentrations of pollutants during the power generation process, which will pollute the atmospheric environment. In this paper, nitrogen oxides (NOx) emission is selected as the main indicator to measure the degree of environmental pollution. The emission objective is the can be formulated as follows:

$$\min F_2 = \min \sum_{t=1}^T \sum_{i=1}^{N_T} [a_i + b_i \cdot P_{i,t}^T + c_i \cdot (P_{i,t}^T)^2 + d_i \cdot \exp(e_i \cdot P_{i,t}^T)] \quad (2)$$

where a_i , b_i , c_i , d_i , and e_i are emission curve coefficients of the i -th thermal generator.

2.2 Constraints

The wind-solar-hydro-thermal complementary power generation system subjects to the following constraints:

(1) Power balance constraints

For each time period, the total power generation of wind power, photovoltaic power, hydropower, and thermal power must balance the system load demand

$$P_t^D = \sum_{i=1}^{N_T} P_{i,t}^T + \sum_{j=1}^{N_H} P_{j,t}^H + \sum_{k=1}^{N_W} P_{k,t}^W + \sum_{m=1}^{N_S} P_{m,t}^S \quad (3)$$

where P_t^D is the load demand at period t ; $P_{j,t}^H$ is the output power of the j -th reservoir at period t ; N_H is the number of reservoirs; $P_{k,t}^W$ is the output power of the k -th wind farm at period t ; N_W is the number of wind farms; $P_{m,t}^S$ is the output power of the m -th solar power plant at period t ; N_S is the number of solar power plants;

The hydropower is a function of reservoir storage and discharge:

$$P_{j,t}^H = C_{1,j} V_{j,t}^2 + C_{2,j} Q_{j,t}^2 + C_{3,j} V_{j,t} Q_{j,t} + C_{4,j} V_{j,t} + C_{5,j} Q_{j,t} + C_{6,j} \quad (4)$$

where $C_{1,j}$, $C_{2,j}$, $C_{3,j}$, $C_{4,j}$, $C_{5,j}$, $C_{6,j}$ are the hydropower coefficients of j -th reservoir; $V_{j,t}$ is the reservoir storage volume of j -th reservoir at period t ; $Q_{j,t}$ is the discharge volume of j -th reservoir at period t .

The wind power is a function of wind speed air density, fan efficiency and rotor radius as follows:

$$P_{k,t}^W = \frac{1}{2} \rho_k A_k^W C_k^W v_{k,t}^3 \quad (5)$$

where ρ_k is the air density of k -th wind farm; A_k^W is the swept area by the turbine blades at k -th wind farm; C_k^W is the wind power coefficient of k -th wind farm; $v_{k,t}$ is the wind speed of k -th wind farm at time t .

The solar power is a function of solar radiation intensity and solar power generator area as follows:

$$P_{m,t}^S = \eta_m A_m^S G_{m,t} \quad (6)$$

where η_m is the efficiency of m -th solar power plant; A_m^S is the solar power generator area of m -th solar power plant; $G_{m,t}$ is the solar radiation intensity of m -th solar power plant at time t .

(2) Generation limits

$$P_{i,\min}^T \leq P_{i,t}^T \leq P_{i,\max}^T \quad (7)$$

$$P_{j,\min}^H \leq P_{j,t}^H \leq P_{j,\max}^H \quad (8)$$

$$P_{k,\min}^W \leq P_{k,t}^W \leq P_{k,\max}^W \quad (9)$$

$$P_{m,\min}^S \leq P_{m,t}^S \leq P_{m,\max}^S \quad (10)$$

where $P_{i,\min}^T$ and $P_{i,\max}^T$ are the lower and upper generation limits of the i -th thermal generator; $P_{j,\min}^H$ and $P_{j,\max}^H$ are the lower and upper generation limits of the j -th reservoir; $P_{k,\min}^W$ and $P_{k,\max}^W$ are the lower and upper generation limits of the k -th wind farm; $P_{m,\min}^S$ and $P_{m,\max}^S$ are the lower and upper generation limits of the m -th solar power plant.

(3) Water balance of cascade reservoir

$$V_{j,t+1} = V_{j,t} + [I_{j,t} + \sum_{k=1}^{N_{uj}} Q_{k,t-T_{kj}} - Q_{j,t}] \quad (11)$$

where $I_{j,t}$ is the inflow of the j -th reservoir at period t ; N_{uj} is the number of upstream reservoirs above the j -th reservoir; T_{kj} is the time delay from reservoir k to j .

(4) Reservoir discharge limits

$$Q_{j,\min} \leq Q_{j,t} \leq Q_{j,\max} \quad (12)$$

where $Q_{j,\min}$ and $Q_{j,\max}$ are the lower and upper discharge limits of the j -th reservoir;

(5) Reservoir storage volumes limits

$$V_{j,\min} \leq V_{j,t} \leq V_{j,\max} \quad (13)$$

where $V_{j,\min}$ and $V_{j,\max}$ are the lower and upper storage volume limits of the j -th reservoir;

(6) Initial and final reservoir storage volumes

$$V_{j,0} = V_j^{\text{start}}, V_{j,T+1} = V_j^{\text{end}} \quad (14)$$

where V_j^{start} and V_j^{end} are initial and terminal storage volume of j -th reservoir.

3 Region search evolutionary algorithm with constraints handling

In our previous work, the RSEA is proposed for solving unconstrained multi-objective problems. However, the short-term wind-solar-hydro-thermal scheduling model includes a series of constraints. This paper extends RSEA with constraint handling method to solve constrained problems.

The details of the RSEA can be seen in the references [11]. When dealing with constraints problems, some modifications are made to the normalization and update procedure of RSEA. The modifications are illustrated as follows.

3.1 Modifications on normalization procedure

The constraint violation value $CV(x)$ of the solution x can be calculated as follows:

$$CV(x) = \sum_{j=1}^J \langle g_j(x) \rangle + \sum_{k=1}^K |h_k(x)| \quad (15)$$

where $g_j(x)$ and $h_k(x)$ denote the j -th inequality constraint and k -th equality constraint, respectively; J is the number of inequality constraints; K is the number of equality constraints; $\langle g_j(x) \rangle$ is the bracket operator, which return the absolute value of $g_j(x)$ if $g_j(x) < 0$, and returns 0 otherwise. The smaller is the constraint violation value, the better is the solution x . When $CV(x) = 0$, the solution x is feasible.

In the normalization procedure, the main task is to estimate ideal point z^* and the nadir point z^{nad} . When handling constrained problems, solution with smaller CV is able to update the nadir point z^{nad} . The pseudo-code of update the z^* and z^{nad} is given in Algorithm 1. In Algorithm 1, $\{e_1, e_2, \dots, e_m\}$ is the extreme points; $ASF(x^c, w_j)$ denotes the achievement scalarization function value of solution x^c corresponding to the j -th weight vector w_j . After updating the z^* and z^{nad} , the objective value of solution x can be normalized as follows:

$$F_j^{\text{norm}}(x) = \frac{F_j(x) - z_j^*}{z_j^{\text{nad}} - z_j^*} \quad (16)$$

where $F_j(x)$ is the j -th objective value of solution x ; $F_j^{\text{norm}}(x)$ is the normalized objective value of solution x .

Algorithm 1 UpdateIdealNadirPoint (x^c)

Input: offspring solution x^c

Output: ideal point z^* , nadir points z^{nad}

1 **for each** $j = 1, \dots, m$ **do**

```

2   if  $F_j(x^c) < z_j^*$  then set  $z_j^* = F_j(x^c)$ ;
3 end for
4    $needUpdateNad = \text{false}$ 
5   for each  $j = 1, \dots, m$  do
6     if  $CV(x^c) \leq CV(e_j)$  then
7       if  $ASF(x^c, w_j) < ASF(e_j, w_j)$  then
8          $e_j = x^c$ 
9          $needUpdateNad = \text{true}$ 
10      end if
11    end if
12  end for
13  if  $needUpdateNad$  then
14    Caculate intercepts
15    Update  $z^{\text{nad}}$ 
16  end if
17  return  $z^*, z^{\text{nad}}$ 

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3.2 Modifications on Update Procedure

The update procedure of RSEA uses region search strategy. As for constrained problems, the constraint violation value needs to be compared in advance when updating the parent solution. The pseudo-code of the update procedure is given in Algorithm 2. In Algorithm 2, $\cos\langle x^c, \lambda_j \rangle$ denotes the cosine similarity between offspring solution x^c and target region weight vector λ_j ; $d_2(x^c, \lambda_k)$ denotes the perpendicular distance between t offspring solution x^c and weight vector λ_i .

Algorithm 2 UpdtaePopulation(MP, x^c)

Input: update pool MP , offspring solution x^c

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1    $region = \underset{j=1:N}{\operatorname{argmax}} \cos\langle x^c, \lambda^j \rangle$ 
2   set  $a = 0$ .
3   while  $a < 1$  and  $MP \neq \emptyset$  do
4     Randomly select an index  $k$  from  $MP$ .
5      $MP := MP \setminus \{k\}$ 
6     if  $region \neq k$  and  $\cos\langle x^c, \lambda^k \rangle < \cos\langle p^k, \lambda^k \rangle$  then
7       continue
8     end if
9     if  $CV(x^c) < CV(p^k)$  then
10      Set  $p^k = x^c$ 
11       $a = a + 1$ 
12      continue
13    end if
14    if  $CV(x^c) = CV(p^k)$  then
15      if  $x^c$  dominate  $p^k$  then
16        Set  $p^k = x^c$ 
17         $a = a + 1$ 
18      else if  $p^k$  do not dominate  $x^c$  &  $d_2(x^c, \lambda^k) < d_2(p^k, \lambda^k)$  then
19        Set  $p^k = x^c$ 
20         $a = a + 1$ 
21      end if
22    end if
23  end while

```

4 Results and discussion

4.1 Coding strategy and Constraints handling

In order to apply RSEA to the multi-objective short-term wind-solar-hydro-thermal scheduling model, the coding strategy needs to be given. In the scheduling model, $T \times NT$ thermal power values and $T \times NH$ reservoir discharge values are the decision variables. Therefore, a vector consisting of a total of $T \times (NT + NH)$ real numbers is used as an individual, where the first $T \times NT$ real numbers represent thermal power generation, and the last $T \times NH$ real numbers represent reservoir discharge.

According to the mathematical model in section 2, there are a large number of inequality constraints and equality constraints in the model, which makes it difficult for the algorithm to produce solutions that obey all constraints in the process of evolution. Although we have added a general constraint handling method to the RSEA algorithm, an additional constraint handling method need to be applied to accelerate the algorithm convergence speed for this model. The additional constraint processing method is to first determine whether the solution satisfies all constraints before the objective evaluation process. If the solution is infeasible, modify the discharge flow of the reservoirs and the power generation of thermal units, so that most of the solutions can become feasible solutions. The detail of this constraints handling process can be seen from our previous research [8].

4.2 Experimental results

A system which consists of one solar power farm, four wind power farms, four reservoirs and three thermal units is used as our study objective. The entire scheduling period is 24 hours, and the time step is 1hour. The solar power, wind power, load demand and the inflow volume of each reservoir are given in table 1. The hydropower generation coefficients, thermal generation coefficients, reservoir limits and generation limits are set the same as reference [8]. The parameters of RSEA is set as follows: population size = 100, neighbourhood size = 20, mutation probability = 1/100, mutation distribution index = 20, number of generations = 2000.

Table 1. The solar power, wind power, load demand and the inflow volume.

Time	P^S	P^W	P^D	R1	R2	R3	R4
1	0	35	750	10	8	8.1	2.8
2	0	32	780	9	8	8.2	2.4
3	0	42	700	8	9	4	1.6
4	0	44	650	7	9	2	0
5	0	30	670	6	8	3	0
6	0	33	800	7	7	4	0
7	0	16	950	8	6	3	0
8	0	12	1010	9	7	2	0
9	0	14	1090	10	8	1	0
10	15	15	1080	11	9	1	0

11	26	22	1100	12	9	1	0
12	35	36	1150	10	8	2	0
13	55	52	1110	11	8	4	0
14	63	68	1030	12	9	3	0
15	57	80	1010	11	9	3	0
16	57	99	1060	10	8	2	0
17	50	93	1050	9	7	2	0
18	44	82	1120	8	6	2	0
19	58	61	1070	7	7	1	0
20	14	48	1050	6	8	1	0
21	0	29	910	7	9	2	0
22	0	40	860	8	9	2	0
23	0	46	850	9	8	1	0
24	0	25	800	10	8	0	0

To verify the performance of RSEA, we first apply RSEA to the system that do not consider solar power and wind power. The Pareto front obtained by RSEA is shown in Fig. 1. Moreover, the non-dominated schemes obtained by MODE-ACM is also shown in Fig. 1. From the figure, it can be seen that most of the solutions obtained by RSEA can dominate the solutions obtained by MODE-ACM, which proved that the convergence of RSEA is better than MODE-ACM. Besides the convergence of the algorithm, the diversity of RSEA is also better than MODE-ACM because RSEA obtained wider Pareto front.

Figure 1. Pareto front obtained by RSEA and MODE-ACM.

After the comparison of RSEA and MODE-ACM, RSEA is applied to the short-term wind-solar-hydro-thermal scheduling model. The Pareto fronts of short-term wind-solar-hydro-thermal scheduling system and the hydro-thermal scheduling system are shown in Fig. 2. It can be seen from the figure that after adding wind power and photovoltaic power into the power system, both the pollutant emission of the system and the cost of thermal power generation are greatly reduced. This demonstrated that multi energy complementary system can not only increase economic benefits, but also reduce the impact of thermal power generation on atmospheric environment.

A typical non-dominated scheme of hydro-thermal system and a typical non-dominated scheme of wind-solar-hydro-thermal system are selected to show scheduling process in detail. Fig.3 and Fig.4 show the typical power generation process in each time step of hydro-thermal system and solar-hydro-thermal system, respectively. Both the two typical schemes are selected

as a compromise scheme between economic and environmental objectives from the whole Pareto front. From the figure, we can see that under the same total power generation, the wind-solar-hydro-thermal system can reduce the thermal power generation, so as to improve the comprehensive benefit of the power system.

Figure 2. Pareto front of hydro-thermal system and wind-solar-hydro-thermal system obtained by RSEA.

Figure 3. Typical power generation process of hydro-thermal system.

Figure 4. Typical power generation process of wind-solar-hydro-thermal system.

5 Conclusions

This paper proposes a multi-objective short-term wind-solar-hydro-thermal scheduling (MOSWS) model. A modification version of region search evolutionary algorithm (RSEA) which can handle constraints is proposed to solve the MOSWS model. From the

experimental results, we can give the following conclusions: (1) RSEA with constraint handling is able to solve the constrained multi-problems, the results show that it performs better than MODE-ACM in terms of both convergence and diversity; (2) Compared with hydro-thermal system, wind-solar-hydro-thermal system can not only increase economic benefits, but also reduce the impact of thermal power generation on atmospheric environment.

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