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Economic environmental dispatch of hydrothermal power system

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ABSTRACT

This paper presents multi-objective differential evolution for economic environmental dispatch of hydrothermal power system, consisting of multi-reservoir cascaded hydro plant with time delay and thermal plants with nonsmooth fuel cost and emission level functions. The problem is formulated as a nonlinear constrained multi-objective optimization problem. Multi-objective differential evolution is proposed to handle economic environmental dispatch of hydrothermal power system as a true multi-objective optimization problem with competing and noncommensurable objectives. Numerical results for a sample test system has been presented to demonstrate the capabilities of the proposed method. The results obtained from the proposed method have been compared to those obtained using nondominated sorting genetic algorithm-II.

1. Introduction

The fossil fuel based generating station releases sulfur oxides (SO_x), nitrogen oxides (NO_x), and carbon dioxide (CO_2) into atmosphere. Atmospheric pollution affects not only humans but also other life-forms such as animals, birds, fish and plants. It also causes damage to materials, reducing visibility as well as causing global warming. Due to increasing concern over the environmental considerations, society demands adequate and secure electricity not only at the cheapest possible price, but also at minimum level of pollution. So the optimal scheduling of generation in a hydrothermal system involves the allocation of generation among the hydro-electric and thermal plants so as to optimize the fuel cost and emission level simultaneously for thermal plants over a short time horizon subject to various equality and inequality constraints. The equality constraints are the power balance constraint, dynamic balance of reservoir storage for cascaded hydro plants, boundary conditions for the reservoir storage, etc. The inequality constraints are the generation limits on the hydro and thermal generators, bounds on the reservoir storage levels and turbine discharge rates, etc.

The electric and hydraulic coupling creates a multidimensional, nonlinear, nonconvex, large-scaled, and combinatorial problem. Therefore, short-term hydrothermal scheduling problem poses a significant challenge to the scheduler, as it possesses a large parametric space to choose from, a possibility of large infeasible and nonuniform areas, and the presence of numerous local optima. To solve this problem, either analytical gradients or numerical researches have been largely resorted to in the past [1,2]. These techniques lead only to locally optimal solutions. The problem is sometimes simplified to satisfy the optimization technique, resulting in a solution that is optimal for only an approximate problem. With the emergence of evolutionary algorithms, attention has been gradually shifted to application of such algorithms to handle the complexity involved in real-world problems. Recently, researchers have solved hydrothermal scheduling problems using evolutionary programming, genetic algorithm and differential evolution [3–8]. Several strategies to reduce the atmospheric pollution have been proposed and discussed [9–11]. These include installation of pollutant cleaning, switching to low emission fuels, replacement of the aged fuel burners with cleaner ones, and emission dispatching. The first three options require installation of new equipment and/or modification of the existing ones that involve considerable capital outlay and hence they can be considered as long-term options. The emission dispatching option is an attractive alternative in which both cost and emission is to be optimized. In recent years, this option has received much attention [12,13] since it requires only small modification of the basic economic dispatch to include emission. In [12] linear programming based optimization procedures has been presented in which the objectives are considered one at a time. Unfortunately, the economic environmental dispatch (EED) problem is a highly nonlinear optimization problem. Therefore, conventional optimization methods that make use of derivatives and gradients, in general, are not able to locate the global optimum. The EED problem has been converted to a single objective problem by linear combination of different objectives as a weighted sum in [13]. The important aspect of this weighted sum method is that a set of pareto-optimal solutions can be obtained by varying the weights. But this requires multiple runs.

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Nomenclature

a_{si}, b_{si}, c_{si}, d_{si}, e_{si} cost coefficients of ith thermal unit
α_{si}, β_{si}, γ_{si}, η_{si}, δ_{si} emission coefficients of ith thermal unit
C_{1j}, C_{2j}, C_{3j}, C_{4j}, C_{5j}, C_{6j} power generation coefficients of jth hydro unit
I_{hjm} inflow rate of jth reservoir at time m
P_{Dm} load demand at time m
P_{Lm} total transmission line losses at time m
P_{sim} output power of ith thermal unit at time m
$P_{si}^{\min}, P_{si}^{\max}$ lower and upper generation limits for ith thermal unit
P_{hjm} output power of jth hydro unit at time m
$P_{hj}^{\min}, P_{hj}^{\max}$ lower and upper generation limits for jth hydro unit
Q_{hjm} water discharge rate of jth reservoir at time m
$Q_{hj}^{\min}, Q_{hj}^{\max}$ minimum and maximum water discharge rate of jth reservoir
R_{uj} number of upstream units directly above jth hydro plant
S_{hjm} spillage of jth reservoir at time m
t_{lj} water transport delay from reservoir l to j
V_{hjm} storage volume of jth reservoir at time m
$V_{hj}^{\min}, V_{hj}^{\max}$ minimum and maximum storage volume of jth reservoir
V_{hj0} initial storage volume of jth reservoir
V_{hjM} final storage volume of jth reservoir
m, M time index and scheduling period
N_s number of thermal generating units
N_h number of hydro generating units
N_{obj} number of objective functions
N number of populations

Furthermore, this method cannot be used to find pareto-optimal solutions in the problem having a nonconvex pareto-optimal front. In [14] a fuzzy multi-objective optimization technique for the EED problem has been proposed. However, the solutions are sub-optimal and the algorithm does not provide systematic framework for directing the search toward pareto-optimal front. An evolutionary algorithm based approach for evaluating the economic impacts of environmental dispatching and fuel switching has been presented in [15]. However, some of nondominated solutions may be lost during the search process. A multi-objective stochastic search technique for the EED problem has been presented in [16]. However, this technique is computationally involved and time consuming. In addition, the search bias to some regions may result in premature convergence. In [17] an improved genetic algorithm based on ε-constraint technique has been proposed for short-term hydrothermal scheduling problem. Differential evolution based on price penalty factor has been used for economic emission scheduling of hydrothermal power systems in [18].

Over the past few years, the studies on evolutionary algorithm have shown that these methods can be efficiently used to eliminate most of the difficulties of classical methods [19–22]. Since they are population-based techniques, multiple pareto-optimal solutions can be found in one single run.

Table 1b
Hourly plant discharge ($\times 10^4 m^3$) obtained from economic dispatch using DE.

Hour	Q_{h1}	Q_{h2}	Q_{h3}	Q_{h4}
1	8.3362	6.3060	17.8872	9.9433
2	8.5319	8.0988	29.6744	12.0618
3	10.7027	8.8625	17.8952	6.9935
4	6.9362	10.0800	16.3305	6.9276
5	6.0031	7.5688	20.7748	10.5759
6	10.9348	6.6435	22.7214	6.4097
7	7.6995	9.4071	22.0010	16.3892
8	9.5346	7.3567	15.0934	14.2255
9	8.3877	7.4126	17.4721	15.3155
10	5.4466	9.1363	15.8292	18.7013
11	8.9893	9.1916	18.8535	14.8151
12	6.0468	8.6976	13.1823	16.3543
13	6.0571	6.8940	15.5305	17.0077
14	7.0745	9.1835	20.9803	13.7694
15	6.5460	6.0000	15.0737	16.5656
16	11.8350	12.5267	17.5244	11.1885
17	6.9297	9.4181	14.3017	20.0000
18	11.3576	8.7709	11.7059	17.3712
19	9.7375	9.5605	15.2593	14.6652
20	7.4200	7.8940	14.1585	13.6127
21	9.2436	8.6400	20.4516	19.0271
22	7.5822	8.9112	12.6739	11.1567
23	8.5471	9.3437	18.1295	16.0888
24	5.1202	6.0959	17.7777	19.8834

Table 1a
Hourly hydrothermal generation (MW), cost, emission and CPU time obtained from economic dispatch using DE.

Hour	P_{h1}	P_{h2}	P_{h3}	P_{h4}	P_{s1}	P_{s2}	P_{s3}	Cost ($)	Emission (ton)	CPU time (s)
1	77.1841	51.1449	52.2256	180.3731	162.3451	128.2428	98.4845	1.1081e+005	51.3742	2554.1
2	78.8558	63.6211	0	194.8222	103.9620	191.7274	147.0115			
3	89.8182	67.8653	42.6194	128.8862	133.3999	144.6583	92.7527			
4	67.8094	74.0903	45.1305	122.5409	127.6482	83.1491	129.6316			
5	60.7817	59.7989	28.5985	155.4223	39.9338	220.1638	105.3010			
6	89.7342	54.0896	17.9972	116.4577	106.5730	261.8515	153.2969			
7	71.8188	70.6232	21.0808	240.5608	117.1022	232.8207	195.9936			
8	82.2621	56.8648	46.2092	225.3513	107.3595	245.9649	245.9882			
9	75.9413	56.9894	42.3658	236.5840	68.6168	266.2380	343.2646			
10	55.6213	67.1986	45.9193	266.1459	127.0529	218.0223	300.0398			
11	81.7154	67.3959	38.2624	242.6222	163.4521	272.6585	233.8935			
12	62.4521	64.6515	50.1193	262.4550	170.8001	250.4170	289.1051			
13	63.2424	53.4107	47.7802	266.0179	146.5428	210.6758	322.3303			
14	71.9963	67.4955	31.0533	239.7457	103.6867	286.0255	229.9971			
15	68.4865	47.9015	49.8270	265.3702	100.1781	245.3043	232.9324			
16	100.5200	83.3534	45.0545	217.6020	146.3439	260.1388	206.9873			
17	71.7730	67.5597	51.2136	292.5302	154.2786	191.1797	221.4651			
18	98.6708	62.5834	52.9563	271.0861	160.8328	249.7878	224.0828			
19	90.2443	64.6798	53.2800	253.1377	114.5106	268.5329	225.6147			
20	75.0511	54.0034	55.9036	243.8470	97.3293	271.4632	252.4024			
21	86.7010	58.2372	41.4933	290.4776	101.9485	205.0962	126.0461			
22	75.6665	59.9253	58.0327	217.8837	76.3932	205.9352	166.1634			
23	82.1675	62.1797	51.9150	265.2661	163.0541	114.2789	111.1387			
24	55.8215	42.0709	52.9268	290.1788	110.5241	100.2243	148.2537			

Recently, multi-objective evolutionary algorithms have been applied to solve the EED problem efficiently [23,24].

This paper proposes multi-objective differential evolution (MODE) for economic environmental dispatch of hydrothermal power system. The problem is formulated as a nonlinear constrained multi-objective optimization problem with competing and noncommensurable objectives. The proposed MODE has been applied to the multi-reservoir cascaded hydrothermal system [27]. Results obtained from the proposed method have been compared to those obtained using nondominated sorting genetic algorithm-II (NSGA-II).

2. Problem formulation

The present formulation treats economic environmental dispatch of hydrothermal power system as a multi-objective mathematical programming which attempts to optimize both cost and emission simultaneously, while satisfying equality and inequality constraints. Typically, the total planning period is one day or 1-week and each planning time interval is 1 h. The following objectives and constraints of the hydrothermal scheduling problem are taken into account.

2.1. Objectives

(i) Cost

The fuel cost function of each thermal generator, considering the valve-point effects, is expressed as the sum of a quadratic and a sinusoidal function. The superimposed sine components represent the rippling effects produced by the steam admission valve opening [25]. The total fuel cost in terms of real power output can be expressed as

$$f_1 = \sum_{m=1}^{M} \sum_{i=1}^{N_s} \Big[a_{si} + b_{si} P_{sim} + c_{si} P_{sim}^2 + \Big| d_{si} \times \sin\left\{ e_{si} \times (P_{si}^{\min} - P_{sim}) \right\} \Big| \Big] \tag{1}$$

(ii) Emission

The atmospheric pollutants such as sulfur oxides (SO_x) and nitrogen oxides (NO_x) caused by fossil-fueled thermal generator can be modeled separately. However, for comparison purposes, the total emission of these pollutants which is the sum of a quadratic and an exponential function [26] can be expressed as

$$f_2 = \sum_{m=1}^{M} \sum_{i=1}^{N_s} \Big[10^{-2} \left(\alpha_{si} + \beta_{si} P_{sim} + \gamma_{si} P_{sim}^2 \right) + \eta_{si} \exp(\delta_{si} P_{sim}) \Big] \tag{2}$$

subject to

(i) Power balance constraints

Table 2b
Hourly plant discharge ($\times 10^4 m^3$) obtained from emission dispatch using DE.

Hour	Q_{h1}	Q_{h2}	Q_{h3}	Q_{h4}
1	7.6534	9.4819	17.8789	8.5413
2	9.3248	7.6139	25.6723	13.8486
3	10.4298	7.2670	29.3773	12.5196
4	7.4242	7.4646	22.3949	6.2651
5	8.2972	8.0361	17.9751	7.4603
6	6.2877	8.2159	15.0620	9.8151
7	9.7950	7.9568	16.9048	14.2529
8	8.6436	6.6236	15.6730	16.5658
9	10.9175	7.7742	19.0852	13.9831
10	7.4852	7.4989	12.4224	14.5134
11	6.9760	11.3591	18.7470	14.5313
12	6.2478	10.0785	16.7690	16.9245
13	7.4089	8.6967	17.0563	14.7275
14	12.9968	7.8923	16.0078	18.0014
15	9.2827	8.7357	17.1763	18.9691
16	9.2800	7.3271	17.9651	14.8864
17	12.6209	7.0483	14.4030	13.4780
18	6.0654	7.3697	15.5224	15.4201
19	6.4466	10.3199	12.2450	13.9288
20	6.6229	8.3130	15.6829	16.3222
21	6.6851	6.9242	19.2998	17.0820
22	6.9953	10.6672	13.3988	14.4119
23	6.0950	9.2656	17.6549	14.4169
24	5.0184	10.0700	13.8095	19.9557

Table 2a
Hourly hydrothermal generation (MW), cost, emission and CPU time obtained from emission dispatch using DE.

Hour	P_{h1}	P_{h2}	P_{h3}	P_{h4}	P_{s1}	P_{s2}	P_{s3}	Cost ($)	Emission (ton)	CPU time (s)
1	72.8927	70.0842	52.2491	164.2363	94.2479	89.4296	206.8602	1.6137e+005	11.4994	2424.4
2	83.4765	58.7585	8.1111	212.5173	131.4950	104.0315	181.6101			
3	88.6363	56.8421	0	187.7741	107.5313	104.3766	154.8396			
4	71.2486	59.1433	15.6653	108.0781	101.7132	116.8784	177.2731			
5	76.6893	63.5417	36.5062	115.7442	123.4453	81.5224	172.5510			
6	62.3159	64.5729	45.4299	153.6293	83.8086	124.6433	265.6001			
7	84.1594	62.3111	42.5211	213.2008	94.4693	153.3358	300.0023			
8	77.5684	52.6858	46.1908	248.1756	114.1620	126.5865	344.6309			
9	88.3105	60.2438	35.9389	233.6686	162.6157	151.0774	358.1449			
10	70.3221	58.7017	49.8772	242.3932	145.5775	173.9056	339.2226			
11	67.9031	79.1446	39.2278	243.1020	126.3710	155.0301	389.2214			
12	63.6991	72.1190	45.5387	264.6775	119.1684	127.9130	456.8844			
13	73.1455	63.7946	44.9272	245.9301	139.3824	169.8219	372.9983			
14	100.4930	58.7799	48.0029	275.5068	127.1373	137.5955	282.4846			
15	85.4778	64.2760	46.6275	275.4952	137.9200	127.9139	272.2895			
16	85.8857	56.2215	45.3510	245.8251	157.9267	156.0239	312.7661			
17	100.0142	54.8721	54.5522	235.1167	121.3665	143.5386	340.5398			
18	63.2246	56.8806	54.3460	255.8146	161.5307	131.9035	396.3000			
19	66.6079	71.7728	57.3181	243.3293	121.6381	134.0870	375.2467			
20	68.0810	59.4114	57.2916	266.9281	153.4484	131.8665	312.9731			
21	68.4591	50.8345	47.4556	274.3724	64.6293	138.5804	265.6686			
22	70.8659	72.2040	58.1848	249.8464	78.8188	122.1095	207.9705			
23	63.9582	64.5502	53.2598	250.9513	71.1233	127.1410	219.0162			
24	54.8763	67.5132	58.8462	288.9725	119.8738	62.6943	147.2237			

$$\sum_{i=1}^{N_s} P_{sim} + \sum_{j=1}^{N_h} P_{hjm} - P_{Dm} - P_{Lm} = 0 \quad m \in M \tag{3}$$

The hydro-electric generation is a function of water discharge rate and reservoir water head, which in turn is a function of storage.

$$P_{hjm} = C_{1j}V_{hjm}^2 + C_{2j}Q_{hjm}^2 + C_{3j}V_{hjm}Q_{hjm} + C_{4j}V_{hjm} + C_{5j}Q_{hjm} + C_{6j} \quad j \in N_h, \quad m \in M \tag{4}$$

(ii) Generation limits

$$P_{hj}^{\min} \le P_{hjm} \le P_{hj}^{\max} \quad j \in N_h, \quad m \in M \tag{5}$$

and

$$P_{si}^{\min} \le P_{sim} \le P_{si}^{\max} \quad i \in N_s, \quad m \in M \tag{6}$$

(iii) Hydraulic network constraints

The hydraulic operational constraints comprise the water balance equations for each hydro unit as well as the bounds on reservoir storage and release targets. These bounds are determined by the physical reservoir and plant limitations as well as the multi-purpose requirements of the hydro system. These constraints include:

(a) Physical limitations on reservoir storage volumes and discharge rates

$$V_{hj}^{\min} \le V_{hjm} \le V_{hj}^{\max} \quad j \in N_h, \quad m \in M \tag{7}$$

$$Q_{hj}^{\min} \le Q_{hjm} \leqslant Q_{hj}^{\max} \quad j \in N_h, \quad m \in M \tag{8}$$

(b) The continuity equation for the hydro reservoir network

$$V_{hj(m+1)} = V_{hjm} + I_{hjm} - Q_{hjm} - S_{hjm} + \sum_{l=1}^{R_{uj}} (Q_{hl(m-t_{lj})} + S_{hl(m-t_{lj})}) \quad j \in N_h, \quad m \in M \tag{9}$$

3. Principle of multi-objective optimization

Most of the real-world problems involve simultaneous optimization of several objective functions. These functions are noncommensurable and often competing and conflicting objectives. Multi-objective optimization having such conflicting objective functions gives rise to a set of optimal solutions, instead of one optimal

Table 3b
Hourly plant discharge ($\times 10^4 m^3$) obtained from best compromise solution of the last generation from MODE.

Hour	Q_{h1}	Q_{h2}	Q_{h3}	Q_{h4}
1	7.5481	9.0534	25.4929	12.3408
2	7.6848	8.2047	17.3138	11.6512
3	7.9487	7.5859	24.8014	8.0028
4	5.0000	8.7566	26.3588	9.1914
5	10.2384	6.7197	15.4862	14.6727
6	9.4535	8.1428	20.3568	6.0000
7	6.1004	8.4274	18.4488	9.4868
8	10.1833	8.3456	14.4178	16.8203
9	11.0171	9.3014	19.1488	15.7754
10	8.3442	7.0278	14.0043	18.0685
11	8.7369	8.0180	13.8040	17.6085
12	8.7806	8.5263	12.4181	18.6940
13	9.9271	11.5586	18.3249	16.0018
14	6.6417	7.3249	19.9519	9.5549
15	6.8989	7.5237	13.2524	13.0759
16	6.1112	6.7957	13.9333	14.0422
17	10.4050	8.1399	13.9023	15.1456
18	7.5817	8.0674	14.8316	11.5087
19	7.3553	10.0557	17.7151	15.4578
20	6.6109	8.4674	19.0810	15.4984
21	7.8460	7.1444	14.2220	19.0657
22	5.7730	8.4653	16.7809	14.5873
23	10.6486	10.9981	11.4483	18.0522
24	8.1644	9.3490	16.1792	19.5415

Table 3a
Hourly hydrothermal generation (MW), cost, emission and CPU time obtained from best compromise solution of the last generation from MODE.

Hour	P_{h1}	P_{h2}	P_{h3}	P_{h4}	P_{s1}	P_{s2}	P_{s3}	Cost ($)	Emission (ton)	CPU time (s)
1	77.1092	62.5890	10.5284	192.5690	141.8005	137.5833	112.2167	1.2682e+005	17.7019	2957.2
2	85.1818	63.7109	52.4888	175.6205	108.0622	179.2887	119.1298			
3	66.5396	61.4729	19.9686	177.1719	113.9821	109.2371	195.4533			
4	59.0334	64.1316	0	137.6876	133.6109	122.8406	128.3438			
5	92.1588	60.1663	28.0696	186.7462	33.9751	115.6603	150.0171			
6	77.7427	52.5891	30.6715	117.5386	130.8717	139.7543	244.6081			
7	56.6319	73.5407	42.6071	190.2242	124.4295	237.5986	264.4960			
8	83.6333	53.1754	35.1309	243.8879	175.0000	148.3619	244.8990			
9	87.8117	77.2217	46.2138	214.4370	108.4942	202.5824	338.7453			
10	76.8343	49.4839	44.4194	239.1829	162.0032	178.0353	298.8785			
11	69.7615	60.0605	49.7020	274.0851	127.7272	207.0698	312.0274			
12	65.6498	64.9834	49.8182	249.3674	137.6628	172.2451	371.6432			
13	89.9006	70.9528	41.4491	269.8821	139.1057	236.6384	276.8090			
14	64.6960	63.2917	52.8142	197.8429	159.0395	202.2523	320.0191			
15	68.1085	53.2112	54.7203	235.2029	149.9201	179.6202	268.7483			
16	85.5423	70.0355	56.9575	262.6281	115.8123	226.7088	303.7013			
17	86.1048	61.3671	54.0305	225.0750	158.6542	193.9670	236.0313			
18	85.7674	63.0967	55.8285	190.1723	155.9677	229.8956	322.9574			
19	60.3766	58.2625	55.6998	251.4554	148.8918	190.2702	272.1150			
20	78.7820	58.6966	48.2428	220.7086	159.6270	184.0118	269.6189			
21	82.2506	54.6957	58.9236	271.7303	100.3916	169.0320	168.4702			
22	66.9446	58.6507	58.1236	219.8763	159.4747	137.9933	139.3840			
23	101.1019	80.6310	58.9060	269.4809	69.0651	142.7705	139.0628			
24	71.1492	56.5806	40.2948	284.8402	123.6026	103.6536	89.5246			

solution because no solution can be considered to be better than any other with respect to all objective functions. These optimal solutions are known as pareto-optimal solutions.

Generally, multi-objective optimization problem consisting of a number of objectives and several equality and inequality constraints can be formulated as follows:

$$\text{Minimize} \quad f_i(x) \qquad i = 1, \ldots, N_{obj} \tag{10}$$

$$\text{Subject to} \quad \begin{cases} g_k(x) = 0 & k = 1, \ldots, K \\ h_l(x) \le 0 & l = 1, \ldots, L \end{cases} \tag{11}$$

where f_i is the ith objective function, x is a decision vector.

4. Multi-objective differential evolution

Differential evolution (DE) is a type of evolutionary algorithm [28] for optimization problems over a continuous domain. DE is exceptionally simple and robust. The basic idea of DE is to adapt the search during the evolutionary process. At the start of the evolution, the perturbations are large since parent populations are far away from each other. As the evolutionary process matures, the population converges to a small region and the perturbations adaptively become small. As a result, the evolutionary algorithm performs a global exploratory search during the early stages of the evolutionary process and local exploitation during the mature stage of the search. In DE the fittest of an offspring competes one-to-one with that of corresponding parent which is different from other evolutionary algorithms. This one-to-one competition gives rise to faster convergence rate. In multi-objective differential evolution (MODE) [29], a pareto-based approach is introduced to implement the selection of the best individuals. Firstly, a population of size, N_P, is generated randomly and objective functions are evaluated. At a given generation of the evolutionary search, the population is sorted into several ranks based on nondomination. Secondly, DE operations are carried out over the individuals of the population. Trial vectors of size N_P are generated and objective functions are evaluated. Both the parent vectors and trial vectors are combined to form a population of size $2N_P$. Then, the ranking of the combined population is carried out followed by the crowding distance calculation. The best N_P individuals are selected based on its ranking and crowding distance. These individuals act as the parent vectors for the next generation. The algorithm of MODE can be described in the following steps:

Step 1. Generate box, R, of size N_P. Parent vectors of size N_P is randomly generated and kept in R.

Step 2. Classify these vectors into fronts based on nondomination [26] as follows:
- (a) Create new empty box R^l of size N_P.
- (b) Compare each vector with all other vectors in R.
- (c) Start with $i = 1$.
- (d) If ith vector is not dominated by any other vector in R, keep ith vector in R^l and go to (f).
- (e) If ith vector is dominated by any other vector in R, go to (f).

Table 4b
Hourly plant discharge ($\times 10^4 m^3$) obtained from economic dispatch using RCGA.

Hour	Q_{h1}	Q_{h2}	Q_{h3}	Q_{h4}
1	7.0832	6.7640	19.6620	12.8953
2	6.7623	10.5459	22.9395	10.6993
3	12.4353	8.6549	18.5449	8.5351
4	9.2483	7.6603	16.3527	11.0107
5	5.0000	7.2059	22.2980	7.6559
6	9.9002	7.4562	19.4469	9.2357
7	6.9191	8.4605	19.8718	16.5644
8	8.2206	7.8409	15.2138	12.5219
9	8.5838	10.3001	21.3334	16.5972
10	8.9605	8.6990	13.8314	11.0406
11	8.0201	9.8283	17.1555	16.0112
12	9.2657	8.9161	20.9970	17.5340
13	5.6792	10.0768	14.9682	16.5986
14	10.0315	7.6272	16.1106	11.2210
15	9.7395	6.9734	12.1003	14.1649
16	8.6097	6.6350	14.3096	14.3525
17	12.0233	8.2726	18.5626	14.8604
18	8.9513	8.2945	11.2162	17.7387
19	5.6988	9.5535	15.5011	17.8069
20	6.9469	7.4873	17.1262	16.2134
21	7.1155	8.5567	15.7642	13.9577
22	6.0564	8.2357	18.2011	17.2648
23	8.3204	10.5601	15.7141	10.5979
24	5.4283	7.3951	22.1392	19.2637

Table 4a
Hourly hydrothermal generation (MW), cost, emission and CPU obtained from economic dispatch using RCGA.

Hour	P_{h1}	P_{h2}	P_{h3}	P_{h4}	P_{s1}	P_{s2}	P_{s3}	Cost ($)	Emission (ton)	CPU time (s)
1	69.0093	54.2493	46.2182	210.3653	102.6608	128.7272	138.7699	1.1294e+005	49.8731	3156.5
2	67.4350	75.8838	26.1606	178.0783	139.7632	128.1384	164.5406			
3	96.8322	64.9036	42.1264	145.6638	74.2120	161.8260	114.4359			
4	82.5453	59.3643	46.1398	164.1487	76.0436	73.2144	148.5441			
5	52.1691	57.3533	20.8884	115.7788	99.5269	192.8401	131.4434			
6	85.3467	59.4126	36.9187	147.0161	107.9196	115.4480	247.9383			
7	66.8740	65.0981	36.0027	227.3657	123.7286	232.5975	198.3335			
8	75.7416	59.9621	48.8474	197.4937	144.7918	216.5555	266.6080			
9	78.1349	72.2622	28.7435	234.6420	159.2136	234.9671	282.0367			
10	80.7141	62.7994	49.9966	193.0478	166.3638	239.3419	287.7364			
11	75.7980	68.7299	45.0250	246.6053	118.5457	255.1471	290.1490			
12	84.2339	63.6036	29.7738	261.7527	116.8251	259.6599	334.1509			
13	59.6212	68.6755	49.9811	252.6479	144.8873	244.5280	289.6591			
14	89.8508	54.3094	49.6836	209.2119	156.5418	291.2072	179.1954			
15	88.8547	51.1746	54.8666	240.6476	128.3157	278.9948	167.1459			
16	82.6512	50.2838	55.6089	245.2747	154.5597	234.2445	237.3772			
17	99.3974	61.2581	48.7033	256.1955	104.7900	280.4924	199.1633			
18	84.3879	60.5442	57.1344	279.0025	94.9969	247.3306	296.6034			
19	60.6838	65.5942	57.7314	277.7878	174.2439	246.0332	187.9258			
20	70.9553	52.5355	55.6419	260.1857	124.9317	189.6304	296.1195			
21	72.0688	59.0354	58.4596	239.2775	163.2151	256.7503	61.1932			
22	63.7339	57.5708	53.1283	270.8331	124.4371	169.4098	120.8870			
23	80.7417	69.5828	58.6400	203.9388	103.9918	208.0102	125.0947			
24	58.6305	51.3929	36.9611	282.6513	149.2873	111.3054	109.7714			

(f) Increment i by one. If $i \leqslant N_P$, go to (d) otherwise go to (g).

(g) $R^{/}$ now contains a sub-box (of size $\leqslant N_P$) of nondominated vectors, referred to as the first front or sub-box. Assign it a rank number equal to one ($I_{rank} = 1$). Remove all the nondominated vectors from R.

(h) Create subsequent fronts or sub-boxes of $R^{/}$ with the vectors remaining in R and assign these $I_{rank} = 2, 3, \ldots$ Finally, all N_P vectors are in $R^{/}$ into one or more fronts.

Step 3. To calculate the crowding distance, $I_{i,dist}$, for the ith vector in any front, F, of $R^{/}$, sort all the vectors in front, F, according to each objective function value in ascending order of magnitude. The crowding distance of the ith vector in its front F is the average side-length of the cuboid formed by using the nearest neighbors as the vertices. Assign large values of crowding distance I_{dist} to the boundary vectors (vectors with smallest and largest function values).

The following procedure is adopted to identify the better of the two vectors. Vector i is better than vector j: (i) if $I_{i,rank} < I_{j,rank}$ or (ii) if $I_{i,rank} = I_{j,rank}$ and $I_{i,dist} > I_{j,dist}$.

Step 4. Perform DE operations over N_P vectors in $R^{/}$ to generate N_P trial vectors and store these vectors in $R^{//}$.

(a) Create new empty box $R^{//}$ of size N_P.

(b) Select a target vector, i in $R^{/}$.

(c) Start with $i = 1$.

(d) Choose two vectors, r_1 and r_2 at random from the N_P vectors in $R^{/}$. Find the vector difference between these two vectors and multiply this difference with the scaling factor F to get the weighted difference.

(e) Choose a third random vector r_3 from the N_P vectors in $R^{/}$ and add this vector to the weighted difference to obtain the noisy random vector.

(f) Perform crossover between the target vector and noisy random vector to find the trial vector. This is carried out by generating a random number and if random number > C_R (crossover factor), copy the target vector into the trial vector else copy the noisy random vector into the trial vector and put it in box $R^{//}$.

(g) Increment i by one. If $i \leqslant N_P$, go to (d) otherwise go to Step 5.

Step 5. Copy all N_P parent vectors from $R^{/}$ and all N_P trial vectors from $R^{//}$ into box $R^{///}$. Box $R^{///}$ has $2N_P$ vectors.

(a) Classify these $2N_P$ vectors into fronts based on non-domination and calculate the crowding distance of each vector. Take the best N_P vectors from box $R^{///}$ and put into box $R^{////}$.

(b) This completes one generation. Stop if generation number is equal to maximum number of generations. Else copy N_P vectors from box $R^{////}$ to the starting box R and go to Step 2.

Table 5b
Hourly plant discharge ($\times 10^4 m^3$) obtained from emission dispatch using RCGA.

Hour	Q_{h1}	Q_{h2}	Q_{h3}	Q_{h4}
1	9.8649	7.7845	22.8217	9.0376
2	5.0553	7.2883	20.0293	11.7807
3	10.0913	8.6110	20.0656	10.1553
4	8.1333	6.5615	27.4112	8.7406
5	11.9690	6.6041	20.8469	11.2760
6	6.6125	6.7269	22.6561	11.0533
7	8.0287	9.6863	19.7343	10.3488
8	9.1715	9.5618	13.7214	9.8133
9	10.0940	9.7973	12.0289	12.4582
10	6.1779	6.8945	15.6896	17.2694
11	5.4568	8.3186	13.1403	12.7358
12	7.5504	8.3352	18.8660	12.1940
13	7.8175	8.1837	16.0912	12.7745
14	6.5892	8.4939	12.0577	13.0708
15	9.4994	9.0361	13.6933	16.1181
16	9.5672	8.8841	14.3728	16.7099
17	7.8499	8.3807	13.9546	16.5190
18	9.6966	11.8698	17.3980	19.8124
19	7.7808	11.5039	10.7336	13.0436
20	7.2041	8.4411	18.6970	15.1779
21	8.0302	8.0200	17.0357	19.9115
22	8.8825	6.8727	21.2202	13.1089
23	8.8444	8.0437	19.1450	18.0121
24	5.0327	8.1003	20.9957	19.6881

Table 5a
Hourly hydrothermal generation (MW), cost, emission and CPU time obtained from emission dispatch using RCGA.

Hour	P_{h1}	P_{h2}	P_{h3}	P_{h4}	P_{s1}	P_{s2}	P_{s3}	Cost ($)	Emission (ton)	CPU time (s)
1	85.3708	60.7148	30.8458	170.0881	91.3582	105.4561	206.1663	1.6004e+005	11.6256	3261.4
2	53.0137	57.7804	40.1756	193.0837	123.7675	117.5800	194.5991			
3	87.8266	66.0729	35.8424	166.4475	116.6197	72.2778	154.9131			
4	76.5378	53.6724	0	141.7412	146.3740	82.7958	148.8787			
5	93.7845	55.3728	24.3689	157.6130	123.6325	67.7421	147.4863			
6	64.1667	56.9915	13.6469	169.1527	75.3794	152.8154	267.8475			
7	73.7842	74.4784	28.8273	171.9676	136.8435	139.6971	324.4019			
8	80.2118	71.5884	46.4358	176.2708	120.5521	164.7499	350.1911			
9	84.5392	71.0988	47.7382	221.3612	150.7124	146.7487	367.8016			
10	60.9455	53.5015	45.2161	270.8958	121.3027	164.8247	363.3137			
11	56.3874	63.5256	49.9351	236.9433	127.2673	168.2384	397.7029			
12	73.8607	64.0471	39.9669	237.3604	161.8935	133.1642	439.7071			
13	76.2251	62.9677	48.0379	244.7271	170.7069	153.0245	354.3108			
14	67.9077	64.6186	52.0737	247.1247	145.3252	158.5674	294.3828			
15	88.3208	67.8878	53.5664	277.5184	96.6988	149.5323	276.4755			
16	88.9863	67.0553	54.4648	279.5081	123.3974	133.1665	313.4214			
17	78.3093	63.7197	55.4324	280.0301	121.2416	159.8683	291.3986			
18	89.9887	78.8636	51.1953	302.6797	73.6528	134.3748	389.2450			
19	77.7519	73.3396	56.3322	241.2778	127.7034	138.6472	354.9478			
20	73.4644	56.0700	50.0601	261.7503	130.1586	134.2533	344.2432			
21	79.1775	53.4042	54.8392	294.9300	93.2495	132.2335	202.1660			
22	84.4370	47.1660	41.2261	236.3547	52.9945	123.9226	273.8990			
23	84.0336	55.7512	49.6903	281.2580	74.1391	140.5236	164.6041			
24	55.0093	56.0440	41.6613	283.8100	80.5841	129.2842	153.6071			

5. Computational flow

Let $[P_{s1}, P_{s2}, \ldots, P_{si}, \ldots, P_{sN_s}, Q_{h1}, Q_{h2}, \ldots, Q_{hj}, \ldots, Q_{hN_h}]^T$ be an initial feasible solution vector and $P_{si} = [P_{si1}, P_{si2}, \ldots, P_{sim}, \ldots, P_{siM}]$, $Q_{hj} = [Q_{hj1}, Q_{hj2}, \ldots, Q_{hjm}, \ldots, Q_{hjM}]$. The elements P_{sim} and Q_{hjm} are the power output of the ith thermal unit and the discharge rate of the jth hydro plant at time m. The range of the elements P_{sim} and Q_{hjm} should satisfy the thermal generating capacity and the water discharge rate constraints in Eqs. (6) and (8), respectively. Storage volume V_{hjm} must satisfy constraints in Eq. (7). Assuming the spillage in Eq. (9) to be zero for simplicity, the hydraulic continuity constraints are

$$V_{hj0} = V_{hjM} + \sum_{m=1}^{M} Q_{hjm} - \sum_{m=1}^{M} \sum_{l=1}^{R_{uj}} Q_{hl(m-t_{lj})} - \sum_{m=1}^{M} I_{hjm} \quad j \in N_h \tag{12}$$

To meet exactly the restrictions on the initial and final reservoir storage in Eq. (9), the water discharge rate of the jth hydro plant Q_{hjd} in the dependent interval d is then calculated by

$$Q_{hjd} = V_{hj0} - V_{hjM} + \sum_{m=1}^{M} I_{hjm} + \sum_{m=1}^{M} \sum_{l=1}^{R_{uj}} Q_{hl(m-t_{lj})} - \sum_{\substack{m=1 \\ m \neq d}}^{M} Q_{hjm} \quad j \in N_h \tag{13}$$

The dependent water discharge rate must satisfy the constraints in Eq. (8). Then P_{hjm} is calculated using Eq. (4) and it must satisfy Eq. (5).

Also to meet exactly the power balance constraints in Eq. (3), thermal generation P_{sd_gm} of the dependent thermal generating unit d_g can then be calculated using the following equation:

$$P_{sd_gm} = P_{Dm} + P_{Lm} - \sum_{\substack{i=1 \\ i \neq d}}^{N_s} P_{sim} - \sum_{j=1}^{N_h} P_{hjm} \quad m \in M \tag{14}$$

The dependent thermal generation must satisfy the constraints in Eq. (6).

6. Simulation results

The proposed method has been applied to a test system [27] consisting of a multi-reservoir cascade of four hydro units and three thermal units with nonsmooth fuel cost and emission level functions. The scheduling period is 24 h with 1-h time interval. The hydro sub-system configuration and network matrix including water time delay are shown in Fig. A1 in Appendix. The load demands and reservoir inflows are given in Tables A1 and A2, respectively. Hydropower generation coefficients, reservoir limits,

Table 6b
Hourly plant discharge ($\times 10^4 m^3$) obtained from best compromise solution of the last generation from NSGA-II.

Hour	Q_{h1}	Q_{h2}	Q_{h3}	Q_{h4}
1	6.9832	7.2249	19.2357	13.9023
2	7.3535	8.4940	19.9754	13.1494
3	12.3512	11.6422	25.8223	9.4345
4	8.3419	9.5368	21.4861	10.2052
5	8.5768	7.9824	19.1731	7.6099
6	5.3150	6.8466	17.4884	15.8467
7	7.1386	8.3386	19.0916	11.5022
8	6.0150	9.4379	19.4873	14.0149
9	6.4433	9.6796	12.3334	15.8409
10	9.4743	8.1260	18.7789	13.7498
11	9.4208	9.4642	15.5615	12.7559
12	8.4248	8.6482	16.1890	13.3810
13	9.9303	10.3052	12.9718	14.8218
14	7.3765	8.4854	15.0544	16.7951
15	7.2649	6.4672	15.8050	16.2270
16	9.8387	9.0515	13.0944	14.6164
17	7.8188	6.9461	25.8023	15.4496
18	9.6955	8.0701	19.6431	15.1521
19	9.2140	6.6372	13.6160	15.1155
20	7.0845	7.9328	13.4979	12.7886
21	9.9220	8.5347	18.8239	18.3347
22	5.9984	6.8246	13.3790	14.1384
23	8.7884	9.8520	17.8885	18.9090
24	6.2297	7.4719	15.9340	17.1671

Table 6a
Hourly hydrothermal generation (MW), cost, emission and CPU time obtained from best compromise solution of the last generation from NSGA-II.

Hour	P_{h1}	P_{h2}	P_{h3}	P_{h4}	P_{s1}	P_{s2}	P_{s3}	Cost ($)	Emission (ton)	CPU time (s)
1	61.0918	57.8551	40.1241	216.6242	158.0853	108.5674	90.6058	1.2720e+005	18.9605	4301.1
2	71.0212	67.2634	46.1457	201.9393	139.4073	139.0800	122.5245			
3	97.7415	79.6049	25.4680	161.4724	101.6860	156.1995	112.6378			
4	81.1206	65.2750	0	155.7055	72.3066	156.2880	100.0056			
5	79.9580	54.1327	36.5865	94.6694	95.0352	160.8507	131.1817			
6	61.8970	58.9562	46.3065	197.6859	132.9652	161.7033	156.3326			
7	67.8731	66.6549	43.9504	182.9267	161.3747	156.4498	292.6650			
8	63.0443	59.1996	31.7327	203.4581	110.8053	213.9885	311.4117			
9	59.2697	68.6453	51.1678	225.6989	143.2625	237.8663	294.8895			
10	84.0871	61.9716	29.5672	209.7711	159.0645	222.1388	298.2002			
11	88.7197	63.9233	50.2530	187.0509	138.4766	201.2940	348.7892			
12	79.0987	53.3727	48.6048	231.2592	129.9800	214.1258	392.5824			
13	86.3812	62.7290	52.6420	240.3222	131.8465	223.8804	299.8191			
14	75.6155	57.9359	55.0612	278.0743	158.6469	212.7662	216.5207			
15	67.0794	48.4932	54.6838	276.9824	162.4412	136.9311	282.1747			
16	87.0804	60.5807	57.9279	259.4457	151.4984	195.8991	259.9531			
17	86.4954	50.1644	0	255.3768	157.2446	198.6314	305.3045			
18	87.6137	59.7718	29.9647	252.7347	145.2636	226.2649	312.7004			
19	86.3128	47.7780	56.2802	215.8092	146.3429	194.2991	294.1004			
20	80.5861	54.1409	57.5508	216.5506	159.8374	188.8105	291.7761			
21	85.0625	65.7586	49.6345	254.1347	124.4647	204.3478	114.4614			
22	57.6083	43.1074	58.8128	242.9482	100.9314	192.5637	151.2717			
23	85.2316	71.9411	55.4935	274.7755	89.7241	138.8071	131.3690			
24	67.9883	43.3172	47.4494	282.1823	60.3324	169.5327	125.1315			

discharge limits and generation limits are given in Table A3. Cost coefficients, emission coefficients and generation limits of thermal generators are given in Table A4.

At first fuel cost and emission objectives have been minimized individually usually differential evolution (DE) to explore the extreme points of the tradeoff surface. Then MODE has been applied

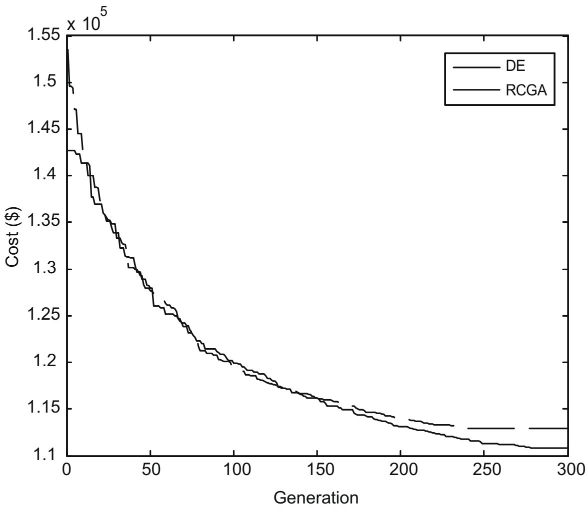


Fig. 1. Cost convergence obtained from both DE and RCGA.

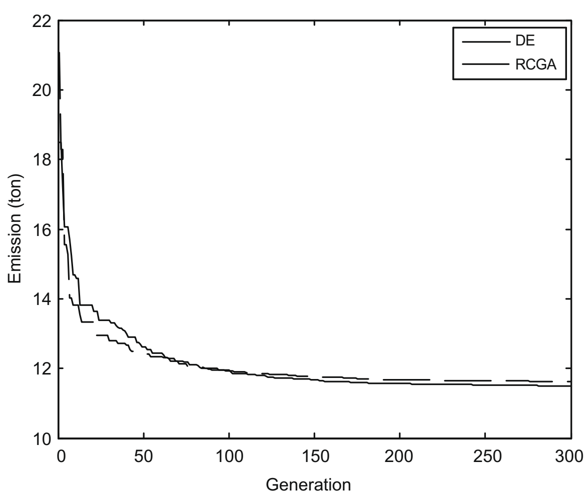


Fig. 2. Emission convergence obtained from both DE and RCGA.

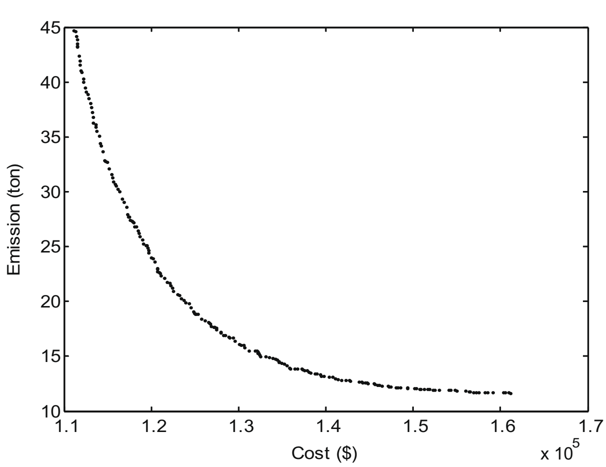


Fig. 3. Pareto-optimal front of MODE in the last generation.

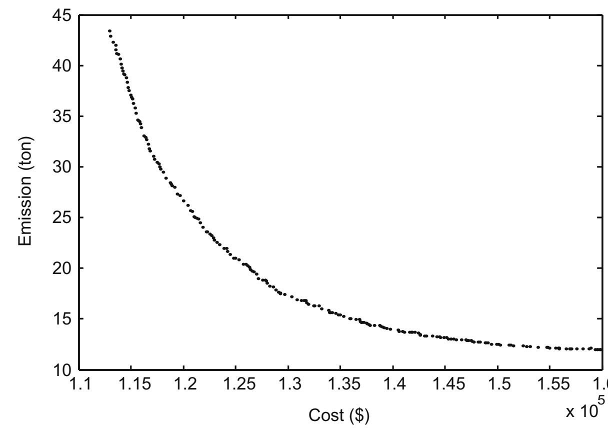
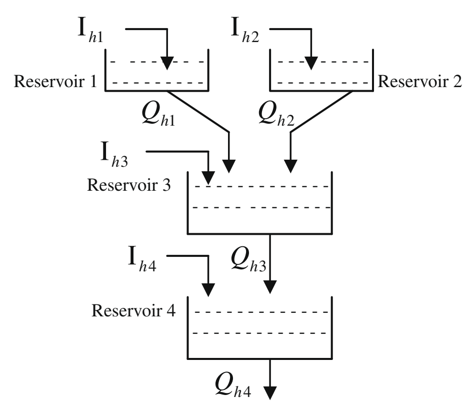


Fig. 4. Pareto-optimal front of NSGA-II in the last generation.



where:

I_{hj} : natural inflow to reservoir j

Q_{hj} : discharge of plant j

Plant	1	2	3	4
R_u	0	0	2	1
t_d	2	3	4	0

R_u : no of upstream plants

t_d : time delay to immediate downstream plant

Fig. A1. Hydraulic system network.

Table A1
Load demands.

Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)
1	750	9	1090	17	1050
2	780	10	1080	18	1120
3	700	11	1100	19	1070
4	650	12	1150	20	1050
5	670	13	1110	21	910
6	800	14	1030	22	860
7	950	15	1019	23	850
8	1010	16	1060	24	800

Table A2
Reservoir inflows ($\times 10^4 m^3$).

Hour	Reservoir				Hour	Reservoir				Hour	Reservoir			
	1	2	3	4		1	2	3	4		1	2	3	4
1	10	8	8.1	2.8	9	10	8	1	0	17	9	7	2	0
2	9	8	8.2	2.4	10	11	9	1	0	18	8	6	2	0
3	8	9	4	1.6	11	12	9	1	0	19	7	7	1	0
4	7	9	2	0	12	10	8	2	0	20	6	8	1	0
5	6	8	3	0	13	11	8	4	0	21	7	9	2	0
6	7	7	4	0	14	12	9	3	0	22	8	9	2	0
7	8	6	3	0	15	11	9	3	0	23	9	8	1	0
8	9	7	2	0	16	10	8	2	0	24	10	8	0	0

Table A3
Hydro power generation coefficients, reservoir storage capacity limits ($\times 10^4 m^3$), plant discharge limits ($\times 10^4 m^3$), reservoir end conditions ($\times 10^4 m^3$) and plant generation limits (MW).

Plant	C_1	C_2	C_3	C_4	C_5	C_6	$V_h^{\min}$	$V_h^{\max}$	V_{hini}	V_{hend}	$Q_h^{\min}$	$Q_h^{\max}$	$P_h^{\min}$	$P_h^{\max}$
1	−0.0042	−0.42	0.030	0.90	10.0	−50	80	150	100	120	5	15	0	500
2	−0.0040	−0.30	0.015	1.14	9.5	−70	60	120	80	70	6	15	0	500
3	−0.0016	−0.30	0.014	0.55	5.5	−40	100	240	170	170	10	30	0	500
4	−0.0030	−0.31	0.027	1.44	14.0	−90	70	160	120	140	6	20	0	500

Table A4
Cost coefficients, emission coefficients and operating limits of thermal generators.

Unit	a_s ($/h)	b_s ($/MW h)	c_s ($/(MW)^2 h)	d_s ($/h)	e_s (rad/MW)	α_s (ton/h)	β_s (ton/MW h)	γ_s (ton/MW^2 h)	η_s (ton/h)	δ_s (1/MW)	$P_s^{\min}$ (MW)	$P_s^{\max}$ (MW)
1	10	2.00	0.0037	18	0.0370	4.091	−5.554E−2	6.490E−4	2.0E−4	2.857E−2	20	175
2	10	1.75	0.0175	16	0.0380	2.543	−6.047E−2	5.638E−4	5.0E−4	3.333E−2	40	300
3	20	1.00	0.0625	14	0.0400	4.258	−5.094E−2	4.586E−4	1.0E−6	8.000E−3	50	500

to solve economic environmental dispatch of hydrothermal power system where both cost and emission objectives have been treated simultaneously as competing objectives. Tables 1a and b show hourly hydrothermal generation, cost, emission, CPU time and hourly plant discharge, respectively, obtained from economic dispatch using DE. Tables 2a and b show hourly hydrothermal generation, cost, emission, CPU time and hourly plant discharge, respectively, obtained from emission dispatch using DE. Tables 3a and b show hourly hydrothermal generation, cost, emission, CPU time and hourly plant discharge, respectively, obtained from economic environmental dispatch corresponding the best compromise solution of the last generation using MODE.

In order to show the effectiveness of the proposed MODE, NSGA-II has been applied to solve this problem. Tables 4a and b show hourly hydrothermal generation, cost, emission, CPU time and hourly plant discharge, respectively, obtained from economic dispatch using real-coded genetic algorithm (RCGA). Tables 5a and b show hourly hydrothermal generation, cost, emission, CPU time and hourly plant discharge, respectively, obtained from emission dispatch using RCGA. Tables 6a and b show hourly hydrothermal generation, cost, emission, CPU time and hourly plant discharge, respectively, obtained from economic environmental dispatch corresponding the best compromise solution of the last generation using NSGA-II.

Figs. 1 and 2 show cost convergence and emission convergence, respectively, obtained from both DE and RCGA. The distributions of 200 nondominated solutions obtained in the last generation of MODE and NSGA-II for economic environmental dispatch of hydrothermal power system are shown in Figs. 3 and 4, respectively.

In DE and MODE, the population size, scaling factor and crossover constant have been selected as 200, 0.65 and 1.0, respectively, for this system. In RCGA and NSGA-II, the population size, crossover and mutation probabilities have been selected as 200, 0.9 and 0.2, respectively. All the algorithms have been implemented in MATLAB 7 on a PC (Pentium-IV, 80 GB, 3.0 GHz).

7. Conclusion

In this paper, multi-objective differential evolution has been implemented to economic environmental dispatch of thermal plants with nonsmooth fuel cost and emission level functions in coordination with multi-reservoir cascaded hydro plants. The problem has been formulated as multi-objective optimization problem with competing fuel cost and emission objectives. Results obtained from proposed multi-objective differential evolution have been compared to those obtained using nondominated sorting genetic algorithm-II. Multi-objective differential evolution achieves better solution and requires less CPU time than nondominated sorting genetic algorithm-II. The proposed multi-objective differential evolution is simple, robust and efficient. The proposed method does not impose any limitation on the number of objectives and can be extended to include more objectives.

Appendix A

See Fig. A1 and Tables A1-A4.

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