HYBRID PSOGSA TECHNIQUE FOR SOLVING DYNAMIC ECONOMIC EMISSION DISPATCH PROBLEM

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Abstract:

In this paper, a new hybrid population-based algorithm is proposed with the combining of particle swarm optimization (PSO) and gravitational search algorithm (GSA) techniques. The main idea is to integrate the ability of exploration in PSO with the ability of exploration in the GSA to synthesize both algorithms' strength. The new algorithm is implemented to the dynamic economic emission dispatch (DEED) problem to minimize both fuel cost and emission simultaneously under a set of constraints. To demonstrate the efficiency of the proposed algorithm, a 5-unit test system is used. The results show the effectiveness and superiority of the proposed method when compared to the results of other optimization algorithms reported in the literature.

1 Introduction

The fundamental objective of dynamic economic dispatch (DED) problem of electric power generation is to schedule the committed generating unit outputs in order to meet the predicted load demand with minimum operating cost, while satisfying all system inequality and equality constraints [1, 2]. Therefore, the DED problem is a highly constrained large-scale nonlinear optimization problem. The valve-point effect introduces ripples in the heat-rate curves and makes the objective function non-convex, discontinuous, and with multiple minima [3-5]. The fuel cost function with valve point loadings in the generating units is the accurate model of the DED problem [6, 7].

Nowadays, strategically utilizing available resources and achieving electricity at cheap rates without sacrificing the social benefits is of major significance. The environmental pollution plays a major role as it had a major threat on the human society. Hence, it became compulsory to deliver electricity at a minimum cost as well as to maintain minimum level of emissions. The lowest emissions are considered as one of the objectives with combined economic and emission dispatch problems, along with the cost economy. Atmospheric pollution due to release of gases such as nitrogen oxides (NO_X), carbon dioxide (CO_2), and sulphur oxides (SO_X) into atmosphere by fossil-fuel based electric power stations affects not only humans, but also other forms of life such as birds, animals, plants and fish, while causing global warming too [8-11]. Generating units may have certain prohibited operating zones (POZs) due to faults in the machines themselves or instability concerns or the valve point effect. Hence, considering the effect of valve-points and POZs in generators' cost function makes the economic dispatch a non-convex and non-smooth optimization problem [12].

The dispatching of emission is a short-term option where the emission, in addition to fuel cost objective,

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is to be optimized. Thus, the DEED problem can be handled as a multi-objective optimization problem and requires only small modification to include emission. Hence, the DEED problem can be converted to a single objective problem by linear combination of various objectives using different weights. The important characteristic of the weighted sum method is that different pareto-optimal solutions could be obtained by varying the weights [13]. In [14-16] the static economic dispatch problem with prohibited operating zones has been solved. A number of reported works has considered the prohibited operating zones in the DED problem [17-20], however, the emission has not considered in these papers.

PSO is an evolutionary computation technique which is proposed by Kennedy and Eberhart [21, 22]. The main difficulty for classic PSO is its sensitivity to the choice of parameters, and they also premature convergence, which might occur when the particle and group best solutions are trapped into local minimums during the search process. One of the recently improved heuristic algorithms is the GSA based on the Newton's law of gravity and mass interactions. The GSA has been verified as a high quality performance in solving different optimization problems in the literature [23]. The same objective for them is to find the best solution (global optimum) among all possible inputs. To overcome these problem, a heuristic algorithm should be equipped with two major characteristics to ensure finding global optimum. These two main characteristics are exploration and exploitation [24].

The aim of this paper proposes a hybrid PSO-GSA for solving the DEED problem with valve-point effects and prohibited operating zones. The PSO is used to find a near global solution, and the GSA is used as a local search to determine the optimal solution at the final.

2 Problem formulation

The objective of the DEED problem is to find the optimal schedule of output powers of online generating units with predicted power demands over a certain period of time to meet the power demand at minimum - both operating costs and emissions simultaneously.

The objective function of the DEED problem can be formulated as following:

$$F_T = w_1 \cdot \sum_{t=1}^{T}\sum_{i=1}^{N} F_{i,t}(P_{i,t}) + w_2 \cdot h \cdot \sum_{t=1}^{T}\sum_{i=1}^{N} E_{i,t}(P_{i,t}) \quad (1)$$
$$\text{for } i = 1, 2, \cdots, N; \; t = 1, 2, \ldots, T$$

where F_T is the total operating cost over the whole dispatch period, T is the number of hours in the time horizon, N is the total number of generating units, w_1 is weighting factor for economic objective such that its value should be within the range 0 and 1, and w_2 is the weighting factor for emission objective which is given by $w_2 = (1 - w_1)$, and h_i is the price penalty factor. $F_{i,t}(P_{i,t})$ and $E_{i,t}(P_{i,t})$ are the generation cost and the amount of emission for unit i at time interval t , and $P_{i,t}$ is the real power output of generating unit i at time period t.

The valve-point effects are taken into consideration in the DEED problem by superimposing the basic quadratic fuel-cost characteristics with the rectified sinusoidal component as follows [12]:

$$F_{i,t}(P_{i,t}) = \begin{pmatrix} a_i P_{i,t}^2 + b_i P_{i,t} + c_i + \\ \left| e_i \times \sin\left(f_i \times \left(P_{i,\min} - P_{i,t} \right) \right) \right| \end{pmatrix} \quad (2)$$

where the constants a_i, b_i, and c_i represent generator cost coefficients and e_i and f_i represent valve-point effect coefficients of the i-th generating unit.

Utilization of thermal power plant that consumes fossil fuel is with release of high amounts of NO_X, therefore they are strongly requested by the environmental protection agency to reduce their emissions. The NO_X emission of the thermal power station having N generating units at interval t in the scheduling horizon is represented by the sum of quadratic and exponential functions of power generation of each unit. The emission due to i-th thermal generating unit can be expressed as

$$E_{i,t}(P_{i,t}) = \left(\alpha_i P_{i,t}^2 + \beta_i P_{i,t} + \gamma_i + \eta_i \exp\left(\delta_i P_{i,t} \right) \right) \quad (3)$$

where α_i ,β_i , γ_i , η_i and δ_i are emission coefficients of the i-th generating unit.

The minimization of the fuel cost and emission are subjected to the following equality and inequality constraints.

2.1 Power balance constraint

The total generated real power should be the same as total load demand plus the total line loss.

$$\sum_{i=1}^{N} P_{i,t} = P_{D,t} + P_{L,t} \tag{4}$$

where $P_{D,t}$ and $P_{L,t}$ are the demand and transmission loss in MW at time interval *t*, respectively.
The transmission loss $P_{L,t}$ can be expressed by using *B* matrix technique [1] and is defined by (5) as,

$$P_{L,t} = \sum_{i=1}^{N} \sum_{j=1}^{N} P_{i,t} B_{ij} P_{j,t} \tag{5}$$

where B_{ij} is the *ij*-th element of the loss coefficient square matrix of size *N*.

2.2 Generation limits

The real power output of each generator should lie between minimum and maximum limits.

$$P_{i,\min} \le P_{i,t} \le P_{i,\max} \tag{6}$$

2.3 Ramp rate limits

The ramp-up and ramp-down constraints can be written as (7) and (8), respectively.

$$P_{i,t} - P_{i,t-1} \le UR_i \tag{7}$$

$$P_{i,t-1} - P_{i,t} \le DR_i \tag{8}$$

where $P_{i,t}$ and $P_{i,t-1}$ are the present and previous real power outputs, respectively. UR_i and DR_i are the ramp-up and ramp-down limits of unit *i* (in units of MW/time period).
To consider the ramp rate limits and real power output limits constraint at the same times, therefore, equations (6), (7) and (8) can be rewritten as follows:

$$\begin{aligned} &\max\{P_{i,\min}, P_{i,t-1} - DR_i\} \le P_{i,t} \le \\ &\min\{P_{i,\max}, P_{i,t-1} + UR_i\} \end{aligned} \tag{9}$$

2.4 Prohibited operating zones

The prohibited operating zones are the range of real power output of a generator where the operation causes undue vibration of the turbine shaft bearing caused by opening or closing of the steam valve. The prohibited operating zones of the unit can be described as follows:

$$P_{i,t} \in \begin{cases} P_{i,\min} \le P_{i,t} \le P_{i,1}^{l} \\ P_{i,k-1}^{u} \le P_{i,t} \le P_{i,k}^{l}, \quad k = 2,3,\ldots, pz_i \\ P_{i,pz_i}^{u} \le P_{i,t} \le P_{i,\max}, \quad i = 1,2,\ldots, n_{pz} \end{cases} \tag{10}$$

where $P_{i,k}^{l}$ and $P_{i,k}^{u}$ are the lower and upper boundary of prohibited operating zone of unit *i*, respectively. Here, pz_i is the number of prohibited zones of unit *i* and n_{pz} is the number of units which have prohibited operating zones.

3 Meta-heuristic optimization

3.1 Overview of the PSO

The particle swarm optimization (PSO) algorithm is introduced by Kennedy and Eberhart based on the social behavior metaphor. In the PSO, a potential solution for a problem is considered as a bird without quality and volume, which is called a particle, flying through a *D*-dimensional space by adjusting the position in search space according to its own experience and its neighbors. In the PSO, the *i*-th particle is represented by its position vector x_i in the *D*-dimensional space and its velocity vector v_i. In each time step *t*, the particles calculate their new velocity, then update their position according to equations (11) and (12) respectively.

$$\begin{aligned} v_i^{t+1} = w \times v_i^t + c_1 \times r_1 \times \left(pbest_i - x_i^t \right) + \\ c_2 \times r_2 \times \left(gbest - x_i^t \right) \end{aligned} \tag{11}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{12}$$

$$w = w_{\max} - \left(\frac{(w_{\max} - w_{\min}}{Iter_{\max}} \right) \times Iter \tag{13}$$

where v_i^t is velocity of particle *i* at iteration t, *w* is inertia factor, c_1 and c_2 are accelerating factor, r_1 and r_2 are positive random number between 0 and 1, $pbest_i$ is the best position of particle *i*, *gbest* is the best position of the group, w_{max} and w_{min} are maximum and minimum of inertia factor, $Iter_{max}$ is maximum iteration, *n* is number of particles.
The PSO begin with randomly placing the particles in a problem space. In each iteration, the velocities of particles are calculated using (11). After defining the

velocities, position of masses can be calculated as (12). The process of changing particles' position will continue until the stop criteria is reached.

3.2 Gravitational search algorithm

The Gravitational Search Algorithm (GSA) is a novel heuristic optimization technique which has been proposed by E. Rashedi et al in 2009 [23]. The basic physical theory based on which GSA is inspired by is the Newton's theory. This algorithm, which is based on the Newtonian physical law of gravity and law of motion, has great potential to be a breakthrough optimization method. In the GSA, consider a system with *N* agent (mass) in which position of the *i-th* mass is defined as follows:

$$X_i = \left(x_i^1, \ldots, x_i^d, \ldots, x_i^n\right), \quad i = 1, 2, \ldots, m \tag{14}$$

where x_i^d is position of the *i-th* mass in the *d-th* dimension and *n* is dimension of the search space. At the specific time *t* a gravitational force from mass *j* acts on mass *i*, and is defined as follows:

$$F_{ij}^d(t) = G(t)\frac{M_i(t) \times M_j(t)}{R_{ij}(t) + \varepsilon}\left(x_j^d(t) - x_i^d(t)\right) \tag{15}$$

where *G(t)* is the gravitational constant at time *t*, $M_i(t)$ and $M_j(t)$ are the masses of the objects *i* and *j*, and *ε* is a small constant, and $R_{ij}(t)$ is the Euclidean distance between the two objects *i* and *j* objects described as follows:

$$R_{ij}(t) = \left\| X_i(t), X_j(t) \right\|_2 \tag{16}$$

The masses of the agents are calculated as following by comparison of fitness:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{17}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{m} m_j(t)} \tag{18}$$

where $fit_i(t)$ represents the fitness value of the agent *i* at time *t*, *best(t)* is maximum fitness values of all agents and *worst(t)* is the minimum fitness.

Randomly initialized gravitational constant *G(t)* is decreased according to the time as follows:

$$G(t) = G_0 e^{-\alpha \frac{t}{T}} \tag{19}$$

where *α* and G_0 are descending cooefficient and initial value respectively, *t* is current iteration, and *T* is maximum number of iterations.
The total force that acts on agent *i* in the dimension *d* is described as follows:

$$F_i^d(t) = \sum_{\substack{j=1 \\ j \neq i}}^{m} rand_j F_{ij}^d(t) \tag{20}$$

where $rand_j$ is a random number interval [0, 1].
According to the law of motion, the acceleration of the agent *i*, at time *t*, in the *d* dimension, $a_i^d(t)$ is given as follows:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{21}$$

Then, the searching strategy can be described by the next velocity and next position of an agent. The next velocity function is the sum of the current velocity and its current acceleration. The current acceleration is described as the initial acceleration calculated from (21). The initial position is calculated from (14) and the initial speed is determined by producing a zero matrix, which has a dim x *N* dimension (dim: dimension of problem, *N*: number of agents). Also, the next position function is the sum of the current position and the next velocity of that agent. These functions are shown as follows:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \tag{22}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{23}$$

were $rand_i$ is a random number interval [0, 1], $v_i^d(t)$ is the velocity and $x_i^d(t)$ is the position of an agent at time *t* in the *d* dimension.
While solving an optimization problem with the GSA at the beginning of the algorithm, every agent is located at a certain point of the search space, which represents a solution to the problem at every unit of time. Next, according to (22) and (23), masses are

evaluated, and their next positions are calculated. Then, gravitational constant *G*, masses *M*, and acceleration α are calculated through (17)-(19) and (21) and updated at every time cycle. The search process is stopped after a certain amount of time.

3.3 The hybrid PSOGSA

The hybrid PSOGSA approach is an integrated approach between PSO and GSA which combines the ability of social thinking (*gbest*) in PSO with the local search capability of GSA. In order to combine these algorithms, the updated velocity of agent *i* can be calculated as follows [24]:

$$V_i(t+1) = w \times V_i(t) + c_1 \times rand_i \times a_i(t) + c_2 \times rand_i \times \left(gbest - X_i(t)\right) \tag{24}$$

where $V_i(t)$ is the velocity of agent *i* at iteration *t*, c_j is a weighting factor, *w* is a weighting function, *rand* is a random number between 0 and 1, $a_i(t)$ is the acceleration of agent *i* at iteration *t*, and *gbest* is the best solution so far.
The updating position of the particles at each iteration is as follows:

$$X_i(t+1) = X_i(t) + V_i(t) \tag{25}$$

In the hybrid PSOGSA, at the beginning of the algorithm, all agents are randomly initialized. Each mass (agent) is considered as a candidate solution. After initialization, gravitational force, gravitational constant, and resultant forces among the agents are calculated using (15), (19), and (20) respectively.
After that, the acceleration of particles is defined as (21) and updated at every time cycle. After calculating the accelerations and with updating the best solution so far, the velocities of all agents can be calculated using (24). Finally, the positions of the agents are defined as (25). The search process is stopped after a certain amount of time.

4 The results and discussion

The feasibility of the proposed method is demonstrated on a 5-unit test system for the given scheduled time duration which is divided into 24 intervals. The 5-unit test system data with non-smooth fuel cost and emission function, B-loss coefficients, and the load demand for 24 intervals are taken from [19, 25, 26] and are given in Tables 1, 2, and 3, respectively.
The algorithms were executed in MATLAB R2015a on a PC with 3.07 GHz CPU and 8-GB RAM. The PSO-GSA parameters used for the simulation are adopted as following: c_1 = 0.5, c_2 = 1.5, *w* = rand[0, 1], α = 20 and G_0 = 100. The population size *N* and maximum iteration number *T* are set to 30 and 100, respectively, for all case studies.
Tables 4, 5, and 6, respectively show the optimal solutions of the dynamic economic dispatch (DED, w1=1, w2=0), dynamic economic emission dispatch (DEED, w1=0.5, w2=0.5) and pure dynamic emission dispatch (PDED, w1=0, w2=1).

Table 1. Data for the 5-unit system

Quantities	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
a_i (\$/(MW)^{2}h)	0.0080	0.0030	0.0012	0.0010	0.0015
b_i (\$/MWh)	2.0	1.8	2.1	2.0	1.8
c_i (\$/h)	25	60	100	120	40
e_i (\$/h)	100	140	160	180	200
f_i (rad/MW)	0.042	0.040	0.038	0.037	0.035
α_i (lb/MW^{2}hr)	0.0180	0.0150	0.0105	0.0080	0.0120
β_i (lb/MWhr)	-0.805	-0.555	-1.355	-0.600	-0.555
γ_i (lb/hr)	80	50	60	45	30
η_i (lb/hr)	0.6550	0.5773	0.4968	0.4860	0.5035
δ_i (1/MW)	0.02846	0.02446	0.02270	0.01948	0.02075
$P_{i,\,min}$ (MW)	10	20	30	40	50
$P_{i,\,max}$ (MW)	75	125	175	250	300
UR_i (MW/h)	30	30	40	50	50
DR_i (MW/h)	30	30	40	50	50
$POZ_{s\text{-}1}$	[25 30]	[45 50]	[60 70]	[95 110]	[80 100]
$POZ_{s\text{-}2}$	[55 60]	[80 90]	[125 140]	[160 180]	[175 200]

Table 2. B-loss coefficients (5-unit system)

$$B = \begin{bmatrix} 0.000049 & 0.000014 & 0.000015 & 0.000015 & 0.000020 \\ 0.000014 & 0.000045 & 0.000016 & 0.000020 & 0.000018 \\ 0.000015 & 0.000016 & 0.000039 & 0.000010 & 0.000012 \\ 0.000015 & 0.000020 & 0.000010 & 0.000040 & 0.000014 \\ 0.000020 & 0.000018 & 0.000012 & 0.000014 & 0.000035 \end{bmatrix} \text{ per MW}$$

Table 3. Load demand for 24 hours (5-unit system)

Time (h)	Load (MW)	Time (h)	Load (MW)	Time (h)	Load (MW)	Time (h)	Load (MW)
1	410	7	626	13	704	19	654
2	435	8	654	14	690	20	704
3	475	9	690	15	654	21	680
4	530	10	704	16	580	22	605
5	558	11	720	17	558	23	527
6	608	12	740	18	608	24	463

Table 4. Hourly power schedule obtained from DEED (w1=1, w2=0)

H	P_1	P_2	P_3	P_4	P_5	Loss
1	22.6579	98.5398	112.6736	40.0000	139.7599	3.6312
2	46.0216	98.5394	30.0000	124.9081	139.7597	4.2288
3	10.0000	97.7067	112.6491	209.8158	50.0000	5.1716
4	59.9542	98.5399	112.6736	124.9079	139.7599	5.8355
5	10.0000	94.8374	112.0098	124.9077	222.9279	6.6829
6	55.0805	98.5395	112.6732	209.8160	139.7588	7.8679
7	68.6665	98.5397	112.6735	124.9078	229.5195	8.3069
8	12.7090	98.5398	112.6735	209.8158	229.5196	9.2577
9	75.0000	100.332	175.0000	209.8169	139.7606	9.9147
10	64.0108	98.5399	112.6736	209.8157	229.5195	10.5595
11	75.0000	20.5886	175.0000	230.7281	229.5201	10.8367
12	53.2154	98.5398	175.0000	124.9079	300.0000	11.6632
13	64.0106	98.5398	112.6736	209.8158	229.5196	10.5595
14	49.6197	98.5397	112.6735	209.8158	229.5196	10.1683
15	75.0000	34.3463	114.4072	209.8159	229.5212	9.0906
16	26.4484	98.5398	112.6737	209.8159	139.7598	7.2375
17	10.0001	20.0000	110.1488	195.0648	229.5191	6.7327
18	55.0791	98.5399	112.6734	209.8157	139.7598	7.8679
19	12.7086	98.5400	112.6736	209.8159	229.5198	9.2577
20	64.0107	98.5399	112.6735	209.8157	229.5196	10.5595
21	39.3528	98.5398	112.6736	209.8159	229.5196	9.9016
22	47.1333	98.5398	112.6735	124.9079	229.5197	7.7742
23	55.2752	98.5398	30.0000	209.8158	139.7597	6.3905
24	70.0715	20.0000	112.6735	124.9080	139.7598	4.4127
Cost=42853.3394 $, Emission=22087.8872 lb, Loss=193.9092 MW						

Table 5. Hourly power schedule obtained from DEED (w1=0.5, w2=0.5)

H	P_1	P_2	P_3	P_4	P_5	Loss
1	61.1248	64.8071	112.6735	124.9079	50.0000	3.5133
2	67.2893	84.1154	112.6735	124.9079	50.0000	3.9861
3	75.0000	98.5399	112.6774	124.9080	68.6167	4.7420
4	74.9999	96.2972	112.6736	124.9079	126.9525	5.8311
5	74.9995	98.5398	126.2320	124.9159	139.7597	6.4469
6	74.9999	98.5399	118.9414	183.5086	139.7596	7.7495
7	75.0000	98.5398	118.5193	202.4505	139.7594	8.2690
8	74.9999	98.5398	145.2560	204.3880	139.7595	8.9432
9	74.9999	100.331	175.0000	209.8158	139.7608	9.9147
10	75.0000	114.719	175.0000	209.8158	139.8306	10.3593
11	75.0000	125.000	175.0000	209.8206	146.0384	10.8590
12	75.0000	125.000	175.0000	211.3129	165.1379	11.4508
13	74.9999	114.763	175.0000	209.8166	139.7737	10.3596
14	75.0000	100.331	175.0000	209.8157	139.7600	9.9147
15	75.0000	98.5396	155.7470	193.8476	139.7597	8.8939
16	74.9998	98.5396	148.7354	124.9079	139.7586	6.9413
17	74.9995	98.5399	126.2392	124.9085	139.7598	6.4469
18	75.0000	98.5400	175.0000	127.3262	139.7597	7.6259
19	74.9999	98.5398	173.0506	176.4919	139.7597	8.8419
20	74.9999	114.785	175.0000	209.8158	139.7634	10.3597
21	75.0000	98.5396	173.2934	203.0181	139.7598	9.6108
22	75.0000	98.5400	174.3446	124.9079	139.7597	7.5523
23	74.9992	96.5785	112.6735	124.9079	123.6070	5.7660
24	74.9995	98.4382	112.6741	124.9078	56.5128	4.5324
Cost=45702.6001 $, Emission=18267.1788 lb, Loss=188.9105 MW						

Table 6. Hourly power schedule obtained from DEED (w1=0, w2=1)

H	P_1	P_2	P_3	P_4	P_5	Loss
1	54.6785	58.2356	116.5718	110.5981	73.3639	3.4480
2	58.0672	62.3836	121.8514	117.9818	78.6016	3.8854
3	63.5261	69.0803	130.2207	129.7503	87.0639	4.6413
4	71.1206	78.4296	141.5517	145.8017	98.8901	5.7936
5	74.9998	83.2693	147.2394	153.9052	105.0170	6.4307
6	75.0000	93.5801	158.7930	170.2750	118.0066	7.6547
7	74.9999	97.2850	162.9871	176.3836	122.4682	8.1238
8	75.0000	103.100	169.0769	185.3854	130.3109	8.8812
9	75.0000	111.392	175.0000	197.9016	140.6181	9.9138
10	75.0000	115.343	175.0000	203.6178	145.3780	10.3381
11	75.0000	119.609	175.0000	209.8641	151.3608	10.8338
12	75.0000	125.000	175.0000	217.2826	159.1889	11.4716
13	75.0000	115.673	175.0000	203.0533	145.6120	10.3376
14	75.0000	111.430	175.0000	197.7360	140.7395	9.9134
15	75.0000	103.135	169.2397	185.4858	130.0167	8.8817
16	75.0000	87.7294	152.3596	161.2403	110.6262	6.9555
17	75.0000	83.2655	147.2436	153.9050	105.0166	6.4307
18	75.0000	93.4857	158.8899	170.3447	117.9344	7.6547
19	75.0000	103.061	169.3818	185.1451	130.2864	8.8804

20	75.0000	115.465	175.0000	203.0490	145.8251	10.3366
21	75.0000	108.579	174.8244	194.0691	137.1487	9.6180
22	75.0000	92.8374	158.1129	169.5503	117.0779	7.5784
23	70.7033	77.9152	140.9393	144.9310	98.2386	5.7274
24	61.8833	67.0629	127.7207	126.2266	84.5138	4.4073
Cost=51953.9046 $, Emission=17852.9791 lb, Loss=188.1381 MW						

Table 7. Comparison results for 5-unit system

Weight	Method	Cost ($)	Emission (lb)	Run time (s)
w1=1; w2=0	PSO [25]	47852	22405	-
	DE-SQP [26]	45590	23567	-
	PSOGSA	42853.3394	22087.8872	40.322
w1=0.5; w2=0.5	PSO [25]	50893	20163	-
	DE-SQP [26]	46625	20527	-
	PSOGSA	45702.6001	18267.1788	40.614
w1=0; w2=1	PSO [25]	53086	19094	-
	DE-SQP [26]	52611	18955	-
	PSOGSA	51953.9046	17852.9791	40.514

Tables 4 and 6 show that the cost is 42,853.3394 $ under DED but it increases to 51,953.9046 $ under PDED, and emission obtained from DED is 22,087.8872 lb but decreases to 17,852.9791 lb under PDED.

Table 5 shows that the cost is 45,702.6001 $ which is more than 42,853.3394 $ (in case of DED) and less than 51,953.9046 $ (in case of PDED), and emission is 18,267.1788 lb which is less 22,087.8872 lb (in case of DED) and more than 17,852.9791 lb (in case of PDED).

Table 7 shows that, the efficiency of the proposed method compare to other methods for DEED problem at different weighting factors. It appears that both fuel cost and emission are less than the other methods reported in the literature. The table also shows the running time for each step of the process.

5 Conclusion

In this paper, a new hybrid PSOGSA technique has been applied to solve the non-convex DEED problem of generating units considering the valve-point effects, prohibited operation zones, ramp rate limits and transmission loss. The proposed technique has provided the best solution in the 5-unit test systems and better solution than the previous studies reported in the literature. The simulation results show the high performance of the PSOSGA algorithm on minimizing fuel cost and reduced emission. The analyses of the results are very promising since the main objectives of the proposed technique were achieved. Future studies will focus on multi-objective economic emissions power dispatch considering renewable energy.

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