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Hybrid genetic algorithm for economic dispatch with valve-point effect

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Abstract

This paper presents an efficient method for solving the economic dispatch problem (EDP) through combination of genetic algorithm (GA), the sequential quadratic programming (SQP) technique, uniform design technique, the maximum entropy principle, simplex crossover and non-uniform mutation. The proposed hybrid technique uses GA as the main optimizer, the SQP to fine tune in the solution of the GA run. Based on the maximum entropy principle, the cost function of EDP is approximated by using a smooth and differentiable function to improve the performance of the SQP. An initial population obtained by using uniform design exerts optimal performance of the proposed hybrid algorithm. The effectiveness of the proposed method is validated by carrying out extensive tests on two different EDP with incremental fuel-cost function taking into account the valve-point loadings effects. The result shows that the proposed hybrid genetic algorithm improves the solution accuracy and reliability compared to other techniques for EDP considering valve-point effects.

Keywords: Hybrid genetic algorithm (HGA); Sequential quadratic programming; Uniform design; Maximum entropy principle; Economic dispatch problem

1. Introduction

Economic dispatch is one of the most important problems to be solved in the operation of a power system. Improvements in scheduling the unit outputs can lead to significant cost savings. The primary objective of the economic dispatch problem (EDP) of electric power generation is to schedule the committed generating unit outputs so as to meet the required load demand at minimum operating cost while satisfying all unit and system equality and inequality constraints [1]. This makes the EDP a large-scale highly non-linear constrained optimization problem.

The input–output characteristics of large units are inherently highly non-linear because of valve-point loadings, generating unit ramp rate limits, etc. Furthermore they may generate multiple local minimum points in the cost function. In light of the non-linear characteristics of the units, there is a demand for techniques that do not have restrictions on the shape of the fuel-cost curves. To obtain accurate dispatch results, approaches without restriction on the shape of incremental fuel-cost functions are needed. Whereas both lambda-iterative and gradient technique methods in conventional approaches to the problems are calculus-based techniques, and require a smooth and convex cost function and strict continuity of the search space. Dynamic programming (DP) [2] imposes no restrictions on the nature of the cost curves and therefore it can solve EDP with inherently non-linear and discontinuous cost curves. This method, however, suffers from the “curse of dimensionality” or local optimality [1].

GA is a stochastic optimization technique, which is based on the principle of natural selection and genetics [3,4]. It combines solution evaluation with randomized, structured exchanges of genetic information between solutions to obtain optimality. Also it searches multiple solutions simultaneously in contrast to conventional optimal algorithms. Therefore, the possibility of finding global optimal solution is increased. The main advantage of GA is that it finds near optimal solution in relatively short time compared with other random searching methods.

In recent years, the interest in these algorithms has been rising fast, for that they provide robust and powerful adaptive search mechanisms [5]. GA has an immense potential for applications in the field of power systems and it has been successfully applied to solve various problems in electric power systems such as economic dispatch [6,7], unit commitment, reactive power control, hydrothermal scheduling, and distribution system planning, etc.

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When compared with the foregoing conventional techniques, GA is well appreciated for their global optimality in complex search space (multiple local optima, multi-objective, non-linear, discontinuous and highly constrained space). Despite the aforementioned success, GA is only capable of identifying the high performance region at an affordable time and displays inherent difficulties in performing local search for numerical applications [8].

To overcome premature convergence and speed up the search process, a hybrid method that integrates the GA with a gradient search algorithm called SQP [9] is proposed to take advantage of both GA and the local search techniques. GA is capable of exploring a large space, yet is slow in fine tuning local search. In contrast, SQP techniques can climb hills rapidly; however, they are blind to the potential hills in the neighbourhood area and sensitive to the initial starting points. The hybrid GA uses a GA to identify the potential hill within a reasonably short period of time, while SQP technique subsequently takes over and rapidly climbs the remaining hill. Therefore, this algorithm increases the possibility of finding global optimal point and improves the convergence speed. The proposed hybrid technique uses GA as a base level search towards the optimal region and SQP method as optimization to do the fine tuning.

In general, the hybrid method offers an exact solution only when the function is smooth and its gradient information are known [8]. The method is proposed to approximate EDP by using a smooth and differentiable function based on the maximum entropy principle. In this way, the performance of the hybrid method is improved. At the same time, to improve rationality of the distribution of initial population, the hybrid technique integrating the uniform design with the genetic algorithm (UHGA) is proposed.

In order to validate the performance of the proposed UHGA, two economic dispatch problems with incremental fuel-cost functions taking into account the valve-point loading effects were tested and the results obtained were compared with those reported in literatures [1,10].

2. EDP formulation

The classic EDP minimizes the following incremental fuel-cost function associated to dispatchable units:

$$\min\ F = \min\left\{\sum_{i=1}^{N_P} F_i(P_i)\right\} \tag{1}$$

where $F_i(P_i)$ is the fuel-cost function of the unit and ith is the power generated by the ith unit, P_i subject to power balance constraints:

$$\sum_{i=1}^{N_P} P_i = P_{\mathrm{D}} + P_{\mathrm{loss}} \tag{2}$$

where P_{D} is the system load demand and P_{loss} is the transmission loss, and generating capacity constraints:

$$P_{i\,\min} \le P_i \le P_{i\,\max}, \quad \text{for}\ i = 1, 2, \ldots, N_P \tag{3}$$

where $P_{i\,\min}$ and $P_{i\,\max}$ are the minimum and maximum power outputs of the ith unit.

The inclusion of valve-point loading effects makes the modeling of the incremental fuel-cost function of the generators more practical. This increases the non-linearity as well as number of local optima in the solution space. Also the solution procedure can easily trap in the local optima in the vicinity of optimal value. The incremental fuel-cost function of the generating units with valve-point loadings is represented as follows [9,11]:

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

where, a_i, b_i and c_i, are the fuel-cost coefficients of the unit, e_i and f_i are the fuel-cost coefficients of the unit with valve-point effects.

The economic dispatch of generation of real power of the generating units is to be done to the required load demand by satisfying the above constraints. The incremental fuel-cost function can be modeled in a more practical fashion by including the valve-point effects [12]. The generating units with multi-valve steam turbines exhibit a greater variation in the fuel-cost functions. The valve-point effects introduce ripples in the heat-rate curves, thereby the number of local optima is increased. Hence, a technique that overcomes these complexities has to be evolved.

3. Entropic smoothing approximation function

Let Ψ_i: $R^n \to R$, $i = 1, 2, \ldots, m$, be differentiable and define a max-type function Ψ: $R^n \to R$, $i = 1, 2, \ldots, m$ by

$$\Psi(x) = \max_i \Psi_i(x) \tag{5}$$

Given any $\mu > 0$, consider the following entropy-type function as a smoothing approximation function of Ψ,

$$\Psi(x, \mu) = \mu\ \ln \sum_{i=1}^{m} \exp\left(\frac{\Psi_i(x)}{\mu}\right) \tag{6}$$

Note that, for $\mu > 0$,

$$\Psi(x, \mu) = \Psi(x) + \mu\ \ln \sum_{i=1}^{m} \exp\left[\frac{\Psi(x) - \Psi_i(x)}{\mu}\right] \tag{7}$$

Moreover,

$$\Psi(x) \le \Psi(x, \mu) \le \Psi(x) + \mu\ \ln m, \quad \forall x \in R^n\ \text{and}\ \mu > 0 \tag{8}$$

Therefore, $\Psi(x, \mu) \to \Psi(x)$ as $\mu \to 0$. This fact allows us to solve the problem without facing the non-differentiability problem of $\Psi(x)$. Since the function (6) can be derived from the dual problem of an entropy optimization problem, we call function (6) an entropic smoothing approximation function. Li [13] discovered a few properties of this function and named it as the aggregate function. Related work can be found in [14–17].

To EDP, the incremental fuel-cost function of the generating units with valve-point loadings (1) are represented as the following function:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + |e_i \sin(f_i(P_{i\,\min} - P_i)| = a_i P_i^2 + b_i P_i + c_i + \max\{e_i \sin(f_i(P_{i\,\min} - P_i), - e_i \sin(f_i P_{i\,\min} - P_i)\} \quad (9)$$

Based on the maximum entropy principle the incremental fuel-cost function can be approximated by entropic smoothing approximation function:

$$\Psi(P_i, \mu) = a_i P_i^2 + b_i P_i + c_i + \mu \ln[e^{e_i \sin(f_i(P_{i\,\min} - P_i)/\mu} + e^{-e_i \sin(f_i(P_{i\,\min} - P_i)/\mu}] \quad (10)$$

The function $\Psi(P_i, \mu)$ provides a good approximation to the function $F_i(P_i)$ in the sense that

$$0 \le \Psi(P_i, \mu) - F_i(P_i) \le \mu \ln 2 \quad \text{and} \quad \mu > 0 \quad (11)$$

It is clear that this function uniformly approximates the maximum function $F_i(P_i)$ when a parameter μ tends to infinitesimal and is greater than $F_i(P_i)$ with an error bound less than $\mu \ln 2$.

Because of approximation, the result obtained by SQP method is approximation of exact result. To handle this problem, the hybrid method proposed in this paper only uses SQP method to find approximation solution not optimum cost. In other word, entropic smoothing approximation function is only used in SQP method not in whole HGA. Thus, approximation does not influence accuracy of HGA.

4. Uniform design

The distribution of the individuals of initial population directly influences the globe convergence and searching efficiency. Therefore, the reasonable setting of initial population is an important problem in the application of GA to perform optimization calculation. Because of introducing SQP method, if the distribution of the individuals of initial population is not reasonable, the HGA sometimes converges to local optima and cannot reach the global optimal point. Therefore, initial population is more important to the HGA proposed in this paper. In order to exert optimal performance of GA, the initial population of GA must reflect the information of solution space scientifically. However, it is difficult to evaluate the distribution of the individuals of initial population. The uniform design is an effective method to solve this problem. It is employed to obtain initial population in this paper.

Because the dimensionality of EDP is large, it is difficult to obtain optimal generating vector of the usable tables of uniform design. So the following method is used in this paper.

Theorem 1. *If (12) and (13) are satisfied, the optimal generating vector of n dimensionalities and* $(1/2)\varphi(n+1)$ *factors uniform design is composed of natural numbers which are prime numbers with* $n+1$ [18].

$$h_i \ne h_j \quad (i \ne j) \quad (12)$$

$$h_i \ne n + 1 - h_j \quad (i \ne j) \quad (13)$$

where $\varphi(n+1)$ is the Euler function of $n+1$; h_i and h_j are the different generating elements in generating vector.

Theorem 2. *If (12) and (13) are satisfied, the optimal generating vector of uniform design with n dimensionalities and* $(1/2)\varphi(n+1) - 1$ *factors is composed of natural numbers which are prime numbers with* $n+1$ *in* $[1, n+1/2)$ *with any one taken out.*

Based on Theorems 1 and 2, for the uniform designs with $(1/2)\varphi(n+1)$ or $(1/2)\varphi(n+1) - 1$ factors, the usable tables can be obtained immediately without any measurement for its uniformity. The good lattice point method is employed to obtain the usable table with optimal generating vector. For the uniform designs with certain factors, n is calculated by formula of Euler function.

5. Hybrid genetic algorithm

5.1. Selection operator

After the evaluation of the initial population, the GA begins the creation of the new generation. The selection used in this paper depends on individual fitness. The best individuals of the present population are kept for the next population. The fitness value in this paper contains the penalty function and does not represent the true objective function.

5.2. Simplex crossover operator

The primary genetic operator is the crossover operator. The purpose of crossover operator is to produce new chromosomes that are distinctly different from their parents, yet remain some of their parents characteristics. It has important function in the capability of searching the optimal solution.

Simplex algorithm is a method which finds optima through improving inferior point by searching from inferior point towards the pivot of $n+1$ initial points of the Simplex for the n-dimensional problem. Simplex algorithm is similar to crossover operator of GA in utilizing information of multi-points. Based on aforementioned analysis, simplex crossover operator [19] is employed in this paper to improve convergence speed and lead the population to the global optimum because of the characteristic of improving inferior point.

5.3. Non-uniform mutation operator [20]

Non-uniform mutation operator is employed in this paper. This operator is described below.

If $P^t = [P_1^t, P_2^t, \ldots, P_n^t]$ is a power output chromosome vector and P_i^t is ith unit's output that is chosen to be mutated, the new output P_i^{mut} will be after mutation

$$P_i^{\mathrm{mut}} = \left(\begin{array}{ll} P_i^t + \Delta(t, P_{i\,\max} - P_i^t), & \text{if } r = 0 \\ P_i^t - \Delta(t, P_i^t - P_{i\,\min}), & \text{if } r = 1 \end{array} \right. \quad (14)$$

where r is a random bit, and function $\Delta(t, y)$ returns a value in the range [0, y] such that the probability of the value returned is close to 0 increases with t

$$\Delta(t, y) = y \times (1 - \xi^{(1-t/\text{gen})^b}) \tag{15}$$

where ξ is a random floating-point number in the interval [0, 1]; t the current generation; gen the maximum number of generations; b is a parameter that determines the degree of dependence on the number of generations. In this way, the operator makes a uniform search at the beginning of the evolution and in later stages narrows the search around the local area of the parameter resembling a hill-climbing operator. For our experiments, b was chosen equal to 2.

5.4. Sequential quadratic programming operator [9,21]

SQP method seems to be the best non-linear programming methods for constrained optimization. It outperforms every other non-linear programming method in terms of efficiency, accuracy, and percentage of successful solutions over a large number of test problems. The method resembles closely to Newton's method for constrained optimization just as is done for unconstrained optimization. At each iteration an approximation is made by the Hessian of the Lagrangian function using a Broyden–Foldfarb–Shanno (BFGS) quasi-Newton updating method. This is then used to generate a quadratic programming (QP) sub-problem whose solution is used to form a search direction for a line search procedure. In this paper, SQP is used as a local optimizer to fine-tune the region explored by GA in its run.

First let us formulate the QP sub-problem for the problem as stated by (1) subject to (2) and (3).

$$\min\ \nabla F_T(P_k)^{\mathrm{T}} d_k + \frac{1}{2} d_k^{\mathrm{T}} H_k d_k \tag{16}$$

subject to

$$c(P_k)+\nabla c(P_k)^{\mathrm{T}} d_k = 0 \tag{17}$$

$$P_{\min} \le P_k + d_k \le P_{\max} \tag{18}$$

where, H_k is the Hessian matrix of the Lagrangian function at the kth iteration, d_k the search direction at the kth iteration, P_k the real power vector at the kth iteration, and $c(P_k)$ is the constraint given by Eq. (2)

$$L(P, \lambda) = F_T(P) + c(P)^{\mathrm{T}}\lambda \tag{19}$$

and is constructed from a quasi-Newton update formula given by:

$$H_{k+1} = H_k - \frac{H_k s_k (s_k)^{\mathrm{T}} H_k}{(s_k)^{\mathrm{T}} H_k s_k} + \frac{q_k (q_k)^{\mathrm{T}}}{(q_k)^{\mathrm{T}} s_k} \tag{20}$$

where

$$s_k = P_{k+1} - P_k \tag{21}$$

$$q_k = \nabla L(P_{k+1}, \lambda_{K+1}) - \nabla L(P_k, \lambda_{K+1}) \tag{22}$$

For each iteration of the QP sub-problem the direction d_k is calculated using the above Eq. (16). The solution obtained is used to form a new iterate given by:

$$P_{k+1} = P_k + \alpha_k d_k \tag{23}$$

The step length value α_k is determined to produce a considerable reduction in an augmented Lagrangian merit function:

$$L_{\mathrm{A}}(P, \lambda, \rho) = F_T(P) - \lambda^{\mathrm{T}}(P) + \frac{\rho}{2} c(P)^{\mathrm{T}} c(P) \tag{24}$$

where, λ is the vector of Lagrangian multiplier and ρ is a non-negative scalar. The procedure will be repeated until the value of s_k has reached some tolerance value.

6. Solution methodology

The proposed HGA for EDP with valve-point effects can be summarized as follows:

- Step 1: Get the data for the system.
- Step 2: Initialize parameter of algorithm and count t.
- Step 3: Generate initial population by the usable tables of uniform design.
- Step 4: Evaluate the objective function and update count t.
- Step 5: Identify the $\mathrm{Fit}_{\mathrm{best}}(t)$ of the current run t.
- Step 6: If $\mathrm{Fit}_{\mathrm{best}}(t) < \mathrm{Fit}_{\mathrm{best}}(t-1)$ replace $\mathrm{Fit}_{\mathrm{best}}(t-1)$ with $\mathrm{Fit}_{\mathrm{best}}(t)$, otherwise go to Step 7.
- Step 7: Generate selection offspring using selection operation.
- Step 8: Generate crossover offspring using simplex crossover operation.
- Step 9: Generate mutation offspring using non-uniform mutation operation.
- Step 10: Take the individuals selected randomly as the initial starting point for the SQP and generate SQP offspring by the final solution obtained using the SQP.
- Step 11: Generate whole offspring with selection offspring, crossover offspring, mutation offspring and SQP offspring.
- Step 12: While (termination criterion not met).

The termination is done when a specified number of iterations met.

7. Simulation results

The proposed UHGA approach was tested with two test cases of EDP with valve-point effects. The software was written in MATLAB 7.0 and executed on a Pentium-IV 2.99 GHz personal computer. Hereinafter, the results represent the average of 30 runs of the proposed method for both the two test cases.

Since $\varphi(28+1) = \varphi(29) = 28 = \varphi(13+1)$ and $\varphi(82+1) = \varphi(83) = 82 = 2(40+1)$, the optimal generating vector of uniform design with 28 dimensionalities and 13 factors and the optimal generating vector of uniform design with 82 dimensionalities and 40 factors are composed of natural numbers which are prime numbers with 29 in (1, 14.5) with any one taken out and 83 in [1, 41.5) with any one taken out, respectively, by Theorem

2. In this paper, the optimal generating vector of uniform design with 28 dimensionalities and 13 factors are all natural numbers in [1, 13]. The optimal generating vector of uniform design with 82 dimensionalities and 40 factors are all natural numbers in [1, 40]. Then the good lattice point method is employed to obtain the usable table with optimal generating vector. Hence the population size was chosen as 28 for test case 1 and 82 for test case 2.

The selection 'crossover' SQP and mutation operation proportions were chosen as 5:8:8:7 for test case 1 and 10:20:20:32 for test case 2. The simulation parameters of the UHGA for the two test systems are fixed as follows, $b=2$, $\mu=1$, and $\text{iter}_{\max}=30$. To validate the comparison of results obtained using the proposed technique with the results obtained using the EP, EP-SQP, PSO and PSO-SQP techniques, solution procedure of the UHGA technique is terminated when the maximum number of iterations is reached.

The fitness function $\text{Fit}(P_i)$ is given as

$$\text{Fit}(P_i)=\begin{cases} F, & \text{if } P_i \text{ is feasible} \\ F \pm F \times g_{\max}, & \text{otherwise} \end{cases} \tag{25}$$

where F is the value of objective function, symbol '$\pm$' is used to keep penalty, $g_{\max}$ is given as

$$g_{\max}=\max\{0, g_i(P), |h_j(P)|, i=1,2,\ldots,m_1, j=1,2,\ldots,m_2\} \tag{26}$$

where $g_i(P)$ are the inequality constraints, $h_i(P)$ the equality constraints, m_1 and m_2 are the number of the inequality constraints and the equality constraints, respectively.

7.1. Case 1

This test case comprises of thirteen generating units, the complexity and non-linearity to the solution procedure is increased. The expected power demands to be met by the all thirteen generating units is 1800 [1] and 2520 MW [22]. The system data can be found from [1]. The problem has a number of local optimum points as there are more possibilities for any method to stick on any one of the local optimum points.

Table 1
Comparison of fuel costs for $P_D = 1800$ MW for case 1

Method	Mean time (s)	Best cost (US$ h^{-1})	Best cost (US$ h^{-1})
EP [1]	157.43	17,994.07	18,127.06
EP-SQP [9]	121.93	17,991.03	18,106.93
PSO [9]	77.37	18,030.72	18,205.78
PSO-SQP [9]	33.97	17,969.93	18,029.99
UHGA	15.33	17,964.81	17,992.92

Table 2
Best result obtained for $P_D = 1800$ MW for case 1 using UHGA

Power	Generation	Power	Generation
1	628.21	8	60.00
2	223.94	9	109.71
3	149.30	10	40.00
4	109.71	11	40.00
5	109.71	12	55.00
6	109.71	13	55.00
7	109.71		

The final fuel costs obtained using the EP, EP-SQP, PSO, PSO-SQP and the proposed method for power demand of 1800 MW were summarized in Table 1. The best results obtained for solution vector, with UHGA with minimum cost of US$ 17,964.81 h^{-1} is given in Table 2. Table 3 reports the dispatch results of the various methods [23], EP-SQP, PSO-SQP and the proposed method for a load demand of 2520 MW. The problem is solved for two different power demands in order to show the effectiveness of the proposed method in producing quality solutions.

It is clear from the Tables 1 and 3, minimum cost and the mean cost value obtained by the proposed method is comparatively less compared to all the other methods. To show the effectiveness of UHGA, the test problems were also experimented using the HGA without initial population obtained by the uniform design.

Table 3
Dispatch results for a $P_D = 2520$ MW for case 1

Generator	Unit generation (MW)			
	GA-SA [9]	EP-SQP [9]	PSO-SQP [9]	UHGA
1	628.23	628.3136	628.3205	628.2330
2	299.22	299.1715	299.0524	299.0288
3	299.17	299.0474	298.9681	299.0288
4	159.12	159.6399	159.4680	159.6077
5	159.95	159.6560	159.1429	159.6077
6	158.85	158.4831	159.2724	159.6077
7	157.26	159.6749	159.5371	159.6077
8	159.93	159.7265	158.8522	159.6077
9	159.86	159.6653	159.7845	159.6077
10	110.78	114.0334	110.9618	77.1613
11	75.00	75.0000	75.0000	77.1613
12	60.00	60.0000	60.0000	89.5992
13	92.62	87.5884	91.6401	92.1414
Total cost (US$ h^{-1})	24,275.71	24,266.44	24,261.05	24,172.25

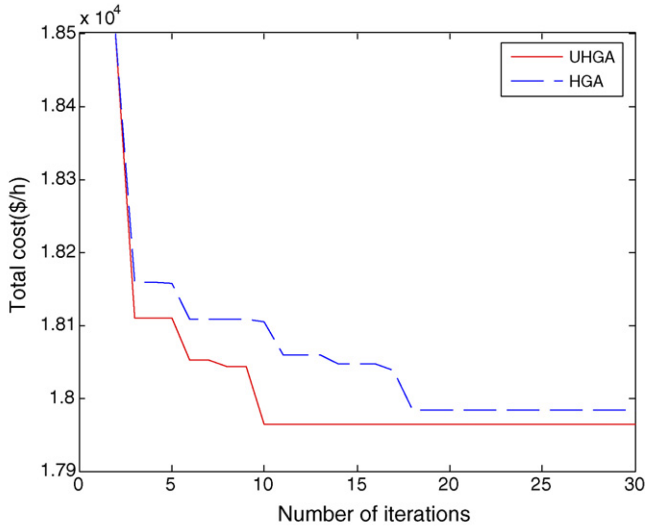

Fig. 1. Convergence characteristics of the UHGA and HGA for case 1 for a $P_D = 1800$ MW.

Fig. 1 shows the convergence characteristics of the UHGA and HGA method for power demand of 1800 MW. Fig. 2 shows the convergence characteristics of the UHGA and HGA method for power demand of 2520 MW. The average number of iterations to reach the optimum solution of the UHGA for power demand of 1800 MW is 8–12 and 2520 MW is 7–10 in all the 30 trial runs.

7.2. Case 2

This test case comprises of 40 generating units. This is a larger system. The number of local optima, complexity and non-linearity to the solution procedure is enormously increased. The required power demand to be met by all the forty generating units is 10,500 MW. The system data can be found from [1]. The final fuel costs obtained using the EP, EP-SQP, PSO, PSO-SQP, MPSO, DEC(2)-SQP(1) and the proposed method were summarized in Table 4. It is clear from Table 4, UHGA has the best probability of the mean cost value and the minimum cost amongst all the methods in this test case. It is noticeable that the mean cost value obtained using UHGA is less than the minimum cost obtained using other methods. Though the solution time of UHGA in case 2 is higher than DEC(2)-SQP(1), it offered better solution quality as compared to DEC(2)-SQP(1). The best results obtained for solution vector, with UHGA with minimum cost of US\$ 121,424.48 h^{-1} is given in Table 5. Fig. 3 shows that the UHGA performed better than HGA in the convergence characteristics. The average number of iterations to reach the optimum solution of the UHGA is 16–18 in all the 30 trial runs. Hence, for power system ELD problems of greater size with more non-linearities, the proposed method is proved to be the best algorithm amongst all the methods.

Table 4
Comparison of fuel costs for case 2

Method	Mean time (s)	Best cost (US\$ h^{-1})	Mean cost (US\$ h^{-1})
EP [1]	1167.35	122,624.35	123,382.00
EP-SQP [9]	997.73	122,323.97	122,379.63
MPSO [24]	–	122,252.27	–
PSO [9]	933.39	123,930.45	124,154.49
PSO-SQP [9]	733.97	122,094.67	122,245.25
DEC(2)-SQP(1) [25]	14.26	121,741.98	122,295.13
UHGA	333.68	121,424.48	121,602.81

Table 5
Best result obtained for case 2 using UHGA

Power	Generation	Power	Generation
1	110.8056	21	523.2789
2	110.8000	22	523.2799
3	97.4052	23	523.2799
4	179.7314	24	523.2832
5	87.8939	25	523.2823
6	140.0000	26	523.2884
7	259.6016	27	10.0000
8	284.6084	28	10.0000
9	284.6046	29	10.0000
10	130.0000	30	97.0000
11	94.0000	31	190.0000
12	168.8002	32	190.0000
13	214.7600	33	190.0000
14	304.5239	34	164.8113
15	394.2796	35	200.0000
16	394.2790	36	200.0000
17	489.2820	37	110.0000
18	489.2799	38	110.0000
19	511.2804	39	110.0000
20	511.2803	40	511.2803

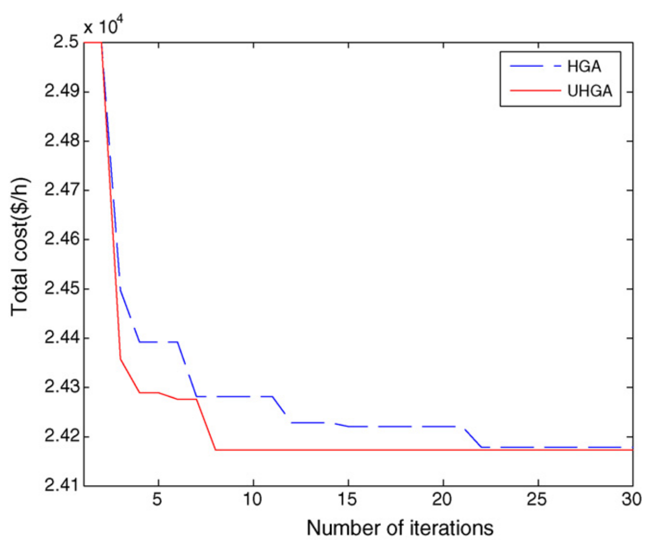

Fig. 2. Convergence characteristics of the UHGA and HGA for case 1 for a $P_D = 2520$ MW.

8. Discussion and conclusion

Traditionally, to solve the EDP effectively, conventional techniques require convex cost function and strict continuity of the search space. But practically the incremental fuel-cost curves of the generating units are inherently highly non-linear and

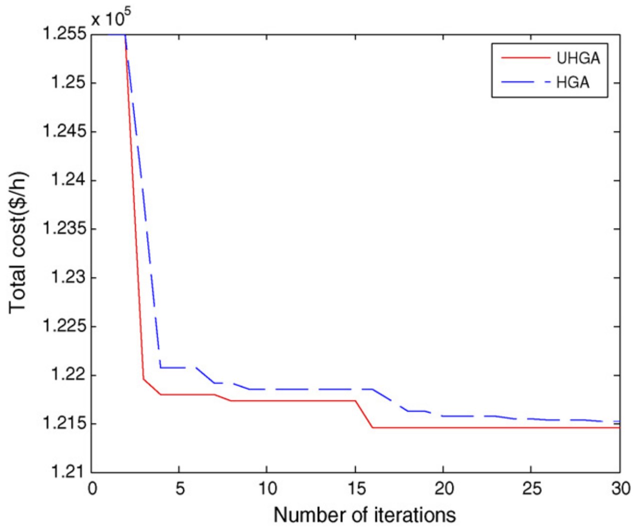

Fig. 3. Convergence characteristics of the UHGA and HGA for case 2 for a $P=10{,}500$ MW.

non-continuous. GA is an important tool for solving complex optimization problems, being applied to solve various problems in various diverse fields. It was also effectively used in solving complex problems in the power system field such as EDP.

GA is faster in finding the high performance region but displays difficulties in performing local search for complex functions. It leads to premature convergence and also has a poor fine tuning of the final solution. To overcome these drawbacks, GA was integrated with SQP. This technique is used to solve the EDP with incremental fuel-cost functions taking valve-point effects into account. SQP proves itself as a best non-linear programming method to solve the constrained optimization problem. The SQP can explore the search space quickly with a gradient direction and guarantee a local optimum solution. But the method is sensitive to the initial point. The hybrid approach for solving the EDP of units with value-point effects produces quality solutions as compared to the one produced by these techniques when applied separately.

It is advantaged to improve the performance of the SQP that the cost function of EDP is approximated by using a smooth and differentiable function based on the maximum entropy principle. An initial population obtained by using uniform design reflects the information of solution space scientifically and exerts optimal performance of the proposed hybrid algorithm.

The performance of the hybrid method was tested for two EDP test cases with valve-point effects included and compared with the results obtained using the methods reported in recent literature. The results show that the proposed UHGA performed much better than other methods compared in terms of convergence performance, minimum cost and probability of attaining better solutions.

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Appendix A. List of symbols

b	parameter that determines the degree of dependence on the number of generations
F	total production cost (US$)
$F_i(P_i)$	incremental fuel-cost function (US$ h^{-1})
gen	the maximum number of generations
N_P	number of generating units
P_D	the system load demand (MW)
P_i	real power output of the ith unit (MW)
$P_{i\,\min}/P_{i\,\max}$	minimum/maximum limit of the real power of the ith unit (MW)
P_i^{mut}	ith unit's new output after mutation (MW)
P_i^t	ith unit's output that is chosen to be mutated (MW)
P_{loss}	transmission loss (MW)
r	a random bit
t	the current generations

Greek letters

$\varphi(n+1)$	Euler function of $n+1$
ξ	a random floating-point number in the interval [0, 1]

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