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A niched Pareto genetic algorithm for multiobjective environmental/economic dispatch

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Abstract

A niched Pareto genetic algorithm (NPGA) based approach to solve the multiobjective environmental/economic dispatch (EED) problem is presented in this paper. The EED problem is formulated as a non-linear constrained multiobjective optimization problem. The proposed NPGA based approach handles the problem as a multiobjective problem with competing and non-commensurable cost and emission objectives. One of the main advantages of the proposed approach is that there is no restriction on the number of optimized objectives. The proposed approach has a diversity-preserving mechanism to overcome the premature convergence problem. A hierarchical clustering algorithm is developed and imposed to provide the decision maker with a representative and manageable Pareto-optimal set. In addition, fuzzy set theory is employed to extract the best compromise solution. Several optimization runs of the proposed approach are carried out on the standard IEEE 30-bus test system. The results demonstrate the capabilities of the proposed approach to generate well-distributed Pareto-optimal non-dominated solutions of the multiobjective EED problem in one single run. The comparison with the classical methods demonstrates the superiority of the proposed approach and confirms its potential to solve the multiobjective EED problem.

Keywords: Economic dispatch; Environmental impact; Multiobjective optimization; Evolutionary algorithms

1. Introduction

The basic objective of economic dispatch (ED) of electric power generation is to schedule the committed generating unit outputs so as to meet the load demand at minimum operating cost while satisfying all unit and system equality and inequality constraints. This makes the ED problem a large-scale highly non-linear constrained optimization problem. In addition, the increasing public awareness of the environmental protection and the passage of the Clean Air Act Amendments of 1990 have forced the utilities to modify their design or operational strategies to reduce pollution and atmospheric emissions of the thermal power plants.

Several strategies to reduce the atmospheric emissions have been proposed and discussed [1–3]. These include installation of pollutant cleaning equipment, 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 short-term alternative in which the emission in addition to the fuel cost objective are to be minimized. Thus, the ED problem can be handled as a multiobjective optimization problem with non-commensurable and contradictory objectives. In recent years, this option has received much attention [4–11] since it requires only small modification of the basic ED to include emissions.

Different techniques have been reported in the literature pertaining to environmental/economic dispatch (EED) problem. In Refs. [4,5] the problem has been reduced to a single objective problem by treating the emission as a constraint. This formulation, however, has a severe difficulty in getting the trade-off relations between cost and emission. Alternatively, minimizing the emission has been handled as another objective in addition to the cost. A linear programming based optimization procedures in which the objectives are considered one at a time was presented in Ref. [6]. However, many mathematical assumptions have to

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be given to simplify the problem. Furthermore, this approach does not give any information regarding the trade-offs involved.

In other research direction, the multiobjective EED problem was converted to a single objective problem by linear combination of different objectives as a weighted sum [7–10]. The important aspect of this weighted sum method is that a set of non-inferior (or Pareto-optimal) solutions can be obtained by varying the weights. Unfortunately, this requires multiple runs as many times as the number of desired Pareto-optimal solutions. Furthermore, this method cannot be used in problems having a non-convex Pareto-optimal front. To avoid this difficulty, the ε-constraint method was presented in Refs. [11–13]. This method optimizes the most preferred objective and considers the other objectives as constraints bounded by some allowable levels ε. The most obvious weaknesses of this approach are that it is time-consuming and tends to find weakly non-dominated solutions.

The recent direction is to handle both objectives simultaneously as competing objectives. A fuzzy multi-objective optimization technique for EED problem was proposed [14]. However, the solutions produced are sub-optimal and the algorithm does not provide a systematic framework for directing the search towards Pareto-optimal front. An evolutionary algorithm based approach evaluating the economic impacts of environmental dispatching and fuel switching was presented in Ref. [15]. However, some non-dominated solutions may be lost during the search process while some dominated solutions may be misclassified as non-dominated ones due to the selection process adopted. A fuzzy satisfaction-maximizing decision approach was successfully applied to solve the biobjective EED problem [16]. However, extension of the approach to include more objectives is a very involved question. A multiobjective stochastic search technique (MOSST) for the multiobjective EED problem was presented in Ref. [17]. However, the technique is computationally involved and time-consuming. In addition, there is no effort to avoid the search bias to some regions in the problem space that may result in premature convergence. This degrades the Pareto-optimal front and more efforts should be done to preserve the diversity of the non-dominated solutions.

Recently, the studies on evolutionary algorithms have shown that these methods can be efficiently used to eliminate most of the difficulties of classical methods [18–21]. Since they use a population of solutions in their search, multiple Pareto-optimal solutions can, in principle, be found in one single run. A non-dominated sorting genetic algorithm was presented for EED problem [22]. However, the technique is computationally involved due to ranking of all population members into different fronts.

In this paper, a niched Pareto genetic algorithm (NPGA) based approach is proposed to solve the EED optimization problem. The proposed approach has a diversity-preserving mechanism to find widely different Pareto-optimal solutions. A hierarchical clustering technique is implemented to provide the power system operator with a representative and manageable Pareto-optimal set. A fuzzy-based mechanism is employed to extract the best compromise solution. The potential of the proposed approach to handle the multiobjective EED problem is investigated. Several runs are carried out on a standard test system and the results are compared to the classical techniques. The effectiveness of the proposed approach to solve the multiobjective EED problem is demonstrated.

2. Problem formulation

The EED problem is to minimize two competing objective functions, fuel cost and emission, while satisfying several equality and inequality constraints. Generally the problem is formulated as follows.

2.1. Problem objectives

Minimization of fuel cost. The generator cost curves are represented by quadratic functions with sine components to represent the valve loading effects. The total \$/h fuel cost $F(P_G)$ can be expressed as

$$F(P_G) = \sum_{i=1}^{N} a_i + b_i P_{G_i} + c_i P_{G_i}^2 + \left| d_i \sin\left[e_i \left(P_{G_i}^{\min} - P_{G_i} \right) \right] \right| \tag{1}$$

where N is the number of generators, a_i, b_i, c_i, d_i, and e_i are the cost coefficients of the ith generator, and P_{G_i} is the real power output of the ith generator. P_G is the vector of real power outputs of generators and defined as

$$P_G = \left[P_{G_1}, P_{G_2}, \ldots, P_{G_N} \right]^T \tag{2}$$

Minimization of emission. The total ton/h emission $E(P_G)$ of atmospheric pollutants such as sulphur oxides SO_x and nitrogen oxides NO_x caused by fossil-fueled thermal units can be expressed as

$$E(P_G) = \sum_{i=1}^{N} 10^{-2} \left(\alpha_i + \beta_i P_{G_i} + \gamma_i P_{G_i}^2 \right) + \zeta_i \exp\left(\lambda_i P_{G_i} \right) \tag{3}$$

where α_i, β_i, γ_i, ζ_i, and λ_i are coefficients of the ith generator emission characteristics.

2.2. Problem constraints

Generation capacity constraint. For stable operation, real power output of each generator is restricted by lower and upper limits as follows:

$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max}, \qquad i = 1, \ldots, N \tag{4}$$

Power balance constraint. The total power generation must cover the total demand P_D and the real power loss in transmission lines P_{loss}. Hence,

$$\sum_{i=1}^{N} P_{\text{G}_i} - P_{\text{D}} - P_{\text{loss}} = 0 \tag{5}$$

Security constraints. For secure operation, the transmission line loading S_{l} is restricted by its upper limit as

$$S_{\text{l}_i} \le S_{\text{l}_i}^{\max}, \qquad i = 1, \ldots, n_{\text{l}} \tag{6}$$

where n_{l} is the number of transmission lines.

2.3. Problem statement

Aggregating the objectives and constraints, the problem can be mathematically formulated as a non-linear constrained multiobjective optimization problem as follows.

$$\underset{P_{\text{G}}}{\text{Minimize}} \ [F(P_{\text{G}}), E(P_{\text{G}})] \tag{7}$$

Subject to

$$g(P_{\text{G}}) = 0 \tag{8}$$

$$h(P_{\text{G}}) \le 0 \tag{9}$$

where g and h are the equality and inequality constraints, respectively.

3. Principles of multiobjective optimization

Many real-world problems involve simultaneous optimization of several objective functions. Generally, these functions are non-commensurable and often competing and conflicting objectives. Multiobjective optimization with such conflicting objective functions gives rise to a set of optimal solutions, instead of one optimal solution. The reason for the optimality of many solutions is that no one can be considered to be better than any other with respect to all objective functions. These optimal solutions are known as *Pareto-optimal* solutions.

A general multiobjective optimization problem consists of a number of objectives to be optimized simultaneously and is associated with a number of equality and inequality constraints. It can be formulated as follows

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

$$\text{Subject to}\ :\ \begin{cases} g_j(x) = 0 & j = 1, \ldots, M \\ h_k(x) \le 0 & k = 1, \ldots, K \end{cases} \tag{11}$$

where f_i is the ith objective functions, x is a decision vector that represents a solution, N_{obj} is the number of objectives. M and K are the numbers of equality and inequality constraints, respectively.

For a multiobjective optimization problem, any two solutions x^1 and x^2 can have one of two possibilities: one dominates the other or none dominates the other. In a minimization problem, without loss of generality, a solution x^1 dominates x^2 if the following two conditions are satisfied:

$$\forall i \in \{1, 2, \ldots, N_{\text{obj}}\} : f_i(x^1) \le f_i(x^2) \tag{12}$$

$$\exists j \in \{1, 2, \ldots, N_{\text{obj}}\} : f_j(x^1) < f_j(x^2) \tag{13}$$

If any of the above condition is violated, the solution x^1 does not dominate the solution x^2. If x^1 dominates the solution x^2, x^1 is called the non-dominated solution. The solutions that are non-dominated within the entire search space are denoted as *Pareto-optimal* and constitute the *Pareto-optimal set* or *Pareto-optimal front*.

4. The proposed approach

Recently, the studies on evolutionary algorithms have shown that these algorithms can be efficiently used to eliminate most of the difficulties of classical methods such as multiple runs and sensitivity to the shape of the Pareto-optimal front. In general, the goal of a multiobjective optimization algorithm is not only guide the search towards the Pareto-optimal front but also maintain population diversity in the set of the non-dominated solutions. Unfortunately, a simple GA tends to converge towards a single solution due to selection pressure, selection noise, and operator disruption [23].

To overcome these difficulties, the NPGA based approach is proposed in this work. The elements of the proposed approach can be described as follows.

4.1. Niched Pareto genetic algorithm

Horn et al. [24] proposed a tournament selection scheme based on Pareto dominance principles. Unlike the technique presented in Ref. [22], only two individuals are randomly selected for tournament. To find the winner solution, a comparison set that contains a number of other individuals in the population is randomly selected. Then, the dominance of both candidates with respect to the comparison set is tested. If one candidate only dominates the comparison set, he is selected as the winner. Otherwise, implement sharing procedure to specify the winner candidate. Generally, the tournament selection is carried out as follows.

Pareto domination tournaments. Consider a set of N population members, each having N_{obj} objective function values. The following procedure can be used to find the non-dominated set of solutions:

Step 1: Begin with $i = 1$.
Step 2: Pick randomly two candidates for selection x^1 and x^2.
Step 3: Pick randomly a comparison set of individuals from the population.
Step 4: Compare each candidate, x^1 and x^2, against each individual in the comparison set for domination using the conditions for domination given in Eqs. (12) and (13).

Step 5: If one candidate is dominated by the comparison set while the other is not, then select the later for reproduction and go to Step 7, else proceed to Step 6.
Step 6: If neither or both candidates are dominated by the comparison set, then use sharing to choose the winner.
Step 7: If $i = N$ is reached, stop selection procedure, else set $i = i + 1$ and go to Step 2.

Sharing procedure. To prevent the genetic drift problem, a form of sharing should be carried out when there is no preference between two candidates. This form of sharing maintains the genetic diversity along the population fronts and allows the GA to develop a reasonable representation of the Pareto-optimal front. Generally, the basic idea behind sharing is: the more individuals are located in the neighborhood of a certain individual, the more its fitness value is degraded [23,24].

The sharing procedure is performed in the following way for the candidate i:

Step 1: Begin with $j = 1$.
Step 2: Compute a normalized Euclidean distance measure with another individual j in the current population, as follows

$$d_{ij} = \sqrt{\sum_{k=1}^{N_{\text{obj}}} \left(\frac{J_k^i - J_k^j}{J_k^{\text{u}} - J_k^{\text{l}}} \right)^2} \tag{14}$$

where N_{obj} is the number of problem objectives. The parameters J_k^{u} and J_k^{l} are the upper and lower values of the kth objective function J_k.
Step 3: This distance d_{ij} is compared with a prespecified niche radius σ_{share} and the following sharing function value is computed as:

$$Sh(d_{ij}) = \begin{cases} 1 - \left(\dfrac{d_{ij}}{\sigma_{\text{share}}} \right)^2, & \text{if } d_{ij} \le \sigma_{\text{share}} \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

Step 4: Set $j = j + 1$. If $j \le N$, go to Step 2, else calculate niche count for the candidate i as follows:

$$m_i = \sum_{j=1}^{N} Sh(d_{ij}) \tag{16}$$

Step 5: Repeat the above steps for the second candidate.
Step 6: Compare m_1 and m_2. If $m_1 < m_2$, then choose the first candidate, else choose the second candidate.

4.2. Real-coded genetic algorithm (RCGA)

Due to difficulties of binary representation when dealing with continuous search space with large dimension, the proposed approach has been implemented using real-coded genetic algorithm (RCGA) [25]. A decision variable x_i is represented by a real number within its lower limit a_i and upper limit b_i, i.e. $x_i \in [a_i, b_i]$. The RCGA crossover and mutation operators are described as follows.

Crossover. A blend crossover operator (BLX-α) has been employed in this study. This operator starts by choosing randomly a number from the interval $[x_i - \alpha(y_i - x_i), y_i + \alpha(y_i - x_i)]$, where x_i and y_i are the ith parameter values of the parent solutions and $x_i < y_i$. To ensure the balance between exploitation and exploration of the search space, $\alpha = 0.5$ is selected. This operator can be depicted as shown in Fig. 1.

Mutation. The non-uniform mutation operator has been employed in this study. In this operator, the new value x_i' of the parameter x_i after mutation at generation t is given as

$$x_i' = \begin{cases} x_i + \Delta(t, b_i - x_i) & \text{if } \tau = 0 \\ x_i - \Delta(t, x_i - a_i) & \text{if } \tau = 1 \end{cases} \tag{17}$$

and

$$\Delta(t, y) = y\left(1 - r^{(1 - t/g_{\max})^{\beta}}\right) \tag{18}$$

where τ is a binary random number, r is a random number $r \in [0, 1]$, $g_{\max}$ is the maximum number of generations, and β is a positive constant chosen arbitrarily. In this study, $\beta = 5$ was selected. This operator gives a value $x_i' \in [a_i, b_i]$ such that the probability of returning a value close to x_i increases as the algorithm advances. This makes uniform search in the initial stages where t is small and vary locally at the later stages.

4.3. Reducing Pareto set by clustering

In some problems, the Pareto-optimal set can be extremely large or even contain an infinite number of solutions. In this case, reducing the set of non-dominated solutions without destroying the characteristics of the trade-off front is desirable from the decision maker's point of view. An average linkage based hierarchical clustering algorithm [26] is employed to reduce the Pareto set to manageable size. It works iteratively by joining the adjacent clusters until the required number of groups is obtained. It can be described as: given a set P whose size exceeds the maximum allowable size N, it is required to form a subset P^* with the size N. The algorithm is illustrated in the following steps.

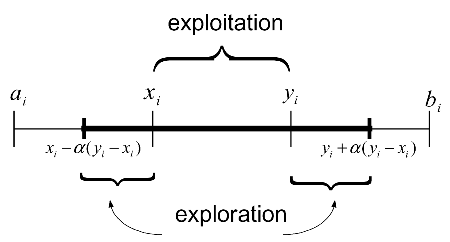

Fig. 1. Blend crossover operator (BLX-α).

Step 1: Initialize cluster set C; each individual $i \in P$ constitutes a distinct cluster.
Step 2: If number of clusters $\leq N$, then go to Step 5, else go to Step 3.
Step 3: Calculate the distance of all possible pairs of clusters. The distance d_c of two clusters c_1 and $c_2 \in C$ is given as the average distance between pairs of individuals across the two clusters

$$d_c = \frac{1}{n_1 n_2} \sum_{i_1 \in c_1, i_2 \in c_2} d(i_1, i_2) \tag{19}$$

where n_1 and n_2 are number of individuals in clusters c_1 and c_2, respectively. The function d reflects the distance in the objective space between individuals i_1 and i_2.
Step 4: Determine two clusters with minimal distance d_c. Combine these clusters into a larger one. Go to Step 2.
Step 5: Find the centroid of each cluster. Select the nearest individual in this cluster to the centroid as a representative individual and remove all other individuals from the cluster.
Step 6: Compute the reduced non-dominated set P^* by uniting the representatives of the clusters.

4.4. Best compromise solution

Upon having the Pareto-optimal set of non-dominated solution, the proposed approach presents one solution to the decision maker as the best compromise solutions. Due to imprecise nature of the decision maker's judgment, the ith objective function is represented by a membership function μ_i defined as [8]

$$\mu_i = \begin{cases} 1 & F_i \leq F_i^{\min} \\ \dfrac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}} & F_i^{\min} < F_i < F_i^{\max} \\ 0 & F_i \geq F_i^{\max} \end{cases} \tag{20}$$

For each non-dominated solution k, the normalized membership function μ^k is calculated as

$$\mu^k = \frac{\sum_{i=1}^{N_{\mathrm{obj}}} \mu_i^k}{\sum_{k=1}^{M} \sum_{i=1}^{N_{\mathrm{obj}}} \mu_i^k} \tag{21}$$

where M is the number of non-dominated solutions. The best compromise solution is the one having the maximum value of μ^k.

5. Implementation of the proposed approach

5.1. The basic modifications

In this study, the basic NPGA has been developed in order to make it suitable for solving real-world non-linear constrained optimization problems. The following modifications have been incorporated in the basic algorithm.

(a) To satisfy the problem constraints, a procedure is imposed to check the feasibility of the initial population individuals and the generated children through GA operations. This ensures the feasibility of Pareto-optimal solutions.
(b) A procedure for updating the Pareto-optimal set is developed. In every generation, the non-dominated solutions in the first front are combined with the existing Pareto-optimal set. The augmented set is processed to extract its non-dominated solutions that represent the updated Pareto-optimal set.
(c) A hierarchical clustering procedure based on the average linkage method is incorporated to provide the decision maker with a representative and manageable Pareto-optimal set without destroying the characteristics of the trade-off front.
(d) A fuzzy-based mechanism is employed to extract the best compromise solution over the trade-off curve and assist the decision maker to adjust the generation levels efficiently.

5.2. Settings of the proposed approach

The techniques used in this study were developed and implemented on 133 MHz PC using FORTRAN language. On all optimization runs, the population size and the maximum number of generations were selected as 200 and 500, respectively. The maximum size of the Pareto-optimal set was chosen as 50 solutions. If the number of the non-dominated Pareto-optimal solutions exceeds this bound, the clustering technique is called. Crossover and mutation probabilities were selected as 0.9 and 0.01, respectively, in all optimization runs.

6. Results and discussions

In this study, the standard IEEE 30-bus 6-generator test system is considered to investigate the effectiveness of the proposed approach. The single-line diagram of this system is shown in Fig. 2 and the detailed data are given in Refs. [6, 11]. The values of fuel cost and emission coefficients are given in Table 1.

Initially, the effect of comparison set size on the proposed approach performance is investigated. The effectiveness of the proposed approach to produce a representative Pareto-optimal front is examined for different sizes starting from a size of 5 to 75% of the population size. Fig. 3 shows the Pareto-optimal front with different comparison set sizes. It is clear that the performance is degraded with the increase of comparison set size. It was observed that 10%

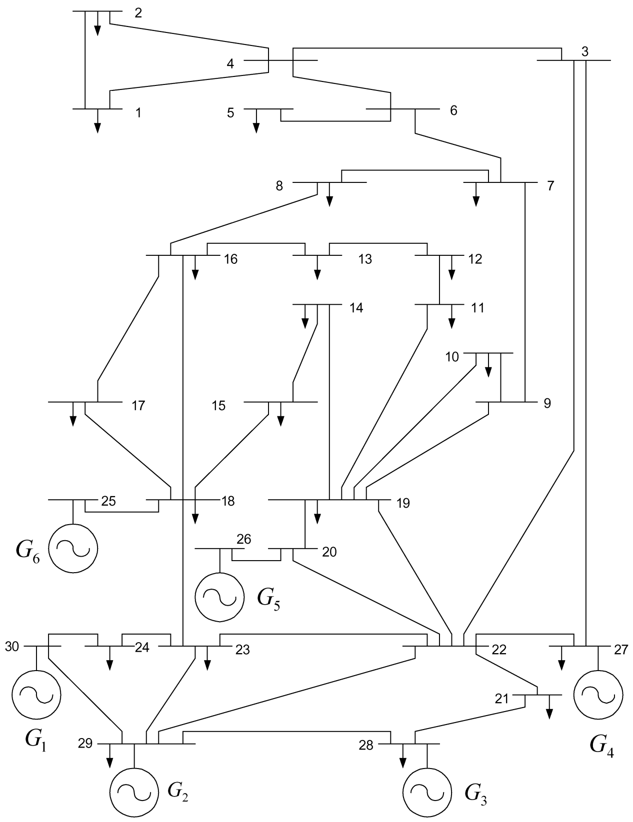

Fig. 2. Single-line diagram of IEEE 30-bus test system.

size gives a satisfactory performance of the proposed approach.

To demonstrate the potential of the proposed approach for different problem complexities and trade-off surfaces, two different cases have been considered as follows.

Case (a). For comparison purposes with the reported results, the system is considered as lossless and the security constrain is released. At first, fuel cost and emission are optimized individually to get the extreme points of the trade-off surface. Convergence of fuel cost and emission objectives are shown in Fig. 4. The best results of cost and emission when optimized individually are given in Table 2.

For completeness, the RCGA was applied to find the Pareto-optimal solutions where the problem was treated as a single objective optimization problem by linear combination of cost and emission objectives as follows

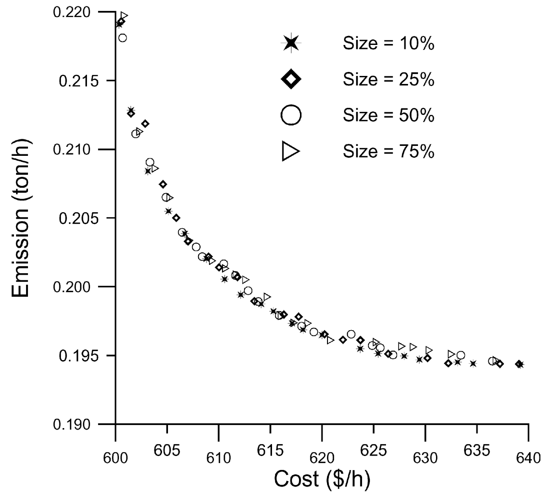

Fig. 3. Effect of the comparison set size on Pareto-optimal front.

$$\underset{P_G}{\text{Minimize}}\; wF(P_G) + (1-w)\lambda E(P_G) \tag{22}$$

where λ is a scaling factor which was selected as 3000 in this study and w is a weighting factor. To generate 50 non-dominated solutions, the algorithm was applied 50 times with varying w as a random number $w = \text{rand}[0,1]$. The Pareto-optimal front of RCGA is shown in Fig. 5. Applying the proposed NPGA based approach, the distribution of the non-dominated solutions in Pareto-optimal front is shown in Fig. 6. It is clear that the solutions are diverse and well distributed over the trade-off curve. Comparing Figs. 5 and 6, it can be concluded that, the non-dominated solutions of the proposed approach not only have better diversity characteristics but also were obtained in a single run.

The run time per generation of the single objective approach to produce only one solution was 14.22 s while that of the proposed approach to produce 50 solutions was 14.46 s. It is quiet evident that the proposed approach run time to generate the entire Pareto set is only 1.7% more than that of the aggregation method to generate only one solution. This demonstrates that the proposed approach is much faster and more efficient than the classical techniques in handling the multiobjective optimization problems.

The results of the proposed approach were compared to

Table 1
Generator cost and emission coefficients

		G_1	G_2	G_3	G_4	G_5	G_6
Cost	a	10	10	20	10	20	10
	b	200	150	180	100	180	150
	c	100	120	40	60	40	100
Emission	α	4.091	2.543	4.258	5.426	4.258	6.131
	β	-5.554	-6.047	-5.094	-3.550	-5.094	-5.555
	γ	6.490	5.638	4.586	3.380	4.586	5.151
	ζ	2.0×10^{-4}	5.0×10^{-4}	1.0×10^{-6}	2.0×10^{-3}	1.0×10^{-6}	1.0×10^{-5}
	λ	2.857	3.333	8.000	2.000	8.000	6.667

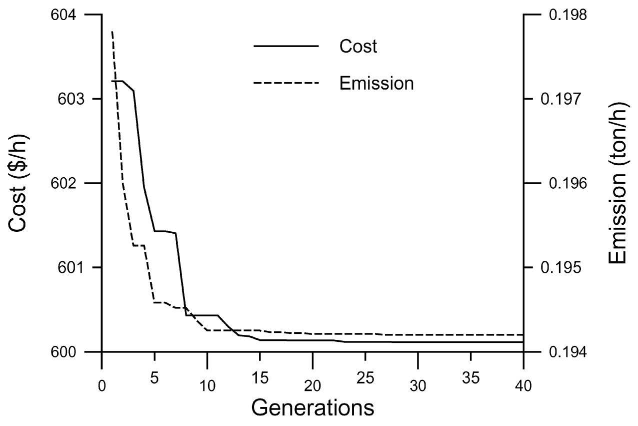

Fig. 4. Convergence of cost and emission objective functions of case (a).

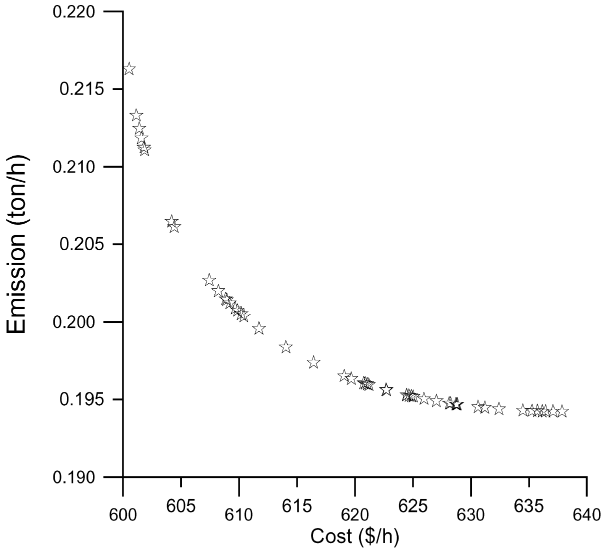

Fig. 5. Pareto-optimal front of objective aggregation in case (a).

those reported using linear programming (LP) [6] and MOSST [17]. The comparison is given in Tables 3 and 4. It is quite evident that the proposed approach gives better results.

Case (b). In this case, the power loss has been taken into account. Convergence of fuel cost and emission objectives when optimized individually are shown in Fig. 7. The best

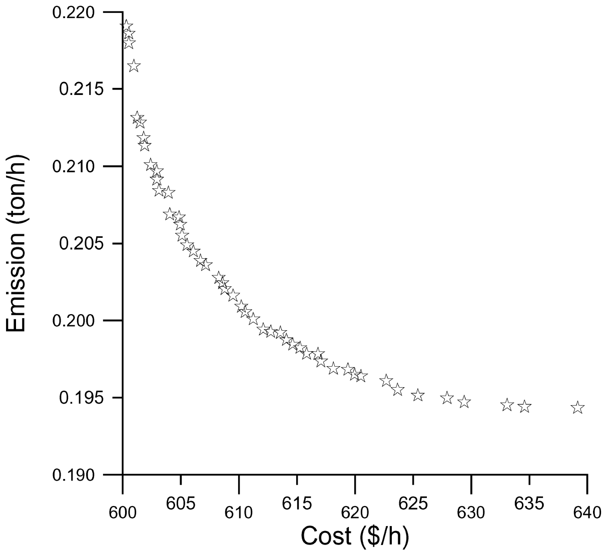

Fig. 6. Pareto-optimal front of the proposed approach in case (a).

results of cost and emission when optimized individually are given in Table 2. The values of the best cost and the best emission objectives with the proposed approach are given in Tables 3 and 4, respectively. The distribution of the non-dominated solutions of RCGA when applied for 50 times is shown in Fig. 8. The distribution of the non-dominated solutions of the proposed approach is shown in Fig. 9. It can be seen that the proposed approach preserves the diversity of the non-dominated solutions over the trade-off front and produce the non-dominated solutions in one single run.

Best compromise solution. The membership functions given in Eqs. (21) and (22) are used to evaluate each member of the Pareto-optimal set. Then, the best compromise solution that has the maximum value of membership function can be extracted. This procedure is applied in both cases and the best compromise solutions are given in Table 5.

7. Conclusion

In this paper, an approach based on the NPGA has been

Table 2
The best solutions for cost and emission optimized individually

	Case (a)		Case (b)	
	Best cost	Best emission	Best cost	Best emission
P_{G_1}	0.10954	0.40584	0.11516	0.41007
P_{G_2}	0.29967	0.45915	0.30552	0.46308
P_{G_3}	0.52447	0.53797	0.59724	0.54349
P_{G_4}	1.01601	0.38300	0.98088	0.38950
P_{G_5}	0.52469	0.53791	0.51421	0.54386
P_{G_6}	0.35963	0.51012	0.35417	0.51501
Fuel cost ($/h)	600.114	638.260	607.777	645.222
Emission (ton/h)	0.22214	0.19420	0.21985	0.19418

Table 3
Test results of best fuel cost of the proposed approach

	LP [6]	MOSST [17]	Proposed	
			Case (a)	Case (b)
P_{G_1}	0.1500	0.1125	0.1080	0.1245
P_{G_2}	0.3000	0.3020	0.3284	0.2792
P_{G_3}	0.5500	0.5311	0.5386	0.6284
P_{G_4}	1.0500	1.0208	1.0067	1.0264
P_{G_5}	0.4600	0.5311	0.4949	0.4693
P_{G_6}	0.3500	0.3625	0.3574	0.3993
Best cost	606.314	605.889	600.259	608.147
Corresp. emission	0.22330	0.22220	0.22116	0.22364

Table 4
Test results of best emission of the proposed approach

	LP [6]	MOSST [17]	Proposed	
			Case (a)	Case (b)
P_{G_1}	0.400	0.4095	0.4002	0.3923
P_{G_2}	0.4500	0.4626	0.4474	0.4700
P_{G_3}	0.5500	0.5426	0.5166	0.5565
P_{G_4}	0.4000	0.3884	0.3688	0.3695
P_{G_5}	0.5500	0.5427	0.5751	0.5599
P_{G_6}	0.5000	0.5142	0.5259	0.5163
Best emission	0.19424	0.19418	0.19433	0.19424
Corresp. cost	639.600	644.112	639.182	645.984

Table 5
Best compromise solutions of the proposed approach

	Case (a)	Case (b)
P_{G_1}	0.2696	0.2227
P_{G_2}	0.3673	0.3787
P_{G_3}	0.5594	0.5560
P_{G_4}	0.6496	0.7147
P_{G_5}	0.5396	0.5500
P_{G_6}	0.4486	0.4424
Cost	612.127	615.097
Emission	0.19941	0.20207

presented and applied to environmental/economic power dispatch optimization problem. The problem has been formulated as multiobjective optimization problem with competing fuel cost and environmental impact objectives. The proposed approach has a diversity-preserving mechanism to find widely different Pareto-optimal solutions. A hierarchical clustering technique is implemented to provide the operator with a representative and manageable Pareto-optimal set without destroying the characteristics of the trade-off front. Moreover, a fuzzy-based mechanism is employed to extract the best compromise solution over the trade-off curve. The results show that the proposed approach

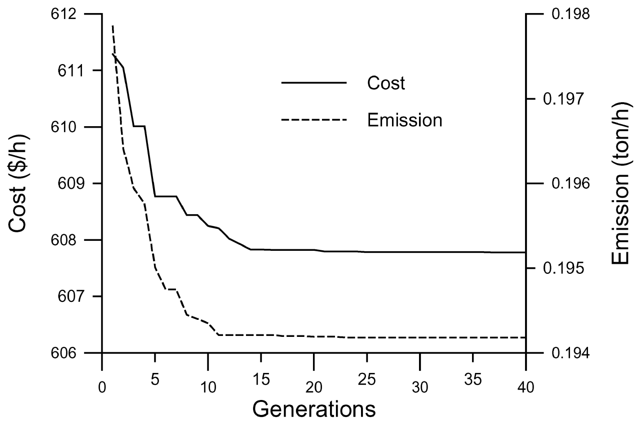

Fig. 7. Convergence of cost and emission objective functions of case (b).

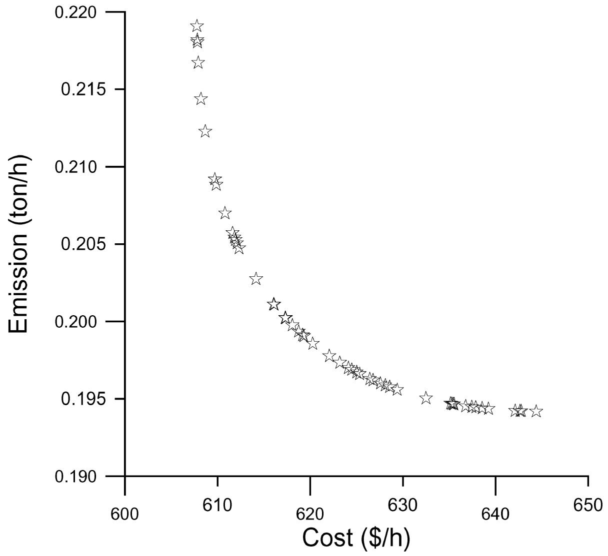

Fig. 8. Pareto-optimal front of objective aggregation in case (b).

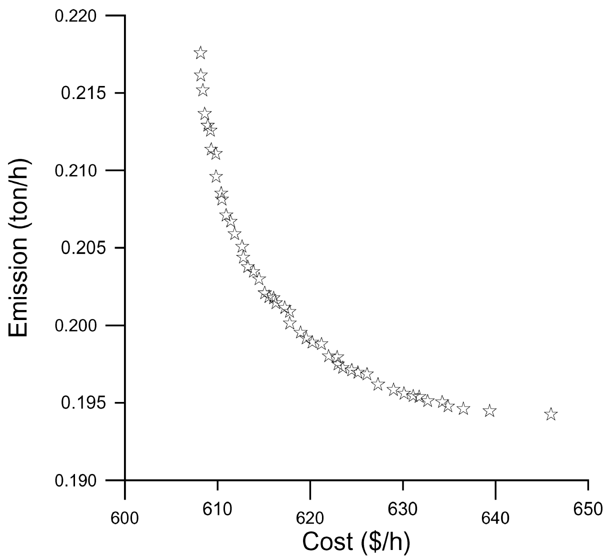

Fig. 9. Pareto-optimal front of the proposed approach in case (b).

is efficient for solving multiobjective optimization where multiple Pareto-optimal solutions can be found in one simulation run. In addition, the non-dominated solutions in the obtained Pareto-optimal set are well distributed and have satisfactory diversity characteristics. The most important aspect of the proposed approach is that any number of objectives can be considered.

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