Environmental/Economic Power Dispatch Using Multiobjective Evolutionary Algorithms

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***Abstract*—This paper presents a new multiobjective evolutionary algorithm for Environmental/Economic power Dispatch (EED) problem. The EED problem is formulated as a nonlinear constrained multiobjective optimization problem. A new Strength Pareto Evolutionary Algorithm (SPEA) based approach is proposed to handle the EED as a true multiobjective optimization problem with competing and noncommensurable objectives. The proposed approach employs a diversity-preserving mechanism to overcome the premature convergence and search bias problems. A hierarchical clustering algorithm is also imposed to provide the decision maker with a representative and manageable Pareto-optimal set. Moreover, fuzzy set theory is employed to extract the best compromise nondominated solution. Several optimization runs of the proposed approach have been carried out on a standard test system. The results demonstrate the capabilities of the proposed approach to generate well-distributed Pareto-optimal solutions of the multiobjective EED problem in one single run. The comparison with the classical techniques demonstrates the superiority of the proposed approach and confirms its potential to solve the multiobjective EED problem. In addition, the extension of the proposed approach to include more objectives is a straightforward process.**

***Index Terms*—Environmental/economic power dispatch, evolutionary algorithms, multiobjective optimization, strength pareto evolutionary algorithm.**

I. 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. 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 both emission and fuel cost is to be minimized. In recent years, this option has received much attention [4]–[8] since it requires only small modification of the basic economic dispatch to include emissions.

Different techniques have been reported in the literature pertaining to environmental/economic dispatch (EED) problem. In [4] the problem has been reduced to a single objective problem by treating the emission as a constraint with a permissible limit. 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 usual cost objective. A linear programming based optimization procedures in which the objectives are considered one at a time was presented in [5]. Unfortunately, the 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 or identify the global optimum. On the other hand, many mathematical assumptions such as analytic and differential objective functions have to be given to simplify the problem. Furthermore, this approach does not give any information regarding the trade-offs involved.

In other research direction, the EED problem was converted to a single objective problem by linear combination of different objectives as a weighted sum [6], [7]. The important aspect of this weighted sum method is that a set of noninferior (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 to find Pareto-optimal solutions in problems having a non-convex Pareto-optimal front. To avoid this difficulty, the ε-constraint method for multiobjective optimization was presented in [8], [9]. This method is based on optimizing the most preferred objective and considering the other objectives as constraints bounded by some allowable levels ε. These levels are then altered to generate the entire Pareto-optimal set. It is obvious that this approach is time-consuming and tends to find weakly nondominated solutions.

The recent direction is to handle both objectives simultaneously as competing objectives. A fuzzy multiobjective optimization technique for the EED problem was proposed [10]. However, the solutions produced are sub-optimal and the algorithm does not provide a systematic framework for directing the search toward Pareto-optimal front. An evolutionary algorithm based approach evaluating the economic impacts of environmental dispatching and fuel switching was

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presented in [11]. However, some of nondominated solutions may be lost during the search process while some of dominated solutions may be misclassified as nondominated ones due to the selection process adopted. A fuzzy satisfaction-maximizing decision approach was successfully applied to solve the EED problem [12]. However, extension of the approach to include more objectives is a very involved question. A multiobjective stochastic search technique for solving the problem was presented in [13]. However, the technique is computationally involved and time-consuming. In addition, the search bias to some regions may result in premature convergence, which degrades the Pareto-optimal front.

Over the past few years, the studies on evolutionary algorithms have shown that these methods can be efficiently used to eliminate most of the difficulties of classical methods [14]. Since they are population-based techniques, multiple Pareto-optimal solutions can, in principle, be found in one single run. A genetic algorithm-based multiobjective technique was presented in [15] where multiple nondominated solutions can be obtained in a single run. However, the problem has been considerably simplified. In addition, the presented technique is computationally involved due to ranking process during the fitness assignment procedure.

In this paper, a new Strength Pareto Evolutionary algorithm (SPEA) based approach is proposed for solving the multiobjective EED optimization problem. The diversity-preserving mechanism embedded in the search algorithm makes it effective in exploring the problem space and capable of finding widely different nondominated solutions. A hierarchical clustering technique is implemented to provide the system operator with a representative and manageable Pareto-optimal set. In addition, a fuzzy-based mechanism is employed to extract the best compromise solution. Several runs are carried out on the standard IEEE test system and the results are compared to the classical techniques. The effectiveness and potential of the proposed approach to solve the multiobjective EED problem are demonstrated.

II. Problem Statement

The environmental/economic power dispatch 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.

A. Problem Objectives

Minimization of Fuel Cost: The generators cost curves are represented by quadratic functions with sine components. The superimposed sine components represent the rippling effects produced by the steam admission valve openings [16]. The total $/h fuel cost $F(P_G)$ can be expressed as

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

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_{Gi} is the real power output of the ith generator. P_G is the vector of real power outputs of generators and defined as

$$P_G = [P_{G_1}, P_{G_2}, \ldots, P_{G_N}]^T \quad (2)$$

Minimization of Emission: The atmospheric pollutants such as sulpher oxides SO_x and nitrogen oxides NO_x caused by fossil-fueled thermal units can be modeled separately. However, for comparison purposes, the total *ton/h* emission $E(P_G)$ of these pollutants can be expressed as [5], [8], [13]

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

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

B. Objective Constraints

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

$$P_{G_i}^{\min} \leq P_{G_i} \leq P_{G_i}^{\max}, \quad i = 1, \ldots, N \quad (4)$$

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,

$$\sum_{i=1}^{N} P_{G_i} - P_D - P_{loss} = 0 \quad (5)$$

Security constraints: for secure operation, the transmission line loading S_l is restricted by its upper limit as:

$$S_{l_i} \leq S_{l_i}^{\max}, \quad i = 1, \ldots, nl \quad (6)$$

where nl is the number of transmission lines.

C. Problem Formulation

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

$$\underset{P_G}{\text{Minimize}} \quad [F(P_G), E(P_G)] \quad (7)$$

$$\text{subject to:} \quad g(P_G) = 0 \quad (8)$$

$$h(P_G) \leq 0 \quad (9)$$

where g and h are the problem constraints.

III. Principle of Multiobjective Optimization

Many real-world problems involve simultaneous optimization of several objective functions. Generally, these functions are noncommensurable 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:

$$\underset{x}{\text{Minimize}}\ f_1(x) \quad i = 1, \ldots, N_{\text{obj}} \tag{10}$$

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

where f_i is the ith objective functions, x is a decision vector that represents a solution, N_{obj} is the number of objectives.

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

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

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

If any of the above conditions 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 nondominated solution. The solutions that are nondominated within the entire search space are denoted as *Pareto-optimal* and constitute the *Pareto-optimal set.* This set is also known as *Pareto-optimal front*.

IV. Proposed Approach

A. Overview

Recently, the studies on evolutionary algorithms have shown that these algorithms can be efficiently used to eliminate most of the difficulties of classical methods which can be summarized as:

- An algorithm has to be applied many times to find multiple Pareto-optimal solutions.
- Most algorithms demand some knowledge about the problem being solved.
- Some algorithms are sensitive to the shape of the Pareto-optimal front.
- The spread of Pareto-optimal solutions depends on efficiency of the single objective optimizer.

In general, the goal of a multiobjective optimization algorithm is not only to guide the search toward the Pareto-optimal front but also to maintain population diversity in the set of the nondominated solutions. Unfortunately, a simple genetic algorithm (GA) tends to converge toward a single solution due to selection pressure and operator disruption [17].

B. Strength Pareto Evolutionary Algorithm (SPEA)[18]

The basic elements of the SPEA technique are briefly stated and defined as follows:

- *External set:* It is a set of Pareto optimal solutions. These solutions are stored externally and updated continuously. Ultimately, the solutions stored in this set represent the Pareto optimal front.
- *Strength of a Pareto optimal solution:* It is an assigned real value $s \in [0, 1)$ for each individual in the external set. The strength of an individual is proportional to the number of individuals covered by it.
- *Fitness of population individuals:* The fitness of each individual in the population is the sum of the strengths of all external Pareto optimal solutions by which it is covered. It is worth mentioning that, unlike the technique presented in [15], the fitness of a population member is determined only from the individuals stored in the external set. This reduces significantly the computational burden of the fitness assignment process. It is worth mentioning that the strength of a Pareto optimal solution is at the same time its fitness.

Generally, the algorithm can be described in the following steps.

Step 1) **(Initialization)**: Generate an initial population and create the empty external Pareto-optimal set.

Step 2) **(External set updating):** The external Pareto-optimal set is updated as follows.

  a) Search the population for the nondominated individuals and copy them to the external Pareto set.
  b) Search the external Pareto set for the nondominated individuals and remove all dominated solutions from the set.
  c) If the number of the individuals externally stored in the Pareto set exceeds a prespecified maximum size, reduce the set by means of clustering.

Step 3) **(Fitness assignment):** Calculate the fitness values of individuals in both external Pareto set and the population as follows.

  a) Assign the strength s for each individual in the external set. The strength is proportional to the number of individuals covered by that individual.
  b) The fitness of each individual in the population is the sum of the strengths of all external Pareto solutions which dominate that individual. A small positive number is added to the resulting sum to guarantee that Pareto solutions are most likely to be produced.

Step 4) **(Selection)**: Combine the population and the external set individuals. Select two individuals at random and compare their fitness.

Select the better one and copy it to the mating pool.

Step 5) **(Crossover and Mutation)**: Perform the crossover and mutation operations according to their probabilities to generate the new population.

Step 6) **(Termination)**: Check for stopping criteria. If any one is satisfied *then* stop *else* copy new population to old population and go to Step 2. In this study, the search will be stopped if the generation counter exceeds its maximum number.

C. 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 nondominated 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 [19] 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 which its 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.

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

$$d_c = \frac{1}{n_1 \cdot n_2} \sum_{i_1 \in c_1,\ i_2 \in c_2} d(i_1, i_2) \tag{14}$$

where n_1 and n_2 are the numbers of individuals in clusters c_1 and c_2 respectively. The function d reflects the Euclidian 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) For each cluster, find the centroid and select the nearest individual to the centroid as a representative and remove all other individuals from the cluster.

Step 6) Compute the reduced nondominated set P^* by uniting the representatives of the clusters.

D. Best Compromise Solution

Upon having the Pareto-optimal set of nondominated solution, the proposed approach presents one solution to the decision maker as the best compromise solution. Due to imprecise nature of the decision maker's judgment, each objective function of the i-th solution is represented by a membership function μ_i defined as [6]

$$\mu_i = \begin{cases} 1 & F_i \leq F_i^{\min} \\ \frac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}} & F_i^{\min} \leq F_i \leq F_i^{\max} \\ 0 & F_i \geq F_i^{\max} \end{cases}. \tag{15}$$

For each nondominated solution k, the normalized membership function μ^k is calculated as

$$\mu^k = \frac{\sum_{i=1}^{N_{\text{obj}}} \mu_i^k}{\sum_{k=1}^{M} \sum_{i=1}^{N_{\text{obj}}} \mu_i^k} \tag{16}$$

where M is the number of nondominated solutions. The best compromise solution is the one having the maximum of μ^k.

V. Implementation of the Proposed Approach

A. Real-Coded Genetic Algorithm

Due to difficulties of binary representation when dealing with continuous search space with large dimensions, the proposed approach has been implemented using real-coded genetic algorithm (RCGA) [20]. 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 $x_i < y_i$. In order 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 nonuniform mutation has been employed in this study. In this operator, the new value x_i' of the parameter x_i after mutation at generation at time 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 very locally at the later stages.

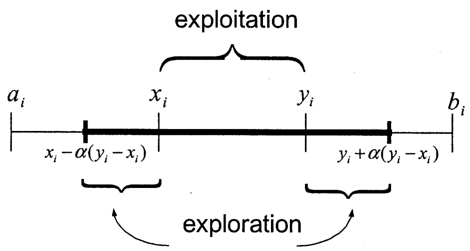

Fig. 1. Blend crossover operator (BLX-α).

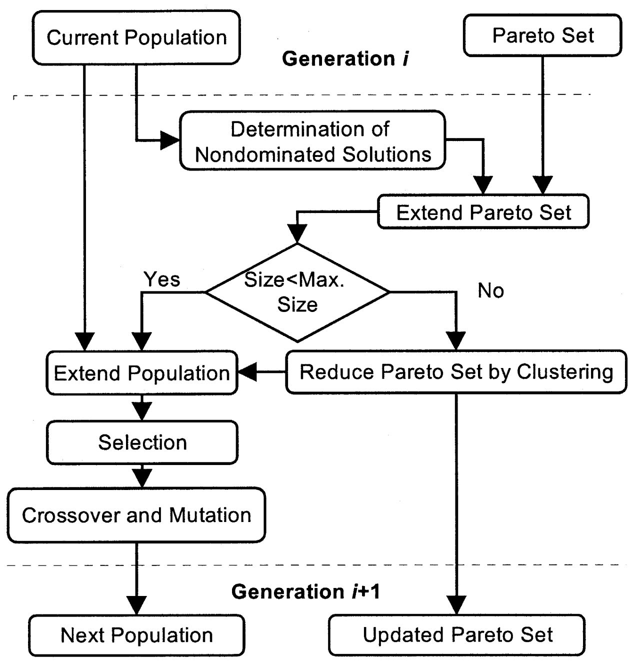

Fig. 2. Strength pareto evolutionary algorithm.

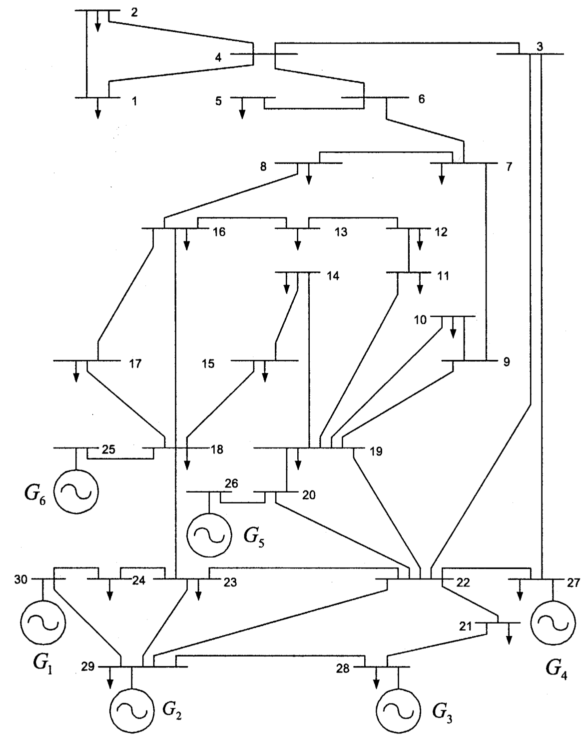

Fig. 3. Single-line diagram of IEEE 30-bus test system.

TABLE I
GENERATOR FUEL 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	2.0E-4	5.0E-4	1.0E-6	2.0E-3	1.0E-6	1.0E-5
	λ	2.857	3.333	8.000	2.000	8.000	6.667

B. The Computational Flow

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

a) 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 nondominated solutions.
b) A procedure for updating the Pareto-optimal set is developed. In every generation, the nondominated solutions in the first front are combined with the existing Pareto-optimal set. The augmented set is processed to extract the nondominated solutions that represent the updated Pareto-optimal set.
c) 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.

The computational flow chart of the proposed approach is shown in Fig. 2.

C. 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 20 solutions. If the number of nondominated Pareto optimal solutions exceeds this bound, the clustering technique is used. The crossover and mutation probabilities were selected as 0.9 and 0.01, respectively in all optimization runs.

VI. RESULTS AND DISCUSSIONS

Having been applied for the first time, the proposed approach was tested on the standard IEEE 30-bus 6-generator test system in order to investigate its effectiveness. The single-line diagram of the IEEE test system is shown in Fig. 3 and the detailed data are given in [5], [8]. The values of fuel cost and emission coefficients are given in Table I.

To demonstrate the effectiveness of the proposed approach, three different cases have been considered as follows:

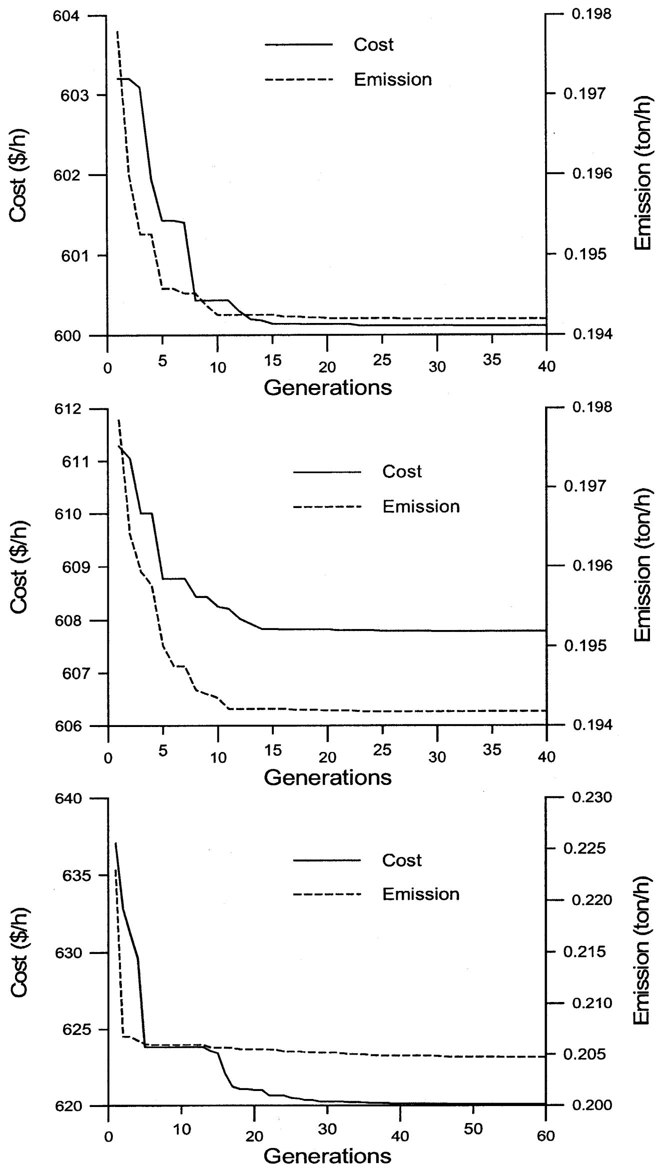

Fig. 4. Convergence of cost and emission objective functions. (a) Case 1. (b) Case 2. (c) Case 3.

Case 1) Only the generation capacity constraint is considered.

Case 2) The power balance constraint is also considered.

Case 3) All constraints are considered.

At first, fuel cost and emission objectives are optimized individually in order to explore the extreme points of the trade-off surface and evaluate the diversity characteristics of the Pareto optimal solutions obtained by the proposed approach. The best results of cost and emission functions when optimized individually are given in Table II. Convergence of fuel cost and emission objectives are shown in Fig. 4.

Case 1: For the purpose of comparison with the reported results, the system is considered as lossless and the security constrain is released. The problem was handled as a multiobjective optimization problem where both cost and emission were optimized simultaneously with the proposed approach. The diversity of the Pareto optimal set over the trade-off surface is shown in Fig. 5. It is worth mentioning that the Pareto optimal set has 20 nondominated solutions. Out of them, two nondominated solutions that represent the best cost and best emission are given in Table III. The results of the proposed approach were compared to those reported using linear programming [5] and multiobjective stochastic search technique [13]. The comparison results are given in Table III. It can be seen that the savings with the proposed approach in the fuel cost are about 5 to 6 $/hr. This demonstrates the potential and effectiveness of the proposed approach to solve multiobjective optimization problems. It can be concluded that the proposed approach is capable of exploring more efficient and noninferior solutions of multiobjective optimization problems.

TABLE II
THE BEST SOLUTIONS FOR COST AND EMISSION OPTIMIZED INDIVIDUALLY

	Case 1		***Case 2***		***Case 3***	
	Cost	*Emission*	*Cost*	*Emission*	*Cost*	*Emission*
P_{G1}	0.1095	0.4058	0.1152	0.4101	0.1375	0.4921
P_{G2}	0.2997	0.4592	0.3055	0.4631	0.3246	0.5419
P_{G3}	0.5245	0.5380	0.5972	0.5435	0.8075	0.6598
P_{G4}	1.0160	0.3830	0.9809	0.3895	0.9792	0.5182
P_{G5}	0.5247	0.5379	0.5142	0.5439	0.1000	0.1267
P_{G6}	0.3596	0.5101	0.3542	0.5150	0.5163	0.5289
Cost	**600.11**	638.26	**607.78**	645.22	**620.09**	654.01
Emission	0.2221	**0.1942**	0.2199	**0.1942**	0.2297	**0.2046**

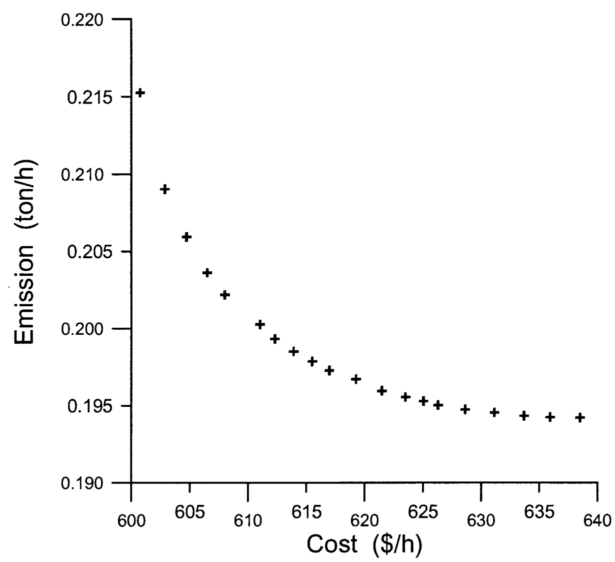

Fig. 5. Pareto-optimal front of the proposed approach in a single run, Case 1.

TABLE III
TEST RESULTS OF BEST COST AND BEST EMISSION OF CASE 1 OF THE PROPOSED APPROACH

	Best Cost			***Best Emission***		
	LP [5]	*MOSST* [13]	*Prop. Case* 1	*LP* [5]	*MOSST* [13]	*Prop. Case* 1
P_{G1}	0.1500	0.1125	0.1062	0.4000	0.4095	0.4116
P_{G2}	0.3000	0.3020	0.2897	0.4500	0.4626	0.4532
P_{G3}	0.5500	0.5311	0.5289	0.5500	0.5426	0.5329
P_{G4}	1.0500	1.0208	1.0025	0.4000	·0.3884	0.3832
P_{G5}	0.4600	0.5311	0.5402	0.5500	0.5427	0.5383
P_{G6}	0.3500	0.3625	0.3664	0.5000	0.5142	0.5148
Cost	**606.31**	**605.89**	**600.15**	639.60	644.11	638.51
Emission	0.2233	0.2222	0.2215	**0.1942**	**0.1942**	**0.1942**

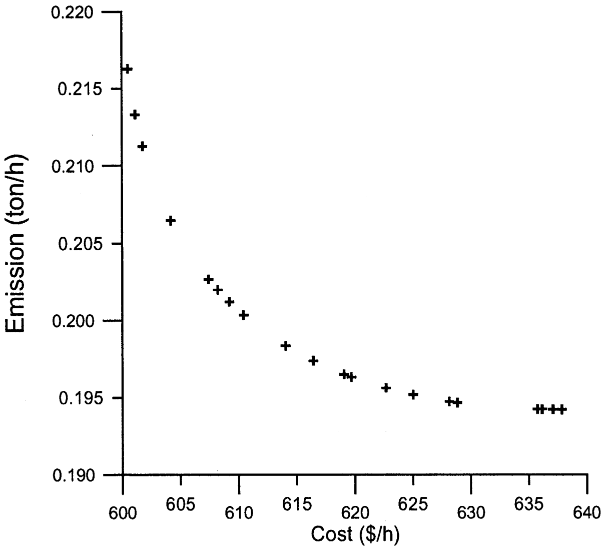

Fig. 6. Pareto-optimal front of linear combination in 20 separate runs, Case 1.

For completeness and comparison purposes, the problem was also treated as a single objective optimization problem by linear combination of cost and emission objectives as follows:

$$\underset{P_G}{\text{Minimize}} \quad wF(P_G) + (1-w)\lambda E(P_G) \tag{19}$$

where the scaling factor λ was selected as 3000 in this study and w is a weighting factor. To generate 20 nondominated solutions, the algorithm was applied 20 times with varying w as a random number $w = \text{rand}[0, 1]$. The Pareto-optimal front of the single objective problem in case 1 is shown in Fig. 6. Comparing the results shown in Figs. 5 and 6, it can be concluded that: **(a)** The 20 solutions shown in Fig. 5 that represent the results of the proposed technique have been obtained in a single run while the solutions shown in Fig. 6 have been obtained in 20 separate runs; **(b)** the solutions of the proposed approach shown in Fig. 5 have better diversity characteristics and well-distributed over the entire trade-off surface; **(c)** there is no guarantee that the single objective optimizer will span over the entire trade-off surface while the proposed approach has an embedded diversity preserving mechanism through fitness assignment procedure.

It is worth mentioning that 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 20 solutions was 14.74 s. It is quiet evident that the proposed approach run time to generate the entire Pareto set is only 3.7% 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.

Case 2: In this case, the transmission power loss has been taken into account. Out of the 20 nondominated solutions in the Pareto optimal set, two nondominated solutions that represent the best cost and best emission are given in Table IV. The distribution of the nondominated solutions obtained in a single run of the proposed approach is shown in Fig. 7. The distribution of the nondominated solutions of the single objective problem for case 2 when solved for 20 times is shown in Fig. 8. It can be seen that the proposed approach is superior and preserves the diversity of the nondominated solutions over the trade-off front.

TABLE IV
TEST RESULTS OF BEST COST AND BEST EMISSION OF CASES 2 & 3 OF THE PROPOSED APPROACH

	Best Cost		***Best Emission***	
	Case 2	*Case* 3	*Case* 2	*Case* 3
P_{G1}	0.1086	0.15975	0.4043	0.47975
P_{G2}	0.3056	0.35339	0.4525	0.52868
P_{G3}	0.5818	0.79600	0.5525	0.67109
P_{G4}	0.9846	0.97176	0.4079	0.53174
P_{G5}	0.5288	0.08684	0.5468	0.12571
P_{G6}	0.3584	0.49709	0.5005	0.53010
Cost	**607.807**	**620.165**	642.603	651.633
Emission	0.22015	0.22826	**0.19422**	**0.20470**

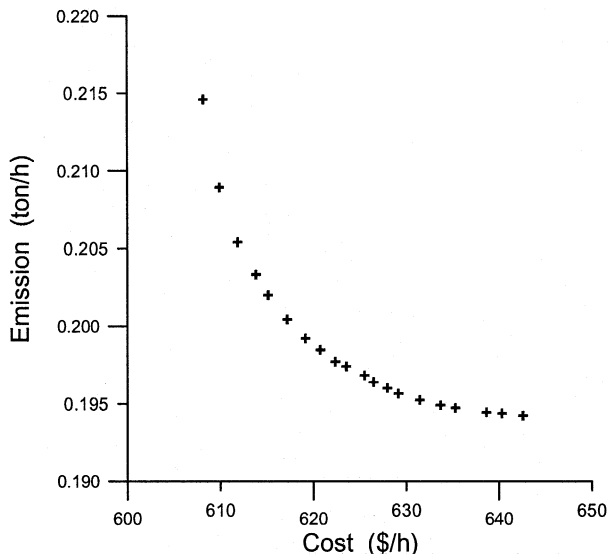

Fig. 7. Pareto-optimal front of the proposed approach in a single run, Case 2.

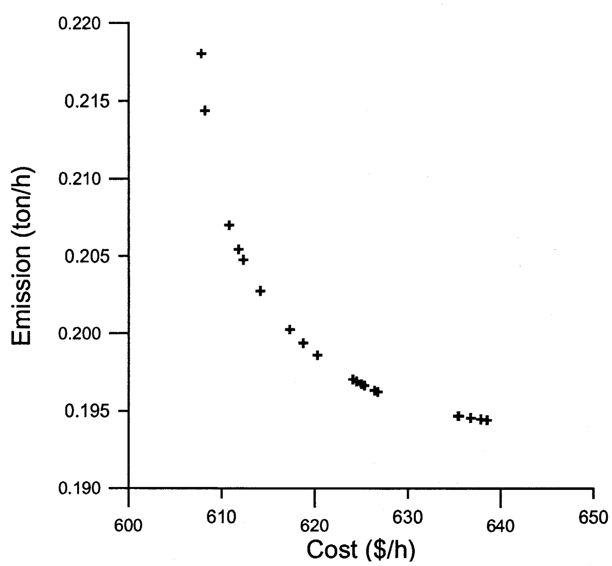

Fig. 8. Pareto-optimal front of linear combination in 20 separate runs, Case 2.

Case 3: In this case, all constraints have been taken into account including security constraints. The maximum line flow capacities used in this case are 115% of the standard values

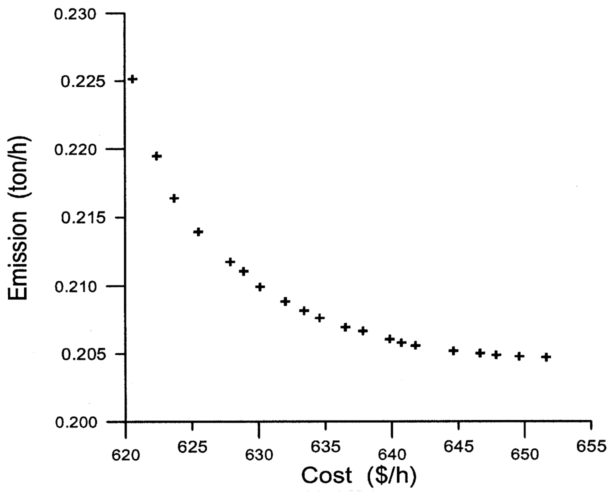

Fig. 9. Pareto-optimal front of the proposed approach in a single run, Case 3.

TABLE V
BEST COMPROMISE SOLUTION OF THE PROPOSED APPROACH

	Case 1	*Case* 2	*Case* 3
P_{G1}	0.2785	0.2594	0.2996
P_{G2}	0.3764	0.3848	0.4474
P_{G3}	0.5300	0.5645	0.7327
P_{G4}	0.6931	0.7030	0.7284
P_{G5}	0.5406	0.5431	0.1197
P_{G6}	0.4153	0.4091	0.5364
Cost ($/h)	610.254	616.069	629.394
Emission (ton/h)	0.20055	0.20118	0.21043

# of Obj	*Case* 1		*Case* 2		*Case* 3	
	Cost	*Emission*	*Cost*	*Emission*	*Cost*	*Emission*
Single	600.11	0.1942	607.78	0.1942	620.09	0.2046
Multi	600.15	0.1942	607.81	0.1942	620.17	0.2047

given in [8]. The values of the best cost and the best emission objectives with the proposed approach are given in Table IV. The distribution of 20 nondominated solutions obtained in a single run of the proposed approach is shown in Fig. 9. It can be seen that the proposed approach preserves the diversity of the nondominated solutions over the trade-off front and solve effectively the problem with all constraints considered.

Best compromise solution The membership functions given in (15) and (16) 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 all cases and the best compromise solutions are given in Table V.

Table VI gives a comparison between the results of single objective optimization given in Table II and that of multiobjective optimization given in Tables III and IV. It is clear that the results in all cases are almost identical. This demonstrates that the search of the proposed approach span over the entire trade-off surface. In addition, the close agreement of the results shows clearly the capability of the proposed approach to handle multiobjective optimization problems as the best solution of each objective along with a manageable set of nondominated solutions can be obtained in one single run.

TABLE VI
BEST SOLUTIONS FOR COST AND EMISSION

# of Obj	*Case* 1		*Case* 2		*Case* 3	
	Cost	*Emission*	*Cost*	*Emission*	*Cost*	*Emission*
Single	600.11	0.1942	607.78	0.1942	620.09	0.2046
Multi	600.15	0.1942	607.81	0.1942	620.17	0.2047

VII. CONCLUSION

In this paper, a novel approach based on the Strength Pareto Evolutionary algorithm has been 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. A diversity-preserving mechanism is developed 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 is efficient for solving multiobjective optimization where multiple Pareto-optimal solutions can be found in one simulation run. In addition, the nondominated solutions in the obtained Pareto-optimal set are well distributed and have satisfactory diversity characteristics. Since the proposed approach does not impose any limitation on the number of objectives, its extension to include more objectives, such as stability and security, is a straightforward process.

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