A NOVEL MULTIOBJECTIVE EVOLUTIONARY ALGORITHM FOR SOLVING ENVIRONMENTAL/ECONOMIC DISPATCH PROBLEM

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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 problem as a true multiobjective problem with competing and non-commensurable 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. The proposed approach is applied to the IEEE 30-bus 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.**

Keywords: Environmental/Economic dispatch, 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. 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 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 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 towards Pareto-optimal front. An evolutionary algorithm based approach evaluating the economic impacts of environmental dispatching and fuel switching was 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.

In this paper, a new Strength Pareto Evolutionary algorithm (SPEA) based approach is proposed for solving the multiobjective EED optimization problem. A diversity-preserving mechanism is developed and imposed on the search algorithm to find widely different nondominated solutions. In addition, a hierarchical clustering technique is implemented to provide the system operator with a representative and manageable Pareto-optimal set. Moreover, a fuzzy-based mechanism is employed to extract the best compromise solution. Several runs are carried out on a standard 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.

2 PROBLEM FORMULATION

The environmental/economic 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.

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 [15]. The total *\$/h* fuel cost $F(P_G)$ can be expressed as

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

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

$$P_G=[P_{G_1},P_{G2},...,P_{G_N}]^T \quad (2)$$

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

$$E(P_G)=\sum_{i=1}^{N} 10^{-2}(\alpha_i+\beta_iP_{G_i}+\gamma_iP_{G_i}^2)+\zeta_i\exp(\lambda_iP_{G_i}) \quad (3)$$

where α_i, β_i, γ_i, ζ_i, and λ_i are coefficients of the i^{th} 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:

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

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:

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

where nl is the number of transmission lines.

2.3 Problem Formulation

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

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

subject to:

$$g(P_G)=0 \quad (8)$$

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

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:

$$\underset{x}{Minimize}\quad f_i(x)\quad i=1,...,N_{obj} \quad (10)$$

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

where f_i is the i^{th} 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 iff the following two conditions are satisfied:

1. $\forall i \in \{1, 2, ..., N_{obj}\} : f_i(x^1) \leq f_i(x^2)$ (12)
2. $\exists j \in \{1, 2, ..., N_{obj}\} : f_j(x^1) < f_j(x^2)$ (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 nondominated solution. The solutions that are nondominated within the entire search space are denoted as *Pareto-optimal* and constitute the *Pareto-optimal set* or *Pareto-optimal front*.

4 THE PROPOSED APPROACH

4.1 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.

It is worth mentioning that 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 nondominated solutions. Unfortunately, a simple GA tends to converge towards a single solution due to selection pressure, selection noise, and operator disruption [16].

4.2 Strength Pareto Evolutionary Algorithm (SPEA)

Similar to other multiobjective evolutionary algorithms, SPEA has the following features [17]: -

- It stores those individuals externally that represent a nondominated front among all solutions considered so far.
- It uses the concept of Pareto dominance in order to assign scalar fitness values to individuals.
- It performs clustering to reduce the number of individuals externally stored without destroying the characteristics of the trade-off front.

On the other hand, SPEA is unique in the following aspects: -

- Unlike the presented technique in [18], the fitness of a population member is determined only from the individuals stored in the external set.
- All individuals in the external set participate in selection.
- A new Pareto-based niching method is provided in order to preserve diversity in the population.

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 the 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 a real value $s \in [0,1)$ called strength for each individual in the Pareto optimal set. The strength of an individual is proportional to the number of individuals covered by it. The strength of a Pareto solution is at the same time its fitness.

(b) The fitness of each individual in the population is the sum of the strengths of all external Pareto solutions by which it is covered. In order to guarantee that Pareto solutions are most likely to be produced, a small positive number is added to the resulting value.

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 7 (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.

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 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 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

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

where n_1 and n_2 are the number of individuals in the 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 nondominated set P^* by uniting the representatives of the clusters.

4.4 Best Compromise Solution

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

$$\mu_i = \begin{cases} 1 & F_i \leq F_i^{\min} \\ \dfrac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}} & F_i^{\min} < F_i < F_i^{\max} \\ 0 & F_i \geq F_i^{\max} \end{cases} \qquad (15)$$

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

$$\mu^k = \frac{\sum_{i=1}^{N_{obj}} \mu_i^k}{\sum_{k=1}^{M} \sum_{i=1}^{N_{obj}} \mu_i^k} \qquad (16)$$

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

5 IMPLEMENTATION OF THE PROPOSED APPROACH

5.1 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) [19]. 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 i^{th} 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

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

and;

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

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.

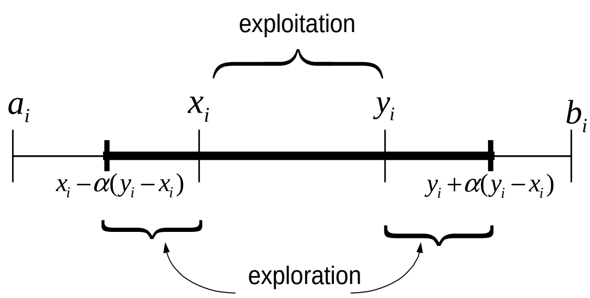

Figure 1: Blend crossover operator (BLX-α)

5.2 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 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.
- A procedure for updating the Pareto-optimal set is developed. In every generation, the nondominated solutions in the Pareto-optimal front are combined with the existing Pareto-optimal set. The augmented set is processed to extract its nondominated solutions that represent the updated Pareto-optimal set.
- 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 of the proposed approach between two consecutive generations is shown in Fig. 2.

5.3 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 nondominated 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.

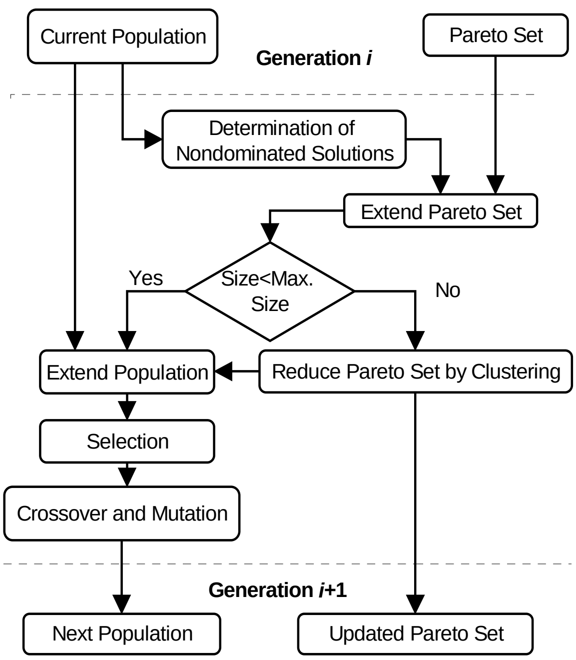

Figure 2: Strength Pareto Evolutionary Algorithm

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. 3 and the detailed data are given in [5,7]. The values of fuel cost and emission coefficients are given in Table 1.

For comparison purposes with the reported literature, 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. Convergences of fuel cost and emission objective functions are shown in Fig. 5. 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:

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

where λ is a scaling factor which was selected as 3000 in this study and w is a weighting factor. To generate 50 nondominated solutions, the algorithm was applied 50 times with varying w as a random number w = *rand*[0,1]. The Pareto-optimal front of RCGA is shown in Fig. 6. Applying the proposed SPEA based approach; the distribution of the nondominated solutions in Pareto-optimal front is shown in Fig. 7. It is clear that the solutions are diverse and well distributed over the trade-off curve. Comparing Figs 6 and 7, it can be concluded that, the nondominated solutions of the proposed approach not only have better diversity characteristics but also were obtained in a single run. It is worth mentioning that the run time per generation of the single objective approach to produce only one solution was 14.22s while that of the proposed approach to produce 50 solutions was 14.74s. 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.

The results of the proposed approach were compared to those reported using linear programming (LP) [5] and multiobjective stochastic search technique (MOSST) [13]. The comparison is given in Table 3 and Table 4. It is quite evident that the fuel cost is much reduced with proposed approach. Also, it can be seen that the best cost and best emission values in tables 3 and 4 are very close to those of Table 2. It can be concluded that the proposed approach produces a well-distributed nondominated solutions.

For each Pareto-optimal solution, the normalized membership function given in (16) is evaluated. The solution that has the maximum value is extracted as the best compromise solution. This solution is given in Table 5 with cost of 610.254 ($/h) and emission of 0.20055 (ton/h).

		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	-5.55	-6.05	-5.09	-3.55	-5.09	-5.56
	γ	6.490	5.638	4.586	3.380	4.586	5.151
	ζ	2E-4	5E-4	1E-6	2E-3	1E-6	1E-5
	λ	2.857	3.333	8.000	2.000	8.000	6.667

Table 1: Generator cost and emission coefficients

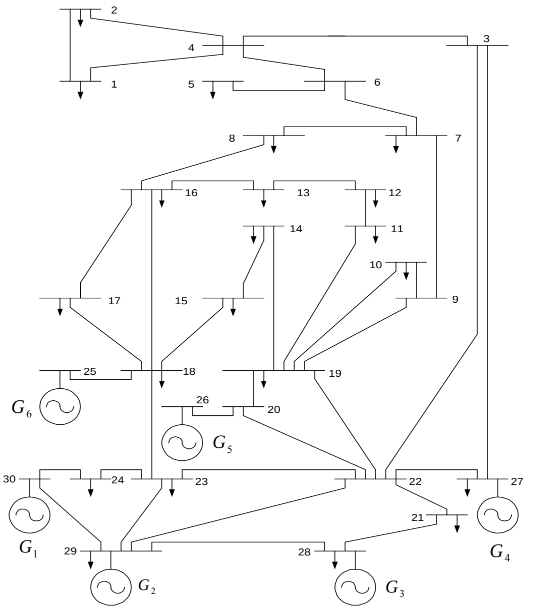

Figure 3: Single-line diagram of IEEE 30-bus test system

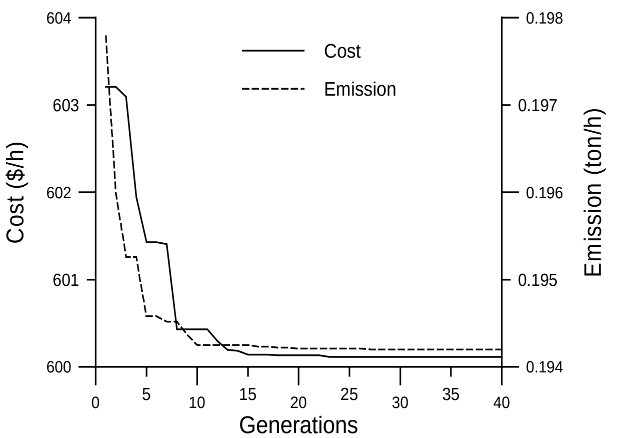

Figure 4: Convergence of cost and emission objective functions

	Best Cost	*Best Emission*
P_{G1}	0.10954	0.40584
P_{G2}	0.29967	0.45915
P_{G3}	0.52447	0.53797
P_{G4}	1.01601	0.38300
P_{G5}	0.52469	0.53791
P_{G6}	0.35963	0.51012
Cost (*$/h*)	**600.114**	638.260
Emission (*ton/h*)	0.22214	**0.19420**

Table 2: The best solutions for cost and emission optimized individually

	LP [5]	*MOSST* [13]	*Proposed*
P_{G1}	0.1500	0.1125	0.1062
P_{G2}	0.3000	0.3020	0.2897
P_{G3}	0.5500	0.5311	0.5289
P_{G4}	1.0500	1.0208	1.0025
P_{G5}	0.4600	0.5311	0.5402
P_{G6}	0.3500	0.3625	0.3664
Cost (*$/h*)	**606.314**	**605.889**	**600.151**
Emission (*ton/h*)	0.22330	0.22220	0.22151

Table 3: Test results of best fuel cost

	LP [5]	*MOSST* [13]	*Proposed*
P_{G1}	0.400	0.4095	0.4116
P_{G2}	0.4500	0.4626	0.4532
P_{G3}	0.5500	0.5426	0.5329
P_{G4}	0.4000	0.3884	0.3832
P_{G5}	0.5500	0.5427	0.5383
P_{G6}	0. 5000	0.5142	0.5148
Emission (*ton/h*)	**0.19424**	**0.19418**	**0.19421**
Cost (*$/h*)	639.600	644.112	638.507

Table 4: Test results of best emission

P_{G1}	P_{G2}	P_{G3}	P_{G4}	P_{G5}	P_{G6}
0.2785	0.3764	0.5300	0.6931	0.5406	0.4153

Table 5: Best compromise solution of the proposed approach

7 CONCLUSION

In this paper, a novel approach based on the Strength Pareto Evolutionary Algorithm has been presented and applied to EED optimization problem. The problem has been formulated as a multiobjective optimization one with competing fuel cost and emission objectives. 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 problems 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. The most important aspect of the proposed approach is that any number of objectives can be considered.

8 ACKNOWLEDGEMENT

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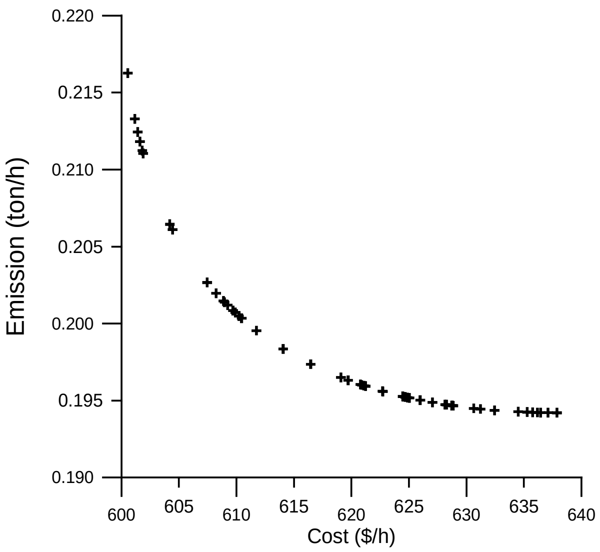

Figure 5: Pareto-optimal front of the aggregation method

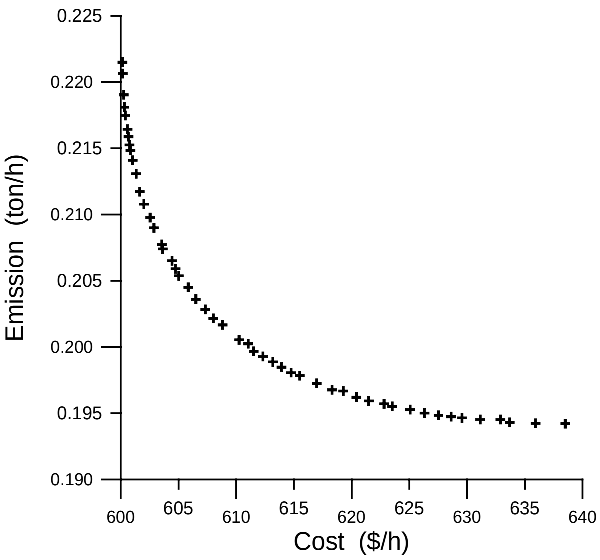

Figure 6: Pareto-optimal front of the proposed approach

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