A New Multiobjective Evolutionary Algorithm for Environmental/Economic Power Dispatch

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Abstract: In this paper, a new multiobjective evolutionary algorithm for Environmental/Economic power Dispatch (EED) optimization problem is presented. The EED problem is formulated as a nonlinear constrained multiobjective optimization problem with both equality and inequality constraints. A new Nondominated Sorting Genetic Algorithm (NSGA) based approach is proposed to handle the problem as a true multiobjective optimization problem with competing and non-commensurable objectives. The proposed approach employs a diversity-preserving technique to overcome the premature convergence and search bias problems and produce a well-distributed Pareto-optimal set of nondominated solutions. A hierarchical clustering technique is also imposed to provide the decision maker with a representative and manageable Pareto-optimal set. Several optimization runs of the proposed approach are carried out on a standard IEEE test system. The results demonstrate the capabilities of the proposed NSGA based approach to generate the true Pareto-optimal set of nondominated solutions of the multiobjective EED problem in one single run. Simulation results with the proposed approach have been compared to those reported in the literature. The comparison shows the superiority of the proposed NSGA based approach and confirms its potential to solve the multiobjective EED problem.

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 nonlinear 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 such as gas scrubbers and electrostatic precipitators, switching to low emission fuels, replacement of the aged fuel-burners and generator units with cleaner and more efficient 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 economic dispatch to include emissions.

Different techniques have been reported in the literature pertaining to environmental/economic dispatch (EED) problem. In [4-5] 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 [6]. Unfortunately, the EED problem is a highly nonlinear and a multimodal optimization problem. Therefore, conventional optimization methods that make use of derivatives and gradients, in general, 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 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 to find Pareto-optimal solutions in problems having a non-convex Pareto-optimal front. In addition, there is no rational basis of determining adequate weights and the objective function so formed may lose significance due to combining non-commensurable objectives. To avoid this difficulty, the ε-constraint method for multiobjective optimization was presented in [11-13]. This method is based on optimization of 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. The most obvious weaknesses of this approach are that it is time-consuming and tends to find weakly nondominated solutions.

Goal programming method was also proposed for multiobjective EED problem [14]. In this method, a target or a goal to be achieved for each objective is assigned and the objective function will then try to minimize the distance from the targets to the objectives. Although the method is computationally efficient, it will yield an inferior solution rather than a non-inferior one if the goal point is chosen in the feasible domain. Hence, the main drawback of this method is that it requires a priori knowledge about the shape of the problem search space.

The recent direction is to handle both objectives simultaneously as competing objectives instead of simplifying the multiobjective problem to a single objective problem. A fuzzy multiobjective optimization technique for EED problem was proposed [15]. 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 [16]. The important aspect of this approach is that it produces several alternatives along the Pareto-optimal front. 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. In addition, no effort has been done to prevent the algorithm from its bias towards some regions. A fuzzy satisfaction-maximizing decision approach was successfully applied to solve the biobjective EED problem regarding minimization of both fuel cost and environmental impact of NO_x emissions [17]. However, extension of the approach to include more objectives such as security and reliability is a very involved question. A multiobjective stochastic search technique for the multiobjective EED problem was presented in [18]. This technique hybridizes genetic algorithms (GA) and simulated annealing in the sense that the selection process of GA is enhanced by local heuristic search for better search capabilities. However, the technique is computationally involved and time-consuming. In addition, its severe drawback is the genetic drift and search bias to some regions in the space that 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.

On the contrary, the studies on evolutionary algorithms, over the past few years, have shown that these methods can be efficiently used to eliminate most of the above difficulties of classical methods [19-22]. Since they use a population of solutions in their search, multiple Pareto-optimal solutions can, in principle, be found in one single run.

In this paper, a new nondominated sorting genetic algorithm (NSGA) based approach is proposed for solving the environmental/economic power dispatch optimization problem. The problem is formulated as a nonlinear constrained multiobjective optimization problem where fuel cost and environmental impact are treated as competing objectives. A diversity-preserving mechanism is added to the search algorithm 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 without destroying the characteristics of the trade-off front. The potential of the proposed NSGA based approach to handle the multiobjective EED problem is investigated and discussed. Several runs are carried out on a standard test system and the results are compared to the classical multiobjective optimization 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.

A. *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

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

where N is the number of generators, a_i, b_i, c_i, d_i, and e_i are the cost coefficients of the 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

$$P_G = [P_{G_1}, P_{G2}, \ldots, P_{G_N}]^T \tag{2}$$

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

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

where α_i, β_i, γ_i, ζ_i, and λ_i are coefficients of the i^{th} generator emission characteristics.

B. *Problem Constraints*

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

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

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,

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

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

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

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.

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

subject to:

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

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

where g and h are the power balance and generation capacity 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:

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

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

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.

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. $\forall i \in \{1,2,\ldots,N_{obj}\} : f_i(x^1) \le f_i(x^2) \quad (12)$
2. $\exists j \in \{1,2,\ldots,N_{obj}\} : f_j(x^1) < f_j(x^2) \quad (13)$

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

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 guide the search towards the Pareto-optimal front but also maintain population diversity in the Pareto-optimal front. Unfortunately, a simple GA tends to converge towards a single solution due to selection pressure, selection noise, and operator disruption [23].

Srinivas and Deb [24] developed NSGA in which a ranking selection method is used to emphasize current nondominated solutions and a niching method is used to maintain diversity in the population. The algorithm includes two main steps: fitness assignment and fitness sharing.

Fitness assignment: it was first proposed by Goldberg [21]. The basic idea of this approach is to find a set of solutions in the population that are nondominated by the rest of the population. These solutions are then assigned the highest rank and eliminated from further contention. This process continues until the population is properly ranked.

Fitness sharing: 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. The neighborhood is defined in terms of a distance measure and specified by the niche radius. In the basic NSGA, sharing was implemented by a distance measure on the parameter space.

B. The Algorithm

The computational flow of the algorithm can be described as follows. At first, the nondominated solutions in the population are identified. These nondominated solutions constitute the first nondominated front and assigned the same dummy fitness value. These nondominated solutions are then shared with their dummy fitness values. After sharing, these nondominated individuals are ignored temporarily to process the rest of population members. The above procedure is repeated to find the second level of nondominated solutions in the population. Once they are identified, a dummy fitness value, which is a little smaller than the worst shared fitness value observed in solutions of first nondominated set, is assigned. Thereafter, the sharing procedure is performed among the solutions of second nondomination level and shared fitness values are found as before. This process is continued until all population members are assigned a shared fitness value. The population is then reproduced with the shared fitness values.

In this study, the basic NSGA 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.

1. 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.
2. Unlike the basic algorithm, sharing is carried out on objective space rather than parameter space since the idea behind sharing is to maintain diversity along Pareto-optimal front which exists only in objective space.
3. 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 its nondominated solutions that represent the updated Pareto-optimal set.
4. 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.

The computational flow of the proposed NSGA based approach is shown in Fig. 1.

C. *Implementation and Settings*

Due to difficulties of binary representation when dealing with continuous search space with large dimension, real-coded GA [25] is used in this study. The decision variables are represented by real numbers within their lower and upper limits. 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, $x_i < y_i$. To ensure the balance between exploitation and exploration of the search space, $\alpha = 0.5$ is selected. The non-uniform mutation [25], which makes uniform search in the initial space and very locally at the later space, has been applied in this study. The techniques used in this study were developed and implemented using the FORTRAN language.

On all optimization runs, the population size was selected as 200 individuals. 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 chosen as 0.9 and 0.001 respectively in all optimization runs.

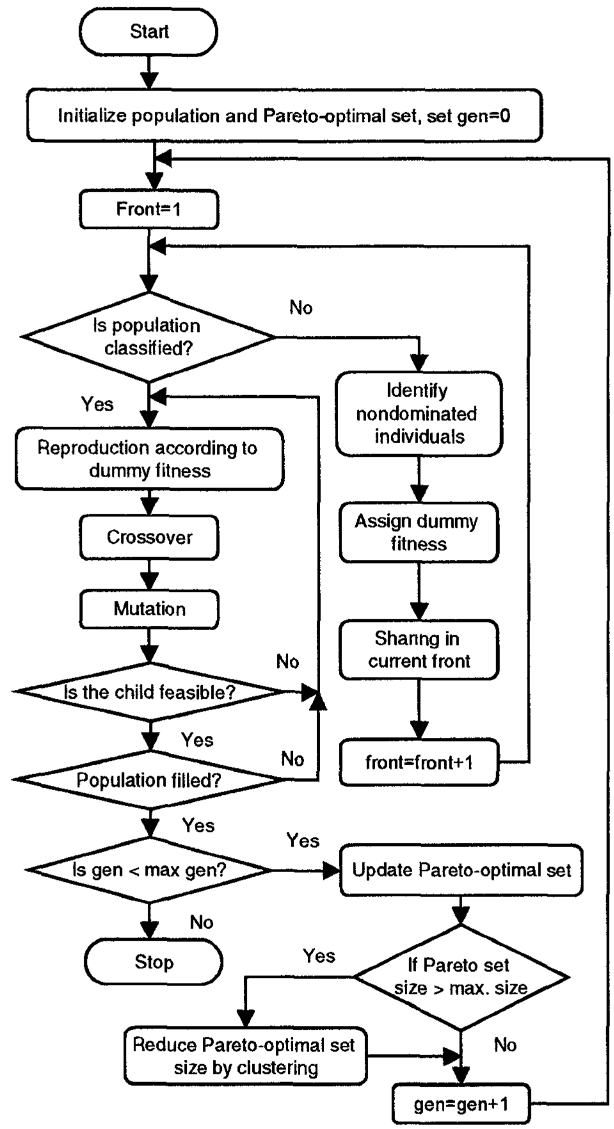

Fig. 1: Computational flow of the proposed approach

5. 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 [6,11]. The values of fuel cost and emission coefficients are given in Table 1. Two different cases are 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 objective functions are shown in Fig. 3. The best results of cost and emission when optimized individually are given in Table 2.

Sharing on both parameter space and objective space has been investigated The results are shown in Fig. 4. It is seen that the sharing on objective space results in better performance compared to sharing on parameter space for the problem in hand. The distribution and the diversity of the nondominated solution in Pareto-optimal front are much better in case of sharing on objective space.

The results of the proposed approach were compared to those reported using linear programming (LP) [6] and multiobjective stochastic search technique (MOSST) [18]. The comparison is given in Table 3. It is quite evident that the proposed approach gives better results.

Case (b): In this case, the transmission power loss has been taken into account. Convergence 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. The values of best cost and emission objectives with the proposed approach are given in table 3. The results of sharing on different spaces are shown in Fig. 6. It is also seen that the diversity of the nondominated solutions is much better in case of sharing on objective space.

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	2.0E-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

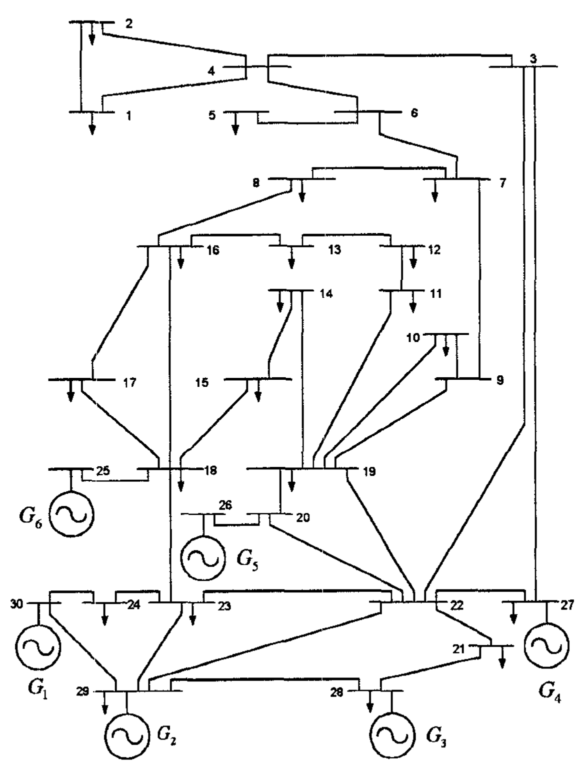

Fig. 2: Single-line diagram of IEEE 30-bus test system

Table 2: The best solutions for cost and emission

	Case (a)		Case (b)	
	Cost	*Emission*	*Cost*	*Emission*
P_{G_1}	0.10972	0.40603	0.11520	0.41023
P_{G_2}	0.29987	0.45900	0.30560	0.46309
P_{G_3}	0.52403	0.53781	0.59734	0.54371
P_{G_4}	1.01605	0.38311	0.98106	0.38954
P_{G_5}	0.52463	0.53803	0.51371	0.54373
P_{G_6}	0.35971	0.51002	0.35427	0.51472
Fuel Cost ($/h)	600.111	638.257	607.777	645.220
Emission (ton/h)	0.22213	0.19420	0.21985	0.19418

Table 3: Fuel cost and emission for different algorithms

	LP	*MOSST*	*Proposed*	
	[6]	[18]	*Case (a)*	*Case (b)*
Best Cost	606.314	605.889	600.285	608.664
Corresp. Emission	0.22330	0.22220	0.22001	0.21907
Best Emission	0.19423	0.19418	0.19449	0.19515
Corresp. Cost	639.600	644.112	635.785	638.001

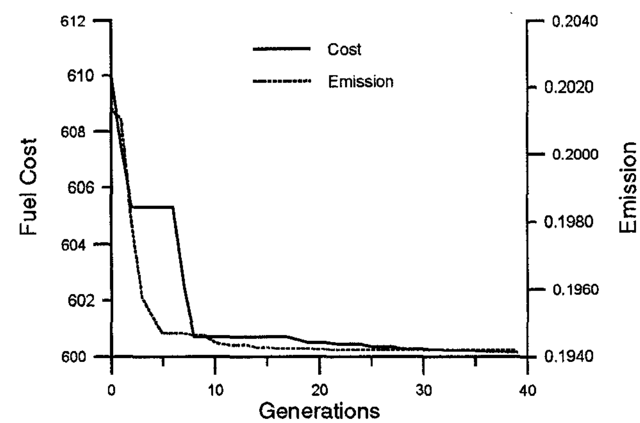

Fig. 3: Convergence of cost and emission objective functions of case (a)

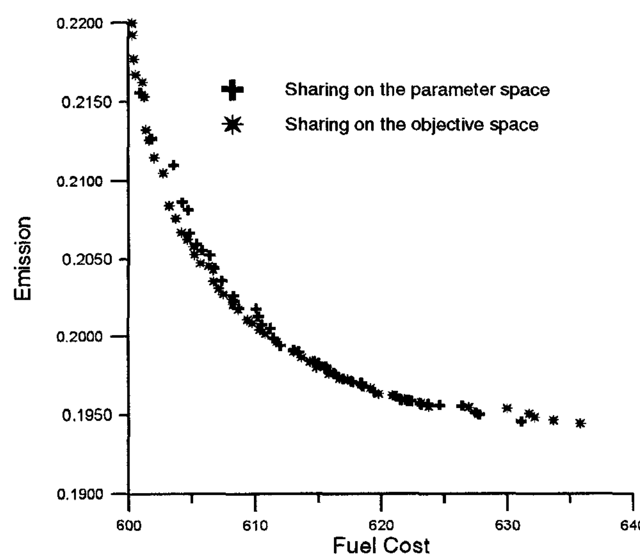

Fig. 4: Pareto-optimal front of the proposed approach in case (a)

6. CONCLUSION

In this paper, a new approach based on the nondominated sorting genetic 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. The results show that the proposed approach is efficient for solving multiobjective optimization in that 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 are that any number of objectives can be considered.

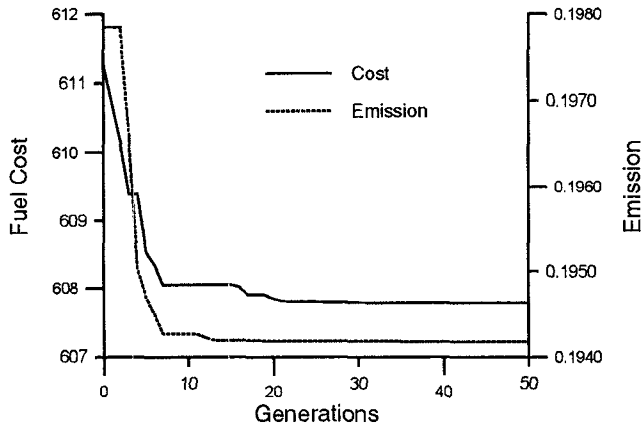

Fig. 5: Convergence of cost and emission objective functions of case (b)

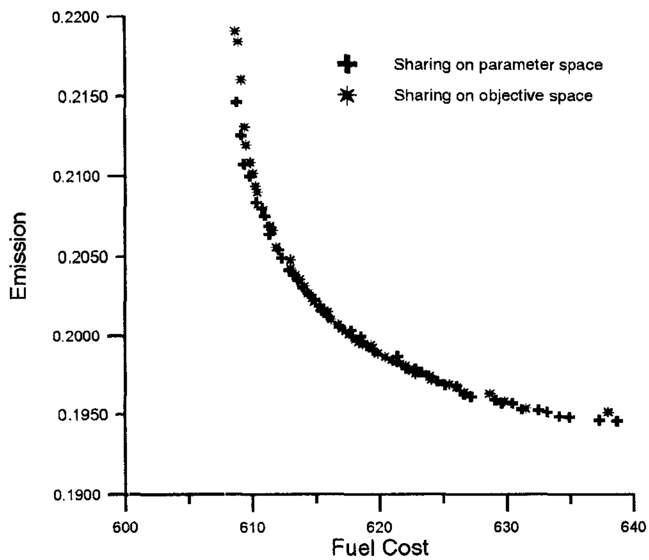

Fig. 6: Pareto-optimal front of the proposed approach in case (b)

7. ACKNOWLEDGEMENT

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