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# A novel multiobjective evolutionary algorithm for environmental/economic power dispatch

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**Abstract**

In this paper, a novel 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 based approach is proposed to handle the problem 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 and produce a well-distributed Pareto-optimal set of nondominated solutions. 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 solution over the trade-off curve. 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 true and well-distributed Pareto-optimal 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 demonstrates the superiority of the proposed approach and confirms its potential to solve the multiobjective EED problem.


*Keywords:* Environmental/economic dispatch; Evolutionary algorithms; Multiobjective optimization

## 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 [1].

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 noncommensurable 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 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

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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 Ref. [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 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 nonconvex 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 noncommensurable objectives. To avoid this difficulty, the $\varepsilon$-constraint method for multiobjective optimization was presented in Refs. [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 $\varepsilon$. 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 noninferior 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 Ref. [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 Ref. [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 nondominated 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 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 developed and superimposed on the search algorithm to find widely different Pareto-optimal solutions. In addition, 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. Moreover, a fuzzy-based mechanism is employed to extract the best compromise solution over the trade-off curve. The potential of the proposed 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 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

#### 2.1.1. 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

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

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 $P_{G_i}$ is the real power output of the $i$th generator. $P_G$ is the vector of real power outputs of generators and defined as

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

#### 2.1.2. 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

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

where $\alpha_i$, $\beta_i$, $\gamma_i$, $\zeta_i$, and $\lambda_i$ are coefficients of the $i$th generator emission characteristics.

### 2.2. Problem constraints

#### 2.2.1. Generation capacity constraint

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

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

#### 2.2.2. 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,

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

#### 2.2.3. 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.

### 2.3. Problem formulation

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

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

subject to:

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

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

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 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:

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

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

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 $x^2$ if the following two conditions are satisfied:

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

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 nondominated solutions. Unfortunately, a simple GA tends to converge towards a single solution due to selection pressure, selection noise, and operator disruption [23].

### 4.2. Nondominated sorting genetic algorithm

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.

#### 4.2.1. Fitness assignment

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. Consider a set of $N$ population members, each having $N_{obj}$ objective function values, the following procedure is used to find the nondominated set of solutions:

*Step 1:* Initiate the individual counter $i$ with $i = 1$.
*Step 2:* For all $j = 1,\ldots,N$ and $j \neq i$, compare solutions $x^i$ and $x^j$ for domination using the conditions given in Eq. (12) and Eq. (13).
*Step 3:* If for any $j$, $x^i$ is dominated by $x^j$, mark $x^i$ as dominated.
*Step 4:* If all individuals in the population are considered, Go to Step 5, else set $i = i + 1$ and go to Step 2.
*Step 5:* All solutions that are not marked dominated are nondominated solutions.

These solutions represent the first front and are eliminated from further contention. This process continues until the population is properly ranked.

#### 4.2.2. 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 $d$ and specified by the niche radius $\sigma_{share}$. Given a set of $n_k$ solutions in the $k$-th front each having a dummy fitness value $f_k$, the sharing procedure is performed in the following way [24] for each solution $i = 1,\ldots,n_k$:

*Step 1:* Compute a normalized Euclidean distance measure with another solution $j$ in the $k$-th nondominated front, as follows:

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

where $P$ is the number of variables in the problem. The parameters $x_k^u$ and $x_k^l$ are the upper and lower bounds of variable $x_k$.

*Step 2:* This distance $d_{ij}$ is compared with a pre-specified parameter $\sigma_{share}$ and the following sharing function value is computed:

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

*Step 3:* Increment $j$. If $j \leqslant n_k$, go to Step 1 else calculate niche count for $i$-th solution as follows:

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

*Step 4:* Degrade the dummy fitness $f_k$ of $i$-th solution in the $k$-th nondomination front to calculate the shared fitness, $f_i^*$, as follows:

$$f_i^* = \frac{f_k}{m_i} \tag{17}$$

This procedure is continued for all $i = 1,\ldots,n_k$ and a corresponding $f_i^*$ is found. Thereafter, the smallest value $f_k^{\min}$ of all $f_i^*$ in the $k$-th nondominated front is found for further processing. The dummy fitness of the next nondominated front is assigned to be $f_{k+1} = f_k^{\min} - \varepsilon_k$, where $\varepsilon_k$ is a small positive 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 [25] 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 $\leqslant N$, 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

$$d_c = \frac{1}{n_1 \cdot n_2} \sum_{i_1 \in c_1,\ i_2 \in c_2} \mathrm{d}(i_1, i_2) \tag{18}$$

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 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, the $i$-th objective function $F_i$ is represented by a membership function $\mu_i$ defined as [8]

$$\mu_i = \begin{cases} 1 & F_i \leq F_i^{\min} \\ \dfrac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}} & F_i^{\min} < F_i < F_i^{\max} \\ 0 & F_i \geq F_i^{\max} \end{cases} \tag{19}$$

where $F_i^{\text{mix}}$ and $F_i^{\max}$ are the minimum and maximum value of the $i$-th objective function among all nondominated solutions, respectively.

For each nondominated solution $k$, the normalized membership function $\mu^k$ is calculated as

$$\mu^k = \frac{\sum_{i=1}^{N_{\text{obj}}} \mu_i^k}{\sum_{k=1}^{M} \sum_{i=1}^{N_{\text{obj}}} \mu_i^k} \tag{20}$$

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

## 5. Implementation of the proposed approach

### 5.1. Real-coded genetic algorithm

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) [26]. 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-$\alpha$) 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 nonuniform 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

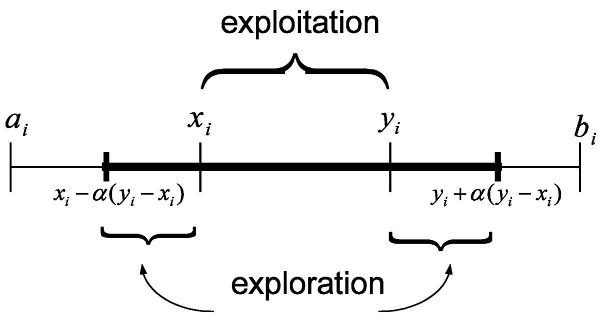


Fig. 1. Blend crossover operator (BLX-$\alpha$).

$$x_i' = \begin{cases} x_i + \Delta(t, b_i - x_i) & \text{if } \tau = 0 \\ x_i - \Delta(t, x_i - a_i) & \text{if } \tau = 1 \end{cases} \tag{21}$$

and;

$$\Delta(t, y) = y(1 - r^{(1-t/g_{\max})^{\beta}}) \tag{22}$$

where $\tau$ is a binary random number, $r$ is a random number $r \in [0,1]$, $g_{\max}$ is the maximum number of generations, and $\beta$ 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.

### 5.2. The computational flow

The computational flow of the proposed 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.

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 its nondominated 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.

The computational flow of the proposed NSGA based approach 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.

## 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 Refs. [6,11]. The values of fuel cost and emission coefficients are given in Table 1. 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 objective functions are shown in Fig. 4. The best results of cost and emission when optimized individually are given in Table 2.

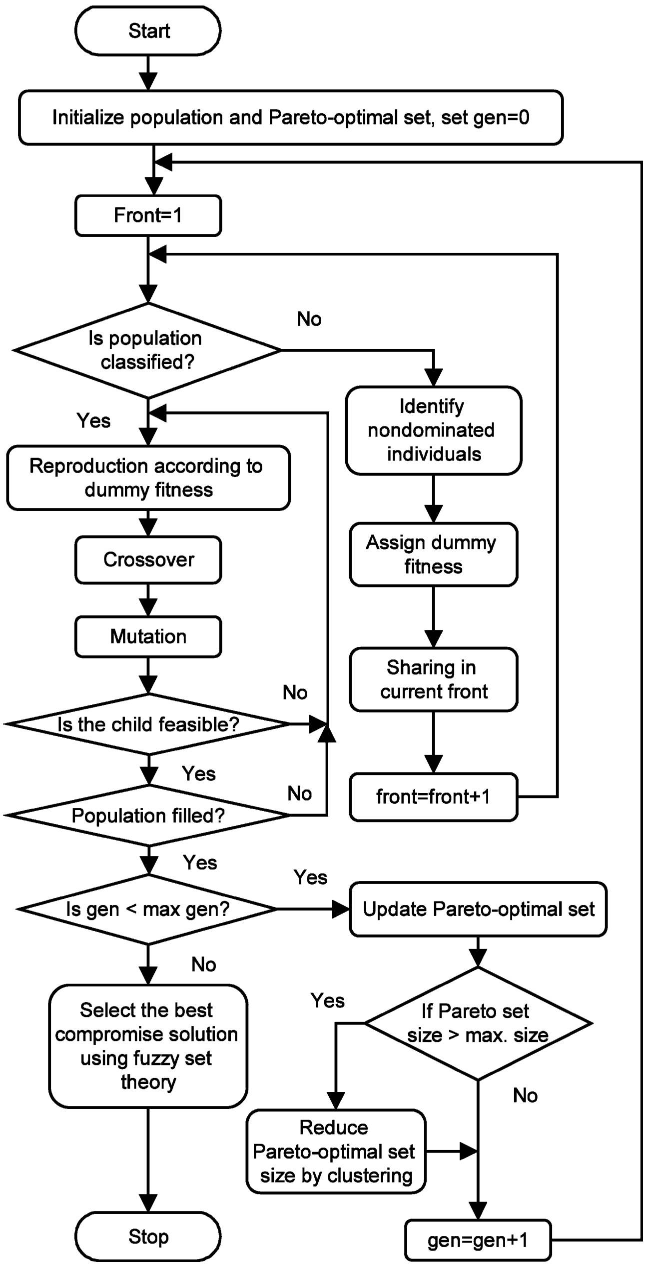


Fig. 2. Computational flow of the proposed approach.

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:

$$\underset{P_G}{\text{Minimize}} \quad wF(P_G) + (1-w)\lambda E(P_G) \tag{23}$$

where $\lambda$ 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 $w = \text{rand}[0.1]$. The Pareto-optimal front of RCGA is shown in Fig. 5. Applying the proposed NSGA based approach; the distribution of the nondominated 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 the results shown in Fig. 5 and Fig. 6, it can be concluded that:-(a) the 50 solutions shown in Fig. 6 that present the results of the proposed technique have been obtained in a single run while the solutions shown in Fig. 5 have been obtained in 50 separate runs; (b) the solutions of the proposed approach shown in Fig. 6 have better diversity characteristics and well-distributed over the 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 impeded diversity-preserving mechanism through fitness sharing procedure.

The results of the proposed approach were compared to those reported using linear programming [6] and multiobjective stochastic search technique [18]. The comparison results are given in Table 3 and Table 4. It can be seen form Table 3 that the savings with the proposed approach in the fuel cost is about 5 to 6 \$/h and the emission is less as well. This demonstrates the potential of the proposed approach as the obtained solution covers and dominates the other solutions given in Refs. [6] and [18]. It can be concluded that the proposed approach is capable of exploring more efficient and noninferior solutions of multiobjective optimization problems.

*Case (b):* In this case, the transmission power loss has been taken into account. Convergence of fuel cost and emission objective functions when optimized individually are shown in Fig. 7. The best 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 Table 3 and Table 4. The distribution of the nondominated solutions of RCGA when applied for 50 times is shown in Fig. 8. The distribution of the nondominated solutions 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.

The membership functions given in Eq. (19) and Eq. (20) 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 for both cases and the best compromise solutions are given in Table 5.

Comparing the results of single objective optimization given in Table 2 with the results of multiobjective optimization given in Table 3 and Table 4, it is clear that the results in both cases are almost identical as given in Table 6. This demonstrates that the search of the proposed approach span over the entire trade-off

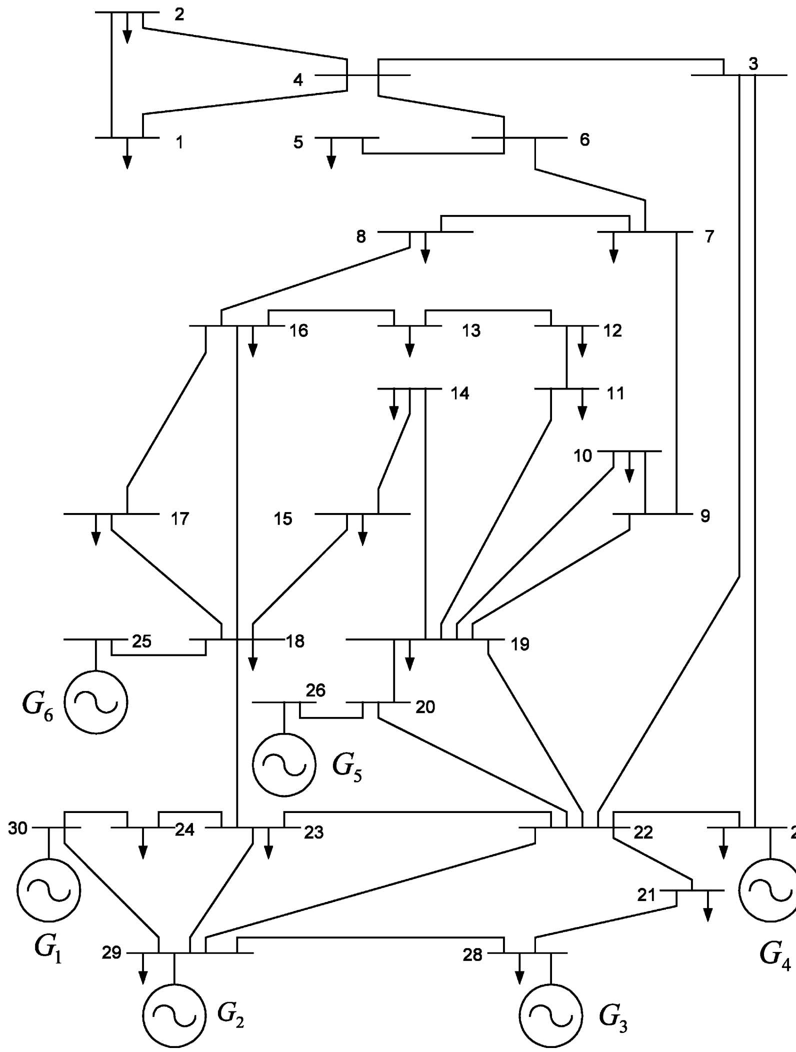


Fig. 3. Single-line diagram of IEEE 30-bus test system.

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.

## 7. Conclusion

In this paper, a novel approach based on the NSGA has been presented and applied to environmental/ economic power dispatch optimization problem. The problem has been formulated as multiobjective optimi-

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 | $\alpha$ | 4.091 | 2.543 | 4.258 | 5.426 | 4.258 | 6.131 |
| | $\beta$ | −5.554 | −6.047 | −5.094 | −3.550 | −5.094 | −5.555 |
| | $\gamma$ | 6.490 | 5.638 | 4.586 | 3.380 | 4.586 | 5.151 |
| | $\zeta$ | 2.0E−4 | 5.0E−4 | 1.0E−6 | 2.0E−3 | 1.0E−6 | 1.0E−5 |
| | $\lambda$ | 2.857 | 3.333 | 8.000 | 2.000 | 8.000 | 6.667 |

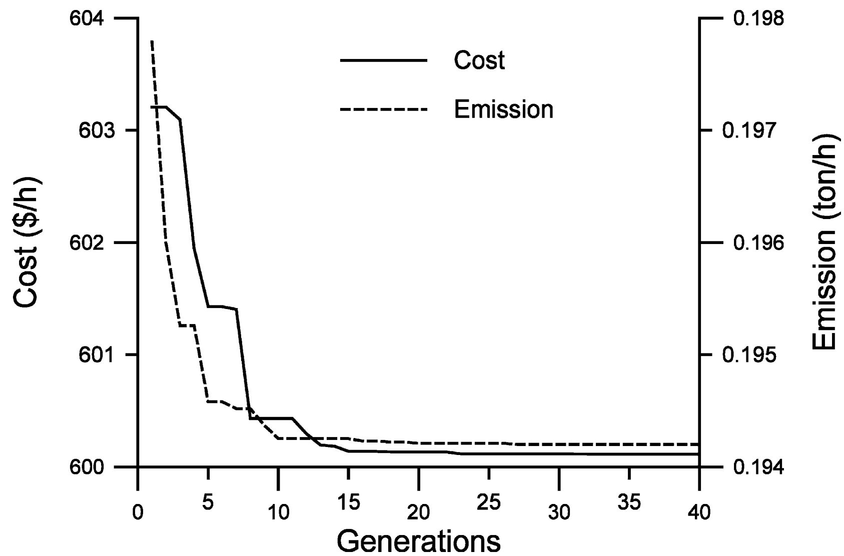


Fig. 4. Convergence of cost and emission objectives of case (a).

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 |

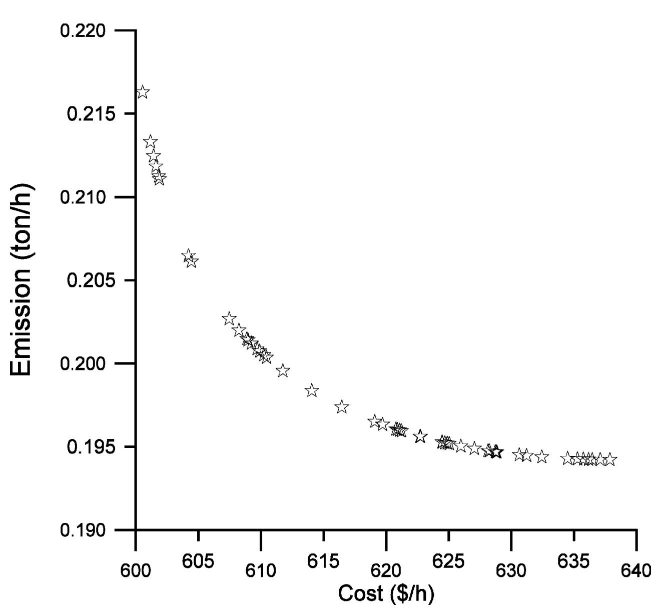


Fig. 5. Pareto-optimal front of objective aggregation in case (a).

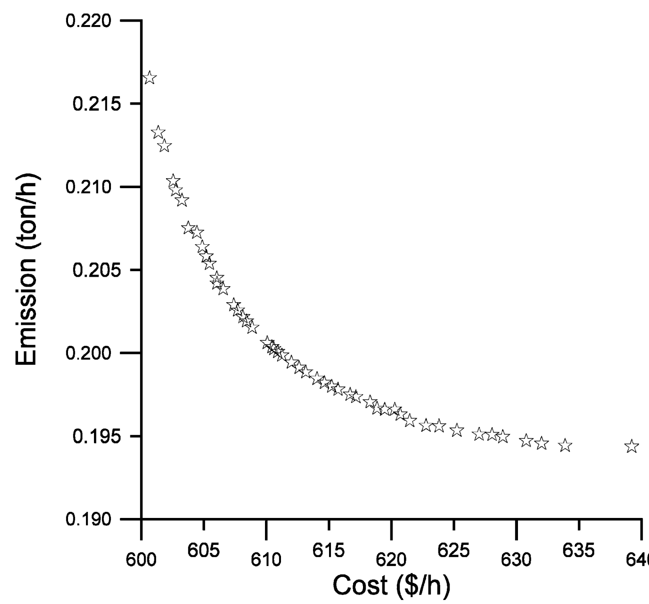


Fig. 6. Pareto-optimal front of the proposed approach in case (a).

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

| | LP [6] | MOSST [18] | Proposed | |
|---|---|---|---|---|
| | | | Case (a) | Case (b) |
| $P_{G_1}$ | 0.1500 | 0.1125 | 0.1567 | 0.1168 |
| $P_{G_2}$ | 0.3000 | 0.3020 | 0.2870 | 0.3165 |
| $P_{G_3}$ | 0.5500 | 0.5311 | 0.4671 | 0.5441 |
| $P_{G_4}$ | 1.0500 | 1.0208 | 1.0467 | 0.9447 |
| $P_{G_5}$ | 0.4600 | 0.5311 | 0.5037 | 0.5498 |
| $P_{G_6}$ | 0.3500 | 0.3625 | 0.3729 | 0.3964 |
| Best cost | 606.314 | 605.889 | 600.572 | 608.245 |
| Corresp. emission | 0.22330 | 0.22220 | 0.22282 | 0.21664 |

Table 4
Test results of best emission of the proposed approach

| | LP [6] | MOSST [18] | Proposed | |
|---|---|---|---|---|
| | | | Case (a) | Case (b) |
| $P_{G_1}$ | 0.400 | 0.4095 | 0.4394 | 0.4113 |
| $P_{G_2}$ | 0.4500 | 0.4626 | 0.4511 | 0.4591 |
| $P_{G_3}$ | 0.5500 | 0.5426 | 0.5105 | 0.5117 |
| $P_{G_4}$ | 0.4000 | 0.3884 | 0.3871 | 0.3724 |
| $P_{G_5}$ | 0.5500 | 0.5427 | 0.5553 | 0.5810 |
| $P_{G_6}$ | 0.5000 | 0.5142 | 0.4905 | 0.5304 |
| Best emission | 0.19424 | 0.19418 | 0.19436 | 0.19432 |
| Corresp. cost | 639.600 | 644.112 | 639.231 | 647.251 |

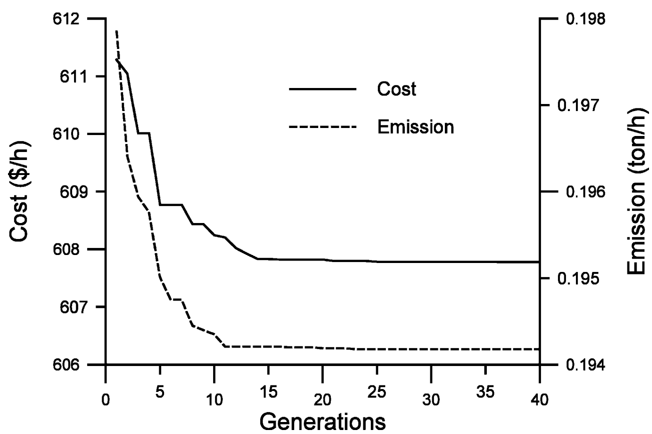

Fig. 7. Convergence of cost and emission objectives of case (b).

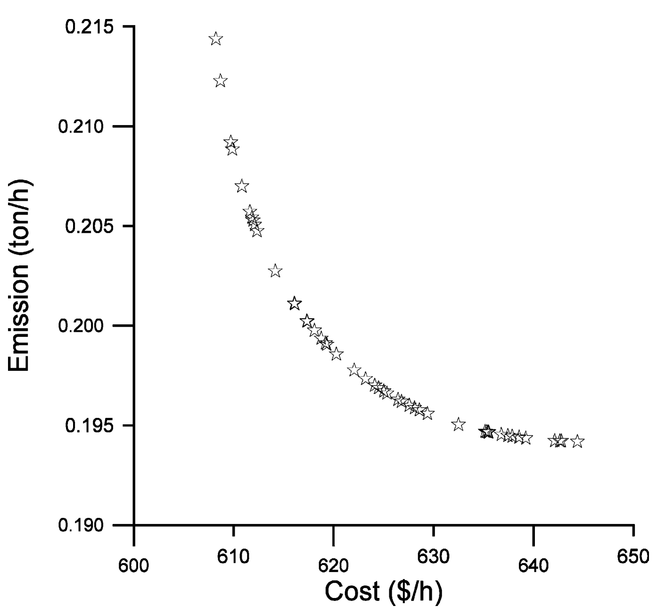

Fig. 8. Pareto-optimal front of objective aggregation in case (b).

zation 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

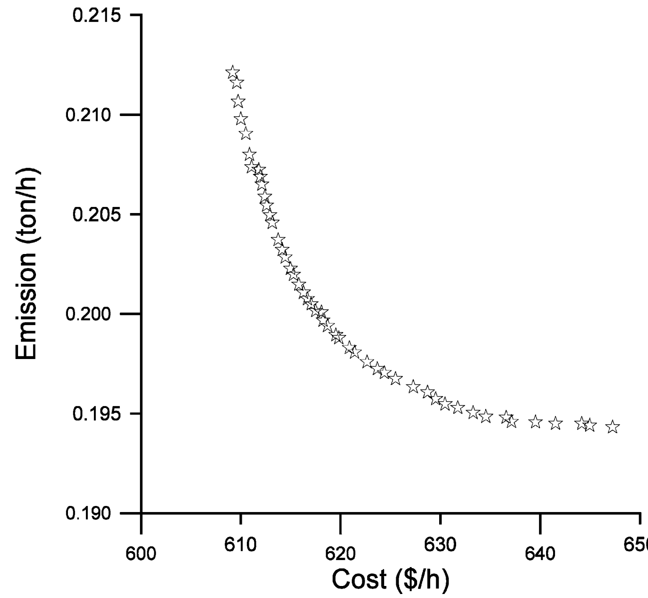

Fig. 9. Pareto-optimal front of the proposed approach in case (b).

Table 5
Best compromise solutions of the proposed approach

| | Case (a) | Case (b) |
|---|---|---|
| $P_{G_1}$ | 0.2571 | 0.2699 |
| $P_{G_2}$ | 0.3774 | 0.3885 |
| $P_{G_3}$ | 0.5381 | 0.5645 |
| $P_{G_4}$ | 0.6872 | 0.6570 |
| $P_{G_5}$ | 0.5404 | 0.5441 |
| $P_{G_6}$ | 0.4337 | 0.4398 |
| Cost | 610.067 | 618.686 |
| Emission | 0.20060 | 0.19940 |

Table 6
The best solutions for cost and emission

| | Case (a) | | Case (b) | |
|---|---|---|---|---|
| | Cost | Emission | Cost | Emission |
| Single objective | 600.114 | 0.19420 | 607.777 | 0.19418 |
| Multiobjective | 600.572 | 0.19436 | 608.245 | 0.19432 |

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. The most important aspect of the proposed approach is that any number of objectives can be considered.

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