Multiobjective Evolutionary Algorithms for Electric Power Dispatch Problem

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***Abstract*—The potential and effectiveness of the newly developed Pareto-based multiobjective evolutionary algorithms (MOEA) for solving a real-world power system multiobjective nonlinear optimization problem are comprehensively discussed and evaluated in this paper. Specifically, nondominated sorting genetic algorithm, niched Pareto genetic algorithm, and strength Pareto evolutionary algorithm (SPEA) have been developed and successfully applied to an environmental/economic electric power dispatch problem. A new procedure for quality measure is proposed in this paper in order to evaluate different techniques. A feasibility check procedure has been developed and superimposed on MOEA to restrict the search to the feasible region of the problem space. A hierarchical clustering algorithm is also imposed to provide the power system operator with a representative and manageable Pareto-optimal set. Moreover, an approach based on fuzzy set theory is developed to extract one of the Pareto-optimal solutions as the best compromise one. These multiobjective evolutionary algorithms have been individually examined and applied to the standard IEEE 30-bus six-generator test system. Several optimization runs have been carried out on different cases of problem complexity. The results of MOEA have been compared to those reported in the literature. The results confirm the potential and effectiveness of MOEA compared to the traditional multiobjective optimization techniques. In addition, the results demonstrate the superiority of the SPEA as a promising multiobjective evolutionary algorithm to solve different power system multiobjective optimization problems.**

***Index Terms*—Economic power dispatch, emission reduction, environmental impact, evolutionary algorithms, multiobjective optimization.**

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. This makes the ED problem a large-scale highly constrained nonlinear optimization problem. In addition, the increasing public awareness of environmental protection and the passage of the U.S. Clean Air Act amendments of 1990 have forced 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, switching to low emission fuels, replacement of the aged fuel-burners and generator units, and emission dispatching. The first three options require installation of new equipment and/or modification of existing equipment, which involves considerable capital outlay and, hence, 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, is 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]–[15].

Different techniques have been reported in the literature pertaining to the environmental/economic dispatch (EED) problem. In [4] and [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 tradeoff relations between cost and emission. Alternatively, minimizing the emission has been handled as another objective in addition to usual cost objective. Optimization procedures based on linear programming, in which the objectives are considered one at a time, were presented in [6]. Unfortunately, this approach does not give any information regarding the tradeoffs involved. In another research direction, the multiobjective EED problem was converted to a single objective problem by linear combination of different objectives as a weighted sum [7]–[9]. The important aspect of this weighted sum method is that a set of noninferior solutions can be obtained by varying the weights. Unfortunately, this requires multiple runs. Furthermore, this method cannot be used to find Pareto-optimal solutions in problems having a nonconvex Pareto-optimal front. To avoid this difficulty, the ϵ-constraint method for multiobjective optimization was presented in [10] and [11]. This method is based on optimization of the most preferred objective and considering the other objectives as constraints bounded by some allowable levels "ϵ." The obvious weaknesses of this approach is that it 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 [12]. However, the solutions produced are suboptimal and the algorithm does not provide a systematic framework for directing the search toward the Pareto-optimal front. A fuzzy satisfaction-maximizing decision approach was successfully applied to solve the biobjective EED problem [13], [14]. However, extension of the approach to include more objectives such

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as security and reliability is a very involved question. A multiobjective stochastic search technique for the multiobjective EED problem was proposed in [15]. However, the technique is computationally involved and time-consuming. In addition, the genetic drift and search bias are severe problems that result in premature convergence. Therefore, additional efforts should be done to preserve the diversity of the nondominated solutions.

On the contrary, the studies on evolutionary algorithms have shown that these methods can be efficiently used to eliminate most of the above difficulties of classical methods [16]–[32]. Since they use a population of solutions in their search, multiple Pareto-optimal solutions can be found in one single run.

Recently, three multiobjective evolutionary algorithms (MOEAs) have been implemented and applied to the EED problem with impressive success [33]–[37]. However, there is a lack of comprehensive comparison among MOEAs, as these algorithms have been implemented individually. On the other hand, the quality and diversity of the nondominated solutions presented in [33]–[37] have not been measured and assessed quantitively.

In this paper, a comparative study among the MOEA techniques has been carried out to assess their potential to solve the real-world multiobjective EED problem. The EED problem is formulated as a nonlinear constrained multiobjective optimization problem where fuel cost and environmental impact are treated as competing objectives. The potential of MOEA to handle this problem is investigated and discussed. A new procedure for quality measure is proposed in this paper in order to evaluate different techniques. 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. Different cases with different complexity have been considered in the study reported in this paper. The MOEA techniques have been applied to the standard IEEE 30-bus six-generator test system. These techniques were compared to each other and to classical multiobjective optimization techniques as well. The effectiveness of MOEA to solve the EED problem is demonstrated.

II. EED 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. Minimization of Fuel Cost

The generator cost curves are represented by quadratic functions and the total fuel cost $F(P_G)$ in (\$/h) can be expressed as

$$F(P_G) = \sum_{i=1}^{N} a_i + b_i P_{G_i} + c_i P_{G_i}^2 \tag{1}$$

where N is the number of generators'; a_i, b_i, and c_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

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

B. Minimization of Emission

The total emission $E(P_G)$ in (ton/h) of atmospheric pollutants such as sulpher oxides $\mathrm{SO_x}$ and nitrogen oxides $\mathrm{NO_x}$ caused by the operation of fossil-fueled thermal generation can be expressed as

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

where $\alpha_i, \beta_i, \gamma_i, \zeta_i$, and λ_i are coefficients of the ith generator emission characteristics.

C. Constraints

1) Generation Capacity Constraint: For stable operation, the real power output of each generator is restricted by lower and upper limits as follows:

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

2) Power Balance Constraint: The total electric power generation must cover the total electric power demand P_D and the real power loss in transmission lines P_{loss}. Hence

$$\sum_{i=1}^{N} P_{G_i} - P_D - P_{\mathrm{loss}} = 0. \tag{5}$$

Calculation of P_{loss} implies solving the load flow problem, which has equality constraints on real and reactive power at each bus as follows:

$$P_{G_i} - P_{D_i} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij}\cos(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)\right] = 0 \tag{6}$$

$$Q_{G_i} - Q_{D_i} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij}\sin(\delta_i - \delta_j) - B_{ij}\cos(\delta_i - \delta_j)\right] = 0 \tag{7}$$

where $i = 1, 2, \ldots, NB$; NB is the number of buses; Q_{Gi} is the reactive power generated at the ith bus; P_{Di} and Q_{Di} are the ith bus load real and reactive power, respectively; G_{ij} and B_{ij} are the transfer conductance and susceptance between bus i and bus j, respectively; V_i and V_j are the voltage magnitudes at bus i and bus j, respectively; and δ_i and δ_j are the voltage angles at bus i and bus j, respectively. The equality constraints in (6) and (7) are nonlinear equations that can be solved using Newton–Raphson method to generate a solution of the load flow problem. During the course of solution, the real power output of one generator, called slack generator, is left to cover the real power loss and satisfy the equality constraint in (5). The load flow solution gives all bus voltage magnitudes and angles. Then, the real power loss in transmission lines can be calculated as

$$P_{\text{loss}} = \sum_{k=1}^{NL} g_k \left[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)\right] \quad (8)$$

where NL is the number of transmission lines and g_k is the conductance of the kth line that connects bus i to bus j.

3) Security Constraints: For secure operation, the apparent power flow through the transmission line S_l is restricted by its upper limit as follows:

$$S_{l_k} \leq S_{l_k}^{\max}, \quad k = 1, \ldots, NL. \quad (9)$$

It is worth mentioning that the kth transmission line flow connecting bus i to bus j can be calculated as

$$S_{l_k} = (V_i\angle\delta_i)I_{ij}^* \quad (10)$$

where I_{ij} is the current flow from bus i to bus j and can be calculated as

$$I_{ij} = (V_i\angle\delta_i) \times \left[(V_i\angle\delta_i - V_j\angle\delta_j) \times y_{ij} + (V_i\angle\delta_i) \times j\frac{y}{2}\right] \quad (11)$$

where y_{ij} is the line admittance, while y is the shunt susceptance of the line.

D. Formulation

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

$$\underset{P_G}{\text{Minimize}} \quad [F(P_G), E(P_G)] \quad (12)$$

$$\text{Subject to: } g(P_G) = 0 \quad (13)$$

$$h(P_G) \leq 0 \quad (14)$$

where g is the equality constraint representing the power balance, while h is the inequality constraint representing the generation capacity and power system security.

III. Multiobjective Optimization

A. Principles and Definitions

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

$$\text{Minimize} \quad f_i(x)\ i = 1, \ldots, N_{\text{obj}} \quad (15)$$

$$\text{Subject to: } \begin{cases} g_j(x) = 0 & j = 1, \ldots, M \\ h_k(x) \leq 0 & k = 1, \ldots, K \end{cases} \quad (16)$$

where f_i is the ith objective function, x is a decision vector that represents a solution, and 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)

$$\forall i \in \{1,\ 2,\ \ldots, N_{\text{obj}}\} : f_i(x_1) \leq f_i(x_2), \quad (17)$$

2)

$$\exists j \in \{1,\ 2,\ \ldots, N_{\text{obj}}\} : f_j(x_1) < f_j(x_2). \quad (18)$$

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 within the set $\{x_1, x_2\}$. 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*.

B. Fitness Assignment

Fonseca and Fleming [16] categorized several MOEA and compared different fitness assignment approaches. They classified these approaches to aggregating approaches, non-Pareto-based approaches, and Pareto-based approaches.

Aggregating approaches combine the problem objectives into a single function that is used for fitness calculation. Although these approaches have the advantage of producing one single solution, they require well-known domain knowledge that is often not available. In addition, multiple runs are required to find a family of nondominated solutions and to identify the Pareto-optimal set. The most popular aggregating approaches are the weighted-sum, goal programming, and ε-constrained methods [17].

To overcome the difficulties involved in the aggregating approaches, alternative techniques based on population policies, selection criteria, or special handling of the objectives have been developed. These approaches are known as non-Pareto-based approaches. The advantage of these approaches is that multiple nondominated solutions can be simultaneously evolved in a single run. These approaches, however, are often sensitive to the nonconvexity of Pareto-optimal sets. The most popular non-Pareto-based approaches are the vector evaluated genetic algorithm (VEGA) [18], multisexual genetic algorithm [19], and weighted min-max approach [20].

The basic idea of the Pareto-based fitness assignment 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. Generally, all approaches of this class explicitly use Pareto dominance in order to determine the reproduction probability of each individual. Some Pareto-based approaches are niched Pareto genetic algorithm (NPGA) [24], nondominated sorting genetic algorithm (NSGA) [23], and strength Pareto evolutionary algorithm (SPEA) [25].

C. Diversity Preservation

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 Pareto-optimal front. Unfortunately, a simple evolutionary algorithm tends to converge toward a single solution due to selection pressure, selection noise, and operator disruption [21]. Several approaches have been developed in order to overcome this problem, preserve the diversity in the population, and prevent premature convergence. These approaches are classified as niching techniques and nonniching techniques. Niching algorithms are characterized by their capabilities of maintaining stable subpopulations (niches).

Fitness sharing is the most frequently used niching technique. The basic idea behind this technique 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_{ij} and specified by the niche radius σ_{share}.

Restricted mating is the most frequently used nonniching technique. In this technique, two individuals are allowed to mate only if they are within a certain distance. This mechanism may avoid the formation of lethal individuals and therefore improve the online performance. However, it does not appear to be widely used in the field of multiobjective evolutionary algorithms [16].

IV. Evolutionary Algorithms

In general, the difficulties associated with the classical optimization methods can be summarized as follows.

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

Recent studies on evolutionary algorithms have shown that these methods can be efficiently used to eliminate most of the above difficulties. In this paper, the most efficient Pareto-based MOEAs have been developed and implemented. Recently, NSGA, NPGA, and SPEA have been recommended as the most efficient multiobjective evolutionary algorithms [22].

A. Nondominated Sorted Genetic Algorithm (NSGA)

Srinivas and Deb [23] 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. Before the selection is performed, the population is first ranked in several steps. At first, the nondominated solutions in the population are identified. These nondominated solutions constitute the first nondominated front and are assigned the same dummy fitness value. To maintain diversity in the population, these nondominated solutions are then shared with their dummy fitness values. Phenotypic sharing on the decision space is used in this technique. After sharing, these nondominated individuals are ignored temporarily to process the rest of the 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 the 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. A stochastic remainder selection is used in this paper.

In the first generation, the nondominated solutions of the first front are stored in the Pareto-optimal set. After ranking in the subsequent generations, the Pareto-optimal set is extended with the solutions of the first front. The nondominated solutions of the extended set are extracted to update the Pareto-optimal set.

B. Niched Pareto Genetic Algorithm (NPGA)

Horn *et al.* [24] proposed a tournament selection scheme based on Pareto dominance. Two competing individuals and a comparison set of other individuals are picked at random from the population. The number of individuals of the comparison set is given by the parameter t_{dom}. Generally, the tournament selection is carried out as follows. If one candidate is dominated by the comparison set while the other is not, then the latter will be selected for reproduction. If neither or both candidates are dominated by the comparison set, then the winner will be decided by sharing. Phenotypic sharing on the attribute space is used in this technique.

C. Strength Pareto Evolutionary Algorithm (SPEA)

Zitzler and Thiele [25] presented SPEA as a potential algorithm for multiobjective optimization. This technique stores externally the individuals that represent a nondominated front among all solutions considered so far. All individuals in the external set participate in selection. SPEA uses the concept of Pareto dominance in order to assign scalar fitness values to individuals in the current population. The procedure starts with assigning 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. Subsequently, 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, one is added to the resulting value. This fitness assignment ensures that the search is directed toward the nondominated solutions and, in the same time, the diversity among dominated and nondominated solutions is maintained.

It is worth mentioning that new and revised versions of MOEA have been presented such as NSGA-II [26], [27], SPEA2 [28], and multiobjective particle swarm optimization [29]. Recently, different studies in analysis, test cases, and applications of MOEA have been discussed [30]–[32].

V. MOEA IMPLEMENTATION

A. Reducing Pareto Set by Clustering

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 tradeoff front is desirable from the decision maker's point of view. An average linkage based hierarchical clustering algorithm [38] used by SPEA [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.

B. Best Compromise Solution

Fuzzy set theory has been implemented to derive efficiently a candidate Pareto-optimal solution for the decision makers [39]–[41]. Upon having the Pareto-optimal set, the proposed approach presents a fuzzy-based mechanism to extract a Pareto-optimal solution as the best compromise solution. Due to the imprecise nature of the decision maker's judgment, the ith objective function of a solution in the Pareto-optimal set F_i is represented by a membership function μ_i defined as [39]

$$\mu_i = \begin{cases} 1, & F_i \le F_i^{\min} \\ \frac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}}, & F_i^{\min} < F_i < F_i^{\max} \\ 0, & F_i \ge F_i^{\max}. \end{cases} \tag{19}$$

where $F_i^{\max}$ and $F_i^{\min}$ are the maximum and minimum values of the ith objective function, respectively.

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

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

where M is the number of nondominated solutions. The best compromise solution is the one having the maximum of μ^k. As a matter of fact, arranging all solutions in Pareto-optimal set in descending order according to their membership function will provide the decision maker with a priority list of nondominated solutions. This will guide the decision maker in view of the current operating conditions.

C. 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) [42]. 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.

1) Crossover: A blend crossover operator (BLX-α) has been employed in the study reported in this paper. 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.

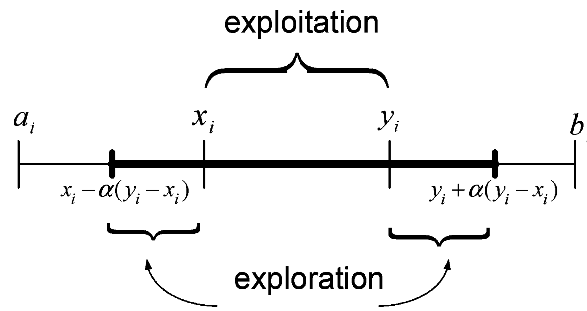

Fig. 1. Blend crossover operator (BLX-α).

2) Mutation: The nonuniform mutation is employed in this paper. In this operator, the new value x_i' of the parameter x_i after mutation at generation t is given as

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

and

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

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 the study reported in this paper, $\beta = 5$ 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.

D. The Computational Flow

In this paper, the basic MOEAs are developed in order to make them suitable for solving real-world nonlinear constrained optimization problems. The following modifications have been incorporated in the basic algorithms.

a) The constraint-handling approach adopted in this paper is to restrict the search within the feasible region. Therefore, 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 the 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 tradeoff curve and assist the power system operator to adjust the generation levels efficiently.

The solution procedure starts with generating the initial population at random. A feasibility check procedure has been developed and superimposed on MOEA to restrict the search to feasible region. The objective functions are evaluated for each indi-

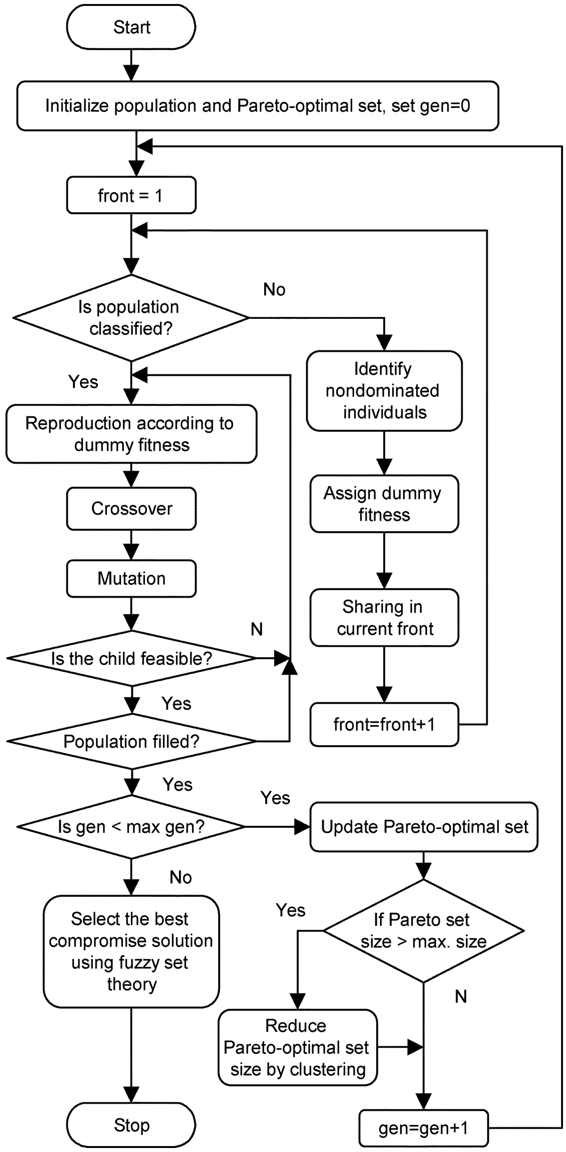

Fig. 2. Computational flow of the developed NSGA.

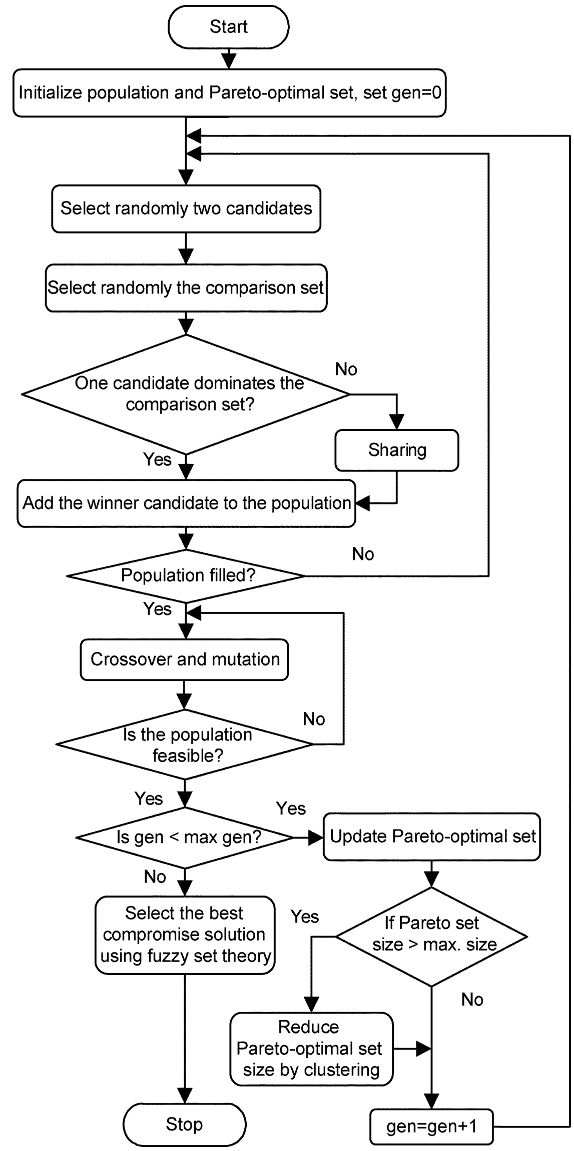

Fig. 3. Computational flow of the developed NPGA.

vidual. The GA operations are applied and a new population is generated. This process is repeated until the maximum number of generations is reached. All techniques used in this paper were implemented along with the above modifications using FORTRAN language.

The computational flow charts of the developed NSGA, NPGA, and SPEA are shown in Figs. 2–4, respectively.

E. Settings of the Proposed Approach

On all optimization runs, the population size was set at 200. The size of the Pareto-optimal set was chosen as 25. If the number of nondominated Pareto-optimal solutions exceeds this bound, the hierarchical clustering technique is called. Since the population in SPEA is augmented to include the externally stored set for selection process, the population size in SPEA was reduced to 175 individuals only. Crossover and mutation probabilities were chosen as 0.9 and 0.01, respectively, in all optimization runs. Several runs have been carried out to set the parameters of each technique in order to get the best results for fair comparison.

VI. Results and Discussions

In this paper, the standard IEEE six-generator 30-bus test system is considered to assess the potential of MOEAs for solving the EED problem. The single-line diagram of this system is shown in Fig. 5. The line data and bus data are given in the Appendix. The values of fuel cost and emission coefficients are given in Table I.

To demonstrate the effectiveness of the MOEA, three different cases have been considered as follows.

Case 1) For the purpose of comparison with the reported results, the system is considered as lossless and the security constraint is released. Therefore, the problem constraints are the power balance constraint without P_{loss} and the generation capacity constraint.

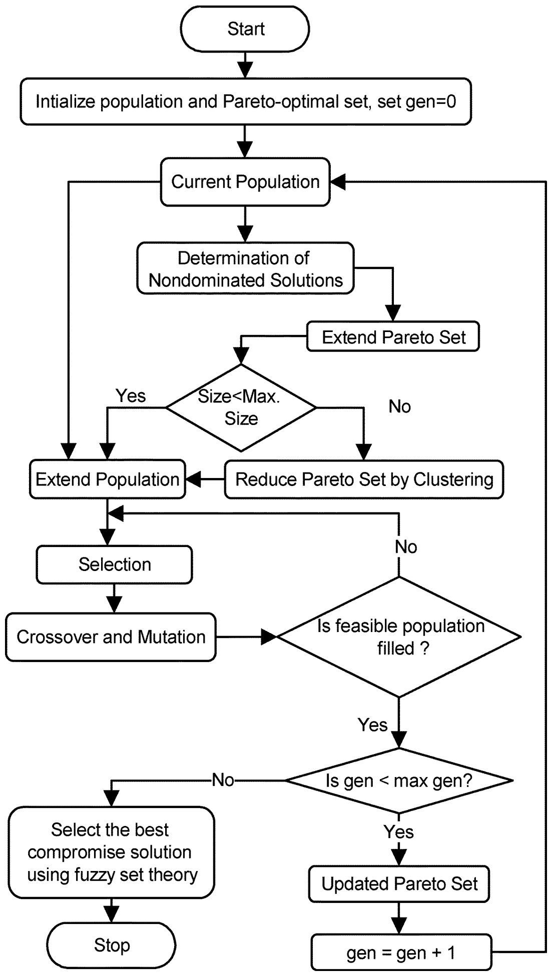

Fig. 4. Computational flow of the developed SPEA.

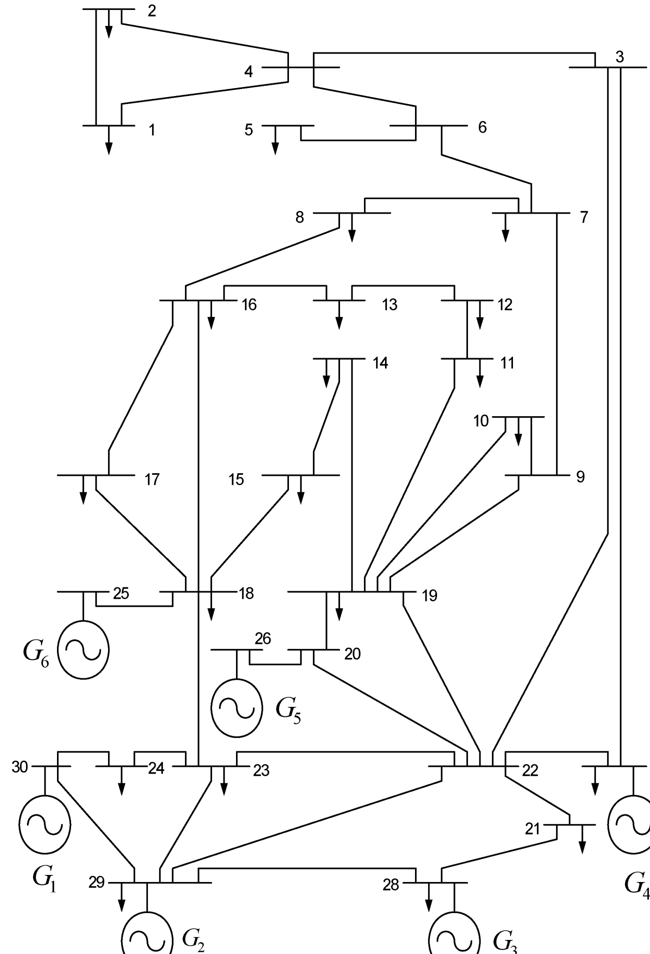

Fig. 5. Single-line diagram of the test system.

Case 2) $P_{\rm loss}$ is considered in the power balance constraint, and the generation capacity constraint is also considered.

Case 3) All constraints are considered.

For fair comparison among the developed techniques, ten different optimization runs have been carried out in all cases considered. Table II shows the problem complexity with all cases in terms of the number of equality and inequality constraints.

At first, fuel cost objective and emission objective are optimized individually to explore the extreme points of the tradeoff surface in all cases. In this case, the standard GA has been implemented as the problem becomes a single objective optimization problem. The best results of cost and emission when optimized individually for all cases are given in Table III.

Case 1: NSGA, NPGA, and SPEA have been applied to the problem and both objectives were treated simultaneously as competing objectives. For NPGA, the niche radius was chosen based on the guidelines in [24], and the size of the comparison set $t_{\rm dom}$ was determined experimentally. The algorithm was tested several times with different $t_{\rm dom}$ starting from 5% to 50% of the population size with a step of 5%. Only a part of the results is shown in Fig. 6 for clarity purposes. Experimental results have shown a favorable value of $t_{\rm dom}$ at 10% for our problem instance whereas the performance degrades for values $t_{\rm dom}$ greater than 20%. Therefore, $t_{\rm dom}$ is set at 10% of the population size.

The Pareto-optimal fronts of all techniques for the best optimization runs are shown in Fig. 7. It is clear that the Pareto-optimal fronts have good diversity characteristics of the nondominated solutions. It is quite clear that the problem is efficiently solved by these techniques. The results also show that SPEA has better diversity characteristics. The best cost and best emission solutions obtained out of ten runs by different techniques are given in Table IV. It is clear that SPEA gives the best cost and best emission compared to others.

The best results of MOEA were compared to those reported using linear programming (LP) [6] and multiobjective stochastic search technique [15]. The comparison is shown in Table V. It is quite evident that the MOEAs give better fuel cost results than the traditional methods as a reduction more than 5 \$/h is observed with less level of emission in the case of SPEA. The results also confirm the potential of multiobjective evolutionary algorithms to solve real-world highly nonlinear constrained multiobjective optimization problems.

Case 2: With the problem complexity shown in Table II, MOEA techniques have been implemented and compared. Fig. 8 shows the Pareto-optimal fronts of different techniques for the best optimization runs. It is evident that the nondominated solutions obtained have good diversity characteristics.

TABLE I
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	5.326	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

TABLE II
PROBLEM COMPLEXITY FOR THE CASES CONSIDERED

	Equality Constraints	***Inequality Constraints***
Case 1	1	6
Case 2	60	6
Case 3	60	47

TABLE III
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	0.1475	0.4693
P_{G2}	0.2997	0.4592	0.3055	0.4631	0.3340	0.5223
P_{G3}	0.5245	0.5380	0.5972	0.5435	0.7864	0.6479
P_{G4}	1.0160	0.3830	0.9809	0.3895	1.0096	0.4734
P_{G5}	0.5247	0.5379	0.5142	0.5439	0.1072	0.1784
P_{G6}	0.3596	0.5101	0.3542	0.5150	0.4806	0.5761
Cost	**600.11**	638.26	**607.78**	645.22	**618.50**	654.14
Emission	0.2221	**0.1942**	0.2199	**0.1942**	0.2302	**0.2016**

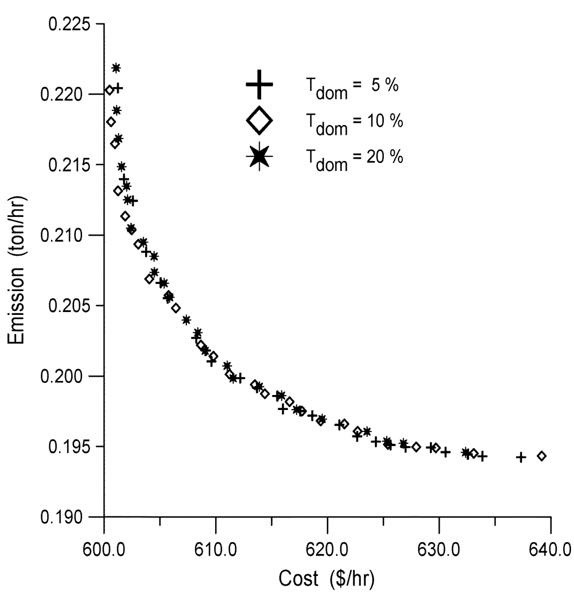

Fig. 6. NPGA with different settings of $t_{\rm dom}$ parameter.

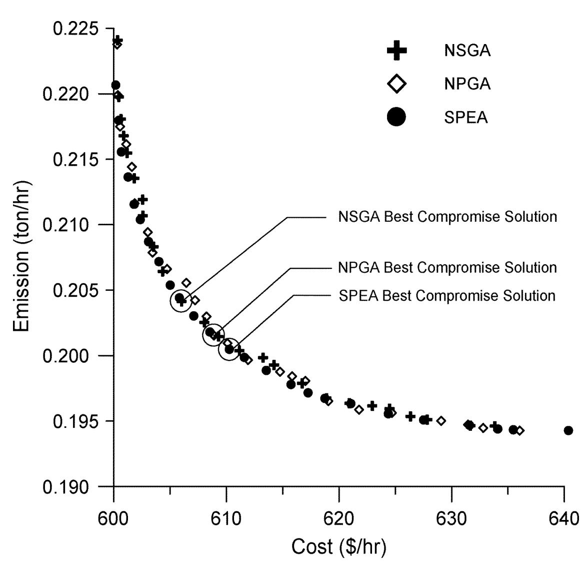

Fig. 7. Comparison of Pareto-optimal fronts, Case 1.

The closeness of the nondominated solutions of different techniques demonstrates good performance characteristics of MOEA. The best solutions obtained out of ten runs by different techniques are given in Table VI.

Case 3: MOEA techniques have been implemented, and the Pareto-optimal fronts of different techniques for the best optimization runs are shown in Fig. 9. In this case, the performance of NSGA is degraded with increasing problem complexity. The best cost and best emission solutions obtained out of ten runs are given in Table VII.

Best Compromise Solution: The membership functions given in (19) and (20) are used to evaluate each member of the Pareto-optimal set for each technique. Then, the best compromise solution that has the maximum value of membership function was extracted. This procedure is applied in all cases,

TABLE IV
BEST SOLUTIONS OUT OF TEN RUNS FOR COST AND EMISSION OF MOEA, CASE 1

	NSGA		*NPGA*		*SPEA*	
	Cost	*Emission*	*Cost*	*Emission*	*Cost*	*Emission*
P_{G1}	0.1038	0.4072	0.1116	0.4146	0.1009	0.4240
P_{G2}	0.3228	0.4536	0.3153	0.4419	0.3186	0.4577
P_{G3}	0.5123	0.4888	0.5419	0.5411	0.5400	0.5301
P_{G4}	1.0387	0.4302	1.0415	0.4067	0.9903	0.3721
P_{G5}	0.5324	0.5836	0.4726	0.5318	0.5336	0.5311
P_{G6}	0.3241	0.4707	0.3512	0.4979	0.3507	0.5190
Cost	**600.34**	633.83	**600.31**	636.04	**600.22**	640.42
Emission	0.2241	**0.1946**	0.2238	**0.1943**	0.2206	**0.1942**

TABLE V
BEST FUEL COST AND EMISSION OUT OF TEN RUNS OF MOEA COMPARED TO TRADITIONAL ALGORITHMS

	LP [6]	*MOSST* [15]	*NSGA*	*NPGA*	*SPEA*
Best Cost	606.31	605.89	600.34	600.31	600.22
Emission	0.2233	0.2222	0.2241	0.2238	0.2206
Best Emission	0.1942	0.1942	0.1946	0.1943	0.1942
Cost	639.60	644.11	633.83	636.04	640.42

TABLE VI
BEST SOLUTIONS OUT OF TEN RUNS FOR COST AND EMISSION OF MOEA, CASE 2

	NSGA		*NPGA*		*SPEA*	
	Cost	*Emission*	*Cost*	*Emission*	*Cost*	*Emission*
P_{G1}	0.1447	0.3929	0.1425	0.4064	0.1279	0.4145
P_{G2}	0.3066	0.3937	0.2693	0.4876	0.3163	0.4450
P_{G3}	0.5493	0.5818	0.5908	0.5251	0.5803	0.5799
P_{G4}	0.9894	0.4316	0.9944	0.4085	0.9580	0.3847
P_{G5}	0.5244	0.5445	0.5315	0.5386	0.5258	0.5348
P_{G6}	0.3542	0.5192	0.3392	0.4992	0.3589	0.5051
Cost	**607.98**	638.98	**608.06**	644.23	**607.86**	644.77
Emission	0.2191	**0.1947**	0.2207	**0.1943**	0.2176	**0.1943**

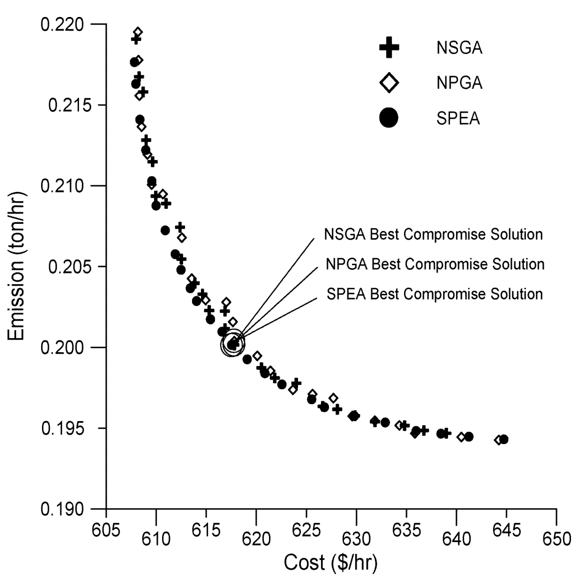

Fig. 8. Comparison of Pareto-optimal fronts, Case 2.

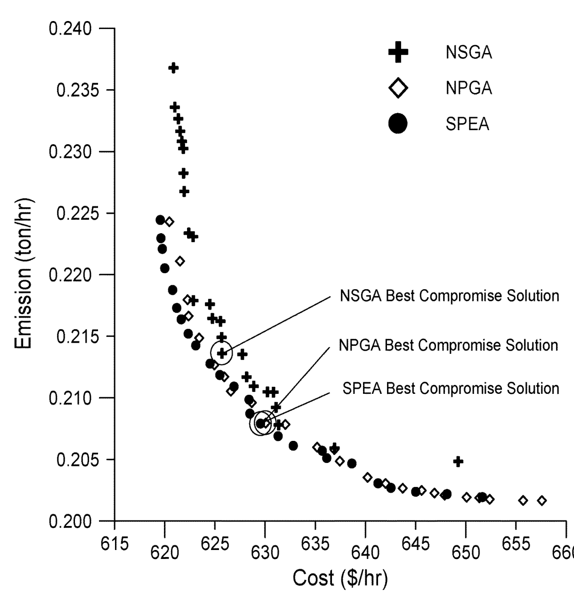

Fig. 9. Comparison of Pareto-optimal fronts, Case 3.

and the best compromise solutions are given in Tables VIII–X for NSGA, NPGA, and SPEA, respectively. The best compromise solutions are also shown in Figs. 8–10. It is clear that there is good agreement between SPEA and NPGA.

VII. A COMPARATIVE STUDY

In this study, a new procedure for quality measure is proposed and compared to some measures reported in the literature

TABLE VII
BEST SOLUTIONS OUT OF TEN RUNS FOR COST AND EMISSION OF MOEA, CASE 3

	NSGA		***NPGA***		***SPEA***	
	Cost	*Emission*	*Cost*	*Emission*	*Cost*	*Emission*
P_{G1}	0.1358	0.4403	0.1127	0.4753	0.1319	0.4419
P_{G2}	0.3151	0.4940	0.3747	0.5162	0.3654	0.4598
P_{G3}	0.8418	0.7509	0.8057	0.6513	0.7791	0.6944
P_{G4}	1.0431	0.5060	0.9031	0.4363	0.9282	0.4616
P_{G5}	0.0631	0.1375	0.1347	0.1896	0.1308	0.1952
P_{G6}	0.4664	0.5364	0.5331	0.5988	0.5292	0.6131
Cost	**620.87**	649.24	**620.46**	657.59	**619.60**	651.71
Emission	0.2368	**0.2048**	0.2243	**0.2017**	0.2244	**0.2019**

TABLE VIII
BEST COMPROMISE SOLUTIONS OF NSGA

	***Case* 1**	***Case* 2**	***Case* 3**
P_{G1}	0.2252	0.2935	0.2712
P_{G2}	0.3622	0.3645	0.3670
P_{G3}	0.5222	0.5833	0.8099
P_{G4}	0.7660	0.6763	0.7550
P_{G5}	0.5397	0.5383	0.1357
P_{G6}	0.4187	0.4076	0.5239
Cost	**606.03**	**617.80**	**625.71**
Emission	**0.2041**	**0.2002**	**0.2136**

TABLE IX
BEST COMPROMISE SOLUTIONS OF NPGA

	***Case* 1**	***Case* 2**	***Case* 3**
P_{G1}	0.2663	0.2976	0.2998
P_{G2}	0.3700	0.3956	0.4325
P_{G3}	0.5222	0.5673	0.7342
P_{G4}	0.7202	0.6928	0.6852
P_{G5}	0.5256	0.5201	0.1560
P_{G6}	0.4296	0.3904	0.5561
Cost	**608.90**	**617.79**	**630.06**
Emission	**0.2015**	**0.2004**	**0.2079**

[43]. Generally, the definition of quality in the case of multi-objective optimization is substantially more complex than for single objective optimization problems. This is because the optimization goal itself consists of the following multiple objectives [43]–[45].

a) The distance of the resulting nondominated set to the Pareto-optimal front should be minimized.
b) A good distribution of the solutions found is desirable.
c) The extent of the obtained nondominated Pareto-optimal solutions should be maximized.

In this section, the above results of the different techniques have been compiled and compared in view of the above objectives. In order to assess the diversity characteristics of the proposed techniques, the best fuel cost and the best emission solutions among the obtained nondominated solutions of each technique given in Tables IV, VI, and VII are compared to those of individual optimization of each objective given in Table III. This indicates how far the extreme solutions are. The agreement and closeness of the results given in these tables are quite evident, as the best solutions of different techniques are almost identical. It can be concluded that the developed techniques have satisfactory diversity characteristics for the problem under consideration as the best solutions for individual optimization are obtained along with other nondominated solutions in a single run.

A performance measure of the extent of the nondominated solutions is presented in [43]. The measure estimates the range to which the fronts spread out. In other words, it measures the normalized distance of the two outer solutions, i.e., the best cost solution and the best emission solution. The average values of the normalized distance measure over ten different optimization runs are given in Table XI. The results show that NPGA has the largest extent of the Pareto-optimal solutions in Case 1, while SPEA has the largest extent in Case 2. In Case 3, NSGA has the largest extent.

On the other hand, the set coverage metric measure [45] for comparing the performance of different MOEA has been examined in this study. The average values of this measure over ten different optimization runs are given in Table XII. It can be shown that the nondominated solutions of NSGA do not cover any of SPEA solutions in Case 3, while those of NSGA are approximately covered by SPEA. In addition, NPGA nondominated solutions barely cover SPEA solutions

TABLE X
BEST COMPROMISE SOLUTIONS OF SPEA

	Case 1	*Case* 2	*Case* 3
P_{G1}	0.2623	0.2752	0.3052
P_{G2}	0.3765	0.3752	0.4389
P_{G3}	0.5428	0.5796	0.7163
P_{G4}	0.6838	0.6770	0.6978
P_{G5}	0.5381	0.5283	0.1552
P_{G6}	0.4305	0.4282	0.5507
Cost	**610.30**	**617.57**	**629.59**
Emission	**0.2004**	**0.2001**	**0.2079**

TABLE XI
NORMALIZED DISTANCE MEASURE OF DIFFERENT TECHNIQUES

	NSGA	*NPGA*	*SPEA*
Case 1	0.93757	0.95001	0.93809
Case 2	0.92211	0.93747	0.94509
Case 3	0.85539	0.81312	0.85363

TABLE XII
PERCENTAGE OF NONDOMINATED SOLUTIONS OF SET B COVERED BY THOSE IN SET A

Set A	*Set B*	*Case 1*	*Case 2*	*Case 3*
NSGA	***NPGA***	27.6	24.0	2.0
	SPEA	3.6	2.4	0.0
NPGA	***NSGA***	25.2	29.2	82.4
	SPEA	2.0	5.6	14.4
SPEA	***NSGA***	52.8	53.2	97.4
	NPGA	58.8	55.6	46.0

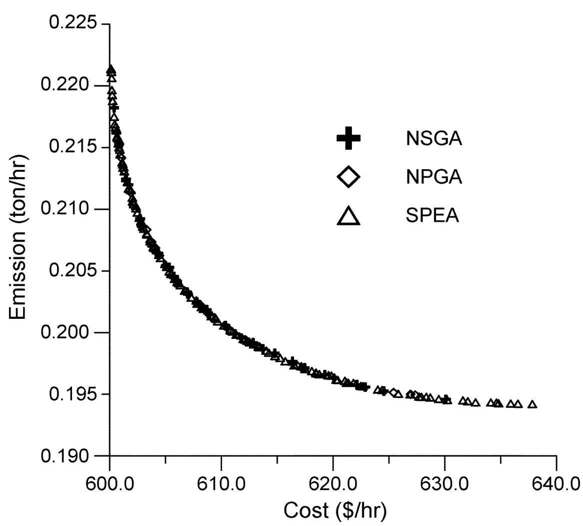

Fig. 10. Pareto-optimal front of elite set of nondominated solutions, Case 1.

with a maximum coverage of 14.4%, while SPEA solutions cover relatively higher percentages of NPGA solutions.

In this study, a new procedure for quality measure of the nondominated solutions obtained by different MOEA is proposed. The main feature of the proposed procedure is that several techniques can be compared simultaneously. The proposed procedure starts with combining all individual nondominated sets of all techniques to form a pool. An index to each solution is added to refer to the associated technique. Then, the dominance conditions are applied for all solutions in the pool. The nondominated solutions are extracted from the pool to form an elite set of Pareto-optimal solutions obtained by all techniques. Having their indexes, the nondominated solutions in the elite set can be classified according to their associated technique.

The proposed procedure has been implemented to measure the quality of the nondominated solutions obtained in each case. For ten different optimization runs with 25 nondominated solutions obtained by each technique per run, the created pool contains 750 solutions. For each case, the nondominated solutions are extracted out of the pool and the elite set is formed. The elite set consists of 181, 165, and 117 for Cases 1, 2, and 3, respectively. The results of the proposed quality measure are given in Table XIII. It can be observed that the SPEA has the majority of the elite set members in all cases. It can be concluded that the most of the nondominated solutions obtained by SPEA are true Pareto-optimal solutions since approximately 71%, 78%, and 69% of the elite set size is contributed by SPEA in Cases 1, 2, and 3 respectively. Also, it can be seen that only one nondominated solutions obtained by NSGA in Case 3 is a member in the elite set. The Pareto-optimal fronts represented by the nondominated solutions in the elite set for Cases 1, 2, and 3 are shown in Figs. 10–12, respectively.

The average value of the normalized distance results of the proposed measure over ten different optimization runs is given in Table XIV. It is worth mentioning that the distance obtained with the proposed measure is that between the outer nondominated solutions of each technique represented in the elite set. It can be seen that the nondominated solutions obtained

TABLE XIII
NUMBER OF PARETO-OPTIMAL SOLUTIONS OF DIFFERENT TECHNIQUES IN ELITE SET OF NONDOMINATED SOLUTIONS

	NSGA	*NPGA*	*SPEA*	*Elite Set Size*
Case 1	36	16	129	181
Case 2	19	17	129	165
Case 3	1	35	81	117

TABLE XIV
NORMALIZED DISTANCE MEASURE OF DIFFERENT TECHNIQUES ON ELITE SET OF NONDOMINATED SOLUTIONS

	NSGA	*NPGA*	*SPEA*
Case 1	0.82937	0.73043	1.00000
Case 2	0.63184	0.93501	1.00000
Case 3	0.00000	0.53827	1.00000

TABLE XV
RUN TIME OF DIFFERENT ALGORITHMS

	NSGA	*NPGA*	*SPEA*
Run time (s)	0.727	0.750	0.671

TABLE XVI
ROBUSTNESS OF MOEA FOR DIFFERENT INITIAL POPULATIONS

	NSGA		*NPGA*		*SPEA*	
	Cost	*Emission*	*Cost*	*Emission*	*Cost*	*Emission*
Min	600.34	0.1946	600.31	0.1943	600.22	0.1942
Max	600.77	0.1949	600.78	0.1944	600.60	0.1943
Ave	600.43	0.1947	600.48	0.1943	600.33	0.1943

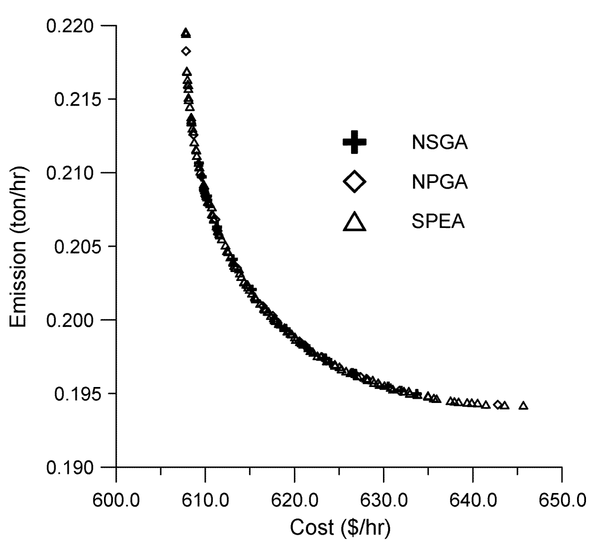

Fig. 11. Pareto-optimal front of elite set of nondominated solutions, Case 2.

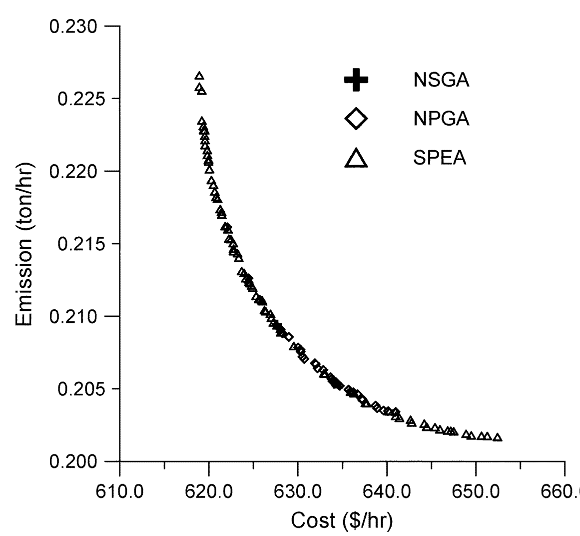

Fig. 12. Pareto-optimal front of elite set of nondominated solutions, Case 3.

by SPEA span over the entire Pareto-optimal front in all cases. In general, it can be concluded that SPEA has the best distribution of the nondominated solutions for the problem under consideration.

With the proposed approach of extracting an elite set from combining the nondominated solutions of all techniques, it can be seen that the proposed measure and the normalized distance measure are consistent and their results have a satisfactory agreement with the simulation results. Also, the proposed measure reflects properly the quality of the nondominated solutions produced by each algorithm. In addition, several techniques can be compared in a single run rather than on a one-to-one basis.

The comparison of the average value of the run time over ten different optimization runs per generation per Pareto-optimal solution of MOEA techniques with Case 1 is given in Table XV. It is quiet evident that the run time of SPEA is less than that of the other techniques.

The robustness of MOEA techniques with respect to different initial populations has been examined in all cases considered. Due to space limitations, the minimum, the maximum, and the average values of the best cost and the best emission in

Case 1 are given in Table XVI. It is clear that all techniques exhibit satisfactory degree of robustness to initial populations. In addition, SPEA gives better average results.

Based on the above comparisons and discussions, it can be concluded that SPEA is better than other techniques for the environmental/economic power dispatch optimization problem since true Pareto-optimal solutions with satisfactory diversity characteristics have been produced in this study.

VIII. Conclusion

In this paper, three multiobjective evolutionary algorithms have been compared and successfully applied to environmental/economic power dispatch problem. The problem has been formulated as a multiobjective optimization problem with competing economic and environmental impact objectives. MOEAs have been compared to each other and to those reported in the literature. In addition, a new and efficient procedure for quality measure is proposed and compared to some measures reported in the literature. The optimization runs indicate that MOEAs outperform the traditional techniques. Moreover, the SPEA has better diversity characteristics and is more efficient when compared to other MOEAs. The results show that evolutionary algorithms are effective tools for handling multiobjective optimization where multiple Pareto-optimal solutions can be found in one simulation run.

In addition, the diversity of the nondominated solutions is preserved. It is also demonstrated that the SPEA has the best computational time. It can be concluded that MOEA has the potential to solve different multiobjective power systems' optimization problems.

Appendix

The line and bus data of the IEEE 30-bus six-generator system are given in Tables XVII and XVIII, respectively.

TABLE XVII
IEEE 30-Bus Test System Line Data

Line #	From Bus	To Bus	Resistance (pu)	Reactance (pu)	Susceptance (pu)	Rating (MVA)
1	1	2	0.0192	0.0575	0.0264	130
2	1	3	0.0452	0.1852	0.0204	130
3	2	4	0.0570	0.1737	0.0184	65
4	3	4	0.0132	0.0379	0.0042	130
5	2	5	0.0472	0.1983	0.0209	130
6	2	6	0.0581	0.1763	0.0187	65
7	4	6	0.0119	0.0414	0.0045	90
8	5	7	0.0460	0.1160	0.0102	70
9	6	7	0.0267	0.0820	0.0085	130
10	6	8	0.0120	0.0420	0.0045	32
11	6	9	0.0000	0.2080	0.0000	65
12	6	10	0.0000	0.5560	0.0000	32
13	9	11	0.0000	0.2080	0.0000	65
14	9	10	0.0000	0.1100	0.0000	65
15	4	12	0.0000	0.2560	0.0000	65
16	12	13	0.0000	0.1400	0.0000	65
17	12	14	0.1231	0.2559	0.0000	32
18	12	15	0.0662	0.1304	0.0000	32
19	12	16	0.0945	0.1987	0.0000	32
20	14	15	0.2210	0.1997	0.0000	16
21	16	17	0.0824	0.1923	0.0000	16
22	15	18	0.1070	0.2185	0.0000	16
23	18	19	0.0639	0.1292	0.0000	16
24	19	20	0.0340	0.0680	0.0000	32
25	10	20	0.0936	0.2090	0.0000	32
26	10	17	0.0324	0.0845	0.0000	32
27	10	21	0.0348	0.0749	0.0000	32
28	10	22	0.0727	0.1499	0.0000	32
29	21	22	0.0116	0.0236	0.0000	32
30	15	23	0.1000	0.2020	0.0000	16
31	22	24	0.1150	0.1790	0.0000	16
32	23	24	0.1320	0.2700	0.0000	16
33	24	25	0.1885	0.3292	0.0000	16
34	25	26	0.2544	0.3800	0.0000	16
35	25	27	0.1093	0.2087	0.0000	16
36	28	27	0.0000	0.3960	0.0000	65
37	27	29	0.2198	0.4153	0.0000	16
38	27	30	0.3202	0.6027	0.0000	16
39	29	30	0.2399	0.4533	0.0000	16
40	8	28	0.0636	0.2000	0.0214	32
41	6	28	0.0169	0.0599	0.0065	32

TABLE XVIII
IEEE 30-Bus Test System Bus Data

Bus	P_D (MW)	Q_D (MVAR)
1	0.00	0.00
2	21.70	12.70
3	2.40	1.20
4	7.60	1.60
5	94.20	19.00
6	0.00	0.00
7	22.80	10.90
8	30.00	30.00
9	0.00	0.00
10	5.80	2.00
11	0.00	0.00
12	11.20	7.50
13	0.00	0.00
14	6.20	1.60
15	8.20	2.50
16	3.50	1.80
17	9.00	5.80
18	3.20	0.90
19	9.50	3.40
20	2.20	0.70
21	17.50	11.20
22	0.00	0.00
23	3.20	1.60
24	8.70	6.70
25	0.00	0.00
26	3.50	2.30
27	0.00	0.00
28	0.00	0.00
29	2.40	0.90
30	10.60	1.90

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