Elitist Multiobjective Evolutionary Algorithm for Environmental/Economic Dispatch

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Abstract- The environmental/economic dispatch problem is a multiobjective nonlinear optimization problem with constraints. Until recently, this problem has been addressed by considering economic and emission objectives separately or as a weighted sum of both objectives. Multiobjective evolutionary algorithms can find multiple Pareto-optimal solutions in one single run and this ability makes them attractive for solving problems with multiple and conflicting objectives. This paper uses an elitist multiobjective evolutionary algorithm based on the Non-dominated Sorting Genetic Algorithm – II (NSGA-II) for solving the environmental/economic dispatch problem. Elitism ensures that the population best solution does not deteriorate in the next generations. Simulation results are presented for a sample power system.

1 Introduction

The ability of multiobjective evolutionary algorithms to find multiple Pareto-optimal solutions in one single run have made them attractive for solving problems with multiple and conflicting objectives. During the last decade, several multiobjective evolutionary algorithms [1] have been proposed which are aimed at finding the Pareto-optimal front and also achieve diversity in the obtained Pareto-optimal front.

The classical economic dispatch problem is to operate electric power systems so as to minimize the total fuel cost. This single objective can no longer be considered alone due to the environmental concerns that arise from the emissions produced by fossil-fueled electric power plants. In fact, the Clean Air Act Amendments have been applied to reduce SO_2 and NO_x emissions from such power plants. Accordingly, emissions can be reduced by three main methods [2]:

- post-combustion cleaning systems
- switching to fuels with lower emission potentials
- dispatch of power generation to minimize emissions instead of or as a supplement to the usual cost objective of economic dispatch.

The third method involves only minor modifications to dispatching programmes for implementing environmental/economic dispatching. Different environmental/economic dispatch algorithms have been outlined in [2]. A review of the potential requirements of utilities regarding system operations to meet the Clean Air Act Regulations is presented in [3].

Environmental/economic dispatch is a multiobjective problem with conflicting objectives because pollution minimization is conflicting with minimum cost of generation. Various techniques have been proposed to solve this multiobjective problem. Ref. [4] was one of the first approaches to solve the environmental/economic dispatch problem considering multiobjective optimization using linear and non-linear goal programming techniques. An ε-constrained technique was used by Yokohama et al. [5] considering economy, security and environment protection as objectives. In this method, a security-based preference index is used to select the optimal solution from the Pareto-optimal solutions obtained. A goal programming technique for solving this multiple criteria decision making problem and evaluate the environmental marginal cost by a non-inferiority surface was proposed by Kermanshahi et al. [6]. A recursive quadratic programming method to solve the emission constrained dynamic economic dispatch by fuel switching was presented in [7]. Dhillon et al. [8] formulated the problem considering uncertainties in system production cost and random nature of load demand. The weighted minimax technique was used to obtain trade-off relation between the conflicting objectives and fuzzy set theory was subsequently used to help the operator choose an optimal operating point. Linear programming (Third Simplex Method) for obtaining the approximate solution to the linearized optimization problem was investigated in [9].

An Hopfield neural network for finding the optimal economic/environmental dispatching of thermal generating units was considered by King et al. [10], where the emission functions for SO_2 and NO_x were weighted and added to the cost objective function, demand requirement constraint and system losses functions. Roa-Sepulveda et al. [11] extended the technique described in [10] for an Hopfield Neural Network and also used Tabu Search by linearly combining the objectives. It was observed that the weighting factor selection was complicated as each weighting factor affects the others. These authors first set the power mismatch weighting factor and then used the method in [10] to calculate those for the emissions.

Chang et al. [12] also addressed the economic and environmental objectives simultaneously by combining them linearly to form a single objective function. By varying the weight, the trade off between fuel cost and environmental cost was determined. Song et al. [13] used a fuzzy logic controlled genetic algorithm for solving the environmental/economic dispatch where the crossover and mutation probabilities were adjusted based on the average fitness of the population. The multiobjective problem was converted to a scalar optimization problem with weighted constraints. Yalcinoz and Altun [14] proposed a solution to the environmental economic dispatch using a modified genetic algorithm which is based on arithmetic crossover operator with real valued genes. This approach also expressed the fitness function (overall objective) as a weighted sum of the total fuel cost and emission (SO_2 and NO_x) objectives.

Some researchers have carried out simultaneous optimization of multiple objectives in the environmental/economic dispatch problem using evolutionary algorithms. In [15] and [16], a hybrid genetic algorithm using an indirect representation for solutions and a decoding procedure that always generates a feasible solution is used. The optimization algorithm generates trade-off curves between cost and emission based on emission dispatching and fuel switching. However, the approach did not yield a good distribution on the Pareto-optimal front. Recently, promising results have been obtained by Abido [17] by using a Non-dominated Sorting Genetic Algorithm (NSGA) to locate the Pareto-optimal solutions with a good diversity.

It has been argued that NSGA suffers from three weaknesses: computational complexity, non-elitist approach and the need to specify a sharing parameter [18]. An improved version of NSGA known as NSGA-II, which resolved the above problems and uses elitism to create a diverse Pareto-optimal front, has been subsequently presented [18].

In this paper, an elitist multiobjective evolutionary algorithm based on NSGA-II is applied to the environmental/economic power dispatch optimization problem. Simulation results considering two and then three objectives simultaneously are presented for a sample test system.

2 Environmental/Economic Dispatch

The environmental/economic dispatch involves the simultaneous optimization of fuel cost and emission objectives which are conflicting ones. The problem is formulated as described below.

2.1 Objective Functions

Fuel Cost Objective

The classical economic dispatch problem of finding the optimal combination of power generation which minimizes the total fuel cost while satisfying the total required demand can be mathematically stated as follows [19]:

$$C = \sum_{i=1}^{n}\left(a_i + b_i P_{Gi} + c_i P_{Gi}^2\right) \tag{1}$$

where

C: total fuel cost ($/hr),
a_i, b_i, c_i: fuel cost coefficients of generator i,
P_{Gi}: power generated by generator i (MW), and
n: number of generators.

The minimum emission dispatch optimizes the above classical economic dispatch including the SO_2 and NO_x emission objectives which can be modeled using second order polynomial functions [2]:

SO_2 Emission Objective

$$E_{SO_2} = \sum_{i=1}^{n}\left(a_{iS} P_{Gi}^2 + b_{iS} P_{Gi} + c_{iS} \right) \tag{2}$$

NO_x Emission Objective

$$E_{NO_x} = \sum_{i=1}^{n}\left(a_{iN} P_{Gi}^2 + b_{iN} P_{Gi} + c_{iN} \right) \tag{3}$$

Units of E_{SO_2} and E_{NO_x} are ton/hr.

2.2 Constraints

The optimization problem is bounded by the following constraints:

Power balance constraints

$$\sum_{i=1}^{n} P_i - P_D - P_L = 0 \tag{4}$$

where

P_D: total load (MW), and
P_L: transmission losses (MW).

The transmission losses can be represented as

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_{Gi} B_{ij} P_{Gj} \tag{5}$$

where

B_{ij} : transmission losses coefficient

Maximum and minimum limits of power generation

The power generated P_{Gi} by each generator should lie between its minimum and maximum limits, i.e.,

$$P_{Gimin} \le P_{Gi} \le P_{Gimax}$$

where

P_{Gimin}: minimum power generated, and
P_{Gimax}: maximum power generated.

2.3 Multiobjective Formulation

The multiobjective environmental/economic dispatch optimization problem is therefore formulated as:

Minimize $[\, C, E_{SO_2}, E_{NO_x} \,]$ (6)

subject to: $h(P_{Gi})=0$ (power balance)

and $P_{Gimin} \le P_{Gi} \le P_{Gimax}$ (generation limits)

3 Elitist Multiobjective Evolutionary Algorithm

Elitism ensures that the fitness of the best solution in a population does not deteriorate as the generation advances. Rudolph [20] has proved that genetic algorithms converge to the global optimal solution of some functions in the presence of elitism. In fact, using elite parents increases the probability of creating better offsprings. For multiobjective optimization problems, individuals found on the non-dominated front are considered as elites. Deb et al. [18] have proposed an elitist Non-dominated Sorting Genetic Algorithm known as NSGA-II which uses both elite-preserving and diversity-preserving mechanisms. The two distinct goals in multiobjective optimization are:

(i) discover solutions as close to the Pareto-optimal solutions as possible
(ii) find solutions as diverse as possible in the obtained non-dominated front

It has been shown [18] that NSGA-II can achieve these two goals well.

3.1 Non-dominated Sorting Genetic Algorithm - II

A description of the NSGA-II algorithm is given in this section. Initially a random population P_o is created. The population is sorted into different non-domination levels. Each solution is assigned a fitness equal to its non-domination level where level 1 is the best level. Binary tournament selection with a crowded tournament operator, recombination, and mutation operators are used to create an offspring population Q_o of size N. The NSGA-II procedure (as in ref. [18]) is outlined below:

NSGA-II

Step 1

Combine parent and offspring populations and create $R_t = P_t \cup Q_t$

Perform a non-dominated sorting to R_t and identify different fronts: F_i, $i = 1, 2, \ldots$

Step 2

Set new population P_{t+1} = null. Set a counter $i = 1$.

Until $|P_{t+1}| + |F_i| < N$, perform $P_{t+1} = P_{t+1} \cup F_i$ and $i = i + 1$.

Step 3

Perform the Crowding-sort(F_i,<c) procedure given below and include the most widely spread ($N - |P_{t+1}|$) solutions by using the crowding distance values in the sorted F_i to P_{t+1}.

Step 4

Create offspring population Q_{t+1} from P_{t+1} by using the crowded tournament selection, crossover and mutation operators.

Crowding-sort(F_i<c)

Step 1

Call the number of solutions in F as $l = |F|$. For each i in the set, first assign crowding distance, $d_i = 0$.

Step 2

For each objective function $m = 1,2,\ldots,M$, sort the set in worse order of f_m or, find the sorted indices vector:

$$I^m = \text{sort}(f_m, >)$$

Step 3

For $m = 1,2,\ldots,M$, assign a large distance to the boundary solutions, or $d_{I_1^m} = d_{I_l^m} = \infty$, and for all other solutions j = 2 to (l - 1), assign:

$$d_{I_j^m} = d_{I_j^m} + \frac{f_m^{(I_{j+1}^m)} - f_m^{(I_{j-1}^m)}}{f_m^{max} - f_m^{min}}.$$

NSGA-II performs a non-dominated sorting of the combined parent and offspring population. Elitism is introduced by maintaining the best non-dominated solutions in fronts until all P population slots are filled. A crowded distance-based niching strategy is used to find solutions from the last front that are to be carried over to the next generation.

3.2 Simulated Binary Crossover and Parameter-based Mutation

The use of real-valued genes in GAs offers a number of advantages in numerical function optimization over binary encodings [21]. The variables are therefore represented as real numbers and the simulated binary crossover [22] and the real-parameter mutation operator are used. With simulated binary crossover (SBX), two children solutions (c_1 and c_2) are created from two parents (p_1 and p_2) as follows [23]:

1) Choose a random number $u \in [0,1)$.
2) Calculate $$\beta_q = \begin{cases} (u\alpha)^{\frac{1}{\eta_c+1}}, & \text{if } u \le \frac{1}{\alpha}; \\ \left(\frac{1}{2-u\alpha}\right)^{\frac{1}{\eta_c+1}}, & \text{otherwise,} \end{cases} \quad (7)$$
   where
   $$\alpha = 2 - \beta^{-(\eta_c+1)},$$
   $$\beta = 1 + \frac{2}{y_2 - y_1} min[(y_1 - y_l), (y_u - y_2)].$$
   y_l and y_u: lower and upper limits of y
   η_c : distribution index for crossover
3) Compute children solutions:
   $$c_1 = 0.5[(y_1 + y_2) - \beta_q |y_2 - y_1|],$$
   $$c_2 = 0.5[(y_1 + y_2) + \beta_q |y_2 - y_1|]$$

The mutation operator [23] is applied as follows:

1) Choose a random number $u \in [0,1)$.
2) Calculate
   $$\delta_q = \begin{cases} [2u + (1-2u)(1-\delta)^{\eta_m+1}]^{\frac{1}{\eta_m+1}} - 1, & \text{if } u \le 0.5, \\ 1 - [2(1-u) + 2(u-0.5)(1-\delta)^{\eta_m+1}]^{\frac{1}{\eta_m+1}}, & \text{otherwise} \end{cases} \quad (8)$$
   where

$$\delta = min[(y - y_l),(y_u - y)]/(y_u - y_l)$$

η_m : distribution index for mutation

3) Calculate the mutated child:
$$c = y + \delta_q(y_u - y_l).$$

3.3 Constrained Tournament Method

In this method, two solutions are picked from the population and the better solution is chosen. With constraints, each solution can be either feasible or infeasible. The constrain-domination principle [24] is defined as follows:

A solution *i* is said to constrained-dominate a solution *j* if any of the following conditions is true.

1) Solution *i* is feasible and solution *j* is not.
2) Solutions *i* and *j* are both infeasible, but solution *i* has a smaller overall constraint violation.
3) Solutions *i* and *j* are feasible and solution *i* dominates solution *j*.

Thus, feasible solutions are ranked according to their nondomination level based on the objective function values such that feasible solutions have better ranks than infeasible solutions. The infeasible solution with a smaller constraint violation is chosen when the tournament takes place between two infeasible solutions.

4 Best Compromise Solution

The algorithm described in the previous section generates the non-dominated set of solutions known as the Pareto-optimal solutions. The decision maker (power system operator) may have imprecise or fuzzy goals for each objective function. To aid the operator in selecting an operating point from the obtained set of Pareto-optimal solutions, fuzzy logic theory is applied to each objective functions to obtain a fuzzy membership function μ_{f_i} as follows [8]:

$$\mu_{f_i} = \begin{cases} 1 & f_i \le f_i^{min} \\ \dfrac{f_i^{max} - f_i}{f_i^{max} - f_i^{min}} & f_i^{min} < f_i < f_i^{max} \\ 0 & f_i \ge f_i^{max} \end{cases} \qquad (9)$$

The best non-dominated solution can be found when eqn. (10) is a maximum where the normalized sum of membership function values for all objectives is highest.

$$\mu^k = \frac{\sum_{i=1}^{N} \mu_{f_i}^k}{\sum_{k=1}^{M} \sum_{i=1}^{N} \mu_{f_i}^k} \qquad (10)$$

where *M* is the number of non-dominated solutions.

5 Simulation Results

The elitist multiobjective algorithm was applied to a 3-generator test system [19] whose data are given below. The system demand is 850 MW in all simulations.

Table 1: Fuel Cost coefficients

Unit i	a_i	b_i	c_i	P_{Gimin}	P_{Gimax}
1	561.0	7.92	0.001562	150.0	600.0
2	310.0	7.85	0.00194	100.0	400.0
3	78.0	7.97	0.00482	50.0	200.0

The system transmission losses is calculated using a simplified loss expression:

$P_L = 0.00003P_{G1}^2 + 0.00009P_{G2}^2 + 0.00012P_{G3}^2$ (MW)

SO_2 and NO_x emission coefficients are taken from [11] and are shown in Tables 2 and 3 respectively.

Table 2: SO_2 Emission coefficients

Unit i	a_{iS}	b_{iS}	c_{iS}
1	1.6103e-6	0.00816466	0.5783298
2	2.1999e-6	0.00891174	0.3515338
3	5.4658e-6	0.00903782	0.0884504

Table 3: NO_x Emission coefficients

Unit i	a_{iN}	b_{iN}	c_{iN}
1	1.4721848e-7	-9.4868099e-5	0.04373254
2	3.0207577e-7	-9.7252878e-5	0.055821713
3	1.9338531e-6	-3.5373734e-4	0.027731524

In all simulations, the population size was chosen as 500 individuals; crossover and mutation probabilities were 0.99 and 0.01 respectively. The distribution index for crossover and mutation were set at 5 and 50 respectively. The simulations were run for 20000 generations.

5.1 Fuel Cost and SO_2 Emission

Firstly, the algorithm is used to optimize the power dispatch for the bi-objective problem: fuel cost and SO_2 emission. The Pareto-optimal front obtained is shown in Figure 1.

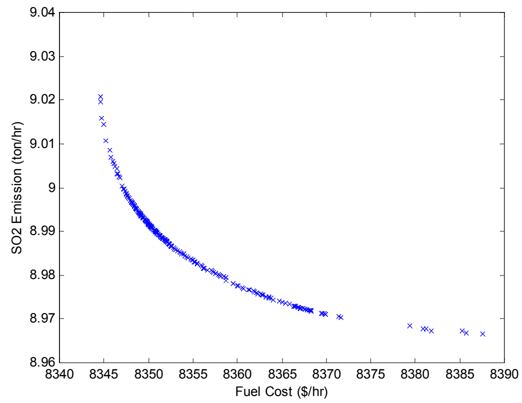

Figure 1: Pareto-optimal front for fuel cost and SO_2 emission

Tables 4 and 5 show the simulation results for best fuel cost and best SO_2 emission as compared to the Tabu search approach from [11].

Table 4: Best fuel cost:

	Tabu Search [11]	NSGA-II
P_{G1}	435.69	436.366
P_{G2}	298.828	298.187
P_{G3}	131.28	131.228
Losses	15.798	15.781
Fuel cost	**8344.598**	**8344.606**
SO_2 Emission	9.02146	9.02083

Table 5: Best SO_2 emission:

	Tabu Search [11]	NSGA-II
P_{G1}	549.247	541.308
P_{G2}	234.582	223.249
P_{G3}	81.893	99.919
Losses	15.722	14.476
Fuel cost	8403.485	8387.518
SO_2 Emission	**8.974**	**8.96655**

From the above tables, it is noted that the best fuel cost obtained by NSGA-II is comparable to that obtained by Tabu search (single objective optimization). Moreover, the best SO_2 emission obtained by NSGA-II is better than that obtained using Tabu search. Transmission losses are also reduced in the solutions found by the elitist multiobjective evolutionary algorithm.

The best compromise solution selected using fuzzy set theory (eqn. (10)) is shown in Table 6.

Table 6: Best compromise solution

P_{G1}	485.886
P_{G2}	263.670
P_{G3}	115.381
Losses	14.937
Fuel cost	8354.419
SO_2 Emission	8.98383

5.2 Fuel Cost and NO_x Emission

Simulations are performed for the two objectives: fuel cost and NO_x emission simultaneously. The Pareto-optimal front obtained is shown in Figure 2.

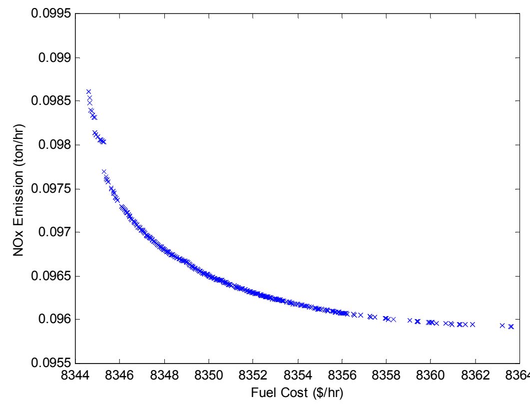

Figure 2: Pareto-optimal front for fuel cost and NO_x emission

Tables 7 and 8 give the simulation results for best fuel cost and best NO_x emission as compared to the Tabu search approach from [11].

Table 7: Best fuel cost

	Tabu Search [11]	NSGA-II
P_{G1}	435.69	435.885
P_{G2}	298.828	299.989
P_{G3}	131.28	129.951
Losses	15.798	15.826
Fuel cost	**8344.598**	**8344.598**
NO_x Emission	0.09863	0.09860

Table 8: Best NO_x emission:

	Tabu Search [11]	NSGA-II
P_{G1}	502.914	505.810
P_{G2}	254.294	252.951
P_{G3}	108.592	106.023
Losses	15.8	14.784
Fuel cost	8371.143	8363.627
NO_x Emission	**0.0958**	**0.09593**

It is observed that the NSGA-II achieves the same best fuel cost as Tabu search while the best NO_x emission found by NSGA-II is comparable to that obtained using Tabu search.

Table 9 shows the best compromise solution selected using fuzzy set theory (eqn. (10)).

Table 9: Best compromise solution

P_{G1}	470.957
P_{G2}	280.663
P_{G3}	113.675
Losses	15.294
Fuel cost	8349.722
NO_x Emission	0.09654

5.3 Fuel Cost, SO_2 and NO_x Emissions

Considering three objective functions: fuel cost, SO_2 emission and NO_x emission simultaneously, simulations results for the Pareto-optimal front were obtained as shown in the 3-D plot of Figure 3.

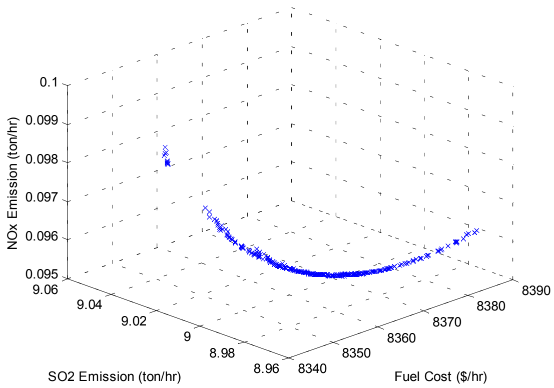

Figure 3: Pareto-optimal front for fuel cost, SO_2 and NO_x emissions

It can be deduced that the algorithm has converged to the Pareto-optimal front given that the solutions obtained are along a clearly identifiable curve. The best solutions for minimum fuel cost, minimum SO_2 emission and minimum NO_x emission are given in Table 10. From this table, it can be deduced that the NSGA-II is equally capable of finding the best solution for each objective when three conflicting objectives are considered simultaneously. Table 11 gives the best compromise taking all three objectives simultaneously into consideration and using fuzzy set theory (eqn. (10)).

Table 10: Minimum values of individual objectives

	Best Fuel Cost	Best SO_2 Emission	Best NO_x Emission
P_{G1}	431.680	538.527	508.367
P_{G2}	302.925	227.817	250.444
P_{G3}	131.314	98.185	105.934
Losses	15.919	14.528	14.745
Fuel cost	**8344.651**	8385.177	8364.993
SO_2 Emission	9.02541	**8.96670**	8.97374
NO_x Emission	0.098922	0.096325	**0.095924**

Table 11: Best compromise solution for 3 objectives

P_{G1}	496.328
P_{G2}	260.426
P_{G3}	108.144
Losses	14.898
Fuel cost	8358.896
SO2 Emission	8.97870
NOx Emission	0.09599

It was shown in [25] that results for NSGA were almost identical when compared to single objective optimization with weighted objectives. Thus, evolutionary algorithms are ideal candidates for solving the multiobjective environmental/economic dispatch optimization problem from the fact that the multiobjective approach yields multiple Pareto-optimal solutions in a single simulation run whereas multiple runs are required for the single objective approach.

6 Conclusions

An elitist multiobjective evolutionary algorithm known as the Non-dominated Sorting Genetic Algorithm - II (NSGA-II) has been used for solving the Environmental/Economic Dispatch problem. Firstly, a biobjective optimization problem is considered where simulations results on a 3-generator test system considering fuel cost and SO_2 emission and then fuel cost and NO_x emission have been presented. Finally, a three-objective optimization problem considering fuel cost, SO_2 emission and NO_x emission simultaneously has been considered. The obtained minimum values of fuel cost and emissions are comparable to those obtained using Tabu search (single objective optimization). Simulation results reveal that the algorithm can identify the Pareto-optimal front with a good diversity for the Environmental/Economic Dispatch problem. Moreover, the solutions are obtained in a single simulation run as compared to single objective approach using weighted objectives which require multiple runs to identify the Pareto-optimal front. Fuzzy set theory is used to select an operating point from the obtained set of Pareto-optimal solutions. The authors are presently investigating the extension of this application to include the power flow model, transmission limitations and generating plant capacity.

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