Multi-Objective Environmental/Economic Dispatch by NSGA-II

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Abstract- *Most real world problems are inherently multiobjective in nature. This is particular true for power systems optimization when the environmental/economic dispatch problem is to be considered. This important problem has until recently been solved by using a weighted sum of the two objectives. However, with the rising potentials of multi-objective evolutionary algorithms (MOEAs), more and more power systems problems are being tackled with multi-objective considerations to find optimal compromise solutions. The main reason is that MOEAs can find multiple Pareto-optimal solutions in one single run compared to conventional methods, which find only one solution at a time and thus require multiple runs to obtain the whole Pareto front. In this paper, the Non-dominated Sorting Genetic Algorithm – II (NSGA-II) is used to solve the environmental/economic dispatch problem for the standard IEEE 30-bus system. Simulation results are compared with those using other MOEAs.*

I. Introduction

Electric power plants are traditionally operated on the basis of least fuel cost strategies without considering the pollutants produced. Fossil-fired electric power plants using coal, oil, gas or their combinations are the major contributors to pollution due to their emissions. These emissions consist of particulate matter such as ash and gaseous pollutants such as carbon oxides, sulphur oxides and oxides of nitrogen. With this growing concern, 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 [1]: post-combustion cleaning systems such as electrostatic precipitators and stack gas scrubbers; 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. These environmental/economic dispatch algorithms are summarized in [1] and the potential requirements of utilities regarding system operations to meet the Clean Air Act Regulations is presented in [2].

The environmental/economic dispatch problem is a constrained multiobjective problem with conflicting objectives because pollution minimization is conflicting with minimum cost of generation. Until recently, methods used to solve this multiobjective problem have transformed it to a single objective one. These methods include linear and non-linear goal programming [3, 4], ε-constrained technique [5], linear programming [6], quadratic programming [7], weighted minimax [8], Hopfield neural network [9], Tabu Search [10], Genetic Algorithm [11, 12, 13]. Some attempts have been made for the simultaneous optimization of multiple objectives in the environmental/economic dispatch problem using evolutionary algorithms [14, 15, 16]. Until relatively recently researchers have realized the potential of evolutionary algorithms in the area of multiobjective optimization. These algorithms are commonly known as Multiobjective Evolutionary Algorithms (MOEAs) and have been successfully applied to various problems with multiple and conflicting objectives [17]. The main advantage of such algorithms is that they can find multiple Pareto-optimal solutions in one single run compared to conventional methods, which find only one solution at a time and thus require multiple runs to obtain the whole Pareto front.

For the environmental/economic dispatch problem, promising results have been obtained using non-elitist MOEAs such as Non-dominated Sorting Genetic Algorithm (NSGA) [18], Niched Pareto Genetic Algorithm (NPGA) [19] and elitist MOEA such as Strength Pareto Evolutionary Algorithm (SPEA) [20]. It has been argued that NSGA suffers from three weaknesses: computational complexity, non-elitist approach and the need to specify a sharing parameter. 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 [21, 22]. More recently, NSGA-II has been applied on the environmental/economic dispatch problem when the transmission losses are approximated using loss coefficients [23]. In this paper, the environmental/economic power dispatch optimization problem is solved by NSGA-II considering exact transmission losses. Simulation results are presented for the standard IEEE 30-bus system.

II. 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.

A. 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 [5]:

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

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 (pu), and
n: number of generators.

The minimum emission dispatch optimizes the above classical economic dispatch including NO_x emission objective which can be modeled using second order polynomial functions [5]:

NO_x Emission Objective

$$E_{NO_x} = \sum_{i=1}^{n} (a_{iN} + b_{iN} P_{Gi} + c_{iN} P_{Gi}^2 + d_{iN} \sin(e_{iN} P_{Gi})) \quad (2)$$

Units of E_{NO_x} are ton/hr.

B. Constraints

The optimization problem is bounded by the following constraints:

Power balance constraints

$$\sum_{i=1}^{n} P_i - P_D - P_L = 0 \quad (3)$$

where

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

The transmission losses is given by

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} \begin{bmatrix} (r_{ij} / V_i V_j) \cos(\delta_i - \delta_j)(P_i P_j + Q_i Q_j) + \\ (r_{ij} / V_i V_j) \sin(\delta_i - \delta_j)(Q_i P_j - P_i Q_j) \end{bmatrix} \quad (4)$$

where

N : number of buses
r_{ij} : series resistance connecting buses i and j
V_i : voltage magnitude at bus I
δ_i : voltage angle at bus I
P_i : real power injection at bus i
Q_i : reactive power injection at bus i

Maximum and minimum limits of power generation

The power generated P_{Gi} by each generator is constrained 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.

C. Multiobjective Formulation

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

Minimize	$[\mathrm{C}, E_{NO_x}]$		(5)
subject to:	$g(P_{Gi}) = 0$	(power balance)	
and	$P_{Gimin} \le P_{Gi} \le P_{Gimax}$	(generation limits)	

III. NSGA-II

Elitism ensures that the fitness of the best solution in a population does not deteriorate as the generation advances. Rudolph [24] 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. [21, 22] 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 [21, 22] that NSGA-II can achieve these two goals well.

The NSGA-II procedure [21, 22] 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 $m = 1,2,...,M$, sort the set in worse order of f_m or, find the sorted indices vector:

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

Step 3

For $m = 1,2,...,M$, 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. The variables are represented as real numbers and the simulated binary crossover [25] and the polynomial mutation operator [26] are used.

IV. 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]:

$$\mu_{f_i} = \begin{cases} 1 & f_i \le f_i^{min} \\ \dfrac{f_i^{max} - f_i}{f_i^{max} - f_i^{min}} & f_i^{min} < f_i < f_i^{max} \\ 0 & f_i \ge f_i^{max} \end{cases} \quad (6)$$

The best non-dominated solution can be found when eqn. (7) is a maximum where the normalized sum of membership function values for all objectives is highest.

$$\mu^k = \frac{\sum_{i=1}^{N} \mu_{f_i}^k}{\sum_{k=1}^{M} \sum_{i=1}^{N} \mu_{f_i}^k} \quad (7)$$

where M is the number of non-dominated solutions.

V. Simulation Results

Simulations were performed on the standard IEEE 30-bus system [5, 6, 18, 19, 20]. Fuel cost and NO_x emission coefficients for this system are given in Tables 1 and 2 respectively. The total system demand is 2.834 p.u.

Table 1: Fuel Cost coefficients

Unit i	a_i	b_i	c_i	P_{Gimin}	P_{Gimax}
1	10	200	100	0.05	0.50
2	10	150	120	0.05	0.60
3	20	180	40	0.05	1.00
4	10	100	60	0.05	1.20
5	20	180	40	0.05	1.00
6	10	150	100	0.05	0.60

Table 2: NO_x Emission coefficients

Unit i	a_{iN}	b_{iN}	c_{iN}	d_{iN}	e_{iN}
1	4.091e-2	-5.554e-2	6.490e-2	2.0e-4	2.857
2	2.543e-2	-6.047e-2	5.638e-2	5.0e-4	3.333
3	4.258e-2	-5.094e-2	4.586e-2	1.0e-6	8.000
4	5.326e-2	-3.550e-2	3.380e-2	2.0e-3	2.000
5	4.258e-2	-5.094e-2	4.586e-2	1.0e-6	8.000
6	6.131e-2	-5.555e-2	5.151e-2	1.0e-5	6.667

In all simulations, the following parameters were used:

- population size = 50
- crossover probability = 0.9
- mutation probability = 0.2
- distribution index for crossover = 10
- distribution index for mutation = 20

The simulations were run for two different cases:

Case 1: System is considered as lossless

Case 2: Transmission losses are considered

A. Case 1

Figs. 1 and 2 show the convergence of the algorithm towards the optimum solution (best fuel cost and best NO_x emission, respectively) for the lossless case. It is to be noted that these figures refer to a single run of NSGA-II. Fig. 3 shows a good diversity in the non-dominated solutions obtained by NSGA-II after 200 generations.

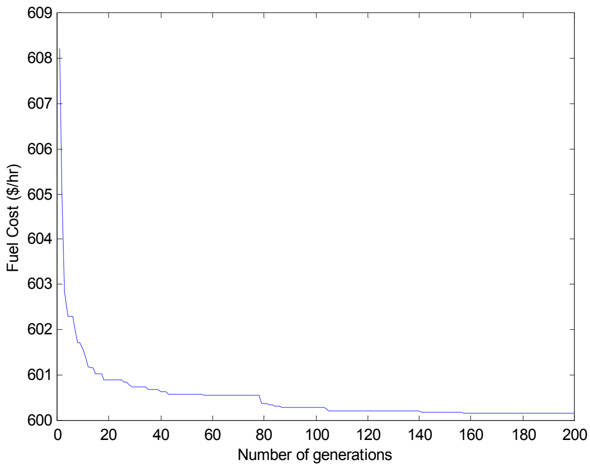

Figure 1: Convergence of fuel cost

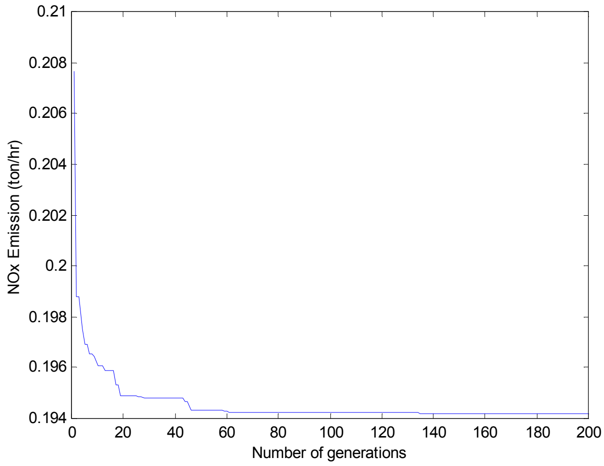

Figure 2: Convergence of NO_x emission

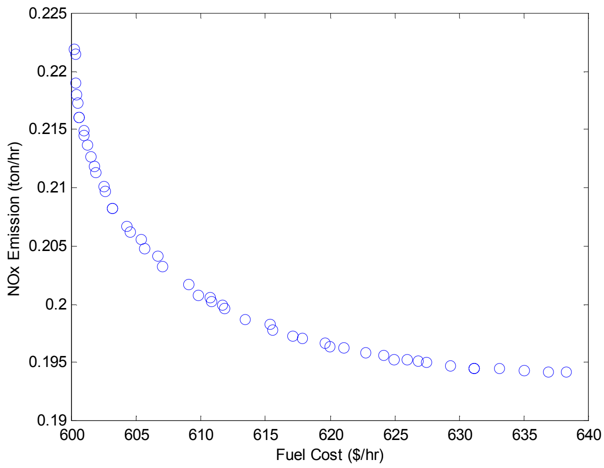

Figure 3: Non-dominated solutions for Case 1

Table 3 and 4 show the best fuel cost and best NO_x emission obtained by NSGA-II as compared to Linear Programming (LP) [5], Multi-Objective Stochastic Search Technique (MOSST) [16], Non-dominated Sorting Genetic Algorithm (NSGA) [18], Niched Pareto Genetic Algorithm (NPGA) [19] and Strength Pareto Evolutionary Algorithm (SPEA) [20]. It can be deduced that NSGA-II finds comparable minimum fuel cost and comparable minimum NO_x emission to the last three evolutionary algorithms. These results confirm that NSGA-II is able to obtain the Pareto front for the problem since the two extreme solutions (minimum of each objective) are found.

Table 3: Best fuel cost

	LP [6]	MOSST [16]	NSGA [18]	NPGA [19]	SPEA [20]	NSGA-II
PG1	0.1500	0.1125	0.1567	0.1080	0.1062	0.1059
PG2	0.3000	0.3020	0.2870	0.3284	0.2897	0.3177
PG3	0.5500	0.5311	0.4671	0.5386	0.5289	0.5216
PG4	1.0500	1.0208	1.0467	1.0067	1.0025	1.0146
PG5	0.4600	0.5311	0.5037	0.4949	0.5402	0.5159
PG6	0.3500	0.3625	0.3729	0.3574	0.3664	0.3583
Best cost	**606.314**	**605.889**	**600.572**	**600.259**	**600.15**	**600.155**
Corresp. emission	0.22330	0.22220	0.22282	0.22116	0.2215	0.22188

Table 4: Best NO_x emission

	LP [6]	MOSST [16]	NSGA [18]	NPGA [19]	SPEA [20]	NSGA-II
PG1	0.4000	0.4095	0.4394	0.4002	0.4116	0.4074
PG2	0.4500	0.4626	0.4511	0.4474	0.4532	0.4577
PG3	0.5500	0.5426	0.5105	0.5166	0.5329	0.5389
PG4	0.4000	0.3884	0.3871	0.3688	0.3832	0.3837
PG5	0.5500	0.5427	0.5553	0.5751	0.5383	0.5352
PG6	0.5000	0.5142	0.4905	0.5259	0.5148	0.5110
Best emission	**0.19424**	**0.19418**	**0.19436**	**0.19433**	**0.1942**	**0.19420**
Corresp. cost	639.600	644.112	639.231	639.182	638.51	638.269

Using the fuzzy logic method given by equation (7), the best compromise solution was calculated and the results are given in Table 5 together with those of the other evolutionary algorithms.

Table 5: Best compromise

	NSGA [18]	NPGA [19]	SPEA [20]	NSGA-II
PG1	0.2571	0.2696	0.2785	0.2565
PG2	0.3774	0.3673	0.3764	0.3820
PG3	0.5381	0.5594	0.5300	0.5351
PG4	0.6872	0.6496	0.6931	0.6941
PG5	0.5404	0.5396	0.5406	0.5361
PG6	0.4337	0.4486	0.4153	0.4302
Cost	610.067	612.127	610.254	609.808
Emission	0.20060	0.19941	0.20055	0.20078

B. Case 2

In this case, the transmission losses are considered and the NSGA-II algorithm was run for 200 generations. Figs. 4 and 5 show the convergence of the algorithm towards the optimum solution (best fuel cost and best NO_x emission, respectively). It is to be noted that these figures refer to a single run of NSGA-II.

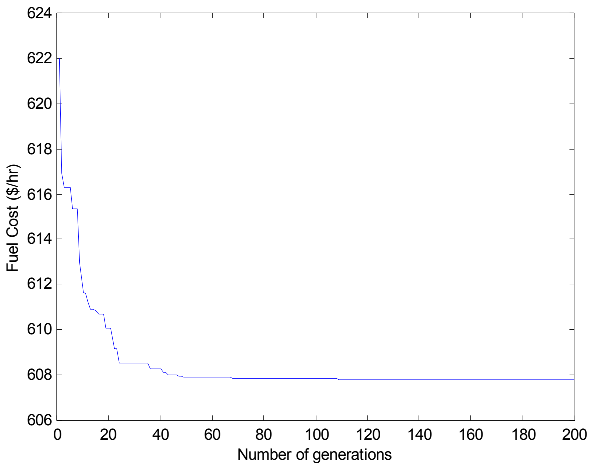

Figure 4: Convergence of fuel cost

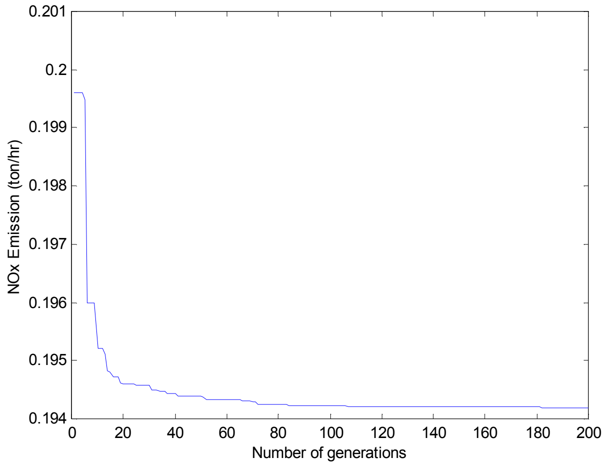

Figure 5: Convergence of NO_x emission

Fig. 6 shows the non-dominated solutions obtained by NSGA-II for Case 2 where a good distribution of the solutions is observed.

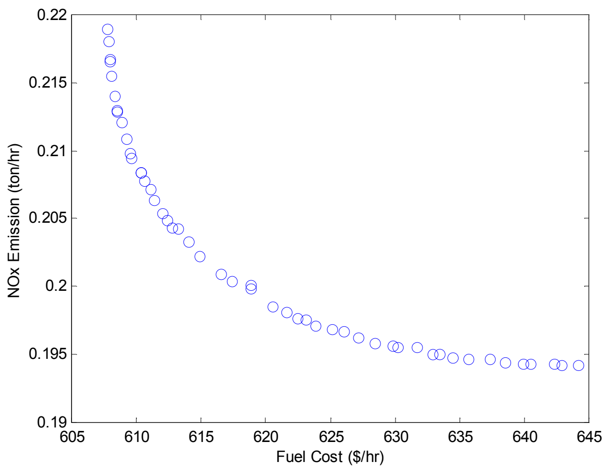

Figure 6: Non-dominated solutions for Case 2

The best fuel cost and best NO_x emission obtained by NSGA-II as compared to NSGA, NPGA and SPEA are given in Table 6. It is observed that NSGA-II again finds better minimum fuel cost and emission level that the evolutionary algorithms.

Table 6: Best fuel cost

	NSGA [18]	NPGA [19]	SPEA [20]	NSGA-II
PG1	0.1168	0.1245	0.1086	0.1182
PG2	0.3165	0.2792	0.3056	0.3148
PG3	0.5441	0.6284	0.5818	0.5910
PG4	0.9447	1.0264	0.9846	0.9710
PG5	0.5498	0.4693	0.5288	0.5172
PG6	0.3964	0.3993	0.3584	0.3548
Best cost	**608.245**	**608.147**	**607.807**	**607.801**
Corresp. emission	0.21664	0.22364	0.22015	0.21891

Table 7: Best NO_X emission

	NSGA [18]	NPGA [19]	SPEA [20]	NSGA-II
PG1	0.4113	0.3923	0.4043	0.4141
PG2	0.4591	0.4700	0.4525	0.4602
PG3	0.5117	0.5565	0.5525	0.5429
PG4	0.3724	0.3695	0.4079	0.4011
PG5	0.5810	0.5599	0.5468	0.5422
PG6	0.5304	0.5163	0.5005	0.5045
Best emission	**0.19432**	**0.19424**	**0.19422**	**0.19419**
Corresp. cost	647.251	645.984	642.603	644.133

Again, it can be deduced that the algorithm is capable of obtaining the Pareto front for the given problem since the minimum of each objective is found.

The best compromise solution selected using fuzzy logic theory (equation (7)) is given in Table 8.

Table 8: Best compromise

	NSGA [18]	NPGA [19]	SPEA [20]	NSGA-II
PG1	0.2699	0.2227	0.2594	0.2697
PG2	0.3885	0.3787	0.3848	0.3645
PG3	0.5645	0.5560	0.5645	0.5545
PG4	0.6570	0.7147	0.7030	0.6951
PG5	0.5441	0.5500	0.5431	0.5619
PG6	0.4398	0.4424	0.4091	0.4186
Cost	618.686	615.097	616.069	616.502
Emission	0.19940	0.20207	0.20118	0.20089

It has been shown that NSGA-II can obtain the Pareto front of the problem and it is therefore ideal for solving the multiobjective environmental/economic dispatch optimization problem which has conflicting objectives 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 with weighted objectives.

VI. Conclusions

In this paper, the multi-objective environmental/economic dispatch problem has been solved using the elitist Non-dominated Sorting Genetic Algorithm - II (NSGA-II). The simulation results have shown that NSGA-II achieves good convergence and diversity when applied to the standard IEEE 30-bus system. Comparison with linear programming, multiobjective stochastic search technique MOSST, non-elitist NSGA, Niched Pareto Genetic Algorithm NPGA and Strength Pareto Evolutionary Algorithm showed that NSGA-II obtains the Pareto optimal solutions. When considering each objective, NSGA-II finds better solutions that the other evolutionary algorithms. 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 front. Besides, fuzzy set theory is used to select an operating point (best compromise solution) from the obtained set of Pareto-optimal solutions.

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