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Solving EED problem by fuzzified Multi Objective Simulated Annealing

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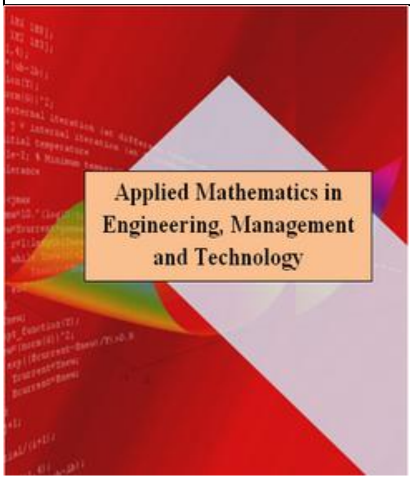

Abstract

The potential and effectiveness of the newly developed Pareto-based Multi objective Evolutionary Algorithms (MOEA) for solving a real-world power system multi objective nonlinear optimization problem are comprehensively discussed and evaluated in this paper. Specifically, non-dominated sorting genetic algorithm (NSGA), niched Pareto genetic algorithm (NPGA), and Multi Objective Simulated Annealing (MOSA) have been developed and successfully applied to an environmental/economic electric power dispatch problem. 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 MOEA have been individually examined and applied to the standard IEEE 30-bus six-generator test system and standard IEEE 118 bus fourteen generator test system. Several optimization runs have been carried out on different cases of problem complexity. The results of MOSA have been compared to those reported in the literature. The results confirm the potential and effectiveness of MOSA compared to the traditional multi objective optimization techniques. One of the main advantages of the proposed approach is its robustness to the initial parameter settings. In addition, the quality of the optimal solution does not rely on the initial guess.

Index Terms—Economic dispatch; Environmental impact; Multi objective optimization; Simulated Annealing.

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 multi objective optimization problem with non-commensurable 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 multi objective 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 non-inferior 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 -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 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]–[20]. Since they use a population of solutions in their search, multiple Pareto-optimal solutions can be found in one single run.

SA algorithm [21], [22] is a derivative-free promising algorithm for handling the combinatorial optimization problems. It has been theoretically proved that SA algorithm converges to the optimal solution [21]. In addition, the SA algorithm is robust i.e. the final solution quality does not strongly depend on the choice of the initial solution. Another strong feature of SA algorithm is that a complicated mathematical model is not required and the problem constraints can be easily incorporated [21].

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(PG) in ($/h) can be expressed as:

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

Where N is the number of generators';a_i ,b_i and c_i are the cost coefficients of the i^{th} generator; and P_{Gi} is the real power output of the i^{th} generator. P_G is the vector of real power outputs of generators and defined as:

$$P_G = [P_{G1}, P_{G2}, \ldots, P_{GN}]^T \qquad (2)$$

B. Minimization of Emission

The total emission in (ton/h) of atmospheric pollutants such as sulpher oxides and nitrogen oxides caused by the operation of fossil-fueled thermal generation can be expressed as

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

Where ζ_i, λ_i, γ_i, α_i and β_i are coefficients of the i^{th} 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:

$$P_i^{\min} \le P_i \le P_i^{\max}, v_i^{\min} \le v_i \le v_i^{\max}$$
$$Q_i^{\min} \le Q_i \le Q_i^{\max} \qquad (4)$$

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

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

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

$$P_{G_i} - P_{D_i} = V_i \sum_{j=1}^{N_B} V_j [G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j)] \quad (6)$$

$$Q_{G_i} - Q_{D_i} = V_i \sum_{j=1}^{N_B} V_j [G_{ij} \sin(\theta_i - \theta_j) - B_{ij} \cos(\theta_i - \theta_j)] \quad (7)$$

where; N_B is the number of buses; Q_{Gi} is the reactive power generated at the i^{th} bus; P_{Di} and Q_{Di} are the i^{th} bus load real and reactive power, respectively; G_{ij} and B_{ij} are the transfer conductance and susceptance between bus i and j bus , respectively; V_i and V_j are the voltage magnitudes at bus i and bus j, respectively; and θ_i and θ_j are the voltage angles at bus and bus , 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

$$P_L(P_i) = \sum_{k=1}^{N_L} g_k [V_i^2 + V_j^2 - 2V_i V_j \cos(\theta_i - \theta_j)] \quad (8)$$

Where N_L is the number of transmission lines and g_k is the conductance of the i^{th} line that connects bus i to bus j.

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

$$S_{L_k} \le S_{L_k}^{\max}, k = 1, 2, ..., N_L \quad (9)$$

It is worth mentioning that the i^{th} transmission line flow connecting bus to bus can be calculated as:

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

Where I^*_{ij} is the current flow from bus i to bus j and can be calculated as

$$S_{L_k} = (V_i \angle \theta_i) I_{ij}^*$$

$$I_{ij} = (V_i \angle \theta_i) \times [(V_i \angle \theta_i - V_i \angle \theta_j) \times y_{ij} + (V_i \angle \theta_i \times j \frac{y}{2})] \quad (11)$$

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

Formulation

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

$$\min_{P_G} [F(P_G), E(P_G)]$$
$$subject \quad to: \quad (12)$$
$$g(p_G) = 0, h(p_G) \le 0$$

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. PROCEDURE FOR PAPER SUBMISSION EVOLUTIONARY ALGORITHMS

A. Non-dominated Sorted Genetic Algorithm (NSGA)

Srinivas and Deb [24] developed NSGA in which a ranking selection method is used to emphasize current non-dominated 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 non-dominated solutions in the population are identified. These non-dominated solutions constitute the first non-dominated front and are assigned the same dummy fitness value. To maintain diversity in the population, these non-dominated solutions are then shared with their dummy fitness values. The phenotypic sharing on the decision space is used in this technique. After sharing, these non-dominated individuals are ignored temporarily to process the rest of population members. The above procedure is repeated to find the second level of non-dominated solutions in the population. Once they are identified, a dummy fitness value, which is a little smaller than the worst shared fitness value observed in solutions of first non-dominated set, is assigned. Thereafter, the sharing procedure is performed among the solutions of second non-domination 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 study.
In the first generation, the non-dominated 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 non-dominated solutions of the extended set are extracted to update the Pareto-optimal set.

B. Niched Pareto Genetic Algorithm (NPGA)

Horn et al [25] 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 later will be selected for reproduction. If neither or both candidates are dominated by the comparison set, then the winner will be decided by sharing. The phenotypic sharing on the attribute space is used in this technique.

IV. SIMULATED ANNEALING ALGORITHM

A. Overview

Simulated annealing is a derivative-free optimization technique that simulates the physical annealing process in the field of combinatorial optimization. Annealing is the physical process of heating up a solid until it melts, followed by slow cooling it down by decreasing the temperature of the environment in steps. At each step, the temperature is maintained constant for a period of time sufficient for the solid to reach thermal equilibrium. At any temperature T, the thermal equilibrium state is characterized by the Boltzmann distribution. This distribution gives the probability of the solid being in a state i with energy E_i at temperature T as

$$P_i = k \exp(-E_i / T)\frac{\partial^2\Omega}{\partial u \partial v} \qquad (13)$$

Metropolis et al. [22] proposed a Monte Carlo method to simulate the process of reaching thermal equilibrium at a fixed value of the temperature T. In this method, a randomly generated perturbation of the current configuration of the solid is applied so that a trial configuration is obtained. Let E_c and E_t denote the energy level of the current and trial configurations respectively. If $E_t<E_c$, then a lower energy level has been reached, and the trial configuration is accepted and becomes the current configuration. On the other hand, if $E_t \geq E_c$ the trial configuration is accepted as current configuration with probability proportional to $\exp(-\Delta E/T)$, $\Delta E= E_t - E_c$. The process continues until the thermal equilibrium is achieved after a large number of perturbations, where the probability of a configuration approaches Boltzmann distribution.
By gradually decreasing the temperature T and repeating Metropolis simulation, new lower energy levels become achievable. As T approaches zero least energy configurations will have a positive probability of occurring.

B. SA Algorithm

At first, the analogy between a physical annealing process and a combinatorial optimization problem is based on the following [21]:

a) Solutions in an optimization problem are equivalent to configurations of a physical system.

b) The cost of a solution is equivalent to the energy of a configuration.

In addition, a control parameter C_p is introduced to play the role of the temperature T. The basic elements of SA are briefly stated and defined as follows:

• **Current, trial, and best solutions,** $x_{current}$, x_{trial} and x_{best}: these solutions are sets of the optimized parameter values at any iteration.

• **Acceptance criterion**: at any iteration, the trial solution can be accepted as the current solution if it meets one of the following criteria; a) $J(x_{trial}< x_{current})$; b) $J(x_{trial}> x_{current})$ and $\exp(-(J(x_{trial})-J(x_{current}))/ C_p)\geq \text{rand}(0,1)$. Here, rand(0,1) is a random number with domain [0, 1] and $J(x_{trial})$ and $J(x_{current})$ are the objective function values associated with and respectively. Criterion b) indicates that the trial solution is not necessarily rejected if its objective function is not as good as that of the current solution with hoping that a much better solution become reachable.

• **Acceptance ratio**: at a given value of C_p, n_1 an trial solutions can be randomly generated. Based on the acceptance criterion, an of these solutions can be accepted. The acceptance ratio is defined as n_2/ n_1.

• **Cooling schedule**: it specifies a set of parameters that governs the convergence of the algorithm. This set includes an initial value of control parameter C_{p0}, a decrement function for decreasing the value of C_p, and a finite number of iterations or transitions at each value of C_p i.e. the length of each homogeneous Markov chain. The initial value of C_p should be large enough to allow virtually all transitions to be accepted. However, this can be achieved by starting off at a small value of C_{p0} and multiplying it with a constant larger than 1, i.e. $C_{p0}= \alpha C_{p0}$. This process continues until the acceptance ratio is close to 1. This is equivalent to heating up process in physical systems. The decrement function for decreasing the value of C_p is given by $C_p=\mu C_p$ where μ is a constant smaller than but close to 1. Typical values lie between 0.8–0.99 [21].

• **Equilibrium condition**: it occurs when the current solution does not change for a certain number of iterations at a given value of C_p. It can be achieved by generating a large number of transitions at that value.

• **Stopping criteria**: these are the conditions under which the search process will terminate. In this study, the search will terminate if one of the following criteria is satisfied: a) the number of Markov chains since the last change of the best solution is greater than a prespecified number; or, b) the number of Markov chains reaches the maximum allowable number.

The general algorithm of SA can be described in steps as follows:

Step 1) Set the initial value of C_{p0} and randomly generate an initial solution $x_{initial}$ and calculate its objective function. Set this solution as the current solution as well as the best solution, i.e. $x_{initial} = x_{current} = x_{best}$

Step 2) Randomly generate an n_1 of trial solutions in the neighborhood of the current solution.

Step 3) Check the acceptance criterion of these trial solutions and calculate the acceptance ratio. If acceptance ratio is close to 1 go to step 4; else $C_{p0}= \alpha C_{p0}$, $\alpha>1$ set , and go back to step 2.

Step 4) Set the chain counter k_{ch}=0.

Step 5) Generate a trial solution x_{trial}. If x_{trial} satisfies the acceptance criterion set $x_{current} =x_{trial}$, $J(x_{trial})=J(x_{current})$, and go to step 6;

else go to step 6.

Step 6) Check the equilibrium condition. If it is satisfied go to step 7; else go to step 5.

Step 7) Check the stopping criteria. If one of them is satisfied then stop; else set $k_{ch}= k_{ch}+1$ and $C_p=\mu C_p$, $\mu<1$, and go back to Step 5.

It worth mentioning that the feasibility of any initial solution that is created randomly or any solution evolved during the optimization process will be checked against the inequality constraints. If unfeasible, the solution will be discarded and another solution will be created. In other words, the feasibility of the solutions is kept during the optimization process.

V. MULTI OBJECTIVE OPTIMIZATION

Many real-world problems involve simultaneous optimization of several objective functions. Generally, these functions are non-commensurable and often conflicting objectives. Multi objective 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 multi objective 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:

$$Minimize\ f_i(x)\ \ i=1,\dots,N_{obj}\ , \tag{14}$$

$$Subject\ to:\ \begin{cases} g_j(x)=0 \ \ j=1,\dots,M\ , \\ h_k(x)\le 0 \ \ \ k=1,\dots,K\ , \end{cases} \tag{15}$$

Where f_i is the i^{th} objective function, x is a decision vector that represents a solution, and N_{obj} is the number of objectives.

For a multi objective optimization problem, any two solutions x_1 and x_2 can have one of two possibilities- one dominates the other or none dominates the other. In a minimization problem, without loss of generality, a solution x_1 dominates x_2 if the following two conditions are satisfied:

1. $\forall i \in \{1,\ 2,\ \dots,N_{obj}\}: f_i(x_1)\le f_i(x_2)$ (16)

2. $\exists j \in \{1,\ 2,\ \dots,N_{obj}\}: f_j(x_1)< f_j(x_2)$ (17)

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 non-dominated solution within the set $\{x_1,\ x_2\}$. The solutions that are non-dominated within the entire search space are denoted as Pareto-optimal and constitute the Pareto-optimal set or Pareto-optimal front.

VI. MOSA 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 trade-off front is desirable from the decision maker's point of view. An average linkage based hierarchical clustering algorithm [23] used by SPEA [23] 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 [23]. 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 imprecise nature of the decision maker's judgment, the i-th objective function of a solution in the Pareto-optimal set, F_i, is represented by a membership function μ_i defined as [39]

$$\mu_i=\begin{cases} 1, & F_i\le F_i^{\min}, \\ \dfrac{F_i^{\max}-F_i}{F_i^{\max}-F_i^{\min}}, & F_i^{\min}<F_i<F_i^{\max}, \\ 0, & F_i\ge F_i^{\max}. \end{cases} \tag{18}$$

where F_i^{max} and F_i^{min} are the maximum and minimum values of the i-th objective function respectively.

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

$$\mu^k=\sum_{i=1}^{N_{obj}}\mu_i^k \Big/ \sum_{j=1}^{M}\sum_{i=1}^{N_{obj}}\mu_i^j \tag{19}$$

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.

VII. RESULTS AND DISCUSSIONS

Case Study I: In this study, the standard IEEE 6-generator 30-bus test system is considered to assess the potential of MOSA for solving the EED problem. The line data and bus data are given in the ref [23]. The values of fuel cost and emission coefficients are given in Table 1.

To demonstrate the effectiveness of the MOSA, 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.

Case 2: P_{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, 10 different optimization runs have been carried out in all cases considered. Table 2 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 trade-off surface in all cases. The best results of cost and emission when optimized individually for all cases are given in Table 3.

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**

Case 1: NSGA, NPGA, and MOSA 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

[23] and the size of the comparison set t_{dom} was determined experimentally. The algorithm was tested several times with different t_{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. 1 for clarity purposes. Experimental results have shown a favorable value of t_{dom} at 10% for our problem instance whereas the performance degrades for values t_{dom} greater than 20%. Therefore, t_{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. 2. 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 MOSA has better diversity characteristics. The best cost and best emission solutions obtained out of 10 runs by different techniques are given in Table 4. It is clear that MOSA gives best cost and best emission compared to others.

TABLE IV
THE BEST SOLUTIONS OUT OF 10 RUNS FOR COST AND EMISSION OF MOEA, CASE 1

	NSGA		NPGA		MOSA	
	Cost	Emission	Cost	Emission	Cost	Emission
P_{G1}	0.1038	0.4072	0.1116	0.4146	0.1089	0.4065
P_{G2}	0.3228	0.4536	0.3153	0.4419	0.2999	0.4578
P_{G3}	0.5123	0.4888	0.5419	0.5411	0.5256	0.5389
P_{G4}	1.0387	0.4302	1.0415	0.4067	1.0174	0.3843
P_{G5}	0.5324	0.5836	0.4726	0.5318	0.5232	0.5373
P_{G6}	0.3241	0.4707	0.3512	0.4979	0.3593	0.5113
Cost	**600.34**	633.83	**600.31**	636.04	**600.17**	638.6531
Emission	0.2241	**0.1946**	0.2238	**0.1943**	0.2222	**0.1942**

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

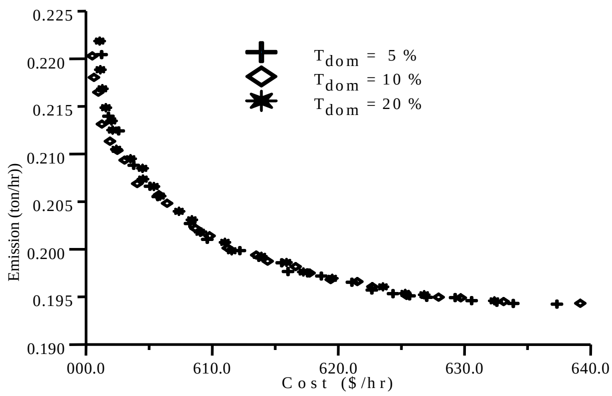

Fig. 1: NPGA with different settings of t_{dom} parameter

TABLE V

THE BEST FUEL COST AND EMISSION OUT OF 10 RUNS OF MOEA COMPARED TO TRADITIONAL ALGORITHMS

	LP [6]	MOSST [15]	NSGA	NPGA	MOSA
Best Cost	606.31	605.89	600.34	600.31	600.17
Emission	0.2233	0.2222	0.2241	0.2238	0.2222
Best Emission	0.1942	0.1942	0.1946	0.1943	0.1942
Cost	639.60	644.11	633.83	636.04	638.65

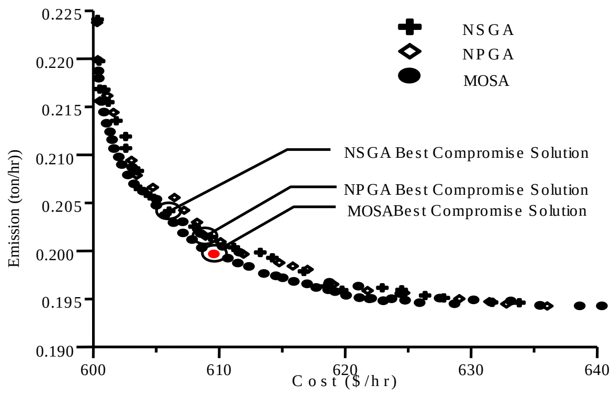

Fig. 2: Comparison of Pareto-optimal fronts, Case 1

<u>Case 2</u>: With the problem complexity shown in Table 2, MOEA techniques have been implemented and compared. Fig. 3 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. The closeness of the nondominated solutions of different techniques demonstrates good performance characteristics of MOEA. The best solutions obtained out of 10 runs by different techniques are given in Table 6.

<u>Case 3</u>: MOEA techniques have been implemented and the Pareto-optimal fronts of different techniques for the best optimization runs are shown in Fig. 4. In this case, the performance of NSGA is degraded with increasing the problem complexity. The best cost and best emission solutions obtained out of 10 runs are given in Table 7.

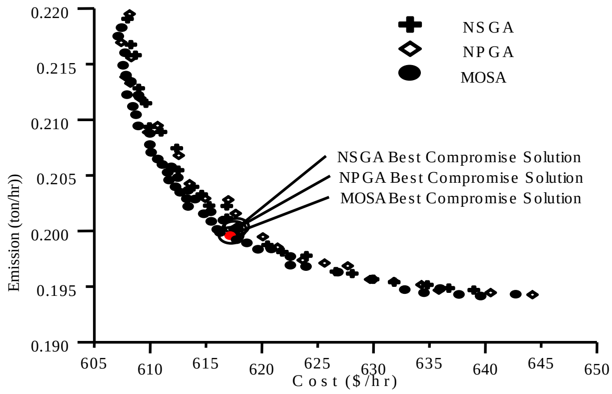

Fig. 3: Comparison of Pareto-optimal fronts, Case 2

TABLE VI
THE BEST SOLUTIONS OUT OF 10 RUNS FOR COST AND EMISSION OF MOEA, CASE 2

	NSGA		NPGA		MOSA	
	Cost	Emission	Cost	Emission	Cost	Emission
P_{G1}	0.1447	0.3929	0.1425	0.4064	0.1281	0.4144
P_{G2}	0.3066	0.3937	0.2693	0.4876	0.3162	0.4451
P_{G3}	0.5493	0.5818	0.5908	0.5251	0.5801	0.5798
P_{G4}	0.9894	0.4316	0.9944	0.4085	0.9578	0.3845
P_{G5}	0.5244	0.5445	0.5315	0.5386	0.5259	0.5346
P_{G6}	0.3542	0.5192	0.3392	0.4992	0.359	0.5050

Cost	**607.98**	638.98	**608.06**	644.23	**607.85**	644.68
Emission	0.2191	**0.1947**	0.2207	**0.1943**	0.2176	**0.1943**

Best compromise solution: The membership functions given in Equation (17) and Equation (18) 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 and the best compromise solutions are given in Table 7 for NSGA, NPGA, and MOSA respectively. The best compromise solutions are also shown in Figs. 3, and 4. It is clear that there is good agreement between MOSA.

TABLE VII
THE BEST SOLUTIONS OUT OF 10 RUNS FOR COST AND EMISSION OF MOEA, CASE 3

	NSGA		NPGA		MOSA	
	Cost	Emission	Cost	Emission	Cost	Emission
P_{G1}	0.1358	0.4403	0.1127	0.4753	0.1321	0.4413
P_{G2}	0.3151	0.4940	0.3747	0.5162	0.3651	0.4588
P_{G3}	0.8418	0.7509	0.8057	0.6513	0.7789	0.6948
P_{G4}	1.0431	0.5060	0.9031	0.4363	0.9286	0.4621
P_{G5}	0.0631	0.1375	0.1347	0.1896	0.1305	0.1947
P_{G6}	0.4664	0.5364	0.5331	0.5988	0.5298	0.6129
Cost	**620.87**	649.24	**620.46**	657.59	**619.70**	651.71
Emission	0.2368	**0.2048**	0.2243	**0.2017**	0.2244	**0.2019**

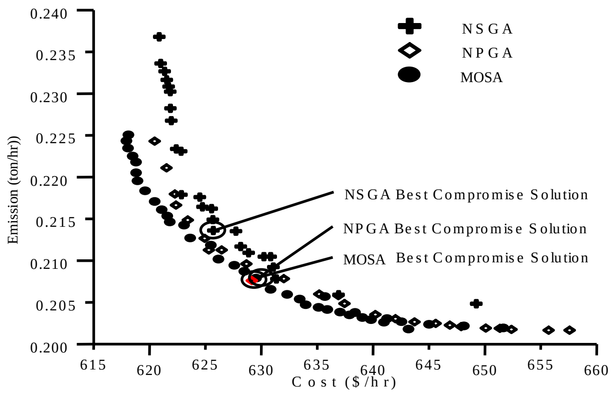

Fig. 4: Comparison of Pareto-optimal fronts, Case 3

Case Study II: In this study, the standard IEEE 118-bus 14-generator test system is considered to investigate the effectiveness of the proposed approach. The single-line diagram of this system is shown in Fig. 5 and the detailed data are given in [26, 27]. The values of fuel cost and emission coefficients are given in Table 8. Two different cases are considered as follows. This is the largest practical test system we could find in the existing literature with complete data required for the EED problem.

Case (a): For comparison purposes with the reported results, the system are considered as the security constrains is released. At first, fuel cost and emission are optimized together to get the extreme points of the trade-off surface. Convergence of fuel cost and emission objective functions are shown in Fig. 6. The best results of cost and emission when optimized together are given in Table 9.

Case (b): In this case, the transmission power loss has been taken into account. Convergence of fuel cost, transmission power loss and emission objective functions are shown in Fig. 7. The best results of cost and emission when optimized together are given in Table 10.

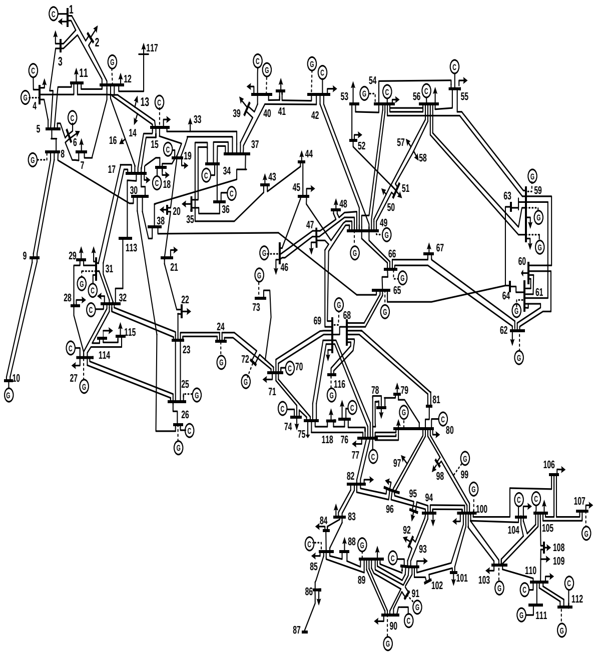

Fig 5. The IEEE 118-bus system configuration.

TABLE VIII
GENERATOR AND EMISSION COEFFICIENTS OF THE IEEE 118-BUS SYSTEM.

NO	a	b	c	α	β	γ	P_{Gmax} (MW)	P_{Gmin} (MW)
P_{G1}	150	189	0.50	0.016	−1.500	23.333	300	50
P_{G2}	115	200	0.55	0.031	−1.820	21.022	300	50
P_{G3}	40	350	0.60	0.013	−1.249	22.050	300	50
P_{G4}	122	315	0.50	0.012	−1.355	22.983	300	50
P_{G5}	125	305	0.50	0.020	−1.900	21.313	300	50
P_{G6}	70	275	0.70	0.007	0.805	21.900	300	50
P_{G7}	70	345	0.70	0.015	−1.401	23.001	300	50
P_{G8}	70	345	0.70	0.018	−1.800	24.003	300	50
P_{G9}	130	245	0.50	0.019	−2.000	25.121	300	50
P_{G10}	130	245	0.50	0.012	−1.360	22.990	300	50
P_{G11}	135	235	0.55	0.033	−2.100	27.010	300	50
P_{G12}	200	130	0.45	0.018	−1.800	25.101	300	50
P_{G13}	70	345	0.70	0.018	−1.810	24.313	300	50
P_{G14}	45	389	0.60	0.030	−1.921	27.119	300	50

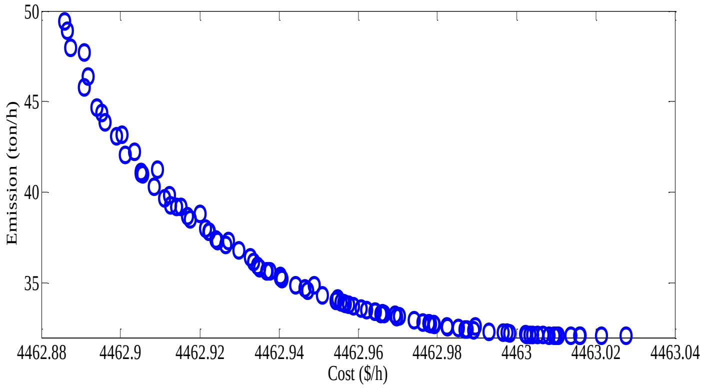

Fig. 6 Pareto-optimal front of the proposed approach in Case (a).

TABLE IX
IEEE 118-BUS SYSTEM BEST COMPROMISE SOLUTIONS FROM DIFFERENT ALGORITHMS, CASE (A).

No. Gen	MOSA	MODE	FMPSO	MOEA	WA
PG1	101.1036	82.1555	94.5703	81.6684	91.1562
PG2	56.1285	50.4606	105.728	108.597	109.584
PG3	74.3127	68.8527	50.992	50.3574	51.4286
PG4	60.7142	83.5687	50.0	50.0378	50.1945
PG5	80.0675	68.1255	75.7894	88.2061	68.3609
PG6	54.9048	50.0254	84.6362	89.5116	90.6869
PG7	51.1069	65.3001	53.3723	50.0	53.5931
PG8	75.6880	66.7923	54.8911	51.6133	56.4637
PG9	56.3091	75.7799	83.6218	82.3149	77.0796
PG10	63.9652	95.4330	52.5273	54.5174	51.234
PG11	71.6162	50.4028	79.5150	84.3849	87.3122
PG12	73.4953	87.1779	106.104	112.184	110.159
PG13	69.8485	65.6425	58.1926	51.427	55.1502
PG14	60.8635	50.1148	50.1546	50.408	50.722
Cost ($/h)	**4494.925**	4508.5	4548.6	4565.1	4558.0
Emission (ton/h)	**36.76389**	37.3536	38.0501	39.7978	39.2491

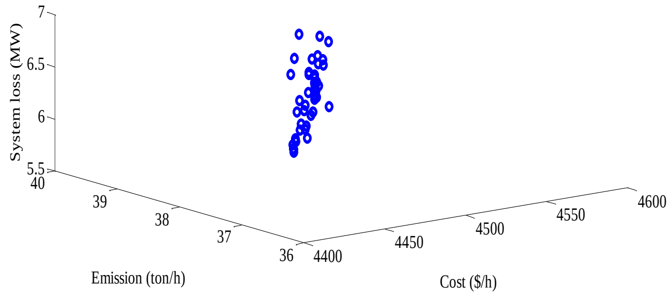

Fig. 7 Pareto-optimal front of the proposed approach in Case (b).

TABLE X
IEEE 118-BUS SYSTEM BEST COMPROMISE SOLUTIONS OF MODE AND MOSA , CASE (B).

	MOSA	MODE
P_{G1}	72.1580	70.9094
P_{G2}	75.5503	51.1464
P_{G3}	64.3251	69.1604
P_{G4}	50.8180	77.3742
P_{G5}	68.5596	68.9120
P_{G6}	80.5832	50.5830
P_{G7}	84.7973	72.0363
P_{G8}	53.2983	69.6698
P_{G9}	73.9362	73.4252
P_{G10}	51.1889	101.0704
P_{G11}	63.1396	53.8714
P_{G12}	75.7774	86.9146
P_{G13}	69.0346	64.1231,
P_{G14}	66.8512	50.1213
Cost ($/h)	**4509.181**	4524.9
Emission (ton/h)	**36.20795**	37.629
System loss MW)	**6.80132**	9.3301

Since, the proposed MOSA is a stochastic search method, another aspect of investigating the effectiveness and robustness of the proposed algorithm is the sensitivity analysis to the MOSA operators used in this study. A robust algorithm will exhibit low sensitivity to the operator variations as evidenced by the Standard Deviation (SD) of the best solution found during the search. Thus, to demonstrate the effectiveness and robustness of the proposed MOSA technique five different optimization runs have been carried out for 40 unit system with valve point effect and to compare the standard deviation of the problems, 6 test problems with variation system demand from 0% to 10% by step 2% than the nominal loads are considered. The computational results are shown in Table 11. Thus, the proposed MOSA technique is a robust optimization algorithm. The proposed algorithm provides SD better results than original MOSA method. To achieve this goal, the system is considered as lossless and the problem was handled as a bi- objective optimization problem where both fuel cost and emission were optimized simultaneously with the proposed approach.

TABLE XI
FITNESS VALUES FOR DEVIATION DEMANDS IN 6-UNIT SYSTEM FOR FIVE TRIALS.

No	Load	Function	Trail 1	Trail 2	Trail 3	Trail 4	Trail 5	S.D. (×10^-3)	CPU
1	2.834	Cost	612.1965	612.1966	612.1965	612.1959	612.1957	0.3982	1.931
		Emission	0.1903	0.1904	0.1903	0.1901	0.1902	0.1020	
		Loss	2.0487	2.0481	2.0481	2.0480	2.0489	0.3666	
2	2.8907	Cost	614.6547	614.6546	614.6542	614.6548	614.6560	0.6002	1.932
		Emission	0.2192	0.2195	0.2191	0.2193	0.2192	0.1356	
		Loss	3.4627	3.46293	3.46276	3.46092	3.46257	0.3971	
3	2.9474	Cost	625.3868	625.3865	625.3871	625.3878	625.3858	0.7013	1.932
		Emission	0.2225	0.2229	0.2230	0.2229	0.2228	0.1720	
		Loss	4.5914	4.5917	4.5913	4.5920	4.5924	0.4030	
4	3.0040	Cost	642.4327	642.4334	642.4326	642.4339	642.4351	0.9012	1.931
		Emission	0.2144	0.2142	0.2141	0.2143	0.2147	0.2059	
		Loss	3.2635	3.2638	3.2641	3.2629	3.2630	0.4587	
5	3.0607	Cost	651.9074	651.9104	651.9079	651.9099	651.9089	1.0012	1.932
		Emission	0.2258	0.2254	0.2256	0.2260	0.2259	0.2154	
		Loss	4.5085	4.5081	4.5091	4.5092	4.5093	0.4630	
6	3.1174	Cost	664.0648	664.0653	664.0651	664.0653	664.0689	1.0479	1.933
		Emission	0.2220	0.2221	0.2222	0.2220	0.2227	0.2608	
		Loss	4.5678	4.5680	4.5688	4.5690	4.5677	0.5352	

I. CONCLUSION

In this paper, three multi objective evolutionary algorithms have been compared and successfully applied to environmental/economic power dispatch problem. The problem has been formulated as a multi objective 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 MOEAs outperform the traditional techniques. Moreover, the MOSA has better diversity characteristics and is more efficient when compared to other MOEAs. The results show that evolutionary algorithms are effective tools for handling multi objective optimization where multiple Pareto optimal solutions can be found in one simulation run. In addition, the diversity of the non-dominated solutions is preserved. It is also demonstrated that the SPEA has the best computational time. It can be concluded that MOEA has potential to solve different multi objective power systems optimization problems.

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