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NSGA-II Technique for Multi-objective Generation Dispatch of Thermal Generators with Nonsmooth Fuel Cost Functions

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Abstract – Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is applied for solving Combined Economic Emission Dispatch (CEED) problem with valve-point loading of thermal generators. This CEED problem with valve-point loading is a nonlinear, constrained multi-objective optimization problem, with power balance and generator capacity constraints. The valve-point loading introduce ripples in the input-output characteristics of generating units and make the CEED problem as a nonsmooth optimization problem. To validate its effectiveness of NSGA-II, two benchmark test systems, IEEE 30-bus and IEEE 118-bus systems are considered. To compare the Pareto-front obtained using NSGA-II, reference Pareto-front is generated using multiple runs of Real Coded Genetic Algorithm (RCGA) with weighted sum of objectives. Comparison with other optimization techniques showed the superiority of the NSGA-II approach and confirmed its potential for solving the CEED problem. Numerical results show that NSGA-II algorithm can provide Pareto-front in a single run with good diversity and convergence. An approach based on Technique for Ordering Preferences by Similarity to Ideal Solution (TOPSIS) is applied on non-dominated solutions obtained to determine Best Compromise Solution (BCS).

Keywords: Combined Economic Emission Dispatch (CEED), Non-dominated Sorting Genetic Algorithm-II (NSGA-II), Pareto-optimal solutions, TOPSIS, Valve-point loading.

1. Introduction

Economic Dispatch (ED) is the process of allocating generation levels, to the various generating units so that the system demand is fully met in the most economical way. The traditional ED has the objective of minimizing the fuel costs [1]. Operating at absolute minimum cost can no longer be the only criterion for dispatching electric power due to the increasing environmental pollution caused by the fossil-fueled electric power plants. It forces the utilities to modify their design to reduce pollution and atmospheric emissions of the thermal power plants [2]. Hence, it is necessary to minimize both emission and cost. However, minimizing the emission and cost are usually two conflicting objectives. Thus, it is not possible to minimize both of them simultaneously and some form of conflicting resolution must be adopted to arrive at a solution [3].

Several Economic Emission Dispatch (EED) strategies have appeared in the literature over the years. Lagrange relaxation method [4], weighted sum method [5], ε-constrained algorithm [6], Linear programming method, [7], Goal programming technique [8] are used to solve the EED problem. However, these classical methods are highly sensitive and frequently converge at local optimum solution and computational time increases with the increase of the dimensionality of the problem.

Later, the use of heuristic optimization approaches such as Genetic Algorithm (GA) [9], Evolutionary Programming (EP) [10] and Differential Evolution (DE) [11] are used to solve the multi-objective constrained optimization problem. Prabakar *et al* have applied modified price penalty factor method to Combined Economic Emission Dispatch (CEED) problem and converted into single objective problem [12]. Recently, the multi-objective evolutionary algorithms (MOEAs) are used to eliminate many difficulties in the classical methods [13]. Because, population of solutions is used in their search and multiple Pareto-optimal solutions can be found in one single simulation run. Some of the popular MOEAs are Non-dominated Sorting Genetic Algorithm (NSGA), Niched Pareto Genetic Algorithm, Strength Pareto Evolutionary Algorithm (SPEA), NSGA-II, Pareto Archived Evolution Strategy etc. [14]. Abido has applied NSGA [15], SPEA [16] and Multi-objective Particle Swarm Optimization (MOPSO) [17] approaches for solving the multi-objective CEED problem. NSGA suffers from computational complexity, non-elitist approach and the need to specify a sharing parameter. An improved version of NSGA known as NSGA-II, which resolves CEED problems and uses elitism to create a diverse Pareto-

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optimal front, has been subsequently presented [18-21]. In addition, TOPSIS method is employed to choose the BCS, which will be useful to the decision maker [20, 21]. Wu *et al* proposed multi-objective DE (MODE) algorithm with elitist archive and crowding entropy based diversity measure to solve the environmental/economic power dispatch problem [22]. The premature convergence using MODE algorithm is overcome by enhanced MODE (EMODE) algorithm to solve EED problem by Youlin Lu *et al* [23]. Though researchers have used several methods for solving single objective ED problem and multi-objective EED problem, but they do not considered valve-point loading effect [1-23].

In general, discontinuity may also be observed in thermal power plants due to valve-point loading. In reality, due to valve-point effect, the cost function is nonsmooth and nonmonotonically increasing and conventional methods such as Lambda-iteration, Gradient method and Newton method have failed to obtain global optimum solution. Hence, stochastic methods such as GA [24], EP [25], Improved EP [26], PSO [27] and DE [28] have been used to solve the ED problem with valve-point loading effect by adding the rectified sinusoidal contribution to the conventional quadratic cost function.

Though researchers considered valve-point effect in the single objective ED problem [24-28], very few works are reported with the consideration of valve-point effect for the CEED problem. Basu [29] analyzed the interactive fuzzy satisfying based simulated annealing technique for CEED problem with nonsmooth fuel cost and emission level functions. The major advantage of this method is obtaining a compromising solution in the presence of conflicting objectives. However, the longer execution time is the drawback of this method. Hemamalini *et al* have applied PSO algorithm to solve emission constrained ED problem with valve-point loading effect. However, this formulation does require the knowledge of the relative importance of each objective and has a severe difficulty in getting the trade-off relations between cost and emission [30]. MODE algorithm has been applied by Basu, for solving EED problems with valve-point loading and extreme points obtained are compared with Partial DE, NSGA-II and SPEA-2 for different test systems. However, the selection of BCS from the estimated Pareto-optimal set is not considered [31]. Also, the transmission line losses are calculated through B_{mn} coefficients [29-31].

In this paper, NSGA-II algorithm is used to solve CEED problem with valve-point effect. Pareto-front obtained by the NSGA-II is compared with reference Pareto-front found by RCGA. In addition, the transmission line losses are calculated through load flow solutions and BCS is obtained by TOPSIS method, which will be useful to the decision maker. The rest of this paper is organized as follows: Section 2 describes the CEED problem formulation. Implementation of NSGA-II for the CEED problem is explained in Section 3. Section 4 incorporates TOPSIS decision approach to determine the BCS. The simulation results of various test cases are presented in Section 5 and Section 6 concludes.

2. Problem Formulation

The multi-objective CEED problem with its constraints is formulated as a nonlinear constrained problem as follows.

$$\text{Minimize } [F(P_g), E(P_g)] \tag{1}$$

subject to power balance and generation capacity constraints, where,

$F\,(P_g)$: Total fuel cost (\$/hr),
$E\,(P_g)$: Total emission (ton/hr).

2.1 Objective functions

The fuel cost function or input-output characteristics of the generator may be obtained from design calculations or from heat rate tests. For large steam turbine generators, the input-output characteristics are not always smooth. Large steam turbine generators will have a number of steam admission valves that are opened in sequence to obtain ever-increasing output of the unit. These “valve-points” are illustrated in Fig. 1.

Ignoring the valve-point loading effects, some inaccuracy would result in the generation dispatch. Therefore, the fuel costs of generators are usually approximated by second-order polynomial when the traditional techniques are used.

The assumptions made the problem easier to solve. However, the loss of accuracy induced by these approximations is not desirable. To model the effects of nonsmooth fuel cost functions, a recurring rectified sinusoidal contribution is added to the second order polynomial functions to represent the input-output Eq. (2) as follows. The total fuel cost in terms of real power output can be expressed as [24],

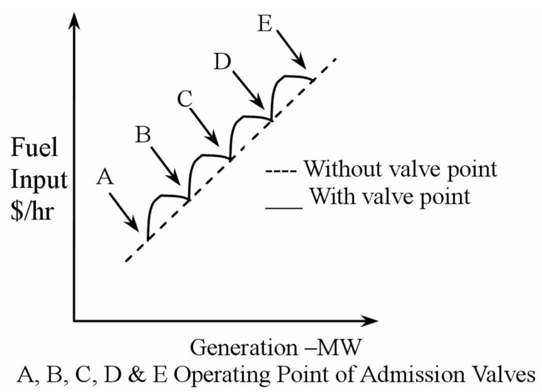

Fig. 1. Incremental fuel cost curve of turbine unit

$$F(P_g) = \sum_{i=1}^{N} a_i + b_i P_{gi} + c_i P_{gi}^2 + \left| d_i \sin\left\{ e_i \left(P_{gi}^{\min} - P_{gi} \right) \right\} \right| \quad (2)$$

where,

$F(P_g)$: Total fuel cost ($/hr),
a_i, b_i, c_i, d_i, e_i : Fuel cost coefficients of generator i,
P_{gi}: Power generated by generator i,
$P_{gi}^{\min}$: Minimum power generation limit,
N : Number of generators.

The total emission of atmospheric pollutants such as Sulphur Oxides (SO_x) and Nitrogen Oxides (NO_x) from a fossil-fired thermal generating unit depends upon the amount of power generated by each unit. For simplification, the total emission generated can be approximately modeled as a direct sum of a quadratic function and an exponential term of the active power output of the generating units and is expressed in the following form [29].

$$E(P_g) = \sum_{i=1}^{N} \alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^2 + \eta_i \exp\ (\delta_i P_{gi}) \quad (3)$$

where,

$E(P_g)$: Total emission (ton/hr),
α_i, β_i, γ_i, η_i, δ_i : Emission coefficients of generator i.

2.2 Constraints

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

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

where,

$P_{gi}^{\min}$: Minimum power generated,
$P_{gi}^{\max}$: Maximum power generated.

Power balance constraint: The total power generated must supply the total load demand and the transmission losses [19].

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

where,

P_d : Total load demand,
P_{loss} : Transmission losses.

The real power loss P_{loss} can be calculated from Newton-Raphson load flow solution, which gives all bus voltage magnitudes and angles; it can be described as follows [22]:

$$P_{loss} = \sum_{k=1}^{N_L} g_k \left[V_i^2 + V_j^2 - 2 V_i V_j \cos(\theta_i - \theta_j) \right] \quad (6)$$

where,

i and j are the total number of buses ($i \neq j$),
k is the k^{th} network branch that connects bus i to bus j,
N_L is the number of transmission lines,
V_i and V_j are the voltage magnitudes at bus i and j,
g_k is the transfer conductance between bus i and j,
θ_i and θ_j are the voltage angles at bus i and j respectively.

3. Implementation of NSGA-II

The NSGA-II algorithm and its computational flow are described in this section.

3.1 NSGA-II

NSGA-II is a fast and elitist multi-objective evolutionary algorithm (MOEA) and implements elitism for multi-objective search, using an elitism-preserving approach. Elitism enhances the convergence properties towards the true Pareto-optimal set. A parameter-less diversity preserving mechanism is adopted. Diversity and spread of solutions are guaranteed without the use of sharing parameters. In this paper, NSGA-II uses simulated binary crossover and polynomial mutation for solving the problem. The crowd comparison operator, guides the selection process towards a uniformly spread Pareto- frontier [18].

3.2 Computational flow

Step1: Initially, a random parent population of size N is created.

Step2: The population is sorted based on the non-domination. Each population is assigned a rank equal to its non-domination level or front number (1 is the best level, 2 is the next best level, and so on). Calculate the crowding distance (CD) of populations in each non-domination level and sort populations in descending order of CD.

Step3: Select two individuals at random. Compare their front number and CD. Select the better one and copy it to the mating pool.

Step4: The Simulated Binary Crossover (SBX) and polynomial mutation have been used to create offspring population of size N.

Step5: Combine the parent population and child population.

Step6: The combined population is sorted according to non-domination and crowding distance. Since all parent and offspring population members are included, elitism is ensured.

Step7: The process can be stopped after a fixed number of iterations. If the criterion is not satisfied then the

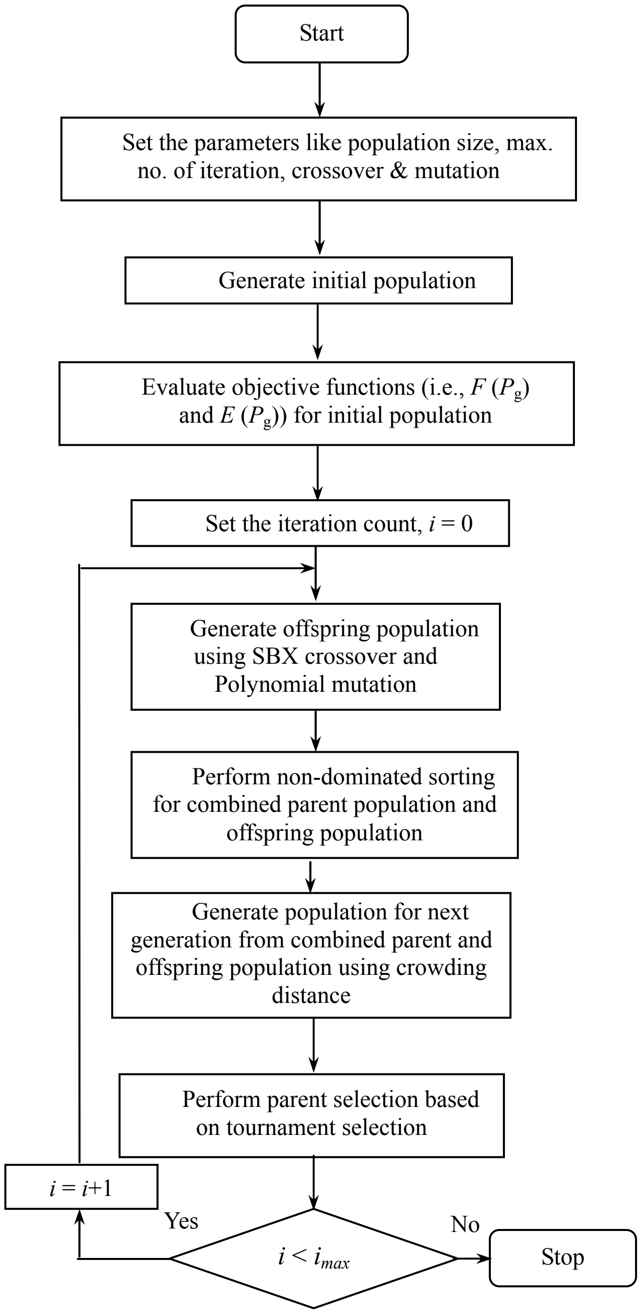

Fig. 2. Computational flow of NSGA-II

procedure is repeated from Step 3 after creating the new population from the parent population [18].

4. TOPSIS Method

In general, the result of MOEAs is a set of non-dominated front. From the best obtained Pareto-front, it is usually required to select one solution for implementation. A multi attribute decision making (MADM) approach is adopted to rank the obtained NSGA-II solutions and the BCS is calculated in a deterministic environment with a single decision maker. From the decision maker's perspective, the choice of a solution from all Pareto-optimal solutions is called a posteriori approach and it requires a higher level decision making approach, which is to determine the best solution among a finite set of Pareto-optimal solutions with respect to all relevant attributes. In this paper, MADM technique based on TOPSIS is employed in posterior evaluation of Pareto-optimal solutions to choose the best one among them. The concept of TOPSIS is described as: In the absence of a natural course of action for overall summary measure and ranking, the most preferred alternative should not only have the shortest distance from the positive ideal solution, but also have the longest distance from the negative ideal solution. Almost all MADM methods require predetermined information on the relative importance of the attributes, which is usually given by a set of normalized weights. The weights of two objectives are calculated by Shannon's entropy method. The entropy method is based on information theory, which assigns a small weight to an attribute if it has similar attribute values across alternatives, because such attribute does not help in differentiating alternatives [20, 21].

The classical MADM model is described as follows:

Let $R = R_{ij}$, i =1, 2....n (no. of Pareto-optimal solutions), j = 1, 2.....m (no. of objectives) is the $n \times m$ decision matrix, where R_{ij}, is the performance rating of alternative X_j (Pareto-optimal solutions) with respect to attribute A_i (objective function values).

To determine objective weights by the entropy measure, the decision matrix needs to be normalized for each objective A_j as

$$p_{ij} = \frac{R_{ij}}{\sum_{p=1}^{n} R_{pj}} \tag{7}$$

As a consequence, a normalized decision matrix representing the relative performance of the alternatives is obtained as

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ p_{n1} & p_{n2} & \cdots & p_{nm} \end{bmatrix} \tag{8}$$

The amount of decision information contained in Eq. (8) and emitted from each attribute A_j (j = 1, 2, ... m) can thus be measured by the entropy value e_j as

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln p_{ij} \tag{9}$$

The degree of divergence d_j of the average intrinsic information contained by each attribute A_j (j = 1, 2, ... m) can be calculated as

$$d_j = 1 - e_j \tag{10}$$

The objective weight for each attribute A_j (j = 1,2, ... m) is thus given by

$$w_j = \frac{d_j}{\sum_{k=1}^{m} d_k} \tag{11}$$

The weighted normalized value v_{ij} is calculated as

$$v_{ij} = w_i \, p_{ij} \tag{12}$$

After determining performance ratings of the alternatives and objective weights of the attributes, the next step is to aggregate them to produce an overall performance index for each alternative. This aggregation process is based on the positive ideal solution (A^+) and the negative ideal solution (A^-), which are defined, respectively by

$$\begin{aligned} A^+ &= (\max(v_{i1})\max(v_{i2}).....\max(v_{im})) = (v_1^+, v_2^+, ...v_m^+) \\ A^- &= (\min(v_{i1})\min(v_{i2})....\min(v_{im})) = (v_1^-, v_2^-, ...v_m^-) \end{aligned} \tag{13}$$

Separation between alternatives can be measured by the n-dimensional Euclidean distance. The separation of each alternative from the ideal solution is given as

$$d_j^+ = \left\{ \sum_{i=1}^{m} (v_{ji} - v_i^+)^2 \right\}^{\frac{1}{2}}, \quad j = 1, 2, ...n \tag{14}$$

Similarly, the separation from the negative ideal solution is given as

$$d_j^- = \left\{ \sum_{i=1}^{m} (v_{ji} - v_i^-)^2 \right\}^{\frac{1}{2}}, \quad j = 1, 2, ...n \tag{15}$$

The relative closeness to the ideal solution of alternative Xj with respect to A^+ is defined as

$$C_j = \frac{d_j^-}{d_j^+ + d_j^-}, \quad j = 1, 2, ...n \tag{16}$$

Since $d_j^- \geq 0$ and $d_j^+ \geq 0$, then clearly, $C_j \in [0,1]$.

Choose an alternative with maximum C_j or rank alternatives according to C_j in descending order. It is clear that an alternative X_j is closer to A^+ than to A^- as C_j approaches 1 [20, 21].

5. Simulation Results and Discussion

The RCGA and NSGA-II algorithms are coded in MATLAB version 7.11 on a PC with Pentium-IV Intel (R) Core(TM) i3-2310M CPU operating at 2.10 GHz speed with 4 GB RAM.

5.1 Description of the test systems

The standard IEEE 30-bus system consists of six generating units with a demand of 283.4 MW and IEEE 118-bus system is composed of 19 generating units with a demand of 3668 MW are taken as test systems, to verify the effectiveness of NSGA-II. The detailed fuel cost coefficients, emission coefficients, the lower and the upper power limits are taken from [12, 26 and 30]. The bus data and the line data are taken from [32]. MATPOWER software is used for power flow calculations [32].

5.2 Parameter settings

The parameter settings of NSGA-II for solving CEED problem is as follows: In general, the population size of six times the number of decision variables is considered. For IEEE 30-bus system, the population size and iteration are set as 40 and 200 respectively. For IEEE 118-bus system, the population size and maximum iteration number are set as 100 and 500 respectively. The crossover probability (P_c) is varied between 0.8 to 0.9 and other parameters such as mutation probability (P_m), crossover index (η_c) and mutation index (η_m) are selected as $1/n$ (where n-number of variables), 5 and 15 respectively [14].

5.3 Generation of reference Pareto-front

To compare the performance of NSGA-II, a reference Pareto-front obtained by using multiple runs of Real Coded Genetic Algorithm (RCGA) with weighted sum approach is considered. In reference Pareto-front generation, CEED problem is treated as single objective optimization problem by linear combination of objectives as follows:

$$\text{Minimize C} = \text{w}f_1 + (1 - \text{w})\, f_2 \tag{17}$$

where,

w is a weighing factor and the sum of weighting factor must be 1.

f_1 is the cost objective and f_2 is the emission objective.

To get 50 non-dominated solutions, the algorithm is applied 50 times with varying weight factors as a uniform random number varying between 0 and 1 in each trial. Different population sizes and iteration numbers are selected depending upon the number of decision variables [20].

5.4 IEEE 30-bus system

In this case, the NSGA-II and RCGA have been applied to solve CEED problem for the standard IEEE 30-bus system. The single line diagram of this system is given in [19]. The power system is interconnected by 41 transmission lines and the total system demand for the 21 load buses are 283.4 MW. Extreme solutions for cost and emission are obtained out of ten trial runs using NSGA-II for IEEE 30-bus system for the problem of CEED without valve-point effect and are reported in Tables 1 and 2 respectively and for the problem of CEED with valve-point effect are reported in Tables 3 and 4 respectively. Extreme solutions for cost and emission are obtained using RCGA also reported in Table 1 to Table 4. Referring to Table 1, PSO algorithm as reported in the literature [30], able to give better results compared to other methods but it needs weight factors to convert multi-objective problem into single objective algorithm and also multiple runs are required to obtain the Pareto-optimal solutions. From the

Table 1. Comparative result of Extreme solution for cost - IEEE 30-bus system in the case of CEED without Valve-point effect

Method	P_1	P_2	P_3	P_4	P_5	P_6	P_L	Cost ($/hr)	Corresponding Emission (ton/hr)	Execution Time (sec)
NSGA-II	0.116	0.305	0.597	0.982	0.512	0.356	0.035	**608.125**	0.2200	98.359
RCGA	0.115	0.306	0.599	0.982	0.513	0.355	0.035	**608.124**	0.2199	4518
PSO[30]	0.128	0.270	0.555	1.005	0.454	0.445	0.025	**606.660**	0.2207	--
NSGA[15]	0.117	0.317	0.544	0.945	0.549	0.396	0.034	**608.245**	0.21664	--
SPEA[16]	0.109	0.306	0.582	0.985	0.529	0.358	0.034	**607.807**	0.22015	--

Table 2. Comparative result of Extreme solution for emission - IEEE 30-bus system in the case of CEED without Valve-point effect

Method	P_1	P_2	P_3	P_4	P_5	P_6	P_L	Emission (ton/hr)	Corresponding Cost ($/hr)	Execution Time (sec)
NSGA-II	0.358	0.465	0.541	0.392	0.576	0.534	0.033	**0.1942**	643.4214	98.359
RCGA	0.411	0.463	0.544	0.390	0.544	0.515	0.033	**0.1942**	645.7139	4518
PSO[30]	0.371	0.467	0.564	0.365	0.522	0.578	0.034	**0.1945**	648.01	--
NSGA[15]	0.411	0.459	0.512	0.372	0.581	0.530	0.032	**0.1943**	647.251	--
SPEA[16]	0.404	0.453	0.553	0.408	0.547	0.501	0.031	**0.1942**	642.603	--

Table 3. Comparative result of Extreme solution for cost of IEEE 30-bus system in the case of CEED with Valve-point effect

Method	P_1	P_2	P_3	P_4	P_5	P_6	P_L	Cost ($/hr)	Corresponding Emission (ton/hr)	Execution Time (sec)
NSGA-II	0.116	0.307	0.594	0.982	0.516	0.354	0.035	**611.057**	0.2198	96.5780
RCGA	0.115	0.306	0.598	0.982	0.513	0.355	0.035	**611.057**	0.2140	4500
PSO[30]	0.099	0.363	0.484	0.874	0.664	0.390	0.039	**626.96**	0.21392	--

Table 4. Comparative result of Extreme solution for emission of IEEE 30-bus system in the case of CEED with Valve-point effect

Method	P_1	P_2	P_3	P_4	P_5	P_6	P_L	Emission (ton/hr)	Corresponding Cost ($/hr)	Execution Time (sec)
NSGA-II	0.389	0.443	0.557	0.404	0.564	0.509	0.033	**0.1942**	645.2484	96.5780
RCGA	0.411	0.463	0.544	0.389	0.544	0.516	0.033	**0.1947**	648.5656	4500
PSO[30]	0.379	0.392	0.499	0.534	0.573	0.487	0.031	**0.19567**	659.44	--

Table 5. Extreme solution for cost - IEEE 118-bus system in the case of CEED without Valve-point effect

System	Method	P_1	P_2	P_3	P_4	P_5	P_6	P_L	Cost ($/hr)	Corresponding Emission (ton/hr)
IEEE118	NSGA-II	640.18	54.086	83.849	285.21	40.495	1.449	12.749	**11577.5**	14.19
	RCGA	673.52	73.064	76.074	299.99	40.000	1.0202	17.653	**11509.7**	14.97
		P_8	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	Execution Time (sec)	
	NSGA-II	30.032	48.723	151.96	190.139	394.83	397.633	590.541		
	RCGA	30.001	10.398	138.69	199.99	399.89	399.950	599.999		
		P_{15}	P_{16}	P_{17}	P_{18}	P_{19}	----	----		
	NSGA-II	3.992	672.044	240.91	36.108	6.9604	----	----	874.859	
	RCGA	3.685	690.625	228.31	5.3177	8.303	----	----	31806.157	

Tables 2 to 4, it can be concluded that, the NSGA-II is capable of providing better results compared to other methods for the CEED problem and it can be observed that the inaccuracy in the resulting dispatch when the valve-point loading effects are ignored. The execution time is also short using NSGA-II, thus computationally more efficient than RCGA. Best Pareto-front obtained in the problems of CEED with valve-point effect and without valve-point effect using NSGA-II and RCGA are shown in Fig. 3. The NSGA-II produces the Pareto-optimal front in a single simulation run and it is clear that the solutions are diverse and well distributed. Furthermore, the Pareto-front generated using NSGA-II and multiple runs Pareto-front obtained using RCGA are almost identical.

5.5 IEEE 118-bus system

Simulations are conducted on the standard IEEE 118-bus, 19 generators-test system applying RCGA and NSGA-II. Two different cases are considered for the study. In the first case, valve-point effect is not considered but in the second case the cost function is modeled as a quadratic function summed with a sine term to include valve-point effect. In both cases, transmission line losses are included for the load demand of 3668 MW. Extreme solutions for cost and emission are obtained out of ten trial runs using NSGA-II for IEEE 118-bus system in the problem of CEED without valve-point effect are reported in Tables 5 and 6 respectively and in the problem of CEED with valve-point

Table 6. Extreme solution for emission - IEEE 118-bus system in the case of CEED without Valve-point effect

System	Method	P_1	P_2	P_3	P_4	P_5	P_6	P_L	Emission (ton/hr)	Corresponding Cost ($/hr)
IEEE118	NSGA-II	314.74	396.63	82.989	299.49	395.52	8.837	22.667	**5.495**	17993.47
	RCGA	310.33	425.52	89.992	299.99	399.99	1.666	18.706	**5.488**	18227.58
		P_8	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	Execution Time (sec)	
	NSGA-II	236.20	49.480	199.66	198.92	340.86	386.81	174.59		
	RCGA	239.99	49.989	199.95	199.99	291.42	399.83	167.68		
		P_{15}	P_{16}	P_{17}	P_{18}	P_{19}	---	---		
	NSGA-II	4.895	303.70	276.89	38.283	39.801	---	---	874.859	
	RCGA	1.645	307.753	292.74	49.988	26.841	---	---	31806.157	

Table 7. Extreme solution for cost - IEEE 118-bus system in the case of CEED with Valve-point effect

System	Method	P_1	P_2	P_3	P_4	P_5	P_6	P_L	Cost ($/hr)	Corresponding Emission (ton/hr)
IEEE118	NSGA-II	641.52	53.23	88.876	298.95	40.559	7.292	14.659	**12002.2**	13.633
	RCGA	650.98	300.00	19.997	249.992	40.001	1.003	22.996	**11994.4**	11.314
		P_8	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	Execution Time (sec)	
	NSGA-II	31.255	47.663	186.136	183.536	383.12	398.262	582.43		
	RCGA	30.002	49.998	100.199	159.993	324.994	399.999	599.94		
		P_{15}	P_{16}	P_{17}	P_{18}	P_{19}	---	---		
	NSGA-II	4.204	624.500	259.765	5.353	14.089	---	---	846.28	
	RCGA	1.001	699.995	202.635	5.000	4.005	---	---	31938.32	

Table 8. Extreme solution for emission - IEEE 118-bus system in the case of CEED with Valve-point effect

System	Method	P_1	P_2	P_3	P_4	P_5	P_6	P_L	Emission (ton/hr)	Corresponding Cost ($/hr)
IEEE118	NSGA-II	334.05	368.85	83.496	295.56	396.76	8.555	22.539	**5.622**	18154.76
	RCGA	301.09	450.14	89.98	299.92	399.89	9.877	22.998	**5.517**	18322.43
		P_8	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	Execution Time (sec)	
	NSGA-II	236.27	47.616	192.93	197.27	310.32	396.01	181.75		
	RCGA	239.99	9.966	199.97	199.94	268.03	393.46	159.02		
		P_{15}	P_{16}	P_{17}	P_{18}	P_{19}	---	---		
	NSGA-II	3.194	341.43	292.58	48.996	12.879	---	---	846.28	
	RCGA	4.977	450.00	224.95	49.99	9.979	---	---	31938.32	

Table 9. Best compromise solution for IEEE 30-bus and IEEE 118-bus system in the case of CEED with Valve-point effect

System	Method	P_1	P_2	P_3	P_4	P_5	P_6	P_L	Cost ($/hr)	Emission (ton/hr)
IEEE30	NSGA-II	0.30946	0.45906	0.54858	0.49112	0.55347	0.50429	---	**635.7946**	0.1948
	PSO[30]	0.14089	0.34415	0.67558	0.83971	0.49043	0.39797	---	**639.65**	0.21105
IEEE118	NSGA-II	348.31	367.56	89.29	296.83	361.70	9.825	21.179	**17374.43**	**5.767**
		P_8	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}		
		238.42	49.90	195.93	195.88	337.58	389.70	182.54		
		P_{15}	P_{16}	P_{17}	P_{18}	P_{19}	---	---		
		1.619	310.875	281.737	49.887	39.032	---	---		

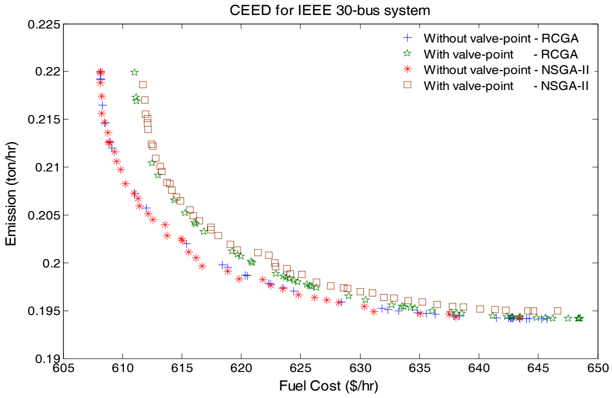

Fig. 3. Reference Pareto-front using RCGA and best obtained Pareto-front using NSGA-II for IEEE 30-bus system

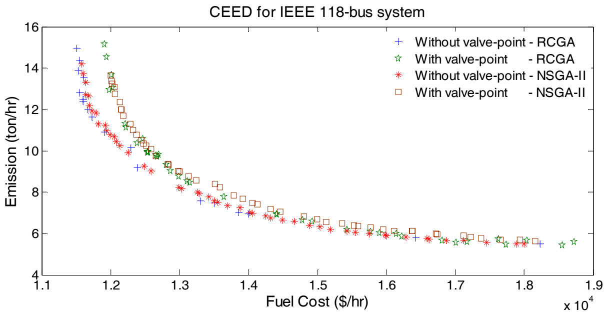

Fig. 4. Reference Pareto-front using RCGA and best obtained Pareto-front using NSGA-II for IEEE 118-bus system

effect are reported in Tables 7 and 8 respectively. Extreme solutions for cost and emission are obtained using RCGA also reported in Tables 5 to 8 and it can be observed that the inaccuracy in the resulting dispatch when the valve-point loading effects are ignored. Execution time of the NSGA-II is very less, thus computationally more efficient than RCGA. Best Pareto-front obtained in the cases of CEED with valve-point effect and without valve-point effect using NSGA-II and RCGA are shown in Fig. 4. The NSGA-II produces the Pareto-optimal front in a single simulation run but RCGA produces the Pareto-front in multiple runs. Furthermore, the Pareto-front generated using NSGA-II and multiple runs Pareto-front obtained using RCGA are almost identical.

5.6 Best Compromise Solution (BCS)

From the estimated Pareto-optimal set, it is usually required to choose one of them for implementation. Moreover, the choice of one solution over the other requires additional knowledge about the CEED problem. MADM technique is commonly used to evaluate the Pareto-optimal solutions and choose the best one Table 1 Comparative result of Extreme solution for cost – IEEE 30-bus system in the case of CEED without Valve-point effect

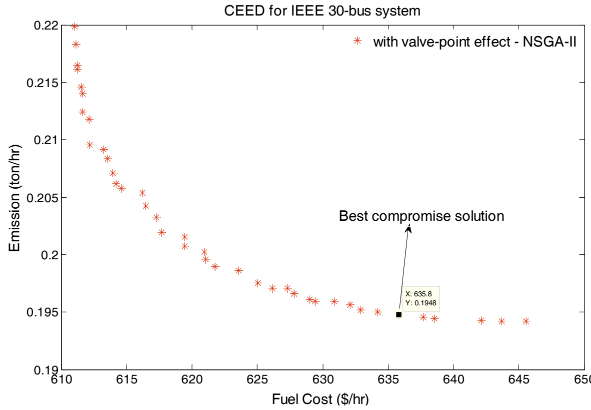

Fig. 5. Best Compromise Solution using TOPSIS method for IEEE 30-bus system

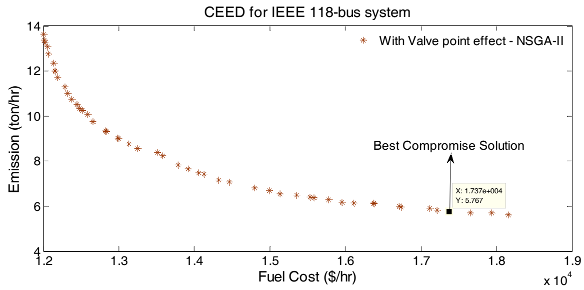

Fig. 6. Best Compromise Solution using TOPSIS method for IEEE 118-bus system

among them. A large number of methods have been developed for solving multiple attribute problems. The concept of TOPSIS from the decision maker's perspective, the choice of a solution from all Pareto-optimal solutions, which is to determine the best solution among a finite set of Pareto-optimal solutions with respect to all relevant attributes is used in this work. This procedure has been applied to NSGA-II results and the BCS is arrived. Table 9 gives the BCS value of IEEE 30-bus and IEEE 118-bus systems. It can be noticed that, NSGA-II is capable of providing better results in the BCS compared to PSO algorithm for IEEE 30-bus system.

Figs. 5 and 6 show the position of BCS on Pareto-front obtained using NSGA-II for the CEED problem of with valve-point effect in IEEE 30-bus and IEEE 118-bus system respectively.

6. Conclusion

In this paper, RCGA and NSGA-II have been applied to solve the CEED problem with complexities of valve-point loading effect and transmission line losses. The problem has been formulated as multi-objective optimization problem with competing fuel cost and emission objectives. By means of stochastically searching multiple points at one time and considering trial solutions of successive iterations, the NSGA-II avoids entrapping in local optimal solutions than conventional methods. The NSGA-II was tested for the IEEE 30-bus and IEEE 118-bus systems and compared with the generated reference Pareto-front by RCGA. In all the cases, valve-point loading effect is included. Simulation results reveal that the NSGA-II can identify the Pareto-optimal front with a good diversity for the CEED problems of with and without valve-point effect. Moreover, the solutions are obtained in a single simulation run with less computational time. The MADM procedure is followed for choosing the BCS from the obtained Pareto-optimal solutions based on TOPSIS.

References

[1] A. J. Wood and B. F. Wollenberg, "*Power Generation, Operation and control*," 2nd ed., New York: Wiley, 1996, pp. 29-32.

[2] A. A. El-kieb, H. Ma and J. L. Hart, "Economic dispatch in view of the clean air act of 1990," *IEEE Trans. Power Syst*., Vol. 9, No. 2, pp. 972-978, 1994.

[3] S. F. J. Brodsky and R. W. Hahn, "Assessing the influence of power pools on emission constrained economic dispatch," *IEEE Trans. Power Syst*., Vol. 1, No. 1, pp. 57-62, 1986.

[4] A. A. El-kieb, H. Ma and J. L. Hart, "Environmentally constrained economic dispatch using the lagrange relaxation method," IEEE Trans. Power Syst., Vol. 9, No. 4, pp. 1723-1729, 1994.

[5] J. Zahavi, L. Eisenbers, "Economic-environmental power dispatch," *IEEE Trans. Power Syst., Man, Cybern*., Vol. 5, No. 5, pp. 485- 489, 1985.

[6] R. Yokoyama, S. H. Bae, T. Morita and H. Sasaki, "Multi-objective optimal generation dispatch based on probability security criteria," *IEEE Trans. Power Syst*., Vol. 3, No. 1, pp. 317-324, 1988.

[7] A. Farag, S. Al Baiyat and T. C. Cheng, "Economic load dispatch multi-objective optimization procedures using linear programming technique," *IEEE Trans. Power Syst*., Vol. 10, No. 2, pp. 731-738, 1995.

[8] J. Nanda, D. P. Kothari and K. S. Lingamurthy, "Economic emission load dispatch through goal programming technique," *IEEE Trans. Energy Convers.*, Vol. 3, No. 1, pp. 26-32, 1988.

[9] Y. H. Song, G. S. Wang, P. Y. Wang and A. T. Johns, "Environmental/economic dispatch using fuzzy logic controlled genetic algorithms," *IEE Proc. of Gener. Trans. Distri.*, Vol. 144, No. 4, pp. 377-382, 1997.

[10] K. P. Wong and J. Yuryevich, "Evolutionary programming based algorithm for environmentally constrained economic dispatch," *IEEE Trans. Power Syst*., Vol. 13, No. 2, pp. 301-306, 1998.

[11] A. A. Abou El Ela, M.A. Abido, S.R. Spea, "Differential evolution algorithm for emission constrained economic power dispatch problem," *Electric Power Syst. Res.*, Vol. 80, pp. 1286-1292, 2010.

[12] S. Prabhakar Karthikeyan, K. Palanisamy, C. Rani, I. J. Raglend and D. P. Kothari, "Security constrained unit commitment problem with operational, power flow and environmental constraints," *WSEAS Trans. Power Syst*., Vol. 4, No. 1, pp. 53-66, 2009.

[13] C. M. Fonesca and P. J. Flemming, "An overview of evolutionary algorithms in multi-objective optimization," *Evol. Comput*., Vol. 3, No. 1, pp.1-16,1995.

[14] K. Deb,"*Multi-objective optimization using evolution algorithms*," New York:Wiley, 2001, pp. 4-9.

[15] M. A. Abido, "A novel multi-objective evolutionary algorithm for environmental / economic power dispatch," *Electric power syst. Res.*, Vol. 65, pp.71-81, 2003.

[16] M. A. Abido, "Environmental/economic power dispatch using multi-objective evolutionary algorithms," *IEEE Trans. Power Syst*., Vol. 18, No. 2, pp. 1529-1537, 2003.

[17] M. A. Abido, "Multi-objective particle swarm optimization for environmental / economic dispatch problem," *Electric power syst. Res.*, Vol. 79, pp. 1105-1113, 2009.

[18] K. Deb, A. Pratap, S. Agarwal and Meyarivan, "A fast and elitist multi-objective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput*., Vol. 6, No. 2, pp. 182-197, 2002.

[19] R. T. F. Ah king, H. C. S. Rughooputh and K. Deb, "Evolutionary multi-objective environmental / economic dispatch: stochastic vs deterministic approaches," *KanGAL report* number 2004019, 2004.

[20] S. Dhanalakshmi, S. Kannan, K. Mahadevan and S. Baskar, "Application of modified NSGA-II algorithm to combined economic and emission dispatch problem," *Electric Power & Energy Syst.,* Vol. 33, pp. 992-1002, 2011.

[21] Li Xuebin, "Study of multi- objective optimization and multi-attribute decision making for economic and environmental power dispatch," *Electric Power Syst. Res.*, Vol. 79, pp. 789-95, 2009.

[22] L. H. Wu, Y. N. Wang, X. F. Yuan and S. W. Zhou, "Environmental / Economic power dispatch problem using multi-objective differential evolution algorithm," *Electric Power Syst. Res*., Vol. 80, pp. 1171-1181, 2010.

[23] Youlin Lu, Jianzhong Zhou, Hui Qin, Ying Wang and Yongchuan Zhang, "Environmental/economic dispatch problem of power system by using an enhanced multi-objective differential evolution algorithm," *Energy Conversion and Management,* Vol. 52, pp. 1175-1183, 2011.

[24] D. C. Walters and G. B. Sheble, "Genetic algorithm solution economic dispatch with valve point loading," *IEEE Trans. Power Syst*., Vol. 8, pp.1325-1331, 1993.

[25] H. T.Yang, P. C.Yang and C. L.Huang, "Evolutionary programming based economic dispatch for units with

non smooth fuel cost functions," *IEEE Trans. Power Syst.*, Vol. 11, No. 1, pp. 112-118, 1996.
[26] G. Ravi, R. Chakrabarti and S. Choudhuri, "Non-convex economic dispatch with heuristic load patterns using improved fast evolutionary program," Electric Power Comp. and Syst., Vol. 34, pp. 37-45, 2006.
[27] J. B. Park, K. S. Lee, J. R. Shin and K. Y. Lee, "A particle swarm optimization for economic dispatch with nonsmooth cost functions," IEEE Trans. Power Syst., Vol. 20, No. 1, pp. 34-42, 2005.
[28] N. Noman and H. Iba, "Differential evolution for economic load dispatch problems," Electric Power Syst. Res., Vol. 78, pp.1322-1331, 2008.
[29] M. Basu, "An interactive fuzzy satisfying-based simulated annealing technique for economic emission load dispatch with nonsmooth fuel cost and emission level functions," Electric Power Components Syst., Vol. 32, pp.163-173, 2004.
[30] S.Hemamalini, P.SishajSimon,"Emission constrained economic dispatch with valve-point effect using Particle Swarm Optimization," TENCON 2008, *IEEE region 10 conference*, pp. 1-6, 2008.
[31] M. Basu, "Economic environmental dispatch using multi-objective differential evolution," *Applied Soft Computing.*, Vol. 11, pp. 2845-2853, 2011.
[32] R. Zimmerman and D. Gan, "MATPOWER, A MATLAB power system simulation package," http://www.pserc.cornell.edu/matpower

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