Application of NSGA-II Algorithm to Generation Expansion Planning

S. Kannan, *Member, IEEE*, S. Baskar, *Member, IEEE*, James D. McCalley, *Fellow, IEEE*, and P. Murugan

***Abstract*—This paper describes use of a multiobjective optimization method, elitist nondominated sorting genetic algorithm version II (NSGA-II), to the generation expansion planning (GEP) problem. The proposed model provides for decision maker choice from among the different trade-off solutions. Two different problem formulations are considered. In one formulation, the first objective is to minimize cost; the second objective is to minimize sum of normalized constraint violations. In the other formulation, the first objective is to minimize investment cost; the second objective is to minimize outage cost (or maximize reliability). Virtual mapping procedure is introduced to improve the performance of NSGA-II. The GEP problem considered is a test system for a six-year planning horizon having five types of candidate units. The results are compared and validated.**

***Index Terms*—Generation expansion planning, multiobjective, nondominated sorting genetic algorithm, optimization, virtual mapping procedure.**

I. Introduction

THE generation expansion planning (GEP) problem seeks to identify *which* generating units should be commissioned and *when* they should become available over the long-term planning horizon [1], [2]. This GEP model is applicable for developing countries like India, where planning is coordinated by central or state government owned utilities for capacity addition. It is also applicable in a market-based industry for companies intending to serve load from multiple generation facilities. The major objectives of GEP are to minimize the total investment and the operating cost of the generating units, and to meet the demand criteria, fuel-mix ratio, and the reliability criteria. GEP is a constrained, nonlinear, discrete optimization problem.

The traditional approach is to formulate this problem as a single-objective optimization problem with constraints. In this approach, the objective may consist of a single term [3]–[8] or it may consist of multiple terms [9], [10]. One may use dynamic programming or genetic algorithm to solve. However, this approach only results in a single optimal solution where tradeoffs between different components of the objective function must be fixed in advance of solution. In order to provide a means to assess tradeoffs between two conflicting objectives, one may formulate the GEP problem as a multiobjective problem. In this case, solution requires a multiobjective algorithm such as NSGA-II. Srinivas and Deb developed NSGA in which a ranking selection method emphasizes current nondominated solutions and a niching method maintains diversity in the population [11]. Multiobjective evolutionary algorithms including NSGA that use nondominated sorting and sharing have been criticized mainly for 1) computational complexity, 2) nonelitism approach, and 3) the need for specifying a sharing parameter. Deb *et al.* alleviated these difficulties in NSGA-II [12], [13].

In comparison with single-objective optimization techniques, the Pareto-based multiobjective optimization methods have a number of advantages in solving constrained optimization problems [13, p. 403]. First, the Pareto-optimal solution set contains trade-off solutions, including solutions that violate constraints so that a solution with a permissible constraint violation can still be considered if there is a substantial gain in the objective function value. Second, decomposing the original single-objective function into multiple, conflicting objectives gives more flexibility in exploring the solution space. As described in [14], this flexibility enables identification of local optima, transformed by the multiobjective approach into tradeoff solutions along the Pareto-front that would otherwise not be found by the single-objective approach.

The goal of this paper is to formulate the GEP problem as a multiobjective optimization and illustrate its solution using Pareto-based multiobjective optimization NSGA-II. Two different multiobjective problem formulations are provided. In addition, the performance of NSGA-II is improved with the virtual mapping procedure (VMP).

The paper is organized as follows: Section II describes the two different multiobjective GEP problem formulations. Section III describes NSGA-II implementation to the GEP problem. Section IV describes obtaining the true Pareto-front. Section V provides test results, and Section VI concludes.

II. Generation Expansion Planning Problem Formulation

The GEP problem is equivalent to finding a set of best decision vectors over a planning horizon that minimizes the investment and operating costs under relevant constraints. To

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illustrate the flexibility of multiobjective optimization, two different problem formulations are provided in this paper. In Section II-A, the GEP problem is formulated to provide trade-off solutions between cost and constraint violations. In Section II-B, the GEP problem is formulated to provide trade-off solutions between investment costs and outage costs.

A. Problem Formulation 1

The general single-objective problem formulation is developed such that the NSGA-II can be applied as explained in [13]. It is assumed the first possible availability date of new generation is two years beyond the current date. The problem is considered with two objectives. Cost is one objective. The soft constraints are transformed into another objective. The hard constraints remain.

1) Cost Objective: The cost objective is represented by the following expression:

$$\min C = \sum_{t=1}^{T} [I(U_t) + M(X_t) + O(X_t) - S(U_t)] \quad (1)$$

where

$$X_t = X_{t-1} + U_t \quad (t = 1, 2, \ldots T) \quad (2)$$

$$I(U_t) = (1+d)^{-2t} \sum_{i=1}^{N} (CI_i \times U_{t,i}) \quad (3)$$

$$S(U_t) = (1+d)^{-2(\mathrm{T}+1)} \sum_{i=1}^{N} \left(CI_i \times \delta_i^{2(T-t+1)} \times U_{t,i} \right) \quad (4)$$

$$M(X_t) = \sum_{s'=0}^{1} \Bigg((1+d)^{-(2.5+t'+s')} \times \sum_{i=1}^{N} ((X_{t,i} \times \mathrm{FC}_i) + \mathrm{MC}_i \times EES_{t,i}) \Bigg) \quad (5)$$

$$O(X_t) = \mathrm{OC} \times \sum_{s'=0}^{1} \left((1+d)^{-(2.5+t'+s')} \right) \quad (6)$$

where $\mathrm{OC} = \mathrm{EENS_t} \times \text{Cost of EENS}$

$$EENS = \sum_{\{j|Y_j > R_j\}} (Y_j - R_j) P(Y_j) Ot_j \quad (7)$$

where

Y_j	system outage capacity at state j;
R_j	system reserve capacity at state j;
$P(Y_j)$	probability of occurring state j;
Ot_j	outage time of state j.

The outage cost calculation of (6), used in (1), depends on expected energy not served (EENS). The equivalent energy function method [2] is used to calculate EENS (and also loss of load probability, LOLP, used in the constraint objective). This equivalent energy function method is capable of finding LOLP without any additional computational effort

$$t' = 2(t-1) \text{ and } T' = 2 \times T - t' \quad (8)$$

$$U_t = \sum_{i=1}^{N} U_{t,i} \quad (9)$$

$$X_t = \sum_{i=1}^{N} X_{t,i} \quad (10)$$

and

C	total cost, \$;
U_t	N-dimensional vector of newly introduced units in the stage t (1 stage = 2 years);
$U_{t,i}$	the number of newly introduced units of type i in stage t;
X_t	cumulative capacity vector of existing units in stage t,(MW);
$X_{t,i}$	cumulative capacity of existing units of type i in stage t,(MW);
$I(U_t)$	present value of investment cost of the newly introduced unit at the tth stage, \$;
$M(X_t)$	present value of total operation and maintenance cost of existing and the newly introduced units, \$;
s′	variable used to indicate that the maintenance cost is calculated at the middle of each year;
$O(X_t)$	present value of outage cost of the existing and the newly introduced units, \$;
$S(U_t)$	present value of salvage value of the newly added unit at tth interval, \$;
d	discount rate;
CI_i	capital investment cost of ith unit, \$;
δ_i	salvage factor of ith unit;
T	length of the planning horizon (in stages);
N	total number of different types of units;
FC	fixed operation and maintenance cost of the units, \$/MW;
MC	variable operation and maintenance cost of the units (energy), \$/MWh;
EES	expected energy served, MWh;
$EENS$	expected energy not served, MWh;
OC	value of outage cost, \$.

2) Constraint Objective: The constraint objective is to minimize the sum of normalized constraint violations. The normalization ensures that all constraint violation terms have value between 0 and 1

$$\min\ C_{err} = R_{\mathrm{err}} + FM_{\mathrm{err}} + LOLP_{\mathrm{err}} \tag{11}$$

where

C_{err}	constraint objective;
R_{err}	reserve margin violation;
FM_{err}	fuel-mix ratio violation;
$LOLP_{\mathrm{err}}$	LOLP value violation.

a) Reserve margin: The selected units must satisfy the minimum and maximum reserve margin

$$(1 + R_{\min}) \times D_t \leq \sum_{i=1}^{N} X_{t,i} \leq (1 + R_{\max}) \times D_t \tag{12}$$

where

R_{min}	minimum reserve margin;
R_{max}	maximum reserve margin;
D_t	demand at the tth stage in MW;
$X_{t,i}$	cumulative capacity of ith unit at stage t.

b) Fuel mix ratio: The GEP has different types of generating units such as coal, liquefied natural gas (LNG), oil, and nuclear. The selected units along with the existing units of each type must satisfy the fuel mix ratio

$$FM_{\min}^{j} \leq X_{t,j} \Big/ \sum_{i=1}^{N} X_{t,i} \leq FM_{\max}^{j} \quad j = 1, 2, \ldots, \mathrm{N} \tag{13}$$

where

$FM_{\min}^{j}$	minimum fuel mix ratio of jth type;
$FM_{\max}^{j}$	maximum fuel mix ratio of jth type;
j	type of the unit (e.g., oil, LNG, coal, nuclear).

c) Reliability criterion: The selected units along with the existing units must satisfy a reliability criterion on loss of load probability (LOLP)

$$LOLP(X_t) \leq \varepsilon \tag{14}$$

where ε is the reliability criterion for maximum allowable LOLP.

3) Operating Constraints: The upper construction limit and the demand constraint are hard constraints.

a) Upper construction limit: Let U_t represent the units to be committed in the expansion plan at stage t that must satisfy

$$0 \leq U_t \leq U_{\max,t} \tag{15}$$

where $U_{\max,t}$ is the maximum construction capacity of the units at stage t.

b) Demand: The selected units must satisfy the demand

$$\sum_{i=1}^{N} X_{t,i} \geq D_t \tag{16}$$

where

$X_{t,i}$	cumulative capacity of ith unit at stage t, MW;
D_t	demand at the tth stage, MW.

B. Problem Formulation 2

The first objective function expresses investment cost, and the second objective function expresses outage cost. This formulation can be viewed as splitting the single-objective function of (1) into two different objectives.

1) Investment Cost Objective: The minimization of investment cost is represented by the following expression:

$$\min C_1 = \sum_{t=1}^{T} \left[I(U_t) + M(X_t) - S(U_t) \right]. \tag{17}$$

2) Outage Cost Objective: The minimization of outage cost (or maximization of reliability) is represented by the following expression:

$$\min C_2 = \sum_{t=1}^{T} \left[O(X_t) \right]. \tag{18}$$

3) Operating Constraints: The reserve margin (12), fuel-mix ratio (13), reliability criterion (14), upper construction limit (15), and demand (16) are modeled as hard constraints.

III. NSGA-II Implementation to GEP Problem

Classical optimization methods can at best find one solution in one simulation run, thereby making those methods inconvenient to solve multiobjective optimization problems. Evolutionary algorithms, on the other hand, can find multiple optimal solutions in one single simulation run due to their population approach. The NSGA-II algorithm, the virtual mapping procedure, and the fitness function evaluation are described in this section. These descriptions are applicable to both problem formulations 1 and 2.

The NSGA-II algorithm is described in [12] and [13]. We selected NSGA-II to solve the GEP problem because it has been demonstrated to be among the most efficient algorithms for multiobjective optimization on a number of benchmark problems [12]. In addition, it has been shown that NSGA-II outperforms two other contemporary multiobjective evolutionary algorithms: Pareto-archived evolution strategy (PAES) [15] and strength-Pareto evolutionary algorithm (SPEA) [16] in terms of finding a diverse set of solutions and in converging near the true Pareto-optimal set. NSGA-II is used for solving both problem formulations 1 and 2.

Section III-A deals with overview of NSGA-II algorithm, Section III-B provides all necessary information regarding implementation and effectiveness of VMP, and Section III-C describes the fitness function evaluation.

A. NSGA-II Algorithm [12], [13]

The NSGA-II algorithm uses nondominated sorting for fitness assignments. One individual is said to dominate another if 1) its solution is no worse than the other in all objectives and 2) its solution is strictly better than the other in at least one objective. All individuals not dominated by any other individuals are assigned front number 1. Individuals dominated only by the individuals in front number 1 are assigned front number 2, and so on. The simulated binary crossover and polynomial mutation generate new offspring, and tournament is then used to select the population for next generation.

1) Simulated Binary Crossover (SBX) [17]: The SBX operator works with two parent solutions and creates two offspring. The difference between offspring and parent depends on crossover index η_c. The crossover index "η_c" is any nonnegative real number. A large value of "η_c" gives a higher probability for creating "near-parent" solutions and a small value of "η_c" allows distant solutions to be selected as offspring. The two offspring created are symmetric about the parent solutions. Also, for a fixed "η_c" the offspring have a spread which is proportional to that of the parent solutions. It has two properties: 1) the difference between corresponding decision variables of the created offspring is proportional to the difference between corresponding decision variables of the parent solutions; 2) offspring having decision variables nearer to those of the parent solutions are more likely to be selected.

2) Polynomial Mutation: The probability of creating a solution near to the parent is higher than the probability of creating one distant from it. The shape of the probability distribution is directly controlled by an external parameter η_m and the distribution remains unchanged throughout the iterations.

3) Selection: Selection is made using tournament between two individuals. The individual with the lowest front number is selected if the two individuals are from different fronts. The individual with the highest crowding distance [12], [13, p. 247] is selected if they are from the same front, i.e., a higher fitness is assigned to individuals located on a sparsely populated part of the front. In every iteration, the N existing individuals (parents) generate N new individuals (offspring). Both parents and offspring compete with each other for inclusion in the next iteration.

B. Virtual Mapping Procedure (VMP) [8]

Convergence problems were encountered when implementing the standard NSGA-II algorithm on the GEP problem. Investigation revealed the reason pertained to the sensitivity of capacity to changes in the decision vector. To illustrate, consider the range of the decision vector lies between [0] and $U_{\max,t}$ as given in (15). The capacity vector is [200 450 500 1000 700]. Let a candidate solution be $U_1 = [5\ 0\ 1\ 1\ 0]$; then its corresponding capacity will be 2500 MW $(5 \times 200 + 0 \times 450 + 1 \times 500 + 1 \times 1000 + 0 \times 700)$. If U_1 changes to [5 0 1 2 0] (via crossover and/or mutation operators), then the capacity is increased from 2500 MW to 3500 MW, a difference of 1000 MW, which is a large deviation.

So VMP was introduced to improve the effectiveness of the NSGA-II in solving the GEP problem. VMP is concerned with the solution representation; it transforms each combination of candidate units for every year into a dummy decision variable, referred to as the VMP variable. The value of the VMP variable for a specific candidate solution is the rank of that solution when all solutions are sorted in ascending order of capacity. For example, the solution [5 0 1 1 0] with capacity of 2500 has VMP value of 190. A change (by crossover and/or mutation) to VMP value of 198 would correspond to a solution of [2 1 2 0 1] with capacity of 2550, a relatively small change in capacity. Without VMP, to get a solution with capacity of 2550 MW, all five variable values must be changed. This may take a very large number of iterations, and in general, moving from suboptimal to optimal may take many iterations.

Since five different types of units are assumed to be available for each stage, the size of the decision vector increases by multiples of five as the number of stages increases. However, when using VMP, the number of decision variables obtained is a multiple of its number of stages; the size of the decision vector becomes 3 for a three-stage problem. Thus, a size reduction of 80% [(15-3)/15, for three stages] is realized. Hence, the dimensionality of the problem, in terms of the number of decision variables, is reduced, and computational time and memory requirements reduce accordingly.

C. Fitness Function Evaluation Using Constrained Tournament Method [13, p. 292]

Since different constraints may take different orders of magnitude, it is essential to normalize all constraints so that they can then be added as the overall constraint violation objective. Problem formulation 1 requires this as per (11), but treatment of operating (hard) constraints in both problem formulations also requires this because the constrained binary tournament method is used [18], where two solutions are picked from the population and the better solution is chosen.

IV. Obtaining the True Pareto-Front

An alternative approach, weighted sum method with (single-objective) GA, is described here to solve the GEP problem. It is used to validate the results obtained using NSGA-II.

A Pareto-optimal set is defined as a set of solutions that are not dominated by any feasible member of the search space; they are optimal solutions of the multiobjective optimization problem. To evaluate the performance of NSGA-II, a reference Pareto-optimal set is needed. One of the classical methods is weighted sum method [13, p. 50]. Using this method only one solution may be found along the Pareto-front in a single simulation run. The real coded GA with SBX crossover and polynomial mutation is used to obtain the true Pareto-front. The major difference between NSGA-II and GA lies in the selection process. In NSGA-II, nondominated sorting is used in the selection process, whereas in the single-objective GA, tournament selection [13, p. 89] is used. The sum of weights is always 1. The weight value for the first objective function is $w1$, and the weight value for second objective function is $w2$, and $w2 = (1 - w1)$. The weight $w1$ is linearly varied from 0 to 1 to produce the Pareto-front. Both the objective function and constraints are normalized.

V. Test Results

The implementation was done using MATLAB version 7.2, on a Dell PC with Pentium dual processor having 3 GHz speed and 3 GB RAM. In this section, subsections Ato C apply to both problem formulations. Section V-D gives results for each problem formulation separately.

A. Test System Description

The forecasted load and other data are taken from [6]. The test system with 15 existing power plants and five types of candidate options is considered for a six-year planning horizon. The planning horizon is divided into three stages (two-year intervals). The forecasted peak demand is given in Table V. The corresponding forecasted peak demand is assumed to be 5000 MW in stage zero, increases to 7000 MW in stage I, 9000 MW in stage II, and 10 000 MW in stage III. Such growth is not atypical in developing countries. Economic and technical data of existing plants are provided in Table VI and candidate plant types for future additions is given in Table VII. The second column in Table VII denotes an upper limit on the number of units of each candidate option per stage which reflects the construction capabilities by plant type. The last column in Table VII is associated with the evaluation of salvage value of a plant that operates beyond the planning horizon.

B. Parameters for GEP

The lower and upper bounds for reserve margin are set at 20% and 40% respectively. The salvage factor (δ) is assumed to be 0.1, 0.1, 0.15, 0.2 and 0.2 for oil, LNG, coal, PWR, and PHWR, respectively. EENS cost is set at 0.05 \$/kWh. The discount rate is 8.5%. It is assumed the first possible availability date of new generation is two years beyond the current date. The year k investment cost is assumed to occur in the beginning of year k; the year k maintenance cost is assumed to occur in the middle of year k and is calculated by the equivalent energy function method [2]. The year k salvage cost is assumed to occur at the end of the planning horizon.

C. Parameters for the NSGA-II Algorithm

The results are sensitive to algorithm parameters, typical of heuristic techniques. Hence, it is required to perform repeated simulations to find suitable values for the parameters. The best parameters for the NSGA-II, selected through ten test simulation runs, are given in Table I.

D. Results and Discussion

The test system uses different types of units (based on type of fuel used: oil, LNG, coal, PWR, and PHWR) as candidate sets. The total number of possible combinations in each stage is 1920. For the six-year period, there are 7.07×10^9 possible combinations.

TABLE I
Best Parameters for Six-Year Planning Horizon

NSGA-II (Parameters)	Parameter values (type)
Population size, N_p	200
Number of iterations	500
P_c, Crossover probability	0.8
P_m, Mutation probability	0.33 (1/3)
Cross over index (η_c)	2 (Simulated Binary Crossover)
Mutation index (η_m)	20 (Polynomial mutation)

TABLE II
Constrained Minimum Solution for Six-Year Planning Horizon

Candidate Type (Capacity in MW)	No. of units selected		
	Stage-I	Stage-II	Stage-III
Oil (200)	4	5	1
LNG C/C (450)	1	2	2
Coal-Bitum. (500)	2	1	0
Nuc.-PWR (1000)	0	0	0
Nuc.-PHWR (700)	3	0	0

The solution with VMP variables has a better Pareto-optimal front both in terms of obtaining the solution and accuracy. The performance depends on the use of the number of decision variables. The number of decision variables is 3 in VMP and 15 with actual variables. Without VMP, it was not able to obtain the Pareto-front.

In the following two subsections, results for each of the two problem formulations are first presented and discussed in terms of extreme solutions. Extreme solutions are solutions lying at the extreme ends of the Pareto-front, i.e., they are solutions for which one of the objectives is given the maximum importance and the other objective is totally neglected. Then results are discussed in terms of the effects of VMP, identification of the Pareto-front, and typical trade-off analysis made possible by the approach.

1) Problem Formulation 1: Here, the aim is to obtain all the solutions with minimum constraint violation (no violation) to maximum constraint violation. The solution with minimum cost and no constraint violation is the constrained minimum.

a) Extreme solution: There is only one extreme solution—the constrained minimum solution, and it is given in Table II and shown on the Pareto-front of Fig. 1. It is the minimum cost solution with all constraints satisfied. The constrained minimum solution has capacity addition of 4350 MW in stage I, 2400 MW in stage II and 1100 MW in stage III, resulting in a cost of \$ 1.2009 e10.

b) Identification of Pareto-front: The Pareto-optimal front obtained using NSGA-II and GA is given in Fig. 1. It shows the trade-off between the cost and sum of normalized constraint violation. The solution for the single objective optimization problem is also illustrated in Fig. 1. In GA technique, the weight $w1$ is linearly varied from 0 to 1 with an increment of 0.005 for each trial. A population size of 200 and maximum iteration of 500 are used. About 200 points are obtained to construct the Pareto-front through GA and the execution time is 13 000

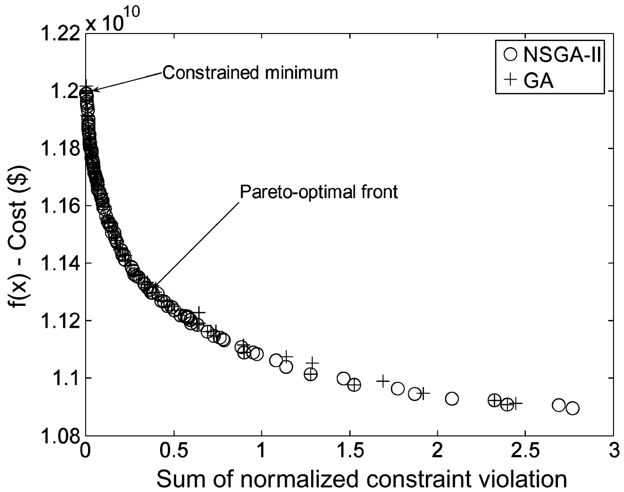

Fig. 1. Constrained minimum, solution of the single-objective optimization problem, and Pareto-optimal set of the multiobjective problem.

TABLE III
ANALYSIS ON CONSTRAINT VIOLATED SOLUTION

Sum of normalized soft constraint violations	Cost $\times 10^{10}$ ($)	Cost Improve -ment (%)	Soft constraints violated		
			Loss of load probability value		
			Stage-I	Stage-II	Stage-III
0	1.2009	0	-	-	-
0.001	1.1988	0.17	-	-	0.0108
0.01	1.1816	1.6	0.0160	-	0.0144
0.1	1.1495	4.3	0.0292	0.0461	0.0727

s (3.61 h). In contrast, NSGA-II produces the Pareto-optimal front in a single simulation run and the execution time is only 800 s. The NSGA-II is computationally more efficient than GA.

c) Trade-off analysis: In many real-world problems, a solution with a permissible constraint violation can still be considered if there is a substantial gain in the objective function. Table III provides a summary of the constrained minimum (first row) and three constraint violated solutions. In each of the constraint-violated solutions, the only constraint violated is the LOLP constraint, i.e., reserve margin and fuel mix ratio constraints are satisfied in all cases. Some decision-makers may perceive the LOLP constraint to be soft because a related index, EENS, is included in the cost objective of (1). Since trade-off solutions between cost and constraint violations are available, the decision maker has a choice to do post-optimality analysis, For example, one might accept the sum of normalized soft constraints of 0.1 (last row, first column of Table III), corresponding to LOLPs of 0.0292, 0.0461, and 0.0727 in Stages I, II, and III, respectively (last row, last three columns of Table III), since this solution provides a cost improvement of 4.3% (last row, third column of Table III).

2) Problem Formulation 2: Here, the aim is to obtain all of the trade-off solutions between investment cost and outage cost.

a) Extreme solutions: The extreme solutions are obtained by solving the problem as a single objective problem where the objective is either 1) investment cost or 2) outage cost. Results of these two cases in terms of investment, outage, and total costs are given in Table IV.

TABLE IV
BEST SOLUTIONS OBTAINED FOR INVESTMENT AND OUTAGE COSTS OPTIMIZED INDIVIDUALLY

Cost ($)	Objective	
	Min. investment cost	Min. outage cost
Investment cost	1.20036e10	1.26242e10
Outage cost	5.61442e6	3.23075e6
Total cost	1.2009e+010 [8]	1.26275e+010

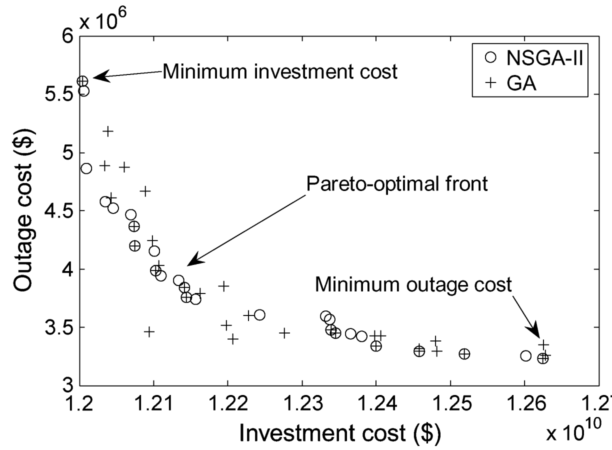

Fig. 2. Pareto-optimal front using NSGA-II and GA.

The same problem is treated as multiobjective, solved with NSGA-II, and results are shown in Fig. 2. Fig. 2 also indicates the two extreme solutions described by Table IV. The minimum investment cost and minimum outage cost is illustrated in Fig. 2.

b) Identification of Pareto-front: The Pareto-front obtained by NSGA-II and GA is given in Fig. 2. It shows the trade-off between the investment cost and the outage cost.

In GA technique, as in the problem formulation, 1, the weight $w1$ is linearly varied from 0 to 1 with an increment of 0.005 for each trial. A population size of 200 and maximum iteration of 500 are used. About 200 points are obtained to construct the Pareto-front through GA and the execution time is 13 500 s (3.75 h). In contrast, NSGA-II produces the Pareto-optimal front in a single simulation run and the execution time is only 800 s. Both algorithms found identical extreme solutions.

NSGA-II found most of the solutions in the true Pareto-front and its computational time is also very less.

c) Trade-off analysis: From Fig. 2, it is clear that the increase in investment cost beyond $1.22e10 does not have much influence on reducing outage cost. This observation will help the decision maker to select a single solution from the Pareto-optimal front having investment cost between 1.2 e10 and 1.22 e10.

VI. CONCLUSION

A very first attempt is made to solve multiobjective GEP problem using NSGA-II, in this paper. Multiobjective optimization enables evaluation of tradeoff solutions between different problem objectives through identification of the Pareto-front. The NSGA-II algorithm with VMP provides that this can be done with very high computational efficiency. This paper describes two implementations of NSGA-II algorithm to the GEP

TABLE V
FORECASTED PEAK DEMAND [6]

Stage (Year)	2007	2009	2011	2013
Peak (MW)	5000	7000	9000	10000

TABLE VI
TECHNICAL AND ECONOMIC DATA OF EXISTING PLANTS [6]

Name (Fuel Type)	No. of Units	Unit Capacity (MW)	FOR (%)	Operating Cost ($/KWh)	Fixed O& M Cost ($/ Kw-Mon)
Oil#1(Heavy Oil)	1	200	7.0	0.024	2.25
Oil#2(Heavy Oil)	1	200	6.8	0.027	2.25
Oil#3(Heavy Oil)	1	150	6.0	0.030	2.13
LNG G/T#1(LNG)	3	50	3.0	0.043	4.52
LNG C/C#1(LNG)	1	400	10.0	0.038	1.63
LNG C/C#2(LNG)	1	400	10.0	0.040	1.63
LNG C/C#3(LNG)	1	450	11.0	0.035	2.00
Coal#1(Anthracite)	2	250	15.0	0.023	6.65
Coal#2(Bituminous)	1	500	9.0	0.019	2.81
Coal#3(Bituminous)	1	500	8.5	0.015	2.81
Nuclear#1(PWR)	1	1,000	9.0	0.005	4.94
Nuclear#2(PWR)	1	1,000	8.8	0.005	4.63

TABLE VII
TECHNICAL AND ECONOMIC DATA OF CANDIDATE PLANTS [6]

Candidate Type	Const-ruction Upper limit	Capa-city (MW)	FOR (%)	Operating Cost ($/KWh)	Fixed O& M Cost ($/ Kw-Mon)	Capital Cost ($/Kw)	Life Time (Yrs)
Oil	5	200	7.0	0.021	2.20	812.5	25
LNG C/C	4	450	10.0	0.035	0.90	500.0	20
Coal(Bitum.)	3	500	9.5	0.014	2.75	1062.5	25
Nuc.(PWR)	3	1,000	9.0	0.004	4.60	1625.0	25
Nuc.(PHWR)	3	700	7.0	0.003	5.50	1750.0	25

problem. One problem formulation enables tradeoff analysis between a cost objective and violations of soft constraints. Another problem formulation enables tradeoff analysis between investment and outage costs. The approach is quite flexible so that other formulations using different objectives and/or a larger number of objectives are possible, enabling generation planners to better understand their options, ultimately resulting in lower cost and higher reliability of supply.

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