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Optimization of India's electricity generation portfolio using intelligent Pareto-search genetic algorithm

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ABSTRACT

Optimization of power generation mix is a significant strategy of climate change mitigation for countries like India. This involves multi-objective optimization of cost reduction, emissions reduction and risk mitigation taking into account relevant constraints. We use a variant of portfolio optimization technique to generate India's 12th five year plan electricity generation portfolio taking into account the carbon costs. For fitness evaluation of a generation portfolio, we use levelized generation costs and a Comprehensive Risk Barrier Index (CRBI), the latter capturing the cost risks modulated by project implementation barrier indices. For constrained optimization, we develop a fast hybrid algorithm, namely, Intelligent Pareto-search Genetic Algorithm (IPGA), which systematically evolves successively efficient frontiers and finally converges to the global Pareto-optimal front. This algorithm combines non-dominated sorting and separate elite population, while utilizing dual mode search for faster convergence and cluster reduction strategy for enhancing diversity. Halting mechanisms have been proposed for local and global Pareto convergence. We apply this generalized algorithm to simulate the impact of carbon costs, risks and barriers on India's optimal generation portfolio.

1. Introduction

New planning and risk management tools are important to respond to uncertainty in climate change and the adaptation/mitigation policies of governments [1]. Optimization of energy strategy portfolios is a critical component of such response. We have formulated a methodology of hierarchical multi-objective optimization of India's energy strategy portfolios in this context [2,3]. Optimization of generation portfolio is a key component of the first level optimization incorporated in this framework. Optimal generation planning is particularly important due to incorporation of Renewables Portfolio Standards, which is fast emerging as a significant constituent of power generation portfolio worldwide. Despite this trend, according to the projections of IPCC, the energy mix supplied to run the global economy in the 2025–30 timeframe will essentially remain unchanged, with more than 80% of energy supply based on fossil fuels [4]. As far as India is concerned, coal will remain the mainstay of power generation during the 12th Plan (2012–2017) providing at least 50% base load power, though renewables' share is growing steadily as mandated by the Electricity Act, 2003.

Though renewables contribute 13% of global energy consumption [5] today, most involve unsustainable uses of wood or hydropower with only 2% share of green new renewables and 6% nuclear. Distributed generation using renewables or otherwise, has a number of advantages. The primary drivers of advancing distributed generation [6] are limiting greenhouse gas (GHG) emissions, avoidance of new transmission circuits and large generating plants, risk reduction in electricity markets, improved power quality, reliability and enhanced energy security. More than doubling of the renewable energy generation in India is projected during the current decade [7] accounting for 25% of the total energy consumed by the year 2020–21.

Optimal generation planning with renewables in the portfolio is an important strategy of climate change mitigation [8]. There are various approaches to this optimization problem. Ref. [9] arrives at an optimal generation mix for Malaysia using two-phase K-best dynamic programming trade-off method, comparing coal, nuclear, solar thermal and biomass technologies based on three criteria, namely, economic cost, reliability and socio-environmental cost. Ref. [10] presents a compromise model for optimal generation mix calculations. A fuzzy linear programming optimization approach for generation planning in India for the year 2020 is indicated in [11] and analytic hierarchy process is employed for green energy sources selection in [12].

Mean variance portfolio theory has been applied to the Irish electricity sector in [13]. A multi-parametric quadratic programming technique is described for fast computation of portfolio problems in [14]. California Energy Commission [15] uses levelized cost

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estimates including carbon costs along with risks to assess the climate change impact of generation technologies. However, in the context of a developing country like India, barriers to project implementation are as important as cost risks while planning capacity augmentation. We, therefore, propose a modified approach where we generate a composite index, namely, Comprehensive Risk Barrier Index (CRBI) and use it along with levelized costs to generate efficient frontiers. To implement constrained optimization, we devise a generalized genetic algorithm and optimize India's 12th five year plan electricity portfolio taking into account the impact of carbon costs.

2. Optimization approach for generation planning

Generally, countrywide policies have multiple objectives. Multi-criteria decision-making (MCDM) methods in an integrated assessment framework offer a better alternative to cost/benefit and similar methods [16]. Since bi-objective optimization is easy to visualize and does not require computation of surfaces, it is proposed for generation planning, the twin objectives of which have to be carefully selected. Essentially, the first will be financial/economic cost criterion and the second would relate to policy/project implementation focusing on the quantification of risks and barriers. Portfolio optimization techniques [14,17–19] can be employed using these twin criteria to generate a Pareto-optimal portfolio.

Portfolio optimization is a bi-objective problem of maximizing portfolio return and minimizing portfolio risk. Risk is estimated by evaluating the standard deviation of the portfolio return, as in the case of Sharpe ratio [20], though there are several ways of defining risk [21]. For generation planning, we use portfolio levelized cost and risk to formulate a minimization problem. For a portfolio, cost and standard deviations are computed by the matrix equations,

$$\text{Portfolio Cost, } f_1(\mathbf{X}) = \text{Expectation of cost vector} = \mathbf{X^T C} \tag{1}$$

$$\mathbf{C} = \text{Column vector of levelized costs}$$

$$\mathbf{X} = \text{Column vector of weights}$$

$$\text{Portfolio standard deviation(risk), } f_2(\mathbf{X}) = (\mathbf{X^T}\Sigma\mathbf{X})^{0.5} \tag{2}$$

$$\Sigma = \text{Covariance matrix}$$
$$= \begin{bmatrix} \sigma1 & 0 & \dots & \dots & 0 \\ 0 & \sigma2 & \dots & \dots & 0 \\ 0 & 0 & \dots & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \dots & \sigma n \end{bmatrix} \times \begin{bmatrix} 1 & \rho12 & \dots & \dots & \rho1n \\ \rho21 & 1 & \dots & \dots & \rho2n \\ \rho31 & \rho32 & \dots & \dots & \rho3n \\ \dots & \dots & \dots & \dots & \dots \\ \rho n1 & \rho n2 & \dots & \dots & 1 \end{bmatrix} \times \begin{bmatrix} \sigma1 & 0 & \dots & \dots & 0 \\ 0 & \sigma2 & \dots & \dots & 0 \\ 0 & 0 & \dots & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \dots & \sigma n \end{bmatrix}$$
$$\sigma_i = \text{Standard deviation of the } i\text{th element(risk)}$$
$$\rho_{ij} = \text{Correlation coefficient between } i\text{th and } j\text{th elements.} \tag{3}$$

The mean variance portfolio optimization problem can then be stated as:

$$\begin{aligned} &\text{Minimize} && f_1(\mathbf{X}),\ f_2(\mathbf{X}) \\ &\text{subject to} && g_1(\mathbf{X}), g_2(\mathbf{X}) \dots, gk(\mathbf{X}) \le 0, \\ & && \text{with } \mathbf{x} \in S, S \in \Re^n \text{ being the decision variable space.} \end{aligned} \tag{4}$$

3. Comprehensive risk barrier index (CRBI)

Apart from the risks associated with each cost component, there are barriers in implementing projects especially in the context of a developing country like India. We use a comprehensive risk barrier index (CRBI) to indicate the combined impact of risks and implementation barriers associated with each portfolio. While risk parameters are estimated using the standard deviations of the respective costs, multi-criteria ranking methods [22] can be used to evaluate the barrier indices. Analytic hierarchy process (AHP) [23,24] has been selected in this work which is an important multi-attribute weighting method making use of pair-wise comparison matrices estimated based on expert judgments. AHP has been implemented using Web HIPRE software [25] to obtain the Perron vector (principal eigenvector) of the reciprocal comparison judgment matrix. We use the consistency measure of this matrix as in Web-HIPRE [26]. Risk and barrier indices are then integrated into a composite index by a suitable combination function. The estimated portfolio cost and portfolio CRBI give the fitness indication of a particular generation portfolio as against its competitors, to be employed as inputs to the bi-objective minimization problem.

We consider the following barrier profiles in the Indian scenario:

(i) Land availability barrier.
(ii) Public policy support/barrier.
(iii) Environmental clearance barrier.
(iv) Infrastructure and resource availability barriers.
(v) Grid connection and market barriers.

In the AHP, the priority vector for each of the barriers is computed using the pair-wise comparison matrix. Individual barrier priority vectors are combined to compute the overall barrier index vector for all energy technologies. If the barrier importance column vector is **B**, and the matrix of barrier priority vectors is **A**, then the overall barrier index vector for various energy technologies, **P** is given by:

$$\mathbf{P} = \mathbf{AB} \tag{5}$$

$$\text{Portfolio barrier index,} \quad B = \mathbf{X^T P} \tag{6}$$

The risk and barrier indices can now be aggregated to form the comprehensive risk barrier index (CRBI) using a suitably weighted risk-barrier combination function. CRBI is an index which captures the combined impact of the risk and barrier random variables. A proportionality function of these independent variables is the simplest approach to capture this impact, though a variety of telescopic functions are possible to accentuate or reduce the impact of each at various regions of the domain. This is the choice to be exercised by the policy maker as to what kind of relative functional priorities need to be attached to the risk and barrier profiles. The simple product function could be replaced by other choices such as $\mathbf{b^2r}$, $\mathbf{br^2}$, $\mathbf{b^2r + br^2}$ etc. where **b** is the barrier random variable and **r** is the risk random variable. In this analysis, we utilize the product function of the risk and barrier indices to generate CRBI.

$$\text{Portfolio CRBI} = K * (\text{Portfolio barrier}) * (\text{Portfolio risk})$$

$$= K * (\mathbf{X^T P}) * (\mathbf{X^T}\Sigma\mathbf{X})^{0.5} \tag{7}$$

where K is a positive constant.

4. Intelligent Pareto-search Genetic Algorithm (IPGA)

Though there are analytical approaches to solve optimization problems, heuristics such as Genetic Algorithm are especially useful for hard problems. Genetic algorithms are intrinsically parallel due to which they can generate a number of near-optimal solutions. They have been gainfully employed in many power sector problems such as economic dispatch [27,28], electric load forecasting [29] and distribution systems configuration [30] etc. The present example is part of the hierarchical multi-objective optimization of India's energy strategies. Since the optimal vectors of the first level are subjected to further optimization at higher levels using macrolevel objective functions, it is important to generate a number of near optimal solutions at lower levels to feed into the optimization process at higher levels. Genetic algorithms fulfill this requirement of making available many solutions for the policy maker. Another reason for the suitability of genetic algorithms is the complexity of the fitness function including CRBI. For evolving correct policy strategies, it is required to consider many fitness functions or their variations, as in the present study. These are easily implemented in a GA heuristic.

We develop a genetic algorithm using evolutionary processes to carry out the portfolio optimization. NSGA-II and SPEA are two genetic algorithms [31] which can be employed for multi-objective optimization. Intelligent Pareto-search Genetic Algorithm (IPGA), proposed for the first level of the hierarchical multi-objective optimization approach, is a new hybrid combining non-dominated sorting feature of NSGA-II and separate elite population feature of SPEA and adding original novel features such as intelligent Pareto-search or dual mode search, Pareto-convergence test, and new cluster reduction strategy. Non-dominated Sorting Genetic Algorithm (NSGA-II) applies non-dominated sorting/selection procedures to the combined parent and offspring populations to form the population of the next generation [32]. A crowded distance-based niching strategy is used to ensure diversity in the selection process. The Strength Pareto Evolutionary Algorithm (SPEA) maintains a separate elite population as a repository of the best solutions found up to a particular generation [33,34]. Diversity enhancement techniques are employed in the selection of elite population. SPEA has been found to provide a better optimal solution compared to Particle Swarm Optimization–Fuzzy satisfaction maximization approach [35].

Reproduction and crossover operators are critical for the success of genetic algorithms [36]. In IPGA, these processes are effectively utilized for the exploration and exploitation of the search space. This algorithm ensures convergence by applying a systematic procedure to generate the global Pareto-optimal front. The advantages of this algorithm over the conventional algorithms are:

(i) It combines non-dominated sorting technique in NSGA and the elite preservation in SPEA.
(ii) It incorporates an efficient cluster reduction strategy to ensure diversity while selecting the elite population.
(iii) It incorporates a dual mode search strategy for efficient exploration and exploitation of the search space for progressively advancing to the global Pareto-optimal front. Exploration strategy first generates a non-dominated elite front from the current test population and then applies genetic operators of reproduction, crossover and mutation to the population to locate at least one point which dominates all the previous elite solutions. If such a point is found, then the exploitation strategy is employed to generate a non-dominated elite front around the identified point, using a combination of reproduction and mutation operators applied to the test population.
(iv) It provides a systematic approach for convergence to the local and global Pareto-optimal fronts with a halting mechanism. If in sufficiently large number of iterations, the efficient frontier obtained thus far is not superseded by a dominating member so that the cluster reduction strategy persists without interruption in all these iterations, it indicates a local Pareto-optimal front. Global solutions are obtained by generating a number of local fronts in random search directions.
(v) The new approach makes the algorithm fast and efficient. In IPGA, the computational complexity of non-dominated sorting of the combined population is $O\{n(M+N)^2\}$, where n is the number of objectives, M, external population size and N, elite population size. This is similar to the computational complexity of NSGA-II and SPEA. But due to the intelligent search strategy adopted for advancing the Pareto-front and also due to the Pareto-convergence test incorporated in IPGA requiring no extra-computations, IPGA is seen to converge in less number of iterations.

5. Algorithm description

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1. Generate the first *non-dominated front* from the initial population of chromosomes. In the present case, each chromosome consists of 20 random decimal digits with two adjacent digits representing the proportion of each energy technology. This decimal representation is converted to percentages to form the proportion vector **X** in the decision variable space.

1.1. We start with a random population of chromosomes R_0^P of size N and a *random* elite population E_0^P of size M such that $N/4 \leqslant M \leqslant N/3$. Initially, we combine these two sets of populations to create the combined test population $T_0^P = R_0^P \mathbf{U} E_0^P$ of size (N + M) and assign fitness values to all the members in terms of levelized cost and CRBI.

1.2. Apply non-dominated sorting procedure to T_0^P to identify the hierarchy of non-dominated fronts F_i, $i = 1,2,3\ldots w$, with F_w representing the last front consisting of weeds. This sorting is carried out using the dominance relation defined [31] as follows:

A solution $\boldsymbol{x}(1)$ is said to dominate another solution $\boldsymbol{x}(2)$, if both of the following conditions are true, namely, (i) the solution $\boldsymbol{x}(1)$ is no worse than $\boldsymbol{x}(2)$ in all objectives (ii) the solution $\boldsymbol{x}(1)$ is strictly better than $\boldsymbol{x}(2)$ in at least one objective.

Now we generate the combined population $C_0^P = E_0^P \mathbf{U} F_1$ and apply non-dominated sorting to the combined front C_0^P to generate the first front G_1. If G_1 contains exactly *M* members, these replace the elites in the set E_0^P to form the next generation elite set E_1^P. If it contains more than M members, go to step 1.4.

1.3. If G_1 has less than *M* members, apply intelligent mutation to T_0^P. The objective of this process is to exploit the search space to generate a non-dominated front which includes the members of G_1. This involves the following:

1.3.1. Modify the test population T_0^P so that the members of G_1 not present in T_0^P are substituted in their positions

1.3.2. Replace in T_0^P, 4 times the deficit, namely, 4 * (*M*-Number of members of G_1), by mutated members of G_1 at random positions other than those chosen in 1.3.1. Mutation of each member is effected at four random positions by four random decimal digits. Go to step 1.2.

1.4. If G_1 has more than M members, cluster reduction strategy is applied to G_1 to choose the most diverse *M* members to replace those in E_0^P. This gives the next generation elite front E_1^P

1.5. The test population T_0^P is now subjected to an evolutionary process by carrying out extensive genetic operations of reproduction, crossover and mutation. In

(*continued on next page*)

reproduction, the weed population (F_w) is replaced by elite members. Mutation and crossover techniques are then applied to randomly selected members of the subject population. Weak mutation is applied at this stage to reduce the interference noise between crossover and mutation operators [37]. This procedure accomplishes the exploration of the search space to identify whether better non-dominated points are available. This yields the next generation test population T_1^P

2. Step 1 above completes one generation of the evolutionary process. This process is now repeated from step 1.2 onwards using the second generation test population T_1^P and elite population E_1^P. During repetition of the process, testing takes place in each generation to check whether a local Pareto-optimal front has been reached. This is tested as follows:
   2.1. In step 1.2 of the evolutionary algorithm, if at least one point dominating all the solutions of the previous front is found, it implies a Pareto-front improvement. This is tested by checking whether G_1 contains less than M members or not, as a Pareto-front improvement will lead to less number of members in the first front thereby avoiding the cluster reduction step 1.4. Therefore, step 1.3 would be carried out in that generation instead of step 1.4. If no such dominating point with a Pareto-front improvement could be found despite thorough exploration of the objective space in sufficient number of predetermined steps, then the final front obtained will be a local Pareto-optimal front. Therefore, if step 1.3 is not executed at all in an integer multiple of M + N continuous generations, then the elite front obtained thereafter, namely, $E^P_{c(\mathrm{M+N})}$ is taken as a local Pareto-optimal front.
3. Now we proceed to generate the *Global Pareto-optimal front*. This is achieved by a procedure identical to the generation of a wave-front from a number of secondary wavelets. The approach is to generate a few local Pareto-fronts in random search directions and then combine them as follows
   3.1. Generate M independent Pareto-optimal fronts by repeating steps (1) and (2) and combine them to obtain the seed population for the global Pareto-optimal front. Non-dominated sorting is applied to this seed population to obtain the first non-dominated front of this population. If it has more than M members, it is taken as the global Pareto-optimal front (Fig. 1). If not, generate more number of independent Pareto-optimal fronts so as to increase the number of members of the global Pareto-optimal front to more than M.

6. Cluster reduction strategy

The cluster reduction strategy employed is as follows: The points are plotted in the bi-objective space as in Fig. 2a. For each point, compute the area of the rectangle whose diagonal is the line segment joining the point to the next adjacent point. Both the end-points are assigned sufficiently high area values. We select points from the cluster based on their spread and frontier smoothness, the former being evaluated by the rectangle area values and the latter by a relative difference function. Accordingly, we define the ordering parameter as the product of these variables.

$$\text{Ordering parameter}(O) = L \times B \times (L + B)/|L - B| \tag{8}$$

where L and B represent the length and breadth of the rectangle respectively.

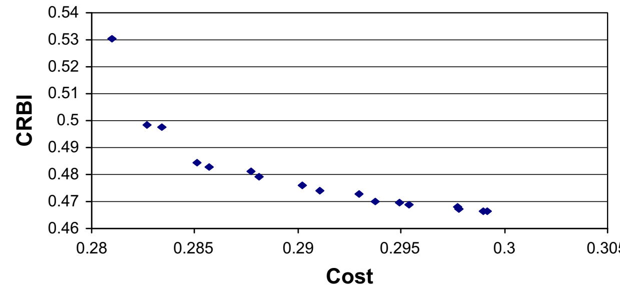

Fig. 1. Global Pareto-optimal Front in case of optimal generation mix.

The points on the cluster are rearranged in the descending order of the ordering parameter and the first M points are chosen from the cluster. This strategy ensures that the most diverse points within the cluster are preserved as elites while simultaneously emphasizing the middle range points. Fig. 2a and b illustrate the cluster reduction obtained through this method.

7. Pareto convergence test

An evolutionary algorithm using Pareto-based ranking and a monotonic selection converges to the global optimum [38]. But the problem is to determine whether the global optimum has been reached. There are stopping criteria suggested in the literature, for example, the rank histogram method [39], Kalman filter based evidence accumulation of the improvement in Pareto-dominance [40], Kalman filter based combination of three different indicators, namely, hypervolume indicator, epsilon indicator and mutual domination rate indicator [41] etc. The concept of ε-dominance has been developed [42] to combine convergence and diversity in multi-objective optimization. The IPGA makes use of an iteration based local Pareto-convergence test which requires no additional computation as follows.

After the first set of elite population is generated, evolutionary operators are applied to the test population C_0^P to search for points which dominate the current elite population members. The test for a Pareto-optimal front is that no point dominating the current non-dominated front be found despite evolutionary operators being ap-

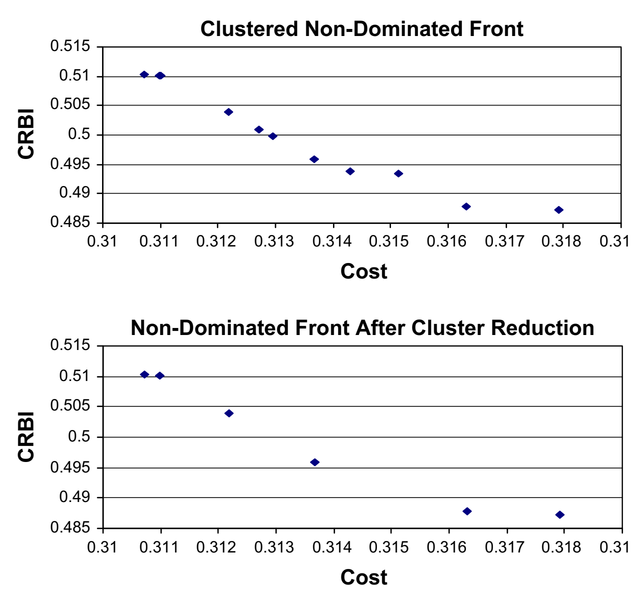

Fig. 2. (a) and (b): Cluster reduction using the ordering parameter.

Table 1
Estimated generation Potential and achievements [45,46].

Energy technology	Estimated potential (MW)	Cumulative achievement (MW)
Hydro	87,400	36,860
Wind	45,195	13,000
Small hydro	15,000	2953
Biomass (including bagasse cogeneration)	21,881	2600
Waste to energy	2700	41

Table 2
Levelized costs of various energy technologies. *Source*: Authors' estimates based on [48,49].

Energy technology	Levelized cost of energy (₹/KW h)
Coal	3.00
Natural gas	4.50
Nuclear	3.30
Hydro	2.90
Wind	3.30
Small hydro	3.30
Biomass	3.80
Waste to energy	4.70
Solar thermal	17.00
Solar PV	15.00

Table 3
Proportion of cost components of various energy technologies. *Source*: Data adapted from [15].

Energy technology	Investment cost (%)	Fuel cost (%)	Operation and maintenance cost (%)	Carbon cost (%)
Coal	51.00	24.00	10.00	15.00
Natural gas	25.00	63.00	6.00	10.00
Nuclear	50.00	32.00	18.00	0.00
Hydro	96.00	0.00	4.00	0.00
Wind	80.00	0.00	20.00	0.00
Small hydro	70.00	0.00	30.00	0.00
Biomass	24.00	50.00	26.00	0.00
Waste to energy	50.00	0.00	50.00	0.00
Solar thermal	84.00	0.00	16.00	0.00
Solar PV	96.00	0.00	4.00	0.00

plied for G generations where $G \geqslant c(\mathrm{M+N})$ where c is a positive integer. If at least one non-dominating point is found in any one of these evolutionary generations, a new non-dominated front is constructed around that point and again the test is applied until successive G generations are unable to detect any dominating points. This test indicates convergence to a local Pareto-optimal front.

For a convex multi-objective optimization problem (where objective functions are convex within a convex feasible region), every locally Pareto-optimal solution is also globally Pareto-optimal [43]. However, many problems are non-convex and hence global Pareto-convergence should be sought for. Global Pareto-convergence is obtained by means of a wave-front generation approach taking local Pareto-fronts as wavelets. We generate M separate local Pareto-fronts in random search directions and taking the combined Pareto-front population as the seed population, its first non-dominated front is generated. If the generated front contains more than M members, then this non-dominated front is taken as the global Pareto-optimal front. If it contains less than M members, then more local Pareto-fronts are generated to combine with them until the global front contains more than M members.

8. Optimal generation mix for India

We apply the algorithm to estimate the optimal generation mix for India's 12th Five Year Plan. India has set a capacity addition target of about 100,000 MW for the 12th Five Year Plan [44] as against the achievement of 62,374 MW during the previous Plan [45]. The bi-objective optimization problem for this generation planning can be stated as follows:

Let $\mathbf{X} = (x_1, x_2, \ldots x_{10})^{\mathbf{T}}$ represent the vector indicating the proportion of each source in the generation mix having ten energy technologies. Let the costs associated with each source be represented by the cost matrix, $\mathbf{C} = (c_1, c_2, \ldots C_{10})^{\mathbf{T}}$. Let $\sum$ be the 10×10 covariance matrix for these energy technologies. Then the optimization problem is as follows:

$$\left.\begin{array}{ll}
\text{Minimize Cost,} & C(\mathbf{X}) = \mathbf{X}^{\mathbf{T}}\mathbf{C} \\
\text{Minimize CRBI,} & F(\mathbf{X}) = (\mathbf{X}^{\mathbf{T}}\mathbf{P}) * (\mathbf{X}^{T}\Sigma\mathbf{X})^{1/2} \\
 & X_i^{(L)} \leq x_i \leq x_i^{(U)}, \quad i = 1, 2, \ldots 10; \text{Variable bounds} \\
 & B = \text{Barrier index of a portfolio} \mathbf{X} \\
 & X_1^{(L)} = 50 \text{ and } x_1^{(U)} = 100; \\
 & \text{Minimum proportion of coal} = 50\% \text{for base load} \\
 & X_2^{(L)} = 3; \text{Minimum proportion of gas} = 3\% \text{for peak load} \\
 & X_i^{(L)} > 0 \text{ for } \; i = 3, 4 \ldots 10, \text{non-zero proportion of other energy technologies} \\
 & X_4^{(U)} = 50, x_5^{(U)} = 32, x_6^{(U)} = 12, \\
 & X_7^{(U)} = 19, x_8^{(U)} = 2.7
\end{array}\right\} \quad (9)$$

$x_i^{(U)}$ for $\;i = 4$ to 8 have been generated from the potential estimates (Table 1).

The decision variable vector $\mathbf{X}$ is represented by a chromosome containing 20 decimal digits, with two consecutive digits representing the proportion of an energy technology which are then converted into percentages. An international estimate of levelized costs of energy is given in [47], assuming coal price of \$2.50 per MMBtu, natural gas price of \$8.0 per MMBtu and 20 years economic life. We use the levelized costs of various energy technologies in Table 2 for the analysis of power generation in India.

We use the data in Table 3 for the proportion of capital, fuel, operation & maintenance and CO_2 costs of various energy technologies.

The risk values (standard deviations) of capital, fuel, operation and maintenance and CO_2 costs are given in Table 4.

The risk estimates in the above table are combined for each energy technology assuming that different cost components of a particular energy technology are uncorrelated which gives an identity matrix as the correlation coefficient matrix. In order to arrive at the portfolio risk, we combine the risk estimates of various energy technologies using Eq. (2). The barrier index vector ($\mathbf{P}$) for the energy technologies obtained through the analytic hierarchy process (AHP) using Web-HIPRE is given in Table 5. The barrier index vector, $\mathbf{P}$ is generated using Eq. (5) assuming equal importance of barriers.

Portfolio mean is arrived at using Eq. (1) and portfolio CRBI is generated using Eq. (7). The bi-objective optimization yields at least M Pareto-optimal points from which *a posteriori* selection is made to locate the optimal generation mix. The decision criterion for this selection is the minimization of a distance metric which measures the deviation of the proposed 12th Plan mix from the actual achievement in the 11th Plan or the simulated results of 12th Plan when deviations are compared. The distance metric (d) selected is a *Tchebycheff metric*[43] in the decision variable space given by:

$$\begin{aligned} &\mathrm{d} = \mathrm{Min} \max_{i=1,2,..10} |(xi - zi)| \\ &\text{subject to } \mathbf{x} \in S, S \in \Re^{n} \end{aligned} \quad (10)$$

where $\mathbf{x}$ represents the solution vector and $\mathbf{z}$ represents the target vector.

An alternative method of making selection from a set of Pareto-optimal solutions is to use the Sharpe ratio [20] defined as follows:

Table 4
Risk values (standard deviations) of cost components of various energy technologies. (*Source*: Authors' estimates based on [15]).

Energy technology	Investment risk	Fuel risk	Operation and maintenance risk	Carbon risk
Coal	0.09	0.06	0.05	0.26
Natural gas	0.06	0.10	0.04	0.26
Nuclear	0.54	0.46	0.40	0
Hydro	0.10	0.00	0.05	0
Wind	0.17	0.00	0.12	0
Small hydro	0.15	0.00	0.09	0
Biomass	0.62	0.10	0.81	0
Waste to energy	0.85	0.10	1.02	0
Solar thermal	0.98	0.00	0.20	0
Solar PV	0.79	0.00	0.20	0

Table 5
Barrier estimates based on AHP.

Energy Technology	Land availability	Public policy	Environmental clearance	Infrastructure and resource availability	Grid connection and market	Barrier Index vector (**P**)
Coal	0.137	0.138	0.126	0.066	0.066	0.1066
Natural gas	0.07	0.243	0.063	0.078	0.066	0.1040
Nuclear	0.349	0.308	0.261	0.197	0.066	0.2362
Hydro	0.07	0.106	0.198	0.066	0.066	0.1012
Wind	0.039	0.031	0.025	0.066	0.215	0.0752
Small hydro	0.05	0.042	0.046	0.066	0.215	0.0838
Biomass	0.096	0.042	0.112	0.132	0.131	0.1026
Waste to energy	0.136	0.037	0.124	0.132	0.131	0.1120
Solar thermal	0.028	0.027	0.022	0.066	0.022	0.0330
Solar PV	0.025	0.027	0.022	0.132	0.022	0.0456

Table 6
Optimal 12th Plan Generation Mix with and without carbon cost.

Energy technology	11th Plan likely achievement	Optimal 12th plan mix without carbon cost	Optimal 12th plan mix with carbon cost
Coal	63.01	63.69	60.46
Natural gas	5.29	3.31	6.10
Nuclear	4.56	0.58	2.72
Hydro	11.1	13.98	10.78
Wind	12	10.95	10.68
Small hydro	1.35	5.48	5.12
Biomass	2.29	0.72	2.29
Waste to energy	0.18	0.14	0.22
Solar thermal	0.11	0.58	0.54
Solar PV	0.11	0.58	1.09

Table 7
Optimal 12th Plan generation mix for various scenarios.

Energy technology	Optimal 12th plan mix with min 6% natural gas with carbon cost	Optimal 12th plan mix with min 6% natural gas without carbon cost	Optimal 12th plan mix with min 3% solar with carbon cost	Optimal 12th plan mix with min 3% solar without carbon cost	Optimal 12th plan mix with carbon cost, risk and no barriers	Optimal 12th plan mix with carbon cost, barriers and no risk
Coal	59.28	61.48	57.97	61.84	59.64	59.91
Natural gas	6.55	6.15	4.73	3.15	3.77	4.84
Nuclear	3.71	1.39	3.81	3.27	5.14	3.80
Hydro	10.59	10.32	11.43	12.22	10.38	6.11
Wind	10.04	10.90	10.05	11.08	10.17	11.06
Small hydro	7.42	5.45	6.00	2.64	5.56	6.34
Biomass	1.20	2.78	2.89	2.64	3.98	4.49
Waste to energy	0.11	0.35	0.12	0.13	0.31	2.19
Solar thermal	0.55	0.58	1.50	1.51	0.52	0.69
Solar PV	0.55	0.58	1.50	1.51	0.52	0.58

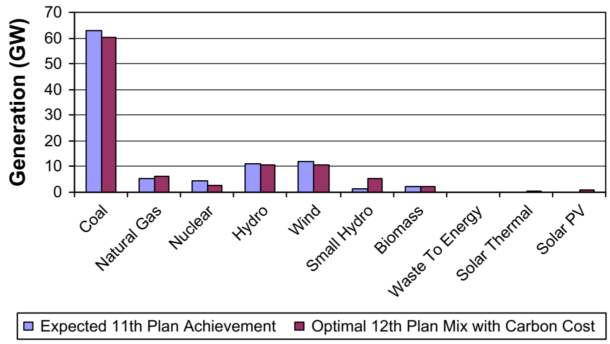

Fig. 3. Expected 11th plan achievement vs. optimal 12th Plan mix with carbon cost.

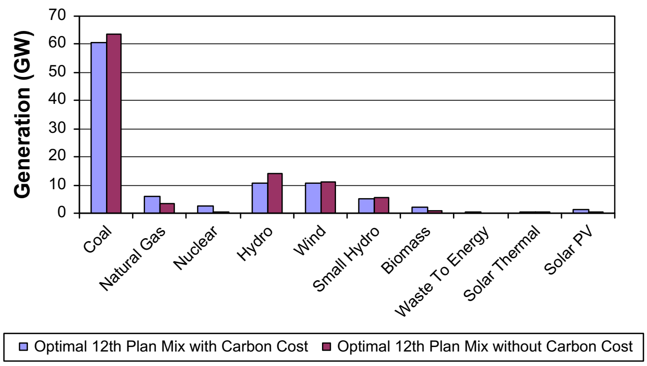

Fig. 4. Optimal 12th Plan mix with and without carbon cost.

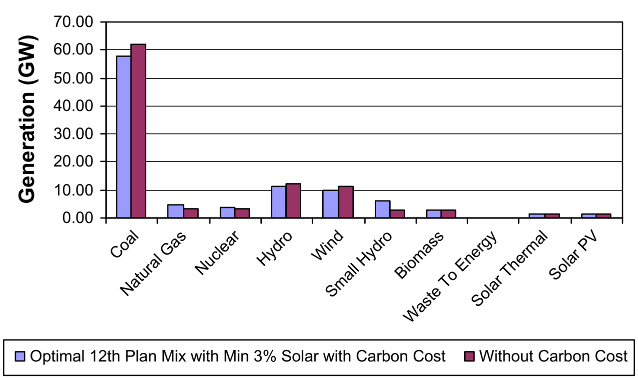

Fig. 5. Optimal 12th Plan mix with minimum 3% solar with and without carbon cost.

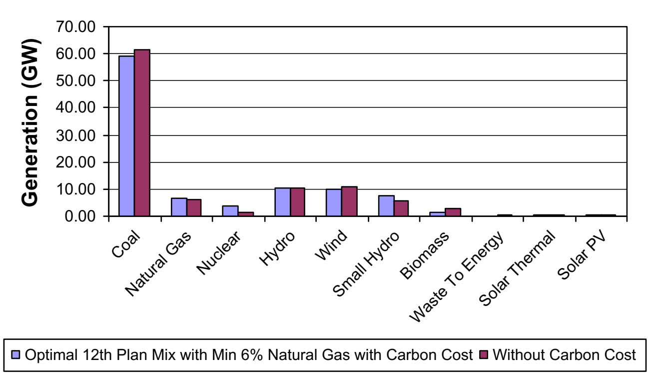

Fig. 6. Optimal 12th Plan mix with minimum 6% natural gas with and without carbon cost.

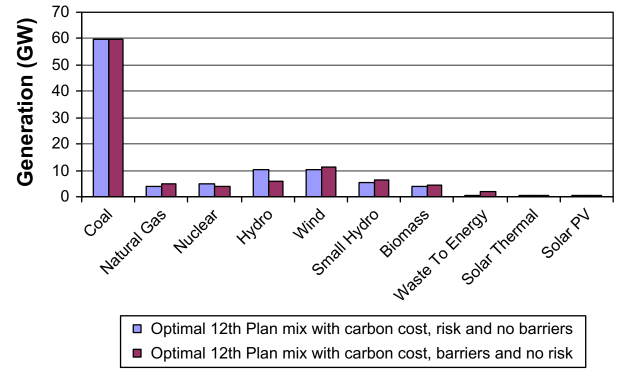

Fig. 7. Optimal 12th Plan mix – risk only and barriers only scenarios.

$$\text{Sharpe Ratio} = (r - r_0)/\sigma \qquad (11)$$

where r is the return from the given portfolio, r_0 the riskless (desired) return, σ is the standard deviation of the portfolio.

9. Results

The results of simulation obtained using IPGA are given in Tables 6 and 7 and Figs. 3–7. The 11th Plan likely achievement in Table 6 has been estimated from [45].

10. Conclusions

This communication focuses on the application of portfolio optimization concepts, suitably modified to include project barriers in the context of a developing country like India, for optimal generation planning. For this purpose, we define the concept of comprehensive risk barrier index (CRBI) to incorporate the key influence exerted by various barriers, in addition to risks, in the execution of projects. Thus generation planning is not solely based on the risks associated with the cost components, but also on the barriers which determine the ease with which the project is commissioned and operated in its socio-economic environment. The composite CRBI function incorporates the ground realities into planning scenarios. While the risks are evaluated by the standard deviations of cost components, barrier indices are estimated through analytic hierarchy process applying pair-wise comparison judgment matrices. The advantage of this construction is that it enables evaluation of the impact of qualitative aspects relating to project implementation in its local context, since these can also be easily incorporated into the judgment matrices of AHP with suitable consistency checks.

Having evolved an optimization model, we propose a genetic algorithm for multi-objective optimization to achieve fast Pareto-convergence and to handle various constraints including minimum or maximum proportion of generation for a particular energy technology. The intelligent Pareto-search genetic algorithm (IPGA) incorporates non-dominated sorting and maintains a separate elite population. It advances the non-dominated front to a Pareto-optimal front by using genetic operators ensuring the diversity of solutions. Dual mode search is employed to build up a non-dominated front from a few non-dominated points and then to locate more efficient points which can advance the non-dominated front to a Pareto-optimal front. This procedure ensures fast convergence by efficient exploration and exploitation of the search space. Finally it incorporates a simple mechanism to identify local Pareto front and also to reach the global Pareto front. Among the global Pareto-optimal solutions, a particular solution is chosen by a suitably designed criterion, say, its nearness to the 11th Plan achievement or for sensitivity scenarios, to a simulated 12th Plan mix.

The algorithm results in a number of Pareto-optimal solutions from which suitable choices can be made based on practical considerations. Various scenarios to study the impacts of carbon costs, risks and barriers have been simulated. The analysis indicates that for some projects like nuclear and hydro, barriers are more significant than risks while the reverse is true in respect of natural gas, wind and waste to energy projects (Table 7). The impact of carbon cost and risk is mainly on the coal, natural gas, nuclear and biomass projects. Carbon cost has only marginal impact on the proportion of solar power in view of its high cost. Therefore, statutory minimum standards have to be prescribed for increasing the use of renewables. The optimal scenario of minimum 3% solar has been simulated which shows that carbon cost regime exerts a positive influence in the form of a secondary incentive.

The optimization methodology proposed offers a comprehensive approach for generation planning in the context of a developing country which can take care of multiple relevant factors while incorporating various constraints. It offers flexibility and choice as it suggests a range of optimal solutions. The algorithm is general in nature and can be employed for a number of similar optimization problems. The computation time required is reasonable and the algorithm can be customized and implemented easily for complex optimization scenarios.

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