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Optimization of India's power sector strategies using weight-restricted stochastic data envelopment analysis

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HIGHLIGHTS

- ▸ Stochastic DEA model appropriate for efficiency optimization of power sector strategies.
- ▸ Optimal strategy portfolios of Indian power sector.
- ▸ Weight-restricted model for outputs with limited substitutability.
- ▸ Efficiency comparison of different DEA models.
- ▸ Design of attributes for economic growth, energy security, energy equity and climate sustainability.

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ABSTRACT

India's power sector has a significant impact on the country's development and climate change mitigation efforts. Optimization of energy planning is therefore, key to achieving the overall planning goals. The hierarchical multi-objective policy optimization is a policy-centric multi-level bottom-up iterative approach, designed from a developing country perspective, utilizing the optimality principle of dynamic programming. It is applied to the Indian power sector by grouping the strategies into three portfolios, namely, power generation mix, demand side efficiency group and supply side efficiency group. Each portfolio is optimized taking into account the objectives of cost minimization and comprehensive risk and barrier reduction. The portfolios are further combined and optimized at a higher level with respect to higher level objectives, namely, economic growth, energy equity, energy security and climate sustainability. This paper focuses on the second level optimization utilizing data envelopment analysis (DEA). Both the deterministic and stochastic variations have been analysed and the results compared in respect of unrestricted as well as restricted weight models. The analysis shows that weight-restricted stochastic DEA model is most appropriate for efficiency optimization of power sector strategies. The methodology can be effectively used for energy planning in developing countries.

1. Introduction

The importance of electricity sector in India in the context of development and sustainability can hardly be overemphasised. During 1994 to 2007, electricity sector in India projected the highest compound annual growth rate of 5.6% among all other sectors (INCCA, Ministry of Environment and Forests, India, 2010). India has set an ambitious target of capacity addition of 100,000 MW for the 12th Five Year Plan (Planning Commission of India, 2011). Optimization of energy strategies to achieve the macro-economic objectives of planning becomes critical for a developing country like India. Large-scale conversion to clean, perpetual, and reliable energy at low cost together with increased energy efficiency are key strategies for solving the problems of climate change, pollution, and energy insecurity (Jacobson and Delucchi, 2011). Optimal generation planning including renewables in the portfolio as well as optimal supply side and demand side energy efficiency planning are, therefore, critical ingredients to be incorporated into an effective sustainable energy development paradigm.

The generation portfolio should incorporate renewables as a key strategy for energy security and emissions reduction. As increased scarcity of resources shifts (André and Smulders, 2004) technical change progressively towards energy-saving technological change at the cost of total factor productivity growth, energy efficiency sector has great potential in India. However, improvements in energy efficiency will require active market interventions to overcome barriers and to

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stimulate drivers (Reddy et al., 2009). Moreover, the actual impact of energy efficiency measures will depend on the price elasticity of demand.

We utilize the hierarchical multi-objective optimization framework (Vazhayil and Balasubramanian, 2012) for addressing the strategy planning issues in the Indian power sector. It essentially follows the dynamic programming approach where the complexity of the problem is tackled by a 'divide and conquer' approach. The optimization problem is divided into a number of subproblems at hierarchical levels. For optimization at each level, objectives appropriate to that level are identified. As the policy strategies combine into portfolios and move up the optimization pyramid, the objectives of optimization get suitably modified in synchronism. The strategies get optimized at different hierarchical levels of objectives. After an entire cycle of optimization is completed, iterative improvement incorporates feedback arising on account of the chosen higher level objectives or corrections due to the assumption of the monotonicity of the objective function in dynamic programming. For the higher level optimization of the power sector, efficiency optimization using DEA (Zhou et al., 2008) is made use of. This paper focuses on the implementation of DEA and identifies appropriate model and presents the results of comparison with alternatives.

The remainder of paper is organized as follows: Section 2 introduces the hierarchical multi-objective optimization model for the Indian power sector. Next section introduces the DEA for constant returns to scale (CRS) and variable returns to scale (VRS) and discusses the evaluation of the input and output parameters of the decision making unit (DMU). Section 4 introduces the stochastic model of the DEA. Section 5 looks at the impact of weight restrictions in DEA models. Results and conclusions are presented in Section 6 and Section 7.

2. Optimization of Indian power sector

We consider a bi-level optimization algorithm for India's power sector. The objectives of optimization are selected based on the approach to the 12th Five Year Plan as well as India's National Action Plan on Climate Change (PMCCC (Prime Minister's Council on Climate Change), India, 2009). The latter focuses on the use of new strategies and technologies in key sectors. The objectives of the first level optimization are project level parameters, namely, levelized cost and Comprehensive Risk-Barrier Index (CRBI). CRBI is a composite index (Vazhayil and Balasubramanian, 2012) capturing the joint influence of cost risks as well as implementation barriers in energy projects. This index has been designed in view of the fact that barriers exert a key influence on project implementation in developing countries. After grouping the power sector strategies into three portfolios, namely, generation mix, demand side efficiency group and supply side efficiency group, each portfolio is optimized using genetic algorithm, for cost minimization and CRBI reduction. These portfolios are further optimized at the second level using weight-restricted stochastic data envelopment analysis. Optimization at each level is sequential (Fig. 1), taking into account the optimality principle of dynamic programming.

For the optimization of the first level portfolios, portfolio optimization methods (Markowitz, 1952; Steuer et al., 2005) are utilized to get a number of near-optimal portfolios with minimum cost and CRBI. The power generation portfolio consists of various generation sources, namely, coal, natural gas, nuclear, hydro and renewable energy sources, the proportion of which constitutes the decision vector. Cost of conserved energy or of conserved fuel and CRBI can be employed as optimization parameters for energy efficiency strategies.

Analytic Hierarchy Process (Ramanathan, 2003), a widely used decision making technique with its applications increasing exponentially in recent times (Sipahi and Timor, 2010), can be used for the evaluation of the barriers. The cost risks are estimated from the standard deviations of the respective costs. In the Indian scenario, we consider the barriers relating to land availability, public policy, environmental clearance, infrastructure and resource availability as well as grid connection and markets.

Objectives of optimization at the second level are: (i) economic growth (ii) energy equity (iii) energy security and (iv) climate sustainability. Economic growth is a key productivity criterion for strategic policies. Energy equity is particularly relevant in the context of developing countries since affordable modern energy is key to improving living standards (Ekholm et al., 2010). Along with growth and equity, energy policies must particularly take into account energy security and climate sustainability. A methodology to identify and assess the impact of climate policies on energy security to guide policy making has been developed in

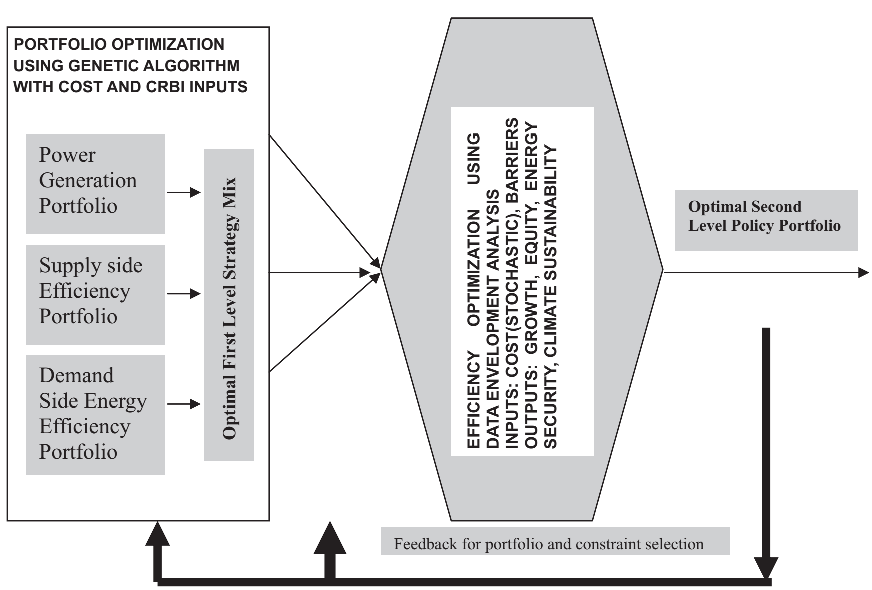

Fig. 1. Hierarchical multi-objective optimization of power sector.

Greenleaf et al. (2009). While some climate policies can reinforce energy security, the same cannot be asserted about all the climate policies and vice versa.

The first level optimization of the three sub-sectoral portfolios using genetic algorithm gives the optimal strategy mix for all the three portfolios. After the first level optimization is completed, these optimal portfolios form inputs to the second level where the relative proportions of these portfolios are determined by evaluating their respective efficiencies with respect to the objectives of second level. In this paper, we focus on this level of optimization using DEA, which is described in detail below.

3. Data envelopment analysis

DEA is an important non-parametric method of measuring the efficiency of multiple-input multiple-output DMUs. It has emerged as a valid alternative to regression analysis (Ray, 2004). First introduced in a seminal paper by Charnes et al. (1978), based on the concept of frontier analysis, called CCR model, it has evolved into a major analytical approach for decision making in assessing the comparative efficiencies of DMUs (Emrouznejad et al., 2008). DEA has been applied to organizations in various areas (Singh et al., 2010; Beriha et al., 2011; Kumar, 2011; Watson et al., 2011). For optimization of energy strategy portfolios at second and/or higher levels, DEA is eminently suitable. Efficiencies are assessed in terms of the ratio of the output function of objectives to that of the input function of costs and barriers.

The efficiency measurement in DEA is of two types, namely, overall technical efficiency and pure technical efficiency, the latter being higher than the former. The CCR model of DEA assumes CRS due to which the efficiency measurement of the model is in terms of the overall technical efficiency (OTE). OTE can be decomposed into two factors, namely, pure technical efficiency (PTE) and scale efficiency (SE). The DEA model for VRS introduced by Banker et al. (1984), called the BCC model evaluates PTE.

The inputs and outputs of DEA may be considered deterministic or stochastic. Generally, inputs are stochastic in real situations. For the power sector portfolios, cost variable can be considered either deterministic or stochastic. If considered stochastic, the corresponding normalized risk value will be its standard deviation. According to the nature of the variables, we may employ deterministic or stochastic DEA. We illustrate both these options for the power sector portfolios. Maximum efficiency at the end of the second stage of optimization is further subjected to iterative improvement using different combinations of input portfolios to arrive at the global maxima of efficiency for the two-stage optimization process.

The DEA model for each DMU (Banker et al., 1984) for VRS may be stated as follows:

$$\left.\begin{aligned} &\text{Max}\, f_0 = \sum_{r=1}^{s} u_r y_{r_0} - \delta \\ &\text{subject to} \sum_{i=1}^{m} v_i x_{i_0} = 1 \\ &\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - \delta \le 0 \quad \text{for } j = 0,1,2,\ldots,n \\ &\mu_r \ge \varepsilon \text{ for } r = 1,2,\ldots,k, \quad v_i \ge \varepsilon \quad \text{for } i = 1,2,\ldots,m \end{aligned}\right\} \tag{1}$$

where ε is a convenient small positive number (non-Archimedean) and δ is unconstrained in sign. u_r, v_i are the output and input weights, respectively of outputs y_r and inputs x_i, estimated by the model. The suffix j represents the index of the DMU with zero indicating the DMU under evaluation. If $\delta < 0$ in the optimal solution, then decreasing returns to scale (DRS) hold at DMU_0. For $\delta = 0$ in the optimal solution, constant returns to scale (CRS) and for $\delta > 0$, increasing returns to scale (IRS) hold at DMU_0. Tsolas (2011) analyzes PTE and SE, as constituent components of OTE, using the DEA model for efficiency determination of bank branches.

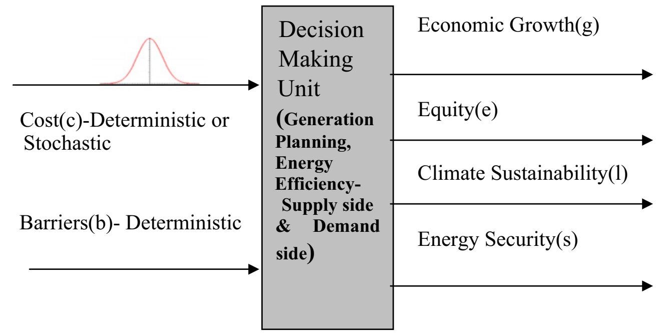

Fig. 2. Decision making unit inputs and outputs.

For the purpose of second stage optimization of power sector strategy portfolios, each portfolio can be viewed as a DMU as shown in Fig. 2.

The inputs to the DMU are cost, deterministic or stochastic, and barriers which are considered deterministic. The outputs of the DMU are key objectives relating to optimization of the energy–economy–climate system, namely, economic growth, energy equity, energy security and climate sustainability. These are serious concerns for all countries and therefore reckoned as over-arching objectives in the optimization paradigm. Each of these macro objectives can be represented by suitable indicators or proxy attributes.

For identifying the functional attributes of economic growth in terms of DMU inputs, we use the decomposition of the growth rate of India described in terms of the growth rates of private consumption, investment, government consumption expenditure and net exports. Based on the economic data from the World Bank world development indicators during 1992–2003, Felipe et al. (2008) derive this decomposition as follows:

$$G\dot{D}P = (C/\text{GDP})\,\dot{C} + (I/\text{GDP})\dot{I} + (G/\text{GDP})\dot{G} + (X/\text{GDP})\dot{X} - (M/\text{GDP})\dot{M} \tag{2}$$

$$= 0.662\,\dot{C} + 0.223\,\dot{I} + 0.118\,\dot{G} + 0.118\,\dot{X} - 0.128\,\dot{M} \tag{3}$$

Growth can be connected to the portfolio shares and portfolio outputs by calculating the investment share of the total cost of the portfolio for producing, say, 100 units of electricity, government share if any, net imports and total consumption cost. Total consumption cost is calculated in terms of (Total cost—investment cost + cost of electricity output) for the portfolio. Then, by using Eq. (3), the proxy attribute for growth can be generated. An alternative is to use a suitable economic growth model, say, Mankiw-Romer-Weil specification (Mankiw et al., 1992).

In order to represent energy security in terms of related indicators, we look at the key characteristics of an energy portfolio. An assessment of energy security with reference to the variety and balance aspects of the energy portfolio (Greenleaf et al., 2009) can be made using the Shannon–Wiener Index (SWI) $= -\Sigma p_i \ln p_i$ or Herfindhal–Hirschmann Index (HHI) $= \Sigma p_i^2$ where p_i represents the share of ith generation mode in the generation mix. Since a lower value of HHI indicates higher energy security and HHI varies between 0 and 1, we take (1-HHI) as one of the indicators of energy security in this analysis. For another indicator, we look at the impact of rebound effect on energy security.

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Rebound effect (R) is defined (Guerra and Sancho, 2010) as follows.

$$R = 1-(\text{actual energy savings(AES)}/\text{potential energy savings(PES)}) \quad (4)$$

Due to rebound effect, energy security is reduced for demand side efficiency sources. This is on account of the fact that the calculated savings may not be achieved in practice due to increased consumption on realization of higher energy efficiency. Therefore, energy security of an efficiency portfolio is proportional to $(1-R)$.

The rebound effect is proportional to the elasticity of energy demand (Guerra and Sancho, 2010). It is as high as 50% to 80% for developing economies like India (Roy, 2000) which may even be over 100% depending on the price elasticity of energy demand. It has therefore been concluded that the conservation efforts, unless accompanied by corrective pricing policies, will be ineffective in actually realizing the predicted efficiency improvement. For the purpose of calculations, we take $R=0.75$ for demand side efficiency portfolio and $R=1.0$ for the other portfolios.

A third factor to be taken into account for determining energy security is the security dependency factor (d). For a generation portfolio, the electricity production from the portfolio becomes assured on commissioning of the project. For an efficiency portfolio, on the other hand, the portfolio output of avoided generation is achieved only when the project becomes operational on the output of the primary generation portfolio. If the primary generation, transmission or utilization does not take place as assumed, the output of efficiency portfolio cannot be realized even if the project is commissioned. In other words, efficiency portfolios are further downstream as compared to generation portfolios and hence energy security index of efficiency portfolios has to be discounted correspondingly. This discounting is implemented through the security dependency factor. For generation portfolio, we define this factor as unity since the output of this portfolio depends only on implementation of projects within the same portfolio. For efficiency portfolios, since avoided generation depends on the primary output of the existing generation/transmission system and the realization of expected savings from the implemented efficiency projects, the security dependency factor is given a value of 0.75. Taking into account the impacts of portfolio spread, rebound effect and dependency factor, we define the energy security index of a portfolio as follows:

$$\text{Energy security index} = d(1-R)\left(1-\sum p_i^2\right) \quad (5)$$

As far as the energy equity objective is concerned, we generate a proxy attribute for equity based on the twin criteria, namely, government investment criterion (Brent et al., 2005) and the total cost criterion. All the portfolios contribute to power generation or avoided power generation. Therefore, on a comparative scale, if a particular portfolio generates electricity without government subsidy, at the same cost per unit as generated by another portfolio with government subsidy, then the generation portfolio without government subsidy is clearly preferable from the energy equity angle. This is because the subsidy becomes available to improve energy access, which will contribute to equity without affecting overall electricity output. Hence upon a comparison of various *generation or avoided generation portfolios*, less government subsidy on the project will contribute to greater energy equity. Further, energy equity is inversely related to the cost of generation of a unit of energy since a lower cost facilitates greater accessibility. This aspect can be further accentuated by a progressive energy pricing regime. Based on these considerations, it is appropriate to define the proxy attribute for equity as follows:

$$\text{Equity index} = (100-\text{percentage share of government subsidy})/\text{cost of energy} \quad (6)$$

For climate sustainability index, we use the carbon emission data of different energy technologies (Table 1) and use the negative of the portfolio emission with appropriate scaling as the climate sustainability index.

Table 1
Carbon emissions for various energy technologies.
(*Source*: Authors' estimates based on UK Parliamentary Office of Science and Technology (2006), Weisser (2007))

CO_2 emission for different energy technologies	
Energy technology	CO_2 emission
Coal	800–1000 gCO_2eq/kW he
Lignite	1100–1700 gCO_2eq/kW he
Oil	700–800 gCO_2eq/kW he
Natural gas	360–575 gCO_2eq/kW he
Nuclear	0.74–1.3 $gCO_2eq/kWhe$
Photovoltaic	43–73 gCO_2eq/kW he
Wind on shore	8–30 gCO_2eq/kW he
Wind off shore	9–19 gCO_2eq/kW he
Hydro	2–9 gCO_2eq/kW he
Biomass	35–99 gCO_2eq/kW he

4. Non-linear programming stochastic DEA model

If the input(s) or output(s) of a DMU is stochastic, the optimization problem can be solved as a non-linear programming problem. There are various approaches to include the stochastic element into the efficiency analysis of DEA, namely, imprecise DEA, bootstrapping, Monte Carlo simulation and chance constrained DEA (Dyson and Shale, 2010), Banker's F tests, chance constrained programming, Varian's statistical test of cost minimization and bootstrapping (Ray, 2004). Chance constrained programming technique (Charnes et al., 1959) converts a linear programming problem with stochastic variables to a non-linear deterministic problem by suitably modifying the objective function to incorporate the stochastic element and changing the constraints to ensure their satisfaction despite stochastic uncertainty, with a specified confidence level. An attempt to use chance constrained DEA for strategy selection is presented in Saen (2011) along with a summary of strategy selection methods that include intuitive models, analytical models, quantitative models and blend intuitive and analytical models.

We employ the chance-constrained programming technique for the stochastic variation of cost input to the DMU. The optimization of the DMU can now be represented as a non-linear programming problem to maximize the efficiency of the DMU, namely, $(u_1g_0+u_2e_0+u_3l_0+u_4s_0)/(v_1c_0+v_2b_0)$ with all inputs and outputs, except cost, considered deterministic (symbols have their meanings given in Fig. 2). We use the inverted utility function method to minimize the reciprocal of efficiency, which makes the DEA model input oriented.

Let $f_0(c,b)=v_1c_0+v_2b_0$ be the input oriented function to be minimized for the first DMU where c is the stochastic variable. The corresponding output of the DMU is set equal to unity. Let $\Phi(.)$ represent the cumulative probability density function of the standard normal variable and s_i denote the value of the standard normal variable at which $\Phi(s_i)=p_i$, where p_i represents the confidence level.

The mathematical formulation of the stochastic optimization problem (Rao, 2010) for each DMU is as follows:

$$\left.\begin{array}{c} \text{Min } k_1\bar{f}_0+k_2\sqrt{\mathrm{Var}(f_0)} \\ \text{where } k_1 \text{ and } k_2 \text{ are constants indicating} \\ \text{relative significance of the average value and its risk} \\ \text{subject to } u_1g_0+u_2e_0+u_3l_0+u_4s_0=1 \\ h_j=u_1g_j+u_2e_j+u_3l_j+u_4s_j-v_1c_j-v_2b_j \\ \bar{h}_j+s_i\sqrt{\mathrm{var}(h_j)}\leq 0 \text{ for each DMU with } j=0,1,2 \\ v_i,u_r\geq\varepsilon, \quad i=1,2; \quad r=1,2,3,4 \end{array}\right\} \tag{7}$$

5. Fixed weight and restricted weight DEA

It is important to determine clearly defined differential efficiencies of the various portfolios under consideration, which requires the DEA to fully rank the DMUs. Adler et al. (2002) describe six general groups of ranking methods in DEA, namely, cross-efficiency matrix, super-efficiency approach, benchmarking, multivariate statistical techniques for computing weights, measure of inefficiency dominance and multi-criteria decision-making models. Determination of common weights is an important approach for the efficiency discrimination in DEA as against the choice of weights by each DMU to maximize its efficiency leading to non-differentiated efficiency sets. DEA with unrestricted weights for each DMU maximizes the efficiency of the DMU often under unrealistic input–output combinations based on the assumption of substitutability of inputs/outputs. This makes the clear ranking of the DMUs difficult. Yang et al. (2010) propose determination of a set of common weights in the DEA efficiency evaluation using multi-objective integer programming. Goal programming method for common weights is described in Makui et al. (2008). Two ranking methods using the concept of coefficient of variation among efficient DMUs with stochastic inputs and outputs are described in Lotfi et al. (2010).

In the case of the power sector portfolios, the inputs are distinct and they are not substitutable in an unrestricted manner. So are the outputs. This leads to the requirement of restricting the weights of the outputs within certain lower and upper bounds. Weighting is also required to discriminate the various Decision Making Units (DMUs) in terms of their efficiencies. It is possible to generate the weighting scheme by means of the Analytic Hierarchy Process or by expert judgement. The weighting chosen will have impacts in terms of portfolio efficiencies, though the impact of change among weighting schemes, namely unrestricted, fixed or restricted weight schemes, is much higher compared to the variations of weights within a particular scheme. We use expert judgment for identifying lower and upper bounds of the outputs depending on the relative significance of output parameters. The inputs, namely, cost and barriers are combined in fixed proportions with barrier weight equal to half of the cost weight, since in the Indian context, project cost is the major determinant of project viability. It may be noted that all inputs and outputs are normalized values indicating proportions and the weights also indicate proportions. Weight restrictions lead to clear ranking of the portfolios in terms of efficiency.

6. Results

6.1. Inputs and outputs of the DMU

The inputs and outputs of the DMU obtained from a typical run of the first level portfolio optimization are given in Table 2. All the indices are normalized values. The overall efficiency is maximized by minimizing the reciprocal of efficiency. For stochastic DEA, the cost risks in the last column of Table 2 are used as standard deviations of cost. For deterministic DEA, the corresponding values are set to zero.

6.2. Efficiencies of unrestricted, fixed weight and restricted weight deterministic DEA

The CCR and BCC efficiencies obtained using the unrestricted weight DEA are given (Coelli, 1996) in Table 3. In these DEAs, inputs and outputs are assumed substitutable, which is not the case in most practical situations (Barnum and Gleason, 2008). It is seen that the efficiencies of both supply side and demand side portfolios are 100% due to greater flexibility of the assigned weights. In the case of optimization of power sector portfolios, the substitutability of outputs is possible to a limited extent. As for the inputs of costs and barriers, a fixed proportion based on their relative significance as determined by expert judgment, seems to be ideal.

The inputs to the DEA procedure are normalized values. The weighting methodology is based on the relative significance that the policy maker assigns to the costs and barriers in policy making. If the weights are restricted to be in fixed proportions,

Table 2
Outputs and inputs for data envelopment analysis.

Portfolio	Outputs				Inputs		
	Growth	Equity	Energy security	Climate index	Cost	Barrier	Cost risk
Generation	0.41	0.11	0.46	0.12	0.63	0.38	0.43
Supply efficiency	0.31	0.04	0.43	0.44	0.28	0.20	0.26
Demand efficiency	0.28	0.85	0.11	0.44	0.09	0.42	0.31

Table 3
Optimal modal weights of CCR and BCC unrestricted weight deterministic DEA (Non-negativity constraints on weights).

Portfolio	CCR overall technical efficiency (OTE)	BCC Pure technical efficiency (PTE)	Scale efficiency	Nature of transformation	Modal weight based on OTE	Modal weight based on PTE
Generation	0.74	1.0	0.74	Decreasing returns to scale	0.27	0.33
Supply efficiency	1.0	1.0	1.0	Constant returns to scale	0.36	0.33
Demand efficiency	1.0	1.0	1.0	Constant returns to scale	0.36	0.33

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Table 4
Optimal modal weights of fixed weight deterministic DEA.

Portfolio	Weighted output	Weighted input	CRS overall technical efficiency (OTE)	VRS pure technical efficiency (PTE)	Scale efficiency	Nature of transformation	Modal weight based on OTE	Modal weight based on PTE
Generation	0.98	2.85	0.344	0.361	0.951	Increasing returns to scale	0.166	0.169
Supply efficiency	0.97	1.33	0.729	0.774	0.942	Increasing returns to scale	0.352	0.363
Demand efficiency	1.03	1.03	1.0	1.0	1.0	Constant returns to scale	0.482	0.468

Table 5
Optimal modal weights of restricted weight deterministic DEA.

Portfolio	Weighted output	Weighted input	CRS overall technical efficiency (OTE)	Modal weight based on OTE
Generation	0.90	2.78	0.323	0.163
Supply efficiency	0.86	1.30	0.662	0.334
Demand efficiency	1.00	1.00	1.000	0.504

Table 6
Optimization parameters of restricted weight deterministic DEA.

Name	Value	Constraints	Status	Slack
Generation efficiency Constraint	−1.88	$h_0 \leq 0$	Not binding	1.88
Supply efficiency constraint	−0.44	$h_1 \leq 0$	Not binding	0.44
Demand efficiency constraint	0.00	$h_2 \leq 0$	Binding	0
Demand efficiency Weighted output constraint	1.00	$u_1 g_2 + u_2 e_2 + u_3 l_2 + u_4 s_2 = 1$	Binding	0
Parameter weight equity	0.50	$u_2 \leq 0.75 \times u_1$	Not binding	0.35
Parameter weight energy security	0.70	$u_3 \leq 0.9 \times u_1$	Not binding	0.31
Parameter weight climate support	0.44	$u_4 \leq 0.4 \times u_1$	Not binding	0.01
Parameter weight equity	0.50	$u_2 \geq 0.1 \times u_1$	Not binding	0.39
Parameter weight energy security	0.70	$u_3 \geq 0.3 \times u_1$	Not binding	0.37
Parameter weight climate support	0.42	$u_4 \geq 0.05 \times u_1$	Not binding	0.36

Table 7
Optimal modal weights of fixed weight stochastic DEA.

Portfolio	Weighted output	Weighted input	CRS overall technical efficiency (OTE)	Modal weight based on OTE
Generation	0.96	8.33	0.11	0.166
Supply efficiency	0.95	3.89	0.24	0.353
Demand efficiency	1.00	3.00	0.33	0.481

Table 8
Optimal modal weights of restricted weight stochastic DEA.

Portfolio	Weighted output	Weighted input	CRS overall technical efficiency (OTE)	Modal weight based on OTE
Generation	1.26	8.33	0.15	0.193
Supply efficiency	1.15	3.89	0.30	0.380
Demand efficiency	1.00	3.00	0.33	0.427

the portfolios are ranked as shown in Table 4. For this case, the ratio of output weights of growth, equity, energy security and climate sustainability, based on expert judgment is 1:0.5:1:0.5, respectively. The ratio of input weights for cost and barriers is 1:0.5. As in the unrestricted case, pure technical efficiencies are equal to or greater than the overall technical efficiencies. However, since the scale efficiencies are very high, the differences are only marginal. The results indicate that the proportion of power generation by means of demand efficiency portfolio, supply efficiency portfolio and new generation is 48:35:17 based on overall efficiency and 47:36:17 based on pure technical efficiency.

Table 5 indicates the impact of the weight restrictions on the outputs. The inputs are maintained with fixed proportion weights. The weight restrictions are incorporated as constraints in the LP model of *Excel Solver*. In the deterministic DEA, there is only marginal difference in modal weights between fixed weight and restricted weight options. The values of various parameters and the details of constraints of the restricted weight deterministic model are given in Table 6.

6.3. Efficiencies of fixed weight and restricted weight stochastic DEA

The optimal efficiencies assuming stochastic nature of cost as a normally distributed random variable are shown in Tables 7 and 8. In the chance constrained stochastic option (Eq. (7)), we use the value of s_i corresponding to a probability of 0.99 for the satisfaction of the constraints (99% confidence level). The stochastic formulation of the DEA results in a non-linear programming problem solved by the *Excel solver*. Optimization parameters of restricted weight stochastic DEA model are shown in Table 9. It is seen that the normalized efficiencies (modal weights) are comparable to those of the deterministic DEA, both in the fixed weight

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Table 9
Optimization parameters of restricted weight stochastic DEA.

Name	Value	Constraints	Status	Slack
Generation efficiency constraint	−4.37	$h_0 \leq 0$	Not binding	4.365
Supply efficiency constraint	−1.11	$h_1 \leq 0$	Not binding	1.105
Demand efficiency Constraint	0.00	$h_2 \leq 0$	Binding	0
Demand efficiency Weighted output constraint	1.00	$u_1 g_2 + u_2 e_2 + u_3 l_2 + u_4 s_2 = 1$	Binding	0
Parameter weight equity	0.202	$u_2 \leq 0.75 \times u_1$	Not binding	1.312
Parameter weight energy security	0.768	$u_3 \leq 0.9 \times u_1$	Not binding	1.049
Parameter weight climate support	0.424	$u_4 \leq 0.4 \times u_1$	Not binding	0.383
Parameter weight equity	0.202	$u_2 \geq 0.1 \times u_1$	Binding	0
Parameter weight energy security	0.768	$u_3 \geq 0.3 \times u_1$	Not binding	0.162
Parameter weight climate support	0.424	$u_4 \geq 0.05 \times u_1$	Not binding	0.323

Table 10
Optimal modal weights of restricted weight determinisic DEA with Bi-level iterative optimization.

Portfolio	Weighted output	Weighted input	Overall technical efficiency (OTE)	Modal weight based on OTE (m)
Generation	1.69	2.79	0.604	0.232
Supply efficiency	1.34	1.34	1.000	0.384
Demand efficiency	1.00	1.00	1.000	0.384

Table 11
Optimal modal weights of restricted weight stochastic DEA with Bi-level iterative optimization.

Portfolio	Weighted output	Weighted input	Overall technical efficiency (OTE)	Modal weight based on OTE (m)
Generation	1.75	6.39	0.27	0.218
Supply efficiency	1.51	2.98	0.51	0.403
Demand efficiency	1.00	2.10	0.48	0.379

Table 12
Twelfth plan generation allocations for India's power sector portfolios.

Portfolio	Potential limitation factor (p_i)	Deterministic DEA potential limited model Weight ($m_i \times p_i$)	Deterministic DEA (Iterative) portfolio power output (MW)	Stochastic DEA (Iterative) portfolio power output (MW)
New generation	1.0	0.232	80,100	78,700
Supply side efficiency	0.1	0.038	13,300	14,500
Demand side efficiency	0.05	0.019	6,600	6,800

and restricted weight cases, though the absolute efficiencies are smaller in the stochastic case due to increased stringency of constraints, which necessitates greater outputs for their satisfaction and therefore greater slacks in non-binding constraints as compared to the deterministic case. Moreover, the greater coefficient of variation of the cost input of the demand side efficiency option has the effect of reducing the optimal efficiency of that option in restricted weight stochastic DEA.

6.4. Optimal twelfth plan power sector portfolios

We use the restricted weight deterministic and stochastic options to arrive at the optimal 12th plan power sector portfolios using bi-level iterative optimization. The modal weights of demand side and supply side portfolios for the deterministic option are identical, though efficiency discrimination among the portfolios is retained in the stochastic case (Tables 10 and 11). It is further seen that the optimal portfolio sets are entirely distinct for the deterministic and stochastic options, which suggests that the stochastic assumption exerts a key influence in the selection of portfolios in iterative optimization.

For actual implementation, the portfolios may be efficiency-limited or potential-limited. Though the modal weights based on efficiencies for the demand side and supply side options exceed that of the generation portfolio, the potential for the full realization of such efficiencies depends on the actual available quantum of generation and the existing efficiency levels in the transmission and distribution segments. In view of this potential limitation, we adopt the following procedure for the apportionment of the 12th Plan generation requirement among the portfolios:

We calculate the potential limitation factor (p) for each portfolio. Considering the current generation capacity as the base, the potential for new generation is taken as unity, assuming that doubling of current generation is feasible at the proposed price levels. The potential for supply side efficiency portfolio is about 10% of current generation capacity, since higher supply side savings are likely to be realised at higher costs of conserved energy. The potential for demand side energy efficiency portfolio is about 5% on account of the added limitation of the distributed and diffuse nature of demand side efficiency projects. Potential limitation factors are significant in the present Indian context. Low costs and greater acceptability of energy efficiency strategies make them attractive options resulting in high modal weights for supply and demand efficiency portfolios. However, since the total generation capacity is less than the actual demand, there is not enough generation to achieve the targets arising out of the efficiency weights, which indicates that the efficiency portfolios of Indian power sector are currently in the potential-limited phase. However, as the power generation rises in proportion to actual demand and the cost of efficiency projects increases after the low-hanging fruits are exhausted, it will enter the efficiency-limited phase. Since the power sector is currently operating in the potential-limited region, potential limitation factors need to be applied. Based on these considerations, we calculate the percentage share of each portfolio as follows.

$$\%\text{ share of }i\text{th portfolio} = m_i \times p_i \times 100 / \sum_i (m_i \times p_i) \tag{8}$$

where m_i is the modal weight and p_i, the potential limitation factor of the ith portfolio.

The 12th Plan generation requirement of 100,000 MW is apportioned using Eq. (8) for both deterministic and stochastic iterative options in Table 12. It may be noted that the generation system planning is carried out in terms of MW estimates. On account of the generation capacity falling short of demand in India, the plants are run at peak plant load factor. Energy outputs of the plants are, therefore, in direct correlation with the generation capacity in MW. The same situation, more or less applies to developing countries, though the model can be supplemented, wherever necessary, by means of energy calculations.

Portfolio shares can be internally apportioned among the portfolio strategies using the optimal first level allocations obtained from the iterative optimization.

Since genetic algorithm is employed for optimization at the first level, it gives a number of optimal or near optimal portfolios. These portfolios are given as input to the second level where the selection of the best first level portfolio is made, based on maximization of efficiency at the second level. Stochastic variations in cost, impact on second level efficiencies, as these efficiencies are computed in terms of costs, risks and barriers of

Table 13
Optimal 12th plan generation mix.

Energy technology	Deterministic DEA generation capacity (MW)	Stochastic DEA generation capacity (MW)
Coal	47,980	47,580
Natural gas	2,804	4,801
Nuclear	2,884	2,143
Hydro	7,690	8,487
Wind	7,850	8,402
Small hydro	6,969	4,029
Biomass	2,403	1,800
Waste to energy	160	171
Solar thermal	641	429
Solar PV	721	857
Total	80,100	78,700

Table 14
Optimal 12th plan supply side strategy mix.

Supply side energy effficiency improvement strategy	Deterministic DEA supply side efficiency based avoided generation (MW)	Stochastic DEA supply side efficiency based avoided generation (MW)
Effective transformer loading	67	63
Phase current balancing	602	563
Low tension (LT) line reconductoring	267	1,375
Single phase to 3-phase line conversion	67	1,625
Using automatic power factor controller in distribution network	334	63
Hydroelectric stations-replacement of cooling water pumps	668	1,125
New 33KV stations	67	250
Using star rated transformers	5,280	3,063
Renovation & modernization of thermal power stations	5681	6063
Conversion of LT to HT lines	267	313
Total	13,300	14,500

Table 15
Optimal 12th plan demand side strategy mix.

Demand Side Energy Efficiency improvement strategy	Deterministic DEA demand side efficiency based avoided generation (MW)	Stochastic DEA demand side efficiency based avoided generation (MW)
Replacing ordinary tube lights energy efficient tube lights	27	24
Replacing incandescent lamps with energy efficient lighting	2373	2131
Introduction of electronic regulators	327	335
Introduction of solar water heaters	55	24
Replacement of TV/CRT monitors by LED monitors	300	24
Using automatic power factor controllers at consumer premises	218	120
Using variable frequency drives for speed control of motors	218	527
Using energy efficient motors	1255	1317
Using fibre reinforced plastic (FRP) bladed fans	300	24
Energy conservation campaign	1527	2275
Total	6600	6800

the first level portfolios and also the internal distribution of portfolio shares. Therefore, those first level portfolios which have greater stochastic cost variations, tend to have lower optimal efficiencies at second level. While deterministic DEA does not distinguish portfolios in terms of cost variations, Stochastic DEA selects those portfolios which have more stochastic resilience. Therefore the portfolios selected in the deterministic and stochastic cases are not the same. This leads to variations in the constituent investments in each portfolio. The shares of various portfolio strategies are given in Tables 13–15. The internal apportionment of each portfolio is purely based on the optimal decision vectors of the first level of the bi-level algorithm and not based on official 12th Plan allocations.

7. Policy implications and conclusions

Current planning methodology in India is a process of aggregation of Plans of various ministries at the level of the Planning Commission. The broad approach to the Plan is evolved by the Planning Commission following a process of wide-ranging consultations with various stakeholders (Planning Commission of India, 2011). Ministries/Departments/Organizations develop the strategies and projects based on stakeholder consultations (Ministry of New & Renewable Energy, India, 2011) to achieve the objectives developed in the Approach Paper. These strategies are aggregated at the level of the Planning Commission and approved after modifications based on further consultations. It has been suggested that (Jebaraj and Iniyan, 2006) formulation of a suitable energy model will help in the proper allocation of renewable energy resources such as solar, wind, bio energy and small hydropower in India. As an improvement to the planning process, this paper suggests the use of optimization techniques to achieve the objectives of planning through a transparent and evidence-based model, which can incorporate the renewable energy and energy efficiency portfolios critical for climate change mitigation.

The objectives of India's 12th Five Year Plan in the energy sector have been identified as faster growth, better inclusion, energy security and sustainability. These objectives have to be incorporated while prioritising the strategies. While a genetic algorithm can optimize the strategies at the first level, the efficiency optimization technique useful for the second and higher stages has been described in detail. It also describes how these objectives can be translated to proxy attributes to indicate economic growth, energy equity, energy security and climate change mitigation. The analysis shows that weight-restricted stochastic DEA model is most suitable for efficiency optimization of strategies as it takes into account the limited substitutability of outputs of the model as well as the stochastic nature of key inputs. The model is capable of discriminating various portfolios.

This procedure is applied to the Indian power sector as this sector is vital in the context of climate change mitigation. The algorithms have been applied to optimize India's power sector portfolios to identify efficient strategy decision vectors by iterative optimization. By grouping the strategies in power sector into three portfolios, namely, generation mix, demand side efficiency group and supply side efficiency group, each portfolio is optimized taking into account the objectives of cost minimization and CRBI reduction. The portfolio of strategies is further optimized at the second level using higher level objectives. The procedure gives a transparent approach to decision making so that sensitivity analysis and scenario projections can be carried out for optimal policy analysis. The methodology generates a number of near-optimal solutions at the first level, which is filtered through higher levels of optimization using the macro-level objectives defined at higher levels. The key aspect of the procedure is to define the proxy-attributes for the objectives at each level, so as to accurately describe them based on portfolio characteristics. Preference information for combining them needs to be incorporated into the weights of the DEA model as well.

The methodology, therefore, is participatory, with the policy maker incorporating ideas of attributes and preference information at various levels of optimization. However, the advantage is that the information is incorporated in a logical and structured manner so that choice can be made based on the scenario results leading to an evidence-based approach to policymaking.

The effectiveness of DEA in determining the efficiencies of decision making units is utilized for the successful implementation of the optimization algorithm. In the deterministic and stochastic versions of DEA, results are compared in respect of both unrestricted and restricted weight models. First, we solve the deterministic DEA model both for the overall technical efficiency of the CCR model and the pure technical efficiency of the BCC model. It is seen that the technical and scale efficiencies are close to unity and there is very little discrimination among the portfolios according to these models. The conventional CCR and BCC models encounter discrimination problems, on account of the assumption of perfect substitutability of inputs/outputs which makes their weights unrestricted. In the present strategy optimization problem, limited or no substitutability of outputs is a more realistic assumption and therefore, fixed weight or restricted weight DEAs are found more appropriate. We solve the deterministic DEA model for both these options which shows that they are useful in clearly discriminating the strategy portfolios based on efficiency.

The issue of stochastic nature of inputs/outputs is also relevant in the use of DEA as an efficiency measurement tool, especially because DEA efficiencies are determined on the basis of a single set of inputs and outputs. However, if the assumption of perfect substitutability of inputs/outputs of conventional DEA holds in a particular case, then stochastic variations of total inputs/outputs will be more relevant than individual variations. In the strategy optimization case, cost has been considered stochastic and therefore, we have considered the chance constrained version of stochastic DEA. Outputs are considered deterministic, as the assumption of limited substitutability of outputs, enables variation of output weights within assigned bounds.

The analysis shows that weight-restricted stochastic DEA model is most suitable for efficiency optimization of strategies as it takes into account the limited substitutability of outputs of the model as well as the stochastic nature of key inputs. The model is capable of discriminating various portfolios.

Bi-level iterative optimization has been employed for the selection of power sector strategies. It is seen that the stochastic assumptions for second level optimization exerts influence on the selection of optimal first level portfolio and also on the optimal efficiencies at second level. Therefore, it would be worthwhile to compare the various methods of introducing stochastic variations into DEA models to analyse their performance in handling such inputs/outputs. Moreover, extension of the methodology for the optimization of the entire energy sector needs to be modelled, which would necessitate optimization of portfolios of higher levels using suitably designed DEA models.

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