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Hierarchical multi-objective optimization of India's energy strategy portfolios for sustainable development

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Received 22 January 2012
Revised 25 March 2012,
19 May 2012
Accepted 25 May 2012

Abstract

Purpose – Optimization of energy planning for growth and sustainable development has become very important in the context of climate change mitigation imperatives in developing countries. Existing models do not capture developing country realities adequately. The purpose of this paper is to conceptualizes a framework for energy strategy optimization of the Indian energy sector, which can be applied in all emerging economies.

Design/methodology/approach – Hierarchical multi-objective policy optimization methodology adopts a policy-centric approach and groups the energy strategies into multi-level portfolios based on convergence of objectives appropriate to each level. This arrangement facilitates application of the optimality principle of dynamic programming. Synchronised optimization of strategies with respect to the common objectives at each level results in optimal policy portfolios.

Findings – The reductionist policy-centric approach to complex energy economy modelling, facilitated by the dynamic programming methodology, is most suitable for policy optimization in the context of a developing country. Barriers to project implementation and cost risks are critical features of developing countries which are captured in the framework in the form of a comprehensive risk barrier index. Genetic algorithms are suitable for optimization of the first level objectives, while the efficiency approach, using restricted weight stochastic data envelopment analysis, is appropriate for higher levels of the objective hierarchy.

Research limitations/implications – The methodology has been designed for application to the energy sector planning for India's 12th Five Year Plan for which the objectives of faster growth, better inclusion, energy security and sustainability have been identified. The conceptual framework combines, within the policy domain, the bottom-up and top-down processes to form a hybrid modelling approach yielding optimal outcomes, transparent and convincing to the policy makers. The research findings have substantial implications for transition management to a sustainable energy framework.

Originality/value – The methodology is general in nature and can be employed in all sectors of the economy. It is especially suited to policy design in developing countries with the ground realities factored into the model as project barriers. It offers modularity and flexibility in implementation and can accommodate all the key strategies from diverse sectors along with multiple objectives in the policy optimization process. It enables adoption of an evidence-based and transparent approach to policy making. The research findings have substantial value for transition management to a sustainable energy framework in developing countries.

Keywords India, Energy sector, Government policy, Decision making, Modelling, Developing countries, Optimisation, Demand-side management

Paper type Conceptual paper

International Journal of Energy Sector Management
Vol. 6 No. 3, 2012
pp. 301-320
© Emerald Group Publishing Limited
1750-6220
DOI 10.1108/17506221211259691

1. Introduction

Energy planning is a key component of macro economic planning due to its close correlation with economic growth and human development. Optimization of energy planning has become extremely important in the context of sustainable development and climate change mitigation imperatives. It has been shown that (Lameira *et al.*, 2011) there are statistically significant relationships among character of governance, potential for sustainable growth and quality of energy management. In the context of a developing country, India, we present a framework for the multi-level, multi-objective optimization of energy strategy portfolios.

Identification of optimal energy policies requires selection from a number of possible alternatives offering varying outcomes including emission reduction. In traditional approaches, a stand-alone model of the economic, energy, climatic and related systems is constructed and the impacts of various policy variables on the system are analysed for policy selection. Since the energy-economy system is quite complex and the representation of macro economic objectives in terms of actionable micro policy strategies is a challenging task, policy planning often reduces to the application of heuristics or informed guesses.

Several analytical models have been devised in the literature (Kanudia and Loulou, 1999; Murthy *et al.*, 2006; Rafaj *et al.*, 2006; Köhler *et al.*, 2006; Božić, 2007; IPCC, 2007) for addressing the challenges of energy system optimization. There are integrated assessment models using knowledge from diverse scientific fields where economic models are combined with environmental or climate change models for policy evaluation or policy optimization (Löschel, 2002). A comparative overview of existing energy system models to assess their suitability for analyzing energy, environment and climate change policies of developing countries is provided in Bhattacharyya and Timilsina (2010), which indicates that the existing energy system models inadequately capture the developing country features and the problem is more pronounced with econometric and optimization models than with accounting models.

A usual approach is to model the energy-economy-climate system in terms of input-output or equilibrium or technology models consisting of a number of parameters. The policies are embedded into such complex models to see their impact on model variables. This approach, besides being not realistic in a developing country context, has three main disadvantages: first, the system is modelled independently of the policies which are to be analysed by the model. Therefore, the system becomes complex and may include parameters which are not necessarily relevant for the policies under consideration. Second, the interaction of the policy variables with the system parameters is not transparent to the policy maker. Third, the top-down and bottom-up conflict arises based on the nature of manifestation of technological change in the model.

Shukla (1997b) compares the top-down and bottom-up approaches to the economic, environmental and energy sector modelling. While bottom-up models begin from a disaggregated representation of the economy mainly at the technological level, top-down models look at aggregate economic behaviour. Bottom-up models are more optimistic based on the possibility of technological progress. Top-down models become pessimistic due to the assumption that the economic behaviour of rational agents under the prevailing economic conditions is the most efficient. Top-down and bottom-up approaches to modelling result (Kandlikar and Morel, 2007) in different cost functions. Moreover, economic modelling in developing countries using the currently available international models presents country specific problems. In present top-down models, developing country realities like underdeveloped markets, vast informal sector, predominant government monopolies, restrictive trade regulations and multifarious barriers to competition are not adequately modelled (Shukla, 1997a). Barriers and other policy issues specific to developing countries pose problems for meaningful policy modelling in these countries (Pandey, 2002). As such, new modelling approaches for the decision-making framework to include barrier representation as well as policy impacts are needed (Worrell *et al.*, 2004) in economic-engineering models.

Polatidis *et al.* (2003) suggest a planning framework for transition to a new sustainable energy system combining integrated assessment (IA), transition management (TM) and multi-criteria analysis (MCA). The framework suggests spatial integration mainly through IA and temporal integration through TM, with MCA providing the qualitative and quantitative dimension. Rotmans (2006) suggests a two-track approach for integrated sustainability assessment, namely, finding new ways to use the current portfolio of IA tools efficiently and effectively, while at the same time developing building blocks to support the next generation tools. Convergence of model rationality and policy rationality is achieved by bringing them together in a participatory process. Once the policy convergence for sustainability is achieved, the key elements of governance can be integrated into TM (Kemp *et al.*, 2005) for achieving sustainability.

We propose an approach for integration of multi-sectoral energy strategies which first identifies the relevant strategy portfolios based on a log frame analysis of the problem. In a multi-sectoral policy domain, a hierarchical approach involving multi-level optimization is suggested for selecting optimal policies. Though the methodology does not integrate spatial and temporal aspects, it can be employed to generate regional policy scenarios at different time periods to design suitable TM framework. The policy-centric approach reduces the complexity of the models and helps the policy maker to correlate the processes, objectives and results, which more than compensates for any loss of generality in such models. Co-production of knowledge as a collaborative effort of scientists and policy makers has been suggested for the integration of their respective domains (Kemp and Rotmans, 2009).

The policy-centric optimization approach focuses on linking strategies to defined planning objectives. At the macro level, the selected energy planning objectives are economic growth, energy equity, energy security and climate sustainability. Climate change mitigation targets incorporated into the optimization process contribute to sustainable development objectives. The key energy related steps to address climate change include use of non-carbon-based energy sources, energy carriers and/or energy carriers that facilitate the use of non-carbon-based energy sources, removal and sequestration of carbon-based atmospheric emissions, and increase of efficiency (Rosen, 2009).

In this essentially bottom-up iterative approach, the objectives are arranged hierarchically. The strategies at the lowest level are identified, which need to be optimized according to their ability to achieve the objectives at that level. In a complex system, it may not be easy to accurately map the micro-strategies to the macro-objectives. This is because, establishing the linkage requires sufficient level of aggregation of strategies to make it a significant policy. To achieve a critical mass of strategies and link them to macro-objectives, they are aggregated into policy portfolios. The portfolios are optimized by attaching objectives of appropriate level to them.

This facilitates the matching of objectives to the level of aggregation of strategies at every step of optimization. The synchronisation of policies and objectives at various levels ensures that the macro-objectives are achieved at the highest level while micro objectives are optimized at lower levels with respect to the corresponding strategies/policies. By iterative execution of this process, multi-level system optimization is achieved in a manner transparent to the policy maker, simplifying the process of modelling and the inherent conflicts associated with the top-down and bottom-up paradigms. Section 2 describes the hierarchical multi-objective policy optimization (HMPO) algorithm in detail.

2. Hierarchical multi-objective policy optimization

The hierarchical policy-centric approach for energy planning makes use of the optimality principle of dynamic programming. It is facilitated by grouping policy strategies based on the commonality of objectives so that they can be locally optimized within the portfolio assuming the monotonicity of the objective function. The portfolios are further optimized with redefined macro-objectives, using methods such as data envelopment analysis (DEA) which assess the efficiencies of the portfolios. Independent optimizations at various levels with objectives appropriate to the respective level generate optimized outputs which feed into the next higher level. Feedback corrections, if any, can be incorporated during iterative optimization.

A related aspect is the multiplicity of objectives. For optimization of heterogeneous policies from different sectors, multiple levels of optimization are designed in view of the fact that the same set of objectives may not apply at all levels. Therefore, the objectives need to be arranged in a hierarchy suitable for sub-sectoral, sectoral and economy wide optimization. Optimal policies from different sectors are combined to form higher level portfolios, using objectives which converge at that level. The convergence of objectives makes them amenable to independent optimization at the respective levels as it facilitates the monotonicity of the objective function.

As the optimization process moves up from the micro to the macro levels, the objectives of optimization also evolve in tandem. By extending this hierarchical process to sufficient number of levels, synchronous optimization of multi-sectoral policies with respect to their hierarchical objectives can be achieved. Once the final level of optimization is reached, the process can be iterated to include additional constraints, if any, identified during the initial run. This method of hierarchical policy optimization is shown in Figure 1.

The dynamic programming approach can be employed in the optimization process to reduce the multi-level optimization problem into simpler single level problems at various hierarchical levels. The methodology of optimization at each level can be chosen independently on account of the Bellman's principle of optimality. According to this principle, an optimal policy is such that whatever the initial state and the initial decisions are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision (Rao, 2010). The application of this principle requires that the objective function be monotonic, which implies that the optimization at a particular level is independent of the optimal outcomes up to that level. For a stochastic process, this requires memory-less Markov state signals for the system states. Choosing objectives proximate to the goals to be achieved at each level of the strategy portfolios,

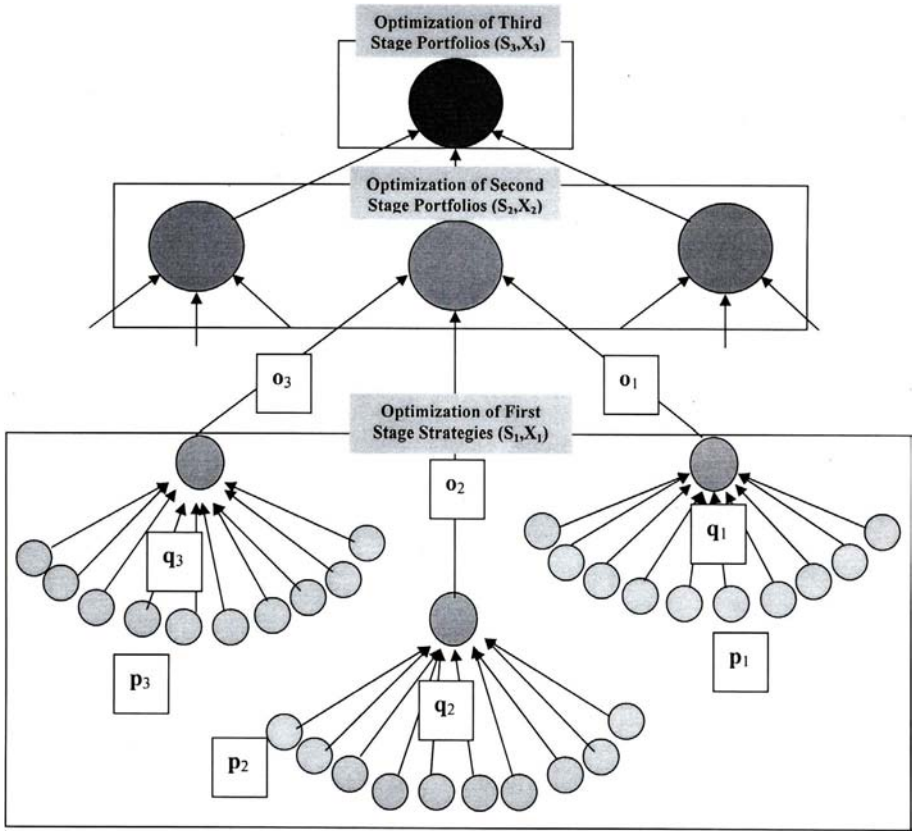

Figure 1.
Hierarchical multi-objective policy optimization

can satisfy the requirement of monotonicity to a great extent. This approach for energy strategy optimization can handle multi-level problems as shown below.

Let $\mathbf{p}_1$ represent the input state variable, $\mathbf{q}_1$ decision vector and $\mathbf{o}_1$, output state variable of each component of the first stage (Figure 1). Then $\mathbf{s}_1 = [\mathbf{p}_1, \mathbf{p}_2, \ldots \mathbf{p}_n]$ represents the first level input state variable vector with $\mathbf{x}_1 = [\mathbf{q}_1, \mathbf{q}_2, \ldots \mathbf{q}_n]$ representing the first level decision variable vector with the transformation function $\mathbf{o}_1. = \mathbf{t}_1(\mathbf{p}_1, \mathbf{q}_1)$**.** The corresponding vectors for the ith stage will be $\mathbf{s}_i$ and $\mathbf{x}_i$. Let $\mathbf{r}$ be the first level return function and $\mathbf{R}$, the second level return function.

Using the transformation function T, we have:

$$\begin{aligned} s_2 &= [o_1, o_2, o_3, \ldots o_n] = [t_1(p_1, q_1),\ \ t_2(p_2, q_2), \ldots t_n(p_n, q_n)] \\ &= T(s_1, x_1) \quad s_{i+1} = T(s_i, x_i) \end{aligned} \tag{1}$$

Considering an additive objective function, we have, for the two-stage system:

$$\begin{aligned} f &= \sum_{i=1}^{n} r'i(q_i, p_i) + R[x_2, s_2] \\ &= r(x_1, s_1) + R[x_2, T(s_1, x_1)] \quad \text{using equation (1).} \end{aligned} \tag{2}$$

We assume the monotonicity of the objective function in order to apply the Bellmann's principle of optimality. For the first stage, we find the optimal value of the objective function considering the return function from that stage only:

$$\mathrm{Opt}(f_1) = \widehat{f}_1(s_1) = \underset{X_1}{\mathrm{Opt}}\{r(x_1, s_1)\} \tag{3}$$

The optimal objective function of the two-stage problem is as follows:

$$\begin{aligned} \mathrm{Opt}(f_2) = \widehat{f}_2(s_2) &= \underset{X_1,X_2}{\mathrm{Opt}}\{r(x_1, s_1) + R[x_2, T(s_1, x_1)]\} \\ &= \underset{X_1}{\mathrm{Opt}}\{r(x_1, s_1)\} + \underset{X_1,X_2}{\mathrm{Opt}}\{R[x_2, T(s_1, x_1)]\} \\ &= \widehat{f}_1(s_1) = \underset{X_2}{\mathrm{Opt}}\{R[x_2, T(s_1, \widehat{x}_1)]\} \end{aligned} \tag{4}$$

The optimal decision vectors for both the stages, optimal $\mathbf{x}_1$ and $\mathbf{x}_2$, can now be chosen by splitting up the optimization problem into two sub-problems:

$$\begin{aligned} \widehat{x}_1 &= \mathrm{Opt}(x_1) = \arg_{x_1} \mathrm{opt}\{\widehat{f}_1(s_1)\} \\ \widehat{x}_2 &= \mathrm{Opt}(x_2) = \arg_{x_2} \mathrm{opt}\{R[x_2, T(s_1, \widehat{x}_1)]\} \end{aligned} \tag{5}$$

where *arg opt* denotes the value of $\mathbf{x}_1$ or $\mathbf{x}_2$ at which the expression that follows is optimal.

If the inputs of the decision-making unit (DMU) are stochastic, then we have to use the expected values of the function instead of deterministic values, assuming Markov decision process for various states, where the probability of state transition depends only on the current state and decision and not on the historical path:

$$\begin{aligned} \widehat{x}_1 &= \mathrm{Opt}\{E[x_1]\} = \arg_{x_1} \mathrm{opt}\{E[\widehat{f}_1(s_1)]\} \\ \widehat{x}_2 &= \mathrm{Opt}\{E[x_2]\} = \arg_{x_2} \mathrm{opt}\{E[R(x_2, T(s_1, \widehat{x}_1))]\} \end{aligned} \tag{6}$$

where $\mathbf{E}[\cdot]$ represents expectation of the random variable.

Equation (5) or (6) can be extended for the iterative optimization of the strategies/policies at n hierarchical levels as shown in the algorithm in Figure 2. The algorithm optimizes the additive n-level objective function by independent single level optimizations. The entire cycle of optimization at different levels can be iteratively repeated to incorporate feedback corrections, if any, arising on account of the assumption of monotonicity. A halting criterion is designed to terminate the algorithm on convergence to the optimal value. This iterative process yields the optimal portfolio with respect to the hierarchy of objective vectors.

3. Energy sector optimization

We consider India's energy sector optimization for sustainable development and climate change mitigation. In India, the energy demand growth of around 6.5 per cent

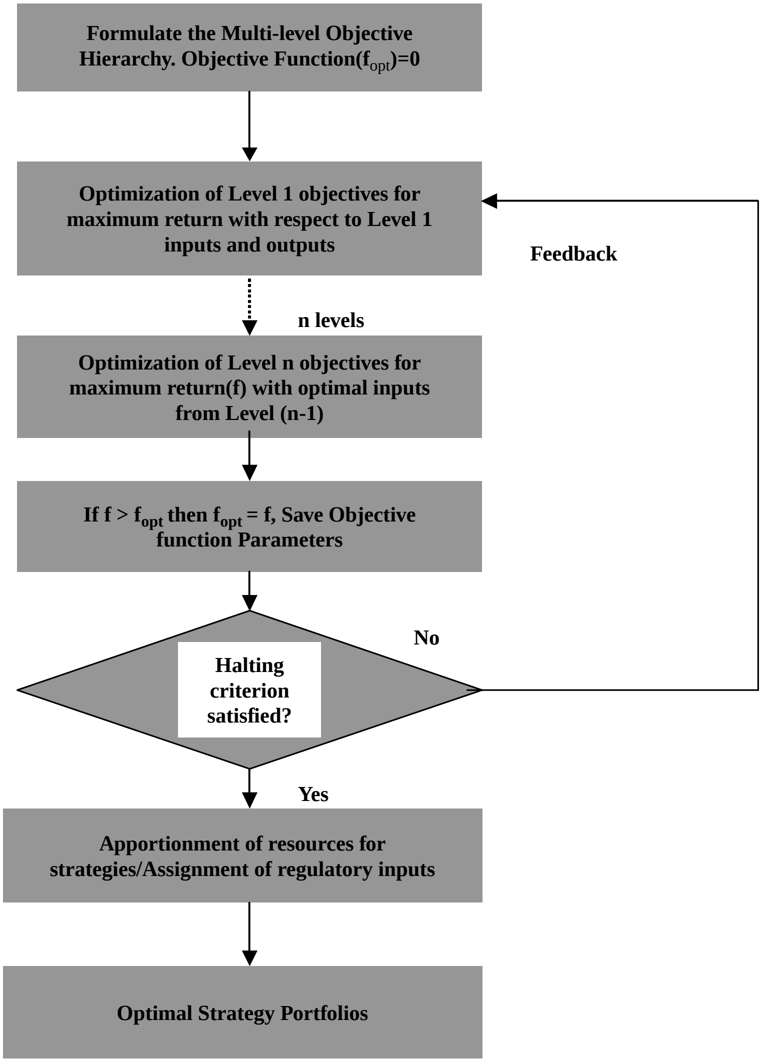

Figure 2.
Hierarchical multi-objective optimization algorithm

per annum has been estimated growing from 522.81 mtoe in 2010-2011 to 738.07 mtoe in 2016-2017 assuming the elasticity of energy demand of about 0.75. Correspondingly, a demand of 1,200 billion units of grid power has been projected by the end of 12th Five Year Plan (2012-2017) with a demand growth of 6 per cent requiring additional generation capacity of 100,000 MW during the 12th Plan (Planning Commission of India, 2011).

For the formulation of the hierarchy of objectives in the context of sustainable development, the important energy sector strategies of India can be grouped into strategies belonging to three groups, namely:

(1) power sector;
(2) transport sector; and
(3) industry, mining and allied sectors (Figure 3).

The key optimization objectives based on the approach to the 12th Five Year Plan are: economic growth, energy equity, energy security and climate sustainability. Sectoral and sub-sectoral portfolios need to be optimal with regard to these objectives. While economic growth and energy security are vital for achieving the developmental goals, equity and emission reduction are key sustainability imperatives. Policies represented by strategy portfolios have to be linked to these objectives at the highest level. At lower level, the objectives are linked to project variables such as cost, risk and barriers. In view of this, higher level objectives are generally represented by means of proxy attributes which take suitably designed functional forms whereas lower level objectives can be described in terms of input variables or their functions.

Each of the three energy sectors are now segregated to form the corresponding sub-sectors for identification of key energy strategies of the 12th Five Year Plan. For power sector, we involve three sub-sectors, namely:

(1) new generation portfolio;
(2) supply side energy efficiency portfolio; and
(3) demand side energy efficiency portfolio.

They are shown in Figure 4 along with their optimization criteria.

For each of the sub-sectors, strategies for achieving the objectives are identified with appropriate optimization criteria. The criteria are cost and comprehensive risk-barrier index (CRBI) at this level. These twin criteria capture the possibility of time and cost over-runs in the execution of projects which are common project management problems in developing countries.

Often, barriers to project implementation are generally not captured in the energy models (Worrell *et al.*, 2004). CRBI rectifies this by combining the cost risk involved in adopting a particular strategy or project, with the barriers encountered for the implementation of that strategy or project in its socio-economic environment.

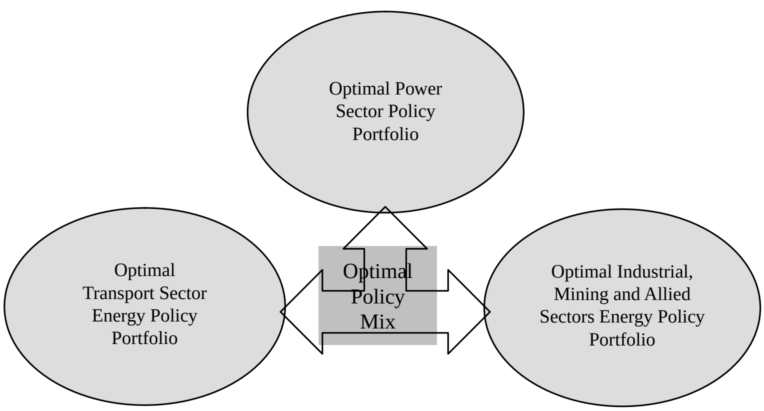

Figure 3.
Energy sector optimization

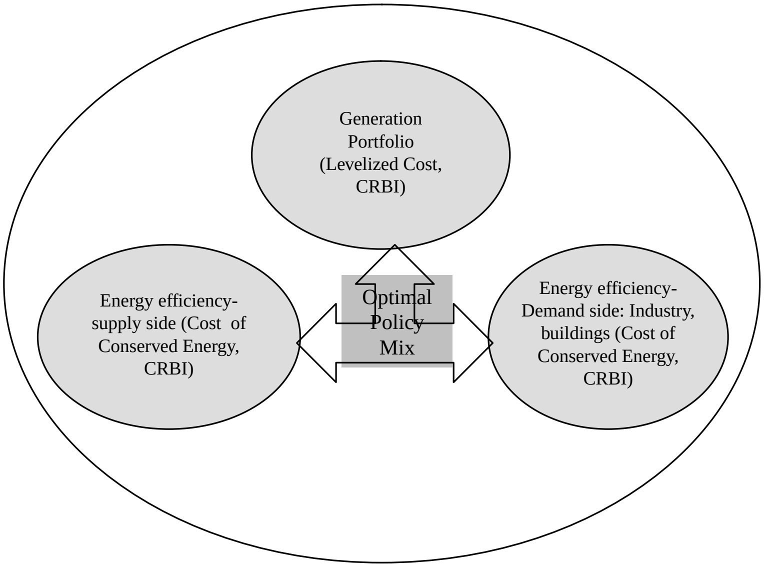

Figure 4.
Power sector optimization

Therefore, CRBI is a combined index which integrates the ground realities of strategy implementation along with the volatility of project costs to guide the choice of optimal policies. Cost risk can be estimated using the standard deviation of the cost variable. To estimate the barrier index, we use the analytic hierarchy process as follows: first, pair-wise comparison of each of the energy strategies with respect to the barrier level is carried out to obtain the reciprocal comparison judgment matrix and then the principal eigen vector of that matrix is computed to obtain the barrier index vector. Consistency of the matrix is verified to validate the outcome. Cost risk and barrier index are then combined using a suitable function, say, by calculating their product, to obtain the value of CRBI to be used in the bi-objective optimization process.

As in the case of power sector, we identify five sub-sectors for the transport sector and four sub-sectors for industry, mining and allied sectors for hierarchical optimization along with suitable first level objective criteria as shown in Tables I and II.

Optimization at each level would require multi-criteria decision methods. Greening and Bernow (2004) provide a description of the use of multi-criteria decision-making methods in an IA framework. Techniques such as value tree analysis, portfolio optimization, analytic hierarchy process, stochastic DEA, linear programming, genetic algorithms, etc. individually or in combination may be used at various levels.

Sub-sectors of transport portfolio	Economic cost-benefit criterion for optimization	Implementation criterion for optimization
(i) Road transport portfolio	Cost of energy for unit output	CRBI
(ii) Water transport		
(iii) Rail transport		
(iv) Air transport		
(v) Intermodal integration	CCE	

Table I.
Transport sub-sectors and optimization criteria

At the sub-sectoral level, mean variance portfolio optimization technique, which converts a single variable stochastic problem into an equivalent bi-variable deterministic problem, is suitable as it does not require computation of surfaces (Steuer *et al.*, 2005). This is a classical technique (Markowitz, 1952), which maximizes the return from a portfolio, while minimizing its expected volatility or risk. As far as the optimization of energy strategies are concerned, this technique can be used to minimize the cost of a strategy as well as its CRBI simultaneously.

For optimization of the power sector strategies at the first level, cost of energy is a significant criterion. In respect of conservation strategy portfolios, the cost effectiveness (CE) supply curve approach (Lutsey, 2008) or the cost of conserved energy (CCE) approach (Sathaye *et al.*, 2006) can be utilized for evaluating this criterion. In these approaches, cost indicates the net cost impacts over the lifetime of the technology.

If the focus is on emission reduction, the CE of emission reduction in respect of mitigation oriented strategies may be estimated (Lutsey, 2008) as:

$$\text{Cost effectiveness value (\$/ton)}\, CE = (1 - NPV)/E_{GHG} \tag{7}$$

I = Initial cost of technology.

E_{GHG} = Emission reduction over average technology lifetime (in tons).

$$\text{Net present value of technology (in \$)}\ NPV = \sum_{t=0}^{n} \frac{(B_t - C_t)}{(1+d)^t} \tag{8}$$

t = Time in years of the technology being evaluated.

Bt = Benefit impacts of technology in year t.

Ct = Cost impacts of technology in year t.

d = Discount rate.

The CCE in respect of energy efficiency strategies is estimated (Sathaye *et al.*, 2006) as follows:

$$\text{Cost of conserved energy (\$/KWh)}\, CCE = I.q/ES \tag{9}$$

$$\text{Capital recovery factor (per year)}\, q = d/[1 - (1+d)^{-n}] \tag{10}$$

Sub-sectors of industry, mining and allied sectors	Economic cost-benefit criterion for optimization	Implementation criterion for optimization
(i) Industrial portfolio	Cost of conserved fuel	CRBI
(ii) Mining portfolio	CE of emission reduction	
(iii) Exploration portfolio		
(iv) Construction portfolio including green buildings	CCE	

Table II. Industry, mining and allied sub-sectors and optimization criteria

I = Capital cost.

ES = Annual energy savings (KWh/year).

n = Life time of the option (years).

I.q in equation (9) represents annuity of investment which is the annual payment to be made to the bank to pay back the project investment with interest.

In a power market where the market price of electricity is growing at the rate of g, the value of the power saved increases in future years. Therefore, the returns from the power saved, form a series of growing annuities. An appropriate financial measure to check the viability of the efficiency project in this context would be to check whether the annuities from the power savings can pay back the investment. For this, the present value of the growing annuities should be equal to the investment. Using the equation for the present value of growing annuities (Damodaran, 2011), we get:

$$I = A(1+g)\frac{[1-((1+g)/(1+d))^n]}{(d-g)} \tag{11}$$

where A is the cost of power saved in the initial year of implementation.

In the growing annuity scenario, from equation (11), we have:

$$\text{Cost of conserved energy (\$/KWh)}\ \ CCE = I.q^*/ES \tag{12}$$

$$\begin{aligned} q^* &= (d-g)/[(1+g)(1-(1+g)/(1+d))^n] && \text{for } d \neq g \\ &= 1/n && \text{for } d = g \end{aligned} \tag{13}$$

Equation (13) assuming $d = g$ is appropriate for calculating the CCE in the Indian power sector.

For second and higher levels of optimization, restricted weight stochastic DEA can be employed. DEA is a method of comparing the efficiencies of DMUs, without knowing the input-output transformation functions. It can be employed in the efficiency determination of energy strategy portfolios. For this purpose, each sub-sector portfolio is considered as a DMU with specified inputs and outputs. The efficiency is estimated as the ratio of a linear combination of outputs to that of inputs. For maximizing the efficiency of each DMU, the fractional programming model is converted into an equivalent linear programming model and solved for optimal efficiency.

In DEA, the efficiency of each DMU is maximized assuming the substitutability of inputs and outputs, which means that the weights of inputs and outputs are allowed to assume all positive values so as to maximize efficiency scores. However, this results in identical efficiency scores for the DMUs in the Pareto frontier. Ranking of DMUs is possible by restricting the weights of inputs and outputs according to their importance, which then becomes restricted weight DEA. The Preference information regarding weights is utilized in this model for efficiency ranking of DMUs (Salo and Punkka, 2011).

4. Optimization of Indian power sector

As an illustration of the application of the algorithm, we consider the optimal portfolios to apportion India's electricity capacity addition target of 100,000 MW as projected in its 12th Five Year Plan, using the dual stage optimization process described above. For the optimization of the Indian power sector, the strategies used for optimization of the three sub-sectors are listed in Table III. In case of comparison of generation technologies, levelized cost estimates including carbon costs, can be employed as the first criterion (California Energy Commission, 2007). CCE can be used for energy efficiency portfolios. CRBI can be employed as the second criterion in all the sub-sectors. For the new generation portfolio, the optimal allocation of generation requirement among the possible generation sources constitutes the decision vector. Similarly, for the supply side and demand side efficiency portfolios, the optimal proportion of power conserved using the respective strategies forms the decision vector.

Genetic algorithm employed at the first level, is capable of identifying a number of near-optimal solutions. They perform well, even when the objective functions are non-convex. The requirement of a detailed specification of the optimization problem is minimal in the case of genetic algorithms. However, their weakness lies in not being able to converge to the most optimal solution quickly. In other words, they find diverse near-optimal solutions, but may not converge to the global deterministic optimum quickly. When the variables employed in optimization are stochastic, a number of near-optimal solutions are more useful in most situations than a single deterministic solution. These near-optimal solutions can be used for the selection of a practical alternative for implementation or they can be gainfully utilized in iterative evaluation of a higher stage optimum. The advantage of being able to generate a number of near-optimal diverse solutions along with the minimal requirement of detailed specification of the optimization problem make genetic algorithms attractive for the first stage of the hierarchical multi-objective optimization algorithm. However, other optimization algorithms such as particle swarm optimization or simulated annealing, etc. can also be employed for this purpose.

Strategy of new generation by multiple sources	Supply side energy efficiency improvement strategy	Demand side energy efficiency improvement strategy
Coal	Effective transformer loading	Replacing ordinary tube lights by energy efficient tube lights
Natural gas	Phase current balancing	Replacing incandescent lamps with energy efficient lighting
Nuclear	Low tension (LT) line reconductoring	Introduction of electronic regulators
Hydro	Single phase to three-phase line conversion	Introduction of solar water heaters
Wind	Using automatic power factor controller in distribution network	Replacement of TV/CRT monitors by LED monitors
Small hydro	Hydroelectric stations-replacement of cooling water pumps	Using automatic power factor controllers at consumer premises
Biomass	New 33 KV stations	Using variable frequency drives for speed control of motors
Waste to energy	Using star rated transformers	Using energy efficient motors
Solar thermal	Renovation and modernization of thermal power stations	Using fibre reinforced plastic (FRP) bladed fans
Solar PV	Conversion of LT to HT lines	Energy conservation campaign

Table III.
Strategies for energy efficiency improvement in power sector

First we apply the minimization of cost and CRBI to the strategies in each of the sub-sectors shown in Table III, to generate the optimal share of each strategy. For this, the typical parameter values have to be estimated for each of the strategies. For example, for the supply side efficiency portfolio, we estimate the costs of conserved energy (C), risk index (R) and barrier index (B) as shown in Table IV.

The CCE is estimated as the ratio of investment to the total energy savings during the lifetime of the technology in a typical case using equation (13). The risk and barrier indices are generated by analytic hierarchic process (AHP) using the pair-wise comparison of the risk and barrier elements for various strategies. Alternatively, where the standard deviations of the costs are known as in the case of new generation sources, the risk values can be taken as the standard deviations. AHP can be implemented using Web-HIPRE software which generates the principal eigen vector of the comparison judgment matrix (HUT, 2003). This matrix is obtained by expert estimates. The principal eigen vector can be used as proxy attribute of risk or barrier variables. Similar estimates have to be made for the strategies in each of the sub-sectors.

Coming to the optimization part, let **X** represent the optimal proportion of the supply side efficiency strategies. We solve for **X** by minimizing the portfolio cost and barrier values using a genetic algorithm. The minimization problem is:

$$\text{Minimize Portfolio Cost, } \mathrm{G}(\mathbf{X}) = \mathbf{X}^{\mathbf{T}}\mathbf{C}$$

$$\text{Minimize Portfolio CRBI, } \mathrm{H}(\mathbf{X}) = (\mathbf{X}^{\mathbf{T}}\mathbf{B})*(\mathbf{X}^{\mathbf{T}}\mathbf{R})$$

Subject to $x_i^{(L)} \leq x_i \leq x_i^{(U)}$, $i = 1, 2, \ldots 10$; variable bounds and other constraints,

where **C, B** and **R** represent cost, barrier and risk vectors, respectively.

The optimal proportions (**X**) of supply side and demand side efficiency strategies generated by using this procedure are given in Table V. Optimal shares of new generation strategies are also obtained in a similar manner.

These optimal portfolios, namely, new generation, demand side efficiency and supply side efficiency portfolios, form inputs to the DMUs of the second stage, which determines the optimal proportion of each sub-sector using weight restricted stochastic DEA. The portfolios are compared by determining their DEA efficiencies with relevant

Supply side efficiency strategy	Cost of conserved energy (C) (Rs/KWh)	Risk index (R)	Barrier index (B)
Effective transformer loading	0.01	0.065	0.337
Phase current balancing	0.19	0.022	0.113
LT line reconductoring	0.90	0.196	0.067
Single phase to three-phase line conversion	1.36	0.13	0.049
Using automatic power factor controller in distribution network	2.12	0.195	0.113
Hydroelectric stations-replacement of cooling water pumps	2.05	0.065	0.067
New 33 KV stations	2.11	0.065	0.038
Using star rated transformers	1.41	0.043	0.067
Renovation and modernization of thermal power stations	1.75	0.022	0.037
Conversion of LT to HT lines	1.69	0.196	0.112

Table IV. Costs, risks and barriers of efficiency strategies

Supply side efficiency strategy	Optimal shares (%) of supply strategies	Demand side efficiency strategy	Optimal shares (%) of demand strategies
Effective transformer loading	0.43	Replacing ordinary tube lights by energy efficient tube lights	0.35
Phase current balancing	3.88	Replacing incandescent lamps with energy efficient lighting	31.34
LT line reconductoring	9.48	Introduction of electronic regulators	4.93
Single phase to three-phase line conversion	11.21	Introduction of solar water heaters	0.35
Using automatic power factor controller in distribution network	0.43	Replacement of TV/CRT monitors by LED monitors	0.35
Hydroelectric stations-replacement of cooling water pumps	7.76	Using automatic power factor controllers at consumer premises	1.76
New 33 KV stations	1.72	Using variable frequency drives for speed control of motors	7.75
Using star rated transformers	21.12	Using energy efficient motors	19.37
Renovation and modernization of thermal power stations	41.81	Using FRP bladed fans	0.35
Conversion of LT to HT lines	1.69	Energy conservation campaign	33.45

Table V.
Optimal shares of efficiency strategies in a portfolio

inputs and outputs. Each of the portfolios is treated as a DMU with stochastic cost and barrier index as inputs. The outputs of the DMU are designed keeping in mind the relevant macro-objectives in terms of the policymaker's priorities. For power sector optimization, economic growth, energy equity, climate sustainability and energy security may be chosen as the outputs of the DMU from a developing country perspective. Once these are chosen, it is necessary to design suitable proxy attributes to represent these outputs in terms of the proportion vectors X as well as other inputs.

The proxy attribute for economic growth can be defined in terms of an appropriately defined growth accounting function. For example, India's growth accounting function could be computed in terms an economic growth model, say, Mankiw-Romer-Weil model (Mankiw *et al.*, 1992), which can be used to estimate the contribution of different policies to economic growth. Similarly, the equity impact of a particular policy is determined by identifying the variables affecting energy equity like the cost of energy and the amount of energy subsidy, etc. These variables can be suitably combined to define an equity function. Energy security is quantified in terms of suitable proxy attributes derived from the portfolio characteristics. Emission reduction objectives can be defined in terms of India's Copenhagen commitment for a reduction of 20-25 per cent cut in emission intensity by 2020 compared to 2005 levels.

The optimal weight of each portfolio is now obtained by maximizing the efficiency of each DMU which is defined as the ratio of the linear combination of outputs to the linear combination of inputs. The weights for combining inputs and outputs can be designed as fixed or bounded. The DEA optimization problem can be solved either using an Excel Solver or using the DEA Programme (Coelli, 1996). The optimal weights of each portfolio in a typical run, based on restricted weights assigned to the inputs and outputs are given in Table VI.

The process can be repeated iteratively to maximize efficiency. Once the optimal shares of each of the strategies and optimal proportions of each of the sub-sectors maximizing the second stage efficiency are determined, the required power generation, say of 100,000 MW can be apportioned among the portfolios using the potential limited portfolio weights given in Table VI. Potential limitation factor is employed to restrict the optimal generation within the potential of each sub-sector. Potential limited portfolio weight, therefore, is the product of the portfolio weight based on overall technical efficiency and the potential limitation factor representing the overall available potential of that portfolio in the sub-sector. This gives the share of new generation, supply side efficiency and demand side efficiency as 78,700, 14,500 and 6,800 MW, respectively.

The quantum of generation assigned to each strategy within a portfolio is obtained by multiplying the above portfolio share by the strategy share in Table V, which is shown in Figure 5. Each bar in the figure represents the generation capacity or avoided generation capacity (for demand/supply efficiency portfolios) of the strategies in various sub-sectors, in the same order as in Table III.

Portfolio	Weighted output	Weighted input	Overall technical efficiency (OTE)	Portfolio weight based on OTE (%) (m_i)	Potential limitation factor (p_i)	Potential limited portfolio weight ($m_i \times p_i$)
New generation	1.75	6.39	0.11	21.8	1.0	21.8
Supply efficiency	1.51	2.98	0.24	40.3	0.1	4.0
Demand efficiency	1.00	2.10	0.33	37.9	0.05	1.9

Table VI. Optimal portfolio weights of bounded weight stochastic DEA

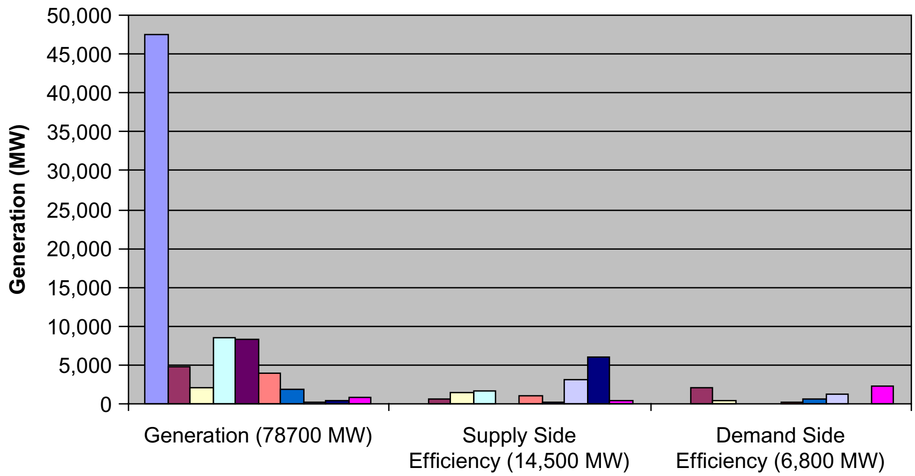

Figure 5. Optimal allocation of 12th plan generation of 100,000 MW for power sector portfolios

Once the optimization of sectoral portfolios is completed, resource allocations are made to implement the strategies. Some of the strategies would require employment of regulatory or institutional arrangements. For energy sector optimization, the optimal sectoral portfolios of power sector, transport sector and industrial, mining and allied sectors are combined by means of efficiency discrimination with respect to the planning objectives at the highest level. It may be noted that the proxy attributes representing the same higher level objective need not exactly be the same at different levels of optimization. This is because the attribute represents the relationship of the objective to the policy. At different levels, the same objective may connect to the policies of respective levels through different proxy attributes. The energy optimization at the highest level gives the investment focus that must be applied to different sectors of the economy in terms of overall energy planning objectives.

5. Conclusions

The focus of this communication is the formulation of a framework useful for energy strategy optimization, prioritisation and resource allocation in a developing country context. Sustainable development is a key imperative of policy planning for which suitable models have to be designed for optimal outcomes. Often, technically advanced complex models have their limitations in developing countries. As a key improvement to this process, HMPO has been formulated for the planning and design of energy strategy framework. These optimized strategies can then be converted to actionable programmes, resource allocations and regulatory instruments by the government departments/organizations to achieve the objectives of the plan. This procedure combined with a suitable TM framework can be employed to attain energy sustainability imperatives.

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 into the optimization process while prioritising the strategies. These macro-objectives cannot be directly incorporated into micro-level strategies. Therefore, a multi-level hierarchy of disaggregated objectives has been proposed with strategy portfolios grouped to suit each set of objectives. A generalized algorithm to optimize policies incorporating various objectives at multiple levels has been described. For this purpose, effective implementable strategies are identified along with hierarchically ordered objectives of optimization. As the objectives become more generalized and aggregated at higher levels, the strategies get organised into portfolios and portfolio of portfolios and so on. At each level, the strategies/portfolios are optimized taking into account the objectives synchronising with the respective strategies/ portfolios. This procedure leads to optimized policies at the highest level, with respect to the macro-objectives set for the plan. By incorporating feedback corrections, if any, and iterative optimization, this procedure can combine, within the policy domain, the bottom-up and top-down processes to form a hybrid modelling approach yielding optimal outcomes, transparent and convincing to the policy makers.

While the methodology is primarily meant for optimization of energy sector policies, it is useful for power system management also, as it can determine the investments to be made for power system loss reduction and efficiency improvement. For example, it has been reported (USAID, 2010) that the most notable practical problems for the introduction of smart grid in India are customer response and cost-benefit analysis.

The comparative insights obtained by means of strategy optimization can throw light on how the smart grid can be gainfully introduced in a phased manner. This would depend on the capability of the new technology to compete, in terms of contribution to system objectives, with new generation as well as with the existing efficiency strategies. Portfolio of smart grid technologies can be incorporated into the optimization framework as another sub-sector within the power sector to determine its optimal share among the sub-sectors, which can then lead to a suitable transition framework.

Choosing the right strategies is extremely important for reliable optimization results. An analysis of the power system can generate likely strategies that need to be taken up for increasing the system efficiency and reducing losses. The portfolio of strategies can be chosen from those generated from such an analysis, which offer the maximum potential for system improvement. If the most effective strategy portfolio is designed based on a technical analysis, the effectiveness and reliability of optimization results would improve considerably. This approach would incorporate further optimization from an additional dimension, namely technology. Here the analysis of the real power system generates the most effective technical strategies, which are then optimized in terms of economic and implementation parameters by the hierarchical multi-objective optimization algorithm.

This highlights the distinct advantages of the hierarchical approach compared to other methodologies, namely, its modularity and flexibility. The application of the optimality principle results in the reduction of a complex optimization problem into smaller problems, solved sequentially. Additional modules can be added along different dimensions to enhance the accuracy of computations by providing better backward or forward linkages. When new technological options arise, they can be incorporated into the optimization framework either as additional strategies in an existing portfolio or as new portfolios without changing the basic optimization structure. Similarly, when the relative prospects of existing options undergo change on account of technology advancement, they can be incorporated in the revised parameter values.

The methodology is general in nature and can be employed in other sectors of the economy as well. Subject to availability of reliable mappings from the domain of inputs to outputs, hierarchical optimization procedures can be extended to optimize all the sectoral strategies of the economy. For example, if the expenditure in the social sectors can be mapped onto return functions such as Human Development Indices and then to development goals, the hierarchical optimization procedure can be employed to identify optimal social sector strategies as well.

The methodology enables adoption of an evidence-based and transparent approach to policy making. However, the reductionist approach to the complex modelling problem, facilitated by the dynamic programming methodology, assumes additive monotonic objective functions. Though this requirement is sought to be achieved by the convergence of strategies/policies and objectives at various hierarchical levels, the extent of satisfaction of the assumptions has direct bearing on the model accuracy. Taking the process forward by incorporating the strategy portfolios of other sectors for extension at economy level as well as assessing the impact of stochastic disturbances are directions of future research, to expand and apply the method for economy wide applications.

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