A stochastic mixed-integer programming approach to the energy-technology management problem

Abstract

As the development and population of North America continues to grow, the demand for environmentally friendly or clean energy generation is becoming more of an issue. We present a model that addresses the energy technologies that may continue to be used and new clean energy technologies that should be introduced in energy generation. The approach involves a Stochastic Mixed-Integer Program (SMIP) that minimizes cost and emission levels associated with energy generation while meeting energy demands of a given region. The results provide encouraging outcomes with respect to cost, emission levels, and energy-technologies that should be utilized for future generation.

Keywords: Clean energy, Two-stage, Scenario, Stochastic programming, Mixed-integer programming

1 Introduction

With current population growth, economic development, and environmental issues, energy generation plays a more increasing role in society. Most new urban areas and some big cities simply purchase energy from neighboring power plants; however, this may not be feasible as their future demands increase. In addition, with current federal regulations and environmental concerns, the decision on how a city should generate power is not a simple one. There are many new technologies and developments involving environmentally friendly or clean energy power plants, each with positive and negative aspects, and some that cannot be used in certain areas. Therefore, there is a need to develop energy models utilizing different clean energy power plants to meet future uncertain demands of a region, while considering federal regulations, environmental concerns, and financial resources of a given area. It is projected that by 2020 the total world energy consumption will increase by 60 percent. The

U.S. Energy Information Administration (EIA) anticipates that total electricity demand will have a 30 percent increase by 2035, which is an average of about 1.0 percent per year [EIA, 2010]. To meet projected demands current energy generation will have to expand. For example nuclear power will have to increase capacity by 12.2 percent, natural gas plants will account for 46 percent in expansions, and renewable energy supply will have to grow by 41 percent [NEMS, 2009]. With the projected increase in electrical demand one effect is the increase in Greenhouse Gas (GHG) emissions, which may have a major impact on many environmental issues including climate change. Over the past decade, there has been a plethora of new clean energy generation technologies and although government agencies plan to integrate such technologies into future energy production, few have assessed which technology best suits given urban areas. We present an energy-technology management model that considers the different factors surrounding energy generation and demand for a specific region so that optimal clean energy technologies are utilized.

The main issues behind modeling the energy-technology management problem is the following: (i) model uncertainty, which may be with respect to energy demand, technology efficiencies, and reliability, (ii) multiple objectives, which include modeling issues and parameter setting, and (iii) model complexity due to the large number of binary variables in the formulation. Powell *et al.* (2010) presents one of the most recent long-term energy models that investigates new technologies and resource allocation, while accounting for uncertainty in demand, wind, rainfall, etc. Zhao *et al.* (2010) also propose a nonlinear energy generation model that involves multiple technology types while constraining emission levels. Recently, the Korean government has sponsored a research institute to specialize in the development of energy technology and the establishment of a long-term strategic energy-technology roadmap in a similar fashion to what we propose [Lee *et al.*, 2009]. The purpose of the contribution is to set up the relevance, framework, and formulations involved in the energy-technology management model. Our model involves uncertainty, mixed-integer variables, and a multi-objective formulation.

Literature on energy-technology management started to became relevant in the 1980s. Fishbone and Abilock (1981) present the technical structure of one of the first Linear Programming (LP) approaches to assess new energy technologies, the MARKet ALocation (MARKAL) model. The Energy Technology System Analysis Programme (ETSAP) introduced MARKAL in the 1980s, which is used today to provide specific energy system feedback at a national to regional level [ETSAP, 2010]. Since then there have been families of different MARKAL models produced, where the basic modeling components involve specific types of energy or emission technologies [De Feber and Gielen, 2000; Gielen *et al.*, 2000; Kanudia and Loulou, 1998; Kypreos and Cadena, 2009]. In 2004, Barreto and Kypreos provide an analysis of energy technology developments and their effect on energy systems embedded in the MARKAL model. The National Energy Modeling System (NEMS) is another energy-economy modeling system that projects generation and energy demands while integrating technology and new improvements over time [NEMS, 2009]. Finding results or models that consider the manner to which different energy technologies can be incorporated to optimize future energy demands has yet to be efficiently addressed by ETSAP or NEMS. Lee *et al.* (2009) consider this idea and provide a four-stage strategic energy technology model that is aimed at reducing environmental damage to make a region that imports most of its energy resources more self-reliant. Lagunes-Díaz *et al.* (2010) investigate electrical energy generation and the effect of adding new energy technologies to the region of Baja California. Powell *et al.* (2010) also address the problem of modeling energy resource allocation, where they develop a long-term investment strategy for new technologies. They consider model uncertainties using an approximate dynamic programming approach. Pereira and Pinto (1991) provide one of the first attempts at such a strategy by designing a stochastic dynamic programming approach to energy management applied to a hydro-plant. Early energy management models have represented investment decisions by an equilibrium balance of energy supply and demand [Hogan, 1975]. Zhao *et al.* (2010) provide a more current energy example of equilibrium modeling, where emission restrictions are included in the design that give different yields depending on the energy generation technology considered.

In addition, there are a variety of publications aimed at new or emerging energy technologies and their potential to improve emissions and reduce environmental damage caused by earlier methods of generation. Distributed energy production involves the novel technology of generating energy from micro plants. El-khattam and Salama (2004) provide a good overview of distributed generation and the benefits of their implementation. Pepermans *et al.* (2005) and Alanne and Saari (2006) evaluate issues with distributed generation when compared to alternative energy technologies. Wind and photovoltaics are two methods of energy generation that have received a lot of attention over the past decade. One of the problems with wind power simply involves the positioning of the wind turbine [Korpaas *et al.*, 2004; Mosetti *et al.*, 1993], which describes a facility location problem. The energy-technology management model may also consider such factors in addition to uncertainties in demand and supply. Clean energy generation such as wind, solar, and hydro usually involve uncertainties in power generation, whereas other methods typically do not have the same level of uncertainty. Castronuovo and Lopes (2004) account for the variability of wind by defining a stochastic process. Bahaj and James (2007) report on various factors involved with solar power when used at the micro-level, such as resident housing. There is also a variety of models that are aimed at capturing uncertainties involved in hydroelectric power generation [Gröwe-Kuska *et al.*, 2000; Cervellera *et al.*, 2006; De Ladurantaye *et al.*, 2009; Jacobs *et al.*, 1995]. Although there is significant literature on the direct impact of various clean energy technologies, few investigations involve the large-scale analysis of managing such technologies to meet future energy demands.

Some energy-technology management models may be classified as extensions to facility location problems where the technology can be thought as the facility. Although energy problems generally have more complex and a greater number of constraints, an inherent subproblem of the model may be one of facility location. Research on facility location problems is abundant and many models have been developed to formulate and solve various location problems. Snyder (2006) provides a complete review on facility location problems. In general, such models can be classified according to their objectives, constraints, solutions, and other attributes [Jia *et al.*, 2007]. For most real-world problems, the input parameters are unknown and stochastic/probabilistic in nature. Stochastic location models capture the complexity inherent in real-world problems through probability distributions of random variables or considering a set of possible future scenarios for the uncertain parameters [Snyder, 2006]. The facility location model that most closely resembles our problem is the dynamic stochastic discrete network model with the p-median objective, capacity constraints, and inelastic demand.

We present a Stochastic Mixed-Integer Programming (SMIP) approach to solve the energy-technology management problem. There are two elements to this modeling, namely: Stochastic Programming (SP) and Mixed-Integer Programming (MIP). Each element is important to capturing the different factors involved in the problem. Wallace and Feten (2003) provide a good overview of SP involved in energy models. SP applications to energy planning can also be found in extensions to MARKAL models [Kanudia and Loulou, 1998]. In addition to MARKAL models, Zerofootprint (0Footprint Inc.) is a non-profit organization that has developed clean energy models dedicated to the reduction of global environmental impact by primarily employing SP models. Many SP models involve the analysis of one type of energy technology system. Gröwe-Kuska *et al.* (2000) design a power management model for a selected plant that involves uncertainty and many energy decisions through SMIPs. SP energy models in the form of portfolio analysis can also be found in the literature [Hochreiter *et al.*, 2006; Eichhorn *et al.*, 2004]. If one considers the energy-technology selection problem, it is similar to portfolio selection problems that involve decisions on portfolio size or selecting a subset of securities to use in the portfolio. There are a number of different financial portfolio problems that address this issue and optimize for specific portfolio goals [Bienstock, 1996; Chang *et al.*, 2000; Crama and Schyns, 2003; Jobst *et al.*, 2001; Shaw *et al.*, 2008; Stoyan and Kwon, 2010]. With respect to portfolio selection this defines an NP-hard problem, where there exists a number of solution methods in the literature. Solution methods for the IP part of the energy-technology management problem may be similar, where for example Beasley *et al.* (2003) employ an evolutionary heuristic, genetic algorithms are used in Lin and Huang (2009) and Ruiz-Torrubiano and Suarez (2009), simulated annealing is the approach of Crama and Schyns (2003), other solution approximations are developed in Chang *et al.* (2000), and exact methods are investigated in Escudero *et al.* (2007) and Shaw *et al.* (2008). Solution methods for energy-technology management problems typically involve initial assumptions and are not as abundant [Kanudia and Loulou, 1998; Powell *et al.*, 2010].

The remainder of the paper is organized as follows: in section 2 we formulate the energy-technology management model for a given region that considers various energy attributes, future uncertainties, and the multi-objective nature of the problem. In section 3 we report on the results of the SP methods ability to capture uncertainties present in the model, multi-objective trade-offs, and how the solution compares to actual results. We also present possible efficiencies with respect to what is used in practice. Finally, in section 4 we conclude our findings and provide future extensions to the current results.

2 Model Formulation

There are a number of different elements to consider in solving the energy-technology management problem. We propose to solve the model using a Stochastic Mixed-Integer Programming (SMIP) approach, which also has various parameters and variables to define. The major aspects necessary to consider in formulating the model are:

1. Identifying the different energy technologies to include in the model, which involve a number of clean energy generation methods;

2. Uncertainties present in the model, such as discrepancies in demand and energy generation (e.g. accounting for variable wind in wind turbines, rainfall in hydro plants, weather conditions in photovoltaics, etc.);

3. The multiple objective nature of the problem, inherently there are a number of model characteristics that one may optimize.

We first consider a version of the energy-technology management problem that accounts for various generation technologies that are only concerned with minimizing cost while meeting energy demands and remaining below a prescribed emission level. This model is typical of what is used in practice. We then expand the formulation to include emission levels in the model and consider a multi-objective problem. Decision variables are related to energy that provides an electrical supply and heating supply. Although the sources of energy that supply electricity can be used to meet heating demands, the heating technologies can only be used as that source of energy. There involve a number of new and efficient clean energy technologies that supply heat, which can be used to heat industrial buildings, houses, water, etc. There are also generation plants that primarily produce electricity and heat is a bi-product of the process that can be used as heating supply, such facilities are known as co-generation plants. The possible sources of electrical supply, for example, are: (i) nuclear energy (ii) solar photovoltaic energy, (iii) hydroelectric energy, (iv) wind turbine energy, (v) biomass energy, (vi) natural gas energy, (vii) petroleum energy, (viii) coal energy, and (viiii) landfill energy. The possible sources of co-generation and heat supply, for example, are: (i) geothermal, (ii) solar thermal, (iii) air-source pump, (iv) district heating, and (v) wood-well gasification. We will assume that the region we consider has the electrical and co-generation capacities for the technologies we define. In cases where the energy technology is not present, the model will allow the technology to be incorporated at future time periods. The idea behind the model is to include all feasible energy technologies for a region and then the optimal solution will provide the one(s) that should be used. Also, the model will uphold a two-stage stochastic programming approach, where uncertainties in future demand and supply will be facilitated in the form of scenario realizations. In a classical two-stage stochastic program with fixed recourse first-stage decisions typically contain all known information with respect to the problem (e.g. current energy demand), whereas second-stage decisions contain a number of random events (described as scenarios) that may be realized. The general idea is to use second-stage scenarios to predict future events that may be realized based on what is known today (first-stage decisions). We also describe the two-stage approach in scenario discussions relevant to our model later in this section, where Figure 1 illustrates the idea of going from scenario s to $s+1$. In addition, the reader may refer to [Birge and Louveaux, 1997] for more information on two-stage stochastic programs. The notation involved in the problem is as follows:

Indices:

- t: time period $1, ..., T$, with a total of T periods.
- s: time stage $1, ..., S$, with a total of S different evolutions.
- ℓ: scenarios in the model 1,...,L, with a total of L scenarios.
- i: electrical energy or co-generation technology $1, ..., I$, with a total of I technologies.
- j: heat generation technology $1, ..., J$, with a total of J technologies.

Decision Variables:

- $x_{i,t}^{\ell,s}$: energy generation from supplier i to be used as electricity in period t for scenario ℓ and scenario evolution s.
- $\widetilde{x}_{i,t}^{\ell,s}$: co-generation from supplier i to be used as heat and electricity in period t for scenario ℓ and scenario evolution s.

$\overline{x}_{i,t}^{\ell,s}$: electrical heat generation from supplier i to be used as heat in period t for scenario ℓ and scenario evolution s.

$y_{j,t}^{\ell,s}$: heat generation from supplier j in year t for scenario ℓ and scenario evolution s.

$b_{i,t}^{\ell,s}$: binary variable involving decisions to build or make additions to energy plant i in year t under scenario ℓ and scenario evolution s.

$\widehat{b}_{j,t}^{\ell,s}$: binary variable involving decisions to build or make additions to heat plant j in year t under scenario ℓ and scenario evolution s.

Parameters:

$d_t^{\ell,s}$: total amount of electricity demanded in the region for period t, under scenario ℓ and scenario evolution s.

$\widehat{d}_t^{\ell,s}$: total amount of heat demanded in the region for period t, under scenario ℓ and scenario evolution s.

$c_{i,t}^{\ell,s}$: operating and maintenance cost of electrical plant i for period t, under scenario ℓ and scenario evolution s.

$\widehat{c}_{j,t}^{\ell,s}$: operating and maintenance cost of heat plant j for period t, under scenario ℓ and scenario evolution s.

p_i: set up cost and financing for adding to an existing electrical plant or building new plant i.

$\widehat{p}_j$: set up cost and financing for adding to an existing heat plant or building new plant j.

γ_i: fractional proportion of co-generation from plant i that is used as electricity supply, where $0 < \gamma_i < 1$.

$\Lambda_{i,t}$: maximum amount of electrical energy that can be generated from energy supplier i in period t.

$\Psi_{j,t}$: maximum amount of heat energy that can be generated from heat supplier j in period t.

$\widehat{\Lambda}_{i,t}$: additional amount of electrical energy that can be generated from plant i in period t due to building or plant additions.

$\widehat{\Psi}_{j,t}$: additional amount of heat energy that can be generated from plant j in period t due to building or plant additions.

$q_{i,t}$: emissions (i.e. CO_2) emitted by electrical plant i for period t.

$\widehat{q}_{j,t}$: emissions (i.e. CO_2) emitted by heat plant j for period t.

Q_t: upper bound on atmospheric emissions level (i.e. CO_2) for period t.

$\hat{l}$: waste disposed while generating electricity at a landfill plant.

l: upper bound on land capacity for a landfill plant.

w_ℓ : weight of scenario ℓ, where $\sum_{\ell=1}^{L} w_\ell = 1$ and $w_\ell \geq 0$.

The decision variables above are used to meet electrical and heating demands for a given region while optimizing for various aspects of the model such as costs or emissions. Heating demands can be met by co-generation plants, electrical heat, or heat generation such as solar thermal generation. Parameter values such as a generation plants operating and maintenance cost encompass all costs associated with running the generation plant, for instance: raw material, employees, plant upkeep, etc. Such parameters may be derived by various methods, in the results of section 3 we use values obtained from the literature [EIA, 2010]. The number of decision variables in the problem are $4\sum_{s=1}^{S} L^s(IT) + 2\sum_{s=1}^{S} L^s(JT)$, with $\sum_{s=1}^{S} L^s(IT) + \sum_{s=1}^{S} L^s(JT)$ binary variables. With this in place we define the energy-technology optimization model, where the objective considers minimizing costs associated with energy generation while meeting energy demands and remaining below a maximum emission level. The framework for the model is consistent with a two-stage SMIP, where at a certain time, S stages and L scenarios are generated to capture future model uncertainties. Below we define the Deterministic Equivalent Program (DEP), where discussions on scenario generation and how second-stage variables are defined will be given later in this section. The energy-technology management SMIP is the following:

$$\min \quad \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{\ell=1}^{L} w_\ell \left(\sum_{i=1}^{I} c_{i,t}^{\ell,s}(x_{i,t}^{\ell,s} + \overline{x}_{i,t}^{\ell,s}) + \widetilde{c}_{i,t}^{\ell,s}\widetilde{x}_{i,t}^{\ell,s} + p_i b_{i,t}^{\ell,s} + \sum_{j=1}^{J} \widehat{c}_{j,t}^{\ell,s} y_{j,t}^{\ell,s} + \widehat{p}_j \widehat{b}_{j,t}^{\ell,s} \right) \tag{1}$$

$$\text{s.t.} \quad \sum_{i=1}^{I} x_{i,t}^{\ell,s} + \gamma_i \widetilde{x}_{i,t}^{\ell,s} \geq d_t^{\ell,s} \qquad \forall\, \ell = 1,...,L,\ s = 1,...,S \quad t = 1,...,T \tag{2}$$

$$\sum_{i=1}^{I} \overline{x}_{i,t}^{\ell,s} + (1-\gamma_i)\widetilde{x}_{i,t}^{\ell,s} + \sum_{j=1}^{J} y_{j,t}^{\ell,s} \geq \widehat{d}_t^{\ell,s} \qquad \forall\, \ell = 1,...,L,\ s = 1,...,S \quad t = 1,...,T \tag{3}$$

$$x_{i,t}^{\ell,s} + \overline{x}_{i,t}^{\ell,s} + \widetilde{x}_{i,t}^{\ell,s} \leq \Lambda_{i,t} + \widehat{\Lambda}_{i,t}\, b_{i,t}^{\ell,s} \qquad \forall\, i = 1,...,I,\ \ell = 1,...,L \quad t = 1,...,T,\ s = 1,...,S \tag{4}$$

$$y_{j,t}^{\ell,s} \leq \Psi_{j,t} + \widehat{\Psi}_{j,t}\, \widehat{b}_{j,t}^{\ell,s} \qquad \forall\, j = 1,...,J,\ \ell = 1,...,L \quad t = 1,...,T,\ s = 1,...,S \tag{5}$$

$$\sum_{t=1}^{T} \hat{l} x_{\bar{l},t}^{\ell,s} \leq l \qquad \forall\, \ell = 1,...,L,\ s = 1,...,S \tag{6}$$

$$\sum_{i=1}^{I} q_{i,t} x_{i,t}^{\ell,s} + \sum_{j=1}^{J} \widehat{q}_{j,t} y_{j,t}^{\ell,s} \leq Q_t \qquad \forall\, \ell = 1,...,L,\ s = 1,...,S \quad t = 1,...,T \tag{7}$$

$$b_{i,t}^{\ell,s} \leq b_{i,(t+1)}^{\ell,s} \qquad \begin{array}{l} \forall\, i = 1, ..., I, \ell = 1, ..., L \\ \quad t = 1, ..., T,\ s = 1, ..., S \end{array} \tag{8}$$

$$\widehat{b}_{j,t}^{\ell,s} \leq \widehat{b}_{j,(t+1)}^{\ell,s} \qquad \begin{array}{l} \forall\, j = 1, ..., J, \ell = 1, ..., L \\ \quad t = 1, ..., T,\ s = 1, ..., S \end{array} \tag{9}$$

$$x_{i,t}^{\ell,s}, \overline{x}_{i,t}^{\ell,s}, \widetilde{x}_{i,t}^{\ell,s}, y_{j,t}^{\ell,s} \geq 0 \qquad \begin{array}{l} \forall\, i = 1, ..., I, j = 1, ..., J \\ \quad \ell = 1, ..., L, t = 1, ..., T \\ \quad s = 1, ..., S \end{array} \tag{10}$$

$$b_{i,t}^{\ell,s}, \widehat{b}_{j,t}^{\ell,s} \in \mathbb{B} \qquad \begin{array}{l} \forall\, i = 1, ..., I, j = 1, ..., J \\ \quad \ell = 1, ..., L, t = 1, ..., T \\ \quad s = 1, ..., S, \end{array} \tag{11}$$

where $i = \bar{l}$ in equation (6) represents a landfill energy plant. In (1)–(11) above, we present a two-stage SMIP where first-stage decisions involve one scenario that is known. In equation (1), the objective function minimizes the cost of using any energy generation technology. Binary variables are associated with costs of technologies that need to be built or added to the system, which may also represent extensions to current generating plants. The model allows energy generation to meet future demands by adding new energy technologies or making extensions to existing ones, which increase their capacity. Constraint (2) requires the model to meet electrical demands, and constraint (3) defines heating demands. Equation (2) maintains that energy demand is met (per time period) by all electrical and co-generation sources present in the model. Equation (3) shows that heat demand can be captured by a product of electrical energy and the proportion of co-generation used for heat generation, as well as heat generation technologies themselves. Constraints (4), (5), and (6) provide upper bounds on the maximum energy generation per source for electrical, heat, and co-generation plants, respectively. These constraints also have binary variables associated with them to account for facility extensions or new generation plants that are added to the model. In some cases, energy generation will have additional constraints associated with the functionality of the generating plant. For example, when a landfill plant no longer has the capacity to store waste it will not be functional. Constraints (4) and (5) can increase the size of their upper bound by building or extending current facilities, which is consistent with changing the value of $b_{i,t}^{\ell,s}$ or $\widehat{b}_{i,t}^{\ell,s}$. Constraint (6) describes the life cycle of the landfill site, where after a certain capacity it cannot be used to generate energy. Equation (7) defines upper bounds on the total emissions possible to be emitted per period as a collection of all energy generation technologies. In a second variant of the energy-technology management problem equation (7) is also minimized, which produces a multi-objective problem. Finally, constraints (8)–(11) are managing and practical constraints, where for example energy can only be produced or energy technologies can only be purchased. Also, constraints (8)–(9) define that once

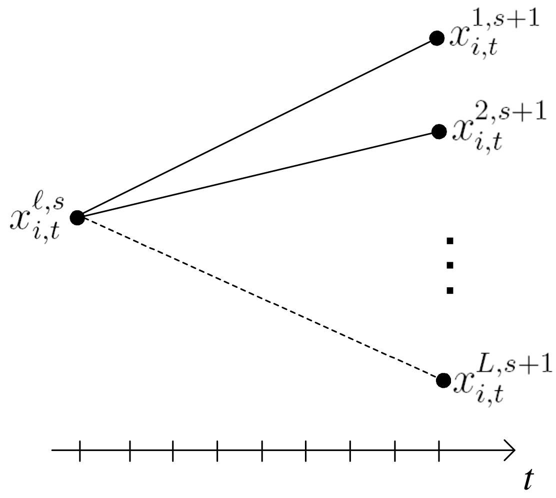

Figure 1: An example of scenarios generated from evolutions s to $s+1$ with respect to t time periods.

an extension or new facility is built it will remain as a valid energy source for future time periods. The number of variables in this problem depend on the number of electrical or heat energy technologies, scenarios, time periods, and time-stages. As mentioned, the number of mixed-integer decision variables in the problem are $4\sum_{s=1}^{S} L^s(IT) + 2\sum_{s=1}^{S} L^s(JT)$. The energy-technology management problem we propose involves a MIP, where depending on the number of variables considered the problem may pose issues in generating solutions.

The model presented in (1)–(11) is primarily focused on keeping energy costs low while remaining under an upper bound for emission levels. Such a model configuration is typically used in practice; however, one may also integrate more aggressive emission reduction models. Taking (1)–(11) and minimizing emissions produces a multi-objective problem. Below is an alternative version of the energy-technology management problem that minimizes costs and emissions:

$$\begin{aligned} \min \quad & \lambda \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{\ell=1}^{L} w_\ell \left(\sum_{i=1}^{I} c_{ivt}^{\ell,s}(x_{i,t}^{\ell,s} + \overline{x}_{i,t}^{\ell,s}) + \widetilde{c}_{i,t}^{\ell,s}\widetilde{x}_{i,t}^{\ell,s} + p_i b_{i,t}^{\ell,s} + \sum_{j=1}^{J} \widehat{c}_{j,t}^{\ell,s} y_{j,t}^{\ell,s} + \widehat{p}_j \widehat{b}_{j,t}^{\ell,s} \right) && (12) \\ & +(1-\lambda) \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{\ell=1}^{L} w_\ell \left(\sum_{i=1}^{I} q_{i,t} x_{i,t}^{\ell,s} + \sum_{j=1}^{J} \widehat{q}_{j,t} y_{j,t}^{\ell,s} \right) \\ \text{s.t.} \quad & (2)-(6), (8)-(11), && (13) \end{aligned}$$

where $0 \leq \lambda \leq 1$. The additional issue of how to define the value of the objective weighting parameter λ can be added to the energy-technology management model above, which is addressed in [Henig and Buchanan, 1997]. In the next section we provide the results when considering problems (1)–(11) and (12)–(13), and illustrate how the models perform with respect to what was actually implemented. The last aspect of the model we present involves the definition of stochastic scenarios $\ell = 1, ..., L$. For every evolution, L scenarios will be incorporated in the model, which may account for discrepancies involving future projections. Figure 1 illustrates how L scenarios will be incorporated into the model as time stages progress. As shown, over the time period ($t = 1, ..., T$) for every evolution that occurs, L scenarios will be introduced to the problem. Hence, scenarios $\ell = 1, ..., L$ define the number of random events involved in the problem and evolutions $s = 1, ..., S$ define the number of times they occur. One may also note that the number of scenario evolutions S included in the model have an exponential effect on the number of variables in the problem. In the next section we use historic values to project future scenario realizations; however, scenarios may be defined by a number of methods. One may refer to [Dupačová *et al.*, 2001; Dupačová, 2002; Hochreiter *et al.*, 2006; Høyland and Wallace, 2001] for more information on scenario generation.

3 Results

We solve the problem presented in (1)–(11) and (12)–(13) using historic data taken from the Energy Information Administration [EIA, 2010]. Information on energy demand, cost, capacities, emissions, etc. is provided from 1998–2008 (refer to Appendix A). In some cases the data was incomplete; however, interpolations and extrapolations were made based on various data resources. We consider the following 16 energy generation facilities in the results we present below: coal plant, petroleum plant, natural gas plant, micro-gas plant, nuclear plant, hydroelectric Conventional plant, micro-renewable plant, hydroelectric pumped storage plant, micro-pumped storage plant, wind turbine, solar thermal/photovoltaic plant, wood and wood-derived fuels plant, geothermal plant, Biomass plant, landfill plant, and purchasing energy off the grid. The actual amount of energy that was produced in the US over that period is also given in [EIA, 2010], which is provided in Appendix A. All models were solved using CPLEX 9.0 on a Pentium 4, 2.4 GHz CPU. CPLEX is able to solve all problems we present below in under 10 seconds, which is expected as the largest problem we solve involves 1000 variables where half are binary variables. CPLEX also solves each problem to optimality except for a few test cases, where integer variables are rounded due to integrality defaults. If the defaults are removed CPLEX will take longer to solve the problem, and there was no significant difference in the solutions for our test cases. For larger size instances this will become more of an issue. We perform three different test cases on known energy data from 1998–2008 and then provide future recommendations from 2009–2019. Using the model presented in (1)–(11), the three test cases we run on historic data from 1998–2008 are the following: (i) an optimization model given known values, (ii) a single scenario SMIP where only the first-stage is known, and (iii) a two-stage SMIP that includes three scenarios. The single scenario in test case (ii) and one of the scenarios in test case (iii) are derived using a linear projection based on historic values. The other two scenarios in test case (iii) are set to be 15% percent higher and lower than the scenario involving the linear projection. More scenarios may be added to the problem and we found that three scenarios was sufficient for our investigation to illustrate model functionality. Finally, we provide the results of our model when we solve a two-stage SMIP energy-technology management problem from 2009–2019.

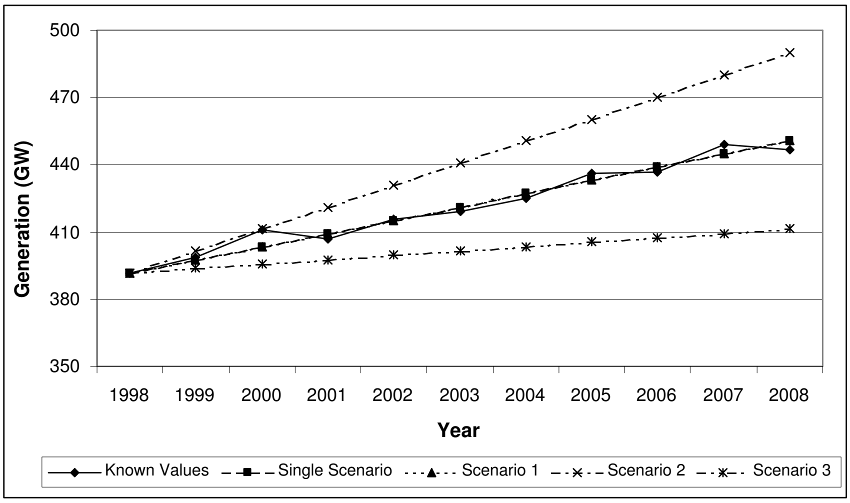

Figure 2: Annual energy generation for known values, single stage, and stochastic scenarios from 1998 to 2008.

Figures 2–6 present the (1)–(11) model results from the three test cases on data taken from 1998–2008. The first test case involves known data, where the solution met all requirements for energy demand and emission levels while minimizing the cost of generation and building or expanding facilities. The graph containing known values in Figure 2 gives the optimized case (i) results, which we also call optimized values in Figure 3. These represent the best results that can be obtained in solving (1)–(11) since all parameters are known. In Figure 2, the single scenario plot provides case (ii) results, where only the first-stage values were known. The values were projected using a linear function for demand, costs, and emission efficiencies. As shown in Figure 2, the single scenario model performs well with respect to the known values. In the worst case it generates 1.7% less energy than needed, where in 5 of the 11 years the model generated less energy than was necessary with an average of 0.6%.

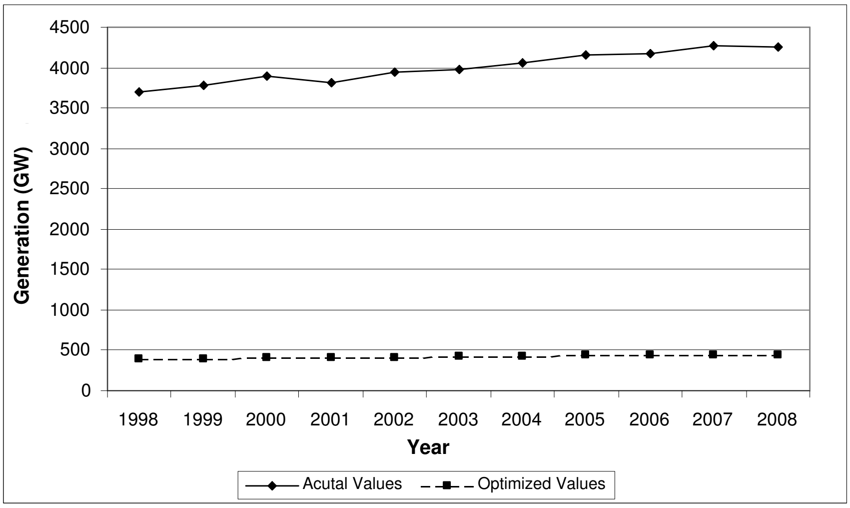

Figure 3: Comparison of annual energy generation for actual and optimized values from 1998 to 2008.

In the remaining 6 years, an average of 0.5% more energy was generated with a high of 0.8% above what was necessary. Table 1 provides the detailed difference between case (i) and (ii) results, where deficiencies in taking one projection improves in the two-stage SMIP model of test case (iii). For the three scenario SMIP the first scenario was equal to the scenario derived in case (ii); however, scenarios 2 and 3 were set to be a percentage higher and lower than scenario 1, respectively. In scenario 2, all energy demands were met with an average of 4.4% generation over the optimized known values. This is due to scenario 2 involving the set of solutions that predicted higher demand values than in scenario 1. Scenario 3 involved the set of solutions where lower energy values than predicted in scenario 1 were used. In scenario 3, all energy demands were lower than what was necessary with an average of 4.5% and a low of 8.7%. In the three scenario SMIP, the recourse decisions provide the model with the capability to switch between scenarios with no violations to feasibility. For example, if the user decides to switch power generation schemes from scenario 3 to 2 at a particular scenario evolution, new facilities or plant extensions are in place such that increased or decreased production is possible. When compared to actual energy generation for this time period, the known optimized values were on average 89.5% higher than what was necessary, as illustrated in Figure 3. In Table 1 the difference in energy cost and generation from optimized known values to actual values and scenarios 1–3 are shown. As provided, the two-stage stochastic model performs much better than what was actually used over this time period.

Figures 4 and 5 provide the cost of energy generation results. When examining the three test cases of Figure 4, the results are consistent with the energy generation results. The

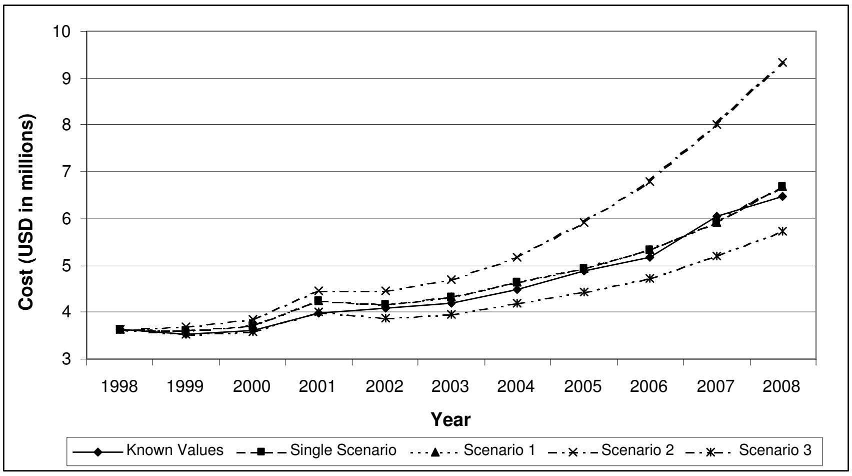

Figure 4: Annual cost of energy generation for known values, single stage, and stochastic scenarios from 1998 to 2008.

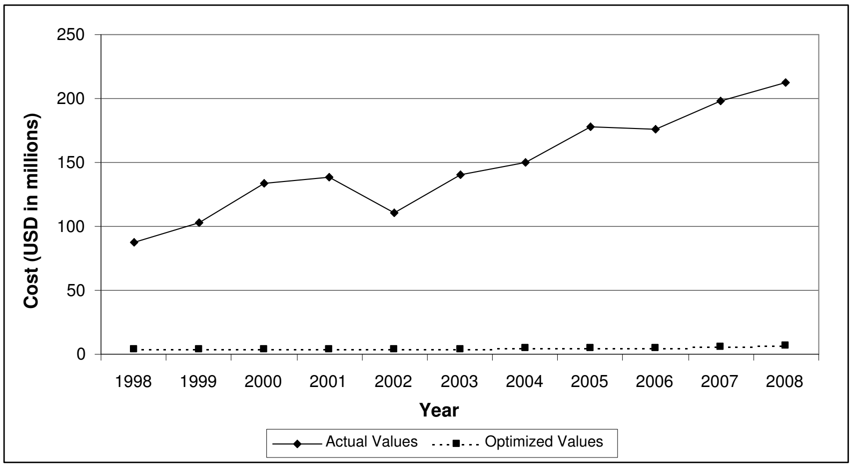

Figure 5: Annual cost of energy comparison from actual values to optimized values from 1998 to 2008.

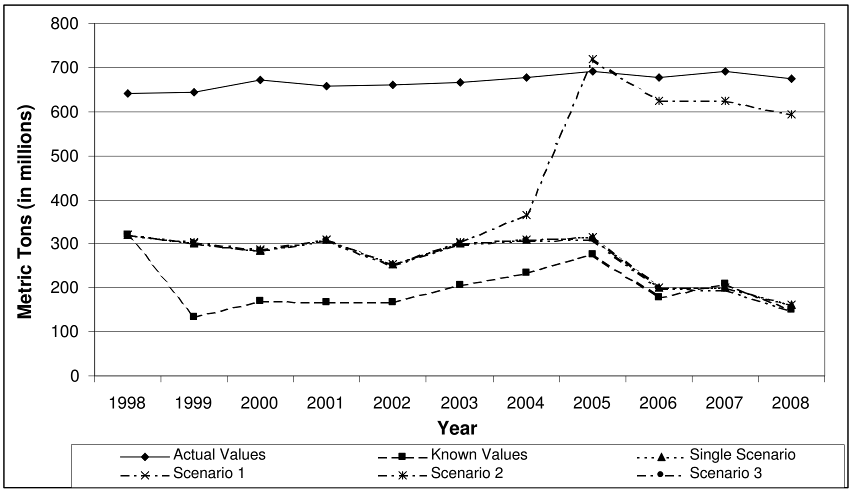

Figure 6: Comparison of annual carbon dioxide emissions for actual values, known values, single stage, and stochastic scenarios from 1998 to 2008.

single scenario model (scenario 1 of the three scenario SMIP) costs an average of 2.4% more than the known case. For test case (iii), scenario 2 costs 17.1% more and scenario 3 costs 5.4% less than the optimized known values, which is also detailed in Table 1. In comparison to what was actually used over this time period, the known values were on average 97% more cost efficient. In addition, the difference in energy generation costs increase in time as you compare the energy-technology management model to the actual values. This is attributed to the optimization model enforcing decisions on building or extending more cost efficient energy generation technologies. Figure 6 illustrates how this may effect emission levels. The optimized known values provide the emission levels in solving (1)–(11). This value may be improved when solving (12)–(13). As shown in Figure 6, all cases are much lower than what was used over that time period with the exception of one year in scenario 2. On average, the optimized known values were 70% lower than the actual values. Also, scenario 1 produced 60%, scenario 2 produced 36.5%, and scenario 3 produced 60% less average emissions than the actual level. Table 2 provides the percent difference in energy emissions from the actual values to optimized known values and scenarios 1–3. As provided, the three scenario SMIP performs well in comparison to the actual emission levels generated over this time period. Scenario 2 does have one year when emission levels were slightly higher than what is used in practiced because the model is set to be below an annual emission level. When emissions are included in the objective of the model (i.e. (12)–(13)), we obtain the results shown in Figure 7 when $\lambda = 0.5$. This model significantly reduces emission levels and all three scenarios have improved results with respect to the case involving optimized known values.

	Cost				Generation			
Year	Actual	S1	S2	S3	Actual	S1	S2	S3
1998	0.9584	0	0	0	0.9962	0	0	0
1999	0.9657	0.0201	0.0404	-0.0002	0.9966	-0.0021	0.0078	-0.0119
2000	0.9730	0.0329	0.0675	-0.0022	0.9972	-0.0180	0.0011	-0.0370
2001	0.9712	0.0636	0.1172	0.0101	0.9974	0.0062	0.0351	-0.0227
2002	0.9631	0.0210	0.0927	-0.0508	0.9967	-0.0003	0.0374	-0.0380
2003	0.9702	0.0364	0.1251	-0.0523	0.9973	0.0054	0.0522	-0.0413
2004	0.9700	0.0353	0.1517	-0.0638	0.9975	0.0047	0.0600	-0.0506
2005	0.9726	0.0119	0.2134	-0.0901	0.9978	-0.0069	0.0560	-0.0698
2006	0.9707	0.0300	0.3141	-0.0887	0.9978	0.0050	0.0768	-0.0667
2007	0.9694	-0.0216	0.3235	-0.1399	0.9980	-0.0093	0.0693	-0.0878
2008	0.9696	0.0306	0.4421	-0.1156	0.9981	0.0083	0.0960	-0.0794

Table 1: Percent difference in energy cost and generation from optimized known values to actual values and stochastic scenarios. S1, S2, and S3 represents scenario 1, 2, and 3, respectively

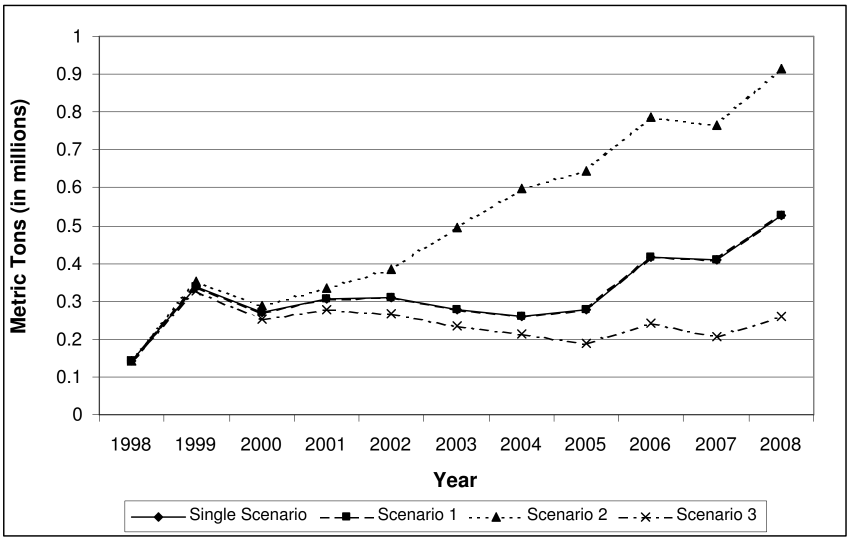

Figure 7: Ratio of annual carbon dioxide emissions for known values when emissions are also minimized in comparison to single stage, and stochastic scenarios from 1998 to 2008.

Year	Known	S1	S2	S3
1998	0.5009	0.5009	0.5009	0.5009
1999	0.7906	0.5306	0.5295	0.5317
2000	0.7482	0.5760	0.5741	0.5780
2001	0.7458	0.5317	0.5284	0.5350
2002	0.7477	0.6172	0.6139	0.6206
2003	0.6907	0.5483	0.5431	0.5534
2004	0.6539	0.5406	0.4621	0.5469
2005	0.6014	0.5442	-0.0407	0.5515
2006	0.7359	0.7031	0.0790	0.7080
2007	0.6985	0.7121	0.0997	0.7174
2008	0.7774	0.7608	0.1217	0.7800

Table 2: Percent difference in emission levels from actual values to optimized known values and stochastic scenarios. S1, S2, and S3 represents scenario 1, 2, and 3, respectively

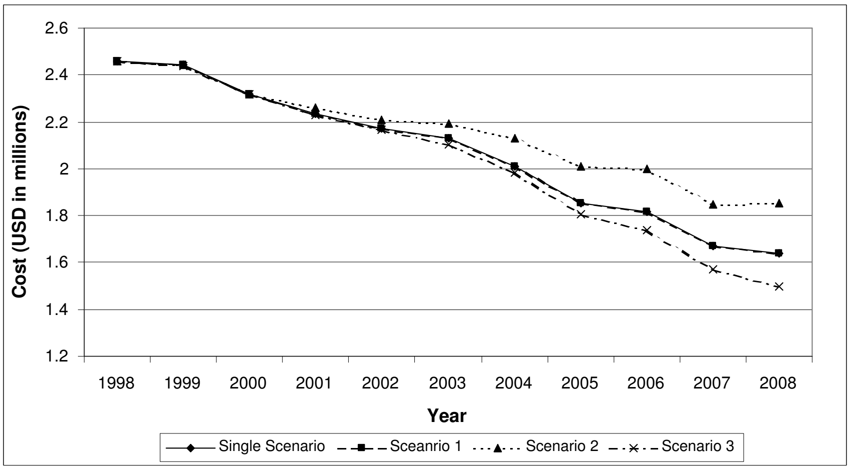

Figure 8: Ratio of annual energy costs for known values when emissions are also minimized in comparison to single stage, and stochastic scenarios from 1998 to 2008.

However, better emission results come with a cost. Figure 8 provides the results when more monetary resources are used to minimize emission levels. On average scenario 1 cost 6.7% more than the known optimized case, and scenarios 2 and 3 cost 15.6% and 2.8% more, respectively. The higher costs of energy generation are associated with the multi-objective nature of model (12)–(13) that involves a trade-off between costs and emission levels defined by λ. Figures 10 and 11 provide the total trade-off in cost and emissions for different values of λ. As illustrated, the greatest improvement in cost can be found when $\lambda = 1$ (Figure 10);

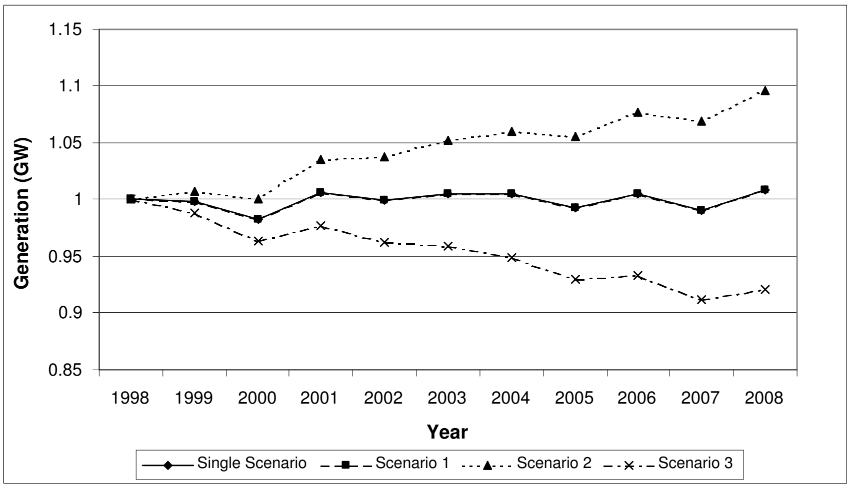

Figure 9: Ratio of annual energy generation for known values when emissions are also minimized in comparison to single stage, and stochastic scenarios from 1998 to 2008.

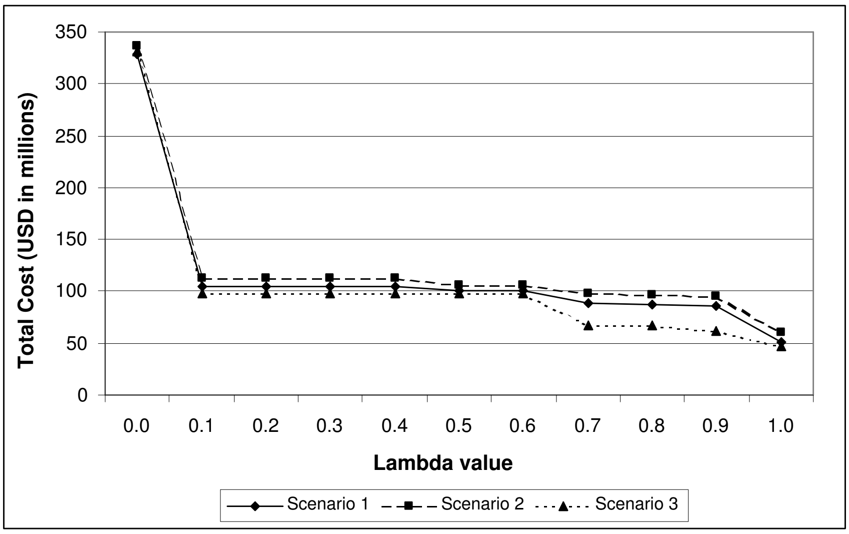

Figure 10: Total cost of energy generation from 1998 to 2008 for different values of λ.

however, this gives the worst emission levels (Figure 11). Using a conservative value of λ provides reasonable costs and emission levels. For λ values of 0.5 in Figures 7–9, the model was more cost efficient than the actual values by 96.7% on average. Figure 9 illustrates that there is no significant change with respect to the energy generation results when emissions are also minimized, which is consistent with the previous values.

The final set of results, Figures 12–13, provides the energy-technology management implications for 2009–2019. Predictions on cost, demand, facility extension costs, emission

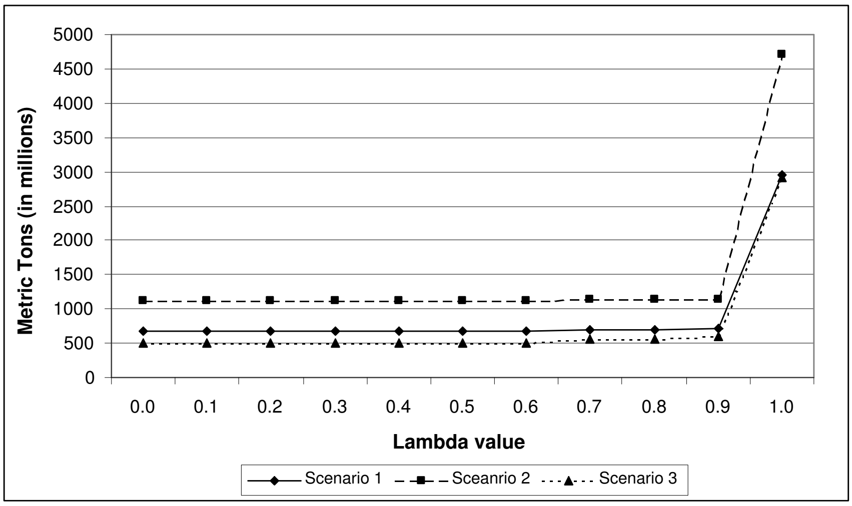

Figure 11: Total emissions of energy generation from 1998 to 2008 for different values of λ.

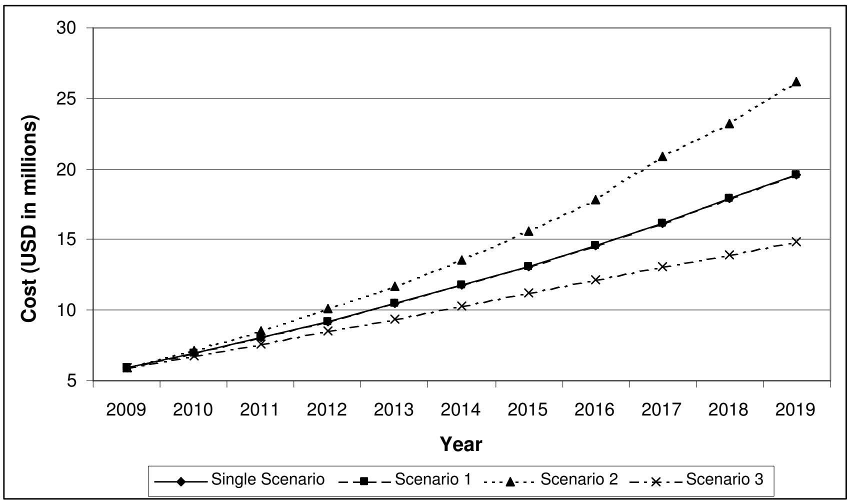

Figure 12: Future annual energy cost using the single scenario and three scenario SMIP from 2009 to 2019.

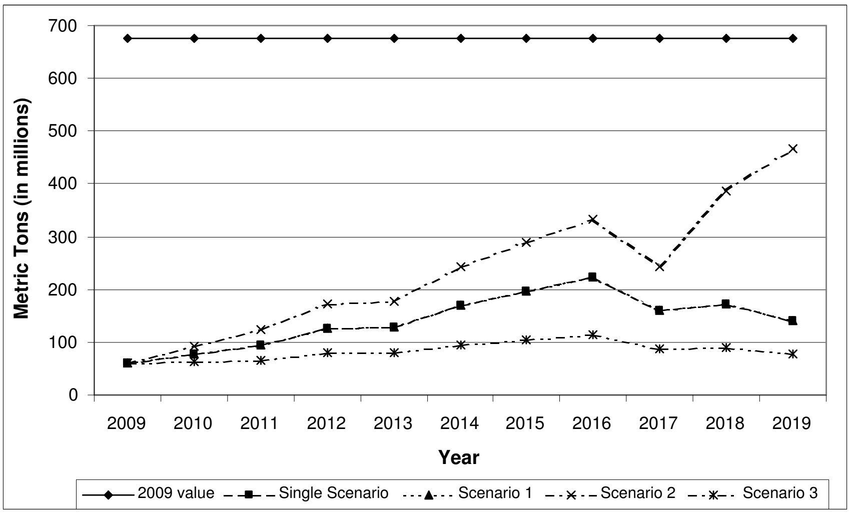

Figure 13: Future annual energy emissions using the single scenario and three scenario SMIP from 2009 to 2019.

efficiencies etc. were generated similarly to what was used in the 1998–2008 results. Since only the energy cost and generation values of 2009 are provided in [EIA, 2010], we used the most expensive cost values of scenario 3 to act as our realized final cost results in Figure 12, and similarly with emission levels in Figure 13. Figure 12 illustrates the cost of energy for the single scenario and three scenario SMIP over this time period. Comparing the results of Figure 12 to the static cost of energy generation in 2009 (which is known), scenario 1,2, and 3 were less expensive on average by 94.2%, 93.1%, and 95.1%, respectively. Figure 13 provides the emission results when (12)–(13) is solved. If we consider the static emission level of 2008 (2009 values are not provided in EIA [2010]), then the results of all three scenarios are still below this level, as illustrated. On average, the three scenario SMIP produces 79.1%, 65.1% and 87.7% less emissions than the emission level of 2008. The results illustrated in this section reflect the improvements that can be achieved by applying the energy-technology management model and will be further discussed in the next section.

4 Conclusion

We provided a unique problem in the energy sector known as the energy-technology management problem. The model and results give value to the problem and validate future investigations. In section 3, it is evident that planning involved with energy production can have great gains with respect to costs, emissions and energy generation. We have developed the framework and modeling approach to effectively do so. In addition, these results are obtained by a model that sets the fundamentals for future research, and warrants further investigation. For example, introducing more variables to the problem such as increasing the number of scenarios will have a strong effect on the final solution; however, an algorithm will have to be derived to generate solutions as commercial solvers such as CPLEX will no longer be able to solve the problem to optimality. As is evident by the results, taking three scenarios in the model gives a greater advantage than the single scenario case. In the 1998–2008 single scenario results, energy demands would have been missed in almost 50% of the test cases. However, in the three scenario model the user would probably have switched to scenario 2, which has a slightly higher cost but all energy demands are met. Scenario 2 did have the poorest emission results of the three and when the multi-objective model was used all three scenarios performed well. Additional future research directions may include the possibility of allowing micro-level energy level production such as households equipped with solar panels to sell electric or heat power they produce. Also, adding additional discount factors to the problem and the possibility for public financial investments may be considered. In conclusion, we have presented a modeling approach for the energy-technology management problem. The results validate future investigations in this area, where an algorithm may be necessary to approach problem complexities.

A Appendix

Parameter values in this section have been taken from [EIA, 2010] and used for the results provided in section 3. Where data is incomplete in the tables below, linear interpolations, extrapolations, or approximations are made based on various data resources (e.g. [ETSAP, 2010; NEMS, 2009]). For example, the maximum capacity of energy generation for each technology is not given in [EIA, 2010]. This value is approximated by assuming that plants are running at approximately 80% capacity in any given year. Actual energy generation in gigawatts (GW) for different technologies from 1998–2009 is the following:

Technology	1998	1999	2000	2001	2002	2003
Coal	1873516	1881087	1966265	1903956	1933130	1973737
Petroleum	128800	118061	111221	124880	94567	119406
Natural Gas	531257	556396	601038	639129	691006	649908
Micro-Gas	13492	14126	13955	9039	11463	15600
Nuclear	673702	728254	753893	768826	780064	763733
Hydroelectric Conventional	323336	319536	275573	216961	264329	275806
Micro-Renewable	77088	79423	80906	70769	79109	79487
Hydroelectric Pumped Storage	4467	6097	5539	8823	8743	8535
Micro-Pumped Storage	3571	4024	4794	11906	13527	14045
Wind	3026	4488	5593	6737	10354	11187
Solar Thermal/Photovoltaic	502	495	493	543	555	534
Wood and Wood Derived Fuels	36338	37041	37595	35200	38665	37529
Geothermal	14774	14827	14093	13741	14491	14424
Biomass	22448	22572	23131	14548	15044	15812

Technology	2004	2005	2006	2007	2008	2009
Coal	1978301	2012873	1990511	2016456	1985801	1755904
Petroleum	121145	122225	64166	65739	46243	38938
Natural Gas	710100	760960	816441	896590	882981	920797
Micro-Gas	15252	13464	14177	13453	11707	10629
Nuclear	788528	781986	787219	806425	806208	798855
Hydroelectric Conventional	268417	270321	289246	247510	254831	273445
Micro-Renewable	83067	87329	96525	105238	126101	143824
Hydroelectric Pumped Storage	8488	6558	6558	6896	6288	4627
Micro-Pumped Storage	14232	12821	12974	12231	11804	11929
Wind	14144	17811	26589	34450	55363	73886
Solar Thermal/Photovoltaic	575	550	508	612	864	891
Wood and Wood Derived Fuels	38117	38856	38762	39014	37300	35596
Geothermal	14811	14692	14568	14637	14840	15009
Biomass	15421	15420	16099	16525	17734	18443

Cost of generating energy from each technology per kilowatthour (kWh) from 1998–2009 (cost = price per kWh) is the following:

Technology	1998	1999	2000	2001	2002	2003
Coal	27.71	33.97	44.05	45.48	33.72	44.69
Petroleum	20.45	20.12	22.32	23.23	21.36	22.75
Natural Gas	30.79	37.74	48.94	50.53	37.47	49.66
Micro-Gas	26.17	32.08	41.60	42.95	31.85	42.21
Nuclear	21.02	18.35	15.89	18.13	18.65	18.95
Hydroelectric Conventional	4.67	5.38	5.74	7.16	6.33	5.79
Micro-Renewable	5.37	6.19	6.60	8.23	7.28	6.66
Hydroelectric Pumped Storage	5.14	5.92	6.31	7.88	6.96	6.37
Micro-Pumped Storage	5.64	6.50	6.93	8.65	7.64	6.99

Technology	2004	2005	2006	2007	2008	2009
Coal	46.43	54.99	53.60	57.99	63.65	51.80
Petroleum	24.31	27.88	29.85	30.88	35.75	40.48
Natural Gas	51.59	61.10	59.56	64.43	70.72	57.55
Micro-Gas	43.85	51.94	50.63	54.77	60.11	48.92
Nuclear	18.93	18.15	19.57	20.32	21.37	21.69
Hydroelectric Conventional	6.60	6.68	6.46	9.32	9.67	8.38
Micro-Renewable	7.59	7.68	7.43	10.72	11.12	9.64
Hydroelectric Pumped Storage	7.26	7.35	7.11	10.25	10.64	9.22
Micro-Pumped Storage	7.97	8.07	7.80	11.25	11.68	10.12

Emission levels in metric tons of carbon dioxide released in the atmosphere from 1998–2008 is the following:

Technology	1998	1999	2000	2001	2002	2003
Coal	513190165.1	515034631.9	539949624	522088432.6	526902589.4	536411060.7
Petroleum	33725130.82	31604241.27	29604422.45	31978975.09	24850775.18	30566125.91
Natural Gas	89306316.55	93570000.55	99143451	100130811.3	103350069.5	94123458.82
Geothermal	102351.8182	103877.4545	98749.36364	96277.63636	101535.2727	101065.9091
Biomass	3483912.545	3474008.455	3353677.909	3531885.545	4065953.182	3799620.818

Technology	2004	2005	2006	2007	2008
Coal	540700791.3	551304922.1	543817224.5	551611846.6	544089103.9
Petroleum	31584945.27	31940439.82	18547134.82	18488136	13063099.36
Natural Gas	100121359.9	104580319.6	110257662.8	118509787.6	114436759.1
Geothermal	103775.1818	102940.0909	102072.2727	102557.4545	104760.0
Biomass	3844755.545	3891918.818	4138444.909	3961883.727	3909744.0

Energy demand in megawatts (MW) from 1998–2009 is the following:

	1998	1999	2000	2001	2002	2003
Demand	391797.8307	398503.3591	410930.7684	406898.5037	415425.567	418900.5962

	2004	2005	2006	2007	2008	2009
Demand	425068.5753	435939.607	436610.0952	448846.2862	446859.2322	427989.517

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