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A Stochastic Mixed-Integer Programming approach to the energy-technology management problem

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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.

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%. The US Energy Information Administration (EIA) anticipates that total electricity demand will have a 30% increase by 2035, which is an average of about 1.0% 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%, natural gas plants will account for 46% in expansions, and renewable energy supply will have to grow by 41% (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, Hobbs, and Pang (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, Mogi, & Kim, 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

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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 & Gielen, 2000; Gielen, Bos, De Feber, & Gerlagh, 2000; Kanudia & Loulou, 1998; Kypreos & Cadena, 1998). In (Barreto & Kypreos, 2004) 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, Beltrán-Morales, Stoyan, and Ortega-Rubio (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, Driesen, Haeseldonckx, Belmans, and Dhaeseleer (2005) and Alanne and Saari (1998) 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, Holen, & Hildrum, 2004; Mosetti, Poloni, & Diviacco, 1994), 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) EIA 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 (Cervellera, Chen, & Wen, 2006; De Ladurantaye, Gendreau, & Potvin, 2009; Gröwe-Kuska, Kiwiel, Nowak, RÖmisch, & Wegner, 2000; 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, Ordóñez, & Dessouky, 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 & 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, Pflug, & Wozabal, 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, Meade, Beasley, & Sharaia, 2000; Crama & Schyns, 2003; Jobst, Horniman, Lucas, & Mitra, 2001; Shaw, Liu, & Kopman, 2008; Stoyan & 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, Meade, and Chang (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, Garín, Merino, and Pérez (2007) and Shaw et al. (2008). Solution methods for energy-technology management problems typically involve initial assumptions and are not as abundant (Kanudia & 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.