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Designing effective and efficient incentive policies for renewable in generation expansion planning

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Designing effective and efficient incentive policies for renewable energy in generation expansion planning

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DEDICATION

I would like to dedicate this thesis to my parents Fumin Zhou and Fengzhen Shao without whose support I would not have been able to complete this work. I would also like to thank my brother Qiang Zhou and friends for their loving guidance during the writing of this work.

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ABSTRACT

We present a bilevel optimization approach to designing effective and efficient incentive policies for promoting renewable energy. The effectiveness of an incentive policy is its capability to achieve a goal that would not be achievable without it. Renewable portfolio standard is used in this thesis as the policy goal. The efficiency of an incentive policy is measured by the amount of intervention, such as taxes collected and subsidies paid, to achieve the policy goal. We obtain the most effective and efficient incentive policies in the context of generation expansion planning, in which a planner makes investment decisions to serve project demand of electricity. A case study is conducted on an integrated coal and electricity network representing the contiguous United States. Numerical analysis from the case study provides insights on the comparison of various incentive policies. The sensitivity of the incentive policies with respect to coal production, energy investment costs, and transmission capacity is also studied.

CHAPTER 1. OVERVIEW

1.1 Introduction to Policies for Renewable Energy

Renewable energy is energy which comes from natural resources such as sunlight, wind, rain, tides, and geothermal heat, which are renewable. Despite significant environmental and social benefits, renewable energy is economically and technically disadvantaged [1]. In 2009, President Barack Obama in the inaugural addresses called for the expanded use of renewable energy to meet the twin challenges of energy security and climate change. The president's plan calls for renewable energy to supply 10% of the nation's electricity by 2012, rising to 25% by 2025. In 2008, only 7% of the U.S. energy consumption came from renewable sources, with 84% from fossil fuels and 9% from nuclear [2].

Key barriers holding back the acceptance of renewable energy technologies, identified by the Office of Energy Efficiency and Renewable Energy at DOE [3], include lack of government policy support, high capital cost, and poor perception by public of renewable energy aesthetics. Often the results of barriers is to put renewable energy at economic, regulatory, or institutional disadvantage relative to other forms of energy supply.

1.1.1 Policies for renewable energy

In an effort to overcome these barriers, many countries around the world have implemented various environmental policies [4, 5, 6, 7, 8], most of which belong to one of the three major types:

- Mandates such as renewable portfolio standard (RPS), which is a regulation that requires

the increased production of energy from renewable energy sources, such as wind, solar, biomass, and geothemal. As of June 2010, mandatory RPS policies have been passed in 31 U.S. states and the the District of Columbia, with six additional states approving conditional or non-mandatory renewable goals. According to a new market study, state renewable portfolio standards will be the most critical driver determining the pace of U.S. renewable growth going forward. Meanwhile, state RPSs would be significantly strengthened if complemented by a federal RPS or energy policy that addresses transmission bottlenecks which will be critical to sustaining renewable growth toward the middle of the next decade.

- Incentives such as carbon tax, which is an environmental tax that is levied on the carbon content of fuels. A carbon tax is a price instrument because it sets a price for carbon dioxide emissions from burning of fossil fuels, such as coal, petroleum products such as gasoline and natural gas. Accordingly, a carbon tax increases the competitiveness of non-carbon technologies compared to the traditional burning of fossil fuels, to help protect the environment.

- Markets such as cap-and-trade, which is a market-based approach used to control pollution by providing economic incentives for achieving reductions in the emission of pollutants. Cap and trade is an environmental policy tool that delivers results with a mandatory cap on emission while providing sources flexibility in how they comply. Successful cap and trade programs reward innovation, efficiency, and early action and provide strict environmental accountability without inhibiting economic growth. Example of successful cap and trade programs include the nationwide Acid Rain Program and the regional NO_x Budget Trading Program in the Northeast. Additionally, EPA issued the Clear Air Interstate Rule (CAIR) on March 10, 2005, to build on the success of these programs and achieve significant additional emission reductions.

1.1.2 Evaluation of an incentive policy

We evaluate the effectiveness of an incentive policy by its capability to achieve a renewable portfolio standard, which requires a minimal percentage of electricity generation come from renewable energy sources. This evaluation is conducted in the context of generation expansion planning (GEP) [9, 10, 11, 12, 13, 14, 15], because the current installed renewable generation capacity is far less than sufficient to meet the renewable portfolio standards set by many states in America [16]. Without policy intervention, generation expansion planning in restructured electricity markets is mainly profit-maximization and cost-minimization oriented [10], which would lead to the least expensive – and most likely the least renewable – energy portfolio. An effective policy would be able to improve the cost competitiveness of renewable energy in the short term and accelerate technology development in the long term.

Besides effectiveness, cost efficiency is another important measure of an incentive policy, which is based on how much intervention it takes to achieve a policy goal. The intervention includes taxes collected, subsidies paid, or GEP cost increase as a result of the policies. The less intervention it takes to achieve a goal, the more efficient a policy is, since taxes and GEP cost increases need to be borne by the energy system and subsidies require expenditure of tax payers' money. Cost efficiency of renewable energy policies is a worldwide grand challenge [17, 18, 19, 20, 21], especially under the current economy.

1.2 Bilevel Optimization for Incentive Policy Design

We presents a novel bilevel optimization approach to designing effective and efficient incentive policies.

A typical optimization problem is a forward problem since it needs to find an optimal given the values of parameters, which include cost coefficients and constraints. Inverse optimization [27, 28, 30, 35, 37] is a branch of bilevel optimization that deals with finding a minimal perturbation of the objective function of an optimization problem in order to make a target solution

optimal.

In the GEP context, the target solution is an expansion strategy that represents a healthier tradeoff between economic benefit and environmental impact but would not be optimal under a cost-minimization framework, and the minimal perturbation is the most efficient incentive policy that could make the target expansion strategy become optimal under the policy intervention. Let the GEP problem be represented with the following mixed integer linear program

$$\min \quad c^\top x \tag{1.1}$$

$$\text{s.t.} \quad Ax \geq b \tag{1.2}$$

$$x \geq 0, x_I \in \mathbb{Z}^{|I|}, \tag{1.3}$$

where $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$, $c \in \mathbb{R}^n$, and $I \subseteq \{1, ..., n\}$. Without any policy intervention, suppose x^* is the optimal solution to the GEP (1.1)-(1.3), which can be expected to include little or no investment in renewable energy.

Suppose our target investment strategy is required to satisfy an additional constraint $H\hat{x} \leq h$, which is represents the policy effectiveness requirement, such as including a healthier portfolio of investment in renewable and non-renewable energy. The incentive policy design problem can be mathematically posed as to find a minimal incentive perturbation Δc, measured by some norm $f(\Delta c, x)$, such that the target solution x becomes optimal to the incentivized GEP:

$$\min_{x, \Delta c} \quad f(\Delta c, x) \tag{1.4}$$

$$\text{s.t.} \quad Hx \leq h \tag{1.5}$$

$$x \in \operatorname{argmin}_{\tilde{x}}\{(c + \Delta c)^\top \tilde{x} : A\tilde{x} \geq b, x \geq 0, \tilde{x}_I \in \mathbb{Z}^{|I|}\}. \tag{1.6}$$

1.3   Research Objective

Many [22, 23, 25, 26] studies have analyzed the environmental policies adopted at the federal and/or state level for promoting renewable energy. Most of these studies focus on the consequences and implications of the policies. The main objective of our research is to address a perhaps more fundamental issue: how the policies should be designed in the first place to be most effective and efficient?

The first objective is to present efficient and efficiency incentive policies design models. For such purpose, recent advances [27, 28] in inverse optimization have provided suitable modeling tools. In [29], we introduced an earlier and over simplified inverse optimization model for incentive policy design, in which the target investment strategy is supposed to be exogenously determined rather than endogenously obtained by the model. The models presented here extend such unrealistic limitation and provide a more powerful decision tool to not only design incentive policies but also obtain the optimal investment tradeoff. Here constraint (??) enforces the effectiveness of the policy, constraint (1.6) anticipates the consequences of the policy, and objective (1.4) minimizes the policy intervention (thus maximize the policy efficiency).

The second objective is to present new algorithm for the incentive policy design models. The incentive policy design model is a complex bilevel problem, in which the the upper level has a nonlinear nonconvex objective function and the lower level involves both continuous and discrete decision variables. As far as we are aware of, there are no existing algorithms for solving bilevel problems of such complexity. We try to propose a heuristic algorithm for this problem.

The third objective is to demonstrate our models and solution techniques through a case study, which is an integrated coal and electricity network of the U.S. continent with real historical data. We compare the effectiveness and efficiency of the mandatory renewable portfolio standard and several incentive policies, representing the production tax credit, investment tax
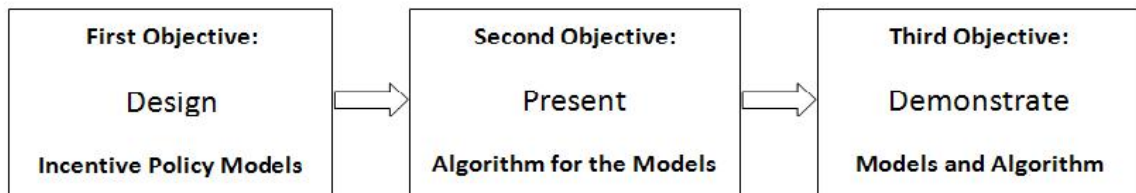
Figure 1.1   Research objectives

credit, carbon taxes, etc.

In summary, the objectives are to:

- Design incentive policies to stimulate the renewable energy's development to overcome the limitations of existing policies.

- Present efficient algorithm to solve the incentive policy design models based on the existing algorithm for the inverse optimization.

- Demonstrate our models and solution techniques through a case study and analyze the sensitivity of our models.

1.4   Thesis Organization

Chapter 2 reviews the relevant literatures about the generation expansion planning, policies for renewable energy and inverse algorithm. Chapter 3 introduces the incentive policy design and mandatory policy models and proposes a heuristic algorithm for the incentive policy design model. Chapter 4 presents a case study on an integrated coal and electricity networks. Algorithm implementation, computational experiment results are reported. Conclusion and future research follow in Chapter 5.

CHAPTER 2.   REVIEW OF LITERATURE

In this chapter, we review some literatures on models for GEP, government incentive policies and inverse optimization.

2.1   Generation Expansion Planning

The optimization models for GEP include: game-theoretic models, stochastic programming models and multiobjective models etc. Chuang et al. [11] and Murphy et al. [15] apply the Cournot model of oligopoly to model GEP. The model of Chuang et al. incorporate plant capacity limitations and energy balance constraint in competitive environments dominated by auction markets. They present an analytical formulation of the generation planning process involving decisions on new plant construction at a single point in time with multiple technology options available. Murphy et al. analyze three capacity expansion models in the context of a restructured electricity industry. The first model assumes a perfect, competitive equilibrium. The second model (open-loop Cournot game) extends the Cournot model to include investments in new generation capacities. The third model (closed-loop Cournot game) separates the investment and sales decision with investment in the first stage and sale in the second stage. Mo et al. [14] and Lopez et al. [12] model the GEP using stochastic programming. Mo et al. provide a method using Markov Chains to handle some uncertainties such as energy demand and prices of energy carriers. The new model can construct a connection between investment decision, time, construction periods, and uncertainty. Lopez et al. present a stochastic programming with probabilistic constraints to consider random events in generation and transmission expansion. Meza et al. [13], Antunes et al. [10] and Ahmed et al. [9]

propose a multiobjective model for generation expansion planning (MGEP). The objectives of the model in [13] are the minimization of investment, operation and transmission costs, environment impact, imports of fuel and fuel prices risks of the whole system. Multiobjective linear programming and analytical hierarchy process are made use of to solve this problem. The model of Antunes et al. is presented to provide decision support in the evaluation of power generation capacity expansion policies. The objective functions are the total expansion cost, the environmental impact associated with the installed power capacity and the environmental impact associated with the energy output. Ahmed et al. use a scenario tree approach to model the evolution of uncertain demand and cost parameters, and fixed-charge cost function to model the economies of scale in expansion costs.

2.2   Policies for Renewable Energy

There exists a vast literature on policies to support renewable energy and reduce gas emission. We list five policies: generation subsidy for renewable energy [5, 23], tax on fossil fuel energy [24], portfolio standards [7], subsidies for R&D [8, 26] and price on carbon [6]. Loiter and Norberg-Bohm [23] present a study of technological and policy history of the development of wind power in the United States. Greenberg and Murphy [5] provide a framework for representing selected price-oriented government regulations in mathematical programming model of a market. Roy et al. [24] evaluate the cost and benefits of energy taxation as a policy instrument to conserve energy and reduce CO_2 emissions. Rader and Norgaard [7] provide the correct use of economics can fashion policies to structure the market so that social goal of reliability, environmental quality and equity are attained most efficiently. Nemet and Baker [26] compare effects of R&D and demand subsidies on the future costs of purely organic photovoltaics (PV) which is not currently commercially available. They combine an expert elicitation and a manufacturing cost model to compare the outcomes of policy choices over various scenarios. Solomon and Banerjee [8] survey the global status of hydrogen energy research and devlopment (R&D) and public policy. Goulder [6] considers alternative tax designs

that different according to the tax treatment of internationally trades goods and the use of tax revenues.

2.3   Inverse Optimization

Inverse problems originated from geophysical sciences [30], in which the values of model parameters must be inferred from values of given observable parameters. Since Burton and Toint published their paper on an instance of the inverse shortest paths problem, inverse problems have been studied extensively by researchers. There has been a number of papers concerning inverse optimization problems, such as inverse linear programming [31], inverse maximum flow and minimum cut [32], inverse minimum assignment [31], inverse minimum spanning tree [33], inverse shortest arborescence [34], etc. The purpose of these inverse problems is to make minimum change on the parameters in these problems so that a given feasible solution will become the optimal one. Existing studies [35, 37] of inverse optimization have mainly focused on inverse linear programming problems, in which the lower level optimization is a linear program. The inverse linear programming problem has first been investigated by [36]. They formulate the inverse linear programming problem as a new linear program. Wang [28] extends this model to inverse mixed integer linear programming problems, which allow the lower level to contain integer variables as well as continuous ones. This is particularly important for GEP, in which the discrete nature of some investment decisions must be taken into account.

CHAPTER 3.   MODELING AND ALGORITHM

3.1   GEP and Policy Design Modeling

In this section, we present our incentive policy design model, which consists of two levels of optimization. At the lower level, a central decision maker is supposed to expand the generation capacity of an energy system to serve projected load with minimum total cost, including both generation costs and investment costs. At the upper level, a policy maker aims to influence the decision of the lower level planner by applying incentive policies. We also introduce a mandatory policy model, in which the generation expansion planner is required to have a certain percentage of power generation from renewable sources. The notations used in this section are are summarized in Section 3.1.1. The optimization models of the GEP and incentive policy design are presented in Sections 3.1.2 and 3.1.3, respectively.

3.1.1   Notations

Sets

- $\mathcal{I}$: Set of coal production nodes.

- $\mathcal{J}$: Set of electricity generation nodes.

- $\mathcal{K}$: Set of transportation links that connect nodes in $\mathcal{I}$ and nodes in $\mathcal{J}$.

- $\mathcal{L}$: Set of transmission lines that connect nodes in $\mathcal{J}$.

Parameters

- G_i: Coal production capacity (ton) at node $i \in \mathcal{I}$.

- P_i^C: Coal production cost (\$/ton) at node $i \in \mathcal{I}$.

- F_k: Coal transportation capacity (ton) at link $k \in \mathcal{K}$.

- P_k^T: Coal transportation cost (\$/ton) at link $k \in \mathcal{K}$.

- A^C, A^E: Rows in the node-arc incidence matrix in the undirected network comprised of $\{\mathcal{I} \cup \mathcal{J}, \mathcal{K}\}$ that correspond to nodes $\mathcal{I}$ and $\mathcal{J}$, respectively.

- D_j: Average electricity demand (MW) at node $j \in \mathcal{J}$.

- B_j^C: Overnight investment cost (\$) of new coal generation units at node $j \in \mathcal{J}$.

- B_j^W: Overnight investment cost (\$) of new wind generation units at node $j \in \mathcal{J}$.

- V_j^C: Variable operating and maintenance (O&M) cost (\$/MWh) for existing coal generation units at node $j \in \mathcal{J}$.

- V_j^W: Variable O&M cost (\$/MWh) for existing wind generation units at node $j \in \mathcal{J}$.

- V_j^{NC}: Variable O&M (\$/MWh) cost of new coal generation units at node $j \in \mathcal{J}$.

- V_j^{NW}: Variable O&M (\$/MWh) cost of new wind generation units at node $j \in \mathcal{J}$.

- F_j^C: Fixed variable O&M (\$/MW) cost of new coal generation units at node $j \in \mathcal{J}$.

- F_j^W: Fixed variable O&M (\$/MW) cost of new wind generation units at node $j \in \mathcal{J}$.

- Q_j^C: Total capacity (MW) of the existing coal generation units at node $j \in \mathcal{J}$.

- Q_j^W: Total capacity (MW) of the existing wind generation units at node $j \in \mathcal{J}$.

- ΔQ_j^C: Total capacity (MW) of one new coal generation unit at node $j \in \mathcal{J}$.

- ΔQ_j^W: Total capacity (MW) of one new wind generation unit at node $j \in \mathcal{J}$.

- T_l: Capacity of transmission line $l \in \mathcal{L}$.

- H: Power transfer distribution factors (PTDF) matrix. PTDF matrix gives the linear relation between net injection at each node and power flow through line. Net injection is the total power flow going into a node less the total power flow going out of it.

- α: Tonnage of coal needed to generate one MWh of electricity (ton/MWh).

- R^C: Discount factor of overnight investment cost for new coal generation units.

- R^W: Discount factor of overnight investment cost for new wind generation units.

- r: Percentage requirement of a renewable portfolio standard.

Lower Level Decision Variables

- f_k: Quantity (ton) of coal transported through link $k \in \mathcal{K}$.

- g_i: Quantity (ton) of coal production at node $i \in \mathcal{I}$.

- x_j: Quantity (MWh) of electricity generated by existing coal generation units at node $j \in \mathcal{J}$.

- y_j: Quantity (MWh) of electricity generated by existing wind generation units at node $j \in \mathcal{J}$.

- Δx_j: Quantity (MWh) of electricity generated by new coal generation units at node $j \in \mathcal{J}$.

- Δy_j: Quantity (MWh) of electricity generated by new wind generation units at node $j \in \mathcal{J}$.

- N_j^C: Integer number of new coal generation units at node $j \in \mathcal{J}$.

- N_j^W: Integer number of new wind generation units at node $j \in \mathcal{J}$.

Upper Level Decision Variables

- $s_j^{B^W}$: Investment subsidy policy (\$) for new wind generation units at node $j \in \mathcal{J}$.

- $s_j^{V^W}$: Production subsidy policy (\$) for existing wind generation units at node $j \in \mathcal{J}$.

- $s_j^{V^{NW}}$: Production subsidy policy (\$) for new wind generation units at node $j \in \mathcal{J}$.

- $t_j^{B^C}$: Investment tax policy (\$) for coal generation units at node $j \in \mathcal{J}$.

- $t_j^{V^C}$: Production tax policy (\$) for existing coal generation units at node $j \in \mathcal{J}$.

- $t_j^{V^{NC}}$: Production tax policy (\$) for new coal generation units at node $j \in \mathcal{J}$.

3.1.2 The generation expansion planning model

In a GEP problem, a planner aims to expand the generation capacity of an energy system to serve projected load with minimum cost. The energy system we consider consists of an electricity generation/transmission network and a coal production/transportation network.

In the electricity network, we use $\mathcal{J}$ to denote the set of electricity generation nodes and $\mathcal{L}$ the set of transmission lines that connect these nodes. In the coal network, $\mathcal{I}$ is the set of coal production nodes and $\mathcal{K}$ is the set of transportation links that connect coal nodes $\mathcal{I}$ an electricity nodes $\mathcal{J}$.

At each coal production node $i \in \mathcal{I}$, the coal production capacity is G_i (ton) and the cost is P_i^C (\$/ton). For each link $k \in \mathcal{K}$, the transportation capacity is F_k (ton) and the transportation cost is P_k^T (\$/ton).

At each electricity generation node $j \in \mathcal{J}$, the overnight investment costs of new coal and wind generation units are B_j^C (\$) and B_j^W (\$), respectively. R_j^C and R_j^W are the respective discount factors that convert the lump sum costs to hourly costs. The variable O&M costs of new coal and wind generation units are V_j^{NC} (\$/MWh) and V_j^{NW} (\$/MWh), respectively. The fixed variable O&M costs of new coal and wind generation units are F_j^C (\$/MW) and F_j^W (\$/MW), respectively. The capacity of one additional coal or wind generation unit is ΔQ_j^C

(MW) or ΔQ_j^W (MW), respectively.

In the undirected network defined by $\mathcal{N} = \{\mathcal{I} \cup \mathcal{J}, \mathcal{K}\}$, we use A^C and A^E to denote the rows in the node-arc incidence matrix that correspond to nodes $\mathcal{I}$ and $\mathcal{J}$, respectively. At each node $j \in \mathcal{J}$, the average electricity demand is D_j (MWh); the total capacity of the existing coal generation units is Q_j^C (MW); the total capacity of the existing renewable generation units is Q_j^W (MW); variable operating and maintenance (O&M) cost for existing coal generation units is V_j^C (\$/MWh); the variable O&M cost for existing renewable power generation units is V_j^W (\$/MWh). For each link $l \in \mathcal{L}$, T_l (MW) is the capacity of transmission line l. We denote H as the power transfer distribution factors (PTDF) matrix and α (ton/MWh) as the tonnage of non-renewable needed to generate a MWh of electricity.

We introduce the decision variables in the GEP model as follows. At each coal production node $i \in \mathcal{I}$, g_i (ton) is the quantity of coal production. For each link $k \in \mathcal{K}$, f_k (ton) is the quantity of coal transported through link $k \in \mathcal{K}$. At each electricity generation node $j \in \mathcal{J}$, x_j, y_j, Δx_j, and Δy_j are MWh of electricity generation by existing coal, existing wind, new coal, and new wind generation units, respectively. N^C and N^W are integer number of new coal and wind generation units. The base case GEP model can be formulated as the following mixed integer linear program.

$$\min \quad (P^C)^\top g + (P^T)^\top f + (V^C)^\top x + (V^{NC})^\top \Delta x + (V^W)^\top y + (V^{NW})^\top \Delta y$$

$$+(R^C B^C + F^C)^\top \Delta Q^C N^C + (R^W B^W + F^W)^\top \Delta Q^W N^W \tag{3.1}$$

$$\text{s.t.} \quad \alpha(x + \Delta x) \leq A^E f \tag{3.2}$$

$$g = A^C f \tag{3.3}$$

$$H(x + \Delta x + y + \Delta y - D) \leq T_l \tag{3.4}$$

$$1^\top(x + \Delta x + y + \Delta y - D) = 0 \tag{3.5}$$

$$0 \leq \Delta x \leq \Delta Q^C N^C \tag{3.6}$$

$$0 \leq \Delta y \leq \Delta Q^W N^W \tag{3.7}$$

$$0 \leq x \leq Q^C \tag{3.8}$$

$$0 \leq y \leq Q^W \tag{3.9}$$

$$0 \leq f \leq F \tag{3.10}$$

$$0 \leq g \leq G \tag{3.11}$$

$$N^C, N^W \text{ integer.} \tag{3.12}$$

The objective function (3.1) is to minimize total GEP costs, including coal production and transportation cost, fixed and variable O&M cost, and discounted overnight investment cost. Constraint (3.2) is the coal supply capacity for electricity generation; (3.3) equates coal production and the amount available for transportation; (3.4) is the electricity transmission capacity limit; (3.5) is the network conservation constraint; (3.6) is the capacity of new coal generation units; constraint (3.7) is the capacity of new wind generation units; constraint (3.8) is the capacity of existing coal generation units; (3.9) is the capacity constraint of existing wind generation units; (3.10) is the capacity constraint of existing coal transportation; (3.11) is the capacity constraint of coal production; and (3.12) requires that the number of new generation units be an integer.

3.1.3   The incentive policy design model

The incentive policy design model is a bilevel optimization problem. The lower level is a GEP problem under tax and/or subsidy intervention:

$$\min \quad (P^C)^\top g + (P^T)^\top f + (V^C + t^{VC})^\top x + (\Delta V^C + t^{VNC})^\top \Delta x$$

$$+ (V^W - s^{VW})^\top y + (V^{NW} - s^{VNW})^\top \Delta y$$

$$+ (R^C B^C + F^C + t^{BC})^\top \Delta Q^C N^C + (R^W B^W + F^W - s^{BW})^\top \Delta Q^W N^W \quad (3.13)$$

$$\text{s.t.} \quad \text{Constraints (3.2)-(3.12).} \quad (3.14)$$

Here t^{VC}, t^{VNC}, t^{BC} are the taxes on $x, \Delta x, N^C$, and s^{VW}, s^{VNW}, s^{BW} are the subsidies on $y, \Delta y, N^W$, respectively.

The upper level's incentive policy design model is

$$\min \quad (t^{VC})^\top x + (t^{VNC})^\top \Delta x + (t^{BC})^\top \Delta Q^C N^C$$

$$+ (s^{VW})^\top y + (s^{VNW})^\top \Delta y + (s^{BW})^\top \Delta Q^W N^W$$

$$+ (P^C)^\top g + (P^T)^\top f + (V^C)^\top x + (V^{NC})^\top \Delta x + (V^W)^\top y + (V^{NW})^\top \Delta y$$

$$+ (R^C B^C + F^C)^\top \Delta Q^C N^C + (R^W B^W + F^W)^\top \Delta Q^W N^W$$

$$- \text{constant} \quad (3.15)$$

$$\text{s.t.} \quad 1^\top (y + \Delta y) \geq r \cdot 1^\top (x + \Delta x + y + \Delta y) \quad (3.16)$$

$$\{x, \Delta x, y, \Delta y, N^W, N^C\} \in \operatorname{argmin}\{(3.13) : \text{Constraints (3.2)-(3.12)}\}. \quad (3.17)$$

The objective function (3.15) is to minimize the total cost of policy intervention, including taxes collected (first line), subsidies paid (second line), and the GEP cost increase (third and fourth lines). The constant term is the GEP cost without policy intervention calculated from (3.1)-(3.12). Constraint (3.16) uses the renewable portfolio standard that require 100r% as the implicit policy goal, and (3.17) is the anticipated response from the lower level.

3.1.4 The mandatory policy model

We also present the GEP under mandatory policy model to provide a benchmark comparison. In this model, no taxes or subsidies are imposed to the objective function, but the renewable portfolio standard is explicitly enforced to the GEP problem as an additional constraint:

$$\min \quad \text{Objective (3.1)} \tag{3.18}$$

$$\text{s. t.} \quad 1^\top(y + \Delta y) \geq r \cdot 1^\top(x + \Delta x + y + \Delta y) \tag{3.19}$$

$$\text{Constraints (3.2)-(3.12).} \tag{3.20}$$

3.2 Algorithm for Incentive Policy Design Model

The base case GEP model (3.1)-(3.12) and the GEP under mandatory policy model (3.18)-(3.20) are mixed integer programs, for which there exist efficient solvers. However, the incentive policy design model (3.15)-(3.17) is a complex bilevel problem, in which the upper level has a nonlinear non-convex objective function and the lower level involves both continuous and discrete decision variables. As far as we are aware of, there are no existing algorithms for solving bilevel problems of such complexity. In this section, we propose a heuristic algorithm for this problem.

We first introduce a revised version of the cutting plane algorithm from [28] for solving the inverse mixed integer linear programming (InvMILP) problem, and then present the heuristic algorithm that uses the InvMILP algorithm as a subroutine to solve the incentive policy design problem (3.15)-(3.17).

3.2.1 Definition of inverse mixed integer linear program

Let $\mathcal{IP}(A, b, c, I)$ denote an instance of mixed integer linear program (MILP)

$$\max_x \{c^\top x : Ax \leq b, x \geq 0, x_I \in \mathbb{Z}\}, \tag{3.21}$$

where $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m, c \in \mathbb{R}^n$, and $I \subseteq \{1, ..., n\}$. An InvMILP is to minimally perturb c in order to make the given feasible solution x^d optimal. In other words, it's to find a direction d that satisfies two conditions. Firstly, the direction d makes given feasible solution x^d optimal to MILP ([28]); secondly, the difference between c and d, measured by $||c - d||$, is minimal among all the directions that can make x^d optimal. In this thesis, we focus our discussion on the weighted L_1 norm, so $||c - d||$ becomes $w^\top |c - d|$, where $w \in \mathbb{R}_+^n$ is a constant vector. The straightforward formulation of the InvMILP under the weighted L_1 norm is

$$\min_d \{w^\top |c - d| : x^d \in \text{argmax}_x \{d^\top x : Ax \leq b, x \geq 0, x_I \in \mathbb{Z}\}\}. \tag{3.22}$$

3.2.2 Cutting plane algorithm for inverse optimization

We first introduce a revised version of the cutting plane algorithm from ([28]) for solving the InvMILP, which we refer to as $\text{Alg}^{\text{InvMILP}}$. The $\text{Alg}^{\text{InvMILP}}$ algorithm solves InvMILP problems defined as follows. For a given solution $\hat{x} \in \mathbb{R}^n$ to the mixed integer linear program (1.1)-(1.3), find a minimal intervention $t, s \in \mathbb{R}_+^n$, measured by $\hat{x}^\top(t + s)$, such that $\hat{x}$ becomes an optimal solution to $\min\{(c + t - s)^\top x : \text{constraints (1.2)-(1.3)}\}$:

$$\min \qquad \hat{x}^\top(t + s) \tag{3.23}$$

$$\text{s.t.} \quad \hat{x} \in \text{argmin}\{(c + t - s)^\top x : \text{constraints (1.2)-(1.3)}\}. \tag{3.24}$$

Here t and s represent tax and subsidy policies, respectively, and the objective function (3.23) is to minimize the dollar amount of incentive policy intervention, either as subsidies paid to wind generation or taxed collected from coal generation. The $\text{Alg}^{\text{InvMILP}}$ algorithm consists of the following steps.

Step 0: Initialize $\mathcal{S}^0 = \emptyset$.

Step 1: Let (y^*, t^*, s^*) be an optimal solution to the following linear program:

$$\min_{y,t,s} \quad \hat{x}^\top t + \hat{x}^\top s \tag{3.25}$$

$$\text{s. t.} \quad A^\top y \le c + t - s \tag{3.26}$$

$$(c + t - s)^\top \hat{x} \le (c + t - s)^\top x^0, \quad \forall x^0 \in \mathcal{S}^0 \tag{3.27}$$

$$y, t, s \ge 0. \tag{3.28}$$

Step 2: Let x^0 be an optimal solution to $\min\{(c + t^* - s^*)^\top x : Ax \ge b, x \ge 0, x^I \in \mathbb{Z}^{|I|}\}$. If $(c + t^* - s^*)^\top \hat{x} \le (c + t^* - s^*)^\top x^0$, then stop. Otherwise update $\mathcal{S}^0 = \mathcal{S}^0 \cup \{x^0\}$ and go back to Step 1.

Theorem 1. *$Alg^{InvMILP}$ terminates finitely with an optimal solution to InvMILP (3.22) [28].*

Remark 1. In Step 0, $\mathcal{S}^0$ is initialized, which denotes the set of known extreme points of the convex hull of $\{Ax \le b, x \ge 0, x_I \in \mathbb{Z}^{|I|}\}$. The set $\mathcal{S}^0$ will be updated as new extreme points are discovered. Step 1 generates a lower bound solution $(c + t^* - s^*)$ that has the minimal intervention but may or may not make $\hat{x}$ optimal. Therefore, Step 2 checks the optimality of $\hat{x}$ with respect to $\min\{(c + t^* - s^*)^\top x : Ax \ge b, x \ge 0, x^I \in \mathbb{Z}^{|I|}\}$. If the answer is positive, then (t^*, s^*) is proved to be the optimal solution to (3.23)-(3.24); otherwise a new extreme point x^0 is generated and added to the set $\mathcal{S}^0$. The Step 1-Step 2 loop continues until the optimality of $\hat{x}$ is confirmed in Step 2. A detailed proof of finite convergence of $Alg^{InvMILP}$ to exact optimality can be found in [28].

Remark 2. Tax only or subsidy only policies can be modeled by adding additional constraints $s = 0$ or $t = 0$ to (3.25)-(3.28), respectively.

Remark 3. Although this algorithm is proved in [28] to finitely converge to the optimal solution to (3.23)-(3.24), it is insufficient to solve the incentive policy design model (3.15)-(3.17). This is because the algorithm only finds the optimal incentive policy for a prescribed GEP solution $\hat{x}$, but the incentive policy design model needs to find the optimal GEP solution

endogenously rather than take it as exogenously provided. As illustrated in Figure 3.1, the GEP problem is inherently cost minimization oriented. Therefore, an incentive policy (t, s) is indispensable to achieve any GEP solution $\hat{x}$ that compromises cost efficiency for more renewable energy. The incentive policy design model (3.15)-(3.17) requires both an optimal GEP solution $\hat{x}$ and the most efficient policy (t, s) to achieve it.
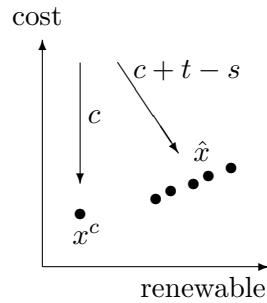
Figure 3.1   Illustration of $\text{Alg}^{\text{InvMILP}}$

3.2.3   Heuristic algorithm for incentive policy design model

In the incentive policy design problem (3.15)-(3.17), the lower level's decisions are not predetermined except that they should satisfy constraint (3.19), so the above algorithm does not directly solve this problem. We propose the following heuristic algorithm for problem (3.15)-(3.17):

Step A: Obtain 1001 GEP solutions. The first 1000 solutions are optimal solutions to (3.13)-(3.14) with 1000 randomly generated incentive policies $(s^{VW}, s^{VNW}, s^{BW}, t^{VC}, t^{VNC}, t^{BC})$.

The 1001st solution is an optimal solution to the GEP under mandatory policy model (3.18)-(3.20).

Step B: For each GEP solution, treat it as $\hat{x}$ and use the $\text{Alg}^{\text{InvMILP}}$ algorithm to obtain the optimal incentive. Among the 1001 incentive policies, choose the optimal one with respect to objective (3.15).

Figure 3.2   Heuristic algorithm for incentive policy design
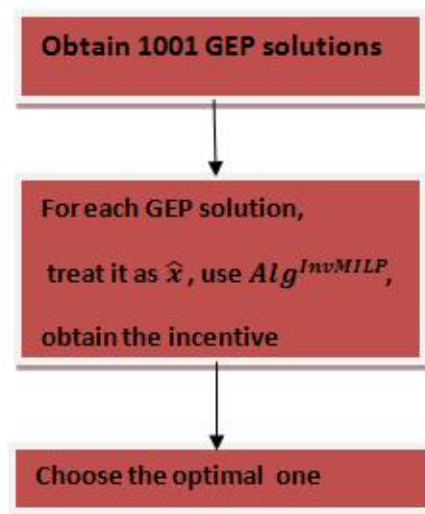
Remark 4. The need for the above heuristic algorithm is justified by two major difficulties of the model (3.15)-(3.17). First, the lower level contains both continuous and discrete decision variables. In a GEP problem, many investment decisions are inherently discrete, e.g., the deci-

sion to invest in a new wind farm in a specific location will incur a significant amount of capital cost that is independent of and non-proportional to the magnitude of generation capacity. This difficulty can be mitigated to some extent by ignoring the integrality constraints, which will reduced the constraint (3.17) to its complementary slackness conditions. The second difficulty with model (3.15)-(3.17) is the non-convexity and nonlinearity of the objective function (3.15). This is much more serious than the first one because there exists a finitely converging exact algorithm for the model with a linear objective function, but even integrality constraints are relaxed, the resulting model is still a nonlinear non-convex mathematical program with complementary constraints, for which even a local optimal solution is in general extremely hard to obtain. The heuristic algorithm we present tries to fish a good solution by randomly generating a large number of GEP solutions and then comparing their corresponding optimal incentive policies. A GEP solution will linearize the objective function (3.15) and make the model finitely solvable to global optimality by $\text{Alg}^{\text{InvMILP}}$.

CHAPTER 4.   CASE STUDY

In this section, we conduct a case study on an integrated energy system that consists of electricity generation/transmission and coal production/transportation networks. The integrated network represents the contiguous United States, which consists of 17 electricity generation nodes, 11 coal production nodes, 29 electricity transmission lines, and 187 transportation links connecting every coal production node with every electricity generation node.

4.1   Data Source

The coal network is illustrated in Figure 4.1 (data source: Energy Information Administration [2]). Table 4.1 summarizes the supply regions that the coal supply nodes represent as well as their production capacity and average minemouth price (data source: [38, 39, 40]). The electricity generation network is illustrated in Figure 4.2 and the regions that the nodes represent are summarized in Table 4.2 (data source: [41]). Table 4.2 also gives the supply and demand of electricity. Electricity transmission capacity data are given in Table 4.3. Table 4.4 presents overnight investment, variable O&M, and fixed O&M costs, which are obtained from [42]. We use α as 0.2.
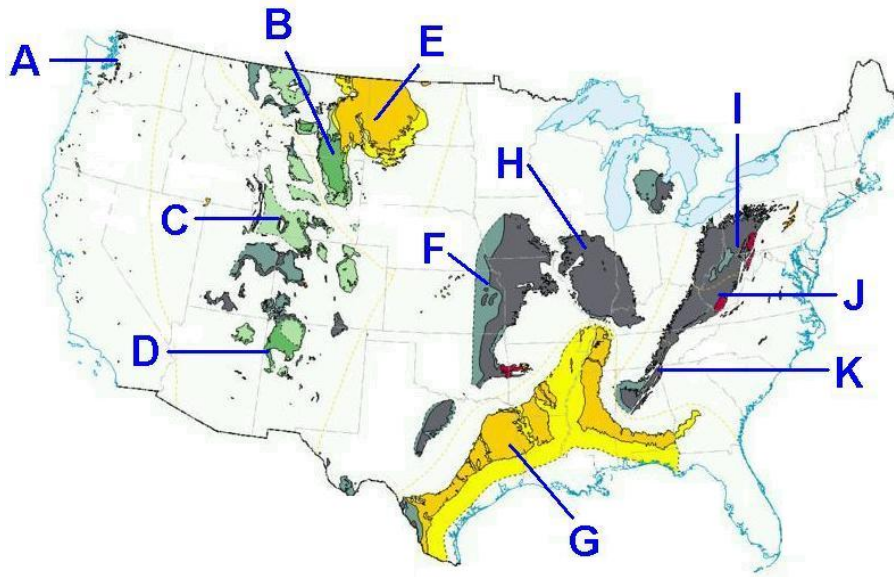
Figure 4.1   Coal supply network

Table 4.1   Coal supply network

Supply node	Region	Productive capacity (10^3 tons)	Average minemouth price (2002 \$/ton)
A	Northwest	8,166	15.90
B	Powder River Basin	53,581	17.48
C	Rocky Mountains	70,508	22.61
D	Southwest	44,173	19.78
E	North Dakota Lignite	33,500	13.27
F	Other Western Interior	3,228	23.28
G	Gulf Coast Lignite	54,549	13.03
H	Illinois Basin	114,917	22.10
I	Northern Appalachia	167,772	24.01
J	Central Appalachia	317,957	25.21
K	Southern Appalachia	29,661	25.36

Figure 4.2   Electric power transmission model

Table 4.2   Existing electricity generation capacity

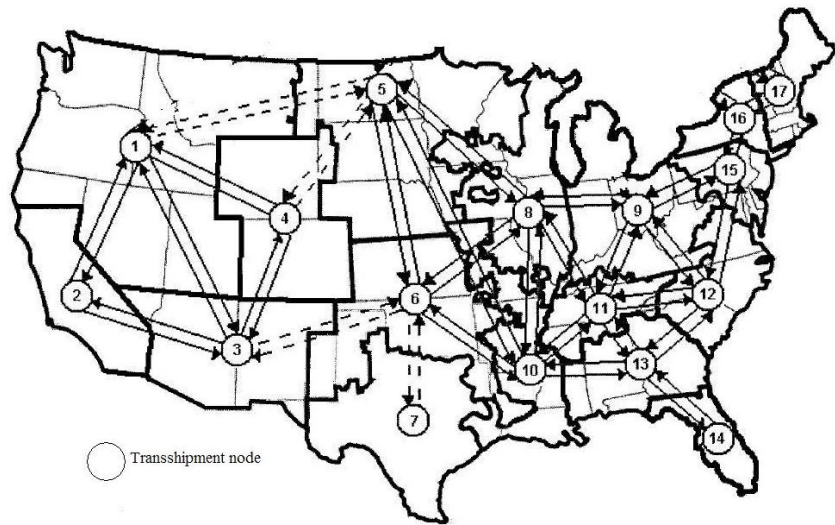| Node j	Region	Q_j^C	Q_j^W	D_j
1	Northwest	1,241	2,765	13,660
2	California	34	2,537	17,234
3	Arizona-New Mexico-Southern Nevada	552	496	8,057
4	Rocky Mountain	1,190	1,527	3,555
5	Mid-Continent	6,672	478	9,940
6	Southwest	8,420	1,199	13,547
7	Texas	3,317	6,698	19,772
8	Mid-America	15,134	3,256	18,904
9	East Central	22,195	300	36,704
10	Energy Electric System	3,981	1	9,291
11	Tennessee Valley Authority	4,067	29	10,756
12	Virginia-Caolinas	7,006	0	21,586
13	Southern Company	9,587	0	15,795
14	Florida Reliability Coordinating	1,785	0	14,819
15	Mid-Atlantic Area Council	7,317	374	19,136
16	New York ISO	1,326	6	11,029
17	ISO New England	973	43	9,137

Table 4.3   Transmission data

Link l	T_l	Link l	T_l	Link l	T_l	Link l	T_l
1-2	6,820	1-3	1,140	1-4	3,050	1-5	150
4-5	310	3-4	650	2-3	9,965	3-6	420
5-6	1,979	5-10	2,020	5-8	2,216	6-8	2,217
6-7	793	6-10	1,640	8-10	2,808	8-11	1,447
8-9	2,898	9-11	1,599	10-11	381	10-13	2,065
11-13	2,740	11-12	2,564	13-14	3,600	12-13	1,019
9-12	2,064	12-15	3,850	9-15	2,343	15-16	2,755
16-17	1,600						

Table 4.4   Cost of new coal and wind generation units

Type	Size (MW)	Total Overnight Cost ($/MW)	Variables O&M ($/MWh)	Fixed O&M ($/MW)
Coal	600	1,534,000	4.46	26,790
Wind	50	1,434,000	0.00	29,480
Wind Offshore	100	2,872,000	0.00	87,050

4.2   Implementation

The heuristic algorithm is programmed in Matlab, Tomlab and Cplex. Matlab is the interface software we use. Tomlab and Cplex are called by Matlab as tools to take charge of the calculations of optimization problems.

MATLAB stands for "MAtrix LABoratory" developed by MathWorks, which allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces. It is one of the fast and most enjoyable ways to solve problems numerically. The version we used in our implementation is Matlab 7.6.0 (R2008a). Tomlab is a general purpose development and modeling environment in MATLAB for research, teaching and practical solution of optimization problems. It enables a wider range of problems to be solved in MATLAB and provides many additional solvers. The version that we use is Tomlab is v6.1. Cplex optimizes are designed to solve large, difficult problems quickly and with minimal user intervention. The version we use is Cplex 11.0.

"MipAssign" is the main function that we use to set up a mix integer linear problem: "Prob = mipAssign(...)". It's then possible to solve the problem by using the Tomlab solver "mipSolve" with the call: Result = mipSolve(Prob).

4.3   Results

4.3.1   Different cases of policies

We first consider the GEP problem under the following cases of policies.

Case 0: GEP with no policies. In this case, no environmental policies are imposed, thus economic benefit is the only criterion for GEP. The base case GEP model (3.1)-(3.12) is solved, and the optimal solution shows that a total investment cost of $(V^{NC})^\top \Delta x + (R^C B^C + F^C)^\top \Delta Q^C N^C = \$1\text{M/hour}$ is spent on new coal-fired generation nationally and

only $(V^{NW})^{\top}\Delta y + (R^W B^W + F^W)^{\top}\Delta Q^W N^W = \$4,000$/hour on new wind generation. Such imbalanced investments would make the current 8% renewable energy portfolio even smaller.

Case 1: GEP with mandatory policy. In this case, the mandatory renewable portfolio standard is enforce to the energy system. Economic benefit is still the only criterion for GEP, but the mandatory policy is treated as an additional hard constraint. The GEP under mandatory policy model (3.18)-(3.20) is solved for the percentage requirement r of renewable portfolio standard ranging from 10% to 25%, and the total GEP cost from the optimal objective function (3.18) is plotted as a function of r in Figure 4.3. Although mandatory policies could effectively enforced policy goals, they are oftentimes unpopular, especially when renewable energy resources and techniques are too scarce and costly to meet the requirements. Figure 4.3 shows that if 25% of renewable generation was required under the current situation, the total GEP cost would be almost doubled, and this cost increase would be borne by the lower level energy system. Moreover, it remains a challenge to share the burden created by the mandatory policy among individual power suppliers in a fair manner.

Case 2: GEP with tax policy. In this case, the tax policy is used to penalize nonrenewable energy investment and generation. No additional constraints are imposed on the GEP problem, but any generation from non-renewable energy is taxed. This policy reflects the Carbon Tax policy. Although carbon taxes are usually on a \$/ton basis and imposed on carbon emissions rather than on electricity generation, we could use the emissions rates to translate such policies to a \$/MWh basis on non-renewable energy generation, which facilitates the comparison with subsidy policies. The tax policy is obtained using our optimal incentive policy design model (3.15)-(3.17) with an additional constraint that $s^{V^W}, s^{V^{NW}}, s^{B^W} = 0$, since subsidies are not used. The GEP costs from the third and fourth lines of (3.15) and taxes from the first line in (3.15) are plotted as functions of r in Figure 4.4. The white bars are GEP costs, the shaded ones are tax costs, and the solid curve is the GEP cost under mandatory policy. This figure shows the effectiveness of tax policies in achieving renewable portfolio standards.
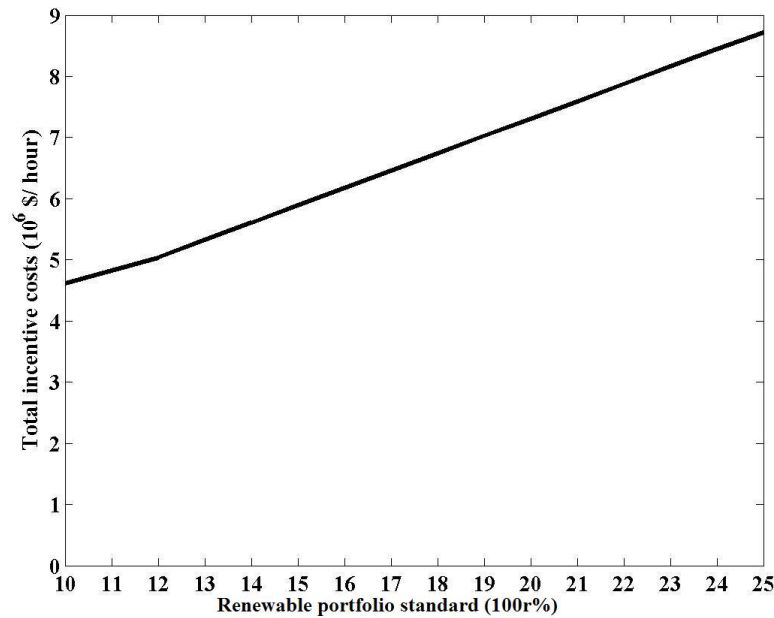
Figure 4.3   GEP costs under mandatory policy

However, the efficiency of the tax policies are extremely low, since the tax costs are close to or even higher than GEP costs. Another drawback is that even when the power suppliers have already achieved $r \times 100\%$ renewable energy generation, it still needs to pay taxes on the remaining $(1 - r) \times 100\%$ non-renewable generation. Therefore, even the most efficient tax policy appears to be too inefficient.

Case 3: GEP with subsidy policy. In this case, the subsidy policy is used to stimulate more renewable energy investment and generation. No additional constraints are imposed on the GEP problem, but any investment in and generation from renewable energy is sub-
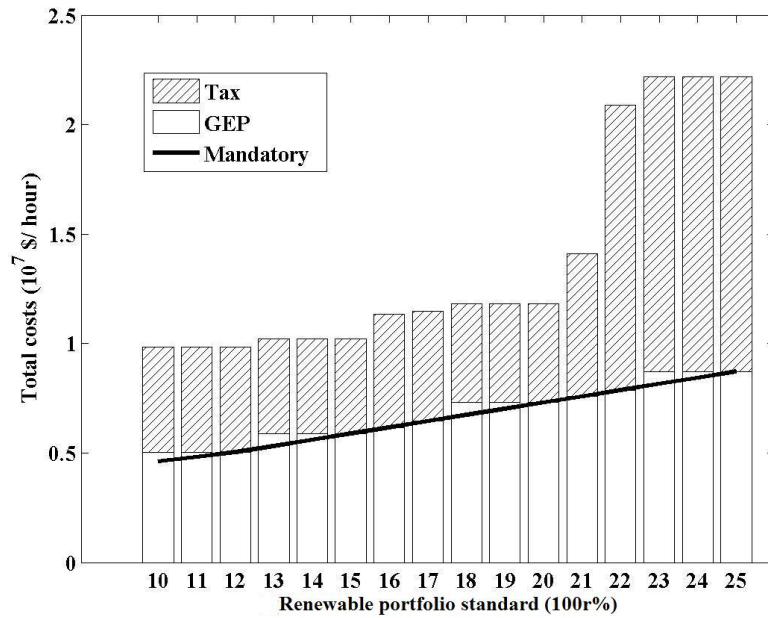
Figure 4.4   GEP costs and taxes under tax policy

sidized. This policy reflects the Renewable Production and Investment Tax Credits policies. The subsidy policy is obtained using our optimal incentive policy design model (3.15)-(3.17) with an additional constraint that $t^{BC}, t^{VC}, t^{VNC} = 0$, since taxes are not used. The GEP costs and subsidies are plotted as functions of r in Figure 4.5. Unlike in Figure 4.4, here the combined white and shaded bars are GEP costs and shaded ones are subsidies from the second line in (3.15), thus the white bars alone represent the net costs to the energy system. This figure shows that, to achieve the same goal, it requires spending much less subsidy dollars than collecting tax dollars. However, the efficiency of the subsidy policies is still low, since the energy system's net costs are not affected by increasing renewable portfolio standards and

only the government (thus tax payers) is baring the costs of a higher renewable energy portfolio.
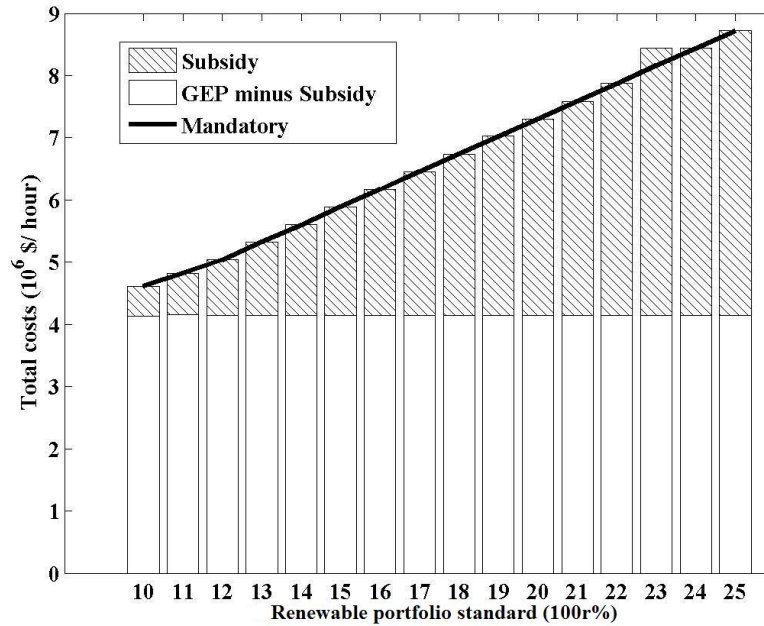

Figure 4.5   GEP costs and subsidies under subsidy policy

Case 4: GEP with combined tax and subsidy policies. In this case, taxes and subsidies can both be used at the same time, so it is a combination of Cases 2 and 3. The optimal incentive policy design model (3.15)-(3.17) is solved. The GEP cost, taxes, and subsidies are plotted as functions of r in Figure 4.6. The white bars are GEP costs, and the two shaded bars, differentiated in the legend, are taxes and subsidies. For all r values, the amount of tax dollars collected and subsidy dollars paid are always very close, thus the GEP costs are also the net costs to the energy system. This figure shows that when tax and subsidy policies are simultane-

ously imposed, they are much more efficient than either one type alone. The combined policies require less taxes and less subsidies, and result in neutral government revenue. It is also worth noting that the incentive policies are particularly efficient when the renewable portfolio goal is below 17%; much more incentives would be needed to achieve a higher policy goal. Of course, this threshold is dependent upon specific data being used, yet it demonstrates the capability of our incentive policy design models to determine appropriate policy goals taking into account the implications to the energy system. Compared to mandatory policy, the incentive policy leads to similar net GEP costs, but it also provides a consistent penalty/incentive mechanism to all power suppliers.

4.3.2   Sensitivity analysis of the policies

We also conduct sensitivity analysis on the efficiency of the policies with respect to coal production costs increase, wind energy investment costs decrease, and transmission capacity expansion.

As fossil fuel reserves become more and more depleted, the production cost can be expected to have an increasing trend in the future. Figure 4.7 is the counterpart of Figure 4.6 with the coal production costs being doubled. Although the GEP costs are almost doubled, the amount of incentives required to achieve a same policy goal is only slightly reduced. This is because wind operation cost is already lower than that of coal, whereas the wind capital investment cost is the real bottleneck that needs to be overcome by policy intervention.

For the past decade, renewable energy techniques have made significant progress and the investment costs continue to fall. Figures 4.8 and 4.9 compare the GEP costs and incentives, respectively, before and after the wind investment costs are reduced by 50%. With such costs decrease, not only the GEP costs are greatly reduced, it also requires much less incentives to achieve a same policy goal. These results demonstrate the sensitivity of the efficiency of
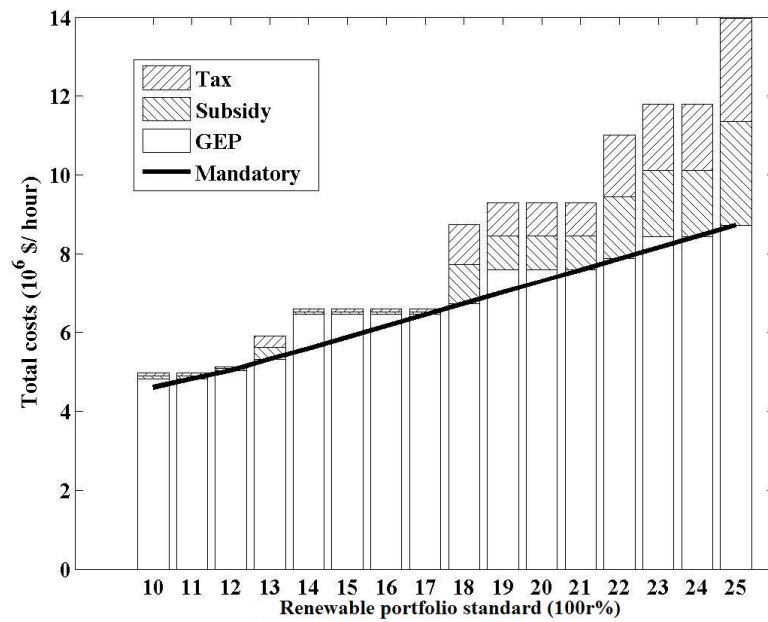
Figure 4.6   GEP costs and incentives under tax-subsidy policy

incentive policies with respect to capital investment cost, which also validate the long-term impact of incentive policies in promoting renewable energy.

Transmission capacity is another factor that could affect the effectiveness and efficiency of policies. In many cases, inadequate transmission capacity is a bottleneck for remote and windy areas to deliver wind power to load zones, thus building new transmission lines could effectively increase renewable energy generation. However, we show an example in which the removal of transmission lines would also increase the efficiency of incentive policies. We consider our electricity transmission network with links 1-2 and 2-3 removed, which makes California
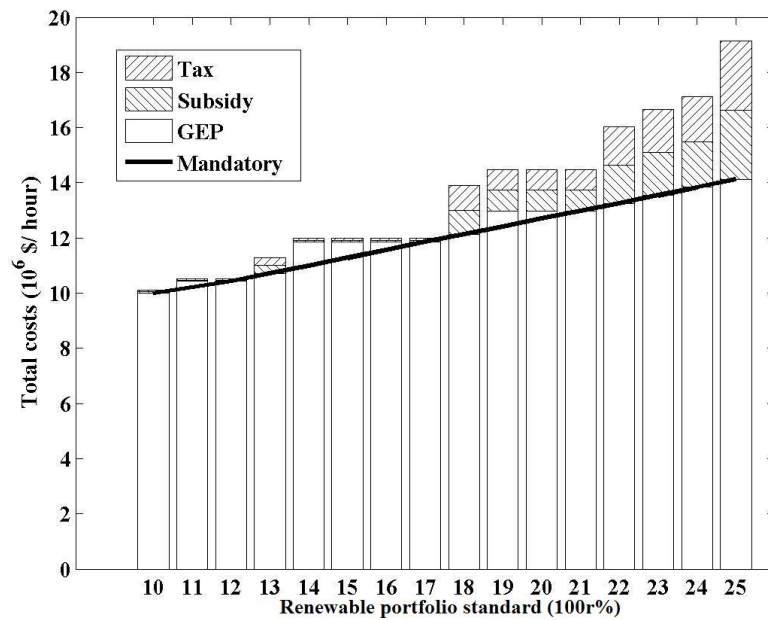
Figure 4.7   GEP costs before and after coal production costs increase

isolated from external supply of energy. Figures 4.10 and 4.11 compare the GEP costs and incentives before and after the removal of the links. Without the two links, although the GEP costs would be higher, it would actually require less incentives to achieve same renewable portfolio goals. This is because wind would become a pivotal resource for electricity generation when external supply becomes unavailable and local coal transportation has reached its limit. Therefore, careful analysis is necessary to determine the actual effect of addition or removal of transmission lines on renewable energy generation and policies.
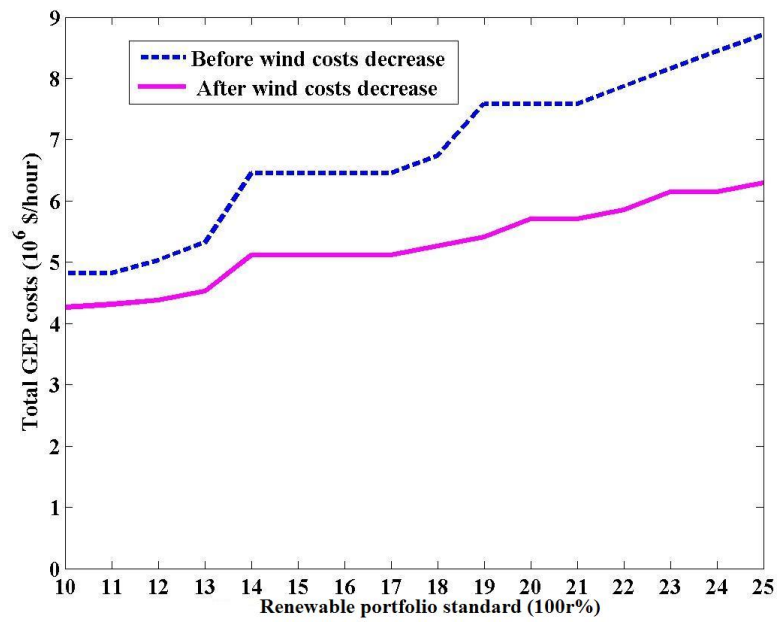
Figure 4.8   GEP costs before and after wind investment costs decrease
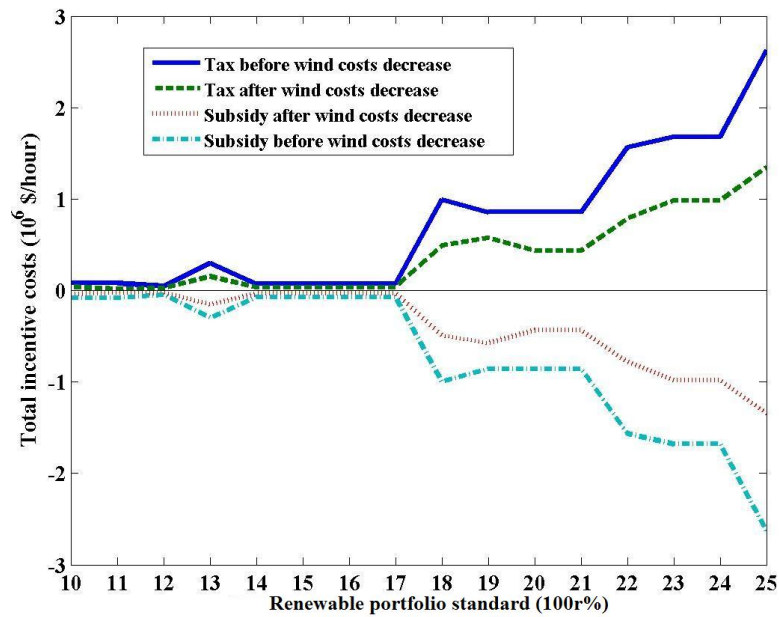
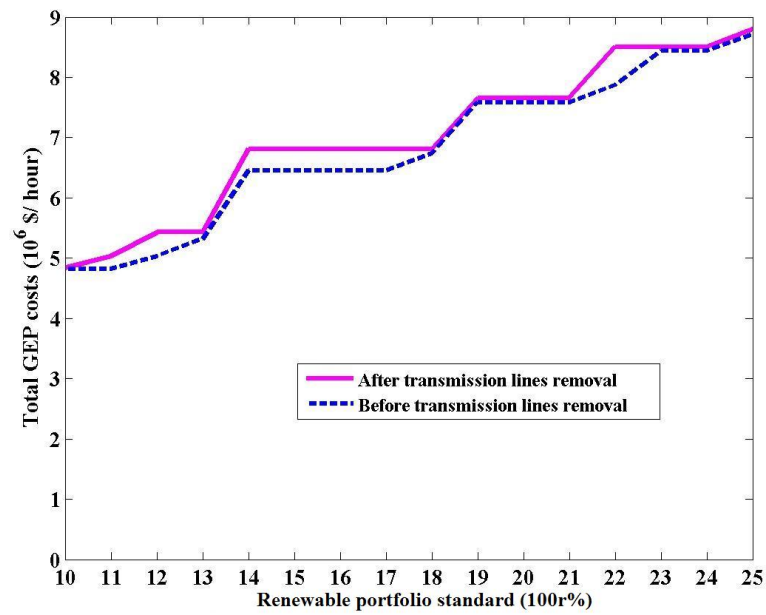Figure 4.9   Incentives costs before and after wind investment costs decrease

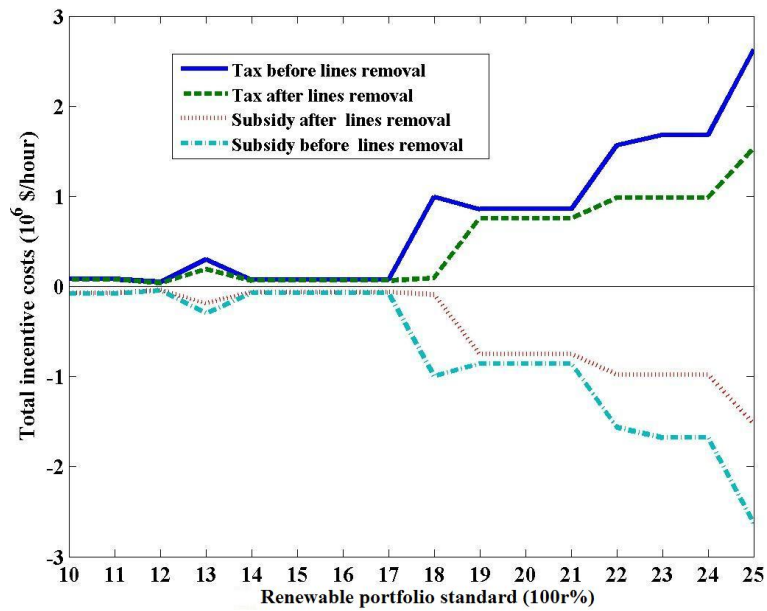Figure 4.10   The total GEP costs in two situations

Figure 4.11   The total incentive costs in two situations

CHAPTER 5.   CONCLUSION AND FUTURE WORK

5.1   Conclusion

We propose a bilevel optimization framework for designing effective and efficient incentive policies to promote renewable energy in a generation capacity planning problem. The effective of an incentive policy is its capability to achieve a goal that would not be achievable without it, whereas the efficiency is defined as the amount of intervention, including tax collected, subsidies paid, and GEP cost increase, to achieve the policy goal. The lower the intervention to achieve a goal, the higher the efficiency.

Our analysis of the incentive policies, as well as the comparison with mandatory ones, are in the context of generation expansion planning problem, in which the energy system makes the investment decisions to meet projected demand. The objective of our proposed inverse optimization model is to achieve a policy goal of renewable portfolio standard by promoting more investment in renewable energy with a minimal amount of policy intervention.

An integrated energy system with a coal production/transportation network and an electricity generation/transmission network representing the contiguous United States is used for a case study to demonstrate our approach. We gain the following insights from the results: (1) incentive policies, if designed carefully with our proposed inverse optimization model, could achieve the same policy goal as mandatory policies both effectively and efficiently; (2) combining taxes and subsidies in an incentive policy is much more efficient than using either one alone; (3) there could exist a policy threshold beyond which the efficiency of incentive policies dramatically drops; (4) renewable investment costs decrease has a greater impact than non-

renewable generation costs increase on the efficiency of incentive policies; and (5) the addition of transmission lines may or may not improve the efficiency of incentive policies.

5.2 Future Work

5.2.1 Future research on modeling

We will incorporate uncertainties about certain data parameters. The real circumstances in the integrated energy system are however characterized by imperfect information about data, namely electricity demands and fuel prices. A stochastic optimization problem formulation would enable handling uncertain data.

5.2.2 Further improvement of algorithm and data

In this thesis, the incentive policy design model is solved by the heuristic algorithm. There is no other heuristic algorithm for the policy design policy, we can't compare the efficiency. In the future study, we will conduct more research on further improvement of our heuristic algorithm. By comparing the optimal solution, we can further study the efficiency of the incentive policy design model. Moreover, the inverse optimization still needs more efficient algorithm. In addition, We will improve data quality and quantity. Many of the assumptions and modeling choices that have been made are the result of data limitations. A more complete and accurate set of data would facilitate a more comprehensive analysis.

5.2.3 Writing an open source software

As far as we know, there is no software available for designing effective and efficient incentive policies. We can write our algorithm into an open source software and publish it for researcher or policy makers to design incentive policies.

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