ENERGY MODELS FOR ELECTRICITY SECTOR WITH GREEN POLICIES AND TECHNOLOGIES

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ENERGY MODELS FOR ELECTRICITY SECTOR WITH GREEN POLICIES AND TECHNOLOGIES

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SUMMARY

A variety of energy models and tools have been used for an comprehensive analysis of the complex energy systems and the design of pathway to sustainable energy world. This thesis analyzes three interesting problems in the electricity sector by developing and using suitable energy models.

Chapter 2 investigates how to incorporate demand responsiveness for policy analysis in the electricity sector using a least-cost model. This study develops its own least-cost model which includes some characteristics for two important policies in the electricity sector, and suggests an iterative approach for incorporating the demand response to price change under new policy. Based on a case study, the state of Georgia, this chapter shows the effects of including demand response on the evaluation of policy.

Chapter 3 is about new technology adoption pathways in the electric power system. In this chapter, by investigating the related status of policies and specifications of electric vehicles and wind power technologies in the U.S., several adoption pathways of the technologies in the U.S. eastern interconnection have been developed. This study develops four-serial models for the estimation of future economic and environmental impacts of the technologies' penetration. The results show that the total greenhouse gas emissions of the entire energy system do not substantially decrease even with a high level of electric vehicle adoption. The combination of two technologies, even more with appropriate policies, can notably decrease the total greenhouse gas emissions.

Chapter 4 is a study about demand response programs, particularly optional time-based rates, for residential customers. This chapter analyzes the main reason that the participation of the current programs is low even though the programs have

benefits. This study investigates two policy tools, a subsidy for flexible residential demand and a shared-savings mechanism based on consumption pattern changes, and examines the implementation of the tools and their potential to overcome the current inefficient operation.

CHAPTER I

INTRODUCTION

The world is trying to transform from fossil fuel based energy systems to clean and smart energy systems. A number of new technologies and policies have been introduced for the transformation, so the energy systems are altered in complex and interdependent ways that are difficult to envision. How to design the transformation efficiently under limited resources, such as time and money, has been of interest recently. Design of the pathway to a sustainable energy world requires systematic approaches based on a comprehensive understanding of multidisciplinary issues, such as the scientific, technical, environmental, economic, and societal issues. During the pathway design, three imperatives are frequently identified [74]: 1) promote national and economic security by increasing energy independence, 2) enhance environmental stewardship and reduce energy and carbon intensity, and 3) generate continued economic growth through innovation in energy technologies and expansion of sustainable energy relevant jobs.

Energy and policy modeling have been used for an comprehensive analysis of the complex energy systems and the pathway design. The analysis is for energy economics, energy system planning, risk and uncertainty modeling, and energy infrastructure planning. The benefits of using modeling are [96] 1) The model can represent a very complex reality into a simpler form that is more suitable to comprehend and analyze. Thus, it can reveal more insights. 2) The model may act as an efficient filter in order to evaluate consequences of certain policies. In reality, such consequences may be difficult to relate to specific measures or policies due to noise. 3) The model can by used for forecasting with higher precision than the statistical methods, such as future prices of electricity in electricity market. 4) Using models enables the participants in a certain projects to gather around a common platform and communicate easily.

Some large-scale models cover the analysis of entire energy systems as well as macro-economy features at the global, national or regional level, e.g. the MARKet ALlocation (MARKAL) [61], PRIMES [79], and the U.S. National Energy Modeling System (NEMS) [69]. Furthermore, a variety of smaller size models and tools have been developed from research laboratories and universities, such as the Energy system modeling center at U.S. Argonne National Laboratory [1] and the Energy Analysis Department at U.S. National Renewable Energy Laboratory [2], and they have been used for their own special purposes respectively at global, regional, local, or project basis. In some cases, several models representing different methodologies are combined, such as The Integrated MARKAL-EFOM System (TIMES) [94] and the MARKAL-MACRO model [54]. The models must be coordinated and one of the main challenges is harmonization of all assumptions and input data [96].

The overarching goal of this thesis is analysis of some decisions on the sustainable pathway by developing suitable energy models based on the methodologies and the ability of systematic approaches, which I have learned from the industrial and systems engineering program. This thesis focuses on analysis of the electricity sector. The electricity generation sector is the largest source of greenhouse gas (GHG) emissions worldwide [32]. The complexity arising from numerous energy sources, technologies, and highly regulated market characteristics makes the electricity generation sector attractive to analyze based on models.

The rest of thesis consists of the following four chapters: Chapter 2: an electricity generation planning model incorporating demand response with new green policies; Chapter 3: integration of electric vehicles and wind into the grid; Chapter 4: demand

[1] $http://www.anl.gov/energy/energy-systems-modeling$
[2] $http://www.nrel.gov/analysis/models_tools.html$

response programs for residential customers; and Chapter 5: conclusions and future work.

More specifically, each chapter contains following contents: Chapter 2 represents the importance of incorporating demand response in the evaluation of electricity generation planning. Energy policies that aim to reduce carbon emissions and change the mix of electricity generation sources, such as carbon cap-and-trade systems and renewable electricity standards, can affect not only the source of electricity generation, but also the price of electricity and, consequently, demand. I develop an optimization model to determine the lowest cost investment and operation plan for the generating capacity of an electric power system. The model incorporates demand response to price change. This chapter shows that both the demand moderating effects and the generation mix changing effects of the policies can be the sources of carbon emissions reductions. In Chapter 3, my colleagues and I develop serial models to analyze future impacts of electric vehicles (EVs) and wind power on the electric power system and light-duty vehicle market. Metrics include greenhouse gas emissions, petroleum consumption, cost of electricity, and total consumer expenditure. We show that the total greenhouse gas emissions of the energy systems do not substantially decrease even with high levels of EV adoption. We explore a range of approaches to reducing the greenhouse gas, by controlling the time of charging and by matching vehicle charging to wind energy. Chapter 4 is a study about demand response programs, particularly optional time-based rates, for residential customers. I try to understand why current existing voluntary time-based rates do not operate well, and explore two approaches to increasing participation in the programs.

CHAPTER II

ELECTRICITY GENERATION PLANNING MODEL INCORPORATING DEMAND RESPONSE WITH NEW POLICIES

2.1 Background

Economic optimization models are used within the electric power sector to plan investment in new capacity; somewhat similar optimization models are used for energy policy planning and evaluation at the national and international level. Some of these analyses use existing energy policy models which have the advantage of widespread use and availability, yet may have the drawback of not being completely transparent or easily modifiable for the quantitative evaluation of policy options, or for evaluating the implications of changes in demand, prices, and technology over time. The objective here is to develop a transparent and flexible optimization model for analysis of the potential effects of energy policies, including changes in price, demand, and generation technologies, and to use this model to evaluate the effects of incorporation of demand response on the results.

Carbon cap-and-trade policies and renewable electricity standards are designed to affect the mix of sources used to generate electricity; either reducing the proportion of high-carbon generation, or increasing the proportion of renewable generation. The effects of these policies on electricity generation have been analyzed with models that assume the projected demand is not affected by the policy choice. However, since electricity demand is affected by price, policies that may affect the price of electricity

This chapter is based on a study published in *Energy Policy* 42: 429-441, 2012.

may affect electricity demand as well. Depending on how future demand is projected, results and analysis from optimization models may vary substantially.

Here we develop an optimization model for a electricity sector, such as a reliability region or a state in U.S. and a small single country, incorporating price elasticity of demand. The model is applied in a case study of a U.S. state, examining the generation, price, and demand implications of a carbon cap-and-trade policy with and without free permits, and a renewable electricity standard (RES).

2.2 Literature Review

In the early 1970s, mathematical programming models of various types were proposed for the capacity expansion planning problem of a power generation system [3, 8, 78]. Since the 1970s, this problem has been studied and developed into different linear, mixed-integer, and non-linear, or deterministic and stochastic models. The objective of these models is to determine not only the type, size, and commission dates for cost-effective new generation, but also the operation of the system. These models usually treat electricity demand, fuel prices, and technology as externally determined.

In the context of deregulation and restructuring of electricity sectors in many countries and U.S. states, a market equilibrium model approach for oligopolistic and competitive restructured electricity markets has been studied with generation capacity expansion planning models [15, 67]. These studies modeled electricity price and demand endogenously.

With advances in modeling methodologies, recent studies have used these models for policy planning and evaluation for the electricity market. Some power generation expansion planning studies developed their own models, which explicitly include a CO_2 emission target constraint and related policy and technologies [27, 64, 89]. Some other studies focused on the potential impacts of new policies on a target electric sector by using existing models developed by the other research groups in the energy analysis research community. Dagoumas et al. [17] and Kalampalikas et al. [52] analyzed impacts of climate polices and an RES, respectively, on the Greek electric sector with the software package WASP-IV (Wien Automatic System Planning) created by the International Atomic Energy Agency (IAEA). Brand and Zingerle [11] analyzed impacts of an RES on the electricity market of the North African Maghreb region based on the DIME model developed by researchers at the Technical University of Delft. Bird et al. [9] examined the impact of RES and cap-and-trade policy options on the U.S. electricity sector using the Regional Energy Deployment System (ReEDS) model, a dispatch and capacity expansion linear programming model developed by the National Renewable Energy Laboratory (NREL). Levin et al. [58] developed a state-level version of the MARKAL (MARKet ALlocation) model, supported under the Energy Technology Systems Analysis Program (ETSAP) of the International Energy Agency (IEA), in order to analyze the impact of an RES or a carbon tax on the costs and technology mix of future electricity generation in a case study of the U.S. state of Georgia. All of these studies compared electricity generation portfolios and economic impacts under a business-as-usual case and new policy cases with the assumption that all input parameters, including demand, are the same under other scenarios.

Some studies incorporated demand endogenously under different scenarios. Linares et al. [59] used the equilibrium model approach for an oligopolistic market to model capacity expansion under the EU ETS (European Emissions Trading System) for the Spanish electricity system, and calculated electricity price and allowance price endogenously. Ko et al. [54] analyzed a series of CO_2 emissions abatement scenarios of the power sector in Taiwan using the MARKAL-MACRO model, which is a extended version of MARKAL incorporating energy demand endogenously and responsive to price.

2.3 Methodology

In this study, we develop a least-cost capacity expansion model designed for a small electricity sector, whose decision change will not affect to large enough fuel markets and environmental markets. The objective function is to minimize the total discounted present value of the cost over a specified planning horizon, including investment costs, operating costs, and carbon policy related costs. Moreover, the objective function contains all related constraints characterizing the policies to be analyzed. A range of modeling issues are addressed in section 2.4, and details of this model are given in section 2.5.

Wietschel et al. [101] developed an iterative algorithm to integrate price-dependent reactions in an optimizing energy emission model for the development of CO_2-mitigation strategies. This algorithm can be categorized as a COBWEB algorithm [66]. In this study, we have developed a COBWEB-type iterative approach to evaluate demand response to price change with above optimization model. Figure 1 shows the brief structure of the approach. Starting with a reference demand projection and other input parameters (technology characteristics, fuel cost, CO_2 price etc.), the capacity expansion model projects future electricity prices. With price elasticities and the reference demand projection, a new demand projection is calculated. This new demand projection is used for the model again, iteratively until price and demand converge. This approach produces an equilibrium demand under each scenario with corresponding expansion plan, electricity generation portfolio, cost and price of electricity. The details of the approach are given in A.1.

Figure 2 illustrates the demand projection approach. $C_1(L)$ is the electricity generation cost curve for the business-as-usual scenario (k is the generation margin), $D(L)$ is the consumer's demand curve, and P_1 and L_1 are the market price and quantity demanded respectively. If a new policy is implemented in which the cost curve shifts up to $C_2(L)$, there is a new market equilibrium price and quantity demanded, P_2

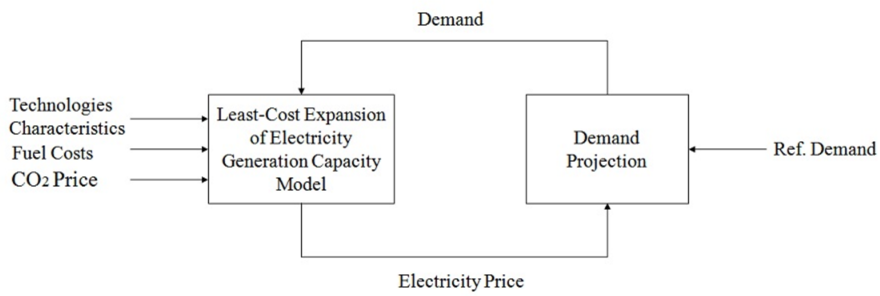


Figure 1: Brief structure of the iterative approach for projection of demand corresponding to electricity generation portfolio.

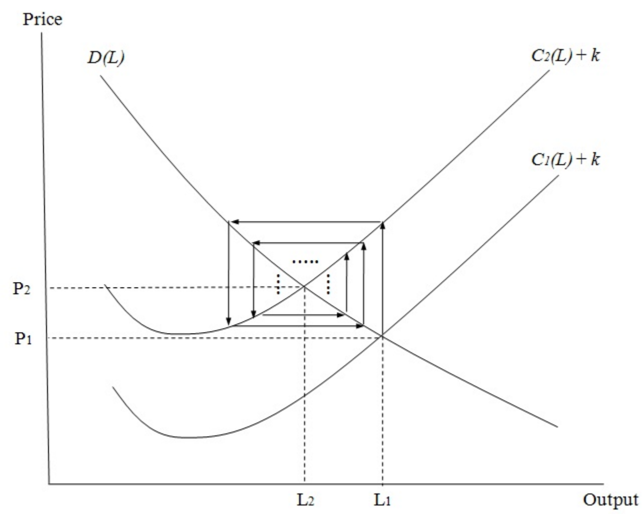


Figure 2: Illustration of the iterative approach to electricity demand, generation mix and price.

and L_2. This approach is iterated to reach equilibrium. Vertical arrows correspond to calculation of a new price of electricity from the model, and horizontal arrows correspond to calculation of a new demand projection.

2.4 Model formulation issues

This section addresses a number of issues central to formulation of the least-cost expansion model.

Retirement of existing power plants Many previous capacity expansion planning studies have not taken into account retirement of existing plants. However, some of current coal power plants have become old, and decisions regarding the power system can be affected by retirement of these plants. In this study, existing power plants can be retired and are never operated after their predetermined lifetime limit. We assume this lifetime limit is 60 years.

Chronological load curve Many previous studies use a load duration curve (LDC) to calculate optimum operating schedules and cost under variable power demand [3, 57, 89, 105]. The models that integrate the LDC directly are particularly suitable for power systems having thermal plants only, or mixed fossil-hydro systems [3]. Electricity generation amounts from all technologies in such a system are fully controlled by system operators, so the only information needed to determine capacity investment and annual operating requirements is the magnitude of the load and not the time at which the load occurs. However, in order to incorporate intermittent wind and solar sources, the intermittency of energy production should be included. One proposed approach to address intermittency is an hour-by-hour simulation, although this has been computationally prohibitive in the past [84]. Progress in computational technologies and algorithms make this approach more feasible; this study takes an hour-by-hour simulation approach with a problem size reducing treatment. Previous studies approximated the LDC stepwise to reduce problem size; in this study, one year is segmented into three seasons (summer, winter, intermediate), and each season is assumed to have a representative hourly load curve.

Initial allowances Under a cap-and-trade system, the initial allowance allocation is a controversial issue: who gets allowances, how many allowances they receive, and whether allowances are given away for free or auctioned, since allowances represent a valuable financial asset and the free initial distribution of a portion of the allowances can be a significant potential source of compensation to emitters. One previous study argued that generators in regulated regions should be indifferent in the long-run between free allocation to generators and an auction [13]. Other studies conclude that a power producer who receives free allowances has exactly the same incentive to reduce emissions as a power producer that receives no free allowances [16, 35, 68]. In our model, as in previous studies, the quantity of initial allowances will not have a direct effect on the utility's investment decision.

However, free allowances can affect the price of electricity, and thus also the demand for electricity. At the initiation of the U.S. SO_2 trading systems, when the U.S. generation system was fully regulated by utility commissions, utility customers were not charged for the sulfur dioxide allowances that utilities received for free, but only for the costs of purchased allowances. Electricity prices were increased for the cost of purchased allowances, or, similarly, many utility commissions granted a credit to price for revenue from selling excess allowances. On the other hand, in the European carbon trading system, some utilities could pass through the market price of carbon dioxide allowances to customers immediately, under the deregulated markets in Europe. The utilities incorporated the "opportunity cost" of the carbon dioxide allowances, and so the benefit of free allowances was not passed down to consumers [91, 103, 104].

Here, we consider a fully regulated power producer that will only pass through costs for purchased allowances. We will compare the results with and without a free initial fixed endowment of annual allowances.

Price of CO_2 Understanding the interaction between the price of CO_2 and the CO_2 emission cap is critical. Cap-and-trade systems generally reduce the emission cap over time. A declining emission cap will increase the CO_2 price. A CO_2 price model quantifying this relationship is needed to model future costs. In this study, we assume that the social marginal cost of Greenhouse Gas (GHG) abatement is equal to the allowance price in a general equilibrium context.

A change in the price of CO_2 can affect power producers' investment decisions and generation planning. First, a high enough CO_2 price can support the installation of low-carbon power plants including natural gas and renewable sources, or power plants with carbon capture and sequestration (CCS) systems. Previous studies have evaluated the economic feasibility of investing in these new technologies. Some analyzed expected cost and efficiency using a simple net present value (NPV) approach [80, 82]. Others included price uncertainty and assessed the option to install the system by expected NPV with a real option approach [55, 1]. In this study, we develop a deterministic model using a simple NPV approach.

Second, for power producers with multiple generation technologies having fixed capacities and differing marginal costs, the supply function is represented by the marginal cost of power generation of each technology. Low marginal cost is one reason that power producers often operate at almost full capacity at nuclear and coal plants but not at natural gas plants, though the levelized cost of electricity from natural gas power plants is lower than that from nuclear and similar to that from coal plants [10]. Increases in the price of CO_2 may change the order of the marginal cost of electricity production technologies. In most situations with unpriced carbon, the marginal cost of coal-derived electricity is less than the marginal cost of natural gas electricity, but coal-based electricity produces about twice the CO_2 emissions of natural-gas-based electricity. In eq.(1), V_i is the marginal cost of a unit electricity production for technology i, $P_{CO2,t}$ is the price of CO_2 at time t, and e_i is the CO_2 emission per unit production of technology i. A high enough CO_2 price, which satisfies eq.(1), can shift the merit order from technology i to technology j, in this case coal to natural gas, and so the electricity portfolio can be substantially altered.

$$V_{Coal,t} + P_{\mathrm{CO}_2,t} \times e_{Coal} > V_{NG,t} + P_{\mathrm{CO}_2,t} \times e_{NG} \tag{1}$$

Renewable Electricity Standard A given percentage of electricity supply maybe required to be generated from a selected set of technologies, such as renewable or low carbon technologies. These may include geothermal, solar, wind, biomass, and new or existing hydro power, as well as nuclear and natural gas. The base level may be defined as a subset of existing generation. For example, for some renewable electricity generation portfolio policies, the base level is defined as the total generation less generation from nuclear, fossil sources with CCS and unqualified hydro.

2.5 Least-Cost Expansion of Electricity Generation Capacity Model

In this section, a deterministic mixed-integer linear programming (MILP) model incorporating the features discussed above is described. The indices, variables, and parameters used in the model are described in Table 16.

The objective function can be written as

$$\begin{aligned}\min \sum_t \frac{1}{(1+r)^t} \Big\{ & \sum_i (C_i w_{i,t} + F_i x_{i,t}) + \sum_{i \backslash biomass} V_{i,t} \sum_s \theta_s \sum_h z_{i,h,s,t} \\ & + \sum_j V_{j,t} \sum_s \theta_s \sum_h z_{biomass,j,h,s,t} \\ & + P_{\mathrm{CO_2},t} [\sum_i e_i \sum_s \theta_s \sum_h z_{i,h,s,t} - (A_t - \alpha_t)] \Big\} \end{aligned} \tag{2}$$

The first term includes capital investment, fixed, and operation costs. Operating costs include fuel costs as well as operation and maintenance costs. Fuels are assumed to be supplied from the global market, and so we assume that fuel prices are exogenous and this model's expansion decisions do not affect fuel prices. The last term shows the cost (benefit) from an excess (saving) of carbon emissions.

Demand Constraint The total power output generated by all technologies must not be less than the total power demand, and peak demand must be met.

Table 1: Indices, parameters, and variables in the model.

Set and Indices	
I	= Generation technologies, $i \in I$
CCS	= Generation technologies with CCS system
J	= Biomass feedstocks, $j \in J$
h	= Time period of hours, $h = 1, 2, ..., 24$
s	= Time period of seasons, $s = 1(summer)$, $2(winter)$, $3(intermediate)$
t	= Time period of years, $t = 1, 2, ..., T$
Parameters	
-Demand-	
r	= Risk-adjusted real discount factor (7%)
$d_{h,s,t}$	= Electricity demand at hour h in season sin year t (MWh)
θ_s	= Number of days in season s (days)
R	= Reserve margin
-Capacity-	
ρ_i	= Maximum capacity factor of technology i (%)
$\rho_{solar,h,s}$	= Solar electricity potential at hour h in season s (%)
$\rho_{wind,h,s}$	= Wind electricity potential at hour h in season s (%)
m_i	= Minimum economic capacity for new generating technology i (MW)
u_i	= Upper bound for generating capacity of technology i (MW)
u_{CCS}	= Upper bound for CO_2 storage capacity (tCO_2)
$u_{biomass,j}$	= Upper bound for power output from j biomass feedstock (MWh)
-Cost-	
C_i	= Annualized capital investment cost of technology i ($/MW)
F_i	= Fixed cost of technology i ($/MW)
$V_{i,t}$	= Variable cost (O&M + fuel cost) of technology i in year t ($/MWh)
δ_s	= Peak demand multiplicative factor ($/MW)
-New Policy-	
e_i	= CO_2e (Equivalent CO_2) emissions from technology i (tCO_2e/MWh)
$P_{CO2,t}$	= price of CO_2 in year t ($/$tCO_2e$)
A_t	= initial allowances of CO_2e in year t (tCO_2e)
Res_t	= Renewable electricity standard in year t (%)

Decision Variables	
$y_{i,t}$	= Capacity expansion (investment) of technology i in year t, integer
$w_{i,t}$	= Total new capacity of technology i until year t (MW)
$q_{i,t}$	= Retirement capacity of technology i in year t (MW)
$x_{i,t}$	= Capacity of technology i in year t (MW)
$z_{i,h,s,t}$	= Electricity generation from technology i at hour h, season s, and year t (MWh)
$z_{biomass,j,h,s,t}$	= Electricity generation from biomass fired plants by using feedstock j at hour h, season s, and year t (MWh)
G_t	= Amount of CO_2 stored until year t (tCO_2)
b_t	= Amount of allowances deposited until year t (tCO_2e)
α_t	= Amount of allowances banked in year t (tCO_2e)

$$\sum_i z_{i,h,s,t} \geq d_{h,s,t} \qquad \forall h, \forall s, \forall t \tag{3a}$$

$$\sum_i \rho_i x_{i,t} \geq (1+R) \times \delta_s \times \max_h (d_{h,s,t}) \qquad \forall s, \forall t \tag{3b}$$

Capacity Change Constraint Based on the existing power plant capacities, the total capacities of each technology will vary with retirement of existing plants and new construction over time. Since the annual capital investment cost should be charged to the new power plants, $w_{i,t}$ represents the accumulated capacity of new investment for technology i until year t.

$$x_{i,t} = x_{i,t-1} - q_{i,t-1} + m_i y_{i,t} \qquad \forall i, \forall t \tag{4a}$$

$$w_{i,t} = w_{i,t-1} + m_i y_{i,t} \qquad \forall i, \forall t \tag{4b}$$

$$w_{i,0} = 0 \qquad \forall i \tag{4c}$$

Retrofitting current existing coal power plants with a CCS system requires more detailed constraints. The retrofitting of the CCS equipment in current viable coal fired power plants is assumed to result in a capacity derating of 30% and reduced efficiency of 43% at the existing coal plant [24].

$$x_{coal\_rv,t} = x_{coal\_rv,t-1} - q_{coal\_rv,t-1} \qquad \forall t \tag{5a}$$

$$y_{coal\_ar,t} = q_{coal\_rv,t-1} \qquad \forall t \tag{5b}$$

$$x_{coal\_ar,t} = x_{coal\_ar,t-1} + 0.7 y_{coal\_ar,t-1} \qquad \forall t \tag{5c}$$

$$w_{coal\_ar,t} = w_{coal\_ar,t-1} + 0.7 y_{coal\_ar,t-1} \qquad \forall t \tag{5d}$$

$$w_{coal\_ar,0} = 0 \tag{5e}$$

where "*coal_rv*" means retrofitting viable coal power plants, and "*coal_ar*" means already retrofitted coal power plants.

Some technology options, including biomass, wind and hydro, are limited physically and/or economically, so these technologies will have, effectively, maximum capacity limitations. In addition, the total capacity of power plants with CCS systems maybe limited due to limits on sequestration site availability.

$$x_{i,t} \le u_{i,t} \qquad \forall i \in I \backslash CCS, \forall t \tag{6a}$$

$$\sum_{i \in CCS} e_i \sum_s \theta_s \sum_h z_{i,h,s,t} + G_{t-1} = G_t \qquad \forall t \tag{6b}$$

$$G_t \le u_{CCS} \qquad \forall t \tag{6c}$$

Generation Constraint The power output generated by each technology must not exceed its maximum available capacity. The power output of solar or wind technology at each hour is determined by solar radiation or wind speed as well as capacity. The power output generated by each biomass feedstock also can not exceed its availability.

$$z_{i,h,s,t} \leq \rho_t x_{i,t} \qquad \forall i \in I, \forall h, \forall s, \forall t \tag{7a}$$

$$z_{solar,h,s,t} \leq \rho_{solar,h,s} x_{solar,t} \qquad \forall h, \forall s, \forall t \tag{7b}$$

$$z_{wind,h,s,t} \leq \rho_{wind,h,s} x_{wind,t} \qquad \forall h, \forall s, \forall t \tag{7c}$$

$$z_{biomass,h,s,t} = \sum_j z_{biomass,j,h,s,t} \qquad \forall h, \forall s, \forall t \tag{7d}$$

$$\sum_s \theta_s \sum_h z_{biomass,h,s,t} \leq u_{biomass,j} \qquad \forall j, \forall t \tag{7e}$$

Renewable Electricity Constraint

$$\sum_s \theta_s \sum_h (z_{biomass,h,s,t} + z_{solar,h,s,t} + z_{wind,h,s,t} + z_{other\_ren,h,s,t})$$
$$\geq res_t \sum_{i \in I \setminus nuclear,hydro,CCS} \theta_s \sum_h z_{i,h,s,t} \qquad \forall t \tag{8}$$

CO_2 Market Constraint In this study, banking of allowances is allowed, but not borrowing [28].

$$b_t = b_{t-1} + \alpha_t \qquad \forall t \tag{9a}$$

$$b_0 = 0 \tag{9b}$$

$$0 \leq \alpha_t \leq A_t \qquad \forall t \tag{9c}$$

2.6 Case Study

To demonstrate the use of the model, we develop a case study for the state of Georgia in the U.S. As of 2011, electricity generation in Georgia is the 9th largest among U.S. states, and the electricity market is a regulated monopoly: about 96% of electric utility and 86% of total capacity is under control of a single company, Georgia Power, a subsidiary of Southern Company. In this case study, the above model and iterative approach will be used for generation expansion planning and to identify the optimal future electricity generation portfolio for Georgia in response to six scenarios;

(1) a base case scenario in which no new energy policy is imposed, (2) an RES scenario in which the utility will be required to meet a RES, (3) a CO_2 market scenario with initial free allowances in which the utility will be required to participate in a federal level CO_2 cap-and-trade program, (4) a CO_2 market scenario without free initial allowances, (5) a both policies scenario with initial free allowances in which both RES and CO_2 market policies are imposed, and (6) a both policies scenario without initial free allowances.

Electricity Demand The Annual Energy Outlook (AEO) 2011 released from the U.S. Department of Energys Energy Information Administration (EIA) projects a 31% increase in U.S. electricity consumption between 2010 and 2035 [24], under the assumption that there is no carbon restriction and no federal renewable portfolio standard.

Based on projections of electricity demand and population for the South Atlantic region in AEO 2011 [24] and projections of population for Georgia [97, 43], we developed a reference future electricity demand projection (see Appendix A.2). Even though Georgia was a net importer of approximately 9700 GWh of electricity in 2005, accounting for 7.3% of total consumption in the state [29], for simplicity we assume that Georgia does not import electricity, so that electricity generation will be equal to demand. Figure 3 shows the reference electricity demand projection under the base case. Based on 2006 hourly load data from Georgia Power [39], projected electricity demands are profiled into three seasonal time slices (winter, summer and intermediate), which each have 24-hourly load data.

Two previous meta-analyses of price elasticity of demand for electricity reported a range of price elasticity estimates. Espey and Espey [34] reported short-run price elasticity estimates ranging from -2.01 to -0.004 with a mean of -0.35, and long-run price elasticity estimates ranging from -2.25 to -0.04 with a mean of -0.85. Dahl [18] reported short-run estimates ranging from -0.14 to -.44 and long-run estimates ranging from -0.32 to -1.89. A recent study concluded that short-run elasticities for residential

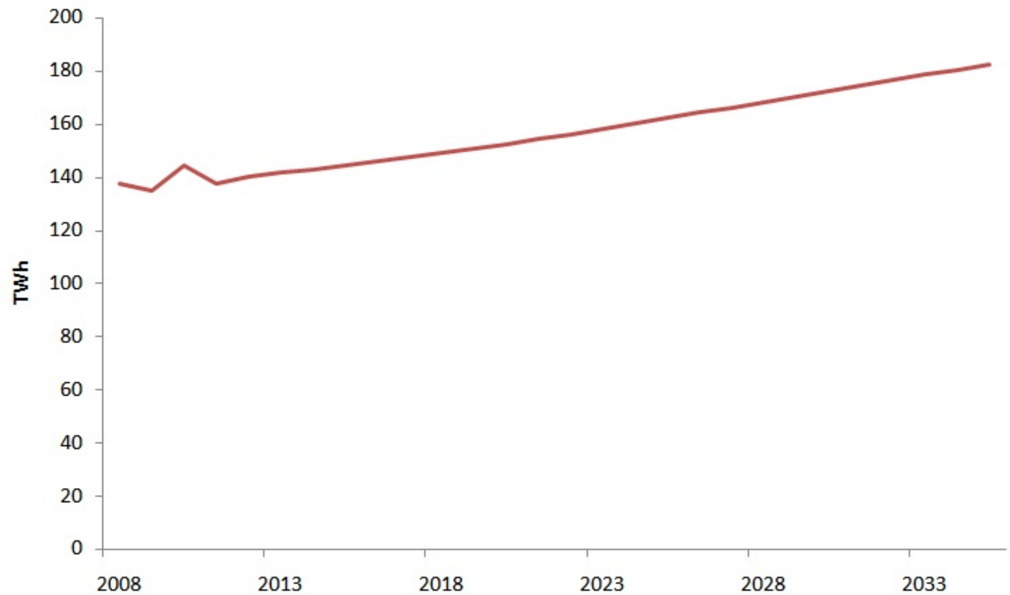


Figure 3: Reference electricity demand for the state of Georgia. The values for 2008 and 2009 are data reported by the EIA; the values for all other years are projections, for which the derivation is provided in A.2.

and commercial sectors in the U.S. are both about -0.2, and long-run elasticities are -0.32 and -0.97 respectively [7]. In this study, we use a short-run elasticity of -0.2 and a long-run elasticity of -1.0. In addition, for sensitivity analysis, we compare demands with zero elasticities and higher elasticities (short-run : -0.4 and long-run : -2.0) under the both policies scenario with initial free allowances. We follow the AEO assumption that the short-run price elasticity is distributed over the first 3-year interval and that the long-run price response occurs through the rest of the period.

Generation technologies Figure 4 represents the 2008 Georgia electricity profile. Georgia relies mostly on coal to generate electricity. There is considerable natural gas generation capacity, although these are primarily used to meet peak demand and overall natural gas generation is relatively low. New large natural gas power plants have been built recently, but the electricity generated from these power plants is mainly used for peak-load demand and their current capacity factors are low. Two

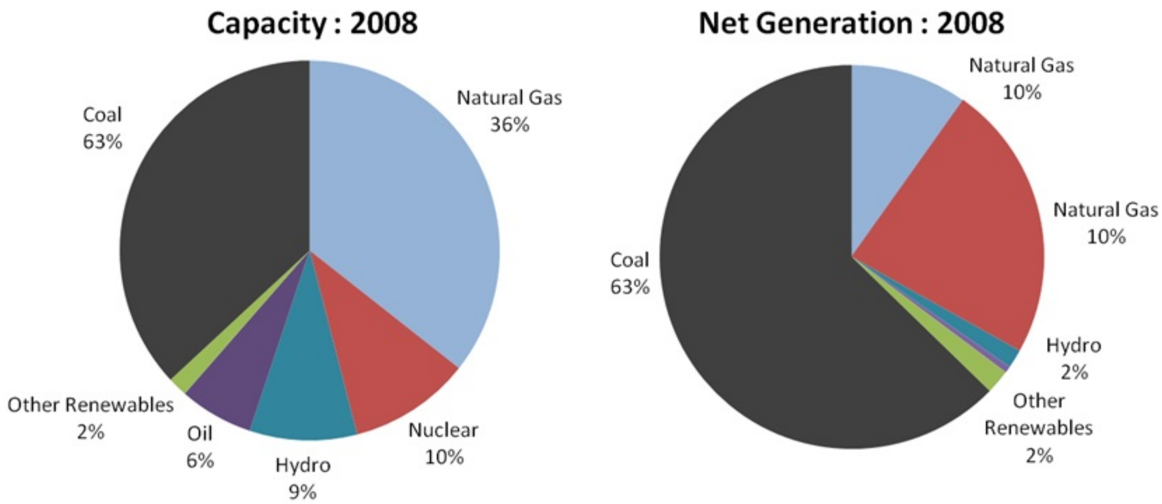


Figure 4: Georgia electricity capacity and generation portfolio (Total: 39 GW and 136 TWh [22])

large nuclear power plants serve base-load demand, and each plant has two reactors. Although Georgia has fairly substantial hydroelectric resources and is also one of the nations top producers of electricity from wood waste, these each contribute 2% of total generation [25, 29].

Future demand for electricity can be met from both existing and new plants. Table 2 shows the technology options for new investment considered in this case study, and the key technology data are summarized in Appendix A.3. The characteristics of generating technologies are mainly based on a report on the assumptions to AEO 2010 [23]. Power plants based on oil and on renewables are assumed to be maintained at the current level without retirement or new investment. With respect to CCS technologies, not all existing power plants are candidates for retrofitting. Only plants greater than 500 megawatts, with heat rates below 12,000 Btu per kWh are considered for CCS retrofits. Georgia has five relatively newly-built coal plants which have 13 boiler units that could be candidates for CCS retrofits [23]. The CCS systems are assumed to remove 90% of the carbon input. The addition of the CCS equipment

Table 2: Technology options for new electricity generation investment in this study.

Technology options for new investment in this study	
Fossil Fuel	Retrofitting current pulverized coal w/ CCS New advanced pulverized coal (PC) w/ or w/o CCS New integrated gasification combined cycle (IGCC) plant w/ or w/o CCS New natural gas combustion turbine (NGCT) New natural gas combined cycle (NGCC) w/ or w/o CCS
Nuclear	New nuclear
Hydro	New Hydro large (> 2.5 MW) New Hydro medium (1 MW – 2.5 MW) New Hydro small (< 1MW)
Renewable	New dedicated biomass New wind offshore New solar photovoltaic (PV)

lowers net capacity and net efficiency of the power plant because some portion of input energy is used to operate the system. Georgia has about 4.9 billion metric tons of CO_2 storage capacity in total, equivalent to 55 years storage of all CO_2 emissions from the electricity sector given the current annual emissions [70], and there is significant additional storage capacity in other southeastern states.

Fuel Costs Future costs for coal and natural gas to the power sector are obtained from the Assumptions to the AEO Reference Case Regional Data Tables for the South Atlantic region [24]. The prices of coal and natural gas (NG) are projected to decline in 2011 and 2012 and keep increasing after then. There is considerable uncertainty in future NG prices due to both the potential new supplies of NG in the U.S., as well potential substantial changes in demand. Paltsev et al. [76] analyzed the price of U.S. natural gas under uncertainties of the scale and cost of resources and pattern of GHG emissions mitigation. The study projected that the high and low NG resource estimates yield NG prices 2% below and 7% above that for the mean estimate in 2030, as well as slight price reductions from a mitigation policy. We developed a sensitivity analysis with 2% lower and 7% higher NG prices; this

Table 3: Fuel Cost Projection [22, 102]

2009$/mmBtu	2010	2015	2020	2025	2030
Coal	2.25	2.14	2.16	2.24	2.31
Natural Gas	5.31	4.90	5.24	5.96	6.45
Nuclear	0.71	0.79	0.81	0.83	0.85

had minimal effect on the results. Cost estimates for nuclear fuel are from the World Nuclear Association [102] with real cost escalation of 0.5% per year. Biomass fuel cost are treated in the following section.

Availability of Renewable Sources Biomass is the primary renewable resource identified for electricity generation in Georgia. Sources of low-cost biomass in Georgia include forestry residues, unmerchantable timber, pulpwood, mill residues, urban wood waste residues and paper mill sludge. [86] concluded that there may be in excess of 18 million tons of biomass in Georgia that could be used for energy each year. The energy density of all dry woody biomass is fairly consistent between different forms; we assume 12.8 MJ/kg, which translates into an annual biomass fuel energy of approximately 240 PJ in Georgia. We use biomass supply curves for Georgia based on delivered cost and availability estimates, shown in Table 4 [58].

Data on maximum wind generation capacity were obtained from the National Renewable Energy Laboratory's Wind Deployment System Model base case scenario, which shows Georgia to have relatively low potential, 130 MW [72]. Similar data for hydroelectric potential are presented by Hall et al. [48][1]. Based on solar radiation data for Georgia [71] and solar PV panel specification [90], solar PV electricity generation profiles for Georgia were developed [92].

RES and carbon market assumptions As a state-scale model, we assume that utility actions do not affect carbon prices. We examine policies based on the American

[1]Small hydro - 230 MW, Medium hydro - 73 MW, Large hydro - 230 MW

Table 4: Biomass delivered cost and availability in Georgia. [58]

Biomass Type	Availability(TBtu)	\$/MMBtu
Pecan hulls	0.1	1.09
Gin trash	3	1.52
Bark, pine	3	1.75
Poultry litter	24	2.75
Peanut hulls	5	2.78
Wood residue	37	2.99
Wood chips	0.1	3
Unmerchantable timber	161	3.3
Corn stalks	2	4.05
Cotton stalks	34	4.12
Pulpwood (hard)	32	4.12
Hay	32	4.38
Pulpwood (soft)	93	4.53
Kenaf	1	5.16
Switchgrass	0.1	6.51
Wheat straw	5	11.29
Rye straw	2	12.96

Clean Energy and Security Act of 2009 (ACES) [28]. The act establishes emission caps that would reduce aggregate GHG emissions for all covered entities to 3% below their 2005 levels in 2012, 17% below 2005 levels in 2020, 42% below 2005 levels in 2030, and 83% below 2005 levels, in 2050. We assume the utility will be given free initial allowances every year as (1 - reduction level) times its 2005 CO_2e emissions level, 90,132 thousand metric tons [22].

As described above, reducing this emission cap is expected to increase the CO_2 price. The U.S. Environmental Protection Agency (EPA) has projected future U.S. CO_2e allowance prices under ACES 2009 from 2012 to 2050 based on two EPA models, ADAGE and IGEM [28]. We have used the average of two projections, shown in Figure 5. ACES also includes a requirement for a renewable electricity generation standard, shown in Table 5.

Other assumptions Even though this case study focuses on the 20 year period from

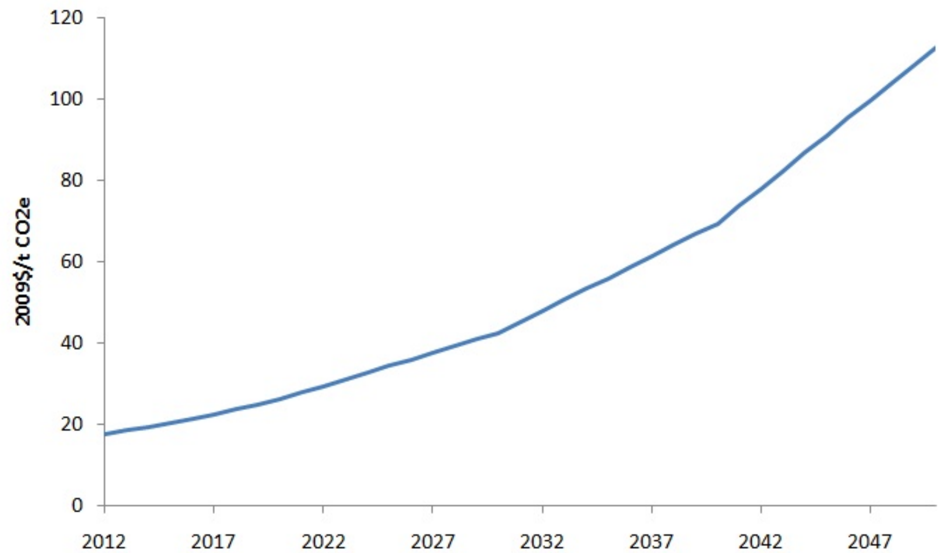


Figure 5: U.S. CO_2e allowance price projection under the CO_2 emission cap-and-trade policy scenarios. This projection is the average of two EPA model projections for the American Clean Energy and Security Act of 2009. [28]

Table 5: ACES Act RES requirement [28]

Renewable Electricity Standard
6% by 2013
9.5% by 2015
13% by 2017
16.5% by 2019
20% by 2030

2010 to 2030, the model is run over the 70-year period from 2010 to 2080 in order to eliminate distortion of results. All parameters after 2035 are set to be the same as in 2035. All inputs and results are reported in constant 2009 dollars. The U.S. DOE [24] expected that the annual yield on the 10-year U.S. Treasury bond would average 5.4% and annual consumer price inflation would average 2.1% from 2009 to 2035. From here, we obtain a risk-free discount factor rate of 3.2%. With about 4% risk-premium, we use 7% real risk-adjusted discount rate to account for the time value of money. This study includes completion of plants that are under construction but are not yet operating. Georgia Power is moving ahead with plans to replace the 1960s vintage coal-fired plant McDonough with a bigger natural gas power plant, consisting of three combined cycles units with 840 MW of generating capacity each; these units are expected to come on-line in 2012 and 2013. Finally, preliminary construction is underway for two additional nuclear reactors on the current Vogtle site near Augusta; the 1200 MW reactors are projected to come on-line in 2016 and 2017 respectively.

2.7 Results of the case study

The model was programmed and implemented in the AMPL optimization package, and was solved using the ILOG CPLEX 11.1 solver. Using the iterative approach described, we developed endogenous demand projections for each scenario. The outcomes of the model provide electricity generation portfolios by fuel, corresponding electricity prices, and CO_2 emissions under each scenario.

Endogenous Demands and Prices

Figures 6 and 7 show demand projections and prices under the different scenarios respectively. The stricter the policies, the higher the price charged and the less demand projected. The scenario with both a carbon cap-and-trade policy and a renewable electricity standard without initial free allowances has the largest price increase, from 9 cents per kWh to 12.2 cents per kWh by 2030, and correspondingly has the lowest demand projection, with 2030 demand projected to be about the same as 2010 demand, despite population growth. With only the RES, the price of electricity increases from 9 cents to 10 cents per kWh by 2020, and the resulting demand stays at the 2010 level until 2020, after which demand increases at a rate similar to the base case projection. From 2020 to 2030, the demand under the scenario with only an RES is about 3 - 6% less than the base case scenario. Either with or without free initial allowances, the demand projection and electricity price under the carbon cap-and-trade policy are very close to those under the scenarios that include both a carbon cap-and-trade policy and a renewable electricity standard. Prices of electricity under the both policies scenarios are similar to those under only CO_2 market scenarios. It implies that the generating cost of biomass electricity is slightly higher than that from coal and natural gas under the carbon emission market. For carbon market policy scenarios with and without free allowances, 2030 demand is lower than the base case by 9% and 23%, respectively.

Generation Capacity and Electricity Output by Fuel

Figures 8 compares electricity generation output portfolios by fuel. Under the base case scenario, increasing future demand is met largely by plants that are already planned. The projected increasing price of natural gas, based on the EIA projections shown in Table 3, increases the gap of marginal costs between coal and natural gas electricity, and results in a relatively constant consumption of coal in the base case. However, the increasing heat rate of NGCC technology makes up for this increasing gap. As a result, current existing old coal power plants are projected to be operated up to their lifetime limit and are replaced by a combination of new coal power (PC) plants and additional new natural gas power (NGCC) plants.

Under the only RES policy scenario, the renewables requirement is primarily met through biomass generation in Georgia. New biomass power plants would replace older coal power plants, and no new, except for planned, coal and natural gas power

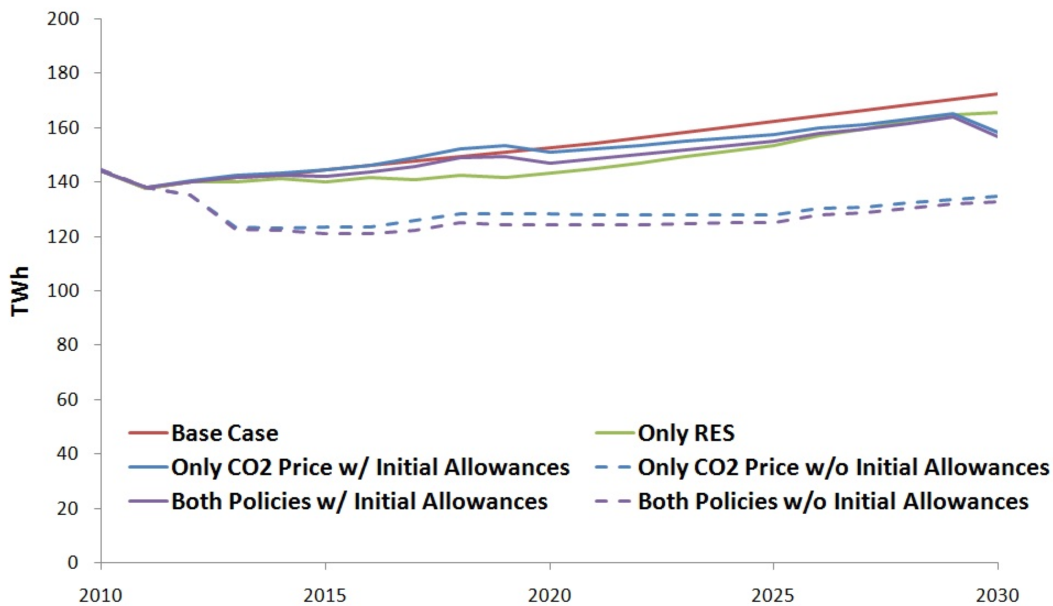


Figure 6: Electricity demand projections under different policy scenarios for the case study. The two dashed lines are for carbon cap-and-trade policies without free initial allowances; these show substantial demand moderation. The other policy scenarios show demand similar to the base case.

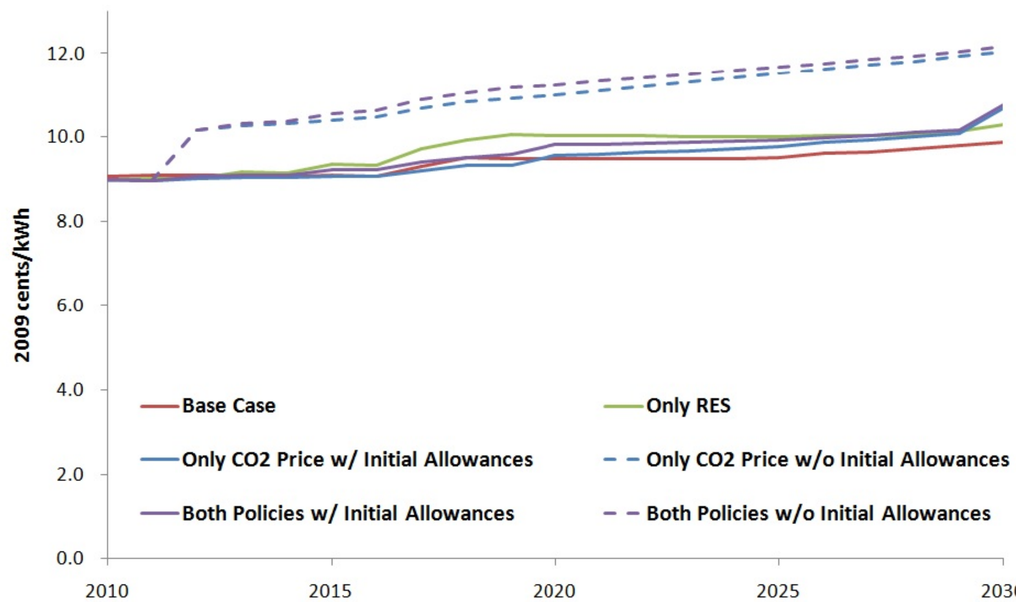


Figure 7: Electricity price projects under different policy scenarios. From the calculated baseline average retail price of 9 cents/kWh in 2009, by 2030 prices would rise gradually in the baseline, no policy scenario, to about 10 cents/kWh, would rise to about 10.3 cents/kWh for renewable energy policies and 10.7 cents/kWh for CO_2 cap-and-trade policies with initial free allowances, and would rise to about 12.2 cents/kWh for policies with CO_2 caps without free allowances..

plants are required. Biomass capacity is about 2,700 MW in 2030, and only a small amount of wind generation capacity, 4MW, is realized. Coal remains the primary fuel and electricity generation from natural gas even decreases.

Under only CO_2 market scenarios, some old coal power plants are retired earlier than their lifetime limit. Moreover, some old natural gas power plants (NGCT) also are retired when the absence of free initial allowances increases prices and reduces the demand for electricity. Either with or without free initial allowances, no additional power plants, except for planned power plants, need to be built in near future, and some new IGCC plants with CCS start operations after 2025. About 1800 MW of new natural gas power (NGCC) replaces old coal power plants under the scenario with free initial allowances. The projected CO_2 price and fuel costs change the merit order between existing pulverized coal (PC) and new natural gas (NGCC) plants from 2015, when the CO_2 price reaches about \$20/ton CO_2. These new NGCC plants are used for base load, and existing NGCT power plants are still used for peak load. The projected CO_2 price will make carbon capture and sequestration systems cost-competitive when the CO_2 price reaches about \$37-\$40/ton CO_2. As a result, both retrofitting and new coal plants with capture systems are built and operated for base load between 2025 and 2030. Without a renewable electricity standard, building of new renewable power plants does not occur. We can conclude that CO_2 market might not strongly induce renewable electricity and renewable electricity generation will be driven only by an RES policy in Georgia.

With both a carbon market and a renewable electricity standard, some old coal power plants are retired earlier, as above, and new biomass, natural gas, and coal with CCS power plants would replace these retiring old coal power plants. Under all scenarios, the estimated cost of solar power technology is too high to be installed.

GHG emissions

The GHG emissions from the entire generation system under different scenarios in

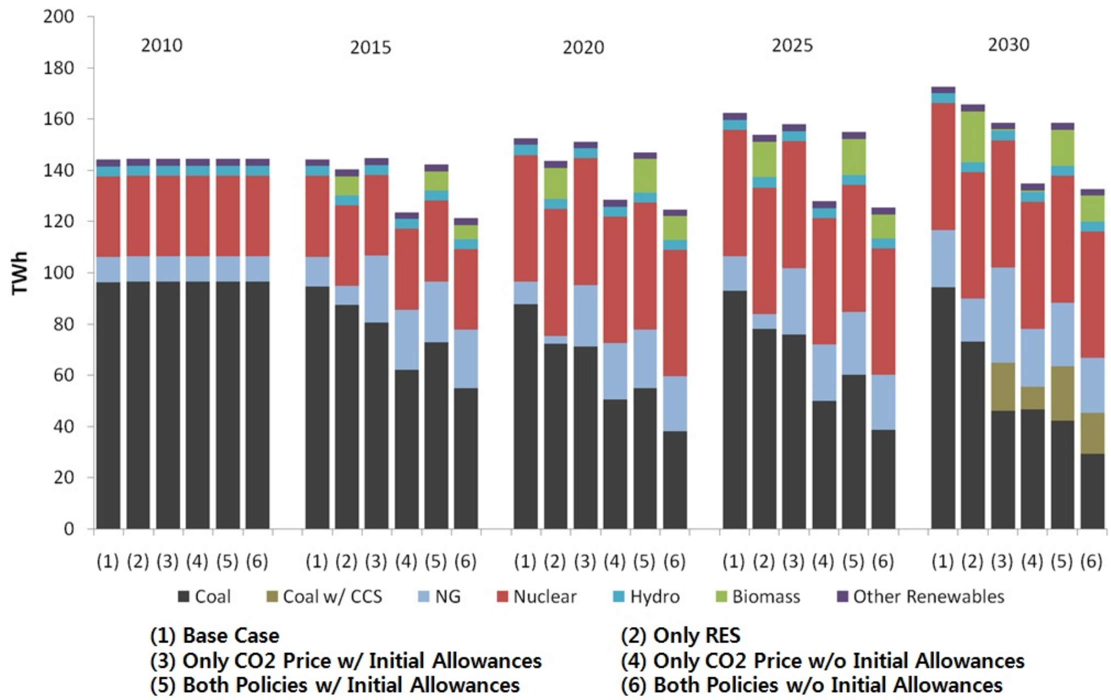


Figure 8: Electricity output by generation technology for the case study. Under the carbon cap-and-trade policies (Scenarios 3 through 6), some CCS systems for coal generation come in by 2030. Under the renewable electricity policies (Scenarios 2, 5, and 6) there is an increase use of biomass for electricity production. Electricity from oil, solar and wind are negligible in all scenarios for this case study and are not shown. (See A.4).

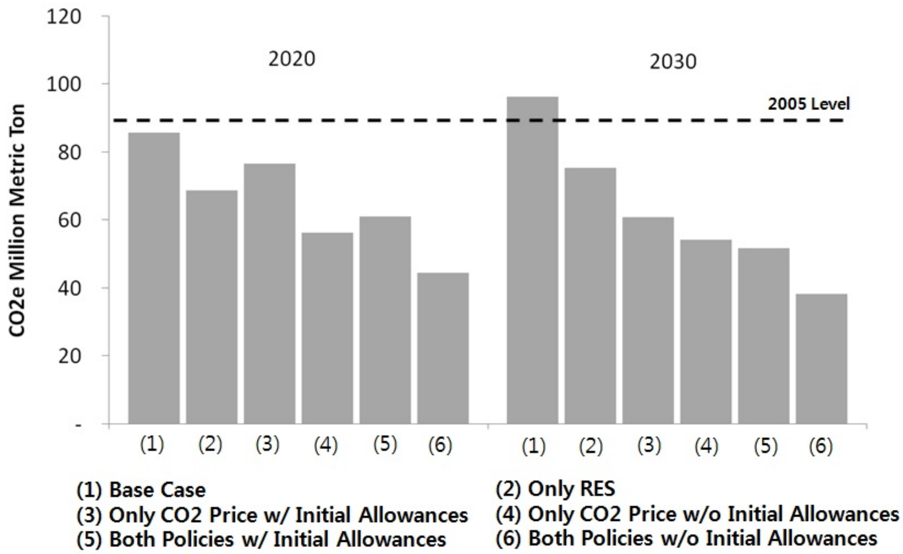


Figure 9: GHG emissions in 2020 and 2030 under different policy scenarios.

2020 and 2030 are presented in Figure 9. Even though planned new natural gas and nuclear power plants reduce 2020 GHG emissions in the base case, the base case GHG emissions in 2030 are about 7% higher than the 2005 level. The RES-only scenario has lower GHG emissions in 2020 than the CO_2 market with free initial allowances, but by 2030 the CO_2 market scenario has lower emissions than the RES scenario. The lower demand under scenario 4, the CO_2 market without free allowances, results in lower GHG emissions. On the other hand, by 2030 GHG emissions under all CO_2 market scenarios are lower than under the RES scenario. The proposed RES maintains a constant 20% renewables after 2020, resulting in higher GHG emissions in 2030 than in 2020 under the RES scenario. The combination of both a CO_2 market and a RES policy produces the lowest GHG emissions.

Overall, Georgia can reduce GHG emissions from the electricity sector under all scenarios. However, the source of the reduction is a little different under each scenario. Even though no new renewable power plants will be built without a RES, large GHG emissions reductions could be achieved from moderated demand. The GHG emissions

Table 6: Case study results showing the two sources of GHG emissions reduction - demand moderation and changes in the generation mix – under a RES, a CO2 price with and without initial allowances, and under both a RES and a CO2 price policies.

GHG emissions reduction with respect to base case		Only RES	Only CO_2 Price w/ Initial Allowances	Only CO_2 Price w/o Initial Allowances	Both Policies w/ Initial Allowances	Both Policies w/o Initial Allowances
2020	Demand Moderation	-6%	-1%	-16%	-3%	-18%
	Generation Mix Change	-14%	-10%	-18%	-25%	-30%
	Total	-20%	-11%	-34%	-29%	-48%
2030	Demand Moderation	-4%	-8%	-22%	-9%	-23%
	Generation Mix Change	-18%	-29%	-22%	-37%	-37%
	Total	-22%	-37%	-44%	-46%	-60%

reduction under energy policies can be attributed two effects: generation mix changes and demand moderation. Table 6 shows the portion of two effects. Generally, the generation mix changing effects are larger than demand moderating effects under most scenarios, but about half of GHG emissions reduction comes from moderated demand under the CO_2 market without free allowances scenario.

Although free CO_2 allowances compensate the utility and reduce electricity price increases, free allowances may have unexpected results. Figure 10 shows the annual GHG emissions under scenario 3 (CO_2 market with free allowances) and scenario 5 (both RES and CO_2 market with free allowances), and compares them with the quantity of free allowances. In both scenarios, no allowances are banked and the actual GHG emissions are sometimes or always less than the allowances. A credit to price for revenue from selling excess allowances sometimes allows a utility to provide cheaper electricity, and resulting demand could be higher than the base case demand, as we have seen in Figure 6 and 7.

Different price elasticities

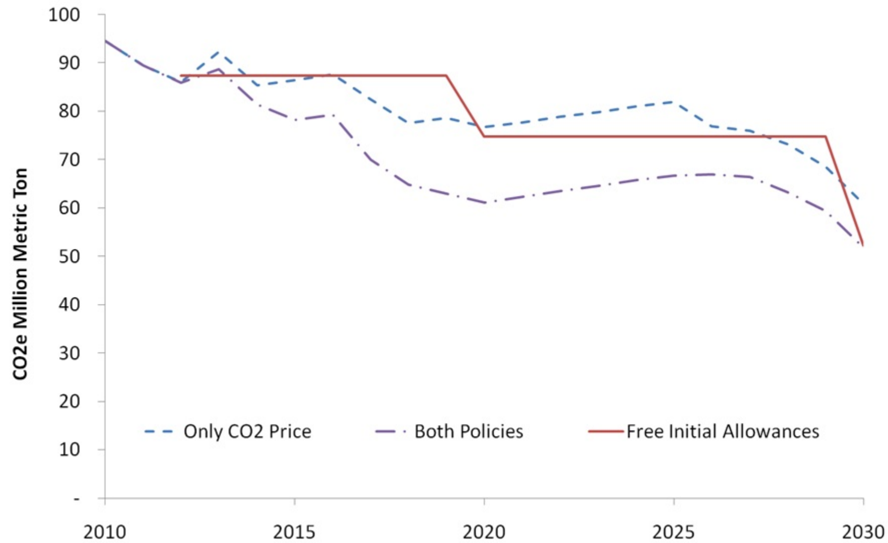


Figure 10: Annual GHG emissions under scenario 3 (CO_2 market with free allowances) and 5 (both RES and CO_2 market with free allowances), as well as the actual quantity of free initial allowances, showing that projected emissions are sometimes or always less than the free allowances.

Price elasticity is a measure of how much demand decreases when price increases. Figures 11 to 14 compare demand projections, prices, generation output, and GHG emissions with different price-elasticity assumptions[2] under the "both policies" scenario with initial free allowances. The demand projection with the zero price elasticities assumption is, as expected, the same as the reference demand, regardless of policy and generation mix, and less demand is naturally projected with higher price elasticities under the policies resulting in higher-cost electricity. Interestingly, doubling the elasticities results in less than doubling of the demand reduction effect. That is, with both an RES and a carbon cap-and-trade policy with free initial allowances, 2030 demand is lower than the reference no-policy scenario by about 9% under the baseline assumption of elasticities, and by about 15% if the elasticities are doubled. Moreover, the price of electricity with high elasticity is less than that with low or

[2]zero elasticities, base elasticities (short-run : -0.2 and long-run : -1.0), and higher elasticities (short-run : -0.4 and long-run : -2.0)

zero elasticity assumption. The zero-elasticity results compare well with the results of Levin et. al. [58], which included a similar case study using the MARKAL model. The detail comparison is shown in Appendix A.5.

Whereas Figures 12 and 14 show that different assumptions about elasticity have only a small effect on projected electricity prices and only a moderate effect on projected total greenhouse gas emissions, Figure 13 shows that different assumptions about elasticity have substantial implications for the projected future generation mix. Specifically, Figure 13 shows that changing the assumption from zero price elasticity to high price elasticity reduces the 2030 carbon capture and storage utilization by about a factor of two, and reduces coal and natural gas generation by about 10% and 25% respectively, while nuclear and renewables remain largely unchanged. This case study illustrates the importance of including price elasticity in electricity generation planning models. As discussed previously, the current and future elasticity of demand for electricity is not precisely known; efforts to improve understanding of demand elasticity and its determinants could contribute to the formulation and analysis of electricity generation policy. Moreover, policies or technologies that can increase demand elasticity could complement generation-focused electricity policies.

Different NG prices

With 2% lower and 7% higher NG prices, the changes in the demand projections and prices under all scenarios are less than 1%. All other results change slightly.

2.8 Conclusion

We have described and evaluated a deterministic least-cost optimization model for the power generation planning of electric systems. The model can address potential carbon reduction and renewables policies and determine optimal investments and operations of an electricity sector, which has various generation options. Demand responsive to price is modeled endogenously, and this study shows the importance of

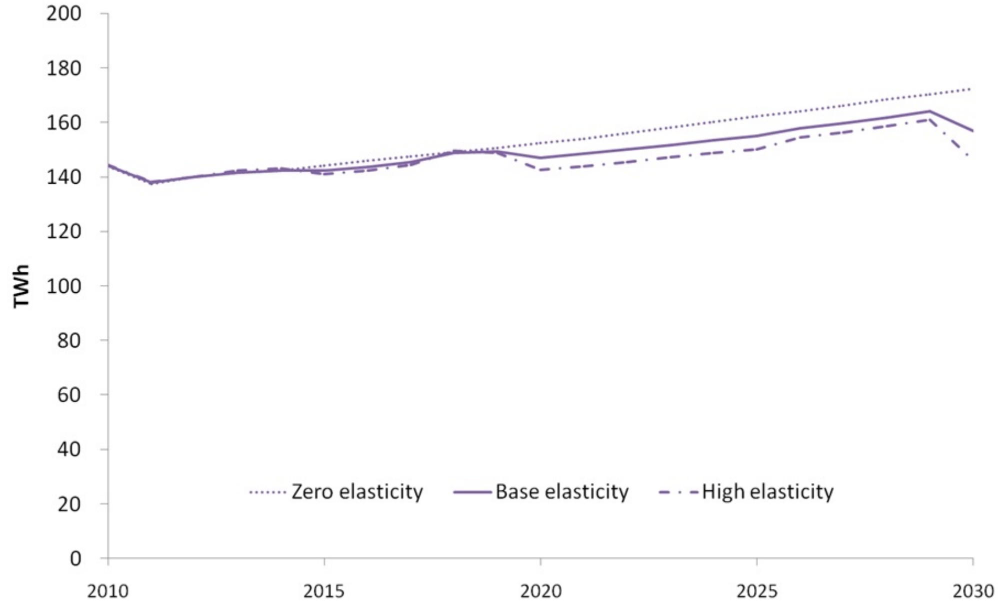


Figure 11: Electricity demand projections with different price-elasticity assumptions under both a renewable electricity standard and cap-and-trade policy with initial free allowances.

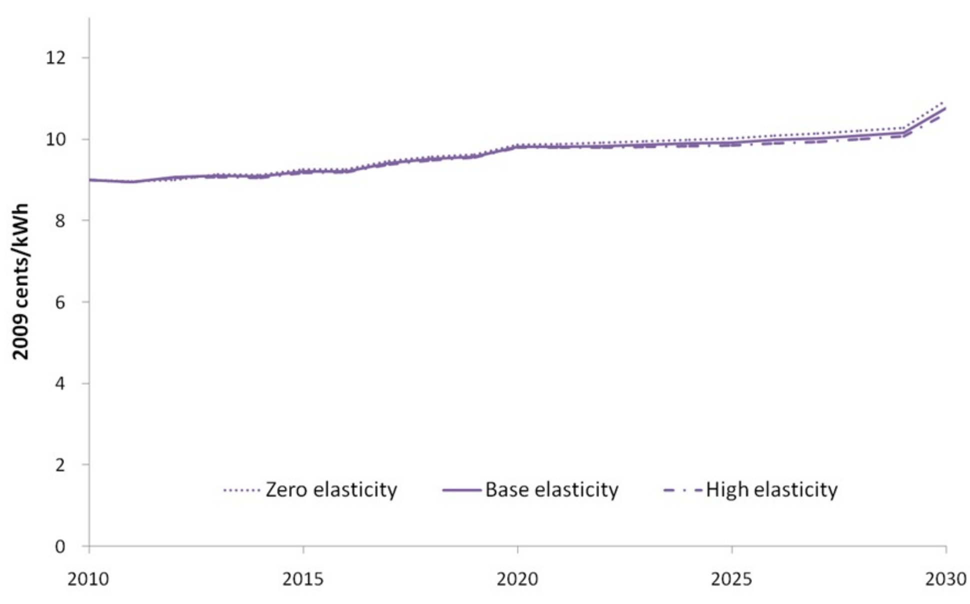


Figure 12: Electricity price projections with different price-elasticity assumptions under both a renewable electricity standard and cap-and-trade policy with initial free allowances.

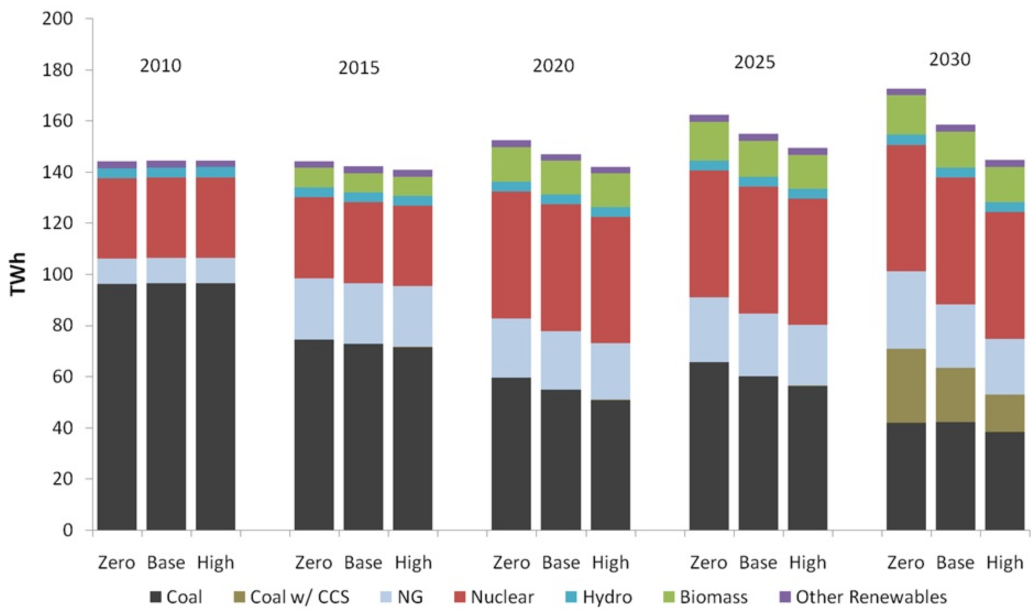


Figure 13: Electricity output by generation technology with different price-elasticity assumptions under both a renewable electricity standard and cap-and-trade policy with initial free allowances.

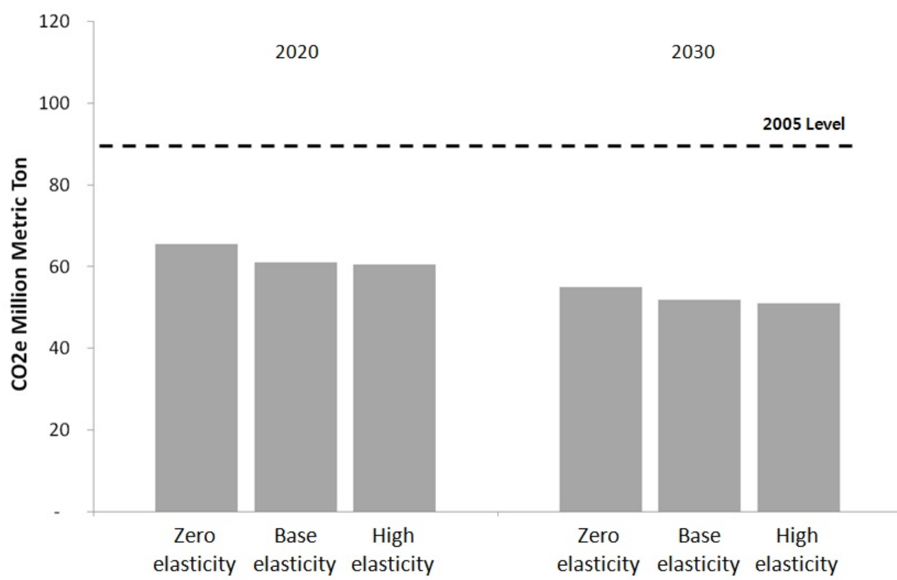


Figure 14: GHG emissions in 2020 and 2030 with different price-elasticity assumptions under both a renewable electricity standard and cap-and-trade policy with initial free allowances.

incorporating potential demand responses to evaluation of policy.

Reduction of GHG emissions can be achieved from less carbon intensive fossil fuel based technologies, including natural gas and installation of CCS, and from renewable technologies, including biomass, wind and solar. In the case study, the projected market price of CO_2 is high enough that the utility will gradually switch to less carbon intensive technologies rather than just buying allowances from the market. However, renewable electricity generation will be driven only by an RES policy until 2030. These result simply that the mix of technologies used to achieve emissions reductions depend on how the policy is designed. Moreover, the design of GHG emission reduction policy for the electricity market can affect the price and consumption of electricity. For example, the case study shows that the policy on initial allocation of carbon allowances can considerably affect prices, demand, and the utility generation mix in the long term. The resulting moderated electricity consumption can also contribute to achieving emission reductions.

There are some limitations to use of the model suggested in this study. First, this kind of model takes the input parameters as given and fixed. This requires that the electricity systems under study is small enough and the other markets, such as fuel markets, are large enough. If the target electricity system is large enough that the model's decision will affect the other markets, other variables would need to be incorporated endogenously. Second, the least-cost model does not include the dynamics of electricity market. Particularly, this model leaves out the competition. Even for the vertically integrated markets, several players exist in actual electricity sector, so the sector might not follow the least-cost pathway.

Nevertheless, we can use the model in this study to approximate future long-term changes in the electricity sector under new policies with less complexity. Expanding this model in order to include the dynamics of actual systems more realistically may be the next challenge of this research field.

CHAPTER III

GRID INTEGRATION OF EV AND WIND

3.1 Background

Numerous renewable electricity technologies are being deployed onto the electric grid, with wind energy currently among the most cost-effective. Wind and solar generation are intermittent and grid integration is challenging. Simultaneously, plans for introduction of electric vehicles (EVs) onto the grid are ramping up, as an approach to reducing petroleum dependence. A number of studies show that EVs can have lower total fuel costs and net emissions than conventional gasoline-powered vehicles (CVs) [19, 33, 47, 77, 87]. Some studies find that integration of substantial numbers of EVs onto the grid could increase electricity demand and potentially result in higher greenhouse gas emissions than CVs under some electric power systems [63, 88]. A potential additional benefit of electric vehicles could be to manage wind and solar electricity by charging during periods of high renewable output. Short and Denholm [85] assess the potential benefits of synergies between plug-in hybrid electric vehicles (PHEVs) and wind energy for reduction of petroleum use and greenhouse gas (GHG) emissions. Wang et al. [100] use a unit commitment model to show that control of PHEV charging and wind energy can reduce the total operating cost of the Illinois electric power system. Gransson et al. (2010) [45] also use a unit commitment model and conclude that integration of PHEVs into a Swedish wind-thermal power system can reduce not only system operating costs but also total GHG emissions from the system.

In this study, we develop four linked models to analyze future impacts of EVs and wind power on the electric power system and light-duty vehicle (LDV) market.

Metrics include cost of electricity, total consumer expenditure, GHG emissions, and petroleum consumption. The models are run for the entire eastern interconnection of the United States. EVs include both plug-in hybrid vehicles and fully battery-electric vehicles ; we limit consideration of EV adoption to the light-duty vehicle fleet. Three market share scenarios for 2025 are considered: (a) S10, in which EVs reach 10% market share, (b) S20, in which EVs reach 20% market share, and (c) S100, in which EVs reach 100% market share. The fuel economy of the CVs is solved endogenously based on the EV market share and the applicable fuel efficiency standard.

Four charging schemes are considered: (1) uncontrolled charging, in which EV owners plug in their vehicles immediately after the last trip of the day and EVs are charged as soon as possible; (2) controlled charging, in which EV owners plug in their vehicles but a grid operator controls charging to minimize cost; (3) controlled charging with annual wind energy balancing, similar to (2) and the electric power systems ensure that annual wind generation meets or exceeds annual EV charging demands; and (4) controlled charging with real-time wind energy matching, similar to (3) but with hourly wind generation meeting or exceeding hourly EV demand.. All of the charging schemes assume charging occurs at home although some public charging infrastructure is built to reduce range anxiety. In order to examine the potential to reduce the cost of wind integration by linking wind energy and electric vehicle charging, we evaluate two cases with a higher renewable electricity standard (RES) than currently in effect in the eastern interconnection: a high RES and uncontrolled EV charging, and a high RES and conventional vehicles. These high RES cases have roughly the same renewable capacity as the controlled charging with real-time wind energy matching case.

3.2 Methodology

The analysis uses four models: (i) For each EV market share scenario, a *light-duty-vehicle fleet* model determines the vehicle characteristics for conventional and electric vehicles for each year over the study period; (ii) a least-cost *capacity planning* model determines the optimum electric generation capacity for each year over the study period; (iii) a *unit commitment* model optimizes the day-ahead unit commitment choices based on information available the day before the delivery of power; and (iv) an *economic dispatch* model optimizes the dispatch of generation and flexible loads during the operational hour.

The capacity planning model of previous chapter 2 has been expanded to integrate the EV charging schemes and more detailed characteristics of wind generation. The capacity planning model was programmed and implemented in the AMPL optimization package, and was solved using the ILOG CPLEX 11.1 solver. Further details of the capacity planning model are given in Appendix B.1.

Together, the unit commitment and economic dispatch models[1] serve to a) validate that the capacity determined by the capacity planning model is sufficient to provide secure system operation, b) determine the unit startup and shutdown costs, and c) determine the amount of wind curtailment due to wind forecast inaccuracy and limitations in demand and supply flexibility. Here, we take secure operation to mean that the system is able to serve demand despite generator limits and wind forecast uncertainty. Generator limits include the time required to startup an offline unit, the minimum and maximum power a unit can deliver and still remain online, and the maximum energy a unit can deliver over a specific time period. Transmission constraints, transmission reliability and generator reliability are typically also

[1]My colleague, Frank Kreikebaum, developed these models.

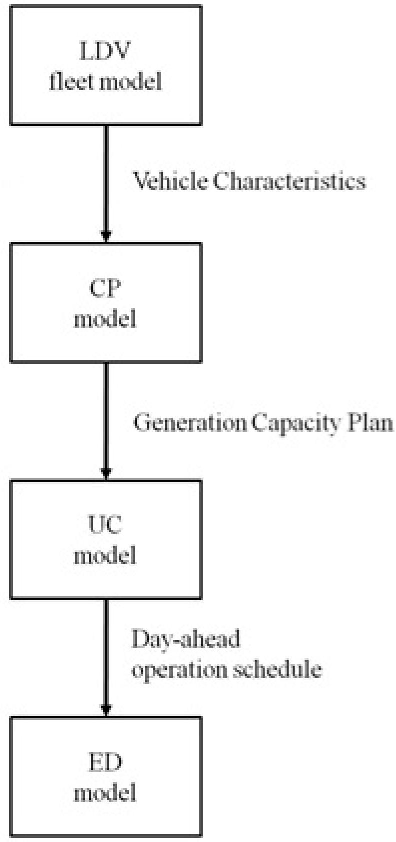


Figure 15: Flow diagram of models, indicating use of a light duty fleet (LDV) model of vehicle fleet characteristics for each year for both electric and non-electric vehicles, a capacity planning model (CP) for the multi-year planning of electricity generation, a unit commitment (UC) model for day-ahead scheduling of electricity production, and an economic dispatch (ED) model that simulates electricity production

included in a security analysis but we do not include them here. The unit commitment and economic dispatch models were programmed in MATLAB and solved in MOSEK. Further details of these models are given in Appendix B.2 and Appendix B.3 respectively.

The models are run in series as shown in Figure 15. First, we run the light-duty-vehicle fleet model for the entire study period, 2010-2030. The output serves as input for the capacity planning (CP) model, which is also run for the entire study period. The output of the capacity planning model is fed into the unit commitment (UC) model which is run for the first day of the sub-period of interest. The results from the first-day of the UC model are fed into the economic dispatch model (ED), which is run for every hour of the first day of the sub-period. The UC and ED models are then rerun for every day in the sub-period of interest. As our focus is on the metrics once EV adoption rates have stabilized, we only run the UC and ED models in 2030. In addition, to reduce the computational burden, the UC and ED models are only run during time periods of demand or supply stress on the system. The chosen sub-periods of interest are the weeks with the highest and the lowest projected annual hourly loads, the week with the highest daily wind potential production, and the week with the lowest wind potential production. The discrepancy between simulating the UC and ED models over a four-week sub-period and over a ten week sub-period was measured. The results indicate that simulating over a four-week sub-period is a reasonable approximation for simulating over a longer sub-period. The eastern interconnection spans 38 states, covering most of the eastern North America, has six reliability councils , and represents 74% of total US electric consumption [24]. In order to get more realistic results and understand regional characteristics, we applied our model to these six councils[2] separately. We aggregate the six regions' results to provide an overall assessment for entire eastern interconnection.

3.3 Data and Assumptions

3.3.1 EV adoption and characteristics

To model the future fuel efficiency of the entire U.S. light-duty vehicle (LDV) fleet, we use the proposed fleet-wide fuel economy standard of 49.6 mpg for model year (MY) 2025, as measured using the National Highway Traffic Safety Administration (NHTSA) method [93]. The NHTSA 49.6 mpg standard determines the Corporate

[2]Florida Reliability Coordinating Council (FRCC), Midwest Reliability Organization (MRO), Northeast Power Coordinating Council (NPCC), Reliability First Corporation (RFC), SERC Reliability Corporation (SERC), Southwest Power Pool, Inc. (SPP)

Average Fuel Economy (CAFE) standard and does not include many of the incentive multipliers included in the EPA standard [37]. Therefore, the NHTSA standard is closer to actual vehicle fuel economy and is used for this study. The standard projects a distribution of sales of vehicle footprints and types (i.e. truck vs. car). Since the standards apply to individual vehicle footprints and type, rather than the fleet as a whole, should actual sales not match the projected distribution, fleet-wide fuel economy may not match the 49.6 mpg overall standard.

We use the proposed model year (MY) 2017-2025 standard and assume vehicle sales are distributed as projected to develop the reference case. For the market share of new light-duty vehicle technology for 2025 we use projections from the US EPA and the NHTSA [30][3], which is that EVs reach 10% market share by 2025, as our base EV adoption scenario. In addition, we consider two more 2025 market share scenarios: 20% and 100%.

We estimate the number of LDVs in the eastern interconnection based on the National Household Transit Survey (NHTS) [42] and the Annual Energy Outlook (AEO) 2011 [24]. The NHTS surveyed households across the entire U.S., recorded the number of vehicles per household and estimated the number of households in each state. Based on this, we estimated the share of vehicles for each state. With AEO 2011 projections for future LDV sales volumes and vehicle stock size, we project the number of LDVs in the eastern interconnection for each year of the study period. Details on the projection are given Appendix B.4. Starting from 2008 sales figures [24], of which 53% and 47% of LDV sales are cars and light-duty trucks respectively, the market share of cars gradually increases to about 64% by 2030. SUVs and vans

[3]Based on the current rule for 2012-16, the report developed four fuel economy scenarios: 47, 51, 56 and 62 mpg as measured by the EPA until 2025, and projected that the market share of fully electric vehicles among new vehicles in 2025 will reach 10% with an emphasis on EVs under the 56 mpg scenario which is equivalent to 49.6 mpg as measured by the NHTSA. These standards will require the fleet to meet an estimated combined average emissions level of 250 g of CO_2 per mile in 2016, equivalent to 35.5 mpg

are projected to comprise 64% and 11% respectively of light-duty truck sales. The EV stocks will reach 8.5%, 17%, and 80% in 2030 under the 10%, 20%, and 100% scenarios,respectively. With the projections of the future LDV sales and stocks, we project the number of vehicles scrapped[4] each year.

All-electric range and fuel efficiency are important characteristics when modeling the impact of EVs on the power system. Most previous studies evaluate plug-in hybrid electric vehicles with an all-electric range between 20 and 60 miles [19, 77, 87]. However, recently introduced fully electric vehicles, such as the Nissan Leaf, have a roughly 100-mile range, and these ranges are expected to increase gradually. In this study, we assume that battery-electric vehicles sold between 2010 and 2030 have a 100-mile range and plug-in hybrid vehicles have a 40 mile all electric range.

EV energy intensities are usually represented in kWh/mile when they are driven in charging-depleting (CD) mode, during which electrical energy is used to drive the vehicle. Plug-in hybrid vehicles are characterized by fuel economy when operating in charge-sustaining (CS) mode, during which the combustion engine is powering the vehicle. The assumptions for EV energy intensities in the CD mode are based on the projection of Argonne National Laboratory [5] and discussed in Appendix B.5. We assume PHEVs operating in CS mode have the same fuel economy as conventional vehicles (CVs). CVs, which we take to be vehicles that do not source energy from the electrical grid, are represented as having a single fuel economy.

The U.S. Department of Energy Annual Energy Outlook (AEO) 2011 projects the fuel economies of new vehicles, vehicle stocks, and the distribution of vehicle type (car and truck). Using fuel economy data from AEO 2011 for MY 2010 through MY 2016 as well as distribution data for 2010-2030, we project fuel economies of new vehicles for each MY through 2030 under the MY 2017-2025 NHTSA standard. We

[4]Vehicles scrapped is calculated as the difference between the vehicle stock changes between current and next years, and the number of new vehicle sales.

assume the average fuel economy of the scrapped vehicles equals the average of the vehicle stocks in the previous year. For each year of each EV scenario, we calculate the required CV fuel economy to meet the NHTSA standard. We also calculate the average fuel economy of the vehicle stock. Given the high fuel economy assigned to EVs by the NHTSA, scenarios with higher EV market share result in a lower required CV fuel economy. Taken to the extreme, this leads to falling CV fuel economy as EV adoption increases. However, we impose the requirement that within a given scenario, CV fuel economies do not decrease as a function of time. In some cases, this leads to fleet-wide fuel economies in excess of the standard. The details on EV fuel economy calculations and CV fuel economy projections are given in Appendix B.6.

3.3.2 Load profile of vehicle charging

The load profile of vehicle charging depends on the charging scheme, the charging rate and the driving pattern. Higher charging rates can provide consumers with the convenience of quick charging but can decrease the lifetime of power system assets [65] and require additional generation capacity [47, 77]. Common charging rates are level 1, rated up to 1.92 kW AC, level 2, rated up to 19.2 kW AC, and DC fast charging. With level 1 charging, only EVs with an all-electric range under 30 miles are viable with overnight charging [100]. Given our assumed EV ranges, we assume EV owners employ level 2 charging, at a rate of 6.6 kW. The EPA/NHTSA report assumes this rate, and the 2012 Ford Focus EV and 2013 Nissan Leaf are equipped with this charger.

The NHTS conducted by the US Department of Transportation surveyed households across the US, tracking the travel of all members of each household for one day. For each trip, the NHTS recorded the start time, travel distance, end time, and vehicle type [41]. In addition, the Metropolitan Statistical Area (MSA) of the

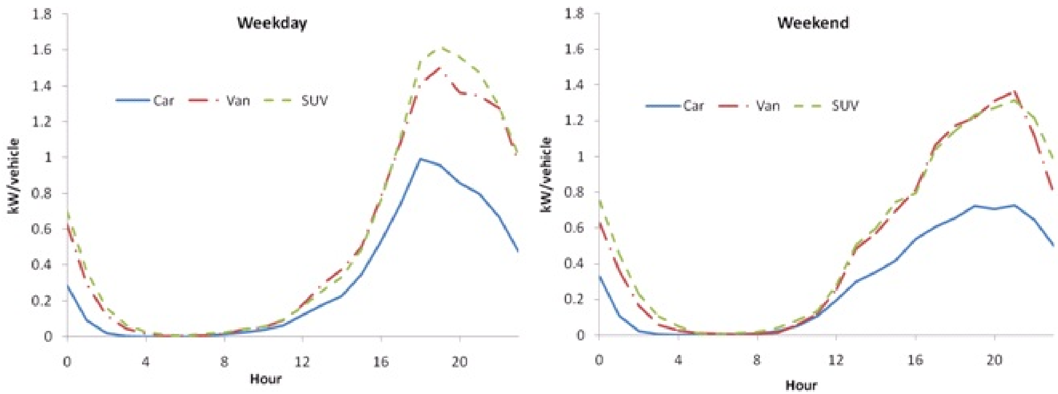


Figure 16: Average charging profiles per vehicle under uncontrolled charging schemes, for weekdays and weekend days, respectively

household was recorded. Based on the NHTS and assumed charging rate, we developed weekday and weekend representative charging profiles for each type of vehicle for use with the uncontrolled charging scheme. Figure 16 shows the uncontrolled charging profile. Based on the NHTS data and assumed energy intensities, we also develop the required daily energy that must be delivered to the EV vehicle fleet to meet daily driving needs. Appendix B.7 contains more details on the uncontrolled charging profiles, the capacity profiles, and the required daily energy.

3.3.3 Integration of Renewable Energy with EV Charging

Both wind and solar power are intermittent sources of electricity that can require additional reserves, additional frequency regulation, and more maintenance of thermal units at high levels of penetration [50, 6, 46, 56, 2]. These requirements lead to integration costs in addition to the busbar cost of wind and solar generation. We consider the potential for EV charging to be a flexible load that can be matched with the availability of intermittent renewable generation in order to reduce integration costs as proposed in [49]. For the controlled charging schemes, we assume that rate incentives ensure that vehicles are plugged in at the end of every journey that terminates at home. To estimate the flexibility of the EV fleet, we use the NHTS data and 6.6 kW charger rating to determine the total amount of grid-connected charging capacity, for each vehicle class for weekdays and weekends, on a per vehicle basis. The integration of the area under each charging capacity curve is larger than the integration of the corresponding uncontrolled charging profile. This indicates that vehicle charging could be scheduled while simultaneously ensuring that sufficient energy is available to meet diurnal driving demands. We assume the grid operator schedules EV charging demands to minimize cost and meet constraints appropriate to the charging scheme. Charging control could be realized via Internet or advanced metering infrastructure (AMI) communication. While the scheduling process could be distributed among third parties or converted to a decentralized process using pricing signals, for this effort we assume the grid operator schedules the charging. With wind power currently available at significantly lower costs than solar power within the eastern interconnection, we assume all intermittent renewable energy is provided by wind generation.

We obtain time-series potential outputs, forecasted outputs, capacity, and levelized cost for thousands of hypothetical onshore wind generation sites in the eastern and central US from the National Renewable Energy Laboratory (NREL) EWITS database [73]. The EWITS database also provides these data, except for levelized costs, for thousands of offshore sites along the eastern seaboard, Gulf coast and Great Lakes. We develop supply curves of onshore wind power for each of the six reliability councils within the eastern interconnection using the EWITS data. We also develop onshore and offshore wind power profiles for high windy, medium windy, and low windy days for six reliability councils. The details on wind power profiles are given in Appendix B.8.

Even though both the Southwest Power Pool (SPP) and the Midwest Reliability Organization (MRO) consume only 15% of eastern interconnection electricity, the wind power potential in these two councils accounts for 73% of eastern and central

US potential. While the other four councils (FRCC, NPCC, RFC and SERC) will likely require a large amount of wind generation to meet existing renewable electricity standards (RES), the supply curves indicate that wind energy generated in MRO or SPP and shipped to the four regions will likely be cheaper than wind energy generated in the four regions. For example, SERC has 1,238 MW of resources under $80/MWh while SPP has 80,377 MW. At least one utility in SERC imports wind from SPP and new transmission has been proposed to transport wind energy from the SPP and MRO regions to eastern regions[5]. We assume that SPP and MRO regions will export their surplus wind power to other eastern regions in proportion to their regional demands. The wind export supply curves include both generation cost and transmission cost, with transmission calculated as shown in Appendix B.8.

3.3.4 Electric Power Systems

The Annual Energy Outlook (AEO) provides basic electricity generation information, including nameplate capacities by generation technology, electricity demand projections, and fuel price projections [24]. The characteristics of the generating technologies are mainly based on the assumptions to AEO 2010 [22].

Based on the 2010 hourly load data of representative utilities in the eastern interconnect [40], we develop 24-hourly load profiles of average weekdays and weekends in three seasons (winter, intermediate, and summer) for each of the six regions for use with the CP model. We assume that the hourly loads for each year in each region scale by a region-specific, year-specific constant to meet the projected annual demand of the region. We also develop hourly load profiles for each region spanning the entire study period for use in the UC and ED models. Profiles are shown in Appendix I.

Some states have enacted state-level renewable electricity standards (RESs), requiring electricity providers to supply a minimum percentage of annual demand using

[5] Clean Line Energy Partners, 2012, http://www.cleanlineenergy.com/projects

renewable energy resources. We require the capacity planning model to satisfy the existing RESs over the study period and assume that no additional RES mandates are passed. We calculate the effective RES mandates for six councils based on the load-weighted average RES mandates of each state. The load-weighted average RES mandate of the entire eastern interconnection is about 9.6%, and the details on the effective RES mandate are shown in Appendix B.10. In addition, to examine the high RES cases, we consider a federal level RES mandate of 33% by 2030, which is the California RES level [21]. Given the lack of carbon emissions restrictions, we assume a carbon price of $0 throughout the study period.

3.4 Results

We present results for 13 cases: the reference case, and four charging schemes combined with three EV adoption scenarios. The reference case assumes all vehicles are CVs and no requirements are imposed upon the electric power sector except meeting load growth and existing RESs. Our CP model indicates the most aggressive case - EV 100% market share and controlled charging with wind real-time matching - is not feasible given the amount of wind resources in the eastern interconnection, so we exclude further analysis of that case. In addition, we originally considered charging in which EV owners plug in their vehicles after every trip rather than only at home; however our CP model produces the same results with the ubiquitous controlled charging schemes as the home controlled charging. Since ubiquitous controlled charging requires more infrastructure without changing the results, we eliminated that charging approach. For all twelve EV cases, we run our models for the six reliability councils separately. All results for the eastern interconnection are the aggregated results for the six reliability regions. The levelized cost of electricity is calculated based on the generation-weighted average of the costs in the six regions.

3.4.1 Energy Consumption

Figures 17 and 18 show electricity and light-duty-vehicle (LDV) gasoline demand projections under the different EV adoption scenarios. Electricity demand in the reference case is expected to increase by 11% over 20 years from 2010 to 2030, and the electricity demands under the three EV scenarios are 1.7%, 3.3% and 15.8% higher than reference demand respectively in 2030. LDV gasoline consumption declines under every scenario due to increasing fuel economy. Even without EV adoption, US gasoline demand decreases by about 20% by 2030. With low EV adoption levels, the CVs are required to be more efficient in order to meet the fuel economy standards. As a result, gasoline consumption under the S10 and S20 EV adoption scenarios is lower by only 2.9% and 4.4% relative to reference case in 2030. Gasoline consumption declines by about 44% in the limit case of 100% market share.

Figure 19 represents the sources of extra electricity in 2030 under the S10 scenario. The positive/negative values mean that the amount of electricity from corresponding sources will increase/decrease with respect to the reference case. The net increased electricity consumption levels in all four charging schemes are the same. For uncontrolled charging, the capacity planning model projects that the extra electricity will be mainly generated from natural gas. The gap between on-peak and off-peak loads increases, and the electric power systems generate more electricity with natural gas, a traditional mid-range and peaking resource. Under cost-minimizing controlled charging and controlled charging with wind energy annual balancing, some portion of the additional electricity comes from low-cost coal power at times when demand is low, and the extra electricity is mainly generated from natural gas. With annual wind energy balancing constraints, wind energy provides more of the energy required to meet the mandated RPSs than in the reference case and some biomass power plants built in the reference case are not built.

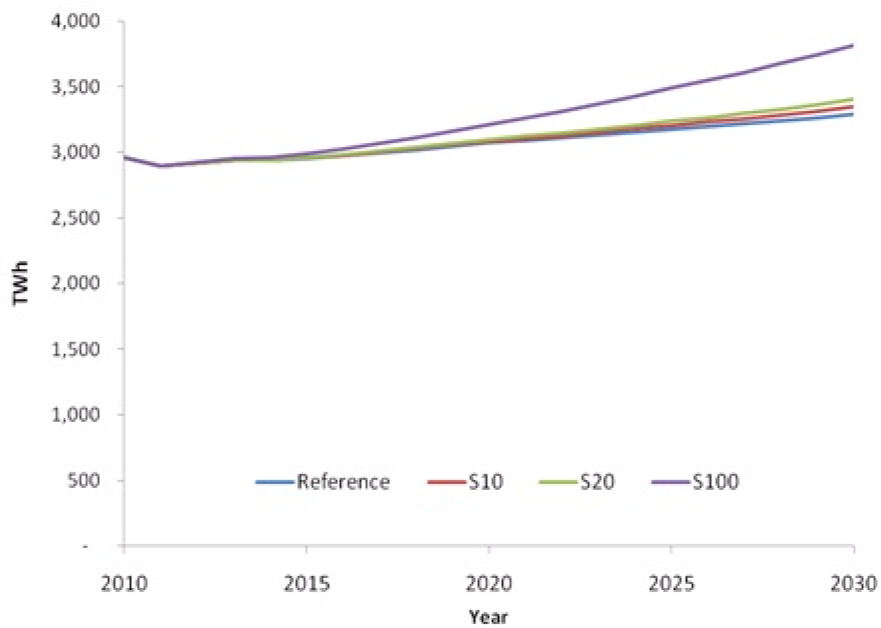


Figure 17: Annual electricity demand projection for the US eastern interconnection in the reference case and for three scenarios of EV adoption. The effect on electricity demand in the S10 (10% EV sales by 2030) and S20 (20% EV sales by 2030) EV adoption scenarios is small; only in the limit case, in which EVs capture the entire market for light duty vehicle sales by 2030, is there a substantial increase in overall electricity demand.

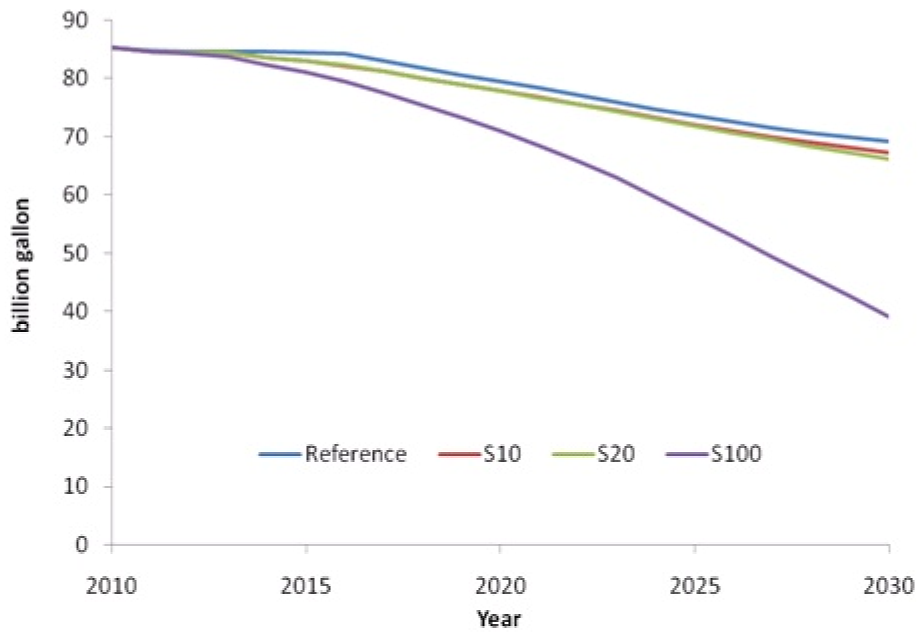


Figure 18: Annual light-duty-vehicle gasoline consumption projection in the US eastern interconnection. The S10 (10% EV sales by 2030) and S20 (20% EV sales by 2030) EV adoption scenarios provide only a small decrease in overall gasoline consumption; only in the limit case of a 100% EV light-duty vehicle market by 2030 does gasoline consumption decline substantially.

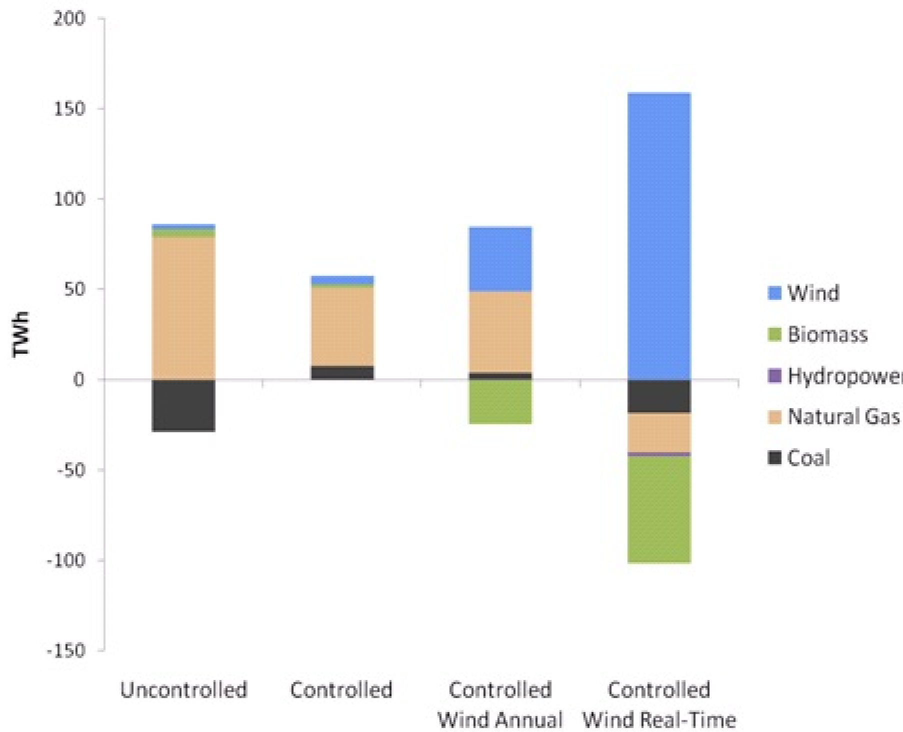


Figure 19: Change in electricity sources due to EV charging demand for four charging schemes with 10% EV market share (S10) in 2030.

Under the controlled with wind real-time matching charging scheme, a large quantity of additional wind power plants - enough to produce about 160 TWh in 2030 - will be required to fulfill EV charging demand on the day with the least wind potential production. The surplus electricity from wind power plants during the other days will be used for non-EV demand, and it replaces both coal and natural gas power plants. Relative to the reference case, a large amount of electricity from biomass will be substituted by wind electricity. Overall analysis for the sources of extra electricity under S20 and S100 scenarios is similar. More detailed analysis on wind energy is given in section 3.4.5.

3.4.2 System Operations and Hourly Load

The unit commitment and economic dispatch models were solved for each of the EV scenarios and charging schemes over the four sampled weeks, for each of the six reliability councils, to verify that the system is secure during these periods and to describe how the system operates with non-EV load and EV charging load. Figure 20 shows an example of system operation over the week containing the annual peak load for the S20 scenario[6] under each of the charging schemes. This example is from the SERC reliability council since results for SERC is the most similar to overall results. In each graph, the red line indicates the amount of non-EV load. Any generation above the red line is used to serve EV charging load. Under the uncontrolled charging scheme, EVs require most of charging load during the early evening, increasing the daily peak load for a summer peaking system like SERC. However, direct control by the grid operator allows the loads to be shifted to the middle of the night, flattening the daily load curve. For wind annual balancing and wind real-time matching schemes, a large amount of wind power serves the EV charging demand during the night.

3.4.3 Vehicle GHG emissions

The GHG emissions per mile of EV travel in the charge depleting (CD) mode can be calculated on an average basis or incremental basis. Average GHG emissions are the total GHG emissions in the electricity sector divided by the amount of total electricity. Incremental GHG emissions are the additional GHG emissions in the electricity sector relative to the reference case divided by the amount of additional electricity from EV charging. For example, the incremental GHG emissions factor for electricity in the S10 scenario with controlled charging is about 390 g CO_2e/kWh, which is similar to that of natural gas electricity, as we can see in Figure 19. Figure 21 shows the GHG emissions per mile of EVs and CVs under the twelve cases. The GHG emissions factor from EVs are much less than that from CVs in every case and the GHG emissions under the S10 and S20 scenarios are lower than those under S100 scenario cases.

[6] Due to its small EV charging demand, the S10 scenario is not shown.

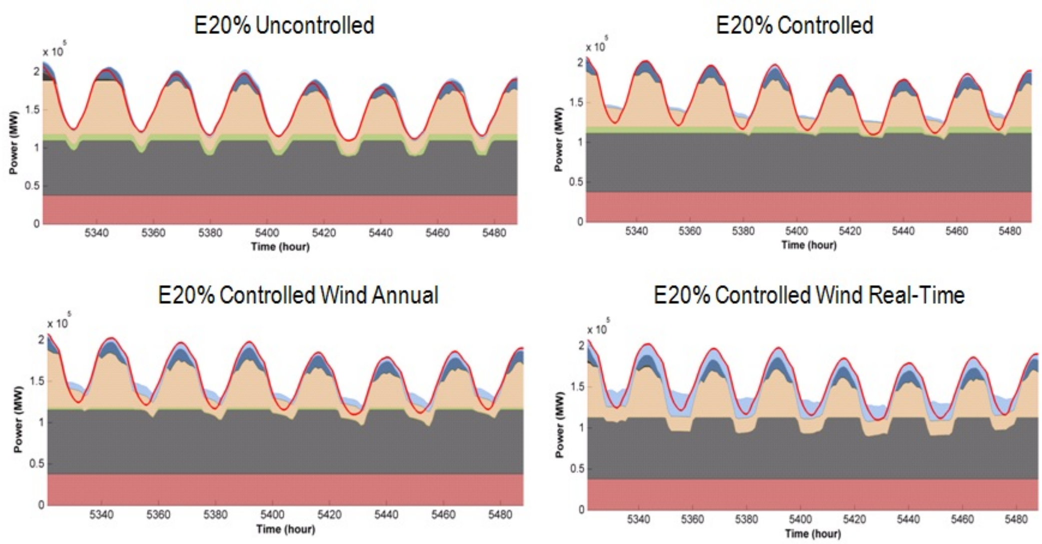
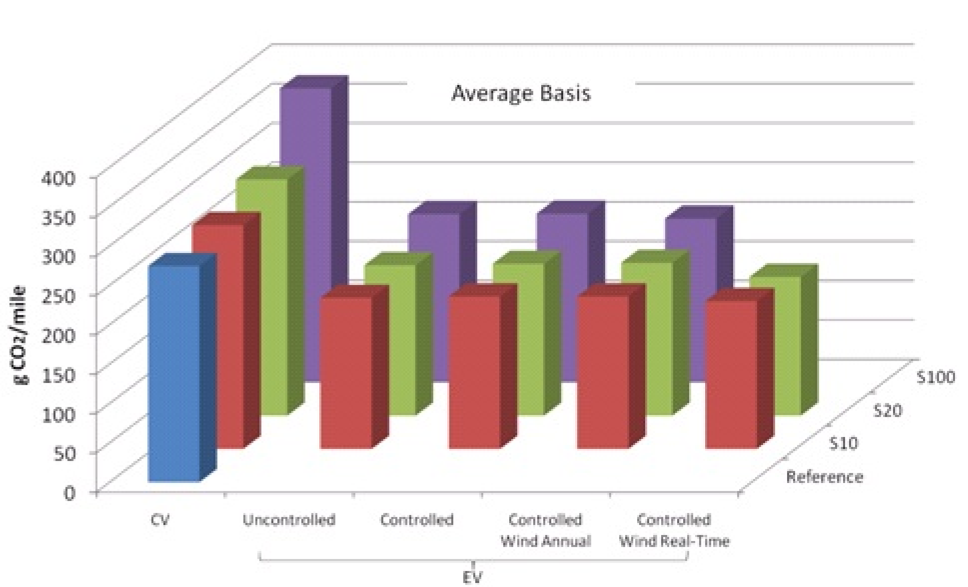


Figure 20: System Operation in 2030 for the week with the peak daily load for uncontrolled charging (top), controlled charging (upper middle), wind annual balancing (lower middle) charging, and real-time wind energy matching (bottom) schemes. The red line shows the non-EV load and generation is categorized by fuel type as nuclear (red), coal (dark gray), biomass (green), natural gas (light brown), hydro (dark blue), and wind (light blue).



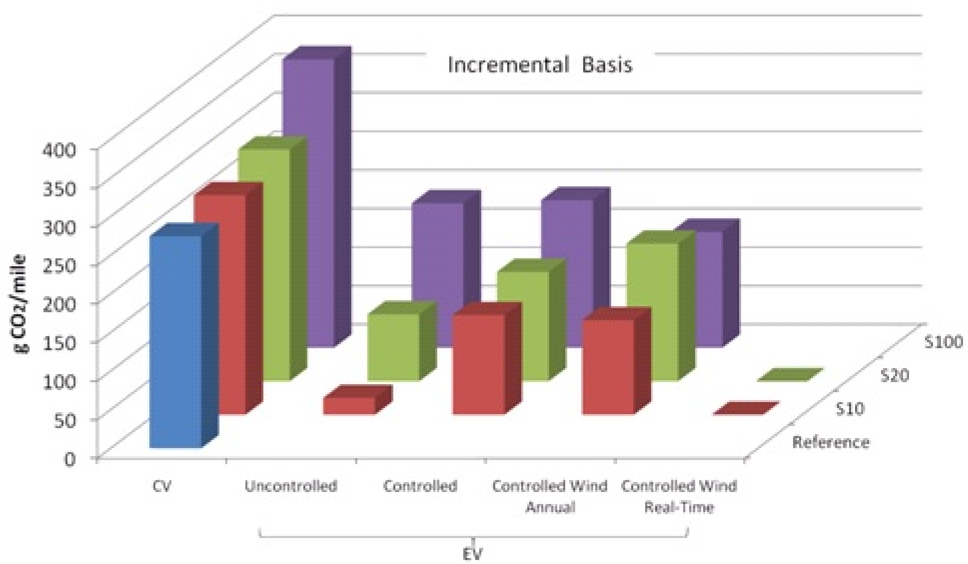


Figure 21: GHG emissions per mile in 2030 under different charging schemes. Zero values mean the electricity sector has less GHG emissions with the given EV charging scheme compared to the reference case.

3.4.4 System GHG emissions

Existing RESs are projected to result in 7.5% reduction of electricity sector GHG emissions by 2030 with respect to the 2010 level, even though total electricity generation is expected to increase 11%. With EV adoption, the electricity sector produces more GHG emissions relative to the reference case for all cases except those using wind real-time matching, due to increased electricity generation. Since the controlled charging scheme increases the utilization of coal power plants, which have the highest GHG emissions per kWh, it has the largest increase in electric power sector GHG emissions. For all except one day per year, wind real-time matching results in more wind electricity than required to charge the EVs. This can be used to supply conventional (non-EV) demand, reducing the GHG emissions of the entire electricity sector. Interestingly, the electric sector produces more GHG emissions under annual wind balancing than under uncontrolled charging with 10% and 20% EV adoption levels: under wind annual balancing, even though the charging demand from EVs equals the of electricity generated from wind, the flattened extra demand results in the power system using more coal relative to the reference case; on the other hand, some coal generation will be replaced with natural gas generation in the uncontrolled charging scheme as shown in Figure 19. Figure 22 represents the sum of GHG emissions from electricity generation and LDV gasoline combustion. Overall, the total GHG emissions reduction level will be 12% in 2030 with respect to 2010 under the reference case. However, for the controlled and the controlled with annual wind balancing charging schemes under the S20 (20% market share) scenario, the sum of GHG emissions surpasses that without EV adoption by about 0.2%. That is, for some EV cases the GHG emission reduction from decreasing gasoline consumption is less than the increased GHG emissions from electricity generation. Only wind real-time matching and wind annual balancing with high EV adoption provide a notable reduction in GHG emissions.

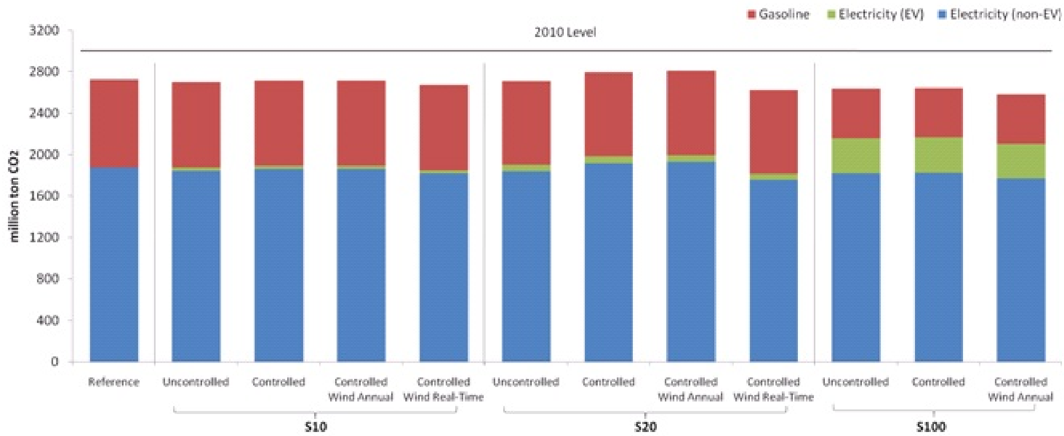


Figure 22: Total GHG emissions from electricity generation and gasoline combustion in vehicles in 2030

Figure 22 contrasts with the results from Figure 21. Although Figure 21 shows that greenhouse gas emissions per mile are lower for EVs than for CVs, overall greenhouse gas emissions with EVs are about the same, or a bit lower, than greenhouse gas emissions with only CVs. There are two reasons for this. First, except under wind real-time matching, the average GHG emission factor per kWh of electricity increases with EV adoption compared to the reference case. As a result, all other non-EV electricity, which is much larger than EV charging demand, has a higher GHG emissions factor. Second, due to the structure of the fuel efficiency standards, the GHG emissions per CV mile is higher with higher EV adoption. These results demonstrate the importance of comparing not only the GHG emissions factor per mile of vehicle travel, but also from a total emissions perspective.

3.4.5 Economic Impacts

Figure 23 presents the levelized generation costs of wholesale electricity under different cases. Even though annual electricity demands under the S10 and S20 EV scenarios are higher than in the reference case, the levelized costs of electricity in the S10 and S20 scenarios under controlled charging are slightly lower than in the

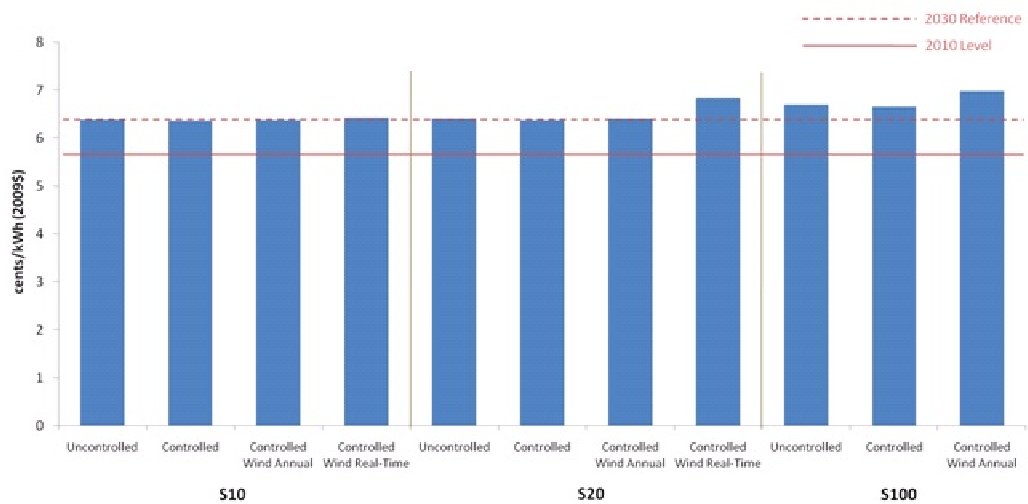


Figure 23: Levelized electricity generation cost in the eastern interconnection in 2030

reference case. Even though the capacity planning model builds lots of new wind power to enable wind real-time matching, the levelized cost of electricity increases 1.7% and 7.3% under the S10 and S20 scenarios respectively. Moreover, while total electricity demand in the S100 EV scenario is 15.8% higher than in the reference case, the levelized cost of electricity in the S100 controlled charging case increases by only 4.5% in 2030. Load control enables the grid operator to shift the charging demand to increase the utilization of lower cost baseload coal and nuclear power plants. Under the S100 wind annual balancing case, the cost of energy increases roughly 10%.

Next, we estimate the total consumer expenditure (TCE) of an EV and CV owners, who buy the vehicle in 2030. We assume the retail energy price is \$0.04/kWh higher than the wholesale cost, to account for transmission and distribution. We assume a gasoline price of \$4 per gallon. Even though battery recharging is less expensive than gasoline refueling, EV upfront costs are greater due to higher vehicle cost and the cost of charging infrastructure. Based on ANL's analysis (ANL 2011) and our projection of fuel economies, we estimate the incremental purchasing cost of each vehicle type. The detailed calculation for incremental purchasing costs in Appendix

Table 7: The net present value of lifetime (13 years) total expenditure compared to conventional vehicle (CV) in each scenario. The numbers show the differences of the costs for EV and CV in the same EV adoption scenario. The negative numbers mean the lifetime cost of EV is lower than that of CV.

		Uncontrolled	Controlled	Controlled Wind Annual Balancing	Controlled Wind Real-Time
S10	Compact	-1110	-1116	-1115	-1099
	Midsize	-1779	-1787	-1785	-1767
S20	Compact	-1844	-1853	-1843	-1734
	Midsize	-2661	-2671	-2660	-2541
S100	Compact	-3979	-3990	-3908	-
	Midsize	-4294	-4306	-4216	-

B.11. We assume each owner pays for one home charger per vehicle as well as a portion of the public charging infrastructure network, as described in Appendix B.12. The infrastructure cost in all cases is $932 per vehicle. TCE includes the incremental cost of non-EV electricity pro rated on a per vehicle basis. With total expenditures for operation of vehicles and incremental upfront costs, we compare the net present value (NPV) of lifetime total costs for compact and midsize passenger cars under each scenario when the vehicles are purchased in 2030. Tables 7 and 8 compare the total costs for electric vehicle (EV) and conventional vehicle (CV). The numbers in Table 8 are the difference of the total costs between EV and CV in the same EV adoption scenario. In contrast, Table 8 shows the difference between the average vehicle TCE in an EV case relative to the TCE of CV ownership in the reference case. This table may be used to compare the cost impacts of setting EV adoption as a goal within the eastern interconnection. The details of specific calculations are shown in Appendix B.13.

The results can be sensitive to the discount rate assumption. The upfront cost of an EV is higher than that of a CV for all cases. In addition, the annual operating cost of an EV is lower than a CV for all cases. Thus, lower discount rates give advantage to EVs and higher rates give advantage to CVs. In this study, we use a discount rate of 4.8%, the average rate for new car loans from 2001 to 2010. With this interest

Table 8: The net present value of lifetime (13 years) total expenditure compared to reference case conventional vehicle (CV) in each scenario. The numbers show the differences between the weighted average total costs for both CV and EV in the EV adoption scenario and that for CV in the reference case. The positive number means the average lifetime cost of vehicle ownership under EV adoption case is higher than that under the reference case.

		Uncontrolled	Controlled	Controlled Wind Annual Balancing	Controlled Wind Real-Time
S10	Compact	721	685	694	777
	Midsize	808	773	781	864
S20	Compact	1516	1469	1522	2110
	Midsize	1696	1648	1701	2291
S100	Compact	1655	1580	2142	-
	Midsize	1336	1261	1830	-

rate, the total costs for CV owners surpass those of EV owners in all cases as shown in Table 7 and the differences of the total costs increase with EV adoption levels. For cases with high EV market share, the required CV fuel economy is lower than cases with low EV market share; thus, the operating fuel costs of CVs in high market share cases are higher than the lower market share cases and in most cases the increased fuel costs surpass the higher operating costs of EVs. This result implies that EVs will be more cost-effective than CVs. However, this does not imply that higher EV adoption scenario is better than the reference case of lower EV adoption cases in terms of TCE. In Table 8, the weighted averages of TCE for both CV and EV owners under EV adoption cases are higher than the total expenditure for CV owners under the reference case. This result implies that the average vehicle owner spends more money under the EV adoption cases than the reference case. This increased TCE can be considered the per vehicle portion of the social cost for reducing greenhouse gas emissions and oil consumption via EV adoption.

3.4.6 Wind Power and High RES

Based on the EWITS database, the eastern interconnection has about 530 GW onshore and 140 GW offshore wind power potential (NREL 2010). With the existing

Table 9: The wind power on the entire eastern interconnection in 2030 under the controlled with annual wind balancing and the controlled with real-time matching schemes. *When we relax the constraints for wind potential capacity, our models require higher capacities than the potential.

		Onshore Capacity (GW)	Offshore Capacity (GW)	Total Generation (TWh)
S10	Controlled Wind Annual Balancing	53	6	230
	Controlled Wind Real-Time	85	9	350
S20	Controlled Wind Annual Balancing	58	6	250
	Controlled Wind Real-Time	137	29	520
S100	Controlled Wind Annual Balancing	116	13	460
	Controlled Wind Real-Time	972	140	3275

RPS, 44GW onshore and 4GW offshore wind power potential will be used to generate 190 TWh in 2030 without EV adoption. Table 5 represents the wind power on the system under the annual wind balancing and real-time matching schemes. In order to implement wind real-time matching, the power systems required considerably more wind power than wind annual matching. In the limit of 100% market share, the winder energy required for real-time matching is more than the wind potential of the eastern interconnect.

The control of EV charging can provide system reliability and economic benefits by reducing generator cycling costs and wind curtailment. Lower cycling costs and lower wind curtailment may increase system reliability, decrease the amount of required generation and transmission, and lower operating costs.

The 33% RES cases show the benefit of controllability more visible. About 280GW onshore and 13GW offshore wind potential are required to meet the high RPS. The cycling costs of the uncontrolled case, 0.07 cents/kWh, are more than twice those of the controlled case, 0.03 cents/kWh. Wind curtailment is about 7% under the uncontrolled case and 1% under the controlled case. If the system is subject to an

RPS, wind curtailment leads to more capacity expansion than is identified in the CP model. The TCEs in Table 8, which do not include cycling costs and curtailment effects, show that controllability makes it easier to integrate more wind power into the systems. The cases with controllability are expected to be even more attractive if curtailment effects and cycling costs are included

3.5 Conclusion

We analyze future impacts of electric vehicles (EVs) and wind power on the electric power system and light-duty vehicle (LDV) market based on three perspectives: petroleum consumption, GHG emissions, and total consumer expenditure. Introduction of electric vehicles can reduce US petroleum demand. Due to the structure of the proposed US fuel efficiency standard, which allows fleet efficiency to be met with a combination of EVs and highly efficient conventional vehicles (CVs), gasoline use is projected to fall in all cases, with or without EVs. However, since the CVs would be required to have correspondingly higher fuel efficiency without EVs, our LDV model analysis shows the additional reduction from EV adoption could be marginal in the low EV adoption level. In addition, even though electric vehicles have lower greenhouse gas emissions per mile than gasoline-powered vehicles, electric vehicles may not provide a net reduction in greenhouse gas emissions. The control of electric vehicle (EV) charging can substantially affect both EV emissions and the future of the electricity generation system. In smart-grid controlled system, their charging can be managed by the electricity system operators to reduce costs and manage loads, and could also be used to support integration of wind or solar power onto the grid. Matching electric vehicle charging to wind energy has the appeal of being able to, in concept, charge electric vehicles entirely with wind energy, resulting in what might be interpreted as essentially zero greenhouse gas emissions from electric vehicles. However, when considering the resulting development and operation of the entire electricity system, the result looks different. If the system operator simply matches the amount of wind energy to the amount of vehicle charging, on an annual basis, the higher emissions from off-peak charging will in effect cancel out the benefits of wind charging of the electric vehicles.

It is possible to provide wind energy for real-time charging of electric vehicles. For the eastern interconnection region of the US, consisting of 36 states, we show that real-time wind charging of electric vehicles is feasible for an EV market share of 20% in 2030. With this charging scheme, system greenhouse gas emissions are lower with EVs than in the reference case. However, if the system operator achieves real-time matching of wind energy to electric vehicle charging, then the extra wind capacity needed to achieve real-time wind matching results in an overall reduction in energy system greenhouse gas emissions. Our analysis shows that EVs will be more cost-effective than CVs in EV adoption scenarios, and the benefit of EV owners relative to CV owners will increase with EV adoption levels. However, the average total consumer expenditure of vehicle owners will be higher with EV adoption rather than the reference case, no EV adoption.

CHAPTER IV

DEMAND RESPONSE PROGRAMS FOR RESIDENTIAL CUSTOMERS

4.1 Description of Problem

4.1.1 Benefits of Demand Response Programs

The definition of "demand response" used by U.S. Department of Energy [98], is "Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized." Demand response programs can be categorized into two groups: incentive-based demand response and time-based rates.

The important benefits of demand response can fall into three perspectives [98]: 1) participants benefit: not only the participants can save money on their bills, but also others can have incentive payments from adjusted loads, 2) Market benefits: the electric power market can lower the wholesale market prices (lower marginal generation costs) from lowering peak demand. Over the long term, sustained demand response lowers aggregate system capacity requirements, allowing utilities to build less new capacity. 3) Reliability benefits: the grid operator can increase operational reliability. How about the environmental perspective? First of all, increasing reliability can reduce the "spinning reserve" level, and corresponding emissions can be reduced. Moreover, even though shifting the electricity demand from on-peak to off-peak can produce more emissions from coal-intensive electric power systems, it can help some renewable technologies to be economically viable and, therefore, reduce emissions. As we saw in the previous chapter, wind energy produces most of its electricity during the off-peak hours and we can coordinate the shifted demand and wind energy. Time-based rates can boost the viability of distributed solar panels [36].

Also, industry organizations and regulatory agencies have favored greater implementation of time-based rates because these rates can reduce the disconnect between retail rates and wholesale prices.

4.1.2 Inefficient operation of optional time-based rates for residential customers

The most common demand response program offered in the U.S. are direct load control, which an incentive-based demand response approach, and time-of-use (TOU) rates [38]. Many utilities now require their larger commercial and industrial customers to be on time-based rates. TOU rates are the most prevalent time-based rate for residential customers, and most experience has been as an optional service, under which the customers have a choice between TOU and standard flat rates. However, only a few residential customers are participating in the programs. About 50% of U.S. residential customers were offered TOU rates by utilities and 1.4% of customers signed up [38]. According to Con Edison, a New York utility providing electricity to roughly 3.2 million customers, as of June 30, 2009, only 2,337 customers were enrolled in its voluntary TOU rate program [81]. Goldman et al.[44] said that modest participation rates have limited the significance of demand response impacts for the vast majority of programs. They concluded that most utilities do not plan to promote their TOU rates aggressively in the future since the programs have not performed as well as originally expected and no longer have the support of utility and state regulators.

A primary objective of optional TOU rates is to improve the welfare of all consumers and the utilities together. In other words, offering an optional TOU rate to customers should reduce the consumers' bills without any loss for the utilities' profits.

So, social welfare should rise. However, Mackie-Mason[60] showed that optional TOU rate can be Pareto superior or Pareto inferior, depending on customers' consumption patterns and other factors. Consider how the offering of optional TOU rates can be Pareto inferior. When optional TOU rates are offered, customers who choose TOU will tend to be those with relatively low peak consumption and relatively high off-peak consumption. Even without any changes in their consumption patterns, their energy bills can decrease. However, the utility must generate the same amount of electricity in each period as before; the generation cost are the same. As a result, either utilities' profits decline or utilities can not offer low enough for TOU rates which are attractive enough residential consumers to choose TOU rates instead of the standard flat rate. Even worse, sometimes the standard flat rate must cover the loss. This makes the utilities or some customers, who are on the standard flat rates and do not change their consumption or choose TOU rates, worse off. An econometric analysis study found these programs to be ineffective at modest participation level, based on several experimental optional TOU rates from a utility in northern California [95].

In summary, utilities' disincentives associated with offering the optional TOU rates is the main reason for inefficient operation of current optional TOU programs. The disincentives encourage utilities not to promote the new rates and not to offer attractively low TOU rates. In this situation, residential customers do not consider participating in the new rates. Or, even if they do consider, customers hesitate to participate because of little bill savings and the risk of higher bills. The operation of the current programs are stuck in a systematically problematic condition.

4.1.3 Time-based rates with increasing flexible residential demand

Residential customers tend to be more price responsive as a group than commercial and industrial customers [38]. The flexibility of residential electricity consumption is expected to increase even more with deployment of smart appliances[1] and electric vehicles (EVs). When these technologies are adopted, residential customers can have more flexibility with less effort. As a result, residential customers could become more likely to volunteer for demand response programs, which could improve the efficiency of existing optional TOU rates. However, appropriate business models and customer incentive structures are required to achieve fair benefits among stakeholders. The benefits can be different based on how the incentives are designed.

EVs are beginning to be adopted. The charging demand will increase household daily electricity usage by about 37% [51], and the electric power system will have to serve the additional demand from EVs. As we saw in the previous chapter, uncontrolled EV charging demand is expected to increase the gap between on-peak and off-peak demand, so it would require most electric power systems to build additional generation capacity and diminish the systems' operational efficiencies. Many utilities have already offered optional TOU rates for EV owners: 1) when a utility offers two options for EV owners – a non-separable TOU rate that adds the electricity used for charging vehicle onto the existing household usage and another which meters the vehicle separately, 2) when the utility offers only a non-separable TOU rate.

4.1.4 Two policy tools for overcoming the inefficient operation

Figure 24 shows the conceptual relationship between monetary benefits (avoided costs) and monetary loss (transaction costs and lost revenue) of a utility as function of the participation level of residential customers on the optional time-based rates. When the participation level x is less than the critical participation level x^* (when

[1]Products that use electricity for its main power source, which have the capability to receive, interpret and act on a signal received from a utility, third party energy service provider or home energy management device, and automatically adjust its operation depending on both the signals contents and settings from the consumer. e.g. clothes washers, clothes dryers, room air conditioners, and dishwashers. [75]

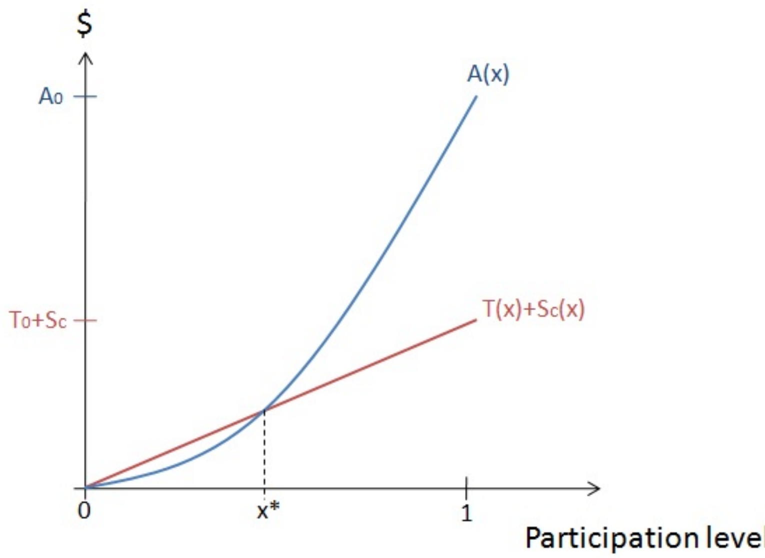


Figure 24: The conceptual relationship between monetary benefits (avoided costs $A(x)$) and monetary loss (transaction costs $T(x)$ and lost revenue $S_c(x)$) of a utility at the participation level of residential customers on optional time-based rates.

a few residential customers who mainly have already relatively low peak consumption and high off-peak consumption will participate in the optional time-based rates), the above inefficient operation happens. However, if we induce more customers to participate in the optional time-based rates and the customers can actually react to the time-varying prices, then the above inefficient operation can be overcome, which means that the utility's monetary benefits are greater than the loss from the time-based rates, so the utility can make higher profits and the residential customers can have more savings at the same time. In this study, we explore two policy tools to induce more customers to participate in the time-based rates: 1) subsidy for flexible residential demand and 2) shared-savings mechanism based on the consumption pattern changes.

First, the subsidy for flexible residential demand is a subsidy for the public to purchase smart appliances and electric vehicles. If more residential customers can purchase smart appliances or electric vehicles, more residential customers may be more willing to participate in optional time-based rates. Second, under the shared-savings mechanism based on consumption pattern changes, some percentage of customers' bill savings will be transferred to utilities in order to compensate the revenue loss of the utilities. For this compensation, the portion of transferred savings can be differentiated among customers based on the actual changes of customers' consumption patterns. Even though utilities offer the same prices for all customers, the utilities can take the higher portion of bill savings from some residential customers who don't change their consumption patterns rather the other residential customers who change their consumption patterns. Then, utilities can offer low enough prices for electricity in the time-based rates and it attracts more customers to participate in the time-based rate.

4.2 The Economic Model and its Implications

In order to explore how two proposed policy tools could work to overcome current inefficient operation of the optional time-based rates for residential customers, we need to understand the relationships between the policy tools and the participation level of residential customers in the optional time-based rates. In order words, we need to see how the participation level changes with and without the tools. For understanding the relationships, we develop an economic model for a sequential game among a regulator, a utility, and residential customers. For simplicity, we use the structure of a simple time-of-use (TOU) rate for the time-based rates in our model, which has two time periods: on-peak and off-peak. We assume that the less peak consumption customers participate in a given TOU rate earlier and the current participation level is $x(0)$ $(Note : 0 \leq x(0) \leq 1)$. In this non-repeated game, each player makes decision at once as following sequences of events, and we assume that this is a perfect information game.

Stage 1 : The regulator will set up differentiated fee rates, $r_i \in [0.1]$, for each customers under the shared-saving mechanism based on the consumption pattern changes. We define $r \in [0, 1]$ as the weighted average of r_i among customers, and r is the market incentive rate for the shared-savings mechanism. The regulator also chooses the funding size of the subsidy for flexible demand (e.g. smart appliance and EVs), K. The regulator wants to maximize social benefits. In this study, we will define the social benefits as the customers' net savings under the condition at which utility will not lose its profits. (We will discuss more about the social benefits in following "Regulator's problem" part)

Stage 2 : A utility has already offered a standard fixed flat rate p_s to the residential customers, and never change the price. However, for the optional TOU rate, the utility decides an optimal price (p_{on}, p_{off}). The utility wants to maximize net earnings (changes in profits).

Stage 3 : Customers decide whether to participate in the TOU rate or not, based on their savings potential. If the customers participate in the TOU rate, they will change their consumption patterns. We assume that customers can not know other customers' fee rates, r_i.

Basically, we will analyze the equilibrium of the above game at different conditions. Based on the backward induction analysis, we will see the relationships among K, r, $\{p_{on}, p_{off}\}$, and the participation level of the residential customers in the optional TOU rate, x. Based on the relationships, we can show the current inefficient operation of the optional TOU rate and we can explore the extent to which tools can help to solve the current problem.

Customers' problem Customers who choose to participate in given TOU rate are forecast to decrease their consumption in the peak and increase their consumption in the off-peak in response to prices in the TOU rate. Suppose that p_{on} and p_{off} are prices under the given TOU rate and p_s is the price of electricity under an initially

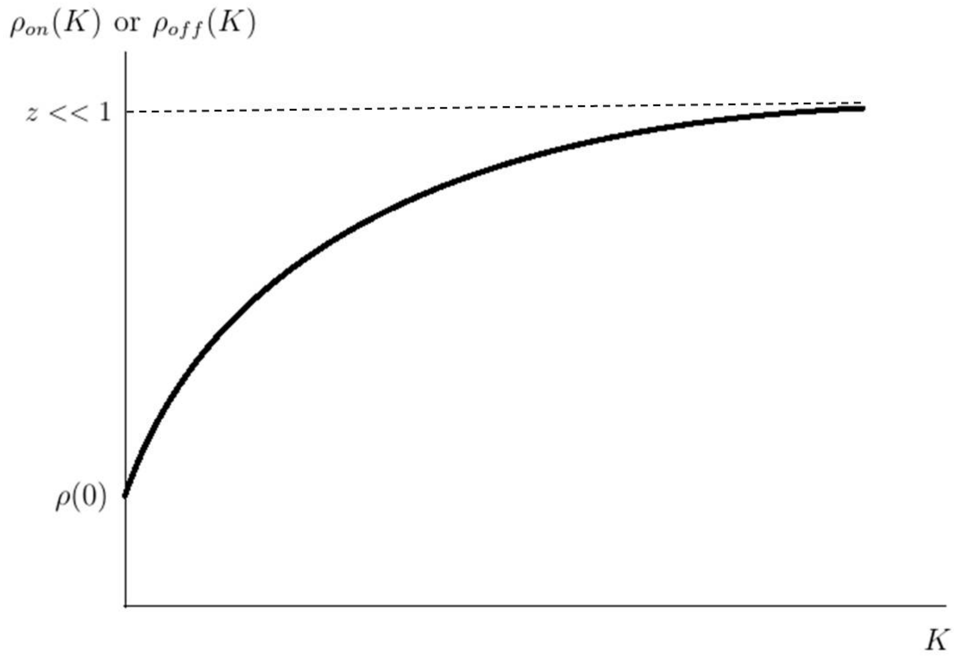


Figure 25: Price elasticity with subsidy K

given standard flat rate. In addition, $\rho_{on}(K)$ and $\rho_{off}(K)$ are price elasticities of on-peak and off-peak electricity, respectively. As show in Figure 25, we assume that the elasticities increase with K and are concave curves ($\rho_{on}(0) > 0$ and $\rho_{off}(0) > 0$, $\rho'_{on}(K) > 0$ and $\rho'_{off}(K) > 0$, $\rho''_{on}(K) < 0$ and $\rho''_{off}(K) < 0$, $\rho_{on}(K) < 1$ and $\rho_{off}(K) < 1$).

Let C_{on} and C_{off} be the aggregate consumption levels of total residential customers at on-peak and off-peak when there exists only a standard flat rate. Figure 26 shows the characteristics of the aggregate consumption levels given prices of time-based rates and funding size, K, of subsidy for flexible demand. If all customers participate in the TOU rate, then the on-peak and off-peak consumption change $C_{on}\left(\frac{p_{on}}{p_s}\right)^{-\rho_{on}(K)}$ and $C_{off}\left(\frac{p_s}{p_{off}}\right)^{\rho_{off}(K)}$, where $p_{on} \geq p_s$ and $p_{off} \leq p_s$, respectively. As a result, the aggregate potential savings are S_p for the entire customers base will be

$$S_p = p_s\left(C_{on} + C_{off}\right) - p_{on}C_{on}\left(\frac{p_{on}}{p_s}\right)^{-\rho_{on}(K)} - p_{off}C_{off}\left(\frac{p_s}{p_{off}}\right)^{\rho_{off}(K)} \tag{10}$$

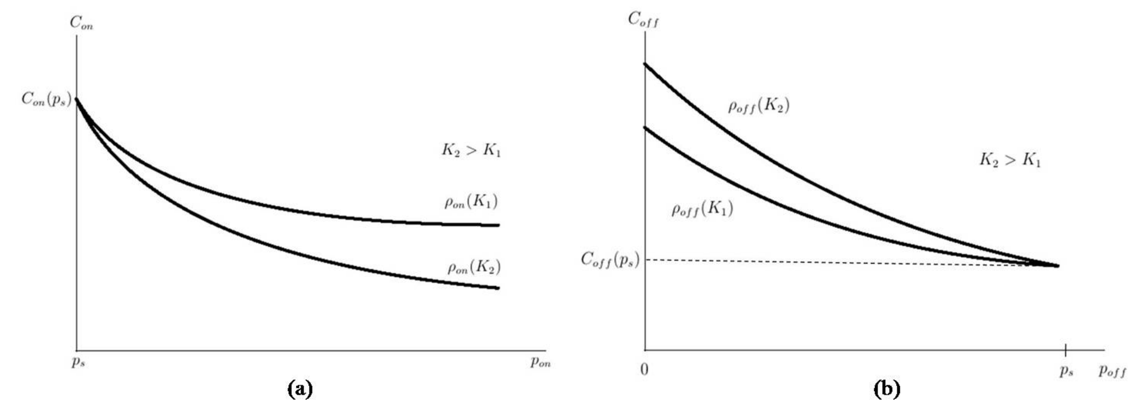


Figure 26: The aggregate electricity consumption levels of entire residential customers at on-peak and off-peak. (a) On-peak consumption C_{on} at given price p_{on} and subsidy K and (b) Off-peak consumption C_{off} at given price p_{off} and subsidy K.

Property 4.1 *Higher prices in a TOU rate result in less customers' potential savings from participation in the TOU rate.*

Proof :

$$\frac{\partial S_p}{\partial p_{on}} = -\left(1 - \rho_{on}(K)\right) C_{on} \left(\frac{p_{on}}{p_s}\right)^{-\rho_{on}(K)} < 0$$
$$\frac{\partial S_p}{\partial p_{off}} = -\left(1 - \rho_{off}(K)\right) C_{off} \left(\frac{p_s}{p_{off}}\right)^{\rho_{off}(K)} < 0$$

□

Property 4.2 *Higher subsidy funding size for flexible demand induces more customers' potential savings from participation in the TOU rate.*

Proof :

$$\frac{\partial S_p}{\partial K} = p_{on} C_{on} \rho'_{on}(K) \left(\frac{p_{on}}{p_s}\right)^{-\rho_{on}(K)} \ln\left(\frac{p_{on}}{p_s}\right) - p_{off} C_{off} \rho'_{off}(K) \left(\frac{p_s}{p_{off}}\right)^{\rho_{off}(K)} \ln\left(\frac{p_s}{p_{off}}\right)$$

Now, the first term and the second term of $\frac{\partial S_p}{\partial K}$ are positive and negative, respectively. Therefore, $\frac{\partial S_p}{\partial K}$ can be either positive or negative. With more subsidy for flexibility, the customers can shift more electricity consumption from on-peak to off-peak. Consequently, the first term represents how much customers can save more money from reducing on-peak consumption. On the other hand, the second term represents how much customers need to pay more money from increasing off-peak consumption. Of course, $p_{on} > p_{off}$. In addition, generally, not all reducing on-peak consumption will be shifted to off-peak. Therefore, we can assume that

$$C_{on}\rho'_{on}(K)\left(\frac{p_{on}}{p_s}\right)^{-\rho_{on}(K)}\ln\left(\frac{p_{on}}{p_s}\right) > C_{off}\rho'_{off}(K)\left(\frac{p_s}{p_{off}}\right)^{\rho_{off}(K)}\ln\left(\frac{p_s}{p_{off}}\right)$$

without loss of generality. Therefore, $\frac{\partial S_p}{\partial K}$ is positive. $\square$

Now, we will define the actual savings as $S_c = x(0)S_p$. Since the funding of the subsidy for flexible demand, K, is collected from ratepayers and most of the ratepayers are defined to be the residential customers of electricity, the net savings of the customers is $S_c - K$. With the shared-saving mechanism, the customers can have $(1-r)(S_c - K)$ for their net savings. The new participation level, x, will be proportional to actual savings in current game, S_c, and the x is greater than or equal to $x(0)$, (*e.g.* $x = x(0) + \beta$). We need to note that the new participation level will not depend on r. Based the assumption that less peak consumption customers participate in a given TOU earlier, little fees, r_i, will be charged to new participants. However, we assume that the regulator can set up the differentiated r_i with which the net bill savings of earlier participants will be higher than the net bill savings of later participants.

Corollary 4.3 *Based on Properties 4.1 and 4.2, the lower prices in the TOU rate and higher funding size for flexible demand will encourage more customers to participate in the TOU rate.*

Utility's problem In pursuit of the TOU rate, the utility can reduce the generation and system operation costs from deferring the need for infrastructure and relieving an overloaded transmission system. Let's define the cost reduction as avoided costs, A. From the TOU rate, the utility can lose some revenue from customers' bill savings, so customers' bill savings, S_c, is defined as utility's lost revenue in utility's problem. In addition, the utility needs to spend some amount of money to install the time-based rate enabling technologies (e.g. smart meters); we will define this as transaction costs, T. Both the avoided costs and transaction costs are proportional to the participation level of the TOU rate. As we discussed previously, the modest participation level results in limited benefits from the TOU rate, but the utility's monetary benefits are greater than the loss from the TOU rate at a high enough participation level. In order to express this relationship, we use the simplest models between the costs and the participation level: Avoided costs are a quadratic function of x and the transaction costs are a linear function of x. The relationships are represented as follows:

$$A(x) = A_0 x^2 \tag{13a}$$

$$T(x) = T_0 x \tag{13b}$$

where $0 \leq x \leq 1$, A_0 and T_0 are the maximum avoided and transaction costs at $x = 1$.

The utility wants to balance the savings from the avoided costs with the lost revenue and transaction costs. In addition, under the shared-savings mechanism, the utility can receive some share of customers' net savings. The incentives from the shared-saving mechanism partially compensate the lost revenue. To be precise, with the TOU rate, the utility doesn't want to lose its profit, but rather wants to increase its profit if possible (from reducing the costs). The utility can set up the prices of the TOU rate in order to maximize its net earnings. The utility's problem can be represented as follows:

$$\max_{p_{on}, p_{off}} U = A(x) - S_c - T(x) + r(S_c - K) \tag{14}$$

Let U be utility's net earnings from offering the TOU rate. The net earnings can be defined as '(the avoided costs) - (the lost revenue and transaction costs) + (the compensation from the shared-saving mechanism)'.

Proposition 4.4 *In order to achieve a certain level of participation, x, the utility can offer the lower prices of the TOU rate, p_{on} and p_{off}, when the utility can take some percentage of customers' bill savings from the shared-saving mechanism.*

Proof : The utility will decide to design p_{on} and p_{off} at which the marginal avoided cost with respect to the prices in the time-based rates is equal to sum of lost revenue and transaction costs with respect to those. From given utility's problem (14), the utility's optimality condition for the equilibrium is

$$\begin{aligned}\frac{\partial U}{\partial p_{on}} &= 2A_0x\frac{\partial x}{\partial p_{on}} - \frac{\partial S_c}{\partial p_{on}} - T_0\frac{\partial x}{\partial p_{on}} + r\frac{\partial S_c}{\partial p_{on}} \\ &= (2A_0x - T_0)\frac{\partial x}{\partial p_{on}} - (1-r)\frac{\partial S_c}{\partial p_{on}} = 0 \qquad (15a)\end{aligned}$$

$$\begin{aligned}\frac{\partial U}{\partial p_{off}} &= 2A_0x\frac{\partial x}{\partial p_{off}} - \frac{\partial S_c}{\partial p_{off}} - T_0\frac{\partial x}{\partial p_{off}} + r\frac{\partial S_c}{\partial p_{off}} \\ &= (2A_0x - T_0)\frac{\partial x}{\partial p_{off}} - (1-r)\frac{\partial S_c}{\partial p_{off}} = 0 \qquad (15b)\end{aligned}$$

(15a) and (15b) can be rearranged as follows:

$$\frac{\partial S_c}{\partial p_{on}} = \frac{1}{(1-r)}(2A_0x - T_0)\frac{\partial x}{\partial p_{on}} \qquad (16a)$$

$$\frac{\partial S_c}{\partial p_{off}} = \frac{1}{(1-r)}(2A_0x - T_0)\frac{\partial x}{\partial p_{off}} \qquad (16b)$$

The utility will decide the optimal prices of a TOU rate, which satisfy equations (16a) and (16b). For a given participation level, x, $(2A_0x - T_0)\frac{\partial x}{\partial p_{on}}$ and $(2A_0x - T_0)\frac{\partial x}{\partial p_{off}}$ are constant and negative (**Corollary** 4.3). The right-hand-sides of (16a) and (16b) increase as r increases. As a result, the left-hand-sides of (16a) and (16b), the marginal lost revenue with respect to prices, will increase with r at the equilibrium. As we can see in Figure 27, the lost revenue is a decreasing and convex function in terms of prices in the TOU rate based on **Property** 4.1 and $S_c = x(0)S_p$

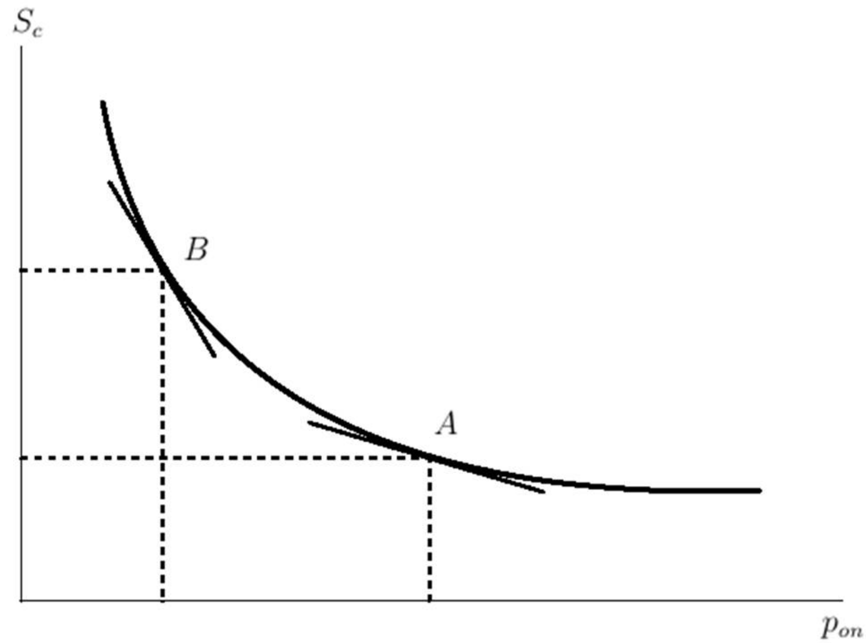


Figure 27: Utility's lost revenue (Customers' bill savings) in terms of price in the TOU rate

$\left(\frac{\partial S_c}{\partial p_{on}} < 0, \frac{\partial S_c}{\partial p_{off}} < 0, \frac{\partial^2 S_c}{\partial p_{on}^2} > 0, \frac{\partial^2 S_c}{\partial p_{off}^2} > 0\right)$. The prices which the utility offers at equilibrium will decrease as r increases. Under the lower prices, the more customers will participate in the TOU rate. At the equilibrium, the lost revenue from customers' bill savings increases, but this increasing loss can be compensated from the shared-saving mechanism. □

Proposition 4.5 *As the participation level, x, increases, even though the regulator lowers the overall incentive rate, r, for the shared-saving mechanism and the utility raises its prices of the TOU rates, the customers' bill savings increase.*

Proof : From the equations, (16a) and (16b), the right-hand-side increases if x increases for given a incentive rate, r. Let's consider two participation levels, $x\prime$ and $x\prime\prime$ ($x\prime < x\prime\prime$). At the equilibrium, the left-hand-side of (16a) and (16b), the marginal lost revenue with respect to prices, will higher with $x\prime\prime$ than those with $x\prime$ initially given $r\prime$. Now, as shown in Figure 28, let's consider when utility takes less incentive

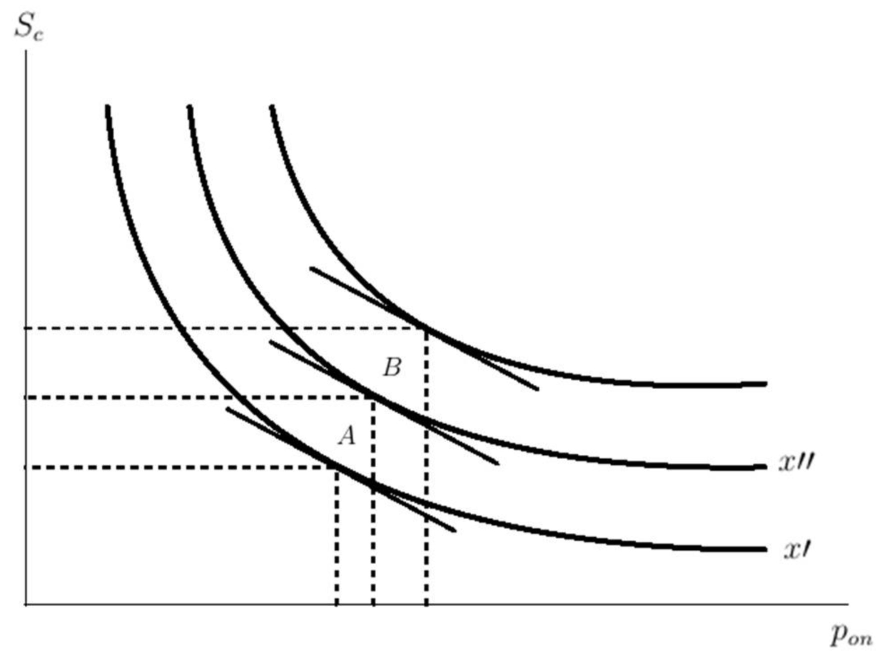


Figure 28: Utility's lost revenue (Customers' bill savings) in terms of price in the TOU rate at different participation levels

r'', which holds following equalities (17a), (17b), and $r' > r''$,

if utility takes less incentive r'', which holds following equalities (17a), (17b), and $r' > r''$, then even though the utility increases prices of TOU rates, the customers' bill savings increase at the equilibrium.

$$\frac{1}{(1-r')}(2A_0x' - T_0)\frac{\partial x}{\partial p_{on}} = \frac{1}{(1-r'')}(2A_0x'' - T_0)\frac{\partial x}{\partial p_{on}} \tag{17a}$$

$$\frac{1}{(1-r')}(2A_0x' - T_0)\frac{\partial x}{\partial p_{off}} = \frac{1}{(1-r'')}(2A_0x'' - T_0)\frac{\partial x}{\partial p_{off}} \tag{17b}$$

□

Proposition 4.6 *In order to achieve a certain level of participation, x, the utility can offer lower TOU rates, p_{on} and p_{off}, when the customers receive some subsidy for flexible demand K.*

Proof : We assumed that the price elasticities of on-peak and off-peak electricity increase with K. Figure 29 shows the two different S_c curves with two different levels

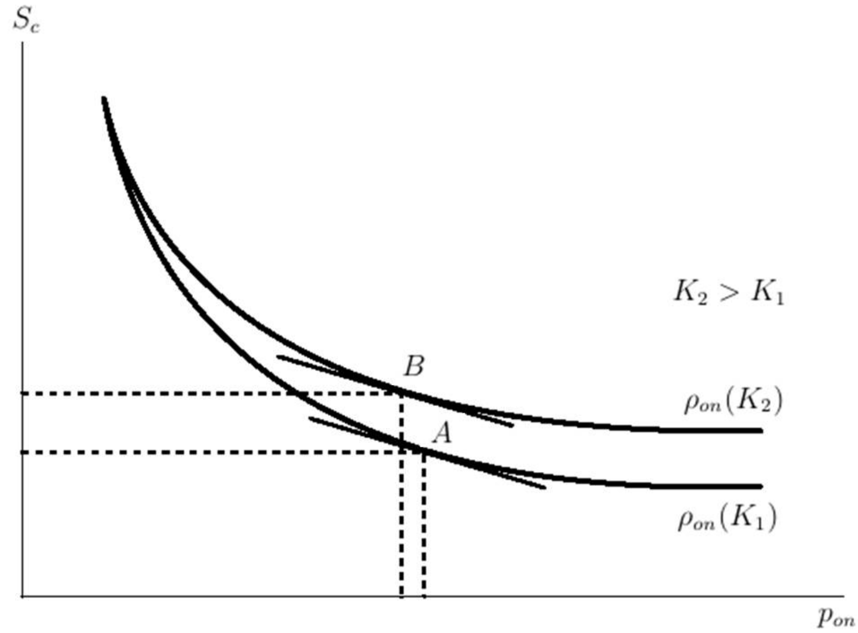


Figure 29: Utility's lost revenue (Customers' bill savings) in terms of price in the TOU rate with different funding size of subsidy, K.

of subsidy, K_1 and K_2, where $K_1 < K_2$. Based on **Property** 4.2, the S_c with K_2 is higher than S_c with K_1 at a given price in the TOU rate. In other words, the S_c curve with K_2 has more curvature than the S_c curve with K_1.

The optimality conditions for the equilibrium, (16a) and (16b), are maintained at a certain level of participation. However, the prices, which the utility offers at the equilibrium, vary with subsidy level, K. Since the S_c curve with higher K has more curvature, the prices at the equilibrium with higher K are lower. As we showed in **Property** 4.2, since the higher subsidy level induces more customers' savings, the lost revenue of the utility increases with K. □

Regulator's problem The objective of the regulator from time-based rates, such as a TOU rate, is maximization of the net social benefits. Some previous studies about demand response programs have focused on net social welfare change [4, 99]. We would like to discriminate between the social welfare in previous studies and the social benefits in this study. The social welfare includes the value of customers' electricity consumption and the net social welfare change under the demand response programs is defined the benefits of both utilities and customers. The net social welfare change can not specify the transfer from utilities to customers, and this fails to consider the case in which the benefits of utilities do not exist and even the utilities have loss [99]. The new policy may not be Pareto efficient, so the policy does not work well.

We could find a similar case from energy conservation policies. In order to make the policy Pareto superior, decoupling policy have been suggested in the electricity sector. A previous study used a new definition of social welfare in its economic model to analyze the decoupling policy [12]. Under the policy, the social welfare is defined as consumer surplus, and the regulator wants to maximize this social welfare under the condition utility's net profit change should be greater than or equal to zero. Under this definition, we can find the way both utilities and customers are better off.

In this study, we define the net social benefits as the customers' net savings under the condition at which utility will not lose its profits. The regulator will decide the subsidy for flexible residential demand, K, and the incentive rate of r for the shared-saving mechanism in order to maximize the net social benefit. Now, the regulator's problem can be given as

$$\begin{aligned} \max_{K,r} \quad & (1-r)\,(S_c - K) \\ s.t. \quad & A(x) - S_c - T(x) + r(S_c - K) \geq 0 && \text{(18a)} \\ & (1-r)(S_c - K) \geq 0 && \text{(18b)} \\ & K \geq 0, 0 \leq r \leq 1 \end{aligned}$$

The two constraints (18a) and (18b) show that both utility's net earnings and customers' net savings should be greater than or equal to zero under the regulator's decision. From the first constraint, (18a), the utility is guaranteed not to lose profits under the time-based rate and new policy tools.

Proposition 4.7 *If the utility has higher monetary loss than benefits from the time-based rate (the participation level is less than the critical participation level, x^*, in Figure 24), the regulator needs to have some positive rate, r, for the shared-saving mechanism. Otherwise, the regulator does not have to have the shared-saving mechanism.*

Proof : The regulator decides the incentive rate, r, for the shared-saving mechanism and the funding size of subsidy for flexible demand. In order to decide r and K at the equilibrium, we can solve the above regulator's problem. Since the problem is a constrained non-linear optimization problem, we can use the lagrangian method to solve the problem as follows.

$$\begin{aligned}\max_{K,r} \quad L\left(K, r, \lambda\right) = &\left(1-r\right)\left(S_c - K\right) + \lambda_1\left[A(x) - S_c - T(x) + r(S_c - K)\right] \\ &+ \lambda_2\left[(1-r)(S_c - K)\right] + \lambda_3 K + \lambda_4 r + \lambda_5(1-r) \qquad \text{(19a)}\end{aligned}$$

The necessary conditions for optimality are

$$\begin{aligned}\frac{\partial L}{\partial r} &= -\left(S_c - K\right) + \lambda_1(S_c - K) - \lambda_2(S_c - K) + \lambda_4 - \lambda_5 \\ &= \left(\lambda_1 - \lambda_2 - 1\right)\left(S_c - K\right) + \lambda_4 - \lambda_5 = 0 \qquad \text{(20a)} \\ \frac{\partial L}{\partial K} &= (1-r)\left(\frac{\partial S_c}{\partial K} - 1\right) + \lambda_1\left[\frac{\partial A(x)}{\partial K} - \frac{\partial S_c}{\partial K} - \frac{\partial T(x)}{\partial K} + r\left(\frac{\partial S_c}{\partial K} - 1\right)\right] \\ &\quad + \lambda_2\left[(1-r)\left(\frac{\partial S_c}{\partial K} - 1\right)\right] + \lambda_3 = 0 \qquad \text{(20b)}\end{aligned}$$

$$\lambda_1\left[A(x) - S_c - T(x) + r(S_c - K)\right] = 0 \qquad \text{(20c)}$$

$$\lambda_2\left[(1-r)(S_c - K)\right] = 0 \qquad \text{(20d)}$$

$$\lambda_3 K = 0 \qquad \text{(20e)}$$

$$\lambda_4 r = 0 \qquad \text{(20f)}$$

$$\lambda_5(1-r) = 0 \qquad \text{(20g)}$$

Let's assume that the regulator decides the funding size of subsidy is less than the customers' bill savings, which is $S_c > K$. From the condition (20c), r must be positive to make the term $A(x) - S_c - T(x) + r(S_c - K)$ zero, or λ_1 should be equal to zero.

Case 1: First, let's consider the case in which $A(x) - S_c - T(x) + r(S_c - K) = 0$, the customers' bill savings are zero. In order to hold this equality, the utility have higher monetary loss than benefits from the time-based rate ($A(x) - S_c - T(x) \leq 0$). Now, the optimal incentive rate, r^*, for the shared-savings mechanism is

$$r^* = \frac{S_c + T(x) - A(x)}{S_c - K} > 0 \tag{21}$$

Then, we have an interior optimal solution of r, and λ_2, λ_4, and λ_5 must be equal to zero. Then, $\lambda_1 = 1$ in order to satisfy the condition (20a). Also, as the participation level, x, increases, the gap between the monetary benefits and loss decreases but the customers' bill savings increase (the numerator decreases and the denominator increases). As a result, r^* is a decreasing function of x. When $A(x) - S_c - T(x) = 0$, $r^* = 0$.

Case 2: Second, if λ_1 is equal to zero, then, from the condition (20a) and $\lambda_i \geq 0$ for all i, λ_4 must be positive. Then, from the condition (20f), the incentive rate must be zero, $r^* = 0$. In addition, since $r^* = 0$, $\lambda_2 = 0$ and $\lambda_5 = 0$. Here, we note that this is only possible when the utility has higher monetary benefits than loss from the time-based rate ($A(x) - S_c - T(x) \geq 0$), and it is a boundary solution.

As a result, the relationship between the optimal incentive rate, which the regulator provides in the shared-savings mechanism, and the participation level of the time-based rate is shown in Figure 30. □

Corollary 4.8 *The value of r will decrease with x until x^*. For the higher x than x^*, r will be equal to zero.*

In summary, the aggregate portion transferred for entire customers' total savings will decrease as more customers participate in the time-based rate. If enough

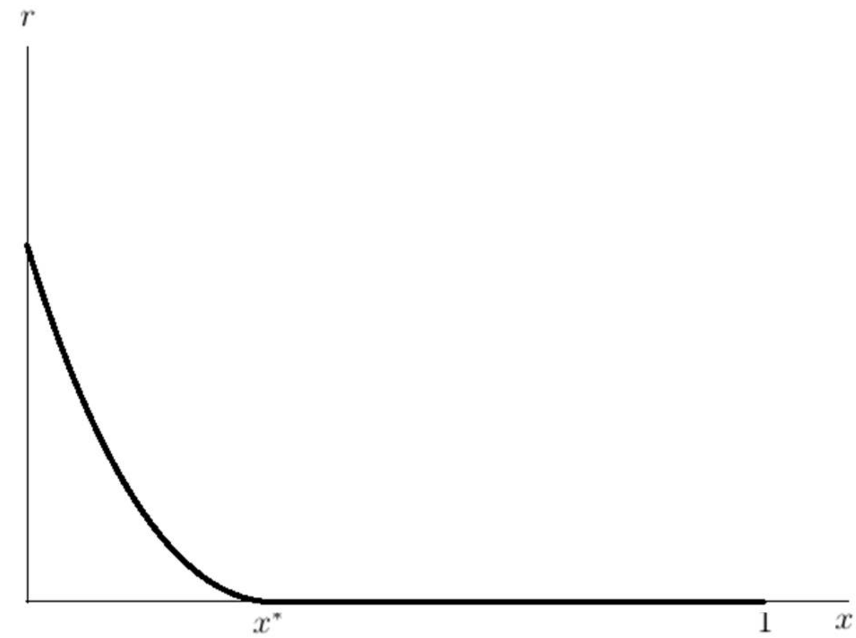


Figure 30: The optimal incentive rate, r, and the participation level of the time-based rate, x

customers participate in the time-based rate and the monetary benefits surpass the monetary loss, customers' bill savings do not have to be shared.

Proposition 4.9 *To increase participation in the time-based rate, x, the regulator can increase the subsidy for flexible demand, K. However, the marginal impact will decrease as x increases.*

Proof : Let's continue to use the proof of Proposition 4.7. We need to focus on condition (20b).

Case 1: In the first case in which $A(x) - S_c - T(x) + r(S_c - K) = 0$, we showed that $\lambda_1 = 1$, $\lambda_2 = 0$, $\lambda_4 = 0$, and $\lambda_5 = 0$. The condition (20b) can be simplified as follows:

$$\frac{\partial A(x)}{\partial K} - \frac{\partial T(x)}{\partial K} - 1 + \lambda_3 = 0 \tag{22}$$

If K is positive, then λ_3 must be zero. So, the above equality can be represented as follows:

$$(2A_0 x - T_0)\,\frac{\partial x}{\partial K} = 1 \tag{23}$$

which is,

$$\frac{\partial x}{\partial K} = \frac{1}{(2A_0 x - T_0)} \tag{24}$$

We can see that when x increases, the partial derivative of x with respect to K decreases. Based on Corollary 4.3 and Property 4.2, x is a increasing concave function of K. As a result, the K at the equilibrium will increase as x increases.

Case 2: In the second case in which λ_1 is equal to zero, we showed $\lambda_2 = 0$, $r^* = 0$, and $\lambda_5 = 0$. The condition (20b) can be simplified as follows:

$$\frac{\partial S_c}{\partial K} - 1 + \lambda_3 = 0 \tag{25}$$

Again, if K is positive, then λ_3 must be zero. So, the above equality can be represented as following based on Corollary 4.3.

$$\frac{\partial S_p}{\partial K} = \frac{1}{x} \tag{26}$$

Similar to Case 1, we can see that when x increases, the partial derivative of S_p with respect to K decreases. Again, we already knew that S_p is a increasing concave function in terms of K. Consequently, the higher x the regulator wants to achieve, the more K the regulator is required to set up. $\square$

4.3 Importance of the Regulator's Problem

We will show that if the regulator's definition of net social benefits is the sum of the utility's net earnings and customers' net savings, the regulator's optimal decisions for the incentive rate, r, for the shared-saving mechanism will be different. As we discussed, this definition can not specify the transfer from utilities to customers, and this fails to consider the case in which the benefits of utilities do not exist and even the utilities have loss. Let U and V be the utility's net earnings and the customers' net savings. Then, the net social benefits, W, can be defined as $U + V = A(x) - S_c - T(x) + r(S_c - K) + (1-r)(S_c - K) = A(x) - T(x) - K$. The social benefits from the time-based rates can be considered as the utility's avoided costs. On the other hand, the social costs can be considered as the utility's transaction costs and the funding of subsidy (the money collected from ratepayers). The customers' savings from the time-based rates can't be included as the social benefits since the utility will have the same amount of monetary loss. Now, let's consider the regulator's problem.

$$\max_{K,r} \quad A(x) - T(x) - K$$

$$s.t. \quad A(x) - S_c - T(x) + r(S_c - K) \geq 0 \tag{27a}$$

$$(1-r)(S_c - K) \geq 0 \tag{27b}$$

$$K \geq 0, 0 \leq r \leq 1$$

The constraints of above problem are exactly same as original regulators' problem which we saw in previous section.

Proposition 4.10 *Under the new definition of social benefits, the regulator sets the incentive rate for the shared-saving mechanism in order to transfer all customers' savings to the utility when the utility has a higher monetary loss than benefits from the time-based rate. Even when the utility has higher monetary benefits than the monetary loss from the time-based rate, the regulator sets a positive rate.*

Proof : We can proceed the similar to the proof of Proposition 4.7. The largrangian form of the problem is the following:

$$\begin{aligned} \max_{K,r} \quad L\left(K,r,\lambda\right) =& A(x) - T(x) - K + \lambda_1\left[A(x) - S_c - T(x) + r(S_c - K)\right] \\ &+ \lambda_2\left[(1-r)(S_c - K)\right] + \lambda_3 K + \lambda_4 r + \lambda_5(1-r) \end{aligned} \tag{28a}$$

The necessary conditions for optimality are

$$\begin{aligned}
\frac{\partial L}{\partial r} =& \lambda_1(S_c - K) - \lambda_2(S_c - K) + \lambda_4 - \lambda_5 \\
=& (\lambda_1 - \lambda_2)(S_c - K) + \lambda_4 - \lambda_5 = 0 && \text{(29a)} \\
\frac{\partial L}{\partial K} =& \frac{\partial A(x)}{\partial K} - \frac{\partial T(x)}{\partial K} - 1 + \lambda_1 \left[\frac{\partial A(x)}{\partial K} - \frac{\partial S_c}{\partial K} - \frac{\partial T(x)}{\partial K} + r\left(\frac{\partial S_c}{\partial K} - 1 \right) \right] \\
& + \lambda_2 \left[(1-r)\left(\frac{\partial S_c}{\partial K} - 1 \right) \right] + \lambda_3 = 0 && \text{(29b)} \\
& \lambda_1 \left[A(x) - S_c - T(x) + r(S_c - K) \right] = 0 && \text{(29c)} \\
& \lambda_2 \left[(1-r)(S_c - K) \right] = 0 && \text{(29d)} \\
& \lambda_3 K = 0 && \text{(29e)} \\
& \lambda_4 r = 0 && \text{(29f)} \\
& \lambda_5 (1-r) = 0 && \text{(29g)}
\end{aligned}$$

Again, let's assume that the regulator decides the funding size of the subsidy is less than the customers' bill savings, which is $S_c > K$. From the condition (29c), r must be positive to make the term $A(x) - S_c - T(x) + r(S_c - K)$ zero, or λ_1 should be equal to zero.

Case 1: First, let's consider the case in which $A(x) - S_c - T(x) + r(S_c - K) = 0$, again, the customers' net savings are zero. In order to hold this equality, the utility has higher monetary loss than benefits from the time-based rate ($A(x) - S_c - T(x) \leq 0$). The optimal incentive rate, r^*, for the shared-savings mechanism is

$$r^* = \frac{S_c + T(x) - A(x)}{S_c - K} > 0 \tag{30}$$

Now, r^* must be equal to one. In order for r to be an interior optimal solution, λ_2, λ_4, and λ_5 must be equal to zero. However, then the condition (29a) can't be satisfied ($\lambda_1(S_c - K) > 0$). When $r^* = 1$, λ_2 and λ_5 can be some positive numbers and the condition (29a) can be satisfied. We note that if $r^* = 1$, the utility's net earning is equal to the social benefits, and the value of social benefits at the equilibrium is zero.

Case 2: Second, if λ_1 is equal to zero, then, from the condition (29a) and $\lambda_i \geq 0$ for all i, both λ_2 and λ_4 must be zero or some positive numbers at the same time. If λ_2 is a positive number, then r must be one. Consequently, from the condition (29f), λ_4 must be zero. It contradicts the condition (29a). Therefore, λ_2 must be zero. Then, both λ_4 and λ_5 must be zero and r^* should be between zero and one ($0 < r^* < 1$) since both λ_4 and λ_5 can't be positive numbers. □

Corollary 4.11 *The value of r will be equal to 1 for $0 \geq x \geq x^*$. Even for $x > x^*$, r will be a positive number between zero and one.*

If the regulator wants to maximize the sum of the utility's net earnings and the customers' bill savings, both the utility's net earnings and the customers' net savings are zero at the equilibrium when the utility has higher monetary loss than monetary benefits. This implies that staying at zero participation level ($x = 0$) is the optimal equilibrium point. Even if the participation level goes beyond the critical participation level, x^*, in which the utility's avoided costs are greater than the sum of transaction costs and lost revenue, the utility can still obtain some compensation for lost revenue from the shared-saving mechanism. Then the customers' bill savings will be reduced. We need to consider that these results reflect how the social benefits are defined.

4.4 Conclusion

Even though time-based rates have benefits for both utilities and customers if the program operates efficiently, we identified the systematic problems in some current existing programs. The main problem is utilities' disincentives associated with offering optional time-based rates. As a result, most voluntary time-based rates have remained at low participation. In this study, based on a game theoretic model, we have explored how two suggested tools could work to mitigate the problem: 1) Under the shared-saving mechanism, the utility can offer lower prices in optional time-based rates while maintaining its profit, 2) the subsidy for flexible residential demand will encourage more residential customers to participate in the time-based rates because of increasing flexibility of their demand with less effort. Consequently, these tools can help to increase the participation level of time-based rates. When the participation level is high enough and the utility's monetary benefits are greater than its loss, then programs can operate efficiently. We proved that the suggested tools can be phased out at that time. However, if the regulator is not seeking to maximize customers' bill savings, the one of suggested tools, the shared-saving mechanism, is still not able to help to solve the current problems.

The model in this study is a single stage sequential game, and we describe the relationships among several decision variables of each stakeholders (regulator, utility, and customers). Based on the relationships, we explained how the tools work in a given situation. However, in order to analyze and understand the dynamics of decisions of the stakeholders, in future work we are planning to expand our model into a dynamic (repeated) game. This would provide a basis for understanding the serial changes of decision variables, and provide further insight into how the tools work.

This study can be used to consider how to apply the two suggested tools into current programs. However, this study has not addressed any applications as a case study. In future research, with appropriate data for both utility-side and customers-side, we can test existing time-based rates and apply our model to design the two tools.

CHAPTER V

CONCLUSION

Chapter 5 summarizes the results of this thesis and describes contributions.

First, I investigated how to incorporate demand responsiveness for policy analysis in the electricity sector. Some previous studies used a large general equilibrium model, such as such as the US National Energy Modeling System (NEMS) [69], for entire energy systems, including the coal and natural gas markets, transportation fuel sector, electricity sector and so on. On the other hand, other studies used a least-cost model, such as the Market Allocation (MARKAL) model [61], in order to focus on the electricity sector in a specific region. The model developed in my first chapter is intermediate between these two approaches, providing transparency in modeling while incorporating a key relationship demand response endogenously. The first chapter uses a least-cost model which includes some characteristics for two important policies in the electricity sector. In addition, it suggests an iterative approach for incorporating the demand response to price change under new policy. By applying the approach into the state of Georgia, as a case study, this study shows the importance of incorporating demand responsiveness to evaluate the effects of energy policies.

Second, I have focused on new technology adoption pathways in the electric power system. Based on four-serial models, my colleague and I provide analysis of future impacts of electric vehicles and wind power on the electric power system and light-duty vehicle market. In addition, by studying the related status of policies and specifications of technologies in the U.S., we developed several adoption pathways of technologies in the U.S. eastern interconnection, and we use our models to simulate the future impacts of the pathways. This study provides a systematic analysis to help decision makers in the adoption of policies and technologies related to electric vehicles and wind power. The results show that the total greenhouse gas emissions of the entire energy system do not substantially decrease even with high level of electric vehicle adoption. The combination of two technologies, even more with appropriate policies, can notably decrease the total greenhouse gas emissions.

Lastly, I have developed more theoretical study. This study analyzed the main reason for the inefficient operation of current demand response programs, particularly optional time-based rates, for residential customers. Participation in these programs is low, even though the programs have benefits and can be Pareto superior. A game-theoretic model was developed in order to describe how the current programs operate and the reason for the inefficiency. The study investigated two policy tools, a subsidy for flexible residential demand and a shared-savings mechanism based on the consumption pattern changes. I examined the implementation of the tools and their potential in order to overcome the current inefficient operation. This study can help policy makers to understand how the given policies work. In addition, this study shows policy coordination between the regulators and utilities to enhance their performances.

Overall, this thesis shows three studies which use some decision science models and tools to analyze several technological and political transformation pathways in the electricity sector. Moreover, the first study provides a methodology to improve the energy model for policy evaluation. However, these studies are somewhat limited by the lack of appropriate data and real-world's applications. For my future research, I will seek access to more appropriate data and more realistic problems to analyze in the electricity sector as well as even several other energy and sustainability sectors. Meanwhile, I will keep studying to develop more useful models and tools.

APPENDIX A

APPENDIX FOR CHAPTER 2

A.1 Endogenous Electricity Demand Projection : Iterative Approach

Figure 31 illustrates the the approach, with the elements of the figure explained below.

Insert ref. demand: Set the reference demand projection as current demand projection, and set no policy scenario.

Run model: Under given scenario and the current demand projection, run the model.

Calculate levelized cost: Based on results of the model, calculate a time-series levelized cost of electricity.

$$\text{Levelized Cost}_t = \text{Annualized Cost}_t \ / \ \text{Annual Generation}_t$$

Calculate electricity price: Based on the levelized cost, calculate new future price of electricity. (We assume a mark up of 4 cents/kWh to account for transmission and distribution and project the retail price of electricity using the levelized electricity wholesale cost projections above.)

First Iteration?: Is this the first iteration?

Set new policy: Set the new price as reference future price, and insert new scenario assumptions into the developed model.

Calculate new demand: Compare the new future price with reference future price,

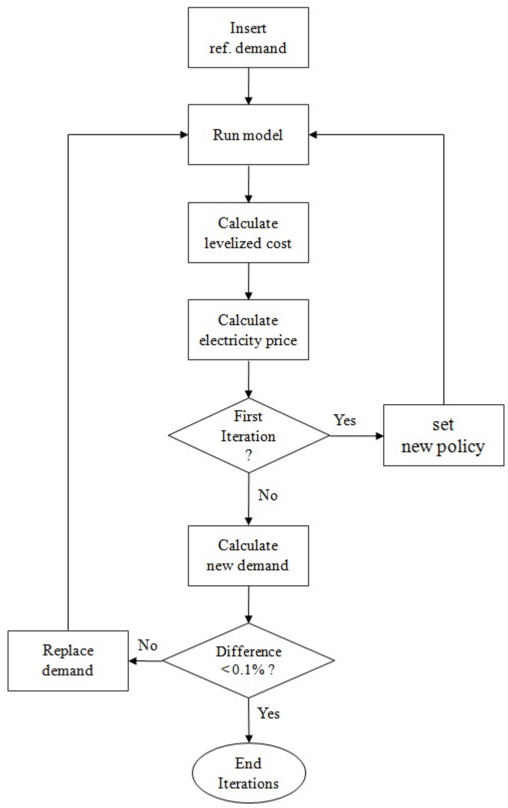


Figure 31: Flow diagram for iterative approach to demand forecasting

and calculate new demand projection by using a price elasticity of ε.

$$new\, demand \;=\; reference\, demand \;\times (1 + \varepsilon\; \frac{new\, price - reference\, price}{reference\, price})$$

Difference < 0.1%?: Is the percentage change from previous step demand projection to new demand projection less than 0.1%?

Replace demand: Replace previous-step the current demand projection with current demand projection, and replace the current demand projection with new demand projection.

A.2 Reference Demand Projection for Georgia

AEO 2011 projects the future electricity demand and population in the South Atlantic region under business as usual [24]. Based on the average of the projections of the Georgia population made by the US Census Bureau and the Georgia Office of Planning and Budget [97, 43], we interpolated and extrapolated the future electricity demand for Georgia as shown in Table 10.

	Delivered Electricity for South Atlantic (TWh) (1)	Net Generation for South Atlantic (TWh) (2)	Population for South Atlantic (million) (3)	Population for Georgia (million) (4)	Electricity Generation for Georgia (TWh) (5)
2008*	803	855	58.8	9.5	138
2009*	779	829	59.4	9.6	135
2010	826	880	60.1	9.8	144
2011	785	836	60.8	10.0	137
2012	796	847	61.5	10.2	140
2013	802	855	62.3	10.3	142
2014	806	858	63.2	10.5	142
2015	814	867	64.1	10.7	144
2016	823	876	65.0	10.8	146
2017	830	884	65.9	11.0	147
2018	838	892	66.9	11.2	149
2019	846	900	67.8	11.3	151
2020	854	909	68.7	11.5	152
2021	862	918	69.7	11.7	154
2022	871	928	70.6	11.9	156
2023	880	938	71.6	12.1	158
2024	891	949	72.5	12.2	160
2025	900	959	73.5	12.4	162
2026	909	968	74.4	12.6	164
2027	919	979	75.4	12.8	166
2028	929	990	76.3	13.0	168
2029	938	999	77.3	13.2	170
2030	949	1,011	78.2	13.4	173
2031	959	1,022	79.2	13.5	175
2032	970	1,033	80.2	13.7	177
2033	978	1,042	81.1	13.9	179
2034	988	1,052	82.1	14.1	181
2035	997	1,062	83.1	14.3	182

Table 10: Calculation of Electricity Generation for Georgia. * historical data, Source for (1)&(3) [22], (2) = (1)*1.065 corresponding to estimates 6.5% US transmission and distribution losses as of 2007 [24], Source for (4) [97, 43], (5) = (2)*(4)/(3).

A.3 Specification of Technology Options

(2009$)	Life time (yr)	Maximum Capacity Factor	Heat Rate (Btu /KWh)	Overnight Cost ($/kW)	Investment Factor	Annualized Capital Cost ($/kW /yr)	Fixed Cost ($/kW /yr)	Variable Cost (mills /kWh)	CO_2e Emission Rate* (lb /kWh)
Retrofit PC	20	0.85	17,800	1,300	1.29	158	52	4.7	0.36
Adv. PC	50	0.85	9,200	2,220	1.29	208	28	4.7	1.9
Adv. PC w/ CCS	50	0.85	11,000	3,500	1.29	327	55	6	0.2
IGCC	50	0.85	8,700	2,570	1.22	227	40	3	1.7
IGCC w/ CCS	50	0.85	10,700	3,780	1.22	334	47	4.5	0.18
NGTC	50	0.85	9,000	690	1.12	61	12	3.7	0.97
NGCC	50	0.85	6,800	980	1.16	82	13	2.1	0.93
NGCC w/ CCS	50	0.85	8,000	1,930	1.16	162	20	3	0.1
Nuclear	60	0.89	10,400	3,820	1.47	400	92	0.5	0
Hydro Large	50	0.44	-	1,830	1.25	166	7	2.5	0
Hydro Medium	50	0.44	-	2,480	1.25	225	11	2.5	0
Hydro Small	50	0.44	-	3,240	1.25	293	15	2.5	0
Biomass	50	0.85	10,000	3,850	1.22	340	66	6.9	0
Wind	20	0.3	-	1,970	1.25	232	87	0	0
Solar	25	0.2	-	6,170	1.14	604	12	0	0

Table 11: Specification of generation technology options [23]. *CO2 emissions are average for Georgia, based on eGrid data [29]

A.4 Electricity Output by Generation Technology

Yr	Scn.	Coal	Coal CCS	NG	NG CCS	Nu-clear	Oil	Hyd-ro	Bio-mass	Wind	Solar	Oth. Ren.
2010	(1)	96.11	0.00	9.84	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(2)	96.28	0.00	9.97	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(3)	96.28	0.00	9.97	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(4)	96.28	0.00	9.97	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(5)	96.28	0.00	9.97	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(6)	96.28	0.00	9.97	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
2015	(1)	94.49	0.00	11.67	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(2)	87.32	0.00	7.44	0.00	31.51	0.00	3.90	7.31	0.000	0.00	2.63
	(3)	80.56	0.00	26.02	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(4)	62.08	0.00	23.42	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(5)	72.81	0.00	23.69	0.00	31.51	0.00	3.90	7.52	0.011	0.00	2.63
	(6)	54.75	0.00	22.83	0.00	31.51	0.00	3.90	5.51	0.005	0.00	2.63
2020	(1)	87.57	0.00	8.82	0.00	49.44	0.00	3.90	0.00	0.000	0.00	2.63
	(2)	72.15	0.00	3.12	0.00	49.44	0.00	3.90	12.23	0.011	0.00	2.63
	(3)	71.18	0.00	23.94	0.00	49.44	0.00	3.90	0.00	0.000	0.00	2.63
	(4)	50.38	0.00	21.97	0.00	49.44	0.00	3.90	0.00	0.000	0.00	2.63
	(5)	54.93	0.00	22.76	0.00	49.44	0.00	3.90	13.18	0.011	0.00	2.63
	(6)	38.04	0.00	21.36	0.00	49.44	0.00	3.90	9.16	0.005	0.00	2.63
2025	(1)	92.71	0.00	13.57	0.00	49.44	0.00	3.90	0.00	0.000	0.00	2.63
	(2)	77.87	0.00	5.87	0.00	49.44	0.00	3.90	13.90	0.011	0.00	2.63
	(3)	75.70	0.00	26.06	0.00	49.44	0.00	3.90	0.00	0.000	0.00	2.63
	(4)	49.92	0.00	21.86	0.00	49.44	0.00	3.90	0.00	0.000	0.00	2.63
	(5)	60.09	0.00	24.52	0.00	49.44	0.00	3.90	14.15	0.011	0.00	2.63
	(6)	38.55	0.00	21.47	0.00	49.44	0.00	3.90	9.23	0.005	0.00	2.63
2030	(1)	94.30	0.00	22.24	0.00	49.44	0.00	3.90	0.00	0.000	0.00	2.63
	(2)	72.97	0.00	16.73	0.00	49.44	0.00	3.90	19.78	0.011	0.00	2.63
	(3)	46.08	18.70	37.19	0.00	49.44	0.00	3.90	0.60	0.000	0.00	2.63
	(4)	46.65	8.77	22.61	0.00	49.44	0.00	3.92	0.60	0.000	0.00	2.63
	(5)	42.12	21.31	24.76	0.00	49.44	0.00	3.93	14.15	0.011	0.00	2.63
	(6)	29.20	15.94	21.41	0.00	49.44	0.00	3.90	10.05	0.005	0.00	2.63

Table 12: Data in TWh for Figure 8. (1) a base case scenario in which no new energy policy is imposed, (2) an RES scenario in which the utility will be required to meet a RES, (3) a CO_2 market scenario with initial free allowances in which the utility will be required to participate in a federal level CO_2 cap-and-trade program, (4) a CO_2 market scenario without free initial allowances, (5) a "both policies" scenario with initial free allowances in which both RES and CO_2 market policies are imposed, and (6) a both policies scenario without initial free allowances.

A.5 Comparison with the MARKAL model

Levin et al.[58] applied the MARKAL model to the state of Georgia in order to address state-scale impacts of a renewable electricity standard (RES) and a carbon tax. Even though the details of policies in Levin et al. are a little different from the policies in this study, by comparing the results of both case studies, we can partially validate the model in this study.

Figure 32 shows the projection of electricity output by generation technology under policy scenarios from the MARKAL model in Levin et al.[58]. In order to validate the model in this study, we project the electricity output by generation technology without demand response to price change under the different policy scenarios in the model in this study. As a result, Figure 33 shows the electricity generation mix results extracting the demand responsiveness from Figure 8. In addition, Tables 13 and 14 show the data for Figures 32 and 33 respectively.

Based on the figures and tables, we can note that the projections of electricity output by generation technology under the base and the RES policy scenarios from both models are similar. Specifically, the base cases (scenario 1) differ by 2% for coal and less than 1% for nuclear by 2030. The smaller amount of coal in the MARKAL model results in a higher natural gas generation amount. In the RES scenario (scenario 2), there is also close agreement with both studies showing 21 TWh of biomass generation in 2030.

Since two studies did not use the exactly same input parameters and assumptions, we can see the small differences between two models' results. Under the CO_2 market scenarios (the cap-and-trade system or carbon tax), we can see more notable differences between two models' results. The model in this study prefers to build CCS systems, but the MARKAL model in Levin et al. decides to build biomass power plants. This difference is mainly due to the assumptions of which technologies each study includes. Levin et al. include the biomass co-firing conversion technology and

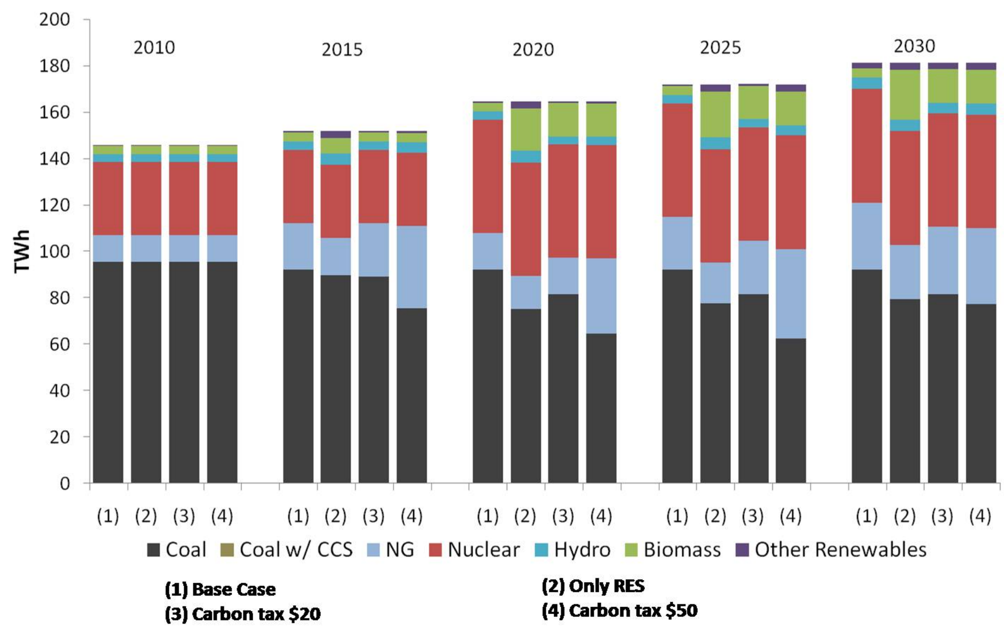


Figure 32: Electricity output by generation technology for the state of Georgia from the MARKAL model [58].

it can be the most cost effective technology under the CO_2 market scenarios. On the other hand, this study focuses on the retrofitting of current existing coal power plants with CCS systems and does not include the biomass co-firing conversion technology. The most cost-effective technology under the CO_2 market scenarios in this study is the retrofitting with CCS systems. We expect that if this study included the biomass co-firing conversion technology instead of the retrofitting with CCS systems, the results under the CO_2 market scenarios in both studies would be more similar.

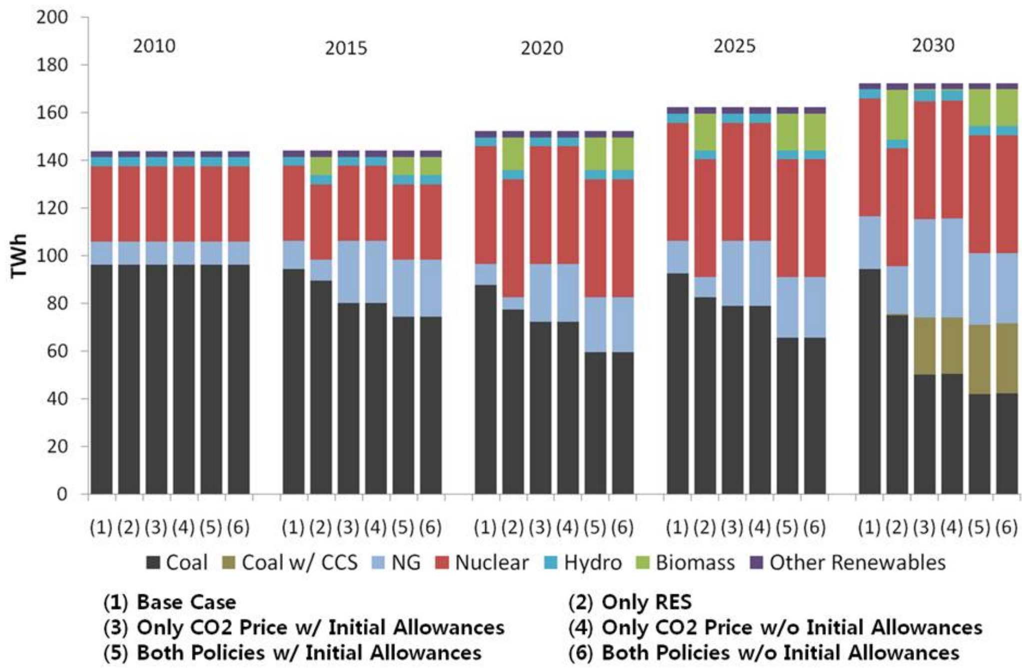


Figure 33: Electricity output by generation technology for this case study without incorporating demand responses.

Yr	Scn.	Coal	Coal CCS	NG	NG CCS	Nu-clear	Oil	Hyd-ro	Bio-mass	Oth. Ren.
2010	(1)	95.52	0	11.39	0	31.50	0	3.52	3.92	0.03
	(2)	95.52	0	11.39	0	31.50	0	3.52	3.92	0.03
	(3)	95.52	0	11.39	0	31.50	0	3.52	3.92	0.03
	(4)	95.52	0	11.39	0	31.50	0	3.52	3.92	0.03
2015	(1)	92.01	0	20.11	0	31.50	0	3.52	4.01	0.72
	(2)	89.60	0	16.13	0	31.50	0	4.97	6.60	3.06
	(3)	88.96	0	23.16	0	31.50	0	3.52	4.02	0.72
	(4)	75.53	0	35.31	0	31.50	0	4.49	4.02	0.96
2020	(1)	92.01	0	15.85	0	48.84	0	3.52	3.60	0.72
	(2)	75.29	0	14.12	0	48.84	0	4.97	18.24	3.08
	(3)	81.44	0	15.73	0	48.84	0	3.52	14.44	0.72
	(4)	64.53	0	32.38	0	48.84	0	3.52	14.44	0.81
2025	(1)	92.01	0	22.77	0	48.84	0	3.52	4.01	0.72
	(2)	77.66	0	17.50	0	48.84	0	4.97	19.83	3.08
	(3)	81.58	0	22.89	0	48.84	0	3.52	14.43	0.72
	(4)	62.34	0	38.68	0	48.84	0	4.49	14.44	3.08
2030	(1)	92.01	0	29.01	0	48.84	0	4.88	4.01	2.42
	(2)	79.55	0	23.28	0	48.84	0	4.97	21.44	3.08
	(3)	81.58	0	29.05	0	48.84	0	4.49	14.44	2.76
	(4)	77.22	0	32.83	0	48.84	0	4.76	14.44	3.08

Table 13: Data in TWh for Figure 32 from the MARKAL model [58]. (1) a base case scenario in which no new energy policy is imposed, (2) an RES scenario in which the utility will be required to meet a RES, (3) a \$20 carbon tax scenario, (4) a \$50 carbon tax scenario.

Yr	Scn.	Coal	Coal CCS	NG	NG CCS	Nu- clear	Oil	Hyd- ro	Bio- mass	Wind	Solar	Oth. Ren.
2010	(1)	96.11	0.00	9.84	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(2)	96.28	0.00	9.97	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(3)	96.28	0.00	9.97	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(4)	96.28	0.00	9.97	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(5)	96.28	0.00	9.97	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(6)	96.28	0.00	9.97	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
2015	(1)	94.49	0.00	11.67	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(2)	89.60	0.00	8.86	0.00	31.51	0.00	3.90	7.70	0.000	0.00	2.63
	(3)	80.26	0.00	25.89	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(4)	80.26	0.00	25.89	0.00	31.51	0.00	3.90	0.00	0.000	0.00	2.63
	(5)	74.24	0.00	24.17	0.00	31.51	0.00	3.90	7.74	0.000	0.00	2.63
	(6)	74.24	0.00	24.17	0.00	31.51	0.00	3.90	7.74	0.000	0.00	2.63
2020	(1)	87.57	0.00	8.82	0.00	49.44	0.00	3.90	0.00	0.000	0.00	2.63
	(2)	77.42	0.00	5.27	0.00	49.44	0.00	3.90	13.70	0.011	0.00	2.63
	(3)	72.13	0.00	24.25	0.00	49.44	0.00	3.90	0.00	0.000	0.00	2.63
	(4)	72.13	0.00	24.25	0.00	49.44	0.00	3.90	0.00	0.000	0.00	2.63
	(5)	59.52	0.00	23.16	0.00	49.44	0.00	3.90	13.70	0.011	0.00	2.63
	(6)	59.45	0.00	23.16	0.00	49.44	0.00	3.90	13.78	0.000	0.00	2.63
2025	(1)	92.71	0.00	13.57	0.00	49.44	0.00	3.90	0.00	0.000	0.00	2.63
	(2)	82.68	0.00	8.26	0.00	49.44	0.00	3.90	15.33	0.011	0.00	2.63
	(3)	78.90	0.00	27.38	0.00	49.44	0.00	3.90	0.00	0.000	0.00	2.63
	(4)	78.90	0.00	27.38	0.00	49.44	0.00	3.90	0.00	0.000	0.00	2.63
	(5)	65.50	0.00	25.43	0.00	49.44	0.00	3.90	15.34	0.011	0.00	2.63
	(6)	65.49	0.00	25.45	0.00	49.44	0.00	3.90	15.34	0.000	0.00	2.63
2030	(1)	94.30	0.00	22.24	0.00	49.44	0.00	3.90	0.00	0.000	0.00	2.63
	(2)	74.97	0.71	19.79	0.00	49.44	0.00	3.90	20.85	0.021	0.00	2.63
	(3)	50.20	23.91	41.31	0.00	49.44	0.00	4.34	0.67	0.000	0.00	2.63
	(4)	50.29	23.91	41.34	0.00	49.44	0.00	4.30	0.60	0.000	0.00	2.63
	(5)	41.74	29.18	30.17	0.00	49.44	0.00	4.01	15.34	0.011	0.00	2.63
	(6)	42.22	29.28	29.66	0.00	49.44	0.00	3.94	15.34	0.000	0.00	2.63

Table 14: Data in TWh for Figure 33 from the model in this study. (1) a base case scenario in which no new energy policy is imposed, (2) an RES scenario in which the utility will be required to meet a RES, (3) a CO_2 market scenario with initial free allowances in which the utility will be required to participate in a federal level CO_2 cap-and-trade program, (4) a CO_2 market scenario without free initial allowances, (5) a "both policies" scenario with initial free allowances in which both RES and CO_2 market policies are imposed, and (6) a both policies scenario without initial free allowances.

APPENDIX B

APPENDIX FOR CHAPTER 3

B.1 Capacity Planning Model

The Capacity Planning (CP) model minimizes the NPV of capacity changes and electricity production over a multi-decade period.

The objective function can be written as

$$\min \sum_{t} \frac{1}{(1+r)^t} \Big\{ \sum_{i} (C_i y_{i,t} + F_i x_{i,t}) + \sum_{i} V_{i,t} \sum_{s} \frac{\theta_s}{3} \sum_{w} \sum_{h} (z_{i,h,s,t} + zev_{i,h,s,t}) + \sum_{j} LC_{wind,j} \sum_{s} \frac{\theta_s}{3} \sum_{w} \sum_{h} zwind_{j,h,s,t} \Big\}$$

Capacity Change Constraint Based on the existing power plant capacities, the total capacities of each technology will vary with retirement of existing plants and new construction over time. Some technology options, including biomass, wind and hydro, are physically and/or economically limited, so these technologies will have, effectively, maximum capacity limitations.

$$x_{i,t} = x_{i,t-1} - q_{i,t-1} + y_{i,t} \qquad \forall i, \forall t \tag{31a}$$

$$x_{i,t} \leq u_i \qquad \forall i, \forall i \tag{31b}$$

Generation Constraint The power output generated by each technology must not exceed its maximum available capacity. The power output of solar or wind technology

Table 15: Indices, parameters, and variables in the model.

Set and Indices	
I	= Generation technologies, $i \in I$
J	= Wind Supply Curve, $j \in J$
h	= Time period of hours, $h = 1, 2, ..., 24$
w	= Wind level (1 = High wind, 2 = mid wind, 3 = low wind)
s	= Time period of seasons (1 = winter weekday, 2 = winter weekend, 3 = intermediate weekday, 4 = intermediate weekend, 5 = summer weekday, 6 = summer weekend)
t	= Time period of years, $t = 1, 2, ..., T$
Parameters	
-Demand-	
r	= Risk-adjusted real discount factor (7%)
$d_{h,s,t}$	= Electricity demand at hour h in season sin year t (MWh)
$dev_{h,s,t}$	= EV charging demand at hour h in season s in year t (MWh) (independent of wind level)
$cev_{h,s,t}$	= EV charging capacity at hour h in season s in year t (MWh) (independent on wind level)
θ_s	= Number of days in season s (days)
-Capacity-	
ρ_i	= Maximum capacity factor of technology i (%)
$\rho_{solar,h,s}$	= Solar electricity potential at hour h in season s (%)
$\rho_{wind,h,s}$	= Wind electricity potential at hour h in season s (%)
u_i	= Upper bound for generating capacity of technology i (MW)
-Cost-	
C_i	= Capital investment cost of technology i (\$/MW)
F_i	= Annual fixed cost of technology i (\$/MW-yr)
$V_{i,t}$	= Variable cost (O&M + fuel cost) of technology i in year t (\$/MWh)
$LC_{wind,j}$	= Levelized cost of potential wind power at the jth step of the supply curve (\$/MWh)
δ_s	= Peak demand multiplicative factor
-New Policy-	
e_i	= CO_2e (Equivalent CO_2) emissions from technology i (tCO_2e/MWh)
Res_t	= Renewable electricity standard in year t (%)

Decision Variables	
$y_{i,t}$	= Capacity expansion (investment) of technology i in year t
$q_{i,t}$	= Retirement capacity of technology i in year t (MW)
$x_{i,t}$	= Capacity of technology i in year t (MW)
$xwind_{j,t}$	= Capacity of technology i in year t (MW)
$z_{i,s,w,h,t}$	= Electricity generation for non-EV use from technology i at hour h, wind level w, season s, and year t (MWh)
$zev_{i,s,w,h,t}$	= Electricity generation for EV charging from technology i at hour h, wind level w, season s, and year t (MWh)
$zwind_{j,s,w,h,t}$	= Electricity generation from new wind capacity in j supply curve level at hour h, wind level w, season s, and year t (MWh)

at each hour is determined by solar radiation or wind speed as well as capacity.

$$z_{i,s,w,h,t} + zev_{i,s,w,h,t} \leq x_{i,t} \qquad \forall i, \forall s, \forall w, \forall h, \forall t \tag{32a}$$

$$\sum_s \frac{\theta_s}{3} \sum_w \sum_h (z_{i,s,w,h,t} + zev_{i,s,w,h,t}) \leq \rho_i x_{i,t} \times 8760 \qquad \forall i, \forall t \tag{32b}$$

$$z_{wind,s,w,h,t} + zev_{wind,s,w,h,t} \leq \rho_{wind,s,w,h} x_{wind,t} + \sum_j zwind_{j,s,w,h,t} \qquad \forall s, \forall w, \forall h, \forall t \tag{32c}$$

$$zwind_{j,s,w,h,t} \leq \rho_{wind,s,w,h} xwind_{j,t} \qquad \forall j, \forall s, \forall w, \forall h, \forall t \tag{32d}$$

$$xwind_{j,t-1} \leq xwind_{j,t} \qquad \forall j, \forall t \tag{32e}$$

$$z_{solar,s,w,h,t} + zev_{solar,s,w,h,t} \leq \rho_{solar,s,h} x_{solar,t} \qquad \forall s, \forall w, \forall h, \forall t \tag{32f}$$

Demand Constraint The total power output generated by all technologies must not be less than the total power demand, and peak demand must be met.

$$\sum_{i} z_{i,s,w,h,t} \geq d_{s,h,t} \qquad \forall s, \forall w, \forall h, \forall t \quad (33a)$$

Case 1: Uncontrolled Charging (33b)

$$\sum_{i} zev_{i,s,w,h,t} \geq dev_{s,h,t} \qquad \forall s, \forall w, \forall h, \forall t \quad (33c)$$

$$\sum_{i \in I \setminus hydro,wind,solar} x_{i,t} \geq \delta_s \times \max_h \left(d_{s,h,t} + dev_{s,h,t}\right) \qquad \forall s, \forall t \quad (33d)$$

Case 2: All controlled Charging (33e)

$$\sum_{h} \sum_{i} zev_{i,s,w,h,t} \geq \sum_{h} dev_{s,h,t} \qquad \forall s, \forall w, \forall t \quad (33f)$$

$$\sum_{i} zev_{i,s,w,h,t} \geq cev_{s,h,t} \qquad \forall s, \forall w, \forall h, \forall t \quad (33g)$$

$$\sum_{i \in I \setminus hydro,wind,solar} x_{i,t} \geq \delta_s \times \max_h \left(d_{s,h,t} + dev_{s,h,t}\right) \qquad \forall s, \forall t \quad (33h)$$

Wind Balancing Constraint

Case 1: Controlled chargingwith annual wind energy balancing (34a)

$$\sum_{s} \frac{\theta_s}{3} \sum_{w} \sum_{h} zev_{wind,s,w,h,t} \geq \sum_{s} \theta_s \sum_{h} dev_{s,h,t} \qquad \forall t \quad (34b)$$

Case 2: Controlled chargingwith real-time wind energy matching (34c)

$$zev_{i,s,w,h,t} = 0 \qquad \forall i \in I \setminus wind, \forall s, \forall w, \forall h, \forall t \quad (34d)$$

Renewable Electricity Constraint

$$\sum_{i \in biomass,solar,wind,other\_ren} \sum_{s} \frac{\theta_s}{3} \sum_{w} \sum_{h} (z_{i,s,w,h,t} + zev_{i,s,w,h,t} \quad (35)$$

$$\geq res_t \sum_{i} \sum_{s} \frac{\theta_s}{3} (z_{i,s,w,h,t} + zev_{i,s,w,h,t}) \qquad \forall t \quad (36)$$

B.2 Unit Commitment Model

In actual power system operation, a Unit Commitment is run before the operating hour to determine which units will be online during the operating hour and determine an initial schedule for how much power each unit will produce. In many systems, the Unit Commitment run spans a 24 hour period, called an operating day, and is run 12 hours before the start of the operating day, resulting in decisions made up to 36 hours before the operating hour. The uncertainty in generator availability, maximum potential production of intermittent generators, and transmission capacity for periods 12-36 hours in advance requires conservative UC. We adopt the convention of 24 hour UC runs performed the day before the operating day. Since UC is normally performed over the course of one operating day, optimization of dispatchable, capacity-factor limited resources like hydro is not optimized over the course of the year. To resolve this, most power systems employ a coarser hydro UC a period on the order of months to years to optimize hydro usage. We do not employ a long-term hydro optimizer. To provide the system maximum flexibility to maintain security, our UC does not limit the amount of renewable curtailment which can occur. This is consistent with actual operating practice which strives to minimize cost. For systems with limited load controllability, high levels of intermittent renewables, and/or inflexible generation, this can result in curtailment of renewable resources. Should the curtailment be severe enough, RPS requirements satisfied in the CP may not be fulfilled in the ED, which would lead to penalties and incentives for utilities to build more capacity. Our UC uses a perfect load forecast and a 24 hour-ahead wind potential production forecast. Assuming UC is run 12 hours before the start of the operating day and forecasts are generated two hours before the UC is performed, forecasts used in the UC extend 38 hours into the future. However, we only have access to 4, 6, and 24 hour-ahead

This model is originally developed by colleague of this study, Frank Kreikebaum, from Electrical and Computer Engineering.

wind production forecasts. Therefore, the 24 hour-ahead was used to represent the forecast input to the UC. Compared to the forecasts used in actual UC, this likely leads to artificially poor forecasts for operating hours 1-10 and artificially accurate forecasts for operating hours 11. While most actual UC processes include reserve and ancillary service requirements, we did not consider them in our UC. In addition, while calculates the carbon emissions by unit and by hour that will result if the UC solution is followed, it does not include emissions associated with startup and shutdown.

The objective function minimizes the variable costs and startup costs of the entire generator fleet over the period of the Unit Commitment

$$\min\Big\{\sum_i\sum_g\sum_h V_{i,g}z_{i,g,h}+\sum_i\sum_g\sum_h S_{i,g}start_{i,g,h}\Big\}$$

Demand Constraints For uncontrolled charging, the total generation during any hour must equal the total demand. In this case, total demand includes conventional load as well as EV charging load. For controlled charging and controlled wind annual, the conventional demand (d_h) must be met during each operating hour. In addition, the energy required by the EV fleet over the UC period must be provided over the course of the UC period. Finally, the amount of power which can be directed to the EV fleet in any given hour cannot exceed the fleet charging capacity of that hour. In addition to the demand constraints applicable to controlled charging and controlled wind annual balancing, real-time wind matching requires that the power directed to the EV fleet in any given hour cannot exceed the amount of wind power generated.

Case 1: Uncontrolled Charging

$$\sum_i\sum_g z_{i,g,h} \geq d_h \qquad \forall h \tag{37a}$$

$$\tag{37b}$$

Case 2: Controlled charging for cost minimizing and controlled charging with annual

Table 16: Indices, parameters, and variables in the Unit Commitment model.

Set and Indices	
i	= Generation technologies, $i \in I$
g	= Generator unit identifier, $g \in G$
h	= Index of operating hours solved in a single Unit Commitment run, $h = 1, 2, ..., 24$
T	= Total number of hours in a single Unit Commitment solution, $T = 24$
Parameters	
-Demand-	
d_h	= Non-flexible Electricity demand at hour h (MWh)
dev	= Energy required over the unit commitment period to meet flexible EV demand (MWh). Only applicable to the controlled charging schemes
cev_h	= EV charging capacity at hour h, only applicable to the controlled charging schemes(MW)
-Capacity-	
$\rho_{max,i}$	= Maximum capacity factor of technology i during UC period (per-unit of nameplate capacity)
$\rho_{min,i}$	= Minimum capacity factor of technology i at which the unit can remain online (per-unit of nameplate capacity)
$\rho_{forecastedwind,h}$	= Forecasted wind energy maximum potential during hour h for a forecast produced before the UC model is run (per-unit of nameplate capacity)
$\rho_{actualwind,h}$	= Wind energy maximum potential during hour h (per-unit of nameplate capacity)
$u_{i,g}$	= Upper bound for generating capacity of unit g of technology i (MW)
-Cost-	
$V_{i,g}$	= Variable cost (O&M + fuel cost) of unit g of technology i (\$/MWh)
$S_{i,g}$	= = startup cost of unit g of technology i \$/start)
-Emissions-	
e_i	= CO_2e (Equivalent CO_2) emissions from technology i (tCO_2e/MWh)

Decision Variables	
$z_{i,g,h}$	= Electricity generation from unit g of technology i at hour h (MWh)
$start_{i,g,h}$	= Startup of unit g of technology i at hour h (1 = startup occurs, 0 = no startup occurs)
$state_{i,g,h}$	= State of unit g of technology i at hour h (1 = online, 0 = offline)

wind energy balancing

$$\sum_i \sum_g z_{i,g,h} \geq d_h \qquad \forall h \tag{38a}$$

$$\sum_i \sum_g \sum_h z_{i,g,h} \geq \sum_h d_h + dev \tag{38b}$$

$$\sum_i \sum_g z_{i,g,h} - d_h \leq cev_h \qquad \forall h \tag{38c}$$

Case 3: Controlled charging with real-time wind energy matching

$$\sum_i \sum_g z_{i,g,h} \geq d_h \qquad \forall h \tag{39a}$$

$$\sum_i \sum_g \sum_h z_{i,g,h} \geq \sum_h d_h + dev \tag{39b}$$

$$\sum_i \sum_g z_{i,g,h} - d_h \leq cev_h \qquad \forall h \tag{39c}$$

$$\sum_{i \in I \setminus wind} \sum_g z_{i,g,h} \leq d_h \qquad \forall h \tag{39d}$$

Minimum Output Constraint The power output generated by each unit must not be less than its minimum power output if the unit is online.

$$-z_{i,g,h} + \rho_{min,i} u_{i,g} state_{i,g,h} \geq 0 \qquad \forall i \forall g \forall h \tag{40a}$$

Maximum Output Constraint The capacity factor of the unit over the operating day must not be larger than the units maximum capacity factor.

$$\sum_h z_{i,g,h} \geq T \rho_{max,i} u_{i,g} \qquad \forall i \forall g \tag{41a}$$

Unit Startup Constraints A unit offline in the prior hour but online in the current hour must be started in the current hour. An offline unit must not supply energy and an online unit must not be supply more energy than its nameplate capacity (for non-wind units) or its forecasted maximum capacity (for wind units).

$$state_{i,g,h} - state_{i,g,h-1} - start_{i,g,h-1} \geq 0 \qquad \forall i \forall g \forall h \tag{42a}$$

$$z_{i,g,h} - \rho_{max,i} u_{i,g} state_{i,g,h} \geq 0 \qquad \forall iinI \setminus wind, \forall g, \forall h \tag{42b}$$

$$z_{i,g,h} - \rho_{forecastwind,h} u_{wind,g} state_{i,g,h} \geq 0 \qquad \forall g, \forall h \tag{42c}$$

B.3 Economic Dispatch Model

The economic dispatch (ED) model determines how much power will be dispatched from each generating unit for the current hour and future hours of the operating day. For every UC solution, the ED model is run once for each hour of the operating day. So, at 12am the ED finalizes the dispatch for 12am-1am but also updates the estimated dispatch for the remaining hours of the day. When run again at 1am, the ED takes the outcomes from 12am-1am as fixed, finalizes the outcomes for 1am-2am and re-estimates the dispatch for 2am-11:59pm. When finalizing the dispatch for the current hour, the maximum potential production of wind generation is set to the observed potential production rather than the day-ahead forecasted value. This is based on with the assumption that intra-hour wind forecasts of aggregate, multi-state potential wind production are perfectly accurate. We make this assumption given the geographic diversity of a multi-state wind generation portfolio and the accuracy of near-term forecasts. However, maximum production of wind generators in subsequent hours is still based on the day-ahead forecast used in the UC. Like the UC, the ED does not limit the amount of renewable curtailment so the ED may curtail wind to minimize the cost of securely operating the system. Should the curtailment be severe enough, RPS requirements satisfied in the CP may not be met in the ED. Reserve and ancillary service requirements are not considered in the ED. In addition, while the ED calculates carbon emissions by unit by hour, it does not include emissions associated with startup and shutdown. The ED model is the same as the UC model, except state variables related to unit state and startup are constrained to the solutions determined in the UC. In addition, variables for prior hours are constrained to the values solved in prior ED runs.

Table 17: Share of vehicles for each region in Eastern Interconnection

Eastern Interconnection Regions	Share of National Vehicles
FRCC	6%
MRO	6%
NPCC	11%
RFC	20%
SERC	25%
SPP	2%
Eastern Interconnection Total	71%

B.4 Estimation of the number of LDVs

The NHTS surveyed the number of vehicles for some households over the entire U.S. and estimated the number of households in each state [42]. We calculate the share of households for each state. Based on the assumption that each household has the same number of vehicles in average, the share of households is the same as that of vehicles for each state. Table 17 shows the share of vehicles in eastern US, and eastern interconnection has 71% of US vehicles.

AEO 2011 projects for future LDV sales and the size of the vehicle stock for entire US [24]. Based on these projections and assumptions for electric vehicle's market share, we calculate the number of electric vehicle sales and size of the vehicle stock, as shown in Figure 34 and 35.

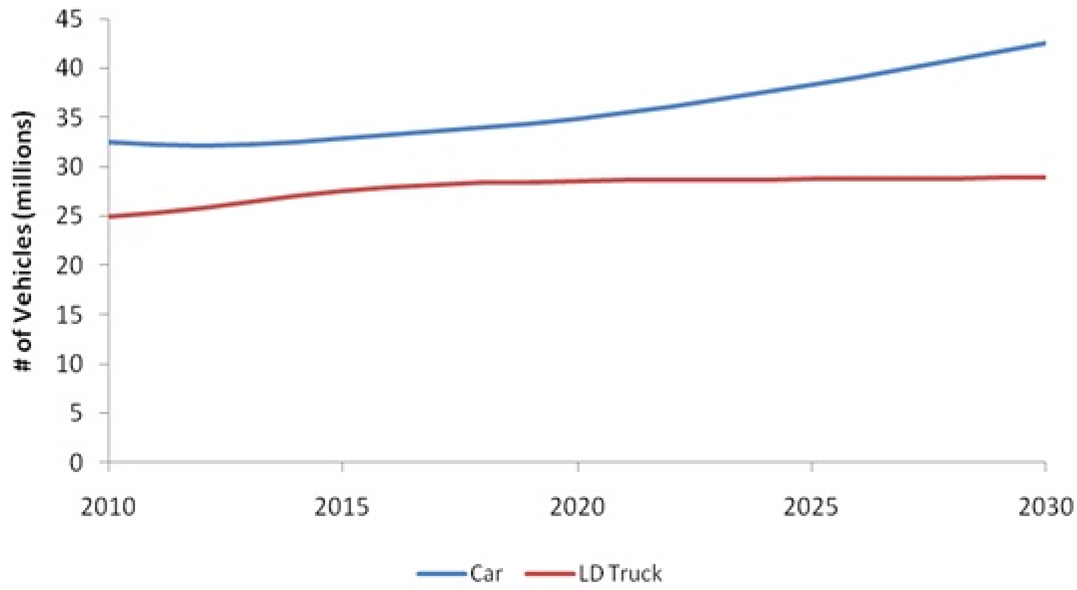


Figure 34: Projections of light-duty vehicles in the eastern interconnect

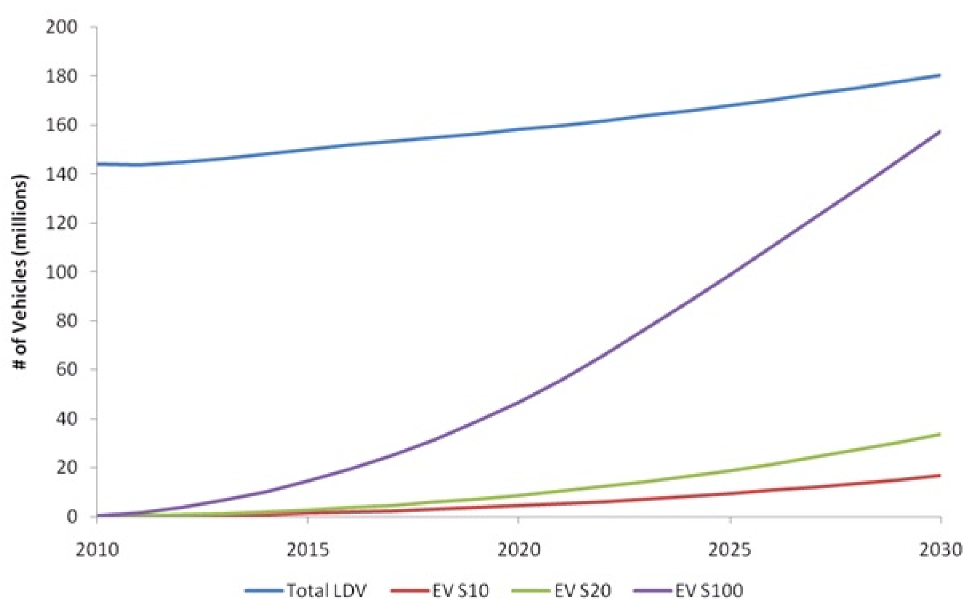


Figure 35: Projected number of total light duty vehicles (except pickup trucks) and EVs

Table 18: Vehicle types in different studies

NHTS	AEO	ANL
Automobile/car/station wagon	Car	Compact
Van	Truck	Midsize
Sports Utility Vehicle		Small SUV
Pickup Truck		Midsize SUV
		Pickup

		AEO Vehicle Types	
		Car	*Truck*
NHTS Vehicle Types	*Automobile/Car/Station Wagon*	100%	
	Van		10%
	Sports Utility Vehicle		64%
	Pickup Truck		26%

Figure 36: Map of AEO vehicle types to NHTS vehicle types

B.5 Energy intensity of new electric vehicles

The assumptions for EV energy intensities in the CD mode are based on the projection of Argonne National Laboratory [5]. The NHTS, AEO and ANL use different vehicle type categories, as shown in Table 18. In this study, since we are using data from all three studies, we need to be able to convert the energy intensities of electric vehicles from a category to another category. Based on the qualitative description provided for these vehicle types, we map from one categorization system to the other as shown in Table 36 – Table 38. Based on the mapping in Table 38, we can convert the energy intensities (Table 39) in ANL categories to those in the NHTS categories (Table 40).

		ANL Vehicle Types				
		Compact	Midsize	Small SUV	Midsize SUV	Pickup
AEO Vehicle Types	Car	48%	52%			
	Truck			4%	47%	48%

Figure 37: Map of ANL vehicle types to AEO vehicle types

		ANL Vehicle Types				
		Compact	Midsize	Small SUV	Midsize SUV	Pickup
NHTS Vehicle Types	Automobile/car/station wagon	48%	52%	-	-	-
	Van	-	-	-	83%	17%
	Sports Utility Vehicle	-	-	7%	29%	64%
	Pickup Truck	-	-	-	-	100%

Figure 38: Map of ANL vehicle types to NHTS vehicle types

Energy Intensity (Wh/mi) - Average Values		2010	2015	2030	2045
EVs - ANL	Compact	231	221	190	182
	Midsize	253	242	208	199
	Small SUV	294	280	240	230
	Midsize SUV	355	336	297	281
	Pickup	432	403	353	340
SI PHEV 40	Compact	244	235	216	206
	Midsize	271	259	236	226
	Small SUV	304	291	263	253
	Midsize SUV	362	346	321	304
	Pickup	431	408	374	362

Figure 39: Fuel Economy of EVs in charge depleting mode for vehicle types in ANL [5]

Energy Intensity (Wh/mi) - Average Values		2010	2015	2030	2045
EV100 Energy Intensity Mapped to NHTS Vehicle Type	Automobile/car/station wagon	242	232	199	191
	Van	368	347	306	291
	Sports Utility Vehicle	401	376	329	315
	Pickup Truck	432	403	353	340
PHEV 40 Energy Intensity Mapped to NHTS Vehicle Type	Automobile/car/station wagon	258	247	226	217
	Van	374	356	330	314
	Sports Utility Vehicle	403	382	351	338
	Pickup Truck	431	408	374	362

Figure 40: Fuel Economy of EVs in charge depleting mode for vehicle types in NHTS

B.6 Fuel economies of New Conventional Vehicles

The National Highway Traffic Safety Administration (NHTSA) regulates Corporate Average Fuel Economy (CAFE) standards and the average fuel economy for new model year vehicles are required to meet this standard. The average fuel economy for new model year vehicles is calculated as Eq. 43a

$$\frac{\sum_i n_i}{\sum \frac{n_i}{f_i}} \tag{43a}$$

where n_i is number of vehicles in type i and f_i is fuel economy of vehicles in type i. The NHTSA uses the petroleum equivalency factor to calculate the MPGe of EVs for MY 2011-2016, as shown in equation Eq. 44a [37]. In the formula, E is the Wh/mi of electricity consumed by the vehicle when tested using the 2-cyle method. We found no evidence to indicate that this method would not be used for the MY 2017-2025 standard. Therefore, we used it to calculate the MPGe of EVs.

$$\frac{1}{E} \times 33705 \times \frac{0.303}{0.830} \times 6.66667 \tag{44a}$$

The NHTSA uses the utility factor (UF) to calculate the MPGe of PHEVs. The utility-factor assumes vehicle does not charge during the day but begins day fully charged. The UF is roughly 0.35 for 20 mile range and 0.6 for 40 mile range. The formula for PHEV fuel economy is shown in equation Eq. 45a [37], where UF is utility factor, FE_{CD} is fuel efficiency of charge depleting mode and FE_{CS} is fuel efficiency of charge sustaining mode. It is not clear if FE_{CD} is calculated in the same manner as an EV. Although the UF method is currently used for the M 2011-MY2016 standard and we found no evidence that it would not be used going forward, we used this formula to calculate the MPGe of PHEVs.

$$FE_{UFweight} = \frac{1}{\frac{UF}{FE_CD} + \frac{1-UF}{FE_CS}} \tag{45a}$$

Since the CAFE standard is calculated using a harmonic mean, given the high fuel economy assigned to EVs by the NHTSA, scenarios with higher EV market share result in a lower required CV fuel economy. Taken to the extreme, this leads to falling CV fuel economy as EV adoption increases. However, we impose the requirement that within a given scenario, CV fuel economies do not decrease as a function of time. Figure 41 shows projections of required fuel economy of new conventional vehicles and their stock.

B.7 Generation of EV Daily Energy Requirement, EV Hourly Demand Profile, and EV Hourly Capacity Profiles

The National Household Transit Survey surveyed the trips made by all members of selected households for one day. Travel via the light-duty fleet is a subset of the reported transit modes. For each of the samples, we generate the following for a representative EV:

Daily energy demand The average daily energy demand for a single vehicle. Calculated using the vehicle type specific energy intensities and the average daily driving distance for the sample.

Hourly demand profile The charging demand of the average vehicle of the sample

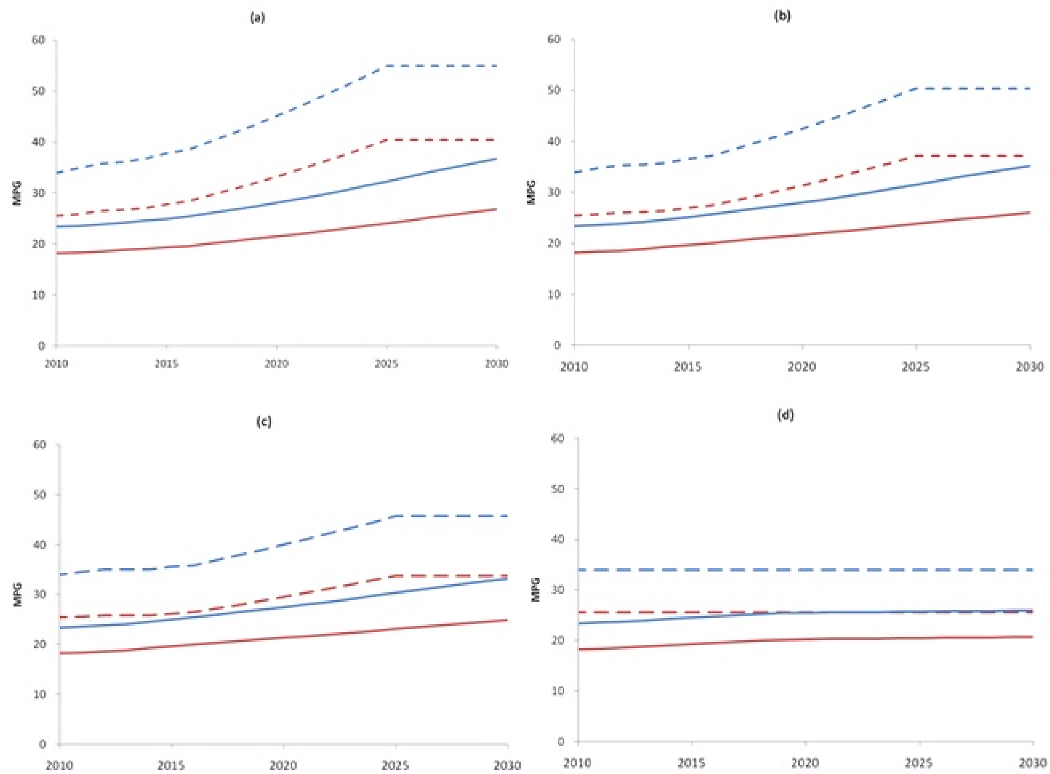


Figure 41: Projection of the fuel economy of new conventional vehicles and their stock, (a) Reference scenario, (b) EV S10, (c) EV S20, and (d) EV S100. Blue is for light-duty car and red is for light-duty truck.

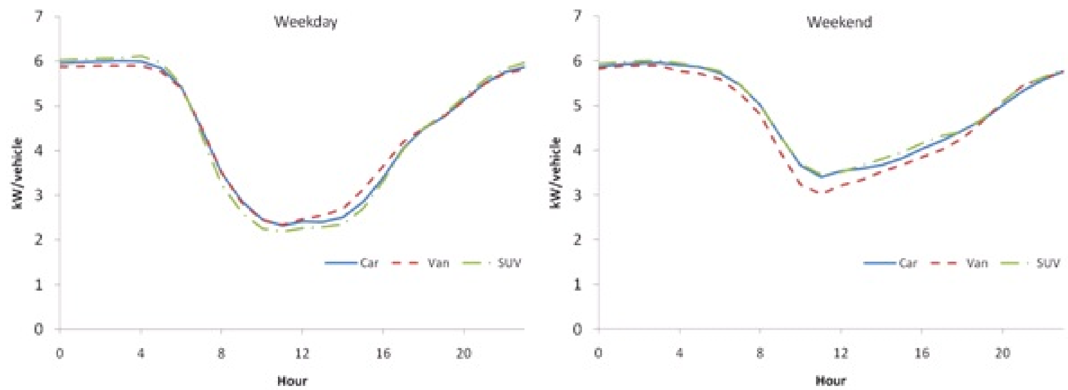


Figure 42: Fraction of EV fleet that is plugged in, times 6.6 kW.

based on an uncontrolled charging scheme whereby the vehicle begins charging upon completion of the last journey of the day and charges at a given uniform rate until all energy used during the day has been restored.

Hourly capacity profile The charging power the average vehicle of the sample can accommodate for every hour of the day if the vehicle is connected to an charging infrastructure as soon as a journey is completed. The use of a fleet-wide capacity profile ignores car-level dynamics where the battery of a given vehicle may not be able to accommodate additional energy until later in the day.

For the controlled charging schemes, we generate charging capacity profiles with the assumption that home charging infrastructure and rate incentives ensure that drivers plug in vehicles throughout the day whenever they are at home. A charging capacity profile is the fraction of the EV vehicle fleet that is connected to charging infrastructure, times the charging power of 6.6 kW. Figure 42 shows the charging capacity profile and how flexibility charging demand has.

B.8 Wind Power Supply Curves and Production Profiles, Inter-Regional Transmission Cost

The EWITS provides the potential capacities and levelized costs for thousands of hypothetical onshore wind generation sites in the eastern and central US. We develop wind power supply curves for 6 reliability councils. For each region, we aggregate the time-series onshore wind power production of the 30 percent of the sites with the lowest cost of energy. Because cost of energy data is not provided for the offshore sites, we include all sites in the aggregate profile for each region. Based on this time series data, we develop onshore and offshore wind power profiles for high wind, medium wind, and low wind days for three seasons (Winter, Intermediate, and Summer) for each region. In order to capture the intermittency of the wind power, we take the high wind day to be the day with the highest total potential wind production when aggregating production across all candidate sites. For example, since we consider SERC onshore sites, SERC offshore sites, MRO onshore sites, and SPP onshore sites to be candidate sites to supply SERC, we pick the day which has the least aggregate production assuming 25% of SERC wind demand is supplied from each of the four candidate regions. Correspondingly, we chose the day with the lowest total potential wind production across all candidate regions as the low wind day. In total, we develop 9 one-day wind profiles for each region.

B.9 Hourly Non-EV Load Profiles

The Federal Energy Regulatory Commission (FERC) provides the annual electric balancing authority area and planning area report, Form No. 714 [40]. This report provides hourly load data of most utilities in US. By aggregating the 2010 hourly load data of some representative utilities in each region, we develop a representative hourly non-EV load profile spanning an entire year.

For the CP, we segment this representative data into weekdays and weekends in three seasons (winter - Jan. Feb. Dec., intermediate - Mar. to May and Sept. to Nov., summer - June to Aug.). By averaging the data, we develop the representative 24-hourly load profiles of conventional load for each segment. By multiplying the ratio between the projection of annual demand and total annual generation in given aggregate load data, we can develop the 24-hourly load profiles of non-EV load for every year.

The UC and ED models sample specific periods from the representative hourly non-EV load profile. Each period contains a contiguous period of hours.

B.10 Effective Region-wide RES

We calculate the effective region-wide RES mandate based on the load-weighted average RES mandates of each state. The Department of Energy (DOE) provides the information about states with renewable portfolio standards. Currently there are 24 states plus the District of Columbia that have RES policies in place. The Database of State Incentives for Renewables & Efficiency (DSIRE) from DOE provides more details on each state's RES, which include the specific schedule for the minimum percentage of renewable electricity every year [21]. Based on the RES schedule of each states and the share of electricity generation amounts of 2008 [24], we generate the region-wide PES as the weighted average of state level standards. As a example, among twelve states in SERC, only four states has the state level standards, Missouri, Illinois, North Carolina and Virginia.load profile. Each period contains a contiguous period of hours.

B.11 Incremental Vehicle Cost

Incremental vehicle cost is taken to be the additional cost of a vehicle, relative to a 2010 vehicle of the same class, to meet a certain fuel economy standard. Incremental cost as a function of technology, vehicle class, year and fuel economy are required for our method. While [31, 5, 14, 26] each contain a subset of this information, no study provides enough information to develop the requested function. The Argonne National Lab study [5] appears to be the closest source. Annexes 2 and 3 of

This part is originally developed by colleague of this study, Frank Kreikebaum, from Electrical and Computer Engineering.

the ANL study present average incremental manufacturing cost and average energy consumption data respectively for five vehicles classes (compact, midsize car, small SUV, midsize SUV, and pickup) at three future time points (2015, 2030, 2045) and for a number of power train types. In addition, Figure 133 of ANL report is a scatter plot of incremental cost as a function of year and fuel economy for compact vehicles. The plot shows that spark-ignition vehicles have the lowest cost and vehicles. Using Figure 133, two linear relationships are derived for 2010, 2015 and 2030, as shown in equations 46a and 46b The first equation relates average incremental cost to the incremental cost of the vehicle with the best-in-class fuel economy. The other relates average fuel economy to best-in-class fuel economy. These relationships are applies to the average values available for the other vehicle classes to estimate the best-in-class fuel consumption and incremental costs as seen in equations 46c and 46d. Given that the vehicle with the best fuel economy has an incremental cost lower or equal to the average fuel economy, we assume this technology will dominate the market.

$$\gamma_{fuelconsumption,t} = \frac{\delta_{average,compact,t} - \delta_{best,compact,t}}{\delta_{average,compact,t}} \times 100\% \tag{46a}$$

$$\gamma_{cost,t} = \frac{C_{average,compact,t} - C_{best,compact,t}}{C_{average,compact,t}} \times 100\% \tag{46b}$$

$$\delta_{best,i,t} = \delta_{average,i,t} \times (1 + \gamma_{fuelconsumption,t}) \tag{46c}$$

$$C_{best,i,t} = C_{average,i,t} \times (1 + \gamma_{fuelcost,t}) \tag{46d}$$

where $\delta_{j,i,t}$ = fuel consumption of type j (average or best-in-class) for vehicle type i in year t, $\gamma_{fuelconsumption,t}$ = fuel consumption adjustment factor for year t, $C_{j,i,t}$ = estimated incremental cost for of type j (average or best-in-class) for vehicle type i in year t, $\gamma_{cost,t}$ = incremental cost adjustment factor for year t.

Applying these linear factors to the other vehicle classes, we arrive upon the results below for CVs.

The ANL report presents EV data for PHEV 10-40 as well as EV 150. The

Table 19: Estimated Best-in-Class Incremental Costs of Spark Ignition vehicles

vehicle type	Fuel Cost ($)		
	2010	2015	2030
Compact	-38	750	1100
Midsize	-40	802	1130
Small SUV	99	896	494
Midsize SUV	-108	681	1170
Pickup	-63	697	1047

Table 20: Estimated Fuel Economy of Best-in-Class Spark Ignition vehicles

vehicle type	Fuel Economy (mpg)		
	2010	2015	2030
Compact	40.0	47.6	57.1
Midsize	37.6	41.3	50.4
Small SUV	33.6	39.1	48.8
Midsize SUV	28.9	33.8	40.6
Pickup	24.0	28.3	35.0

projected energy intensities for 2030 PHEVs and EVs are as much as 20% below the 2010 values. To provide conservative results, we assume the 2010 energy intensities apply to all years. Also, this analysis uses EVs with a 100 mile range and PHEVs with a 40 mile range. We adjusted the average ANL results to account for the lower battery size and higher energy intensities using the method seen in equation O.5. The resulting incremental costs are shown in Table 21 and 22.

$$C_{R,i,t} = C_{r,i,t} - B_{act,i,t}P_{bat,i,t} + R_i\epsilon_{2010,i}\frac{B_{act,i,t}}{B_{usable,i,t}}P_{bat,i,t} \tag{47a}$$

where $C_{R,i,t}$ = Estimated cost of EV with R mile range of type i in year t based on 2010 energy intensities ($), $C_{r,i,t}$ = Cost of EV with r mile range of type i in year t per ANL study ($), $B_{act,i,t}$ = Actual battery capacity of EV of type i in year t (kWh), $P_{bat,i,t}$ = Price of actual battery capacity in year t ($/kWh), R_i = Range of vehicle of type i (miles), $\epsilon_{2010,i}$ = 2010 EV energy intensity (kWh/miles), $B_{usable,i.t}$ = Usable battery capacity of EV of type i in year t (kWh).

Table 21: Adjusted Incremental Costs of EV 100 vehicles using 2010 Energy Intensities

vehicle type	Incremental Cost ($)		
	2010	2015	2030
Compact	24608	13162	6728
Midsize	26877	14276	7205
Small SUV	30883	16123	7839
Midsize SUV	37317	19402	9530
Pickup	45434	23582	11533

Table 22: Adjusted Incremental Costs of PHEV 40 vehicles using 2010 Energy Intensities

vehicle type	Incremental Cost ($)		
	2010	2015	2030
Compact	16137	9984	6943
Midsize	17673	10802	7369
Small SUV	19106	11301	7414
Midsize SUV	22515	13089	8507
Pickup	26529	15227	9722

We assume the EVs have the same lifetime as the CV vehicles. In addition, we assume there is no incremental difference in end-of-life value between the EVs and CVs. This simplifies potential tradeoffs between the potential resale value of EV batteries and the potential reduced lifetime of the EVs compared to CVs.

As described in Appendix B.6, the fuel economy standard applicable to the CV vehicles sold in a given year is determined based on the EV market share and EV energy intensities. However, the ANL incremental cost data is for a fixed fuel economy at each of the 3 data points (2010, 2015, 2030). The results from other studies, such as [14] suggest a linear relationship between incremental cost and fuel economy. We assume this linear relationship applies and calculate the incremental cost of a vehicle of a given fuel economy and model year by linear interpolation between the ANL values.

$$P_{i,t} = P_{i,\underline{t}} + (\delta_{i,t} - \delta_{i,\underline{t}})(\frac{P_{i,\bar{t}} - P_{i,\underline{t}}}{\delta_{i,\bar{t}} - \delta_{i,\underline{t}}}) \tag{48a}$$

where $P_{i,t}$ = Incremental price of vehicle in year t of type i (\$), $P_{i,\underline{t}}$ = Incremental price of ANL vehicle of type i in the ANL time period greater than or equal to time t (\$), $P_{i,\bar{t}}$ = Incremental price of ANL vehicle of type i in the ANL time period less than or equal to time t (\$), $\delta_{i,t}$ = Specified fuel economy of vehicle of type i in year t (mpg), $\delta_{i,\underline{t}}$ = Fuel economy of ANL vehicle of type i in the ANL time period less than or equal to time t (mpg), $\delta_{i,\bar{t}}$ = Fuel economy of ANL vehicle of type i in the ANL time period greater than or equal to time t (mpg).

B.12 Charging Infrastructure Cost

The charging station connects the EVs onboard charger with the electrical grid. We assume Level 2, 6.6 kW charging. As with EV batteries, charging station costs are projected to decrease with volume. Electrification Coalition [26] assumes a public charging station cost of $1875 and a private charging station cost of $300 in 2030. For 2030, Electrification Coalition assumes a minimum of 0.5 public charging stations per vehicle and a maximum of 1.5 public charging stations per vehicle. For the uncontrolled charging scheme, we assume the minimum projection of 0.5 public charging stations per vehicle. For the controlled charging schemes, we originally assumed the maximum projection of 1.5 charging station per vehicle. However, we found that the load flexibility provided with controlled charging was equal if the vehicle was only plugged in when home or plugged in whenever stopped. Due to the additional cost of public charging stations, we therefore assumed 1 private charging station and 0.5 public charging stations per vehicle. No charging was modeled at the public chargers, as it is expected to be a small amount of total charging. However, the cost of public chargers was included to reduce range anxiety.

Electrification Coalition assumes a charging station lifetime of 10 years. We assume a lifetime of 13 years for the private charging station, to match the assumed lifetime of the average vehicle. Based on conversations with an auto manufacturer, we assumed 75% of the cost of a public charging station lasts 40 years. This cost represents costs such as conduit installation and wiring. The remaining 25% of the cost is assumed to last 13 years. We model charging station cost as an upfront purchase of a home charging station at the time of vehicle purchase and ongoing payments towards the financed cost of 0.5 public charging stations per vehicle.

B.13 Total Consumer Expenditure

Before we calculate the total consumer expenditure (TCE) of vehicle owners, we have three important assumptions: Vehicles will be purchased in 2030, No tax advantage of purchasing a EV vs. a CV vehicle (i.e. the current EV tax credits have expired), No gas tax applied to electricity used to charge EVs

The TCE consists of upfront costs and operating costs. The upfront costs are vehicle purchasing costs and installation costs of charging infrastructure for EVs. The operating costs are mainly fuel costs, costs for gasoline refueling or electricity charging. Based on the calculated incremental vehicle costs in Appendix B.11, estimates of charging infrastructure costs in Appendix B.12, projections of electricity price from our models, and the assumed gasoline price, we basically develop cash flows of each vehicle type during its lifetime, which we assume 13 years in this study, and calculate the net present value (NPV) of the cash flows. The numbers in Table 1 and 2 are calculated as equation 49a and 49b respectively.

$$(X + IC_{EV} + CC + FC_{EV,i}) - (X + IC_{CV,i} + FC_{CV,i}) \tag{49a}$$

$$\begin{aligned} s_{EV,i}(X + IC_{EV} + CC + FC_{EV,i}) + s_{CV,i}(X + IC_{CV,i} + FC_{CV,i}) + A_i \\ - (X + IC_{CV,R} + FC_{CV,R}) \end{aligned} \tag{49b}$$

where, X = Purchasing cost of Model Year (MY) 2010 vehicle, IC_{EV} = Incremental cost of MY 2030 electric vehicle, relative to MY 2010 vehicle, $IC_{CV,i}$ = Incremental cost of MY 2030 conventional vehicle, relative to MY 2010 vehicle in case i, $IC_{CV,R}$ = Incremental cost of MY 2030 conventional vehicle, relative to MY 2010 vehicle in reference case, no EV adoption case, CC = Charging infrastructure costs per EV, $FC_{EV,i}$ = NPV of electricity charging costs for the EV in case i (and partially gasoline refueling costs for PHEV), $FC_{CV,i}$ = NPV of gasoline refueling costs for the CV in case i, $FC_{CV,i}$ = NPV of gasoline refueling costs for the CV in reference case, no EV adoption case, $s_{EV,i}$ = 2030 market share of EVs in case i, $s_{CV,i}$ = 2030 market share of CVs in case i, A_i = Additional cost per vehicle due to change in electricity price on consumer's non-vehicle electricity costs in case i relative to reference case.

The numbers from equation 49a are the difference of the total costs between EV and CV in the same EV adoption scenario. In contrast, the numbers from equation 49b shows the difference between the TCE of average vehicle owners in an EV case relative to the TCE of CV ownership in the reference case.

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