MODELS TO ENABLE ESTIMATION OF MARGINAL CO_2 EMISSIONS IN ELECTRICITY PRODUCTION AND URBAN MOBILITY SYSTEMS

by

Vineet Raichur

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Doctoral Committee:

Professor Steven J. Skerlos, Co-Chair
Professor Richard Gonzalez, Co-Chair
Professor Fred Feinberg
Assistant Professor Jeremiah Johnson

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ABSTRACT

Models to Enable Estimation of Marginal Co_2 Emissions in Electricity Production and Urban Mobility Systems

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CO_2 produced from the combustion of fossil fuels for energy production in electricity and transportation sectors is the biggest source of climate change causing greenhouse gases (GHG) in the U.S. GHG mitigation policies will affect how the existing systems operate and methods are necessary to examine the marginal effects and resulting change in CO_2 emissions to evaluate the effectiveness of these policies. This dissertation develops models of electricity production and commuters' choice of travel modes to enable the quantification of marginal CO_2 emissions.

Electricity production systems constantly balance the demand and supply of electricity while functioning under a set of Operating Constraints (OCs). The model of electricity production developed in this dissertation incorporates major system OCs, which were either excluded or simplified in the previously used models, but are necessary to achieve reliable estimates of marginal CO_2 emissions. The model was applied to evaluate the strategy for reducing CO_2 emissions through increased utilization of existing Natural Gas (NG) generating units and reduced utilization of more CO_2 intensive coal units. The analysis finds that about 27% less

reduction in CO_2 emissions could be achieved than estimated previously. The role of various OCs in limiting the extent to which CO_2 emissions can be reduced is examined to inform future policy decisions.

Reducing the use of personal vehicles and increasing the utilization of public transportation and non-motorized modes such as biking has been considered as a CO_2 mitigation measure. The second part of the dissertation develops models of commuting mode choices in Portland, Oregon to examine the potential for reducing vehicle miles traveled. The study compares the effectiveness of two mechanisms through which mode choices can be influenced – by varying the attributes of specific modes and by changing attitudes that determine how individuals value these attributes. The study develops a modeling approach that can predict individual-level mode choices as opposed to population level aggregate choices as done in previous studies. Because people can travel for different distances, the ability to predict individual-level choices is necessary to estimate passenger-miles traveled with specific modes and resulting CO_2 emissions in a more deterministic manner.

Chapter 1

Introduction

Carbon dioxide (CO_2) produced from the combustion of fossil fuels for energy production accounted for 91% of the total greenhouse gas (GHG) emissions in the U.S. in 2013 (U.S. EPA. 2015). In 2007 Supreme Court of the United States acknowledged the role of CO_2 and other GHG emissions as a leading cause of global temperature rises and the resulting climate change issues. Based on this fact the Supreme Court categorized CO_2 as an air pollutant, which gives the U.S. Environmental Protection Agency (EPA) the authority to regulate CO_2 pollution under the Clean Air Act (U.S. Supreme Court 2007). Electricity production and transportation sectors account for nearly 31% and 27% of the total emissions respectively and at least 95% of these emissions are in the form of CO_2 emissions from fossil fuel combustion (U.S. EPA. 2015). EPA proposed Clean Power Plan (CPP) in 2014 with an objective to reduce CO_2 emissions from electricity production in the U.S. to the levels equivalent to 70% of the levels in year 2005 by year 2030 (U.S. EPA. 2014). EPA and the National Highway Traffic Safety Administration (NHTSA) have jointly developed standards to regulate both fuel economy and GHG emissions of the newly manufactured light-duty passenger vehicles (U.S. EPA. 2010). In addition to these federal level regulations, some states have also set up state-wide GHG reduction goals. California has set the target for GHG emissions to 40%

below 1990 levels by 2030 (State of California 2015). Oregon has set the targets to at least 75% below 1990 levels by 2050 (State of Oregon 2007).

Introduction of these CO_2 mitigating policies are expected to influence the manner in which existing electricity production and transportation systems are utilized in addition to encouraging development and adoption of next generation low CO_2 intensive technologies. For instance, one of the four strategies proposed under CPP aim to reduce CO_2 emissions from electricity production by increasing electricity production derived from existing Natural Gas (NG) generating units and reducing production from coal units (U.S. EPA. 2014). This dissertation develops models of electricity production and commuters' choice of travel modes to quantify marginal GHG emissions to enable the evaluation of the effectiveness of specific GHG reduction policies based on strategies to change the utilization of existing system. The need for examining marginal effects in order to evaluate the effectiveness of GHG mitigation policies is discussed in the following section with a brief overview of the literature in consequential life cycle assessment.

1.1. Consequential Lifecycle Assessment

Lifecycle assessment (LCA) is a systematic approach for conducting an inventory of materials and energy consumed and wastes and emissions created during the lifecycle of a product/system and determining the environmental impact of these activities (ISO 2010). An LCA study consists of four phases during which goal and scope of the problem is defined, inventory of resource consumption and waste production is conducted, potential environmental impact is determined from the inventory and the results are interpreted to inform decision making (ISO 2010). LCA has evolved in to a robust methodology used widely to conduct comprehensive environmental impact assessment (Finnveden et al. 2009).

Literature on LCA methodologies has formally categorized the tool into attributional LCA (ALCA) and consequential LCA (CLCA) (Brander et al. 2008; Earles and Halog 2011; Finnveden et al. 2009; Thomassen et al. 2008). ALCA provides an accounting of environmental impact over the lifecycle of a product/system and attributes the overall impact to individual processes within the lifecycle. Therefore, ALCA provides information about the average environmental impact attributable to a unit product. ALCA studies have been commonly used in identifying opportunities to improve the environmental performance of products and also in marketing to develop eco-labeling schemes to compare the products on their direct environmental impacts (ISO 2010). CLCA on the other hand provides information on the change in environmental impact resulting from the consequences of specific changes within the product/system's lifecycle. While there is no single method that is generally preferred over the other, CLCA is considered to be more relevant for decision making and quantifying change in environmental impacts resulting from these decisions (Brander et al. 2008; Earles and Halog 2011; Finnveden et al. 2009). One of the main differences between ALCA and CLCA approaches is the use of average data in ALCA studies whereas CLCA studies require marginal data.

A CLCA study on the production of ethanol to substitute gasoline consumption in U.S. conducted by Searchinger et al. (2008) illustrates the significance of this issue. Previous ALCA studies (e.g., Wang et al. 1999) have found that the displacement of gasoline by ethanol (on equivalent energy basis) produced from corn grown in the U.S. leads to 20% reduction in GHG emissions. The CLCA study concluded that the GHG emissions could possibly increase by 47% (Searchinger et al. 2008). The increase is mainly due to the expansion in agricultural land use in response to the increase in demand for corn and other grains.

The response of the agricultural sector to increase land use for growing grains is an example of the marginal effects that CLCA studies aim to capture in order to determine the change in environmental impact. Venkatesh et al. (2012) conducted a CLCA study to examine the change in GHG and other air emissions from electricity production in response to change in NG prices. They find that the life cycle GHG emissions could be reduced by about 7-15% due to low NG prices in comparison to almost 50% reductions estimated by previous LCA studies that did not account for marginal emissions.

The marginal effects could arise from within or outside the immediate lifecycle of the product/system. Decisions regarding the consideration of specific marginal effects within the scope of a CLCA significantly influence the environmental impact assessment outcomes of these studies and several researchers have proposed guidelines to encourage the use of systematic approaches in future works (Earles and Halog 2011; Ekvall and Weidema 2004; Finnveden et al. 2009). The timeframe for the analysis could be one of the basis to determine the relevant marginal effects to be considered in the study (Ekvall and Weidema 2004; Finnveden et al. 2009; Weidema, Frees, and Nielsen 1999). Short-term marginal effects take in to account changes in utilization of the existing system. Long-term effects consider changes in the existing system itself (e.g., increase or decrease in capacity, installing new technology, etc.). The focus of this dissertation is to develop methods to quantify short-term marginal CO_2 emissions in electricity and personal mobility systems.

1.2. Electricity Production

CLCA researchers have noted the need for estimating marginal GHG emissions from electricity production systems to more accurately estimate changes in emissions resulting from marginal changes in either demand or supply of electricity over the short-term (Finnveden et al. 2009; Lund et al. 2010; Weidema et al. 1999). Several other studies in the past have examined the marginal effects in order to determine the change in environmental impact resulting from important developments such as the introduction of carbon prices (Newcomer, Blumsack, et al. 2008), a ban on new coal generating unit construction (Newcomer and Apt 2009) and integration of wind generating units (Denny and O'Malley 2007).

While hourly electricity demand data is often publicly available, hourly production supply information from specific power plants is rarely available. Public information on production supply usually only exists at the aggregated annual and monthly levels. Therefore, previous CLCA studies of electricity grids have made exogenous assumptions about the long-term marginal generation technology (e.g., coal or natural gas) and assume it will produce all marginal supply (Dones, Ménard, and Gantner 1998; Finnveden 2008; Gaudreault, Samson, and Stuart 2010; Lund et al. 2010). This approach has two main limitations. First, the technology being used on the margin has to be exogenously assumed, and second, for any given technology on the margin, the emission rates of individual generators vary widely.

Electricity production systems are complex networks that dynamically balance the supply of electricity with its demand. The balancing of demand and supply typically happens within a region called Power Control Area (PCA). A PCA refers to a region with specific generation capacity under a single authority that manages production and transmission of electricity into a single coordinated network to meet the region's electricity demands (U.S. EPA. 2013). As the electricity load increases, more power plants are deployed or output is increased from individual power plants that are online and operating at partial capacity. In order to achieve least cost power generation, units are generally dispatched in the order of least to most expensive with respect to their operating costs. Power plants with lower efficiency generally appear later in the dispatch order than those with higher efficiency, since lower efficiency power plants require more fuel and hence have higher operating costs per unit of electricity produced. Since efficiency is a key determinant of emission rates, understanding the dispatch order is a central element to understanding the marginal emissions from electricity grids. (Mathiesen, Münster, and Fruergaard 2009; Weber et al. 2010) acknowledge the need for improved methods to estimate marginal emissions in CLCA studies and note that the use of dispatch models could be a viable solution.

Further, the electricity production systems operate under a set of constraints to achieve "economic dispatch". According to (U.S. DOE 2005), "Economic dispatch is an optimization process crafted to meet electricity demand at the lowest cost, given the operational constraints of the generation fleet and the transmission system". Several studies (Denny and O'Malley 2007; Newcomer and Apt 2009; Newcomer, Blumsack, et al. 2008) have modeled the electricity production system to examine the marginal effects. The approaches followed in these studies to simulate dispatch capture the cost aspect of economic dispatch but ignore or greatly simplify Operating Constraints (OCs) under which the electricity production systems function. The electricity production model presented in this dissertation builds on the existing dispatch modeling literature and incorporates several OCs within a real power network that were either omitted or simplified in previously used models. The inclusion of these constraints is found to be critical to achieve robust estimates of marginal CO_2 emissions from electricity production (Raichur, Callaway, and Skerlos 2015).

1.3. Urban Transportation

Urban personal mobility is a complex system and people are making choices about where to live, which transportation mode to take (e.g., public transit or drive a personal vehicle), how many automobiles to own and what kind of automobile to own. These choices ultimately determine the GHG emission impacts from personal mobility. There have been a few full-scale CLCA studies on the urban transportation systems (Chester and Horvath 2012; Chester et al. 2013). These studies highlight the need for understanding how choices change in response to specific transportation policies to quantify marginal CO_2 emissions.

Personal mobility in the U.S. is currently dominated by automobile use. Reducing vehicle miles traveled through increased utilization of public transportation and non-motorized modes such as biking is often considered as one of the strategies to reduce environmental impact in general from personal mobility (Chester et al. 2013; U.S. DOT 2010). Such decisions come under the purview of city planning and are effective at addressing other issues such as congestion, local air pollution and providing access to transportation for people who cannot drive.

Public transportation is known to cause about 53% lower CO_2 emissions compared to the personal vehicle use (U.S. DOT 2010). In addition to these direct benefits, public transit helps reduce congestion which could further reduce emissions by improving driving conditions (TTI 2012). It is expensive however, to expand public transit services to all parts of urban and sub-urban areas. Use of non-motorized modes such as biking is not practical when traveling long distances. Therefore, in order to increase public transit ridership and decrease personal vehicle use, multi-modal systems in which commuters can use their personal vehicles or bikes to reach a transit station and then use public transit to reach their destination are considered (Arentze and Molin 2013; Molin and van Gelder 2008).

Traditionally used urban transportation planning models have focused on personal vehicle use and the planning of associated infrastructure (roads, freeways, parking structures, etc.) (Eckelman 2013; Rodier 2015). In addition, these models were developed primarily to forecast travel demand as a continuous variable in response to the long-run changes in population demographics in a mostly static mode share scenario. Therefore, they are ill-equipped for analyzing the impacts arising from marginal effects of today's transportation policies aimed at affecting transportation choices (Domencich and McFadden 1975; Rodier 2015).

Discrete choice models were first used to study travel demand by D. L. McFadden (1974). These models statistically relate the choice made by an individual to his/her attributes and the attributes of the alternatives available to the person. Therefore, they are capable of modeling change in choices in response to change in attributes. Travel demand studies based on discrete choice models have brought behavioral realism to transportation planning (Bhat and Koppelman 1999; Cantillo, Ortúzar, and Williams 2007; Hatzopoulou and Miller 2010; Hensher and Rose 2007; Horne, Jaccard, and Tiedemann 2005; Washbrook, Haider, and Jaccard 2006).

The study was designed in collaboration with the city planning authority in Portland, Oregon (Metro) (Portland Metro 2013) and the objective was to study choice of travel modes used for commuting in the existing system to find ways to leverage the existing system to reduce personal vehicle use. This objective is contrary to most of the previous works that study mode choices under hypothetical/future system scenarios. Commuters' mode choices can be influenced by either varying the attributes of specific modes or by changing how individuals value these attributes. Models are developed to explore both these mechanisms. In the first modeling approach individual attitudes are incorporated into the choice model. In the second approach a random coefficient model is used, which has the ability to estimate individual-level preferences for mode related attributes. The goal is to compare the effectiveness of change in attitudes vs change in mode related attributes (parking costs, bus fares, etc.) in reducing personal vehicle use. This comparison (for same set of individuals) has not been observed in previous studies.

Transportation choice studies in the past have used random coefficient models, which accounted for some variation in the preferences. These models however, did not have the capability to estimate where in the distribution a specific individual would lie. One of the models used in this study has the capability to estimate individual-level preferences. This improvement is significant in order to translate a specific change in mode share to change in CO_2 emissions because the amount of emissions produced depends on the distances traveled using a specific mode. The individual-level preferences allow us to predict individual-level mode choices. Coupled with the information on daily commuting distances, CO_2 emissions from each individual's commute can be quantified. The data requirements in this study are unique given these objectives. We conducted a stated preference study in Portland to collect required data. Details of the study are discussed in Section 4.2.

The dissertation is organized as follows. Chapter 2 reviews the literature specific to the electricity dispatch modeling and discrete choice modeling research. Development of proposed electricity dispatch and commuting mode choice models is discussed later in Chapter 2. Chapter 3 presents the discussion on the impact of carbon pricing on electricity production and CO_2 emissions using the proposed electricity dispatch model. Chapter 4 presents the analysis of mode choice for commuting in Portland metro area. Summary of major findings and directions for future research are discussed in Chapter 5.

Chapter 2

Methods

2.1. Models of Electricity Production

2.1.1. Introduction

Several studies in the past have used dispatch models to examine the marginal effects of either additional demand (Blumsack, Samaras, and Hines 2008; McCarthy and Yang 2010; Newcomer and Apt 2009; Newcomer, Blumsacka, et al. 2008) or changes to production system (Denholm and Holloway 2005; Denny and O'Malley 2007; Newcomer and Apt 2007). (Venkatesh et al. 2012) use a dispatch model to study the short run effect of changes in Natural Gas (NG) prices on the relative utilization of different fuels for electricity production and estimate changes in system-wide air emissions. Dispatch models used in (Blumsack, Samaras, and Hines 2008; Newcomer and Apt 2009; Newcomer et al. 2008), follow a least cost-based ordering approach to establish a dispatch order where the generators are dispatched from low fuel consumption cost to high fuel consumption cost until the demand for a specific hour is met. It is assumed that all generators are available at maximum rated capacity whenever needed. A similar least cost-based dispatch ordering was used in (Denny and O'Malley 2006, 2007). However, instead of having a predetermined dispatch order, a linear programming optimization problem was formulated where the objective was to minimize a linear cost function. This problem was formulated for each hour and solved to generate an optimal hourly production schedule.

As an alternative to least cost dispatch modeling, it is possible to create a dispatch ordering based on the type of fuel and generation technology used. For instance, the available generating capacity can be grouped into categories based on the type of fuel as done in (McCarthy, Yang, and Ogden 2007; Mccarthy, Yang, and Ogden 2009; McCarthy and Yang 2010). Such models dispatch an entire fleet of power plants based on fuel type (not by individual power plant) up to their maximum available capacity in a given hour. If demand is not met by one type of plant (e.g., nuclear), the model moves through the queued set of plant types and dispatches generation by fuel type (e.g., coal then NG) until demand is satisfied. The work presented in (Denholm and Holloway 2005) uses a similar approach in an effort to estimate system-wide emissions reductions achievable from using large scale energy storage systems.

In (Gil and Joos 2007), a load duration curve (LDC) is utilized to determine the dispatch order on a fuel-type basis and to identify marginal generating units. A LDC is the hour-by-hour demand data for a year arranged in descending order of magnitude. Power plants are dispatched depending on their fuel type in a specific order (nuclear, hydroelectric, coal, gas and oil) to fill the area under the LDC. Therefore, all technologies that are dispatched above the minimum demand point on LDC will operate at the margin during some time of the year.

In (Kelly, Sivaraman, and Keoleian 2009) power plants are categorized on the basis of their historical Capacity Factor (CF). A power plant's CF is the ratio of its actual electricity output over a period of time (usually one year) to its output if it had operated at maximum rated capacity for the same period of time. A CF of (1.0 to 0.8), (0.8 to 0.2) and (0.2 to 0.0), constitute a typical definition for power plants that serve as base load, intermediate load, and peak load, respectively. Base load power plants are dispatched first followed by intermediate and peak load plants, constituting an approach similar to fuel based dispatch.

These studies follow from the principle that PCAs aim to achieve "Economic Dispatch" within their networks. According to (U.S. DOE 2005), "Economic dispatch is an optimization process crafted to meet electricity demand at the lowest cost, given the operational constraints of the generation fleet and the transmission system". The cost-based dispatch approaches and fuel-based dispatch approaches described above aim to capture the cost aspect of economic dispatch but ignore or greatly simplify Operating Constraints (OCs). In one exception, (Sioshansi and Denholm 2010) uses a cost-based optimization approach to select resources and include several OCs of power plants such as minimum and maximum operation levels, ramp up and ramp down limits, minimum down and up times, etc. System wide operating reserve requirements are also modeled. However, the model was not created with publicly available data, outages are not considered, and the model was not validated with data from real power networks.

The dispatch model presented in this dissertation addresses a wider set of OCs while applying a more tractable approach in a real PCA, resulting in a validated model that can be utilized for two purposes: 1) using hourly demand data with aggregated annual production supply data to create an estimate of hourly production for specific generators in a given year, and 2) to create a forecast of hourly generation schedules for a future year where demand, costs, and production capacities are input as exogenous scenarios. These model outputs can be utilized for estimating changes in production and emissions as electricity demands or production capacity change marginally. The model cannot be used for estimating long-term effects. The model also does not account for consequences outside the system in question. For instance, reduced use of some fuel for electricity production may lead to greater export and use of that fuel elsewhere. While the model can be used to evaluate uncertainties in parameters such as fuel prices, etc. it cannot be used under major structural changes in the electricity production system. In this model, we begin with a fuel-based dispatch approach and then, within a fuel type, make dispatch decisions based on least cost deployment of individual power plants. The main contribution of this work is that it shows the importance of including system OCs by using independent model estimates with real data from power networks. The six categories of OCs considered are:

1. Season specific rated capacity – An increase in ambient temperatures during summer leads to reduced output capacity in comparison with winter. For example, during summer the density of inlet air drops resulting in a decrease in the mass flow rate which ultimately reduces the power output capacity of NG turbines (Boyce 2006).
2. Scheduled Outages – Nuclear generators have predetermined maintenance cycles and outages that typically last for about 4 weeks. Oil and NG power plants have outages that typically last 1-2 weeks.
3. Forced Outages – Large and old coal power plants may be unavailable for nearly 10% of the year due to forced/unplanned shutdowns.
4. Season specific hydroelectric (hydro) resource availability – The amount of rainfall is not constant through the year.
5. Ancillary Services (AS) – To ensure reliable operation of the grid, the operators are required to maintain on-line reserve of flexible generating units. This can lead to more expensive NG power plants being used even when cheaper coal capacity (that takes longer to ramp up to capacity) is available.
6. Fuel Switching (FS) – Oil and NG power plants commonly switch between the two fuel types depending on fuel prices and availability.

Several types of OCs were omitted from the model. First, we do not explicitly model transmission constraints because detailed transmission network data are often not readily attainable. In the case studies presented in this work, we show that this is not a significant exclusion. We also found that ramp rate constraints (the rate at which units can increase or decrease electricity production) and explicit constraints on annual capacity factors did not significantly impact model performance in comparison to the six OCs above and therefore did not require consideration.

2.1.2. Operating Constraints Based Dispatch Model

The operating constraint based dispatch model (OC Model) was developed in two stages. The first version of the model was based on data from year 2004 and the model was most recently updated based on data from 2012. In this section steps in the first version of the OC Model are discussed. This is followed by application of the model in Electric Reliability Council of Texas (ERCOT) PCA. Validation of the model estimates against the actual electricity production values in this PCA demonstrates the value of incorporating OCs to accurately estimate CO_2 emissions from electricity production. Development of the second version of the model is discussed in the following Section 2.1.3.

Step 1: Demand Information Processing

Demand values for the PCA are available on an hourly basis for the entire year (FERC 2009). To account for the transmission (and other) losses between production and consumption, we make a 5% addition (U.S. EIA 2010b) to every hour's demand. This number can be adjusted in cases where a better estimate is known. Next, known imports are subtracted from the demand values to determine the net electricity to be produced by the installed capacity within the region in question. To handle this in regions with low import rates (e.g., ERCOT) each hour's demand can be uniformly reduced by the annual aggregate import percentage. However, for regions with large and variable import rates uniformly discounting demand values will result in inaccurate production targets thus affecting the selection of marginal units. A more detailed modeling, taking into account seasonal and/or daily trends would be necessary.

Step 2: Supply Information Processing

The supply information for a PCA was obtained from several sources including the eGrid database (U.S. EPA. 2009), Energy Information Administration 860 (U.S. EIA 2009a) and EIA 906 (U.S. EIA 2010a). Table 2.1 provides a list of major input factors along with their respective data sources used in this work. Typically, a power plant will have one or more generating units. When more than one generating unit (referred to as unit hereafter) is available at a power plant, we expect that the decision to operate a specific unit will depend on factors such as operating cost, fuel used, efficiency, age and maintenance requirements (specific to each unit). Therefore we model each unit as an individual entity for dispatching rather than the entire power plant. Because we do not have specific generator heat and emissions rate curves (which vary with generator output), we are using annual average heat rate (Btu/kWh) from (U.S. EIA 2010a) and annual average emissions rate (lb CO_2/MWh) from (U.S. EPA. 2009). Although this introduces a small error into our model, we are primarily interested in annual (or longer) marginal emissions changes, and therefore we expect the effect of this error to be relatively small.

The next step is to categorize generating units and establish the dispatch order based on the type of fuel they consume. Due to their low marginal operating costs, nuclear and coal resources appear lower in the dispatch order. These are followed by oil and NG units which have higher operating costs as well as more flexibility to meet variations in demand.

Table 2.1. Summary of major datasets used in the OC Model and their sources

Dataset	Source
Hourly demand	(FERC 2009)
Total annual imports	(U.S. EPA. 2009)
Unit prime mover type	(U.S. EIA 2009a)
Unit nameplate capacity	(U.S. EIA 2009a)
Unit's summer capacity	(U.S. EIA 2009a)
Unit's winter capacity	(U.S. EIA 2009a)
Heat rate	(U.S. EIA 2010a)
Capacity factors	(U.S. EIA 2010a; U.S. EPA. 2009)
CO_2 emission rate	(U.S. EPA. 2009)
SO2 emission rate	(U.S. EPA. 2009)
Monthly hydro production values	(U.S. EIA 2010a)
Annual production values	(U.S. EIA 2010a; U.S. EPA. 2009)
Monthly production values	(U.S. EIA 2010a)
Monthly fuel costs	(U.S. EIA 2009b)

Most of the oil and NG units can be fueled by either oil or NG (U.S. EIA 2010a). Such units require special attention since in some regions (e.g., NY) such plants may rapidly shift between using oil and NG in response to increasing prices and/or availability of fuel. This Fuel Switching behavior presents a challenge in determining the instantaneous fuel type used by oil/NG units. Knowing the exact fuel type is critical in determining operating costs which ultimately decides the dispatch order. In ERCOT PCA however, use of oil as a primary fuel source is negligible and therefore the Fuel Switching behavior is not considered.

Step 3: Scheduled Outages

The next step in the modeling process is to consider longer term operating decisions such as maintenance. The scheduling of maintenance operations needs to be accomplished while ensuring sufficient capacity is always available to meet instantaneous demands. Nuclear units have predetermined and binding maintenance schedules since critical tasks such as refueling have to be accomplished along with general and preventative repairs. These tasks generally last one month and are repeated on an 18 month cycle, typically occurring in spring or fall (U.S. EIA 2010c) due to lower electricity demand in these seasons.

Unlike nuclear units, coal and NG units do not have strictly defined outage cycles. In the OC Model we assume that each of these units will be off-line for a specific amount of time, and we force the largest unit to be off-line at the lowest point in the LDC and follow this approach until scheduled outages are scheduled for all units. The approach is discussed further in Appendix 1.

Step 4: Forced Outages

In addition to planned outages, a significant amount of potential capacity from coal and NG units can be lost due to unexpected breakdowns. This results in either a 'forced outage' or 'forced derating' depending on whether the breakdown caused total or partial loss of a unit's production capacity. Following the data and analysis presented in (ORNL 1986) it can be observed that the Forced Outage Rate (FOR) and Forced Derating Rates (FDR) for a given unit are strongly correlated with the number of years it has operated. Using this correlation, FOR and FDR are determined for each unit based on its age and nameplate capacity. Additional details on this approach can be found in Appendix 2.

Step 5: Nuclear Resource Allocation

Having considered long-term planning and outages, we now consider allocation of production capacity to meet instantaneous demands. This begins by scheduling the nuclear generators. Nuclear units are assumed to be operational all the time at their season specific rated capacity except during scheduled maintenance. Forced outages are not considered.

Step 6: Hydro Resource Allocation

Next, production planning for hydro sources is considered. Production from hydroelectric units is subject to significant seasonal variation depending on the availability of water. We start by analyzing hydro energy production data on a monthly basis (U.S. EIA 2010a) for each unit ($E_{hydro\_month\_i}$) and assuming hydro units would produce electricity during peak load hours of the month. We begin by ranking hours of the month by load (rank 1 = highest load). Then, as many hydro units (each with capacity C_{hydro_i}) as possible are dispatched in the N highest ranked hours, where N is the maximum value such that the constraint $N^* C_{hydro\_i} \leq E_{hydro\_month\_i}$ is satisfied. This process is continued until all available hydro resources are exhausted. This is possible because it is typically the case that total hydro capacity is much less than the total load. Further, all hydro generators are assumed to have the same cost and therefore individual generating units can be treated identically. Therefore if $N^* C_{hydro\_i} < E_{hydro\_month\_i}$, hydro generation is allocated to the $N+1^{st}$ hour to use the remaining energy. This approach doesn't explicitly model factors such as reservoir levels and other environmental constraints which might affect the utilization of hydro resources. However, these could be added in a straightforward manner in regions where such issues are expected to be significant. In the case of high intermittent renewables penetrations, for instance, the ranking could be done on the basis of net load (i.e. load minus intermittent renewables).

Step 7: Allocation of Other Renewable Resources

Other renewable energy resources besides hydro (wind, biomass, solar, etc.) are scheduled by equally allocating their production across all hours of the year. This does not reflect the fact that some of these renewable sources are intermittent, but ignoring intermittency does not create significant modeling errors for the PCAs that the modeling has been applied to (i.e., ERCOT and

NYISO), since the overall contribution of these sources is small in the years studied here (2004 and 2005). As these sources gain in importance, the model should be supplemented to include intermittency based on the operating characteristics of specific resources (e.g., daily and seasonal availability of sunlight in case of solar energy units).

Step 8: Coal Resources Allocation

After renewable energy units, coal generating units are considered. These are assumed to be continuously operational except for scheduled and forced outages. Coal units remain online as demand fluctuates. They may reduce their output when the demand decreases and increase their output up to their maximum production capacity when needed. We also consider that production from the coal fleet is limited by the requirements to maintain Ancillary Services (AS) in ERCOT. AS are backup systems required to ensure instantaneous balance between demand and production, resolve issues such as unexpected increase in demand, loss of production capacity, etc. Due to the need for high ramping capabilities, NG power plants are typically used for AS. In order to maintain sufficient AS required to ensure reliable production and delivery of electricity, approximately 5000 MW of NG capacity is maintained online at all times. Further details about the AS market segment in ERCOT and the algorithm used to account for AS is described in Appendix 3.

Above, we have considered scheduled maintenance, forced outages and AS – allowing the model to estimate the total coal production required for each hour of the year. The exact steps involved in calculating hourly coal production targets are described in Appendix 4.

Next, it needs to be determined which coal units will be used to meet the total coal demand and their level of output ($\boldsymbol{x}$ in Equation 2.1). Determining which coal unit is used is important given the high variability in emissions factors among the coal generating fleet. To address this issue, we formulate the Linear Programing (LP) optimization shown in Equation 2.1.

$$\boldsymbol{min_x} \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} (\boldsymbol{A_i x_i})$$

$$\boldsymbol{Such\ that} \begin{cases} \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} (\boldsymbol{B_i x_i}) \geq \boldsymbol{b} \\ \boldsymbol{ll_i} \leq \boldsymbol{x_i} \leq \boldsymbol{ul_i} \end{cases}$$

Equation 2.1.

Where,

$\boldsymbol{N}$ = Number of available generating units;

$\boldsymbol{A_i}$ = Operation cost of unit $\boldsymbol{i}$ (\$/MWh);

$\boldsymbol{B_i}$ = Season depending capacity of unit $\boldsymbol{i}$ (MW);

$\boldsymbol{x_i}$ = Level of output for unit $\boldsymbol{i}$ (ratio of unit's hourly output to its maximum season dependent capacity);

$\boldsymbol{b}$ = Hourly demand (MW);

$\boldsymbol{ll_i}$ = Lower limit on unit $\boldsymbol{i}$'s output (ERCOT 2010);

$\boldsymbol{ul_i}$ = Upper limit on unit $\boldsymbol{i}$'s output (ERCOT 2010)

The objective is to minimize the total cost of production from coal for that hour and the constraint is to meet or exceed the coal production target. Additionally, the partial loads any unit can take are constrained by lower and upper limits on its output. Minimum operating limit of a coal unit is defined as the level of output (percentage of the unit's nameplate capacity) below which the process of electricity production cannot be technically sustained. The process of shutting down and turning on has a very detrimental effect on the components of the coal unit leading to increased outages, high maintenance costs and reduced unit life in the long run (NREL 2012). Therefore, instead of shutting down when the demand decreases (for e.g., during night hours), coal units are generally kept operational at their minimum operating levels.

Step 9: NG Resource Allocation

To determine which NG units are operational in a given hour, we begin by considering Combined Heat and Power (CHP) units. CHP units operate in three main sectors - commercial, industrial and electric (U.S. EIA 2012). Units in the commercial and industrial sectors primarily produce steam/heat and electricity as demanded by the host facility, whereas units in the electric sector primarily produce electricity for public sale (U.S. EIA 2012). CHP units in the first two sectors are therefore treated as not available for dispatch and total observed production from these units is uniformly distributed over the year. CHP units in the electric sector are treated as regular (non-CHP) NG units.

The dispatch for the non-CHP units is then determined by subtracting the total production from all other resource types (the sum of production by nuclear, renewables, coal and CHP) from the modified demand values from step 1. Then, using a load duration curve (LDC), the allocation of NG resources begins with the hour of maximum demand (left most point on LDC) and moving right towards hours with lower demand values. Units are dispatched in least cost order operating at full season-specific rated capacity until the electricity demand at a specific hour is fully met.

2.1.2.1. Application and Validation of the OC Model in ERCOT

ERCOT manages the production and distribution of electricity within a part of Texas which represents about 90% of the demand for electricity in the state (ERCOT 2015a). The following are key features of ERCOT's production system in 2004:

- Nuclear, coal and NG resources supplied bulk of the region's power demands while oil, hydro and other renewables had a small share (~1%) in the resource mix (U.S. EIA 2010a);
- Fuel switching was not a common practice (U.S. EPA. 2009);
- Electricity imports were less than 1% of annual demand (U.S. EPA. 2009); and,
- Congestion within the transmission system was minimal (ERCOT 2004).

Details of model validation are discussed in Appendix 6. In brief, the OC Model estimates for annual aggregate production and CO_2 emissions by fuel type are within 1% of actual values. The values for monthly production for all fuel types fall within 10% variation of actual production in almost all cases. On the other hand, monthly production estimates from a least cost based dispatch model with no OCs considered (referred to as NOC Model hereafter) show deviations up to 107% for nuclear, 48% for coal, and 62% for NG. The comparison of the mode estimates with and without considering OCs shows that the OCs are needed to provide accurate estimates of annual generation and emissions from specific types of generating units.

2.1.3. Operating Constraints Based Dispatch Model – Version 2

The second version of the dispatch model was developed specifically for ERCOT to examine the effectiveness of the specific CO_2 mitigation policy. The original operating constraint based dispatch model (henceforth called the OC1 Model), was setup based on conditions prevailing in year 2004. The main differences between 2004 and 2013 in ERCOT were that in 2004:

1. NG prices were high enough that NG units did not compete directly with coal units for dispatch;
2. Production from non-hydro renewable resources such as wind was negligible.

In this section a second version of the OC1 Model, called the OC2 Model is developed, which will address these two issues and make the model better representative of ERCOT's electricity production system in 2013. In doing so, we incorporate methods to more accurately represent the nature of competition between coal and NG units and the intermittency in production from wind units.

2.1.3.1. Output from Wind Energy Units

We begin by providing the OC1 Model the ability to simulate total hourly production from the entire wind energy fleet accounting for the seasonal and daily patterns in output. We apply a multiple regression model using the data on total hourly wind energy production during 2012 in ERCOT available from (Electric Reliabiltiy Council of Texas ERCOT 2013). Using this data we calculate the fleet-wide hourly capacity factor, which is the ratio of total energy produced to total installed capacity at each hour. This hourly capacity factor is the dependent variable $\boldsymbol{Y}$ in the regression model of Equation 2.2. The advantage of working with hourly capacity factor, instead of the actual energy output, is that in future scenarios the installed capacity could vary and since the hourly capacity factor is known, the actual energy produced can be calculated as a product of installed capacity and the capacity factor.

We include three categories of explanatory variables: dummy variables to identify each month ($\boldsymbol{X_i}$), dummy variables to identify each hour in a day ($\boldsymbol{Z_j}$) and hourly demand for electricity ($\boldsymbol{W}$). The dummy variables to identify month and time of day were included to account for seasonal and daily trends in wind energy output. Hourly demand for electricity was included since wind energy output and demand for electricity are negatively correlated to some extent (Electric Reliabiltiy Council of Texas ERCOT 2013).

$$\boldsymbol{Y = \alpha + \beta_i X_i + \gamma_j Z_j + \delta W + \epsilon}$$

Equation 2.2.

Where,

$\boldsymbol{Y}$ = hourly capacity factors during one whole year;

$\boldsymbol{X}$ = dummy variable to identify each month $\boldsymbol{i}$ = 1, 2, . . ., 12;

$\boldsymbol{Z}$ = dummy variable to identify each hour in a day $\boldsymbol{j}$ = 1, 2, . . ., 24;

$\boldsymbol{W}$ = hourly demand for electricity;

$\boldsymbol{\alpha}$ = constant term in the regression;

$\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ = coefficients corresponding to variables $\boldsymbol{X}$ and $\boldsymbol{Z}$;

$\boldsymbol{\delta}$ = coefficient corresponding to variable $\boldsymbol{W}$.

We use this regression model, estimated using data from 2012, to simulate total hourly wind production in all counterfactual scenario analyses. The three coefficients ($\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, and $\boldsymbol{\delta}$) capture the "mean effects" corresponding to seasonal and daily trends observed in the data. Hourly wind production is simulated with these mean effects and random disturbance (ε) such that the simulated output has the same variance as the training data. With this approach, seasonal trends in wind production observed in year 2012 are reproduced. In order to produce a seasonal trend observed in year 2013, we assign weights to coefficients $\boldsymbol{\beta}$ corresponding to the monthly dummy variables. These weights are determined as ratios of normalized monthly production in 2013 to corresponding values in 2012. Monthly production values are normalized by dividing them by total annual production in respective years. These weights therefore, capture the variation in monthly production across two years. This approach works effectively in this case because the annual capacity factor remains same in both years.

2.1.3.2. Substitutability between Coal and NG units

(Kaplan 2010; Macmillan, Antonyuk, and Schwind 2013) theorize that not all coal and NGCC units will be able to freely compete (on the basis of marginal operating costs) with each other and observe that constraints related to the transmission system could limit the extent of this competition. Therefore, some coal units will continue to operate at higher levels of output even when there are NGCC units with marginal operation cost lower than these units. Without a detailed map of the transmission system within ERCOT it is not possible to directly measure the effect of transmission system capacities on the extent to which coal and NG units are substitutable. In lieu of a direct approach based on transmission system data, we propose an approach which uses historical data on monthly production from individual coal and NG units and data on coal and NG prices to identify those coal units that may not be affected by a decrease in NG prices relative to coal.

Figure 2.1 presents the monthly price of NG in Texas during the period of 2009 – 2013 (U.S. EIA 2013c). During this period NG prices on average were highest in 2010 ($4.56/MMBTu) and lowest in 2012 ($3.04/MMBTu). Coal prices on the other hand have remained more or less constant in comparison with NG prices. We observe that the drop in NG prices in 2012 coincides with an increase in the share of ERCOT electricity production from NG resources to 45% from 38% in 2010 (ERCOT 2014).

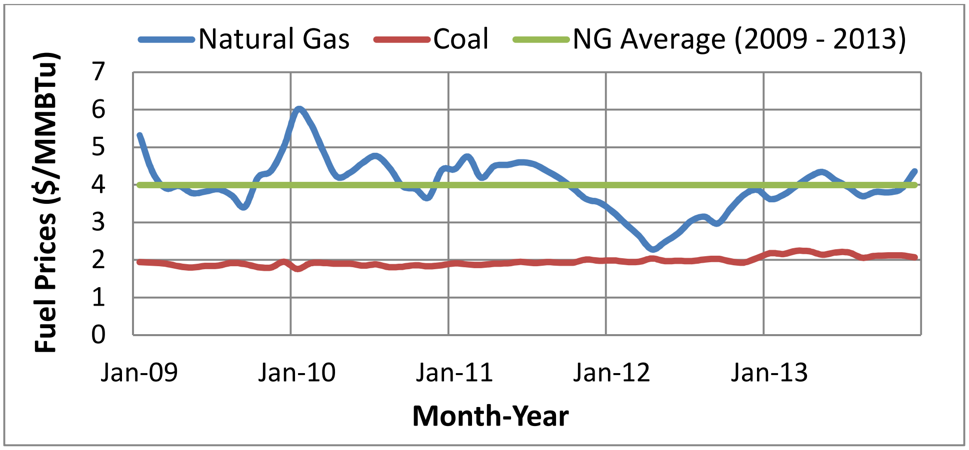

Figure 2.1. Historical coal and NG prices in Texas

We set up a multiple regression model (Equation 2.3) estimated using the data from the years 2012 and 2013. We chose these two years to ensure that we have enough data points covering a wide range of coal and NG prices to estimate the regression model.

$$\boldsymbol{A_k = \eta_k + \theta_k B + \lambda_k C}$$

Equation 2.3.

Where,

k = index to identify each of the coal and NG units in the data;

A = monthly capacity factors during 2012-2013;

B = difference between NG and coal prices for each month during 2012-2013;

C = total observed monthly production from all coal and NG units during 2012-2013;

$\boldsymbol{\eta}$ = constant term in the regression;

$\boldsymbol{\theta}$ and $\boldsymbol{\lambda}$ = coefficients corresponding to $\boldsymbol{B}$ and $\boldsymbol{C}$;

The dependent variable $\boldsymbol{A}$ is the actual monthly capacity factor for each unit during 2012-2013 calculated using data from EIA 906/920 (U.S. EIA 2013b). We chose capacity factor as the dependent variable instead of the actual monthly production to ensure that the coefficients of the model for all units are on the same scale. The explanatory variable $\boldsymbol{B}$ is the difference between NG and coal prices for each month. An increase in the value of $\boldsymbol{B}$ indicates that the price of NG is increasing relative to coal. The regression is run for each unit separately. The coefficient of interest is $\boldsymbol{\theta}$, which corresponds to the explanatory variable $\boldsymbol{B}$. Estimates of $\boldsymbol{\theta}$ will help us understand how each of the coal and NG unit responded to the change in NG prices relative to coal prices. The hypothesis for coal units is that an increase in the value of $\boldsymbol{B}$ should correspond to an increase in the value of $\boldsymbol{A}$, since operation costs for coal units is decreasing relative to NG units. Coal units that conform to this hypothesis will have a positive value for coefficient $\boldsymbol{\theta}$. Increasing values of $\boldsymbol{B}$ should lead to a decrease in the value of $\boldsymbol{A}$. Therefore, NG units that conform to our hypothesis will have a negative value for the coefficient $\boldsymbol{\theta}$.

$\boldsymbol{C}$ is the difference between total monthly demand and the total monthly production derived from resources other than coal and NG during a specific month. $\boldsymbol{C}$ is included as a control to account for any variation in production from coal and NG units caused by a variation in demand and production from other resources types (nuclear, wind and other renewables).

If all coal and NG units were perfect substitutes for each other we would have observed coefficient $\boldsymbol{\theta}$ to be positive for each coal unit and negative for each NG unit. However, only 50% of the coal units, accounting for nearly 46% of the total coal production capacity, were found to have statistically significant positive coefficient $\boldsymbol{\theta}$. Similarly, 46% of the non-CHP NG units, accounting for 46% of the total non-CHP NG production capacity were found to have statistically significant negative coefficient $\boldsymbol{\theta}$. Nearly 84% of the non-CHP units with negative coefficient $\boldsymbol{\theta}$ are in fact NGCC type units. These results therefore demonstrate the imperfect nature of competition between coal and NG units.

The coefficient $\boldsymbol{\theta}$, which is used to determine if a coal unit is substitutable, could in fact reflect the effect of transmission system constraints combined with the effects of factors such as minimum operating limit on coal units, heat rates, unit age, outage rates and perhaps long-term fuel purchase contracts as well. Isolating the effects of individual factors may not be possible with the data that we have. However, this is not a concern in this study because we do not use the coefficients directly in our model. Only the information about which coal units are substitutable is used to update the OC1 Model. Further, OC1 Model already accounts for several OCs and this heuristic approach to identify non-substitutable coal units accounts for the effects of the factors not already considered.

2.1.3.3. Dispatch of Coal and NGCC Units

In the OC2 dispatch model, the production from coal and NG units is scheduled after production from nuclear, renewable resources, and NG CHP units have been accounted for in a specific hour. To determine the total hourly production needed from coal and NGCC units, we account for scheduled maintenance and forced outages of coal and NG units, AS and production from other resource types lower in the dispatch order. The exact steps involved with calculating hourly coal and NGCC production targets are described in Appendix 5. Given the total hourly production target we need to determine how much production needs to be derived from each coal and NGCC unit.

To determine the level of output to be derived from each coal and NG unit, we formulate the linear programing optimization shown in Equation 2.4. The solution to Equation 2.4 determines the hourly output from each coal and NGCC unit.

$$\boldsymbol{min_x \sum_{n=1}^{N} (Cost_n x_n)}$$

$$\boldsymbol{Such\ that} \begin{cases} \boldsymbol{\sum_{n=1}^{N} (Capacity_n x_n) \geq Production\ Target} \\ \boldsymbol{ll_n \leq x_n \leq ul_n} \end{cases}$$

Equation 2.4.

Where,

$\boldsymbol{N}$ = Number of available generating units;

$\boldsymbol{Cost_n}$ = Operation cost of unit $\boldsymbol{n}$ (\$/MWh);

$\boldsymbol{Capacity_n}$ = Season depending capacity of unit $\boldsymbol{n}$ (MW);

$\boldsymbol{x_n}$ = Level of output for unit $\boldsymbol{n}$ (ratio of unit's hourly output to its maximum season dependent capacity);

Production Target = Total production to be derived from coal and NGCC fleet (MWh);

$\boldsymbol{ll_n}$ = Lower limit on unit $\boldsymbol{n}$'s output;

$\boldsymbol{ul_n}$ = Upper limit on unit $\boldsymbol{n}$'s output.

Individual coal and NGCC units are assumed to be continuously operational except for scheduled and forced outages. They may increase or decrease their output in response to demand fluctuations constrained by the minimum operating limit on the lower end and full seasonal capacity on the higher end. Minimum operating limits for coal units are obtained from (ERCOT 2010). NGCC units are assumed to be able to decrease their level of output all the way up to zero. In reality however, NGCC units are subject to minimum operating limits. Moreover, on power plant level, these limits for NGCC are in fact higher than those for coal power plants (Black & Veatch 2012). NGCC power plants comprise of flexible GT type units which results in higher ramp rates (Black & Veatch 2012), shorter warm startup times and shorter offline times between warm startups compared to coal units (NREL 2012). In addition, in comparison to the coal fleet, NGCC fleet comprises of numerous, but smaller plants. Combined effect of these factors make the NGCC fleet quite flexible so that they can be shut down, turned on and ramp to desired level of production feasible on a daily basis. Therefore, the assumption that NGCC units have zero minimum operating limit does not adversely affect OC2 Models predictions.

About half the coal capacity was identified to be unaffected by decreases in NG price and consequential increases in production from NG resources. In other words, about half of the coal units do not compete with NGCC units. However, these coal units are still competing with other coal units for dispatch. Therefore, the allocation of coal and NGCC units is performed in two phases. In the first phase the linear programming problem presented in Equation 2.4 is solved for just coal units, without considering competition with any NGCC units. The level of output for each coal unit is thus determined for each hour. In the second phase, Equation 2.4 is solved again with both coal and NGCC units. The first phase levels of output for coal units are then used as lower limits of operation. This approach ensures that production from coal units that are not competing with NGCC units is not displaced by any cheaper NGCC units (when NG prices are sufficiently low), but they are competing with other coal units. NGCC units that are cheaper to operate than coal units will displace production from more expensive coal units.

2.1.3.4. Dispatch to Meet Residual Demand

At this stage the production from nuclear, wind, coal, NG CHP and NGCC units has been dispatched. Any shortfall in the hourly demand at this stage will be supplied by NGCC units unutilized previously; NG ST and GT units. Residual demand is determined by subtracting total production already dispatched from hourly demand. Unutilized NGCC, NG ST and GT units are then dispatched, at each hour, in the order of their least cost of operation, at full seasonal capacity till the residual demand is met.

2.1.4. OC2 Model Validation

The OC2 Model was used to estimate electricity production and heat consumption values in ERCOT generators for 2012 with results shown in Figure 2.2. All estimates of resource mix and annual aggregate heat input match within 5% of the actual values. Estimates of monthly aggregate production from nuclear, wind, coal and NG resources match within +/- 10% of the actual values.

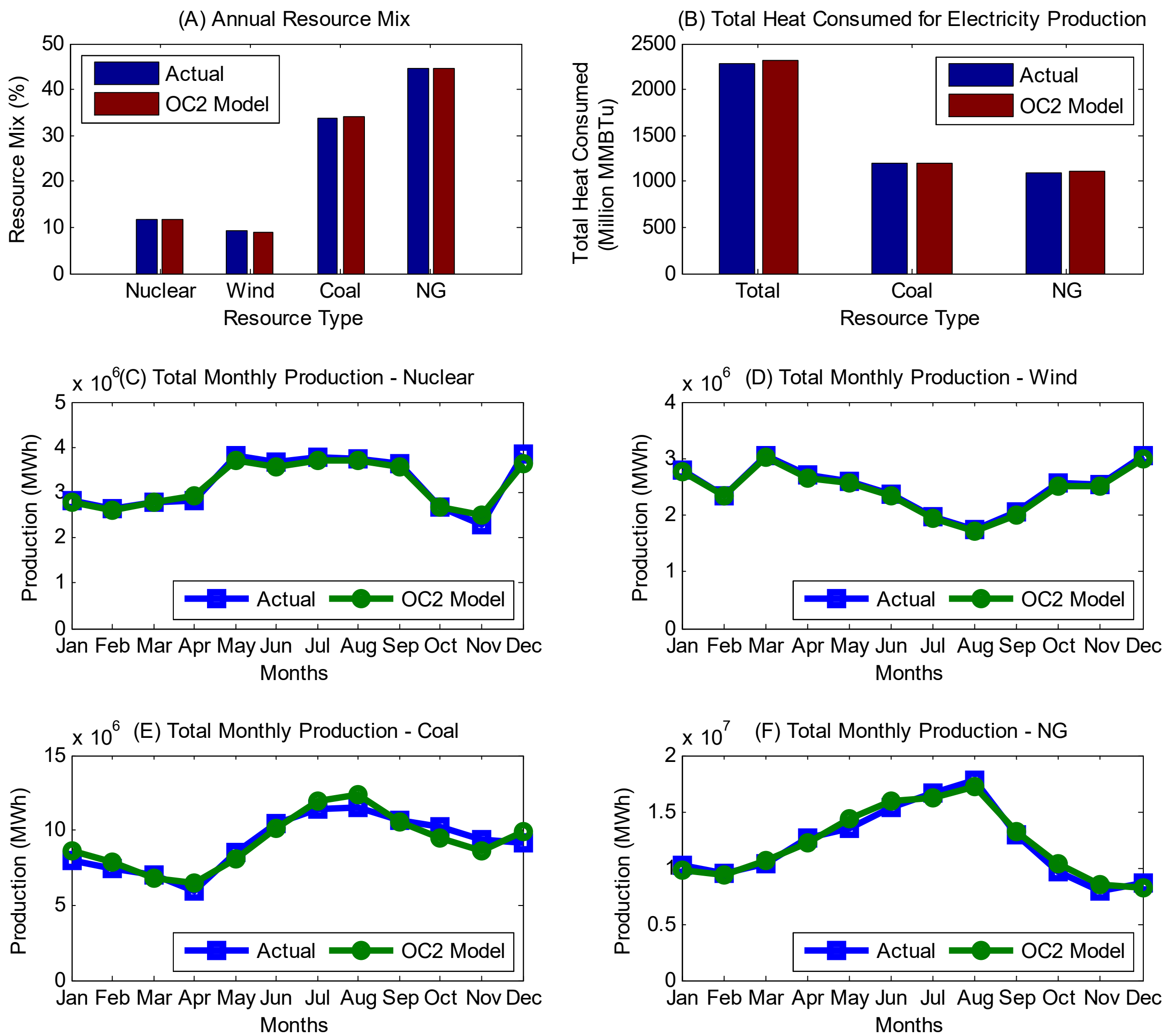

Figure 2.2. OC2 model results for ERCOT 2012

As a further validation of our approach to account for imperfect competition between coal and NG units we compared the extent to which actual and estimated capacity factors for coal power plants in 2012 correlate with the coefficients $\boldsymbol{\theta}$. This analysis is done on the power plant level because coefficients $\boldsymbol{\theta}$ were estimated on power plant level. The magnitude of coefficient $\boldsymbol{\theta}$ for a specific coal plant indicates the extent to which it is substitutable. A coal plant with a larger, positive $\boldsymbol{\theta}$ is more readily substituted by production from cheaper NG units relative to a coal plant with θ closer to zero. We observe that the capacity factors estimated by the OC2 Model correlate well (-69%) with the values of θ and to a similar extent to which actual capacity factors correlate (-71%) with θ. In comparison, the capacity factors estimated without the information on non-substitutable coal units correlate poorly (-24%) with θ. These observations prove that the approach to account for imperfect competition between coal and NG units improves the estimates of production for each coal power plant in addition to the aggregate production from coal and NG fleet. Detailed results from this analysis are presented in Table 2.2.

Table 2.2. Comparison of Actual and Estimated Coal Power Plant Annual Capacity Factors in year 2012

Power Plant Name	Coefficient θ*	Annual Capacity Factors		
		Actual (U.S. EIA 2013b)	Estimated with Coal and NG Imperfect Competition	Estimated without Coal and NG Imperfect Competition
Big Brown	0.027	0.698	0.732	0.549
Coleto Creek	-0.063	0.981	0.802	0.708
Fayette Power Project	0.109[+]	0.560	0.499	0.551
Gibbons Creek	0.319[+]	0.380	0.595	0.682
J K Spruce	-0.120	0.736	0.753	0.677
J T Deely	0.190[+]	0.460	0.596	0.632
Limestone	0.162[+]	0.709	0.583	0.652
Martin Lake	0.069	0.705	0.753	0.491
Monticello	0.105[+]	0.423	0.415	0.414
Oak Grove	0.177[+]	0.707	0.573	0.631
Oklaunion	0.175[+]	0.492	0.530	0.612
San Miguel	0.040	0.805	0.771	0.747
Sandow No 4	-0.007	0.839	0.807	0.746
Sandow Station 5	0.131	0.751	0.709	0.573
Twin Oaks Power One	0.292[+]	0.493	0.485	0.484
W A Parish	0.016	0.598	0.726	0.512
Coefficient of correlation with θ		-71%	-69%	-24%

* Coefficient θ corresponds to the difference between monthly coal and NG prices during the period 2012-2013 as discussed in the Section 2.1.3.2

[+] Coefficient θ those are positive and statistically significant at 95% confidence interval

2.1.4.1. OC2 Model Applied in a Counterfactual Scenario

In order to demonstrate the ability of the OC2 Model to forecast production for an independent scenario, we use the model set up with supply information for the year 2012 to estimate electricity production and heat consumed for the year 2013. The production scenario for 2013 differed from 2012 in two main aspects. First, NG prices on average increased from $2.97/MMBTu in 2012 to $3.86/MMBTu. Second, the seasonal pattern in wind production differed with significantly higher production in 2013 during March – June compared to 2012. Figure 2.3 presents the resource mix, annual aggregate heat input and monthly aggregate production from nuclear, wind, coal and NG resources using the OC2 Model. All estimates match within +/- 10% of the actual values except for instance in which monthly aggregate production from coal units in January is over-estimated by 11%.

Figure 2.3 suggests that the OC2 Model presents a close representation of the current electricity production system. We can therefore use the OC2 Model to estimate the response of the electricity production system to the introduction of carbon prices over the short-term.

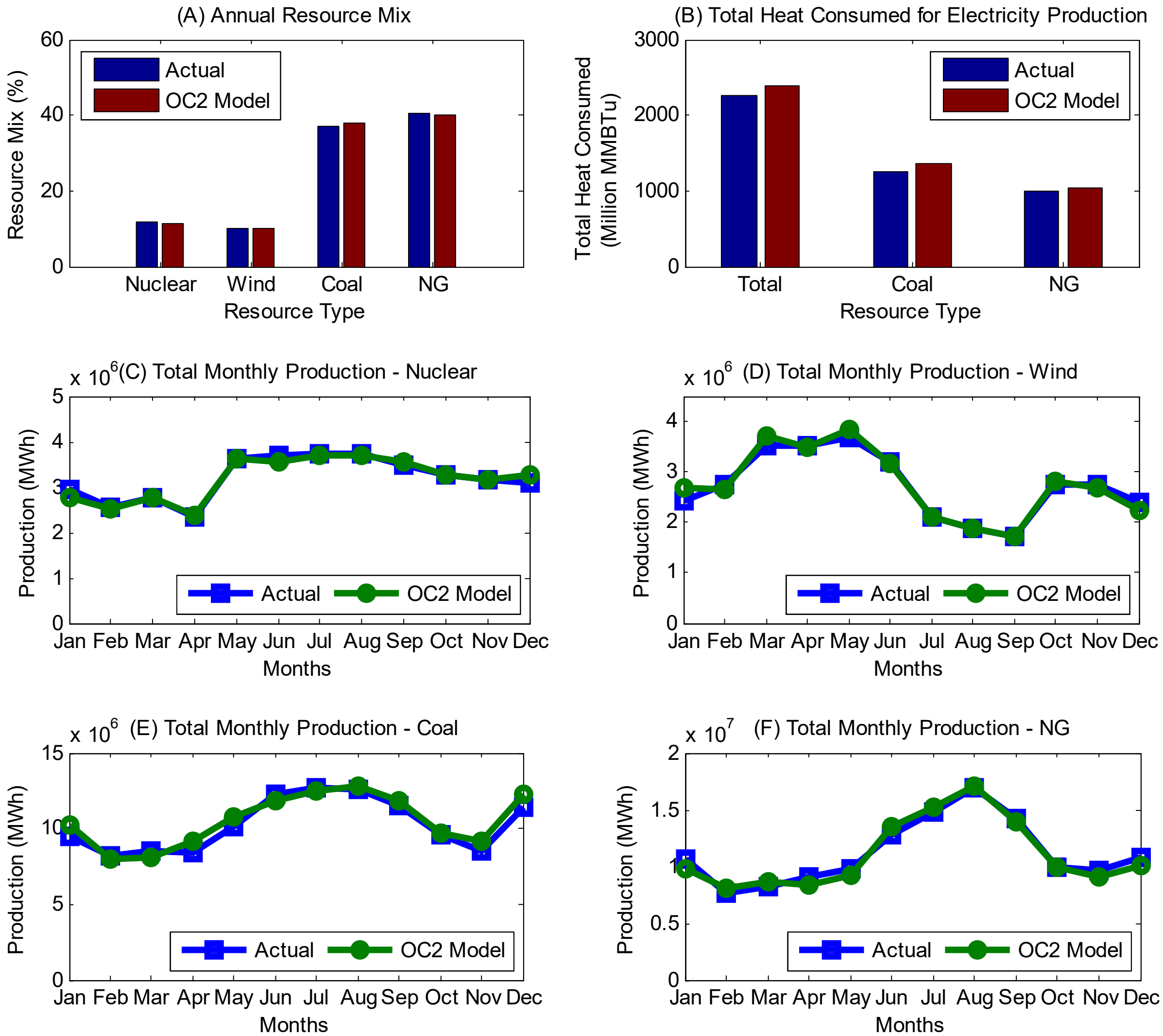

Figure 2.3. OC2 Model results for ERCOT 2013

2.2. Models of Commuting Mode Choices

2.2.1. Introduction

Discrete choice models are generally derived under the assumption of utility maximizing behavior of the decision maker. In other words, a decision maker chooses the alternative that generates his/her highest utility. The Logit model is one of the most commonly used discrete choice models in the transportation literature (Berry, Levinsohn, and Pakes 1995; Domencich and McFadden 1975; Goldberg 1995, 1998; Guadagni and Little 1983). Equation 2.5 presents the form of a standard logit model. The Utility ($\boldsymbol{U_i}$) of option $\boldsymbol{i}$ is modeled as a linear function of the observed attributes of alternative $\boldsymbol{i}$ and their corresponding partworths $\boldsymbol{\beta}$. All decision makers are assumed to have the same preference towards the attributes included in the model (same $\boldsymbol{\beta}$ for all decision makers). The unobserved part of the utility $\boldsymbol{\varepsilon_i}$, derived from the attributes unobserved by the researcher, is assumed to be independent and identically (IID) distributed and follow a double exponential distribution for all alternatives.

$$\boldsymbol{U_i = \beta X_i + \varepsilon_i}$$

Equation 2.5.

Where,

$\boldsymbol{X_i}$ – Attributes corresponding to alternative $\boldsymbol{i}$

$\boldsymbol{U_i}$ – Utility of alternative $\boldsymbol{i}$

$\boldsymbol{\varepsilon_i}$ – Randomly distributed unobserved portion of the utility

$\boldsymbol{\beta}$ – Unknown parameters

The assumption regarding the distribution of the unobserved portion of the utility allows us to calculate the choice probability in a straightforward manner. The probability $\boldsymbol{P_i}$ of choosing an alternative $\boldsymbol{i}$ is given by Equation 2.6 below.

$$\boldsymbol{P_i = \frac{e^{\beta X_i}}{\sum_i e^{\beta X_i}}}$$

Equation 2.6.

Logit models are desirable because of the ease of estimation and calculation (Brownstone and Train 1999). Their most significant limitation is their Independence from Irrelevant Alternatives (IIA) property (Train 2009). The IIA property states that the ratio of the choice probabilities for any two alternatives is independent of the existence and attributes of other alternatives. As a result of this property, logit models predict that a change in the attribute of one alternative (or the introduction/elimination of an alternative) changes the choice probabilities of other alternatives proportionately. This proportional substitution pattern can be unrealistic in certain choice situations (Train 2009).

Studies such as (Brownstone, Bunch, and Train 2000; Brownstone and Train 1999; McFadden and Train 2000; Train 2009) have used random coefficient models in which the preference for attributes are allowed to vary across the population. This allows for correlations between preferences for attributes across alternatives and thereby allow for disproportionate substitution (higher rate of substitution between similar alternatives) (Train 2009). These studies have found that incorporating preference heterogeneity can not only address the IIA issue, but also provide a more realistic estimate of consumer choice. Therefore, these models are well suited for examining marginal choice effects in response to specific transportation decisions. Mode choice studies in the recent times have moved to using heterogeneous models of choice (Arentze and Molin 2013; Cherchi and Ortúzar 2002; Greene, Hensher, and Rose 2006; Hensher and Rose 2007; Molin and van Gelder 2008).

The mode choice work presented in this dissertation utilizes the heterogeneous choice models that have been successfully used in the past. We take two approaches to generalize and model heterogeneity in choice. In the first approach we incorporate individual attitudes in to the choice model as latent variables. The modeling technique known as Integrated Choice and Latent

Variable model (ICLV) has been used to study the choices in the past (Ashok, Dillon, and Yuan 2002; Hess and Beharry-Borg 2011; Kuppam, Pendyala, and Rahman 1999; Walker 2001) .

The random coefficient modeling approaches used previously account for variation in partworths across the population by assuming a distribution of specific form. These models however, did not have the capability to estimate where in the distribution a specific individual would lie. In the second approach we use a Hierarchical Bayes (HB) model, which is a random coefficient logit model estimated using Bayesian estimation techniques (Allenby and Rossi 1998; Rossi, Allenby, and McCulloch 2006). Bayesian estimation technique is one of the approaches that allows to not only estimate the variation in partworths in the population, but also determine where in distribution of partworths does an individual lie (Train 2009).

2.2.2. Integrated Choice and Latent Variable Model

A key innovation of this project is to include respondent's unobserved attitudes and perceptions in the choice model in order to investigate their role in the choice of travel modes along with the traditional (observed) attributes of the travel modes. In other words, we hypothesize that commuters' attitudes (e.g., attitude towards environmental conservation), which are unobserved as opposed to age, income and other demographics characteristics, influence their mode choices. Individual attitudes are unobservable and therefore, they are called latent variables. Latent attitudes manifest in the form of observable behaviors known as indicators. An example to illustrate the concept of latent variable is the use of standardized tests such as SAT to measure a student's academic aptitude. We understand the concept of academic aptitude, but unlike variables such as age or height, it cannot be objectively measured. Students are typically tested on critical reading, mathematics and writing tasks, skills that are necessary to succeed in undergraduate studies. It is hypothesized that a student's combined scores on these tasks represents his/her academic aptitude. In other words the combined scores are used to infer a student's academic aptitude in comparison to other students on a common scale. In this example, scores on individual tasks are observable variables or indicators which are manifestations of a student's latent academic aptitude.

Indicators, which can include responses to carefully constructed survey questions, can be used to create a measurement of individual attitudes on a specific scale (Walker 2001). List of survey questions used to collect data on respondents' attitude related behaviour indicators is provided in Appendix 10. The integrated choice modeling framework shown in Figure 2.4 consists of two components, a traditional logit-based choice model and a latent variable measurement model. A simultaneous estimator is used, which results in a set of parameters that provide the best fit to both the choice and the latent variable indicators. This model has been called the Integrated Choice and Latent Variable (ICLV) model in the literature, though it has not received wide-spread attention mostly because of the unique data requirements and complex estimation procedures involved.

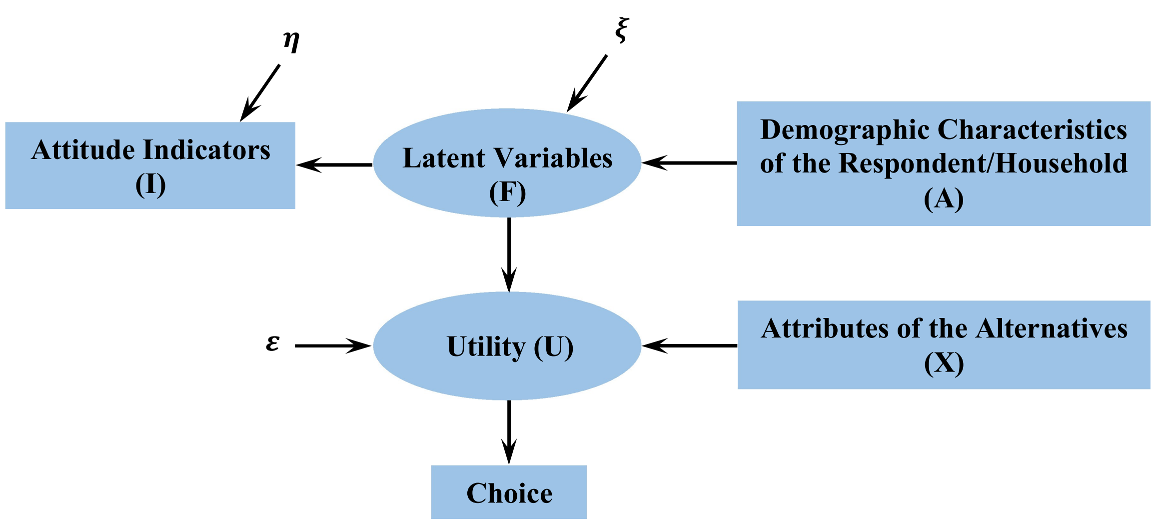

Figure 2.4. Integrated choice and latent variable (ICLV) model

Notation used in Figure 2.4:

- Rectangular box signifies an observed variable;
- Ellipse signifies an unobserved or latent variable;
- Greek letters (η, ξ and ε) signify a disturbance term (error in either measurement or relation between constructs), which are also unobserved and some conventions also assign disturbance terms circles or ellipses for consistency with other unobserved variables;
- Straight arrows signify the assumption that variables at base of arrow "cause" variables at head of arrow

The ICLV model can be described with a set of three equations as shown below. Equation 2.7 and Equation 2.8 correspond to the latent variable model and

Equation 2.9 corresponds to the choice model.

$$\boldsymbol{I_m = \alpha_m F + \eta_m} \qquad \boldsymbol{Where, \eta \sim Normal(0, \sigma_\eta)}$$

Equation 2.7.

$$\boldsymbol{F_n = \gamma A_n + \xi_n} \qquad \textbf{Where}, \boldsymbol{\xi \sim Normal(0, \sigma_\xi)}$$

Equation 2.8.

$$\boldsymbol{U_{ni} = \beta X_i + \theta(F_n * X_i^d) + \varepsilon_{ni}} \qquad \textbf{Where}, \boldsymbol{\varepsilon_{ni} \sim IID\ Double\ Exponential}$$

Equation 2.9.

Where,

$\boldsymbol{I_m}$ – Attitude indicator $\boldsymbol{m}$

$\boldsymbol{\alpha_m}$ – Factor loading

$\boldsymbol{F_n}$ – Latent variables (known as factors in the traditional factor analysis literature) corresponding to respondent $\boldsymbol{n}$

$\boldsymbol{A_n}$ – Observed demographic characteristics of respondent $\boldsymbol{n}$

$\boldsymbol{\gamma}$ – Coefficient corresponding to demographics characteristics $\boldsymbol{A_n}$

$\boldsymbol{U_{ni}}$ – Utility derived by respondent $\boldsymbol{n}$ by choosing alternative $\boldsymbol{i}$

$\boldsymbol{X_i}$ – Observed attributes of alternative $\boldsymbol{i}$

$\boldsymbol{\beta}$ – Partworths corresponding to attributes of the alternatives

$\left(\boldsymbol{F_n} * \boldsymbol{X_i^d}\right)$ – Latent variable and alternative identifying dummy variable interaction term

$\boldsymbol{\theta}$ – Partworths corresponding to the latent variable and alternative dummy variable interaction term

2.2.2.1. Latent Variable Model

A specific indicator may be influenced by one or several attitudes and some of these attitudes may not be observed. Therefore, responses to attitudinal indicator questions are not a direct measure of attitudes, but they are simply manifestations of underlying attitudes that include measurement error (Hess and Beharry-Borg 2011; Walker 2001). Therefore, the responses to attitudinal questions should not be used directly in the choice model as explanatory variables but as latent variables to properly account for their measurement error. There is a two-step process involved when incorporating attitudes in the choice model. The measurement model is the first step (described by) where the responses to indicator questions $\boldsymbol{I}$ are treated as dependent variables accounted for by the latent attitude variables $\boldsymbol{F}$. $\boldsymbol{\alpha}$ is an estimated parameter that determines the effect of each latent variable on the respective indicators. $\boldsymbol{\eta}$ is a random error term that is assumed to be normally distributed with zero mean and standard deviation estimated along with other parameters. These are standard assumptions followed in the factor analysis (Gorsuch 1983) followed in the latent variable modeling studies (Ashok et al. 2002; Hess and Beharry-Borg 2011; Walker 2001).

The second step of the latent variable part of the model (described by Equation 2.8) involves a linear regression that relates the observable variables $\boldsymbol{A_n}$ such as socio-demographic characteristics of the respondent/household to the latent variable $\boldsymbol{F}$. $\boldsymbol{\gamma}$ are the coefficients of the linear regression model, which permit modeling of differences in latent variable means on the basis of specific explanatory variables $\boldsymbol{A_n}$ (e.g., respondents' demographic characteristics), and ξ are the random disturbance term that are assumed to be normally distributed among the respondents with a zero mean and a standard deviation estimated along with other parameters. These are also standard assumptions within the latent variable framework.

2.2.2.2. Choice Model

The choice model part (described by Equation 2.9) is a standard logit model except that the utility $\boldsymbol{U}$ is defined as a function of latent attitudes $\boldsymbol{F}$ derived in the previous steps along with the observed attributes Xi of the alternatives. Latent variable $\boldsymbol{F}$ is interacted with alternative specific dummy variables $\boldsymbol{X_i^d}$ in order to induce difference in utilities across alternatives. This is necessary because latent variables $\boldsymbol{F}$ vary across respondents, but do not vary across alternatives and a variable's partworth can be measured only if it contributes to the utilities of different alternatives differently (Train 2009). $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ are the estimated coefficients of the utility function corresponding to the mode attributes and latent variables respectively. The error term $\boldsymbol{\varepsilon}$ is assumed to be IID among the alternatives and follows a double exponential functional form, which makes the choice model a Logit model. This assumption allows us to calculate the probability of respondent $\boldsymbol{n}$ choosing alternative $\boldsymbol{i}$ as described by Equation 2.10.

$$\boldsymbol{P_{ni}} = \frac{\boldsymbol{e^{\beta X_i + \theta\left(F_n * X_i^d\right)}}}{\sum_i \boldsymbol{e^{\beta X_i + \theta\left(F_n * X_i^d\right)}}}$$

Equation 2.10.

2.2.2.3. Estimation of Parameters

Maximum likelihood techniques similar to those followed in (Walker 2001) were used to estimate the unknown parameters of the ICLV model. The parameters of the latent variable and the choice models were estimated simultaneously. Therefore, the maximum likelihood estimation approach in this case follows the logic of jointly maximizing the likelihood of observing the choices and the responses to the attitude indicator questions. This means that the estimation of latent variable is informed both by the data on choices and the data on responses to attitudinal questions and vice versa as well as the influence of all the error terms in the model and their covariances.

The key point of the ICLV model is that both attitudes and the attributes of the modes are included in the choice modeling and estimated simultaneously. From a computational and modeling standpoint the simultaneous approach is more efficient and does a better job of handling the joint distribution of the parameters (relative to, say, a sequential process of first fitting a factor analysis model to the attitude data and then using the latent variables as predictors in the choice model).

2.2.3. Hierarchical Bayes Model

The basic form of the Hierarchical Bayes (HB) model used in this work is described by Equation 2.11. The model is called "hierarchical" because the utility distribution is defined on two levels. On the first level the partworths for attributes are assumed to vary across respondents described by a multivariate normal distribution. This distribution is characterized by a vector of means $\boldsymbol{\alpha}$ and variance-covariance matrix $\boldsymbol{D}$. This approach accounts for taste heterogeneity by allowing the partworths to vary across respondents.

$$\boldsymbol{U_{ni} = \beta_n X_i + \varepsilon_{ni}}$$

$$\boldsymbol{\beta_n \sim Multivariate\ Normal(\mu, D);\ \varepsilon_{ni} \sim IID\ Double\ Exponential}$$

Equation 2.11.

Where,

$\boldsymbol{X_i}$ – Vector of attributes describing alternative $\boldsymbol{i}$

$\boldsymbol{U_{ni}}$ – Utility derived by respondent $\boldsymbol{n}$ by choosing alternative $\boldsymbol{i}$

$\boldsymbol{\varepsilon_{ni}}$ – Unobserved portion of the utility assumed to be IID double exponential

$\boldsymbol{\beta}_n$ – Vector of partworths for respondent $\boldsymbol{n}$

$\boldsymbol{\mu}$ – Vector of means of the distribution of respondents' partworths

$\boldsymbol{D}$ – Variance-covariance matrix of the distribution of respondents' partworths

On the second level, it is assumed that the unobserved part of the utility is IID double exponential. This assumption allows us to determine the probability of respondent $\boldsymbol{n}$ choosing alternative $\boldsymbol{i}$, given respondent $\boldsymbol{n}$'s partworths, in a manner similar to a multinomial logit model as described in Equation 2.12.

$$\boldsymbol{P_{ni}} = \frac{\boldsymbol{e^{\beta_n X_i}}}{\sum_i \boldsymbol{e^{\beta_n X_i}}}$$

Equation 2.12.

The benefit of HB over the ICLV model is that HB allows each respondent to have their own set of choice parameters, thus accounting for individual differences (aka heterogeneity) in the tradeoffs between choice attributes. HB model is estimated with the model built in the Sawtooth software tool which was also used for conducting conjoint studies (Sawtooth Software 2009).

Chapter 3

CO_2 Reduction from Increased Utilization of Natural Gas Units in ERCOT

3.1. Introduction

In the recently proposed CPP, increasing the utilization of existing low CO_2 emitting generating units is outlined by the EPA as a short-term strategy to reduce CO_2 emissions from electricity production (U.S. EPA. 2014). This is a short-term strategy because it seeks to alter the utilization of the existing system within a time period typically shorter than the period during which demand and installed generating capacity can change significantly. In this study we examine the potential for reducing CO_2 emissions over the short-term in ERCOT by increasing production from low CO_2 emitting units and analyze the manner in which the OCs of the existing system govern the shift in production and change in CO_2 emissions.

The CPP lays out CO_2 reduction goals that each state is required to meet, but it provides the states with the authority to adopt any policy measure necessary to meet their CO_2 reduction goals by the year 2030. Consistent with the EPA's analysis we consider carbon pricing as a proxy for different forms of regulations that the states could adopt to incentivize utilization of existing low CO_2 emitting units.

A price on CO_2 emissions generated from electricity production will affect the electricity production system both on a long-term and short-term basis. Over the long-term, carbon pricing is expected to motivate firms involved in the electricity business to invest in low CO_2 emitting technologies for generation capacity as concluded by (Bergerson and Lave 2007; Nicholson, Biegler, and Brook 2011; Sekar et al. 2007; Wise et al. 2007). In this study we focus on the short-term effects. Over the short-term, carbon prices are expected to decrease the utilization of high CO_2 emitting units by increasing their marginal operation costs relative to low CO_2 emitting units.

In the year 2013, electricity in ERCOT was mainly produced by NG (40%), coal (38%), nuclear (12%) and wind (10%) units (ERCOT 2014). In the same year, NG units comprised 68% of the total installed electricity production capacity in ERCOT (U.S. EIA 2013a) with an average fleet-wide capacity factor of 28% (U.S. EIA 2013b). In the same year, coal–fired units comprised 24% of the installed capacity (U.S. EIA 2013a) with an average fleet-wide capacity factor of 70% (U.S. EIA 2013b). NG fleet on average has a lower CO_2 emitting factor (1164 lb CO_2/MWh) compared to the coal fleet (2224 lb CO_2/MWh) (U.S. EPA. 2013).

Nuclear units currently operate close to their maximum capacity (U.S. EIA 2013b) and wind units are not available for dispatch. Further, marginal operating costs of nuclear and wind units are lower than those for coal and NG units. Assuming there are no changes in these conditions, the introduction of carbon pricing is expected to increase the utilization of NG units by displacing equivalent production from coal units and reduce CO_2 emissions. Natural Gas Combined Cycle (NGCC) type units in particular are technically capable of supplying base load[1] (U.S. EPA. 2014). Gas Turbine (GT) and Steam Turbine (ST) type units, which are also common

[1] In the year 2013, NGCC units comprised 45% of the total installed electricity production capacity in ERCOT (U.S. EIA 2013a), while supplying nearly 33% of total annual electricity demand with an average fleet-wide capacity factor of 35% (U.S. EIA 2013b).

technologies in the NG fleet, are generally used as peak load units because they are less efficient than NGCC units (40% less efficient on average (U.S. EIA 2013b)). Therefore, understanding the influence of the OCs of the existing system on the competition between coal and NG units is critical for determining the effectiveness of carbon prices in reducing CO_2 emissions.

The short-term effects of carbon prices on electricity production have been examined by (Moore and Apt 2014; Newcomer, Blumsack, et al. 2008; Peterson, Whitacre, and Apt 2011) in the past. Most recently, the authors of (Moore and Apt 2014) have studied the effects of carbon pricing and compared its cost effectiveness with renewable energy portfolio standards as CO_2 reducing strategies. Part of their analysis considered the grid in ERCOT in 2012 and a NG price level of \$4/MMBTu. Under these circumstances they find that a CO_2 reduction of about 38% could be achieved at a carbon price of \$25/tonne CO_2. In (Newcomer, Blumsack, et al. 2008), the authors analyzed the short-term effects of carbon prices on CO_2 emissions in ERCOT considering the grid in year 2004 and a NG price level of \$7.79/MMBTu. They find that a maximum of 3.4% reduction in CO_2 emissions could be achieved at a carbon price of \$50/tonne CO_2 under the assumption of zero elasticity in the demand for electricity. This disparity in the estimates for reducing CO_2 emissions under carbon prices is primarily due to the variation in assumed NG prices. At higher NG prices (as assumed in (Newcomer, Blumsack, et al. 2008)), higher levels of carbon prices are necessary to bridge the gap in marginal costs of coal and NG units and change the dispatch order leading to a specific amount of CO_2 reduction. The dispatch model developed in (Newcomer, Blumsack, et al. 2008) was also used in (Peterson et al. 2011) to study the effects of carbon prices on emissions attributable to electricity consumed by electric vehicles. The authors find that a \$50/tonne CO_2 carbon price results in negligible reduction in CO_2 emissions from electric vehicle use.

The studies presented in (Moore and Apt 2014; Newcomer, Blumsack, et al. 2008; Peterson et al. 2011) use economic dispatch models of the type developed in (Kelly et al. 2009; McCarthy and Yang 2010; Newcomer and Apt 2009; Sioshansi and Denholm 2010). These models do not account for the system OCs which were found in (Raichur et al. 2015) to be necessary for achieving robust estimates of economic dispatch for different types of generating units. Further, the work described in (Moore and Apt 2014; Newcomer, Blumsack, et al. 2008; Peterson et al. 2011) treat all NG units as perfect substitutes for coal units. In other words, they assume that any NG unit could replace any coal unit when NG units are cheaper to operate than coal units. As (Kaplan 2010; Macmillan et al. 2013) point out, this is unlikely and factors such as transmission constraints may limit which coal units could be substituted by NG units. For instance, if NGCC units are built in locations quite distant from coal units they may typically rely on different transmission paths and they may not be able to transmit electricity to load centers originally served by coal units. Supporting this concern, the work of (Venkatesh et al. 2012) finds that the OC associated with the minimum operating limit of coal units restricts the extent to which production from coal units could be displaced by NG units.

This study examines the influence of various OCs on the ability of carbon pricing to affect CO_2 emissions from electricity production, using ERCOT as a case-study. OC2 Model is used in this study to estimate the change in CO_2 emissions resulting from carbon pricing policies.

3.2. Effects of Carbon Pricing

In this section we study the effect of carbon prices on the relative utilization of coal and NG units, along with associated CO_2 emissions. Carbon prices are applied to all coal and non-CHP NG units. In the presentation of results, the production scenario in ERCOT in 2013 was considered as the baseline against which changes in resource mix and CO_2 emissions are estimated.

Counterfactual scenarios are first developed by applying carbon prices to all coal and non-CHP NG units. The carbon price is varied from \$0 – \$30/ton CO_2 in increments of \$5/ton CO_2 while all other aspects of dispatch are assumed to remain same as the production scenario in 2013. Carbon pricing increases the marginal cost of all fossil fuel units, but the increase in costs for coal units with higher CO_2 emission rates is greater than that for NG units. Within the NG resource type ST and GT units on average have higher emission rates compared to NGCC units. Therefore, marginal costs of ST and GT units increase to a greater extent than NGCC units under a carbon price scenario.

Table 3.1 presents the resource mix and CO_2 emissions at each level of carbon price. \$0/ton CO_2 case is in fact the 2013 baseline scenario where production from coal (38%) is at its maximum and overall CO_2 emissions (200 million short tons) is also at its maximum. As carbon prices are applied, units with lower CO_2 emissions rates become more cost effective to operate. This leads to an increase in the utilization of low CO_2 emitting NG units, which leads to an overall decrease in CO_2 emissions. This trend continues until carbon price reaches \$20/ton CO_2 at which point the production form NG units hits a maximum of almost 50%. CO_2 emissions reach a minimum of 179 million short tons (11% reduction) at \$20/ton CO_2 and stay the same at higher carbon prices. These estimates of CO_2 reduction are sensitive to changes in fuel prices. Results of the analysis of the effect of change in fuel prices on production and CO_2 emissions once a certain carbon price is introduced are presented in Appendix 8. We find that an increase in NG prices relative to coal leads to an increase in emissions and reduces the amount of CO_2

reduction achieved at a carbon price of \$20/ton CO_2. Similarly, a decrease in coal prices relative to NG leads to an increase in emissions as well.

The results suggest, contrary to previous studies (Newcomer, Blumsack, et al. 2008; Peterson et al. 2011) and consistent with (Moore and Apt 2014), that carbon prices can lead to significant reduction in CO_2 emissions over the short-term by shifting production from coal to NG units (assuming zero price elasticity of demand). However, contrary to the analysis in (Moore and Apt 2014), we find that carbon prices have an upper bound on their effectiveness in reducing CO_2 emissions that is derived from the OCs of the electricity production system. The manner in which these OCs limit the extent to which production from coal can be displaced by NG units is discussed in the following Section 3.3.

These reductions in CO_2 emissions are associated with an increase in the system-wide cost of electricity production. In order to determine how cost-effective carbon pricing is at reducing CO_2 emissions we determine the cost per short ton of CO_2 reduced for each level of carbon pricing. The cost of CO_2 reduction is determined as the ratio of additional cost of electricity production to the quantity of CO_2 emissions reduced at a specific carbon price in comparison to the baseline scenario. Carbon pricing can add to the system-wide cost of electricity production in two ways:

1. The cost incurred by the fossil fuel generating units per ton CO2 emitted;
2. Increased utilization of NG units increases the consumption of NG fuel, which is more expensive than coal.

Table 3.1. Reduction in total CO_2 emissions achieved under different scenarios of carbon price[2]

Carbon Price ($/ton CO_2)	Resource Mix (%)				Total CO_2 Emissions (million Tons)	Reduction in CO_2 Emissions (%)	Cost of Reduction w/o Carbon Price[a] ($/ton CO_2 reduced)	Cost of Reduction w/ Carbon Price[b] ($/ton CO_2 reduced)
	Nuclear	Wind	Coal	NG				
0	12	10	38	40	200	-	-	-
5	12	10	35	42	194	-3%	2	155
10	12	10	32	46	187	-7%	5	134
15	12	10	30	48	181	-9%	7	141
20	12	10	29	49	179	-11%	8	164
25	12	10	28	49	178	-11%	9	199
30	12	10	28	50	178	-11%	9	235
35	12	10	28	50	178	-11%	9	271

[a] Cost of CO_2 reduction calculated without considering carbon price as a cost to the generating units
[b] Cost of CO_2 reduction calculated considering carbon price as a cost to the generating units

Carbon price paid by the generating units may not be considered as costs because it only leads to transfer of wealth between generators, government entities and consumers of electricity. This is particularly true if the policy is designed to be revenue neutral (e.g., carbon tax plan adopted by British Columbia, Canada) (Ministry of Finance, British Columbia 2012) by recycling the tax revenue back to the consumers and businesses in the form of tax breaks or subsidies. In order to inform the readers about the scale of costs from carbon prices paid by the generating units relative to the fuel costs, we present costs of CO_2 reduction in Table 3.1 calculated both with and without considering carbon price as cost.

We observe that the relationship between carbon prices and the corresponding costs of CO_2 reduction is nonlinear in nature. CO_2 reduction is most cost effective at a carbon price of $5/ton

[2] A more detailed version of Table 3.1, which contains details on electricity production costs, and determination of cost of CO_2 reduction, has been provided in Appendix 7.

CO_2 and the cost effectiveness steadily decreases up to the carbon price level of \$20/ton CO_2. Beyond this point there is no significant increase in the utilization of NG units and there is no significant reduction in CO_2 emissions. Therefore the cost of CO_2 reduction plateaus out from this point forward. Given this is a short-term analysis, the fleet is fixed whereas in the longer term the NG capacity could be increased to increase cost-effectiveness and reduce total system emissions.

3.3. Analysis of Operating Constraints

Here we consider the extent to which specific OCs contribute to the estimates of CO_2 reduction under carbon pricing. Detailed results are presented in Appendix 9. In brief, we find that two OCs considered in the OC2 Model have profound influence on the estimates of resource mix and CO_2 emissions reduction:

1. **Imperfect substitution between coal and NG units** – this constraint ensures that production from specific coal units is not inappropriately substituted by competing NG units when in reality in ERCOT not all coal units are affected by the competition from NG units. If this factor is not accounted for, it is estimated that more production from coal is substituted by NG units than would occur in reality.
2. **Minimum operating limit for coal units** – this constraint ensures that production from individual coal units does not drop below a specific level, specified by the operating characteristics of the plants, when either demand decreases or production from cheaper resources is available. As in the case of the removal of the transmission proxy, the resource mix for NG resources is significantly over-estimated when the minimum operating limit for coal units is reduced to zero.

Figure 3.1 presents the estimates of CO_2 reduction achieved at different levels of carbon prices when imperfect substitution and coal units' minimum operating constraints are not considered. When not considering these OCs the maximum amount of CO_2 reduction achieved by carbon pricing (at \$30/ton CO_2) is over-estimated by about 24%. This observation is consistent with the findings in (Moore and Apt 2014) in which the authors find that about 37% reduction in CO_2 emissions can be achieved at a carbon price of \$25/ton CO_2 applied to all fossil units in ERCOT.

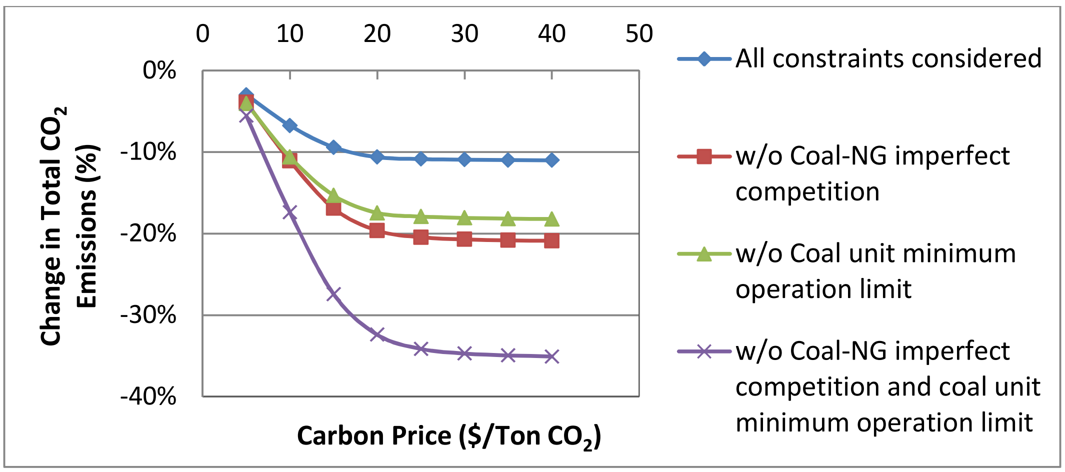

Figure 3.1: Comparison of reduction in CO_2 under different carbon price levels applied to coal and non-CHP NG units

The influence of coal units' minimum operating limits on the estimates of CO_2 reduction needs further discussion. The estimates of CO_2 reduction presented in Table 3.1 were determined under the assumption that coal units are kept operational at all hours except during scheduled and forced outages. Their output can be increased up to their full seasonal capacity or decreased down to their minimum operating limits depending on the demand for electricity and production from competing generation resources. This assumption is reasonable given that the coal units cannot go through on/off cycles as easily as NG units and coal units have been observed in the past to be continuously operational in order to supply baseload.

In 2012 however, low NG prices during Feb – June meant that most of the coal units were less economical than NG units to keep operating at their minimum operating limit. Consequently, several units were shut down for extended periods of time during this period. On average, about half of the coal units shut down for a period of two and half months (U.S. EPA. 2012). Modeling the decision making process to shut down the coal units is beyond the scope of this work. Nevertheless, the possibility that some coal units could shut down, in which case minimum operating limits are not binding, should be considered while estimating the shift in production from coal to NG units and consequent CO_2 reduction under carbon pricing.

Figure 3.1 presents the estimates of CO_2 reduction in a scenario where the coal units' minimum operating limits are not binding and the units are allowed to operate anywhere between zero to 100% capacity depending on the demand for electricity and fuel prices. This represents an extreme scenario in which coal units can go through on/off cycles as necessary.

In reality however, this would not be possible and once shut down the units remain offline for an extended period of time. This is also the reason why it could be expected that in order to ensure adequate online generating capacity only a select few units would be allowed to shut down. The units that are online are subject to the minimum operating constraints whereas units that are shut down are not. Therefore, the two scenarios examined here in which minimum operating constraints for all coal units are binding and not binding represent two extreme scenarios. The CO_2 reduction estimates in these scenarios represent the bounds on the amount of CO_2 reduction that can be achieved. In other words, the amount of CO_2 reduction that can be achieved with carbon pricing could most likely be somewhere between 11% and 18%.

3.4. Discussion

In this analysis we estimated the reduction in CO_2 emissions that can be achieved in ERCOT by increasing the utilization of NG generating units relative to coal using carbon price as a proxy policy measure. Results of this analysis and the model validation (discussed in Section 2.1.4) demonstrate that imperfect substitution between coal and NG units is an important factor to be considered when marginal operating costs of NG units are comparable to those for coal units. In this study, we find that 11% - 18% reduction in CO_2 emissions could be achieved by increasing the utilization of NG units relative to coal units. We have used the annual average heat rate and CO_2 emissions rates for each generating unit. These values reflect the reduction in efficiency at lower levels of operation as observed in year 2012. Under carbon pricing however, coal units are expected to operate at output levels significantly lower than observed previously. This will result in further reduction in heat rates and increase in CO_2 emission rates.

The estimates of CO_2 reduction are about 26% lower than the estimates reported in the literature and the exclusion of imperfect substitution between coal and NG units and the minimum operating limits for coal units primarily leads to an over-estimation of CO_2 reduction benefits. Addressing these two factors before introducing a policy measure aimed at increasing the utilization of existing NG units in ERCOT could enable greater CO_2 reductions.

Generalization of these results to other regions may not be possible, especially in PCAs that regularly trade electricity with neighboring PCAs. Unlike ERCOT, which is an isolated system, PCAs that have transmission ties with neighboring PCAs could be in a position to circumvent the OCs that limit the amount of production from coal that can be displaced by NG. These issues will need careful attention as individual states evaluate different strategies, which could include strategies developed jointly with neighboring states to comply with the CPP ruling.

Analysis of the OCs indicates a need for increased flexibility and substitutability between different types of generating units in the electricity production system. Coal units operating at close to minimum operating limits may not be able to economically sustain their operations over the long-term. Therefore, the dependence on large baseload coal power plants may not be feasible. Over the long-term investments in new production technologies should focus on resource types which are flexible to take full advantage of favorable changes such as a decreasing NG prices and also respond efficiently to new regulations.

Chapter 4

Commuting Mode Choice Analysis in Portland

4.1. Introduction

The work presented in this chapter was conducted in collaboration with the city planning authority in Portland, Oregon (Metro) (Portland Metro 2013) and the objective was to study choice of travel modes used for commuting to find ways to leverage the existing system to reduce personal vehicle use. Given Oregon's GHG reduction targets (State of Oregon 2007), there is great interest in understanding mode choice behavior and generating more accurate estimates of GHG reductions that could be achieved by reducing personal vehicle use and shifting to other modes of transportation.

Metro extensively relies on the Oregon Department of Transportation's GreenSTEP model (Greenhouse gas Strategic Transportation Energy Planning) (U.S. DOT 2010) to study GHG reduction from different strategies. The model uses average factors to estimate change in CO_2 emissions and is not quite capable of examining realistic scenarios of marginal choice effects. This issue is similar to issues faced by other top-down transportation planning models as noted by Domencich & McFadden (1975) and Rodier (2015).

Both ICLV and HB models (described in Sections 2.2.2 and 2.2.3 respectively) were used in the study to enable scenario planning within a policy framework. One benefit of modeling both latent variables and choice is that policy makers now have two routes to influence behavior: the traditional choice attribute route (e.g., subsidize bus fare, increase parking costs, etc.) and the attitude route (e.g., develop public awareness programs around relevant attitudes, tailor campaigns within regions based on distribution of relevant attitudes, etc.).

One drawback of using choice models with individual-level preferences is their extensive data requirements. It is necessary to observe multiple choices made by each decision maker under varying levels of attributes to accurately estimate heterogeneous partworths (Hess and Train 2011). For instance, if one decision maker is observed to always choose the cheapest alternative and another decision maker always chooses the most expensive alternative, then an inference can be made that the two individuals value the price attribute differently.

Panel data, in which each decision maker is observed to make multiple choices under varying levels of attributes, is generally unavailable. One instance of the availability of such data is the Puget Sound Transportation Panel Survey (PSRC 2002). The data was collected during 1989 – 2002 for Puget Sound, a geographic region consisting of four counties surrounding Seattle, WA. In the situation where appropriate panel data is unavailable, previous studies have conducted Stated Preference surveys to gather data on choices made (as stated by the survey respondents) under specific conditions (Arentze and Molin 2013; Horne et al. 2005; Molin and van Gelder 2008; Washbrook et al. 2006). We follow the same approach in this study.

4.2. Stated Preference Survey

Stated preference data was collected through an online survey in December 2013. Survey respondents included residents of the Portland metropolitan area including the city of Portland and the region surrounding the city center spanning across seven counties[3], which are considered by Metro in their planning activities. Recruitment of the respondents for the survey was managed by Research Now (Research Now 2013), who also guaranteed a distribution across the seven counties.

The survey questionnaire included four sections. First three sections collected data regarding household demographics, current commuting arrangements and responses to a series of questions measuring specific attitudes and perceptions of the respondent. The fourth section of the survey consisted of a choice based conjoint (CBC) study.

In a CBC study, participants are asked to compare a set of alternatives (alternatives defined as bundle of specific attributes) and indicate which alternative they are most likely to choose. Participants are offered multiple choice scenarios in which the levels of attributes are varied to generate multiple versions of specific alternatives. The selection of the attribute levels to present the participants follows traditional principles from design of experiments. Respondents are asked to choose one alternative in each choice scenario. With this approach we observe multiple choices made by each respondent and observe the trade-offs they make when comparing attributes and their levels for different alternatives and can use this information in estimating individual-level partworths.

[3] Clackamas, Washington, Multnomah, Columbia and Yamhill – in the state of Oregon
Clark and Skamania – in the state of Washington

Table 4.1 presents the complete list of attributes and their levels used in this study. Not all attributes are relevant to all alternatives and these are called alternative-specific attributes (e.g., bus fare is an attribute related to the bus mode but not the car mode). Table 4.2 represents the design of CBC tasks.

Table 4.1. Attributes and their levels in the conjoint study

Attributes	Levels		
	1	2	3
Fuel economy (mpg)	25	40	55
Fuel price ($/gal)	3.50	4.50	5.50
Parking charge ($/month)	0	100 (roughly $5/day)	200 (roughly $10/day)
Tri Met fares ($/month) (Regular/Senior or Honored)	75 / 20 (~$3.75/day / $1/day)	100 / 26 (~$5/day / $1.30/day)	125 / 32 (~$6.25/day / $1.60/day)
Free Park & Ride facilities	Available	Unavailable	
Bike & Ride facilities (at nominal charge)	Available	Unavailable	
Real-time info on transit schedule and mobile ticketing	Available	Unavailable	
Bike lanes on busy roads	Unmarked	Marked and separate	
Travel time change relative to current travel time (%, negative means shorter)	-25% of current travel time	0 (remains same)	+25% of current travel time
Availability of sidewalks	Available	Unavailable	

1208 complete responses were received. There was good representation across the seven counties in comparison to the U.S. Census (U.S. Census Bureau 2013). There is some under-representation among the lower income households and over-representation in the higher income groups. Most of the other demographics correspond to the individuals who completed the survey rather than their household. Therefore, these distributions may not be comparable with the corresponding values from census data as done in the case of county-wise population and household income distributions.

Table 4.2. Attributes and the modes used in conjoint study

<table>
<tr><th>Mode</th><th>Car</th><th>Car + Transit</th><th>Transit (+ Walk)</th><th>Bike + Transit</th><th>Bike</th><th>Walking</th></tr>
<tr><td rowspan="10">Attributes</td><td>Fuel economy</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Fuel price</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Parking charge</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>Park and ride facility</td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td>Bike locker facility</td><td></td><td></td></tr>
<tr><td></td><td colspan="3">Transit fare</td><td></td><td></td></tr>
<tr><td></td><td colspan="3">Real-time schedule info and mobile ticketing for transit</td><td></td><td></td></tr>
<tr><td colspan="4">Travel time change (in percent) relative to the currently experienced travel time</td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td colspan="2">Bike lanes</td><td></td></tr>
<tr><td></td><td></td><td>Sidewalks</td><td></td><td></td><td>Sidewalks</td></tr>
</table>

Percentage share of the modes currently used for commuting as reported by the respondents is presented in Table 4.3. Driving a personal vehicle (termed simply as ‘Car’ hereafter) at 81% share is the most popular mode of commuting transportation in this sample. The section on current commuting arrangements also asked the respondents to provide information regarding the major crossroads nearest to both the origin and destination of their daily commute. Usable data was gathered for 30% of the respondents. Latitude-Longitude combinations have been derived for locations of both origin and destination for these respondents.

Table 4.3. Percentage share of commute modes currently used (self-report)

Current Mode Share	
Driving a car	81%
Carpooling	1%
Driving + transit	4%
Biking	2%
Biking + transit	1%
Walking only	4%
Transit	6%
By motorcycle	0.3%

4.3. Model Estimation Results

We begin the estimation process by analyzing the responses to attitude indicator questions in the survey. We perform exploratory factor analysis to identify specific indicators that can be grouped together to derive measurement of a specific attitude. Based on this analysis two statistically significant factors emerged. Based on the attitude indicator questions associated with these factors they were identified as Exercise/Active Lifestyle and Environmental Conservation. The ICLV model was then estimated under the assumption that two factors (associated with specific indicators) influenced the choice of modes for commuting. Table 4.4 presents the estimated parameters of the ICLV model.

Table 4.4. Estimated parameters for the ICLV model

Table 4.4. A) Parameters corresponding to the latent variable sub-model

Parameter Category	Parameter	Estimate	Standard Error
ξ	Exercise - Standard deviation	0.406	0.036
	Environment - Standard deviation	0.208	0.039
α	Exercise – indicator 2	0.692	0.097
	Exercise – indicator 3	1.663	0.165
	Exercise – indicator 4	2.087	0.199
	Environment – indicator 2	0.912	0.257
	Environment – indicator 3*	0.280	0.191
η	Exercise – indicator 1 Standard deviation	1.202	0.025
	Exercise – indicator 2 Standard deviation	0.945	0.020
	Exercise – indicator 3 Standard deviation	0.967	0.021
	Exercise – indicator 4 Standard deviation	0.987	0.023
	Environment – indicator 1 Standard deviation	1.161	0.024
	Environment – indicator 2 Standard deviation	1.320	0.027
	Environment – indicator 3 Standard deviation	1.091	0.022
γ	Exercise – Male*	0.013	0.008
	Environment – Female	0.021	0.010
	Exercise – Male*	0.000	0.013
	Environment – Female*	0.001	0.014

* Not significant at 95% confidence level

Table 4.4. B) Parameters corresponding to the choice sub-model

Parameter Category	Parameter	Estimate	Standard Error
β_1	Car	3.267	0.172
	Car + Transit	1.866	0.291
	Transit	1.171	0.298
	Bike + Transit*	0.100	0.133
	Bike	-3.464	0.475
	mpg level 1	-0.201	0.053
	mpg level 2*	0.077	0.053
	Gas price level 1	0.394	0.053
	Gas price level 2	-0.107	0.053
	Parking cost level 1	1.218	0.057
	Parking cost level 2	-0.127	0.052
	Park-ride level 1 (available)	0.332	0.037
	Bike-locker level 1 (available)	0.144	0.055
	Bus fare level 1	0.377	0.030
	Bus fare level 2*	0.049	0.030
	Real-time info level 1 (available)	0.051	0.022
	Travel time level 1	0.526	0.026
	Travel time level 2*	0.004	0.026
	Bike lane level 1 (unmarked)	-0.605	0.046
	Sidewalk level 1 (available)	0.503	0.032
β_2	Car + Transit – Exercise	4.230	0.500
	Transit – Exercise	9.898	0.971
	Bike + Transit – exercise	10.151	1.016
	Bike – Exercise	15.956	1.620
	Walk – Exercise	17.835	1.723
	Car + Transit – Environment	13.729	2.587
	Transit – Environment	14.315	2.742
	Bike + Transit – Environment	5.185	1.255
	Bike – Environment	-10.861	2.316
	Walk – Environment *	-1.125	1.304

* Not significant at 95% confidence level

Parameters of the HB model are estimated using the standard Bayesian techniques used in Sawtooth (Sawtooth Software 2009). The software tool produces estimates of partworths for each individual participant in the survey. Table 4.5 presents summary (mean and standard deviation) of the estimated individual-level partworths for the HB model.

Table 4.5. Estimated parameters for the HB model

Parameter β	Mean	Standard Deviation
Car	5.944	7.546
Car + Transit	3.118	3.381
Transit	2.286	3.082
Bike + Transit	-2.352	2.477
Bike	-4.930	4.398
mpg level 1	-0.534	0.566
mpg level 2	0.194	0.459
Gas price level 1	0.866	0.908
Gas price level 2	-0.191	0.482
Parking cost level 1	2.781	1.963
Parking cost level 2	-0.158	0.815
Park-ride level 1 (available)	0.885	0.494
Bike-locker level 1 (available)	0.709	0.547
Bus fare level 1	0.962	0.620
Bus fare level 2	0.049	0.396
Real-time info level 1 (available)	0.027	0.358
Travel time level 1	1.093	0.874
Travel time level 2	0.154	0.385
Bike lane level 1 (unmarked)	-0.564	0.782
Sidewalk level 1 (available)	1.132	0.799

Table 4.6. Variables and their levels for base case scenario

Attributes	Levels
Fuel economy (mpg)	25
Fuel price ($/gal)	4.5
Parking charge ($/month)	0
Tri Met fares ($/month)	100
Real-time info on transit schedule and mobile ticketing	Unavailable
Bike lanes on busy roads	Unmarked
Travel time change relative to your current travel time	0 (unchanged)
Availability of sidewalks	Available
Free Park & Ride facilities	Available
Bike & Ride facilities (at nominal charge)	Unavailable

4.4. Counterfactual Scenario Analysis – ICLV Model

Counterfactual scenarios in this section have been developed to assess the effect attitudes or changes in attitudes might have on the mode choice probability of an individual. We present counterfactual estimates based on the responses of a single person who has a particular latent variable profile. In order to make forecasts over a population it is necessary to integrate over the latent variable distribution. The probability P_{ni} of an individual n choosing a travel mode i is given by Equation 4.1 below. β and θ are obtained from Table 4.4, X_i is the set of travel mode attributes for base case scenario as presented in Table 4.6 and $\boldsymbol{F_n}$ is a set of the values of latent variables "Exercise" and "Environment," which vary depending on the scenario as presented in Table 4.7.

$$\boldsymbol{P_{ni}} = \frac{e^{\beta X_i + \theta\left(F_n * X_i^d\right)}}{\sum_i e^{\beta X_i + \theta\left(F_n * X_i^d\right)}}$$

Equation 4.1.

As presented in Table 4.4, the two latent variables included in the ICLV model, Exercise and Environment, are normally distributed among the respondents with zero mean and standard deviation of 0.4 and 0.2 respectively. Counterfactual scenarios are generated to develop unique combinations of both latent variables and for each scenario we calculate the probability of an individual choosing a specific travel mode as presented in Table 4.7. The results indicate that change in attitudes (with all other mode related attributes kept constant) can bring about significant shifts in modes chosen. People who rate high on Exercise show some preference toward manual modes (Bike, Walk and Bike + Transit). People who rate high on Environment show some preference toward transit related modes (Transit, Car + Transit). These results will be discussed in greater detail in the Discussion Section.

Table 4.7. ICLV model counterfactuals for the single-mode scenario

Latent Variable		% Mode Share					
Exercise	Environment	Car	Car + Transit	Transit	Bike + Transit	Bike	Walk
0	0	81	11	7	1	0	0
0.4	0	12	9	51	6	2	20
-0.4	0	97	2	0	0	0	0
0	0.2	22	47	31	1	0	0
0	-0.2	98	1	0	0	0	0

4.5. Counterfactual Scenario Analysis – HB Model

Counterfactual scenarios in this section have been developed to study the effect that change in specific travel mode related attributes has on the probability of choosing a mode. Baseline scenario is based on the currently used modes. For each counterfactual scenario a specific attribute is varied to obtain $\boldsymbol{X_i}$ that is then used in Equation 4.2 to determine the choice probabilities.

$$\boldsymbol{P_{ni} = \frac{e^{\beta_n X_i}}{\sum_i e^{\beta_n X_i}}}$$

Equation 4.2.

Variations in attributes $\boldsymbol{X_i}$ for the counterfactual scenarios can be grouped into two categories – changes in favor of car users (e.g., gas price decreases to \$3.5/gallon from \$4.5/gallon) and changes in favor of transit users (e.g., transit fare reduces to \$75/month from \$100/month). We study the effects these changes have on mode choice probability of an individual who is representative of the entire sample. Further, we also investigate if changes in favor of car users will have any effects on transit users and vice versa, which can give us a handle on unintended consequences of policies. Therefore, this leads to three sets of counterfactual analyses from the point of view of three individuals –

1. Representative of the overall sample (results presented in Table 4.8) – Parameters β_n drawn randomly from all respondents
2. Representative of current Car users (results presented in Table 4.9) – Parameters β_n drawn randomly from a sample of current Car users
3. Representative of current Transit users (results presented in Table 4.10) – Parameters β_n drawn randomly from a sample of current Transit users

Table 4.8. HB counterfactual scenarios based on partworths derived for all individuals

Scenario		% Mode Share					
		Car	Car + Transit	Transit	Bike + Transit	Bike	Walk
	Base Case	64	10	17	1	2	6
Changes in favor of transit users	Gas price increases to $5.5/gallon	56	14	20	1	3	7
	Parking cost increases to $200/month parking	37	25	25	2	4	8
	Transit fare reduces to $75/month	61	12	19	1	2	5
	Real-time information available for transit users	63	11	17	1	2	5
	Bike locker facility available	64	10	16	1	2	6
	Travel time reduced by 25% for transit users	59	13	19	1	2	5
Changes in favor of car users	Transit fare increases to $125/month	68	8	14	1	3	7
	Car fuel economy increases to 55 mpg	67	9	15	1	2	5
	Travel time reduced by 25% for car users	68	8	15	1	2	6

Table 4.9. HB counterfactual scenarios based on partworths derived for current car users

Scenario	Car	Car + Transit	Transit	Bike + Transit	Bike	Walk

Base Case	73	9	11	1	1	5
Gas price increases to $5.5/gallon	65	13	14	1	2	6
Parking cost increases to $200/month	44	25	20	2	3	7
Transit fare reduces to $75/month	70	10	13	1	1	4
Real-time information available for transit users	72	10	11	1	1	5
Bike locker facility available	73	9	11	1	1	5
Travel time reduced by 25% for transit users	68	13	13	1	1	4
All changes occurring simultaneously	41	27	22	2	2	5

Table 4.10. HB counterfactual scenarios based on partworths derived for current transit users

Scenario	Car	Car + Transit	Transit	Bike + Transit	Bike	Walk
Base Case	19	21	55	1	2	3
Transit fare increases to $125/month	22	18	51	1	3	5
Car fuel economy increases to 55 mpg	23	20	52	1	2	2
Travel time reduced by 25% for car users	23	18	52	1	2	3
All changes occurring simultaneously	32	15	45	1	3	4

4.6. Discussion

In this analysis we have considered only a few factors affecting choices. Many design variables such as location of the park and ride lot, frequency of services, time spent to access the stations, etc. will have to be carefully considered. Some of the less tangible factors such as quality of service, comfort and conditions at the park and ride lot will also affect the choice of these alternatives.

4.6.1. Preferences toward multi-mode mobility options

The project had a specific interest in multi-model mobility options. We tested two forms of dual-mobility options - Car + Transit and Bike + Transit. The order of preference for these two multi-mode options in the context of their single mode constituent parts, as evident from both

ICLV and HB model estimates of partworths, is, Car followed by Car + Transit, Transit, Bike + Transit and Bike. Considering the group Car, Car + Transit and Transit we can observe a natural progression with preferences with Car being the most preferred (which is the most used option in the sample) followed by Car + Transit before moving on to Transit. This indicates that the alternative with the combination of two modes has a preference in between the two single modes. We see the same pattern for the case of Transit, Bike + Transit and Bike. The result that multi-mode options are predicted to rank higher than either of their single mode constituents provides promising evidence that multi-mode mobility can play an important role in future mobility choice. It suggests that there is an opportunity to move some Car users to Car + Transit rather than Transit alone.

This phenomenon can also be observed in the counterfactual scenario analyses. For instance, in the scenario based on the HB model where the parking cost increases from zero to $200/month, we observe a significant decrease in the choice probability for Car and a corresponding increase in Transit and Car + Transit choice probability. However, the choice probability for Car + Transit is almost twice that of Transit. In other words, we can say that car users may responded to increases in parking cost by a higher preference for a mode that includes Car as a constituent rather than moving to a completely different mode (transit only).

4.6.2. Role of attitudes

Attitude shifts could play an important role in bringing about changes in the distribution of mode shares. As evident from the analyses based on HB model results, changes in mode related to attributes (e.g., increase in parking cost, increase in transit fare, etc.) do not produce major shifts from motorized modes to Bike or Walk. In other words, for the range of attribute values examined in this study, utility derived by choosing Bike or Walk almost never surpasses that for motorized modes and hence the probability of choosing Bike or Walk is negligible in comparison to motorized modes. However, following the analyses based on ICLV model, having a latent attitude that is positive on Exercise increases the probability of choosing the Bike, Walk and Bike + Transit modes. Therefore, an awareness regarding the benefits of active lifestyle could be effective in increasing the choice probability of non-motorized modes more so than changes in parking costs or transit fare (at least within the range of those attributes used in this study). This brings about the potential for embedding policy models about mobility in other related settings such as work-related wellness programs.

4.6.3. Factors that can bring about a shift away from Cars

It is evident from both the ICLV and HB model estimates of partworths that respondents have the strongest preference towards Car, and their survey responses (revealed preferences) shows that 81% use Car as the exclusive commuting mode. Results from the counterfactual analyses based on the HB model indicate that a few mobility-related attributes may be able to shift choice from Cars to other modes. One such important factor is the parking cost. An increase in parking cost is most effective in bringing about a shift from Cars to Transit and the multi-mode option Cars + Transit. Further, individuals are more sensitive to parking cost than other types of costs such as gas price and bus fares. This is the traditional way to influence choice, i.e., change attributes of the choice options. This complements our finding that there are other routes to changing mobility behavior through changing relevant attitudes.

4.6.4. Sensitivity to changes in cross-mode attributes

"Cross-mode attributes" refer to the attributes of modes excluding the mode currently used by an individual. Change in parking cost for Car observed by a current transit user would be an example of change in cross-mode attributes. We are able to understand how individuals respond to changes in cross-mode attributes by performing HB model based counterfactual analyses separately for transit users and car users. Increasing fuel economy and decreasing travel time for Car users are examples of changes that are observed to have somewhat of a significant effect. We observe that an increase in the fuel economy of Cars and decrease in travel time for car users could increase the probability of current transit users to shift to choosing Cars. Though the effect is not very significant, it nevertheless indicates the potential for some unintended consequences of strategies aiming to improve automobile fuel economy and relieving congestion.

Chapter 5

Summary and future work

This dissertation presents models of electricity production and commuting mode choices that can be used to examine marginal effects and change in CO_2 emissions in response to specific GHG mitigation policies. Application of the dispatch model in decision making was demonstrated through an analysis of a part of the EPA's CPP aimed at reducing GHG emissions from electricity production through increasing the utilization of existing NG generating units. Commuter mode choice models were used to evaluate the potential for reducing personal vehicle miles traveled in Portland metro area through increased use of the existing public transportation infrastructure.

5.1. Electricity Production System Modeling

One of the significant contributions of the electricity dispatch modeling work presented in this dissertation is the methods to incorporate major operating constraints of the electricity production system using publicly available data. Validation of the model was performed by comparing the estimates of electricity production by fuel type with observed values. Validation of the model demonstrates that the exclusion of operating constraints leads to systematic errors in the estimates of amount of electricity production derived from each type of generating unit and consequently generates erroneous estimates of CO_2 emissions.

Application of the model in evaluating the potential for CO_2 reduction from increased utilization of existing NG generating units in ERCOT further demonstrates the value of using an operating constraint based dispatch model. The study finds that the amount of reduction in CO_2 emissions that can be achieved is about 27% lower than the estimates produced by the models that did not incorporate operating constraints. Minimum operating limits for coal units and the imperfect substitution between coal and NG units were found to significantly restrict the extent to which production from coal units could be substituted by NG units. This insight into the dynamics of the electricity production system wouldn't have been possible with the least-cost based dispatch models.

Observations from this analysis indicate a need for increased flexibility in the system for policies such as carbon pricing to be effective. This increased flexibility of the grid could also enable greater integration of intermittent renewable resources such as wind and solar without adversely affecting the system reliability. In fact, the EPA also proposes increasing the generation capacity from renewable resources as one of the four strategies to reduce CO_2 emissions under the CPP. Future research can explore the extent to which these two strategies are complimentary in nature and, whether design and adoption of these strategies in a synchronized manner could lead to more cost-effective compliance of CO_2 reduction targets under CPP.

The work presented in this dissertation focused on ERCOT to a large extent and demonstrated the advantages of developing and using operating constraint based dispatch models. Though the model performed reasonably well in estimating the utilization of specific generating units for electricity production in NYISO, some challenges remain in expanding the model applicability in other PCAs. For instance, NYISO imports significant amount of electricity to meet the demand for electricity. The model could be further improved by incorporating methods to model electricity production in neighboring PCAs which regularly import/export significant amounts of power. Since CO_2 is a global GHG, any reduction outside of a PCA's boundaries is equally beneficial. Models of joint dispatch in two PCAs taking into account the import/export of power could open additional opportunities for cost-effective CO_2 reduction strategies.

Regions such as New York, ISO are subject to significant transmission congestion issues unlike ERCOT. Constraints arising from transmission congestion may lead to unexpected patterns in the utilization of existing generating units. Efforts in the future could be focused on understanding the impact of transmission congestion and developing methods to incorporate congestion as an operating constraint.

5.2. Choice Modeling for Commuting Mode Choices

The commuting mode choice study presented in this dissertation takes a closer look at one aspect of a complex urban transportation system. The ultimate goal of the choice modeling effort is to enable the quantification of change in CO_2 emissions resulting from a shift in mode choices. A HB model capable of estimating individual-level partworths is utilized to aid in this effort. Such micro level analysis, though data-intensive, has many advantages and opens up opportunities to increase accuracy of transportation planning forecasting activities, especially when geospatial data corresponding to major transportation infrastructure is available. For instance, the city of Portland maintains an extensive geospatial database of its public transportation infrastructure (TriMet 2015). The dataset includes latitude-longitude coordinates of all transit routes, transit stations along these routes and park and ride lots. Individual-level mode choice predictions (enabled by the HB model) could be coupled with this geospatial data using suitable GIS tools to more accurately estimate change in distances traveled using specific modes. This capability is particularly useful for determining change in vehicle miles traveled in case of multi-mode options where distances traveled using constituent modes is uncertain without the information on the origin and destination of the commuter and the location of the park and ride lots. This has been a limitation of several studies in the past that have attempted to quantify reduction in CO_2 emissions from shifting miles traveled from Car to some multi-mode option (Horne et al. 2005; Parshall et al. 2010; Poudenx 2008).

The outcomes of the counterfactual analyses based on ICLV and HB models demonstrate that the mode choice behavior can be influenced through two mechanisms – by varying the attributes associated with each mode and by changing individuals' attitudes which in turn change how individuals value different modes and their attributes. Similar effects have been observed in the case of public health policy measures directed towards reducing smoking. (Hu, Sung, and Keeler 1995) analyzed the effectiveness of Proposition 99, the California Tobacco Tax and Health Promotion Act of 1988. Proposition 99 raised the tax on each package of cigarettes by 25 cents and allocated 20% of the revenue generated through taxation to be spent on anti-smoking multimedia campaigns and various community intervention programs through local health departments and public schools to change attitudes toward smoking. The study concludes that both taxation and media campaigns were successful in reducing the sales of cigarettes in California. The recently published U.S. Surgeon General's report (HHS 2014) also finds that taxation and anti-smoking media campaigns are effective at reducing smoking. The Surgeon General's report also notes that the media campaigns have been effective at preventing the initiation of tobacco use among youths and adults. Change in mode choices may most likely be realized more quickly by varying mode attributes while change in attitudes through various educational/awareness programs may take longer to deliver outcomes. Public awareness campaigns could be effective at influencing first-time commuters to reconsider driving as a default commuting option. How effective can combined strategies be at affecting mode choices is an important question that needs further attention.

While the mode choice models have been discussed in the context of GHG emissions mitigation, the methods are applicable for examining other urban travel related issues such as localized air pollution and congestion. In fact, GHG emissions reduction and other city planning objectives could be complimentary in nature. Model developed in this dissertation could be applicable in identifying opportunities to jointly address various city planning issues.

APPENDICES

Appendix 1. Modeling approach for scheduling maintenance outages for coal and oil/NG units

The process begins with the analysis of the hourly demand data to determine the time frame during which the outages are to be scheduled. The demand data for both spring and fall time frames considered separately are subject to quadratic approximation to determine a best fit quadratic curve of the form (Equation 5.1) that captures general seasonal trend in demand values.

$$y = ax^2 + bx + c \qquad \text{Equation 5.1.}$$

Where,

x = {set of serial hour numbers}

y = {demand values at respective hour numbers}

These curves provide with reference points and boundaries within which outages are scheduled as shown by the schematic in Figure 5.1. We begin with the point (x_0, y_0) during spring where the value of y is the least and center the outage of the largest unit at the corresponding hour x_0. Considering point (x_0, y_0) as reference we can determine the origin of the first outage (x_1, y_1) as shown below. Duration of outage for each unit is determined from (NERC 2010) based on fuel consumed (coal, oil or NG), unit size, prime mover type (steam, gas turbine and combined cycle gas turbine) and age.

$x_1 = x_0 - (out\_dur / 2)$

Where, *out_dur = duration of outage specific to unit size, fuel, age and prime mover type*

$y_1 = f(x_1)$

We then move to the second curve (fall) and locate the outage of the second largest unit in the same manner. The outage of third largest unit will be again scheduled in spring starting at (x_2, y_2). The reason for going back and forth between spring and fall with each traverse is to achieve a balanced distribution of capacity loss between two seasons. The point (x_2, y_2) can be determined as shown below.

$y_2 = y_1 + Cap_1$

Where, Cap_1 = nameplate capacity of unit 1

$f'(y_2) = \{x_2, x_3\}$

The solution to the above equation results in two values x_2 and x_3. The distance between these points determines the number of outages that can be scheduled. Precisely, $(x_3 - x_2)/ out\_dur$ rounded to the nearest integer will be the number of units for which outage can be scheduled during this time interval. We move back and forth between spring and fall curves following the allocation process described above until outages for all the units have been scheduled.

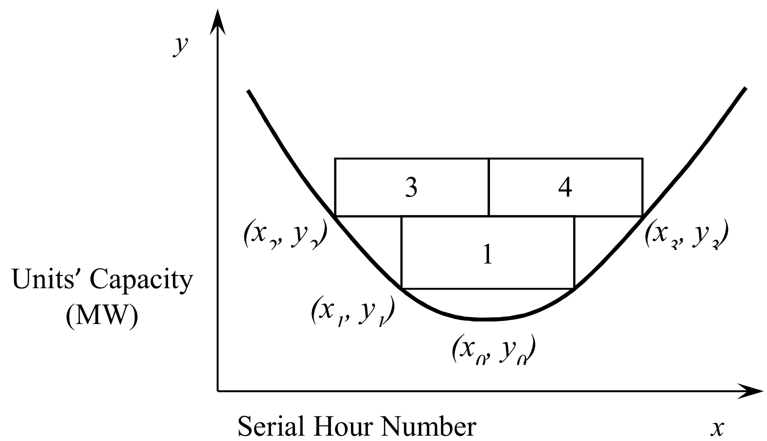

Figure 5.1. Schematic for scheduling maintenance outages

Appendix 2. Approach for modeling forced outage and forced derating for coal and oil/NG units

Following the data and analysis presented in (ORNL 1986) it can be observed that the Forced Outage Rate (FOR) (i.e., the percentage of time per year that the unit is off-line) for a given generating unit is strongly correlated with the number of years it has been operated. Using this correlation, a linear formulation is derived and FOR is determined from (ORNL 1986) based on generator age and size (nameplate capacity). Given the FOR percentage and the assumed length of time for each outages, the number of outages per year can be determined. In our forced outage model, these outages for a specific unit are imposed randomly throughout the year in a manner which avoids its scheduled maintenance.

We follow the same approach as described above while modeling forced outages for oil/NG units. Outage durations and the number of instances of outages for oil/NG units are different from coal units and are determined from (NERC 2010) specific for unit size, prime mover type (steam, gas turbine and combined cycle gas turbine).

Following a similar approach and data source (ORNL 1986), we estimate a relationship between the unit's age and Forced Derating Rate (FDR). Using this correlation we estimate the percentage of capacity lost annually due to forced derating and uniformly discount the production capacity of each unit by this percentage.

Appendix 3. Modeling ancillary services in the context of operations in ERCOT

Ancillary Services (AS) are defined by the U.S. Federal Energy Regulatory Commission (FERC) as, "those services necessary to support the transmission of electric power from seller to purchaser given the obligations of control areas and transmitting utilities within those control areas to maintain reliable operations of the interconnected transmission system" (FERC 2015). Ancillary services consist of several categories of services to resolve issues ranging from instantaneous balance of demand and production of electricity to restarting the system after a blackout. Modeling all aspects of the AS market segment within a PCA is beyond the scope of this work.

Regulating and Responsive Reserve (RR) services are the two categories of AS that need to be considered because they directly influence marginal production and CO_2 emissions by requiring a significant amount of NG generating capacity to be online at all times. Regulating services are intended to maintain the system frequency at the nominal value of 60Hz under normal operating conditions of the grid. RR services are intended to restore a balance between demand and production in case of an unexpected loss of generation capacity (contingency events).

Regulating services are provided by generating units with high ramp rates and that are online and operating at some part load. RR services are provided by online generation resources with high ramp rates and load resources, known as Load acting as Resource (LaaR), to which supply can be curtailed temporarily (ERCOT 2009). Both of these services require generating resources with high ramping capabilities to be online and operating at part loads. NG and hydro units qualify for this purpose (ERCOT 2009), but with negligible hydro capacity in ERCOT, NG units almost always provide AS. Therefore, a significant amount of NG generating capacity is maintained online at all hours and this has a direct impact on the utilization of other resource types and overall emissions from electricity production.

In 2004 ERCOT had a requirement of 2300 MW of RR across all hours (Potomac Economics 2005). Up to 50% of this requirement could be met by LaaR (ERCOT 2009). Regulating services are further grouped into two categories – Regulation-Up and Regulation-Down services. Regulation-Up and Regulation-Down requirements are determined by ERCOT at each hour after evaluating the instantaneous operating conditions (demand forecast, forecast of production from wind resources, etc.). Average Regulation-Up and Regulation-Down service requirements in 2004 were 875 MW and 925 MW (Potomac Economics 2005). Table 5.1 summarizes the quantities of each type of AS that need to be procured on an hourly basis and some limitations on the generating units that are committing to provide these AS.

Data on the procurement of AS on an hourly basis is available from ERCOT (ERCOT 2015b). These data include a list of generating units and the amount of generating capacity committed by these units towards various AS. We observe that NGCC and GT types NG units mainly supply RR and Regulation Services. Further, it is also observed that a unit can commit to more than one type of AS at a time. However, characteristics such as ramp rates of the units and the factors responsible for committing a specific amount of capacity towards AS are not available from this data source. Therefore, some assumptions have been made during the modeling of AS and they are listed below.

Table 5.1. Ancillary service requirements in ERCOT in 2004

Ancillary Service Type		Quantity Required (Potomac Economics 2005)	Limitations on the Units (ERCOT 2013)
Responsive Reserve	Load acting as Resource	1150 MW	
	From generation	1150 MW	Up to 20% of unit's maximum capacity can be committed
Regulation Service	Regulation-Up	875 MW (on average in 2004)	Amount of regulation service that each unit can commit to is limited to - Ramp-up rate * 5[4] * 0.7[5]
	Regulation-Down	925 MW (on average in 2004)	Amount of regulation service that each unit can commit to is limited to - Ramp-down rate * 5 * 0.7

Important Modeling Assumptions:

- Quantity of Regulation-Up and Regulation-Down services required on hourly basis is not known. Annual average Regulation-Up and Regulation-Down services acquired in 2004 is known from (Potomac Economics 2005) . These values are used in the model across all hours.
- Units are assumed to commit to either Regulation-Up or RR. Both these AS utilize the ramping up capability of the unit when deployed. In reality, the units decide to commit a specific amount of ramping capacity towards either Regulation-Up or RR depending on the market prices while making sure that their collective commitment does not exceed the total ramp up capacity. Instead of modeling this complex decision making process, we

[4] This is the amount of capacity that an unit can ramp up/down to in 5 minutes. The system operator performs balancing of load and generation every 5 minutes. Regulation services are required to automatically balance load and generation and maintain a system-wide frequency of 60 Hz within the period of 5 minutes (ERCOT 2013).

[5] The factor 0.7 limits the amount of ramping capability of a unit committed to Regulation service. The unit can utilize 30% of its ramping capability during regular energy production (ERCOT 2013).

follow an approach based on the assumption that units commit their maximum allowed ramping capability to either Regulation-Up or RR service at any given point of time.

- The units that are committing to either RR or regulating service are assumed to be operating at their minimum operating limit. The minimum operating limit for NGCC and GT units is assumed to be 50% of maximum generation capacity (Black & Veatch 2012). Spare capacity, excluding minimum operation and any commitment to AS, is available to be dispatched regularly along with other resources.
- Units are assumed to have the same up and down ramp rate. Ramp rate is assumed to be 5% of a unit's capacity per minute for NGCC units and 8% for GT units (Black & Veatch 2012).

Hourly AS Modeling Algorithm:

- NGCC and GT units are randomly selected to provide AS. Unless the units are unavailable due to scheduled or forced outage, same units will be used for AS throughout the year.
- 20% of the capacity of the first unit in the list is committed to RR. 50% of the capacity is locked in to the minimum operation of the unit. Min(30% capacity, ramp-down rate*5*0.7) is committed to Regulation-Down service.
- We move down the list of units till both RR and Regulation-Down requirements are met.
- Units that have not been committed to RR are used to supply Regulation-Up service. 50% of the capacity is locked in to the minimum operation of the unit. Min(50% capacity, ramp-up rate*5*0.7) is committed to Regulation-Up service.
- We move down the list of units till Regulation-Up requirement is also met.

Units that have been committed to any type of AS will have to be online and operating at the minimum operating limit (before dispatching the spare capacity). In addition, the Regulation-Down service requires some units to maintain a minimum amount of production at all times. Given the AS service requirements in 2004 we observe that NG units produce on average about 5000 MW of electricity across all hours. This behavior is evident from the Figure 5.2 below where coal units can be observed to reduce their output to accommodate more flexible but more expensive NG units providing AS (Smitherman 2009).

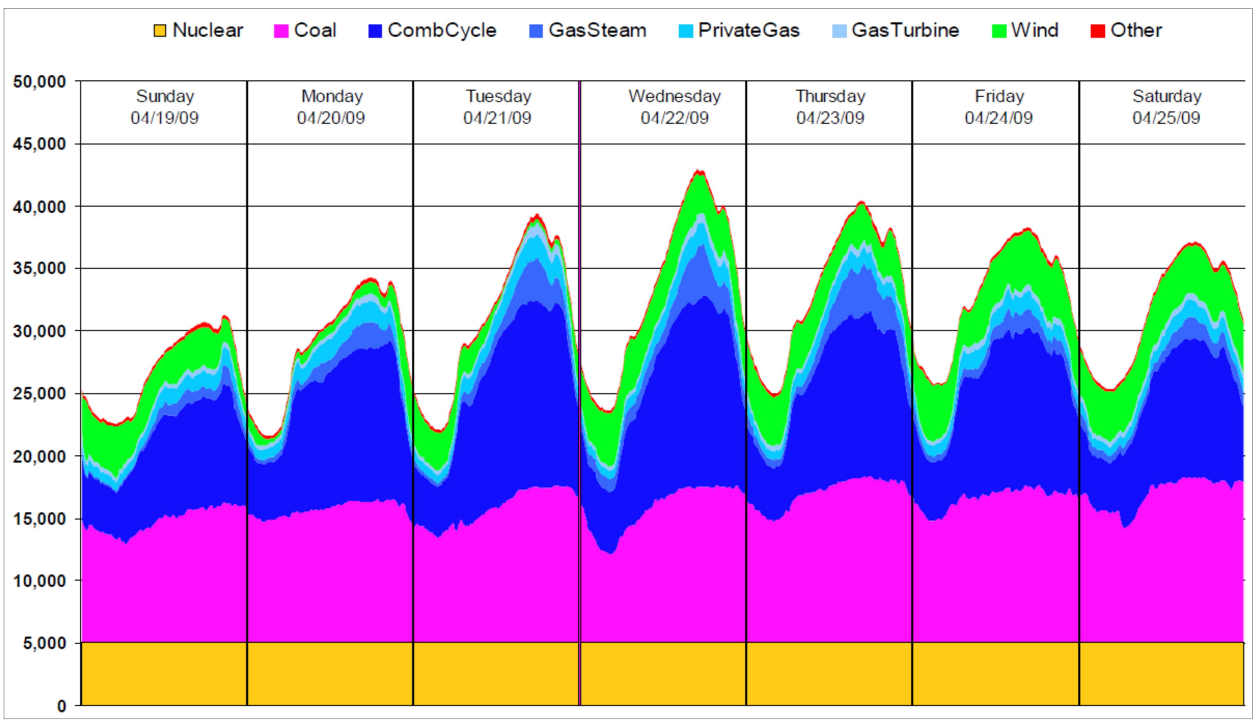

Figure 5.2. ERCOT typical spring week generation by fuel type (Smitherman 2009)

In 2012 the RR requirement in ERCOT was increased from 2300MW to 2800MW. Up to 50% of this requirement could still be met by LaaR (ERCOT 2013)**.** Average Regulation-Up and Regulation-Down service requirements in 2012 were 518 MW and 438 MW (Potomac

Economics 2013). Table 5.2 summarizes the quantities of each type of AS procured and some limitations on the generating units that are committing to provide these AS.

Table 5.2. Ancillary service requirements in ERCOT in 2012

<table>
<tr><th colspan="2">Ancillary Service Type</th><th>Quantity Required
(Potomac Economics 2005)</th><th>Limitations on the Units
(ERCOT 2013)</th></tr>
<tr><td rowspan="2">Responsive Reserve</td><td>Load acting as Resource</td><td>1400 MW</td><td></td></tr>
<tr><td>From generation</td><td>1400 MW</td><td>Up to 20% of unit’s maximum capacity can be committed</td></tr>
<tr><td rowspan="2">Regulation Service</td><td>Regulation-Up</td><td>512 MW (on average in 2012)</td><td>Amount of regulation service that each unit can commit to is limited to - Ramp-up rate * 5 * 0.7</td></tr>
<tr><td>Regulation-Down</td><td>438 MW (on average in 2012)</td><td>Amount of regulation service that each unit can commit to is limited to - Ramp-down rate * 5 * 0.7</td></tr>
</table>

Appendix 4. Determination of hourly production targets for coal fleet

The following Figure 5.3 presents the production scenario for a hypothetical day. Points A and B represent time of the day with minimum and maximum demand values. At point A, maximum available coal capacity combined with production from resource lower in the dispatch order (nuclear, hydro and other renewable resources) exceeds the total demand not leaving room for production from SR supplying oil/NG units. In this situation production from coal will be reduced since it is the most expensive resource type online. Production target for the coal fleet at point A is thus determined as shown in Equation 5.2.

$$\text{Coal Production}_{A} = D_{A} - (P_{\text{Nulcear}} + P_{\text{Hydro}} + P_{\text{CHP}} + P_{\text{Other renewables}}) - (2300 / (2{*}0.2)) \quad \textbf{Equation 5.2.}$$

Where,

D_A = *Demand at point A;*

$P_{Nulcear}$ = *Production from nuclear units;*

P_{Hydro} = *Production from hydro units;*

P_{CHP} = *Production from NG CHP units;*

$P_{Other\ renewables}$ = *Production from other renewables such as wind, biomass, solar, etc.*

At point B the demand value is high enough so that the need for production from NG units exceeds SR mandate (5750 MW). There is no need to cut back coal production to accommodate NG resources. Therefore, production target for coal fleet is set to its maximum available instantaneous capacity (after considering maintenance, forced outage, etc.) as shown in Equation 5.3.

$$\text{Coal Production}_B = \text{Maximum Available Coal Capacity}_B$$

Equation 5.3.

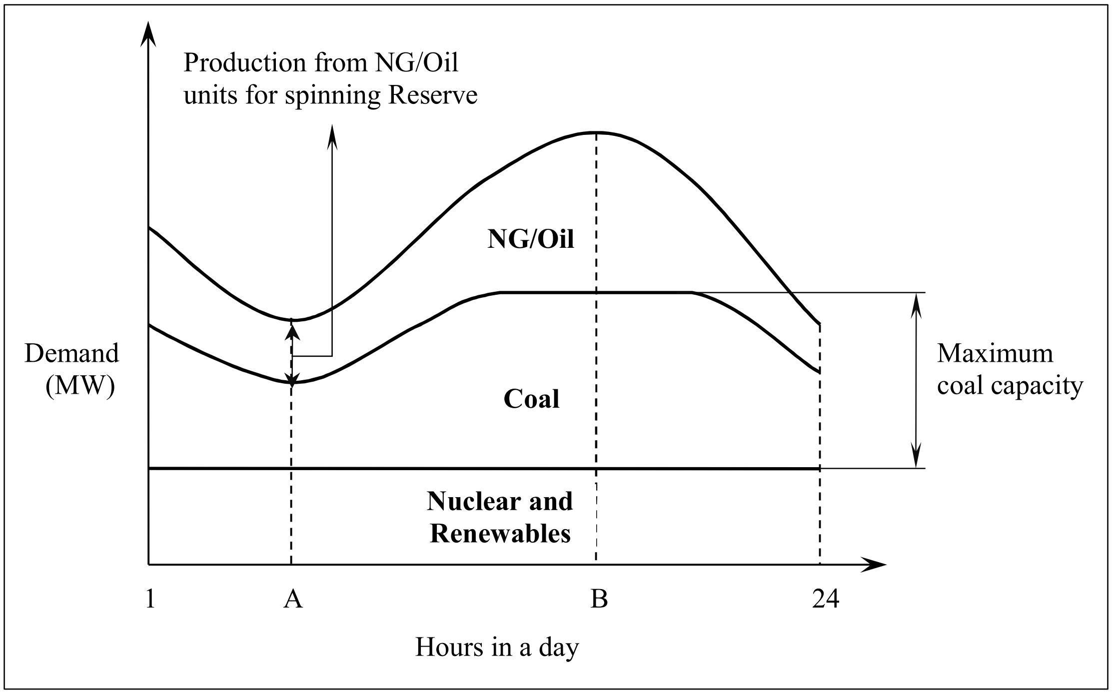

Figure 5.3. Schematic diagram used to determine hourly production target for coal resources

Appendix 5. Determination of hourly production targets for coal and NGCC fleet

The following Figure 5.4 presents the production scenario for a hypothetical day. Points A and B represent time of the day with minimum and maximum demand values. At point A, maximum available capacity from coal and NGCC units combined with production from resource lower in the dispatch order (nuclear, wind, NG CHP and other renewable resources) exceeds the total demand not leaving room for production from SR supplying NG units. In this situation production from coal and NGCC units will be curtailed just enough to make room for SR units. Production target for the coal and NGCC fleet at point A is thus determined as shown in Equation 5.4.

$$\boldsymbol{Coal + NGCC\ Target_A = D_A - (P_{Nuclear} + P_{Wind} + P_{CHP} + P_{Other\ renewables}) - \left(\frac{2300}{2*0.2}\right)}$$

Equation 5.4.

Where,

D_A = *Demand at point A;*

$P_{Nulcear}$ = *Production from nuclear units;*

P_{Wind} = *Production from wind units;*

P_{CHP} = *Production from NG CHP units;*

$P_{Other\ renewables}$ = *Production from other renewables such as hydro, biomass, solar, etc.*

At point B the demand value is high enough that coal and NGCC units could operate at maximum available capacity given a certain production from SR supplying NG units. Therefore, production target for coal and NGCC fleet is set to its maximum available instantaneous capacity (after considering maintenance, forced outage and forced derating) as shown in Equation 5.5.

$$\boldsymbol{Coal + NGCC\ Target_B = \ Maximum\ Available\ Coal\ and\ NGCC\ Capacity_B}$$

Equation 5.5.

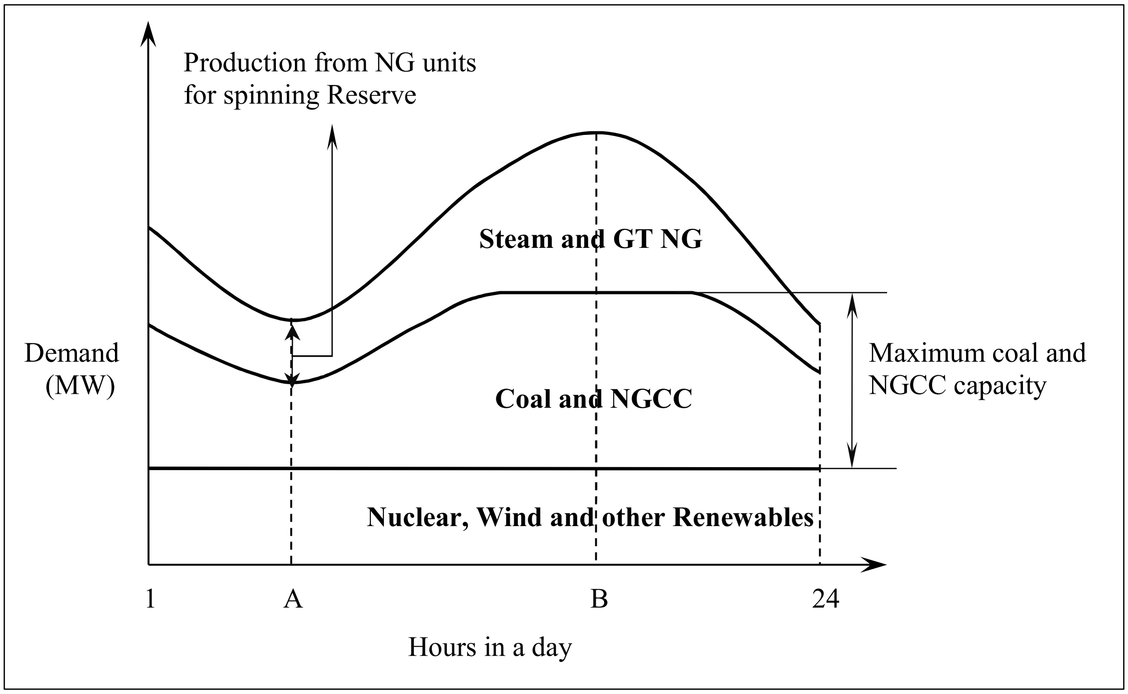

Figure 5.4. Schematic diagram used to determine hourly production target for coal and NGCC resources

Appendix 6. Case study – ERCOT 2004

Figure 5.5.A presents hourly production by fuel type estimated by the OC Model for the entire year 2004. Nuclear and coal units form the bulk of the baseload supply while NG units are deployed to supply the rest of the demand. A negligible amount of energy is derived from hydro and other renewable units. For comparison, Figure 5.5.B provides hourly generation as would be determined by a least cost based dispatch model with no OCs considered (referred to as NOC Model).

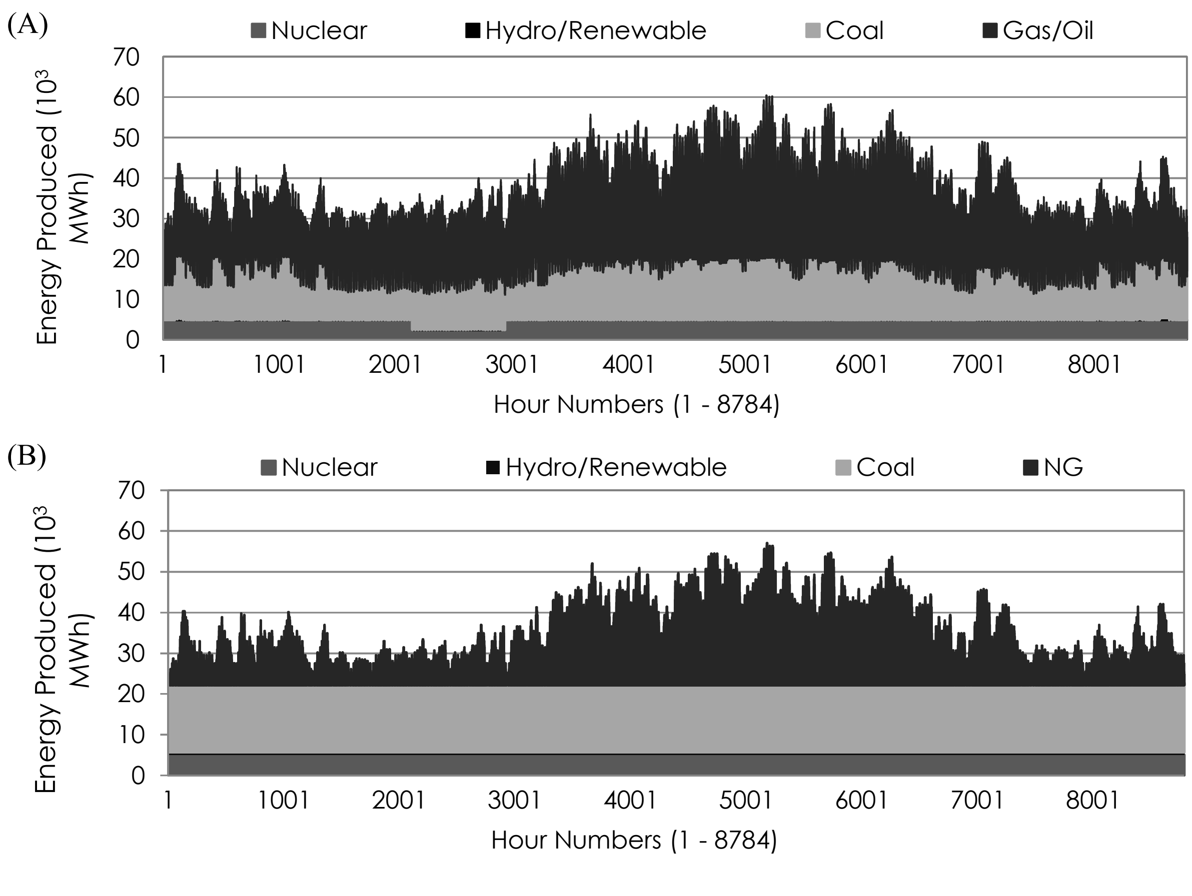

Figure 5.5. ERCOT 2004 Instantaneous resource mix estimates (A). As predicted by OC Model (B). As predicted by NOC Model

Next, we check the CO_2 emission values estimated by the OC Model relative to values available for 2004 (U.S. EPA. 2009) in Table 5.3. The OC model estimates emissions from coal and NG units within 1%. The NOC Model over-estimates emissions from coal units by 24% and underestimates emissions from NG units by 48%.

Table 5.3. Estimated total annual emissions with OC and NOC Model for ERCOT

	Coal		NG	
	CO_2 Emissions (Million Short Tons)	%ΔE	CO_2 Emissions (Million Short Tons)	%ΔE
Actual	134	-	82	-
OC Model	135	1%	82	0%
NOC Model	166	24%	43	- 48%

% ΔE = percentage change between total estimated emissions (with OC and NOC Model) and actual total emissions

In Figure 5.6.A we compare the aggregate annual production estimated by the OC Model with actual aggregate annual production. It is observed that estimates from Figure 5.5.A, aggregated at the annual level in Figure 5.6.A, are within +/- 5% of the actual production resource mix values provided by (U.S. EIA 2010a). Estimates from NOC Model (Figure 5.5.B) aggregated at the annual level has variations ranging from 12-32% depending on the fuel type.

Next, Figure 5.6 B, C and D compare aggregated monthly production estimates from the OC Model with actual aggregated monthly production values disaggregated by fuel type as derived from (U.S. EIA 2010a). It is observed that the OC Model estimates for nuclear and coal are within +/- 10%. They are usually overestimates, which leads to an underestimation of production from NG units due to their location in the dispatch order. The NG estimates are within +/- 10% except for two cases (-11% in March and -10% in November). These higher variations in spring and fall are likely due to OC Model assumptions about when maintenance occurred relative to the exact time maintenance occurred. Monthly production estimates from NOC Model show deviations up to 107% for nuclear, 45% for coal, and 72% for NG.

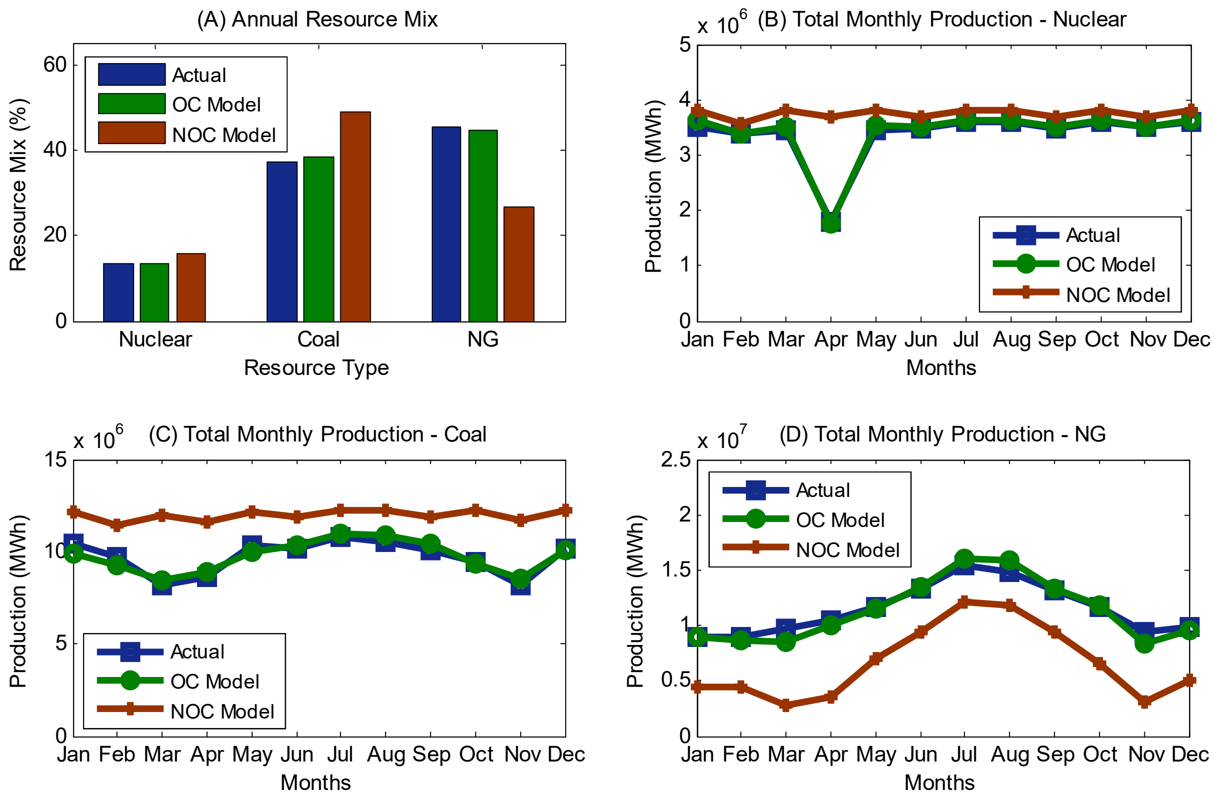

Figure 5.6. ERCOT 2004 Aggregate annual and monthly production estimates

Appendix 7. Resource mix, CO_2 emissions and cost of electricity production at various levels of carbon prices

Table 5.4. Resource mix, CO2 emissions and cost of electricity production at various levels of carbon prices

Carbon Price ($/ton CO_2)	Resource Mix (%)				CO_2 Emissions (Million Short Tons)			Reduction in CO_2 Emissions (%)	Cost from Fuel Consumption (Million USD)	Cost from Carbon Price (Million USD)	Total Cost of Electricity Production (Million USD)	Cost of CO_2 Reduction w/o Carbon Price ($/ton CO_2 reduced)	Cost of CO_2 Reduction w/ Carbon Price ($/ton CO_2 reduced)
	Nuclear	Wind	Coal	NG	Coal	NG	Total						
0	12	10	38	40	139	61	200[0]	-	5765[0]	0	5765[0]	-	-
5	12	10	35	42	130	64	194	-3%	5779	905	6684	2	155
10	12	10	32	46	118	68	187	-7%	5836	1734	7570	5	134
15	12	10	30	48	110	72	181	-9%	5902	2521	8423	7	141
20	12	10	29	49	105	73	179[20]	-11%	5943[20]	3313	9256[20]	8	164
25	12	10	28	49	105	74	178	-11%	5953	4130	10082	9	199
30	12	10	28	50	104	74	178	-11%	5957	4950	10908	9	235
35	12	10	28	50	104	74	178	-11%	5961	5772	11732	9	271

[0] – Corresponds to the baseline scenario with \$0/ton CO_2 of carbon price

[20] – Corresponds to the scenario with \$20/ton CO_2 of carbon price

$$\textit{Cost of } CO_2 \textit{ reduction with carbon price} = \frac{\textit{Total cost of electricity production}^{20} - \textit{Total cosst of electricity production}^{0}}{\textit{Total } CO_2 \textit{ emissions}^{0} - \textit{Total } CO_2 \textit{ emissions}^{20}}$$

$$\textit{Cost of } CO_2 \textit{ reduction} = \frac{9256-576}{200-179} = 164 \frac{\$}{ton\ CO_2}$$

$$\textit{Cost of } CO_2 \textit{ reduction without carbon price} = \frac{\textit{Cost from fuel consumption}^{20} - \textit{Cost from fuel consumption}^{0}}{\textit{Total } CO_2 \textit{ emissions}^{0} - \textit{Total } CO_2 \textit{ emissions}^{20}}$$

$$\textit{Cost of } CO_2 \textit{ reduction} = \frac{5943-576}{200-179} = 8 \frac{\$}{ton\ CO_2}$$

Appendix 8. Sensitivity of CO_2 reduction under carbon pricing to variation in fuel prices

We determined that a carbon price of \$20/ton CO_2 leads to 11% reduction in CO_2 emissions compared to the 2013 levels. In the following analysis we study how the variation in fuel prices affects CO_2 emissions achieved once a specific carbon price is set. The baseline scenario for this analysis is the year 2013 during which coal prices were \$1.97/MMBTu and NG prices were \$3.86/MMBTu on average. For this analysis both coal and NG prices are varied above and below 2013 levels. Coal prices are varied from \$1 – 4/MMBTu in steps of \$0.5/MMBTu and NG prices are varied from \$2 – 8/MMBTu in steps of \$1/MMBTu. Change in emissions relative to the levels in the baseline case is determined at various combinations of coal and NG prices. Results from this analysis are presented in Table 5.5. Carbon prices increase the utilization of NG units by making them cheaper to operate relative to coal units. This effect created by carbon price is reduced when NG prices increase relative to coal or when coal prices decrease relative to NG.

Table 5.5. Percentage change in CO_2 emissions under carbon pricing (\$20/ton CO_2) and varying fuel prices

		Coal Prices (\$/MMBTu)						
		1	1.5	2	2.5	3	3.5	4
NG Prices (\$/MMBTu)	2	-11%	-11%	-11%	-11%	-11%	-11%	-11%
	3	-10%	-11%	-11%	-11%	-11%	-11%	-11%
	4	-3%	-8%	-11%	-11%	-11%	-11%	-11%
	5	1%	-2%	-6%	-10%	-11%	-11%	-11%
	6	2%	0%	-2%	-4%	-9%	-11%	-11%
	7	2%	2%	0%	-1%	-4%	-7%	-10%
	8	2%	2%	2%	0%	-1%	-3%	-6%

Change in CO_2 Emissions (%)

2%

-1%

-3%

-9%

-11%

Appendix 9. Analysis of the role of OCs in coal and NG units' re-dispatch

In this section we discusses the analysis of the influence of each OC on the dispatch process at carbon price level of $20/ton CO_2 which corresponds to a maximum displacement of coal production and maximum reduction in CO_2 emissions. Under this scenario resource mix and CO_2 emission estimates are obtained using OC2 Model by excluding consideration of one OC at a time.

Table 5.6 presents the results from this analysis. It should be noted that the following analysis was conducted to study the role of OCs under a carbon price scenario. Conclusions should not be drawn regarding the significance of OCs in the overall OC2 Model.

Table 5.6: Effect of each OC on resource mix and CO_2 emissions from coal and NG units under a carbon pricing

	Resource Mix (%)		CO_2 Emissions			
	Coal	NG	Coal Units (Million Short Tons)	% Change from baseline	NG Units (Million Short Tons)	% Change from baseline
Carbon price $20/ton CO_2 (baseline)	29	49	105	-	73	-
Season specific rated capacity	30	48	109	3%	72	-2%
Scheduled Outages	30	47	109	3%	72	-3%
Forced Outages	30	48	111	6%	72	-2%
Ancillary services	26	52	95	-10%	73	-1%
Coal-NG imperfect competition	20	58	74	-30%	87	18%
Coal unit lower operation limit	23	55	83	-21%	83	13%
Wind simulation	29	48	108	2%	73	0%
NOC* Model	9	67	31	-70%	94	28%

* No operating constraints considered in the model (NOC Model)

Appendix 10. Attitude indicator questions

List of survey questions used to collect data on respondents' attitude related behaviour indicators:

1. I do exercise to be fit.
2. I enjoy risky and exciting events.
3. Environmental regulations hurt the economy.
4. I don't like crowds.
5. I interact with others via social networking.
6. I set the thermostat low in winter and high in summer to conserve energy.
7. I value privacy and comfort of car driving more than the health and environmental benefit of biking and walking.
8. For food, given a choice, I would choose fruits and vegetables over meat.
9. I would definitely wear a helmet when biking.
10. Scientific evidence is lacking that fossil fuel burning contributes to global warming.
11. I feel safer and more secure in a car than on a bus or train.
12. I would not ride a bike on unprotected bike routes that share with heavy vehicle traffic.
13. If I have a choice, I would rather walk, bike, and/or ride transit to stay healthy and reduce pollutant and CO_2 emissions.
14. I can get some work done while riding transit.
15. Knowing how long my trip will take is most important for me regardless of all other factors.

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