EVALUATING HIGH PENETRATION OF INTERMITTENT RENEWABLE ELECTRICITY POLICIES

by

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Dedicated to the late Dr. Wally Tyner

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ABSTRACT

Wind and solar generation are intermittent generation sources. System integration costs include the costs of spinning reserves, increased transmission costs and storage costs. The overarching research problem examines evaluation of different policies that lead to high penetration of intermittent renewable electricity sources. The first research question examined the emissions reduction benefits and system integration costs of policy mandates for high penetration of intermittent renewable electricity technologies for Midcontinent Independent System Operator (MISO). The second research question examines the total systems costs of mandates for renewable electricity generation and a carbon tax using a TIMES model for MISO. The third research question examined the emissions and costs of policy mandates for high penetration of wind and solar electricity generation technologies for MISO when short-term operational constraints are considered. TIMES minimizes the total system cost subject to constraints of capacity activity, commodity use, satisfying demand, and peaking reserve. The US EPA 9 region model contains end use technologies for commercial, industrial, residential and transport sectors. The technologies that do not serve end use demands with electricity have been removed. The number of time slices which are the time divisions of the year was increased to 288 to help capture wind and solar generation dynamics at higher levels of penetration and help better understand spinning reserves requirements and costs. Based on the candidate sites for solar and wind generation, the costs include expected transmission costs, and any investment and production costs specific to the candidate sites costs.

The results show that as the level of the mandate for wind and solar generation increases, their costs increased. Emissions saving from the mandates were converted to reductions in the Social Costs of Emissions (SCE) (See Section 2.4.4 for the definition) to compare system cost to with the savings in SCE. The savings in the SCE increase as the level of the mandate increases. However, the savings in SCE do not justify the system cost increases associated with the mandates.

The carbon tax and mandate policies implemented held the overall emission reductions constant where a 35% reduction of CO2e emissions from 2020 levels by 2050 in compared to the reference scenario. The carbon tax (Policy I) had the lower of Levelized Marginal Cost of Electricity (LMCOE) (discounted value of generation for a year based on the generation weighted Marginal Cost of Electricity), while the mandate (Policy II) had the higher of LMCOE. Similarly,

Policy I had the lowest of discounted total system cost and Policy II had higher discounted total system cost.

The cost to society is underestimated when short-term operational constraints are ignored. The addition of short-term operational constraints led to increased total systems cost and greater emissions savings as the level of the mandate increased. Adding short-term operating constraints also gives a more complete understating of CO_2e emissions savings for the different scenarios as there is a decrease in coal generation and increase in natural gas generation led to increased CO_2e emissions savings. The addition of short-term operational constraints shows on one hand the impact of the policy and on the other hand the consequences of not including some of the cost realities.

CHAPTER 1. INTRODUCTION

The electricity sector is inextricably linked with climate change, as the sector is a significant contributor to CO2 emissions. In the US, electricity generation was the largest source CO2 emissions with 5,742.6 million metric tons of carbon dioxide equivalents (26.7% of CO2 equivalents) emissions in 2017 (EPA, 2018). Governments across the globe target mitigation and adaptation measures to avoid potentially severe impacts of climate change (Greenblatt and Wei, 2016). The Paris Accord calls for governments to develop policies to restrict the increase in mean global warming to two degrees Celsius since preindustrial times (UNFCCC, 2015). The US intended to reduce emissions by 26%-28% below its 2005 level by 2025 as a part of the agreement (Greenblatt and Wei, 2016). However, more recently, the US has withdrawn from the Paris Accord.

The Levelized Cost of Electricity (LCOE) examines building and operational costs of a generation technology (British Petroleum, 2017). The LCOE of wind generation has decreased from 124 $/MWh in 2009 to 43 $/MWh in 2018, and for solar PV the LCOE has decreased from 248 $/MWh in 2009 to 43 $/MWh in 2018 (Lazard Capital, 2018). Based on LCOE, the costs of intermittent renewable electricity have decreased. Given the decreasing costs, it is not surprising that renewable electricity sources such as wind and solar will be an important component of low carbon electricity systems (Jacobson et al., 2015). Policy instruments can be used to stimulate higher levels of renewable energy penetration (Herath and Tyner, 2019). These policy instruments include mandates, subsidies, carbon taxes and regulations. As such, there are different policies that lead to high penetration of intermittent renewable electricity sources.

Prior studies have overstated the potential for expanding renewables. Connolly et al. (2016) used a bottom up energy system model to simulate a smart energy system concept in which there is a 100% renewable energy system in Europe. The study defined a smart energy system as connecting the electricity, heating, cooling, and transportation sectors. The results show that it is possible to have a 100% renewable energy system in a limited number of scenarios. In most scenarios, the intermittent renewable generation share could reach up to 80%. There are large uncertainties regarding cost assumptions and the widespread availability of electricity storage technologies in this study. Mathiesen et al. (2015) used a bottom up energy systems model to simulate a smart energy system with energy storage options, which provides the flexibility required for high levels of renewable energy penetration of up to 50%. This result arises from the assumption that in the future, the most efficient transport fuel will be electricity and this may not be plausible. However, this study also assumes widespread energy storage systems. Jacobson et al. (2015) used a grid integration model that included load, capacities, transmission, distribution, storage and maintenance to find that for the 2050–2055 US electricity sector, the social cost for a system that contains wind, water and solar is significantly lower than a system with only fossil fuels. This study assumes large-scale energy storage availability and integration of the electricity and transport sectors. For all such studies, there is also uncertainty regarding technologies, carbon and gas prices, and electricity storage costs and ignore system integration costs and short-term operational constraints.

When the share of wind and solar generation in total generation grows, the system integration costs need to be considered. When wind or solar generation sources are not available, some kind of backup system must be in place to supplant the renewable electricity (Gowrisankaran, et al., 2016). Without storage, electricity supply and electricity demand have to be equal at all times to avoid blackouts and cascading outages (Gowrisankaran, et al., 2016). There are also increased transmission costs associated with wind and solar generation (Fürstenwert et al., 2015). System integration costs could significantly increase the overall costs of electricity generation. A model at a single region level with detailed technological representation needed to evaluate policies that lead to high penetration of wind and solar generation across the Midcontinent Independent System Operator (MISO) footprint has been used. Then the model can be used to evaluate different policies that lead to high penetration of intermittent renewable electricity, costs should be included in evaluation of cost-benefit analyses of renewable electricity generation mandates; comparing a mandate where all economic agents must respond equally regardless of cost to carbon taxes where economic agents to self-select their level of individual effort; and when considering mandates with short-term operational costs have added. There is a difference between who accrues the benefits of emissions reductions and who pays the higher electricity costs. The world society as a whole benefit from the emissions reduction, but it is the electricity consumers in the MISO region that pay for the higher electricity costs. There is a mismatch as a limited number of the people pays costs for which there is a benefit to everyone, which is an issue. To incent MISO electricity consumers to bear this additional cost, it may be necessary for other beneficiaries to provide some benefit to these consumers. The calculation of monetary values of savings in emissions has been done using valuations for emissions that reflect the Social Costs of

Emissions (SCE). The valuations for the different Social Costs of Emissions are widely debated in the literature and there is no consensus. The Intergovernmental Panel on Climate Change (IPCC) and the Interagency Working Group on Social Cost of Carbon use a SCC value based on various integrated assessment models which is typically $40 per ton or less (Pindyk, 2019). Pindyck (2019) suggests that most experts believe that the SCC value should be between $80 and $300 per ton. The social cost for SO_2 can range between $19 per ton to $670 per ton (Shindell 2015). The social cost for PM 10 can range between $5.6 per ton to $ 14,068 per ton (Hainoun et al., 2010). The social cost for PM 2.5 can range between $25,860 per ton to $219,960 per ton (Goodkind et al., 2015).

The overarching research problem examines evaluation of different policies that lead to high penetration of intermittent renewable electricity sources. The first research question examines the following: What are the emissions reduction benefits and system integration costs of policy mandates for high penetration of intermittent renewable electricity technologies for Midcontinent Independent System Operator (MISO)? The second research question examines the following: What are the total systems costs of mandates for renewable electricity generation and a carbon tax using a TIMES model for MISO. The third research question examines the following: What are the emissions and costs of policy mandates for high penetration of wind and solar electricity technologies for MISO when short-term operational constraints are considered?

The specific objectives for first research question are: a) examining the total systems cost of 30%, 40% and 50% mandate for wind and solar generation, b) determining savings in Carbon Dioxide equivalents (CO_2e), Sulphur Dioxide (SO_2), Particulate Matter 10 micrometers and smaller (PM 10), and Particulate Matter 2.5 micrometers and smaller (PM 2.5) emissions due to the mandates, c) converting the savings in emissions to reductions in the SCE, d) comparing the increases in the system costs due to mandates with the savings in SCE . The specific objectives for second research question include examining costs comparisons of a mandate for wind and solar generation and a carbon tax. The specific objectives for third research question include examining the updated total systems cost of 30%, 40% and 50% mandate of wind and solar generation and examining the updated CO_2e emissions saving due to the addition of short-term operating constraints. This allows for the examination of on one hand the impact of the policy and on the other hand the consequences of not including some of the cost realities.

The hypotheses for the first research question include total systems cost increasing as the level of the mandate for wind and solar generation increasing, CO_2e, SO_2, PM 10, PM 2.5 emissions saving increasing as the level of the mandate for wind and solar generation increasing and the benefits of emissions reduction will not justify the costs. The hypotheses for the second research question include a higher level of the carbon tax having lower costs than a mandate for renewable electricity generation. The hypotheses for the third research question include the addition of short-term operating constraints leads to higher total systems costs higher CO_2e emissions saving.

Both top-down and bottom-up modeling approaches that can be used to address the overarching research question. Top-down models examine the economy as whole and therefore, typically with the use of constant elasticity of substitution production functions, examine the electricity sector for policy analysis (Herbst et al., 2012). A drawback of this approach is the lack of technological detail regarding electricity generation options, and therefore substitution possibilities, needed to assess policies relating to the electricity sector (Ossenbrink et al., 2019). In general, top-down models focus on the sector level and use data to produce econometric summaries of sectoral responses to policy and technical changes. Bottom-up models are partial equilibrium models that examine the electricity sector with a great deal of technological detail, and hence more credible substitution possibilities (Herbst et al., 2012). Bottom-up models contain individual technologies, their installed bases, possibilities for alternative future investments and costs are explicit. It is possible to observe substitution of one technology for another in response to policy, with either top-down or bottom-up models. Importantly, the details of how things change are clear with the bottom up approach and therefore are important to address questions regarding renewable electricity policies. One possibility would be to use bottom-up models such production cost models. PLEXOS and PROMOD are examples of production cost models that are used to examine policy issues. PLEXOS contains sub-hourly time slices that allow for examination of ramping issues and therefore is suited for studies that examine wind and solar integration (Papadopoulos et al., 2014). Given the sub-hourly time slices, PLEXOS may not be suitable for use over a long-term planning horizon. PROMOD determines least cost security constrained unit commitment and security constrained economic dispatch for existing generators with transmission for the electricity system (Barrows et al., 2014). As the model does not look at future generator expansion, PROMOD may not be suitable for use over a long-term planning horizon. In general, production cost models typically examine the electricity system at small timesteps and contain substantial technological and operational detail, but may not have the ability to examine the electricity system over a long-term planning horizon (Garcés, 2004).

Another possibility would be to use top-down models to examine high penetration of intermittent renewable electricity. The Global Change Assessment Model (GCAM) and Prospective Outlook on Long-term Energy Systems (POLES) are two examples of top-down models that are used to examine policy issues. GCAM employs a baseline for generation based on the Annual Energy Outlook (Anderson et al., 2016). Primary energy is represented using supply curves (Edmonds et al. 1994). Electricity generation is modeled using logit-choice competition between fuel types and transmission is not modeled as there is a lack of spatial information. On the other hand, POLES is a world partial equilibrium simulation model that examines the energy sector until 2050 (Criqui & Mima, 2012). The model represents upstream production through end use demand and associated greenhouse gas emissions. The model uses year-by-year dynamic recursive modelling methodology that contains endogenous international energy prices and lagged adjustments of supply and demand for different regions in the world (Criqui & Mima, 2012). As the model examines the entire energy sector for the world, transmission cannot be represented due to the vast spatial information requirements. In general, top down models do not have adequate technological representation to address the variation of output from renewable generation sources or their costs of integration with the grid to examine high penetration of intermittent renewable electricity.

Bottom-up capacity expansion models are better suited to examine high levels of penetration of intermittent renewable electricity. One such example would be HAIKU. The base version of HAIKU only contains 12 time slices without temporal chronology and represents capacity investment and retirement over a long-term planning horizon accounting for system operations (Palmer et al., 2011). The model does not optimize transmission and does not have the flexibility regarding time slices to address the variation of output from renewable generation sources or their costs of integration with the grid.

To address the research questions, The Integrated MARKAL-EFOM System (TIMES) model will be used. The TIMES model (a descendent of the MARKAL model) is a bottom-up optimization model with detailed technological representation that contains elements of dispatch models, but with non-chronological time blocks, as well as economic interactions (Loulou et al., 2016). TIMES contains flexibility regarding time slices to address the variation of output from renewable generation sources or their costs of integration with the grid to answer the research question.

There is a tradeoff between increasing the number of time slices and the attendant increase in computational burden and increased data requirements. An increase in the number time slices allows for better representation of wind and solar generation fluctuations. Lueken, et al. (2012) showed that the variability of renewable electricity can affect CO_2 emissions abatement as penetration levels increase for renewable electricity. It is important to have enough time slices to capture some of the wind and solar resource availability.

The results inform policymakers of costs and impacts of renewable electricity generation sources at high levels of penetration and would enable more informed future electricity generation choices. The TIMES model will be used to address the following research question to evaluate policies that lead to high penetration of intermittent renewable electricity. The subsequent chapters are as follows: Chapter 2 focuses on evaluating mandates that lead to high penetration of intermittent renewable electricity generation; Chapter 3 provides a comparison of the costs of mandates for renewable electricity and carbon tax policies; Chapter 4 considers implications of short-term operational constraints on high penetration of intermittent renewable energy generation capacity; and Chapter 5 concludes.

CHAPTER 2. EVALUATING MANDATES THAT LEAD TO HIGH PENETRATION OF INTERMITTENT RENEWABLE ELECTRICITY

2.1 Introduction

System integration costs include the costs of spinning reserves, increased transmission costs and storage costs and should be considered from a total system cost perspective (Fürstenwert et al., 2015). The study defines spinning reserves to be non-renewable generation capacity that ensures that the required supply of electricity is maintained even when there is fluctuation in wind and solar generation. This chapter takes into account system integration costs as defined by Fürstenwert et al. (2015). System integration costs may not be an important consideration at lower penetration levels (i.e. below 30%) of wind and solar generation, but they need to be considered at higher (i.e. 30% and higher) levels of penetration (Hirth et al., 2015). Wind and solar electricity generation sources will be an important component of a low carbon energy system (Jacobson et al., 2015). As such, system integration costs for renewable generation sources are an important consideration for policy analysis as wind and solar generation reach high levels of penetration.

Typically, studies that examine benefits of renewable energy polices only take into account CO_2 emissions reductions (Zhai et al., 2012). However, other emissions that have greater global warming potential on a ton for ton basis such methane (CH_4) and nitrogen oxides (NO_X) should also be considered. In addition to these greenhouse gas reductions, the benefits from reductions in SO_2, PM 10, and PM 2.5 should also be considered. Considering system integration costs and taking into account the benefits from reductions in a more complete list of emissions informs policymakers of costs and benefits of renewable electricity generation sources at high levels of penetration and would enable more informed future electricity generation choices.

This chapter evaluates hypothetical mandates that have been defined for this chapter for the Midcontinent Independent System Operator (MISO) to increase the share of wind and solar generation in this region. The MISO region consists of the load balancing authorities across parts of 15 different states. The states are Arkansas, Illinois, Indiana, Iowa, Kentucky, Louisiana, Michigan, Minnesota Mississippi, Missouri, Montana, North Dakota, South Dakota, Texas and Wisconsin. To accomplish this task a single region version of The Integrated MARKAL-EFOM System (TIMES) model has been used (Loulou et al., 2005). The model accounts for system integration costs as mentioned above. The model also examines CO_2e, SO_2, PM 10, PM 2.5

emissions. The savings from reductions of emissions are converted to monetary values to determine the reductions in the SCE by using the model to track emissions and using a post-optimization analysis to assess policy.

In summary, the research question that is being examined here is the following: What are the emissions reduction benefits and system integration costs of policy mandates for high penetration of intermittent renewable electricity technologies for the Midcontinent Independent System Operator (MISO)?

2.2 Literature Review

Studies have used various modelling techniques to examine renewable electricity policies. Ortega et al. (2013) used operating margin factor (average CO_2 emissions for all power plants) and build margin factor (the generation weighted average emissions factor) to examine avoided CO_2 emissions of renewable electricity generation by examining the displacement of generation plants due to renewable energy policies for Spain. The study found that the overall benefits were greater than the costs of the feed-in tariff. However, their study only examined avoided CO_2 emissions, not other emissions, and did not consider system integration costs. Gowrisankaran, et al. (2016) combined costs used in other studies to include integration costs, variability costs, and spinning reserves costs to come up with the total social cost of intermittency for Tucson, Arizona. The study found that for 20% solar generation, there is a total cost of $46 per MWh for intermittency. Both reserve costs and total social costs increase as the penetration of solar energy increases. Frank (2014) examined the net benefits of different low and no-carbon electricity technologies for the US using avoided emissions and avoided costs rather than levelized costs. The study found that nuclear, hydro, and combined cycle natural gas generation have far more net benefits than wind or solar generation even with a $50 per ton carbon price. However, this study did not consider system integration costs or non-CO_2 emissions. Frank (2014) and Gowrisankaran, et al. (2016) did not use capacity expansion models to examine their research questions. To answer research questions regarding policies associated with investments in renewable generation technologies, a detailed technological representation of the energy system is needed, which is found incapacity expansion models.

Studies have also used capacity expansion models to examine renewable electricity policies. Zhai et al. (2012) used an energy systems optimization model to examine a 10% solar electricity generation mandate in different US states. The study found a reduction in terms of grams per Watt (g/W) of solar PV installed of 670 to 1,500 for CO_2, 0.01–7.80 for SO_2, and 0.25–2.40 for NO_x for the different states. This study did not consider wind generation and did not examine costs of high penetration of wind and solar generation. Lantz, et al. (2016) used an electricity sector capacity expansion model, which included a national wind-specific energy standard to find that wind generation will displace natural gas and coal generation through 2030 and displace other renewables by 2050 for the US. The study found that 404 GW of wind generation capacity will be needed by 2050 and that this level of capacity would be equivalent to 35% wind generation penetration. The limitations of that study include a lack of complete systems operational details and expenditures of all generation and transmission planning and investment, which can lead to underestimation of costs. The mentioned studies used capacity expansion models and only examined wind or solar, but not both generation sources. To examine policies related to intermittent generation technologies both solar and wind generation sources need to be considered.

Other studies have examined both wind and solar generation sources using capacity expansion models. Frew, et al. (2016) used a linear programming model of the US power system with diverse energy sources to examine scenarios for Renewable Portfolio Standard (RPS) targets from 20% to 100% for the US. The study finds potential feasibility of a 100% RPS target, but there are large uncertainties regarding technologies and generation sources. Their study handled issues of intermittency through increased transmission network capacity, renewable electricity overgeneration and electricity storage. MacDonald, et al. (2016) use a national electricity sector model with scenarios varying natural gas prices and renewable generation costs and weather systems data to examine the US electricity sector. The study found that moving away from regional electricity grids to a national grid reduces costs for wind and solar generation and that it is also possible to reduce CO_2 emissions by 33–78% relative to 1990 levels for the power sector. The results depend on the assumptions that there will be fossil fuels usage limits, there will be low-cost storage, and generator and transmission purchase costs will be fully amortized over thirty years. The study contends that the emissions reductions would be possible without an increase in the levelized cost of electricity with the LCOE in 2030 (11.5 ¢ per kWh). However, there is a large degree of uncertainty especially regarding the LCOE in 2030 since the assumptions about fossil fuels usage limits and low-cost storage are likely not realistic. Neither of these studies examined system integration costs. Any examination of policies related to high penetration of wind and solar generation needs to consider system integration costs.

As wind and solar electricity sources scale to high penetration levels, the cost of integrating non-dispatchable energy sources leads to increases in per unit generation costs and total systems cost increases. Many studies in the literature have found that there are increased costs associated with high penetration of intermittent renewable generation. Brouwer, et al. (2014) used a unit commitment and economic dispatch model to find that when wind generation increases to 20% of total generation, the combined size of all other reserves should increase by 7% to ensure reliability of electricity supply. The study also found that when wind generation increases to over 30% there is oversupply of wind power at times, requiring curtailment of wind generation, and the increased demand for reserves leads to an increase in direct system cost of 1–6 €/MWh. Mai, et al. (2014) examined high renewable electricity generation scenarios for the US electricity system using an electricity sector capacity expansion model and found that biomass, geothermal, hydropower, solar, and wind can contribute up to 80% of 2050 annual electricity generation, which includes 49–55% from wind and solar PV generation. The study found a 69–82% decrease of annual GHG emissions, but there is also a 3%–30% increase in electricity prices associated with the scenario, which does not consider increased systems cost or costs of storage. Although, the mentioned studies examined increased costs associated with wind and solar generation, not all system integration costs were considered.

In summary, the existing studies ignore the system costs of producing electricity from wind and solar. In addition, they only examine CO_2 emissions savings, but not the reductions in CH_4, NO_X, SO_2, PM 10 and PM 2.5. Examining emissions savings from all the mentioned emissions and incorporating system costs of producing electricity from wind and solar provides a better picture of the costs and benefits of using these resources. This chapter uses an electricity sector model with technological detail at hourly time slice resolution to take into account emissions reduction benefits from CO_2 and non-CO_2 emissions and system integration costs of policy mandates for high penetration of intermittent renewable electricity technologies for MISO.

There are different approaches that can be used to address the research question of this chapter. Dispatch models examine energy systems at small time resolutions, but do not have representation of the electricity sector over a long time period (Garcés, 2004). As such, dispatch models would not fit the research question. Another possibility would be to use top-down models.

Top-down models traditionally represent the sector as a whole to examine policy issues (Herbst et al., 2012). The top-model model GTAP disaggregates the electricity different electricity generator types and transmission and distribution (Peters, 2016). Top down models do not typically have adequate technological representation to address the variation of output from renewable generation sources or their costs of integration with the grid. The TIMES model (a descendent of the MARKAL model) is a bottom-up optimization model with detailed technological representation which contains elements of dispatch models, but with non-chronological time blocks. The objective function in TIMES is to minimize the discounted total system cost which consists of capital, operating costs, process, infrastructure, conversion and end use technologies (Loulou, et al., 2016).

The MARKAL model has been modified and used for studies globally (Schafer and Jacoby, 2006). TIMES has been used to examine renewable energy policies. Amorim, et al. (2014) used a modified TIMES model to develop a cost-effective method to achieve a decarbonized electricity sector by 2050 for Portugal using hourly supply and demand dynamics. That study also examines the interconnection with the Spanish electricity system. The study found underinvestment and underutilization of renewable electricity sources, but when combined with the Spanish electricity system, renewable electricity sources became cost effective. The study contained increasing prices for crude oil, natural gas and coal, as well as greatly decreasing wind and solar investment costs. Rečka and Ščasný (2016) used TIMES to look at EU emission allowance prices for GHG emissions in the Czech Republic. The study found that for a low price of EU allowances to emit greenhouse gasses, coal generation will be the main generation source, but nuclear generation will be the main generation source for medium and high prices for EU allowances to emit greenhouse gasses. Natural gas generation increases for all emission allowance prices. The share of renewable generation only increased to about 20% when there were high natural gas prices and a high price of EU allowances to emit greenhouse gasses.

There have been studies that have used the TIMES model with hourly time slices to better capture renewable generation variation to address system integration costs. Kannan and Turton (2016) use a TIMES model with hourly time slices to examine climate change policies while phasing out nuclear generation for Switzerland. The study finds that with the phasing out of nuclear generation, centralized gas power plants along with renewables, including abundant hydroelectricity, comprise most of the electricity generation. Yang et al. (2015) used a TIMES model of California to assess the prospects for reducing GHG emissions by 80% compared to 1990 levels. The study found that Carbon Capture and Sequestration (CCS) is an important component of emissions reduction, and it is possible to achieve an 80% reduction of GHG, but the cost of reducing GHG is between $9 to $124 per ton of CO_2 equivalent. The study assumed that centralized production of energy carriers via coal gasification, natural gas steam reforming, biomass gasification and water electrolysis that can incorporate CCS. Hourly time slices are designed to help examine costs associated with spinning reserves. However, these studies did not consider costs of increased transmission and storage.

The contributions of this study are a more complete examination of reductions in the SCE from emission savings and better depiction of costs by examining system integration costs for policies that lead to high penetration of solar and wind generation. The TIMES model contains technological detail that allows for the study of emissions savings related to policies of wind and solar generation. While many studies in the literature only examine CO_2 emissions saving, this study also values the reductions in emissions of CH_4, NO_X, SO_2, PM 10 and PM 2.5. Examining emissions savings from all the mentioned emissions provides a better picture of benefits, especially when converted to reductions in the SCE using social costs of the respective emissions. Hourly time slices better capture renewable generation dynamics and helps better understand spinning reserves costs. Transmission costs associated with wind and solar generation plants have been added as an investment cost. Storage costs have also been added to the model. Assessing all the mentioned costs contributes to a better understanding of system integration costs. Details of the modifications made to the TIMES model are found in the methodology section.

2.3 Methodology

2.3.1 Model

The US EPA 9 region TIMES model contains technological details of the electricity and transportation sectors based on census regions for the US. The objective function of this model minimizes the discounted total system cost, which consists of resource extraction costs, costs of processing and conversion of energy carriers, capital costs, operating and maintenance cost of infrastructure, and end use energy service technologies for the transportation and electricity sectors for the US (Lennox, 2019). The model contains data regarding resource extraction, processing, and conversion, as well as demand data for both the transportation and electricity sector. The model depicts resource supply, resource processing, resource conversion and end use demand where the total energy produced has to be at least the level of energy demanded (Lennox, 2019). For the purposes of this research, the transportation sector has been removed, but transportation electricity for light duty vehicle and trains remains in the model at fixed aggregate generation of the electricity commodity levels. From a regional perspective, the model focuses only on the electricity sector for the geographical footprint of MISO as a single, aggregate region. Building the model at the single region level allows for assessing costs and impacts of renewable generation sources at the system level taking into account other resources in the network. The following equations (1), (2) and (3) are taken from (Loulou et al., 2016):

This model solves the following optimization problem with inelastic demand:

$$\text{Min} \sum_{k,i,t} \text{Variable Activity}_{k,i}(t) c_{k,i}(t) \quad \textbf{(1)}$$

$$\text{s.t.} \sum_{k} \text{Variable Activity}_{k,i}(t) \geq \text{Demand}_{i}(t) \text{ where } i=1,\ldots,I \text{ and } t=2015,2020,\ldots,2050 \quad \textbf{(2)}$$

$$\text{and} \sum_{k,i,t} \text{VariableActivity}_{k,i}(t) \mathbf{B}_{k,i}(t) \geq \mathbf{b} \quad \textbf{(3)}$$

In Equation (1), Variable Activity is a vector of all variables relating to electricity generation and c is the cost vector. In Equation (2), I is the different demand categories and k is the end use technologies associated with the demand category. The objective function of this model is to minimize the total discounted system cost satisfying demand, capacity activity, commodity use, and peaking reserve (Loulou et al., 2016). The first constraint requires satisfying demand where the exogenous demand has to be satisfied by activity of the end use technologies (Loulou et al., 2016). The second constraint is the set of all other constraints that have been implemented and are shown in Equations (4), (5), (6), (7), (8) and (9) have been adapted from (Loulou et al., 2016).

To address the research question of this chapter, as shown in the following, the optimization problem has been modified to remove the non-electricity activity variables. The modifications allow for the focus on policy analysis for the electricity and prevents substitution of technologies across non-and electric and electric technologies. For example, capacity and technologies related to the biofuels and industrial processes have been removed, while the capacity and technologies related coal, natural gas, oil that are relevant for electricity generation remains. As such, the capacity activity and peaking reserve constraints only pertain to electricity generation.

The costs Equation (1) that are not related to the electricity generation have been removed. The costs in Equation (1) are exogenous and come from Lennox (2019). The commodities that do not relate electricity generation have been removed from the model. The demand in the right-hand side of Equation (2) are exogenous. The demands that do not relate to the electricity sector have been removed.

In this chapter the objective function is:

$$\text{Total costs} = \sum_{t=2015}^{2050} \text{Discount}(t) \times \text{Annual Cost}(t) - \text{Salvage}(T) \quad \textbf{(4)}$$

Equations (4) and (5) have been adapted from (Loulou et al., 2016). The components of annual cost that have been used are shown in the following Equation (5).

$$\begin{aligned}\text{Annual Cost}(t) = {} & \text{Investment}(t) + \text{Decommission}(t) + \text{Fixed cost}(t) \\ & + \text{Variable cost}(t) + \text{Tax}(t)\end{aligned} \quad \textbf{(5)}$$

The components of Annual Cost in (5) are investment costs, decommission costs, fixed operating and maintenance costs, variable operating and maintenance costs, commodity flow costs, taxes, salvage costs. The index T in Equation (4) represents the end of the planning horizon. Investments costs include annualized investment costs for electricity generation facilities, but transmission costs are not included. Decommission costs include costs of dismantling electricity generation processes that have reached their end of lifetime. Fixed costs include fixed operating and maintenance costs as well as surveillance costs of determining the lag time to dismantle a power plant. Variable costs include variable operating and maintenance costs. Commodity flow costs include mining costs, processing costs and delivery costs. Taxes include direct taxes as well as subsidies associated with electricity generation and commodity flows. Salvage costs include the value of commodity flows and electricity generation processes left over after the end of horizon, which in this case is 2050.

$$\text{Capacity Activity}_{t,s} \leq \text{Availability Factor}_{t,s} \times \text{Capacity to Activity Factor}_{t,s} \times \text{Capacity}_{t,s} \quad \textbf{(6)}$$

Equation (6) shows the capacity activity constraint where t is the time period and s in the time slice. The capacity activity constraints require that the activity cannot exceed the product of the availability factor, capacity to activity factor and capacity in the current period. The availability factor is the amount of time within a time period that an electricity generator can generator electricity (Loulou et al., 2016). For the different coal generator types, the availability factor ranges from 0.82 to 0.94 annually, but the availability factor for coal decreases over time due to aging coal plants being less effective. The availability factor for natural gas generation is 0.9 annually. The model was updated for wind and solar generation, there are now availability factors in every time slice to capture the variation in available wind and solar resource during the time slice and this is discussed with candidate plants for wind and solar generation. There288 hourly time slices in the model. Capacity is defined as the amount of a certain electricity technology during the hourly time slice and the units are in GW. Because the activity level applies for the entire hour, the units can be as interpreted as GW or GWh. The capacity to activity factor is a conversion factor that converts capacity to activity. In the model, activity is defined to satisfy demand as electricity generation and the units are in PJ. To convert from capacity in GWh to activity in PJ the conversion factor 31.536 is used. Capacity of a generation technology used in the current period does not exceed existing capacity and that of new investments.

$$\text{Commodity use}_{t,s} \leq \text{Commodity production}_{t,s} + \text{Trade}_{t,s} \qquad \textbf{(7)}$$

The commodity use constraint, (7) where t is the time period and s in the time slice, requires that commodities used in a time slice cannot exceed supply coming from commodity production and trade in terms of import and export (Loulou et al., 2016). The units for commodity use, commodity production and trade in the model is PJ. In this single region model, trade does not occur.

$$\text{Electricity Generation}_{t,s} \geq \text{Demand}_{t,s} + \text{Transmission losses}_{t,s} \qquad \textbf{(8)}$$

The demand constraint, (8) where t is the time period and s in the time slice, requires that electricity generation technologies must supply end use energy services at least as great as the amount of demand and transmission losses. The units for electricity generation, demand and transmission losses in the models are PJ. (Loulou et al., 2016). The transmission efficiency is assumed to be 93.5%.

$$\Sigma_G \text{Capacity to Activity Factor} \times \text{Peak Fraction}_{G,t,s} \times \text{Capacity}_{G,t,s} \geq (1+\text{Peaking Reserve}) \times \text{Capacity Required for Electricity Demand}_{t,s} \quad \textbf{(9)}$$

In Equation (9) where t is the time period and s in the time slice, capacity is the sum of existing and new investments for the generator type (G) and the capacity to activity factor is 31.536 (Loulou et al., 2016). For each generator type there is an associated fraction of capacity in the peak equation. The units for capacity are GWh. The peaking reserve is a percentage. The peaking reserve constraint requires that, within a time slice, electricity generation must be greater than the average demand by the peaking reserves. The planning reserve margin of 19.2% based on NERC (2018) has been used for the peaking reserve constraint.

Table 2.1 shows the net demand for electricity of each sector. The US EPA 9 region model contains end use technologies for commercial, industrial, residential and transport sectors. The technologies that do not generate electricity have been removed. The demands in the model are for end uses. A downside of having fixed aggregate generation of the electricity commodities for the entire region is that substitution possibilities for satisfying end use demand from non-electricity commodities and technologies has been eliminated. Demand data is at an annual time resolution. Annual national demand was summed based on the existing 9 regions in the EPA model. The share of MISO electricity generation of national electricity generation was used to calculate demand for MISO. For annual demand, the ratio of MISO demand to national demand is assumed to be the same as the share of MISO electricity generation to national electricity generation. Only overall electricity demand operates at an hourly time slice level; demand for end uses operate at an annual level. Appendix Table A1 contains the duration of each time-slice as a fraction of a year. To convert annual electricity demand to hourly time slice level, MISO load curve data is used to determine the electricity demand for each time slice fraction. Appendix Table A2 shows the demand in each time slice as a fraction of total demand. In the industrial sector, petroleum refining technologies that produce both electricity and another product such as asphalt, liquefied petroleum gas, natural gas and petrochemical feedstocks have been kept in the model at fixed aggregate generation of the electricity commodity levels and the byproducts are not valued. Appendix Tables

A3, A4, A5 and A6 provide a breakdown for the commercial sector, residential sector, transportation and industrial sector respectively.

Table 2.1. Annual Electricity Demand by Sector

Sector (PJ)	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
Commercial	1328	1311	1314	1307	1313	1332	1345	1363
Industry	1134	1245	1336	1413	1443	1461	1472	1483
Residential	1419	1412	1387	1384	1403	1429	1455	1479
Transport	17	26	40	60	82	109	142	180
Total	3898	3994	4077	4164	4241	4331	4414	4505

The existing 12 time slices (3 seasons: summer, winter and intermediate and 4 times of day: day am, day pm, night, and peak) of the US EPA 9 region model did not capture the variation of renewable generation sources throughout the day. To deal with this, the number of time slices has been increased to 288 hourly slices. Hourly time slices help capture wind and solar generation dynamics at higher levels of penetration and helps better understand spinning reserves requirements and costs. The updated time slices included hourly data for Fall Weekday (FWDAY), Fall Saturday (FSAT), Fall Sunday (FSUN), Winter Weekday (WWDAY), Winter Saturday (WSAT), Winter Sunday (WSUN), Spring Weekday (SPWDAY), Spring Saturday (SPSAT), Spring Sunday (SPSUN), Summer Weekday (SUWDAY), Summer Saturday (SUSAT), Summer Sunday (SUSUN) categories. However, temporal chronology is not maintained.

Dispatch is incorporated based on the hourly MISO load curve for 2015. The load data comes from Energy Online (2019). The data has been added by having a dummy technology. The technology has an input commodity of electricity and output commodity of "dummy" electricity. The technology has fixed availability factors shown in Appendix Table A2. This was to ensure sure that generation followed the MISO generation data at the time slice level even though there is end use demand is annual and fix the availability factors and. The demand categories have the dummy electricity commodity as the input commodity and the demand category such as space heating as the output category as the demand for the commodity electricity is derived demand from the demand for end use energy services. For the commercial, residential and transport sectors the demands are shown in Appendix Tables A3, A4, and A5, respectively. The model determines generating unit dispatch based on investment, operating and maintenance costs, and technical specifications such as efficiency and availability factor. The peaking reserve constraints for wind generators have a capacity credit fraction in the peak equation is 0.5, while the fraction is 0.3 for solar generators. For coal the fraction of capacity in the peak equation is 0.9, while the fraction is 0.95 for natural gas, nuclear and hydro generators. For battery storage, the fraction of capacity in the peak equation is equal to 1. The peaking reserve constraints are implemented for all of the time slices. A planning reserve margin of 19.2% based on NERC (2018) has been used for the peaking reserve constraint in this study. The peaking reserve constraint allows the model to determine the spinning reserves needed for hourly dispatch and the costs associated with the spinning reserves needed to ensure reliability even if there are uncertainties such as outages and maintenance. The investment, operations and maintenance costs of spinning reserves are components of total systems cost. As the share of wind and solar generation increases, more spinning reserves is needed which increased total systems costs.

There are two different options to add renewables into MISO in the current TIMES framework. One possible way would be to have a single representative plant for each state in the MISO region introduced as a technology in the modeling framework. This method would not properly capture the generation potential of the region as a single plant would represent a state. A significant disadvantage of this approach is that the generation potential of different regions would be lost in the averaging process. Typically, wind and solar plants are found in regions in which the generation source is readily available which would have a higher average availability factor. However, there are wind and solar plants in regions where the resource is highly intermittent, which would have a lower average availability factor. By averaging, the average availability factor is mischaracterized for the state as a whole. While this method is less time and data intensive, it requires picking sites and averaging them to come up with a single representative site.

A better method would be to select candidate plants and add these candidate plants as individual technologies in the modeling framework. A candidate plant is a plant that is representative of the solar or wind plants of a particular geographical region as wind and solar plants in that region would have similar capacity factors. There are 22 solar candidate plants and 24 wind candidate plants added to the model. This method is data and time intensive, but captures the generation potential in greater detail. For this study, the candidate plant approach is used. For solar, Global Horizontal Irradiation (GHI) data based on the National Solar Radiation Database (Habte et al., 2017) was used to come up with high and low availability factor generation sites for each state. The data was from 2011 to 2015. Appendix Table A7 contains solar candidate site summary of availability factor information for the hourly time slices.

Wind generation data comes from different existing wind sites. Wind generation data from the Wind Integration National Dataset (Draxl et al., 2015) was used to estimate high and low availability factor generation sites for each state. The original 5-minute generation data was averaged to get to hourly values. Before averaging, if the wind speed in meters per second (m/s) was less than or equal to 2.5 or if wind speed is greater than or equal to 12 m/s, generation was set to 0. These cut-in and cut-out values were selected based on Sedaghat et al. (2017). Appendix Table A8 contains wind candidate site summary of availability factor information for the hourly time slices. Having availability factors in every time slice allows for better capturing the variation in available wind and solar resource during the time slice.

For coal power plants, investments in retrofits are required for operation. A plant can choose between low NO_X Burner, Selective Catalytic Reduction, Selective Non-Catalytic Reduction, or a combination for NO_X reductions including: flue gas desulfurization (FGD); for SO_2 reductions fabric filters and cyclones; and electrostatic precipitators for PM10 reductions (Lennox, 2019). Under current regulations, all of the retrofits need to be installed, but for this model there was a choice for NO_X reductions retrofits following the EPA 9 region model implementation. There are also life extension retrofit costs that have to occur every 5 years. The life extension costs have been added based on Equation 1 from Energy Information Agency (2019). There are coal power plants of different sizes that require different boiler, turbine and generator and balance of plant retrofit costs. Regression analysis was used to estimate an equation to generalize life extension costs. Equation 1 gives a USD per kW investment cost at time t. There are increased costs if a plant has FGD installed and FGD would equal 1 in Equation 10. If the retrofit costs become sufficiently high, it will be more economical to retire the plant and replace it with another generation source.

$$\text{Investment cost}_t = 16.53 + (0.126 \times \text{age}_t) + (5.68 \times \text{FGD}) \qquad \textbf{(10)}$$

Based on the candidate sites for solar and wind generation, the costs include expected transmission costs, and any investment and production costs specific to the candidate sites. These costs have been updated using Augustine et al. (2018). Appendix Table A9 shows the total investment costs for new generation technologies, while Appendix Table A10 shows the operating and maintenance costs for new generation technologies. The TIMES model does not optimize transmission and as such the spatial distribution of the electricity system is not represented. To represent increased transmission costs associated with wind and solar generation, new wind and solar plants must also incur investment costs for transmission expansions. As spatial distribution is not considered, the transmission costs are an average cost. Regardless of location, there is a USD 114 per kW transmission cost for all new wind and solar plants. As the share of wind and solar generation in total generation increases, transmission costs also increase leading to an increase in the total system cost.

Pumped hydro is used in the model as storage. Based on Environmental Protection Agency (2019) there are 2.74 GWh of capacity from one plant of pumped hydro in the MISO region. Only the regions close to this plant will be able to use the storage from pumped hydro plant, so pumped hydro capacity is not allowed to increase. Battery storage has also been added to the model in which the electricity commodity is stored in one time slice and used in another time slice based on costs from Augustine et al. (2018). Based on Environmental Protection Agency (2019) there is only 175.2 MWh of capacity from one plant of battery storage in the MISO region. The model allows for increased capacity of battery storage. However, as temporal chronology has not been maintained, the depiction of storage is simplistic where energy in PJ is stored in one time slice and released in another time slice. In the peaking reserve constraint, storage has a fraction of 1 in the equation. As the share of wind and solar generation increases, the model has to maintain the peaking reserve constraint which leads to an increase in total systems cost.

2.3.2 Reference Scenario

The growth rate for demand is not uniform across residential, industrial, commercial and transportation sectors. The wind and solar electricity potential in each state for different renewable generation types is based on Lopez et al. (2012). The base year for the model is 2015. Table 2.2 shows the MISO capacity and generation shares in 2015. Based on Bakke et al. (2019), there are 42 GW of wind and 36 GW of solar in the MISO interconnection queue. In reality, not all of the plants in the interconnection queue will be built. However, for this chapter, all the wind and solar capacity in the interconnection queue is assumed to be built linearly over time and the cost of adding the capacity is a component of the total systems cost. The wind and solar capacity are added to the model linearly over time to reach the totals by 2050. NERC (2018) found that 17.3 GW of coal could be retired by 2022 for the MISO region while maintaining system reliability and resource adequacy. In this chapter, 17.3 GW of coal generation capacity is retired from 2015 to 2050. The coal generation capacity retirements are hardwired based on Energy Information Agency (2019) data and occurs on the year specified in that data. Appendix Table A11, A12 and A13 contain average prices over the planning horizon for natural gas, coal and oil respectively and comes from Lennox et al. (2013). Depending on the costs and technical parameters of generation sources, the model will choose not to use certain generation sources. In this chapter, capacity retirement for generation sources has been updated according to Environmental Protection Agency (2019) and Energy Information Agency (2019). Appendix Table A14 shows the average emissions of electricity generation by generator type.

Table 2.2. MISO Capacity and Generation in 2015

Generation Source	Capacity (GW)	Capacity Share (%)	Generation (%)
Coal	59.2	42.4	50
Nuclear	12.4	8.9	16
Natural Gas	58.0	41.6	24
Oil	2.0	1.5	0
Hydro	3.6	2.6	1
Wind	2.4	1.7	7
Other	1.7	1.2	1
Total	139.4	100.0	100

Source: Potomac Economics (2016)

2.3.3 Mandates Implemented

There are 3 different mandates that have been implemented. The first is a 30% mandate of wind and solar generation by 2050. The second is a 40% mandate of wind and solar generation by 2050, and a final 50% mandate of wind and solar generation by 2050 is considered. The mandates are achieved by increasing wind and solar generation linearly to achieve the mandated goal by wind and solar generation by 2050. The model determines the appropriate mix of solar and wind generation to fulfill the mandate. Figure 2.1 shows the effect of renewable mandates on the supply.

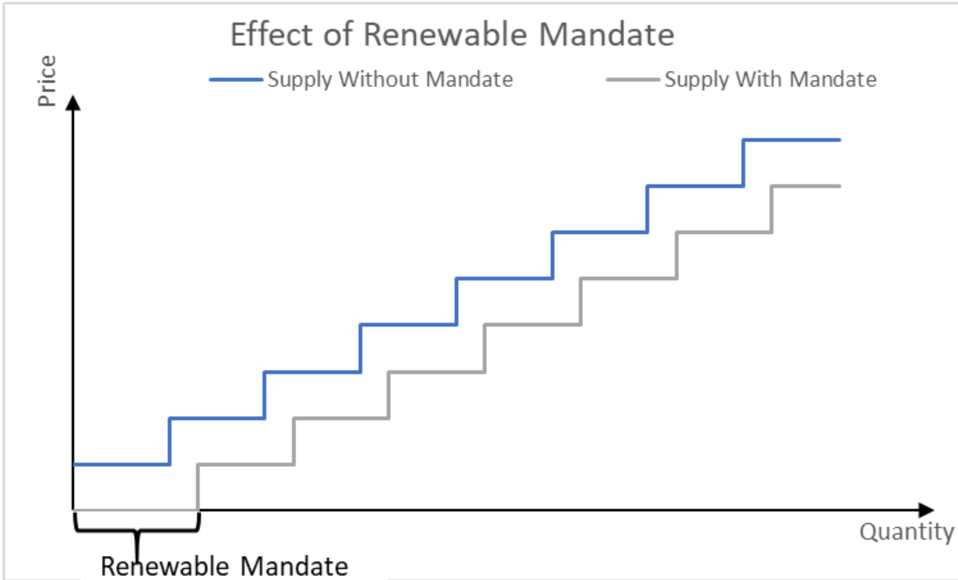

Figure 2.1 Effect of Renewable Mandates on Supply

There is a shift in the supply curve as there are very low marginal cost steps being forced in which represents wind and solar mandates implemented. A mandate policy forces the generation mix to the specified wind and solar generation. Wind and solar generation have no fuel costs or variable operating and maintenance costs.

2.4 Results

2.4.1 Generation Results

This section provides the generation and capacity results for all the scenarios. Figure 2.2 shows the generation mix for all the reference scenarios over time. Appendix Graph A1 gives the capacity projections. In all the scenarios, coal generation decreases over time. Coal is used less for generation over time due to retrofit and life extension costs, which lead to coal generator capacity retirements. Coal generation goes from 1609 PJ (38% of generation) in 2020 to 435 PJ (9% of generation) in 2050 in all scenarios except for the 50% mandate in which the mandate displaces some coal. For the 50% mandate, coal generation starts from 1609 PJ (38% of generation) in 2020, but less than in the other scenarios for each time period and ends at 405 PJ (8% of generation) in 2050. Coal generation is decreasing due to life extension costs in the reference scenario, and there has to be a 50% mandate to further reduce coal generation.

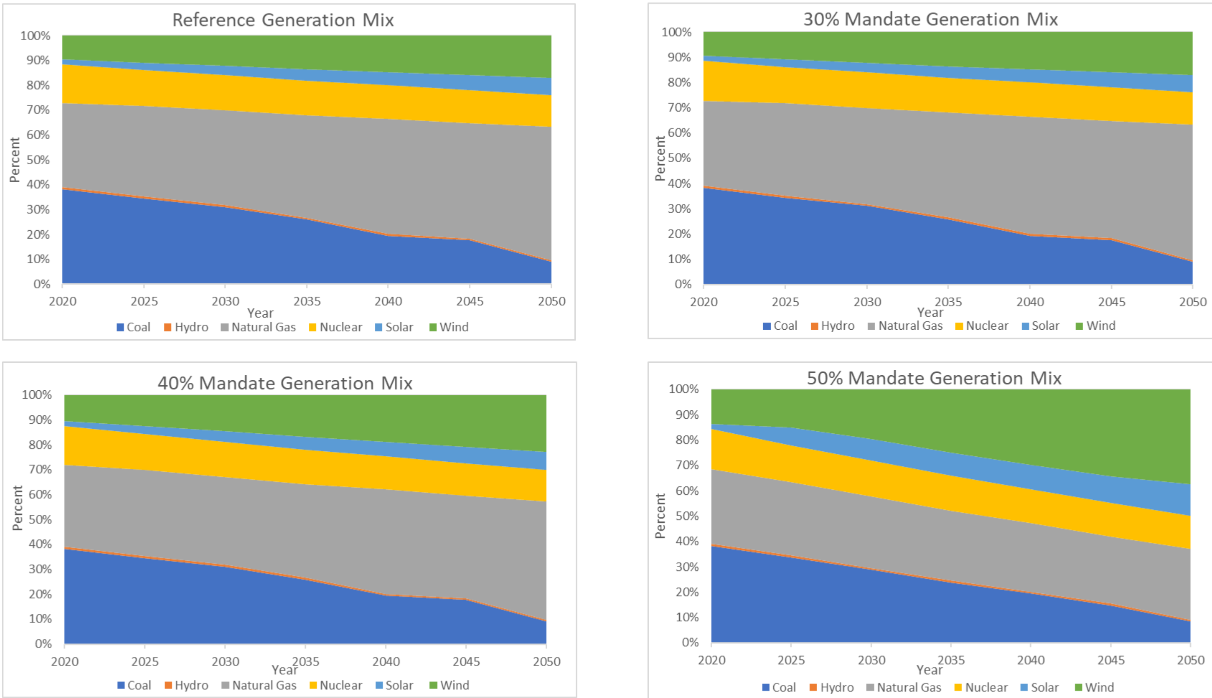

Figure 2.2. Generation mixes for the Different Scenarios

In the reference scenario, natural gas generation increases to offset the bulk of coal generation decreases. In 2020, there are 1418 PJ (34% of generation) of natural gas generation and generation increases to 2578 PJ (53% of generation) in 2050. Natural gas has capacity similar to coal in 2015, but was used mainly for peaking (MISO 2016). However, with natural gas prices expected to stay low, natural gas generation will increase over time (EIA 2019). Advanced combined cycle natural gas generation begins generation in 2025. Advanced combined cycle natural gas has higher thermal efficiency and replaces both retiring coal and eventually combined cycle generation. For the 30% mandate, in 2020 there are 1378 PJ (33% of generation) of natural gas generation, and it increases to 2285 PJ (47% of generation) in 2050. For the 40% mandate, in 2020 there are 1309 PJ (31% of generation) of natural gas generation and it increases to 1803 PJ (37% of generation) in 2050. For the 50% mandate, in 2020 there are 1240 PJ (29% of generation) of natural gas generation and it increases to 1351 PJ (28% of generation) in 2050. It appears that the mandate policy for renewable generation leads to natural gas displacement to fulfill the mandate. The displacement of natural gas depends on the level of the mandate.

For all the scenarios, nuclear generation goes from 661 PJ (16% of generation) in 2015 to 621 PJ (14% of generation) in 2020 (due to plant retirement) and remains the same until 2050. The hydro generation stays at 35PJ (1% or less of generation) in all time periods. Although there is oil generation capacity, it is not used. The planned wind and solar capacity additions in the reference scenario lead to an increase in the wind and solar generation share. In 2050, wind generation is 824 PJ (17% of generation). In 2050, solar generation is 326 PJ (7% of the generation). In the reference scenario, the total share of wind and solar generation grows to 24% in 2050. There is no new investment in battery storage and a small of amount of the existing battery storage capacity is used over time. Given the costs of battery storage, it is cheaper to use natural gas as spinning reserves rather than to invest in and use battery storage for the peaking reserve constraint. The percentage of combustion turbine natural gas capacity of overall natural gas capacity is an indication of the use of natural gas as spinning reserves. Both combustion turbine natural gas and combined cycle natural gas are used spinning reserves. The percentage of combustion turbine natural gas capacity in overall natural gas capacity is 47% for all the scenarios in 2020. For the reference scenario the percentage in 2050 is 49%, for the 30% mandate the percentage is 50% in 2050, for the 40% mandate the percentage is 52% in 2050 and 50% mandate the percentage is 55% in 2050. As the depiction of battery storage is simplistic, a better depiction of battery storage might lead to different results. However, the costs of battery storage could decrease in the future. Future cost decreases could lead to investment and use of battery storage.

2.4.2 Emissions Results

The reference scenario leads to the emissions presented in Table 2.3. In this scenario, CO_2e emissions decrease over time. There is a 29% decrease of CO_2e from 2020 levels to 2050 levels. With the rise in life extension costs, there is a decrease in coal generation. Although, natural gas generation increases over time, it is less CO_2e intensive than coal generation. Over the 2020 to 2050 time period there is a 20% decrease in SO_2 emissions. Natural gas generation is increasing over time, but it is less SO_2 intensive than coal generation. So, there is a decrease in SO_2 emissions over time. In the 2020 to 2050 timeframe, there is a 41% decrease in PM 10 emissions. Natural gas generation increases, and it is less PM 10 intensive than coal generation. As such, there is a decrease in PM 10 emissions over time. From 2020 to 2050 there is a 53% decrease in PM 2.5 emissions. Natural gas generation, which is less PM 2.5 intensive than coal generation, increases over time. So, there is a decrease in PM 2.5 emissions over time.

Table 2.3. Reference Scenario Emissions

kilotons	2020	2025	2030	2035	2040	2045	2050
CO_2e	968,076	926,981	890,498	853,329	824,658	804,570	749,065
SO_2	4022	3925	3787	3625	3510	3408	3251
PM 10	543	500	464	419	392	368	319
PM 2.5	319	294	271	233	209	184	150

Table 2.4 shows the CO_2e emissions saving for different scenarios. Hockstad & Hanel (2018) was used to convert methane (CH_4) and nitrogen oxides (NO_X) to CO_2e. The conversion factor for CH_4 to CO_2e is 30, while the conversion factor NO_X to CO_2e is 298. Although CO_2e declines in the reference scenario over time, the mandates lead to a further emissions savings. CO_2e emissions savings follow a linear pattern consistent with the mandates. The 50% mandate in particular leads to a large CO_2e emissions saving of 23.1% in 2050. The results indicate that mandates can be used as a policy tool to decrease CO_2e emissions. Appendix Tables A13, A14 and A15 gives the kilotons saving for SO_2, PM 10 and PM2.5 for the different scenarios respectively.

Table 2.4. CO_2e Savings for Different Scenarios (Kilotons)

Policy	CO_2e kilotons Savings (% from reference)						
	2020	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
30% Mandate	15,400 (1.6%)	20,139 (2.2%)	24,990 (2.8%)	29,678 (3.5%)	33,479 (4.1%)	39,029 (4.9%)	42,343 (5.7%)
40% Mandate	24,473 (2.5%)	37,810 (4.1%)	52,874 (5.9%)	66,460 (7.8%)	73,145 (8.9%)	94,958 (11.8%)	107,953 (14.4%)
50% Mandate	32,803 (3.4%)	57,885 (6.2%)	88,517 (9.9%)	112,091 (13.1%)	125,091 (15.2%)	162,779 (20.2%)	172,843 (23.1%)

2.4.3 Cost Results

The Marginal Cost of Electricity (MCOE) is the cost of producing an additional unit of electricity in a given time slice (Loulou 2016). The Marginal Cost of Electricity is determined by the model. As the MCOE can change within scenarios over time, another metric is needed to compare electricity costs across different scenarios. To compare across scenarios, the Levelized Marginal Cost of Electricity (LMCOE) was calculated based on Lu (2015). LMCOE gives discounted value of generation for a year based on the generation weighted MCOE and gives the ability to compare across different scenarios. Table 2.5 shows the LMCOE for different scenarios.

Going from the reference scenario, with 8% renewable generation in 2015, to the levels required in the mandates leads to an increase in the LMCOE. The 50% mandate leads to approximately a 12% increase in the LMCOE, which can be misleading. The cost of a mandate should be examined from a total system cost perspective instead.

Table 2.5. Levelized Marginal Cost of Electricity for Different Scenarios

Policy	**Levelized Marginal Cost of Electricity (¢/kWh)**	**Percent Change from Reference Case**
Reference	5.697	
30% Mandate	6.070	6.55%
40% Mandate	6.211	9.02%
50% Mandate	6.378	11.95%

It is also important to examine the cost increases associated with the mandates. Figure 2.2 shows the increase in total systems cost over time for different scenarios compared to the cost of that year in the reference scenario. The components of systems cost are fuel cost, investment cost, variable operating and maintenance cost and fixed operating and maintenance cost. Coal retrofit costs are included in fixed operating and maintenance cost. Commodity transportation costs and salvage costs have not been considered in this definition.

$$\text{Total system cost}_t = \Sigma_G \text{ Fuel cost}_{G,t} + \Sigma_G \text{ Fixed O\&M cost}_{G,t} + \Sigma_G \text{ Variable O\&M cost}_{G,t} + \Sigma_G \text{ Investment cost}_{G,t} \quad \textbf{(11)}$$

Equation 11 gives the system cost for period t. Figure 2.2. shows the increase in total system costs over time due to renewable generation mandates relative to the reference case. As the mandate level increases, the total systems cost also increase. The incremental total systems costs for the 30% mandate is a 1.0% increase over the reference in 2020 and a 5.6% in 2050; for the 40% mandate there is a 3.3% increase over the reference in 2020 and a 14.0% in 2050; and for the 50% mandate there is a 5.8% increase over the reference in 2020 and a 22.6% in 2050.The discounted total system cost for the 30% mandate has 1.0% increase over the reference in 2020 and a 4.0% in 2050; for the 40% mandate there is a 3.3% increase over the reference in 2020 and a 10.6% in 2050; and for the 50% mandate there is a 5.6% increase over the reference in 2020 and a 17.1% in 2050. The discounted total system cost is higher than the LMCOE for the 40% and 50% renewable electricity mandates, and lower for the 30% mandate. A breakdown of total systems cost is shown in Appendix Table A12.

The increase appears to be linear, following the linear implementation of the mandates. The cost increases are mainly driven by investment costs as well as operation and maintenance costs. Natural gas is used as spinning reserves for the increased solar and wind generation for all the scenarios, which leads to increased investment costs and operation and maintenance cost associated with natural gas. Given uncertainty of future fuel costs and that not all short-term variation of renewable generation sources and ramping, start-up and shut-down costs of other generation sources in the system are included, the cost results should be considered a lower bound for potential cost increases.

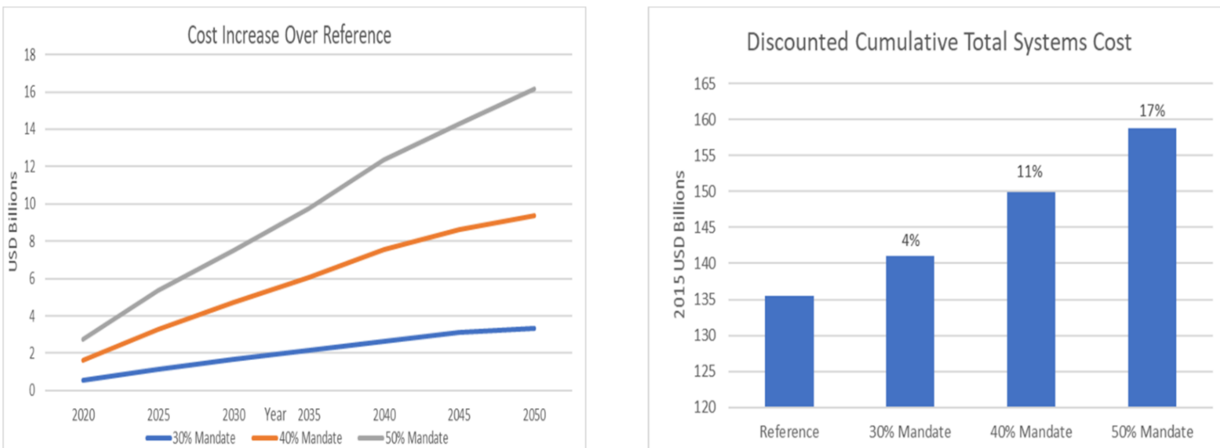

Figure 2.3. Incremental and Total Increase in Total System Costs Over Time Due to Renewable Generation Mandates Relative to the Reference Case

2.4.4 Total System Costs of Emissions and Benefits from Reductions in the Social Costs of Emissions

Having examined the costs associated with high penetration of renewable generation, it is also important to examine the benefits. The benefits that are being examined are emissions savings of CO_2e. Appendix Table A13 shows the SO_2 kilotons savings for the different mandate levels. Mandates do not seem to be an effective policy tool to decrease SO_2 emissions. Appendix Table A14 shows the PM 10 kilotons savings for different scenarios. Mandates may not be the most effective policy tool to decrease PM 10 emissions.

Appendix Table A15 shows the PM 2.5 kilotons saving for the different mandate levels. Mandates focused on renewables may not be the most effective policy tool to decrease PM 2.5

emissions. Other emission reduction policies such as a carbon tax may be more effective methods to decrease emissions such as SO_2, PM 10 and PM 2.5. Coal power plants are expensive to build but cheap to run, but costs of running coal plants increase as they age (Energy Information Administration, 2019). With the decrease in coal generation there is already a large decrease in emissions in the reference scenario.

The calculation of monetary values of savings in emissions has been done using valuations for emissions that reflect the Social Costs of Emissions (SCE). CO_2e has been valued at $40/ton based on the Social Cost of Carbon (SCC) from the Interagency Working Group on SCC (2013) data. The SCC is the monetized damages associated with an incremental increase in carbon emissions in a given year (Interagency Working Group on Social Cost of Carbon, 2013). The value has been estimated using three different integrated assessment models that examine climate impacts. The damages included agricultural productivity, human health and property damages have then been valued using a 3.5% discount rate. Pindyck (2019) argues that the SCC is higher and should be valued between $80-$100. The social cost for SO_2 has been valued at $95/ton based on the average of the damage function across a variety of different scenarios and assumptions examined by Shindell (2015). That study considered the damages including agricultural productivity and human health damages. Given the differences in the scenarios, taking the average may give a better point estimate given that there are differences in the valuation in the different scenarios. The social cost for PM 10 has been valued at $2,496 per ton based on the social damage function for the marginal damage costs (Hainoun et al., 2010). The study considered the damages including human health damages including illness and mortality for one country. The social cost for PM 2.5 has been valued at $94,000 per ton based on the marginal damage costs (Goodkind et al., 2019). The study considered the damages including human health damages including illness and mortality. The valuation used is the US valuation and different localities may have different valuations. The valuations for the different types of emissions are widely debated in the literature. To get overall benefits, the emission reductions have been multiplied by respective valuation for each emission type and summed. Table 2.6 shows the total reductions in the SCE for different scenarios. If the value of the SCC is switched to another value, then the conclusion that renewable electricity is not beneficial could change.

Table 2.6. Total Reductions in the Social Costs of Emissions for Different Scenarios

Total Benefits (Billion USD)	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
30% Mandate	0.62	0.81	1.00	1.19	1.34	1.56	1.69
40% Mandate	0.98	1.51	2.11	2.66	2.93	3.80	4.30
50% Mandate	1.31	2.32	3.54	4.48	5.00	6.51	6.91

The distance of the emissions from the location of consumption of electricity is not considered. Emissions would have a greater impact on people who live closer to a power plant than do those who live farther away from a power plant. As such, the benefits are average benefits across space and depend on the per ton valuations of emissions. Figure 2.4 shows the discounted total savings in SCE and the system costs for different scenarios. Given the results show that the system costs are larger than the savings in the SCE for all the scenarios.

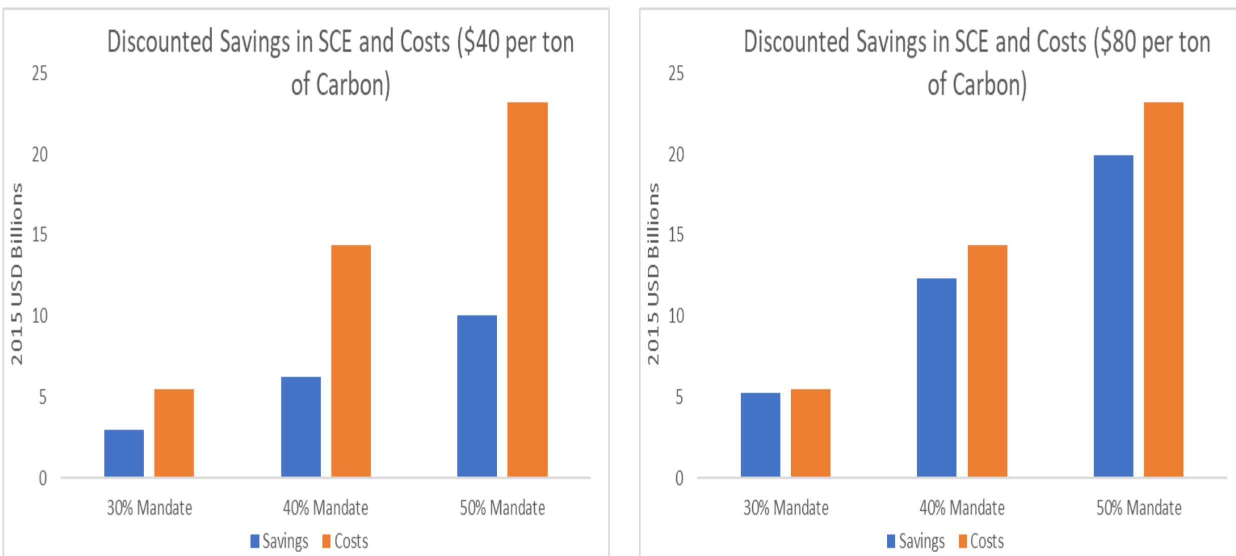

Figure 2.4. Discounted System Costs and Savings in SCE of the Different Mandates

Overall, the benefits do not justify the cost increases associated with the mandates. For all the mandates, even with a Social Cost of Carbon valued at $80/ton, the costs are greater than emissions reduction benefits. There is considerable disagreement on the Social Cost of Carbon. It is possible with a very high Social Cost of Carbon that the benefits would be greater than the cost increases. The world as a whole benefit from the emissions reduction, but it is electricity consumers in the MISO region would be paying for the higher electricity costs. There is a mismatch as a limited number of the people pays costs for which there is a benefit to everyone. If such altruistic behavior on the part of those who agree to pay the costs to obtain the benefits for a bigger group inspires other regions and countries to likewise behave in a cooperative way for the greater good, then maybe it makes sense. However, there is a danger of free riding.

It is possible that other policies could lead to larger reductions in the SCE with lower system costs. Mandates reduce CO_2e emissions. As most of the emissions reduction come from coal generation reductions, the net impact depends on what gets substituted for coal. Consider an example where the heat rate of coal is 10,000 Btu/kWh and the heat rate of natural gas is 8,000 Btu/kWh. The emissions for the different electricity generation by generator type come from Appendix Table A14 which shows the average emissions per PJ. Table 2.7 shows the emissions savings per kWh of technology substitution.

Table 2.7 Emissions Savings per kWh of Technology Substitution.

	SO_2 (lb/kWh)	**NO_X (lb/kWh)**	**PM 10 (lb/kWh)**	**PM 2.5 (lb/kWh)**	**CO_2 (lb/kWh)**
Combined Cycle Natural Gas Replaces Bituminous Coal	0.38	0.15	0.02	3.0E-3	1.12
Combined Cycle Natural Gas Replaces Sub-Bituminous Coal	0.35	0.12	0.02	3.0E-3	1.18
Combined Cycle Natural Gas Replaces Lignite Coal	0.30	0.07	0.01	3.0E-3	1.23
Wind or Solar Replaces Bituminous Coal	0.38	0.15	0.02	3.0E-3	2.05
Wind or Solar Replaces Sub-Bituminous Coal	0.35	0.12	0.02	3.0E-3	2.12
Wind or Solar Replaces Lignite Coal	0.30	0.07	0.01	3.0E-3	2.16

The table shows that if natural gas generation replaces coal generation, then there is a reduction of CO_2e, but not other emissions. If coal generation is replaced by wind or solar generation, there is a decrease in all emissions as wind and solar generation does not produce emissions. In reality, the effect of replacement of coal is between the natural gas case and the wind and solar case. Generally, there is not a lot of latitude for reducing one set of emissions relative to another given that the amount of electricity is fixed.

2.5 Conclusion

There is both an increase in the LMCOE and discounted total systems costs as the mandate level increases. The cost results should be considered a lower bound for potential cost increases as generation fluctuations, variations in future fuel costs and ramping, start-up and shut-down costs of other generation sources have not been considered. Given the costs of natural gas and battery storage, battery storage is still expensive and the model uses natural gas as spinning reserves instead. For the 50% mandate compared to the reference scenario, the percentage of combustion turbine natural gas capacity of overall natural gas capacity in 2050 increases from 47% to 55%. There are savings in the SCE and the savings increase as the level of the mandate increases. However, the savings in the SCE do not justify the system cost increases associated with the mandates. Another policy such as a carbon tax could lead to higher emissions reductions if it would decrease coal generation. The results would inform policymakers of costs and impacts of polices that lead to a high penetration of wind and solar generation sources and would enable more informed future electricity generation choices.

CHAPTER 3. A COMPARISON OF COSTS OF MANDATES FOR RENEWABLE ELECTRICITY AND CARBON TAX POLICIES

3.1 Introduction

The emissions from fossil-fuel based energy sources are a negative externality for society due to the damage to health and the environment caused by greenhouse gas (GHG) emissions including CO_2 emissions (Environmental Protection Agency, 2001). However, renewable energy sources do not have the associated negative externalities of fossil-fuel based energy sources because they do not contribute to GHG emissions. Two types of policies may help internalize the negative emissions externality from fossil-fuel based energy sources. The first type of policy is command and control such as mandates for renewable electricity generation and the second type of policy uses market-based instruments such as cap and trade, taxes and subsidies. There are benefits and costs to both command and control policies and market-based instruments.

Currently, there are 29 states with a mandate in the form of a Renewable Portfolio Standard (RPS) (Barbose, 2019). A carbon tax has not been implemented to reduce carbon emissions in the US. Wiesmeth (2012) argued that command and control policies such as regulations for emissions pollutants such as mercury could prevent firms from using certain harmful pollutants. However, regulations may not be welfare optimizing policies, due the fact that regulating pollutants does not consider the economic costs of pollution abatement. Command and control policies impose more welfare costs than a tax policy. Stavins (2003) showed that market-based instruments are better for ameliorating externalities than command and control policies from a social welfare perspective. Market-based instruments set either a price or a market-level quota combined with a market for tradeable permits and allow market agents to choose whether or not to pollute. Economists prefer market-based policies because they allow economic agents to self-select whether to contribute to pollution abatement, as well as their level of individual effort. This is preferable because the agents who can most cost-effectively provide abatement services will respond, whereas under a mandate system, all agents must respond equally regardless of cost. This chapter compares the total systems cost of a mandate for emissions reductions and a carbon tax using a single region version of The Integrated MARKAL-EFOM System (TIMES) model for MISO. A TIMES model at a single region level is suitable to compare a mandate for emissions reductions and a carbon tax as there is a detailed technological representation needed to evaluate policies that lead to high penetration of wind and solar generation. In reality, Renewable Portfolio Standards are implemented at the state level and not at the Independent System operator level. Independent System Operator level implementation of mandate and carbon tax policies do not properly reflect the realities of state level implementation of renewable electricity policies, and provide only a lower bound on the cost RPS imposition at state level across multiple states.

3.2 Literature Review

This chapter will focus on the costs associated with mandates for emissions reductions and carbon taxes. There have been backward looking studies. Carley (2009) used a fixed effects vector decomposition regression model with state level data from 1998 to 2006 to examine the impact of RPS adoption. The study found that states that employed an RPS did not have statistically significantly higher shares of renewable generation than states that did not have an RPS, holding all else constant. However, the study also found that RPSs increased the total amount of renewable generation in the US. Lin and Li (2011) use a difference-in-difference regression model to examine the effect of a carbon tax on per capita CO_2 emissions for Denmark, Finland, Sweden, the Netherlands and Norway. The study found that for Finland the carbon tax significantly reduced per capita CO_2 emissions. For Denmark, Sweden and Netherlands the carbon tax reduced per capita CO_2 emissions, but the results were not statistically significant. For Norway, the carbon tax did not reduce per capita CO_2 emissions. The unexpected results are due to tax exemptions for high emitting sectors such as oil and natural gas exports found in Norway.

Crane, et al. (2011) used an economic assessment framework to estimate the economic costs and emissions reductions from a command and control national mandate of 25% RPS by 2025 using coal as the baseload generation source for the US. The study projected that the policy would reduce GHG emissions by 670 million metric tons per year until 2025 from 2008 levels. Although the reduction of the first 100 million metric tons would cost $36 per metric ton annually, the next 300 million metric tons would cost $56 per metric ton annually and the remaining 270 million metric tons would cost $70 per metric ton annually. The total cost of the policy would be $35 billion annually. This study did not consider the use of a carbon tax and did not examine the difference in cost to get the same emissions reductions or renewable adoption with different policies.

Coffman, et al. (2012) used a bottom-up electricity sector model for Hawaii to estimate the emissions savings employing a policy of RPS and a GHG weighted Clean Energy Standard (CES), a policy that specifies that a certain percentage of total electricity generation coming from zero or low emission technologies. Nuclear and natural gas generation are included as low emission generation technologies. Wind, solar, hydro and geothermal are included as zero emission generation technologies. The study found that the GHG weighted CES was ineffective in increasing renewable electricity generation, but lead to substitution to fossil-based sources primarily natural gas generation. On the other hand, the RPS was more expensive, but lead to increased renewable electricity generation. This study did not look at emissions reductions.

Green (2008) used a simulation model to examine the impacts of a carbon tax and cap and trade scheme on electricity generation and electricity price risk for the UK. The study found that a cap and trade scheme increased price volatility faced by generation plants due to fuel prices, and that the plants would prefer to use fossil fuels as the generation source. The study also found that a carbon tax led to less fuel price volatility faced by generation plants compared to a cap and trade scheme and that the plants would prefer to use nuclear power as the generation source in the presence of the carbon tax. The simulation model did not capture the energy sector in detail as does a bottom-up electricity sector model. Di Cosmo and Hyland (2013) use time series data to examine the long-run price and income elasticity of demand for electricity for Ireland. The study found that a carbon tax that increased over time from €21.5 in 2012 to €41 in 2025 per ton of carbon emitted would reduce emissions by 860,000 tons of carbon per year until 2025 and generate €1.1 billion per year in revenue for Ireland. Di Cosmo and Hyland (2013) did not consider a command control policy.

Many studies in literature did not compare costs of mandates for emissions reductions and carbon taxes. To address the existing knowledge gap mentioned above, this chapter considers both command and control policies and market-based instruments using a detailed bottom-up electricity sector model for a significant electricity market area in the US, MISO. This chapter uses a more complete depiction of costs by using the detailed technological depiction of electricity in the TIMES model which allows for better examination of the costs of mandates for renewable electricity and carbon taxes that has not been thoroughly examined in the literature. A mandate for renewable electricity is an example of a command and control policy and a carbon tax is an example of a market-based instrument, and both these policies have different total systems cost.

This chapter examines a command and control policy versus a market-based solution that holds the overall emission reductions constant.

3.3 Modeling an Emission Tax

The dynamic optimization model used in Chapter 2 minimizes the discounted total system costs of producing electricity for a given demand. To introduce a carbon tax into this system one may follow different approaches including but not limited to:

a. Include a fix carbon tax regardless of the emissions time horizon. This type of carbon tax is expected to shift generation of elasticity towards lower carbon intensive technologies. This approach is not difficult to implement, but ignores the fact that the marginal damage of CO_2 emissions increases as its stock in the atmosphere grows over time (Pereira and Sauma, 2020).

b. Introduce a time varying carbon tax scheme to take into account the fact that the marginal damage of CO2 emissions increases over time. To accomplish this task the optimization problem defined in the second chapter should be modified to take into account the social cost of carbon over time and determine an optimal time path for the carbon tax to minimize the system costs including the social coast of carbon (Barron et al., 2018).

Given the complexity of determining an optimal time path of a carbon tax policy, we determined a time varying implicit carbon tax scheme for a given emissions reduction target using the model described in Chapter 2, as explained in the next section.

3.4 Policies

The reference case is identical to the reference case of Chapter 2. The following two policies have been defined and examined in this chapter:

Policy I: A time varying implicit carbon tax scheme is defined to achieve 35% reduction in CO_2e emissions in 2050 compared with 2020 with a liner trend. That is a reduction in total emissions from 968,076 kilotons in 2020 to 629,249 kilotons in 2050. To implement this policy the following steps have been followed:

i. A set of constraints was defined and added to the model used in Chapter 2 to enforce the emissions reduction target mentioned above. Specifically, the following constraints were added:

$$\Sigma_{p,s,2020}\text{Electricity Generation}_{p,s,2020} \times CO_2e\ \text{Emissions}_{p,s} \leq 968{,}076 \quad \textbf{(1)}$$

$$\Sigma_{p,s,2025}\text{Electricity Generation}_{p,s,2025} \times CO_2e\ \text{Emissions}_{p,s} \leq 911{,}605 \quad \textbf{(2)}$$

$$\Sigma_{p,s,2030}\text{Electricity Generation}_{p,s,2030} \times CO_2e\ \text{Emissions}_{p,s} \leq 855{,}134 \quad \textbf{(3)}$$

$$\Sigma_{p,s,2035}\text{Electricity Generation}_{p,s,2035} \times CO_2e\ \text{Emissions}_{p,s} \leq 798{,}663 \quad \textbf{(4)}$$

$$\Sigma_{p,s,2040}\text{Electricity Generation}_{p,s,2040} \times CO_2e\ \text{Emissions}_{p,s} \leq 742{,}192 \quad \textbf{(5)}$$

$$\Sigma_{p,s,2045}\text{Electricity Generation}_{p,s,2045} \times CO_2e\ \text{Emissions}_{p,s} \leq 685{,}721 \quad \textbf{(6)}$$

$$\Sigma_{p,s,2050}\text{Electricity Generation}_{p,s,2050} \times CO_2e\ \text{Emissions}_{p,s} \leq 629{,}249 \quad \textbf{(7)}$$

In equation (1) - (7), p is the different electricity generation by generator type, s is the different time slices and CO_2e emissions is the emissions per PJ of CO_2e emissions from CO_2, NO_X and CH_4. The units for electricity generation is PJ and the units for CO_2e emissions is kilotons per PJ. Appendix Table A14 which shows the average emissions per PJ for the different electricity generation by generator type.

ii. The modified model was solved and the shadow price of each constraint is observed. The shadow prices on the constraints of step i. represent the marginal discounted value of emissions.

iii. Using the shadow prices obtained from the above stage a new optimization model was defined and solved. This model used the shadow prices as a set of time varying tax on carbon emissions. The emissions reduction constraints removed from this optimization model. The results of steps ii. and iii. were identical.

Policy II: A mandatory expansion in the share of wind and solar was imposed to achieve the same emissions reduction as *Policy I* for 2050. A 38% mandate of wind and solar generations by 2050 was required to achieve the emissions reduction target of *policy I* for 2050. The mandated share was enforced linearly over the time period of 2020 and 2050.

3.5 Results

3.5.1 Generation Results

Table 3.1 shows the shadow prices of the mandates implemented in Policy I. The resulting implicit shadow prices are less than \$15/ton before 2030 and \$26/ton of CO_2e in 2050. This is significantly less than the Social Cost of Carbon (SCC) calculated by the Interagency Working Group on Social Cost of Carbon (2013) of \$40. The results arise from the assumption that the 42 GW of wind and 36 GW of solar in the MISO interconnection queue will be implemented linearly. The assumption of adding 42 GW of wind and 36 GW of solar generation, along with low natural gas price helps reduce a large amount of CO_2e emissions as the wind and solar generation displace other CO_2e emission intensive generation sources such as coal. In reality, not all the plants in the interconnection queue will be built, in which case the shadow prices could be higher.

Table 3.1. Shadow Price from 35% Reduction of CO_2e Emissions by 2050 from the Reference Case

Year	**CO_2e Emissions Mandate Upper Bound (kilotons)**	**Shadow Prices (Discounted 2005 USD per ton)**
2020	968,076	2.90
2025	911,605	2.99
2030	855,134	4.56
2035	798,663	14.08
2040	742,192	18.47
2045	685,721	23.27
2050	629,249	25.19

Figure 3.1 shows the evolution of the generation mix for Policy I over the planning horizon. Coal generation is initially the largest generation source with 38% of generation while natural gas is 34% of generation, but decreases over time. Coal generation goes from 1609 PJ (38% of generation) in 2020 to 171 PJ (4% of generation) in 2050. Coal generation is decreasing due to the age of those generators and the high costs of life extension in addition to the costs associated with the carbon tax, which combined to make coal generation uncompetitive with natural gas. The carbon tax policy decreases coal generation even more than the reference scenario.

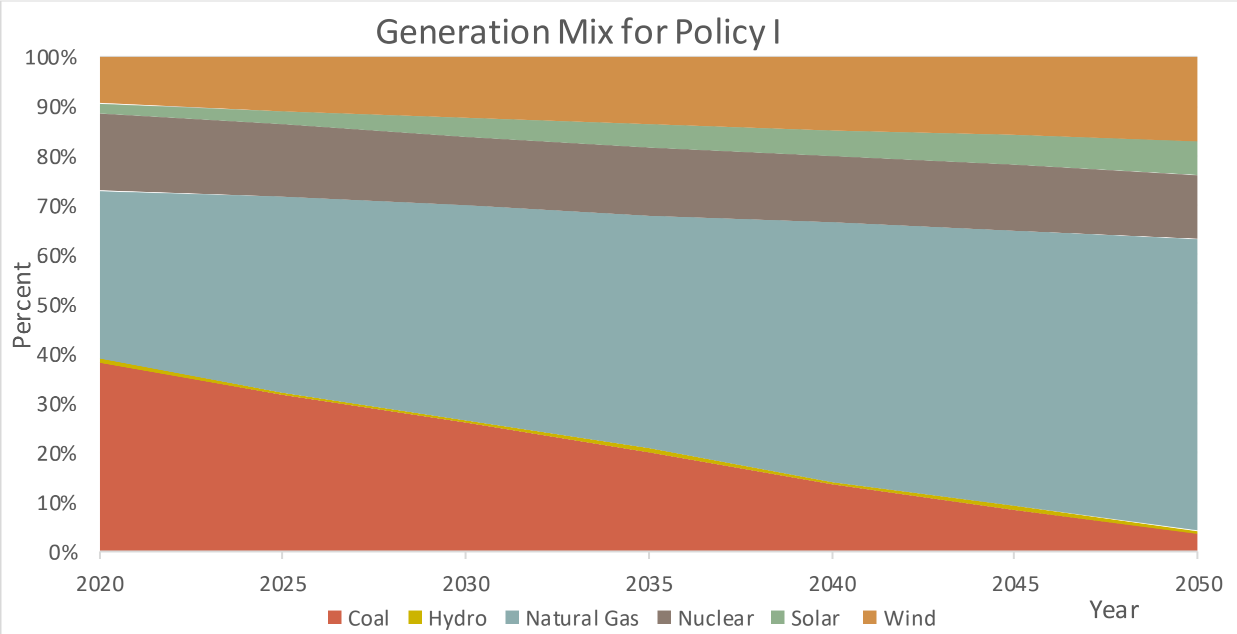

Figure 3.1 Generation Summary for Policy I

In 2020, there are 1418 PJ (34% of generation) of natural gas generation increasing to 2843 PJ (59% of generation) in 2050. Advanced combined cycle natural gas generation begins to come online in 2025. Advanced combined cycle natural gas is more efficient than coal and conventional combined cycle natural gas and replaces coal generation and the retiring combined cycle generation over time. Natural gas prices are expected to stay low, and if so, natural gas generation will increase over time even with the carbon tax (EIA 2019). Under Policy I and Policy II, nuclear generation goes from 661 PJ (16% of generation) in 2015, but with planned retirements, nuclear generation decreases over time to 621 PJ (14% of generation) in 2020 and remains the same through 2050. Hydro generation stays at 35PJ (1% or less of generation) in all time periods. Although there is oil generation capacity, it is not used. In 2050, wind generation is 824 PJ (17% of generation). In 2050, solar generation is 326 PJ (7% of generation). Similar to the reference scenario, there is no new investment in battery storage and the small of amount of existing battery storage capacity is used over time.

Figure 3.2 shows the generation summary for Policy II. In this scenario, coal generation goes from 1609 PJ (39% of generation) in 2020 to 435 PJ (9% of generation) in 2050. Coal is used less for generation over time due to retrofitting and life extension costs, which lead to coal generator capacity retirement. Natural gas generation replaces coal generation. This mandate policy has the same decreases coal generation as the reference scenario.

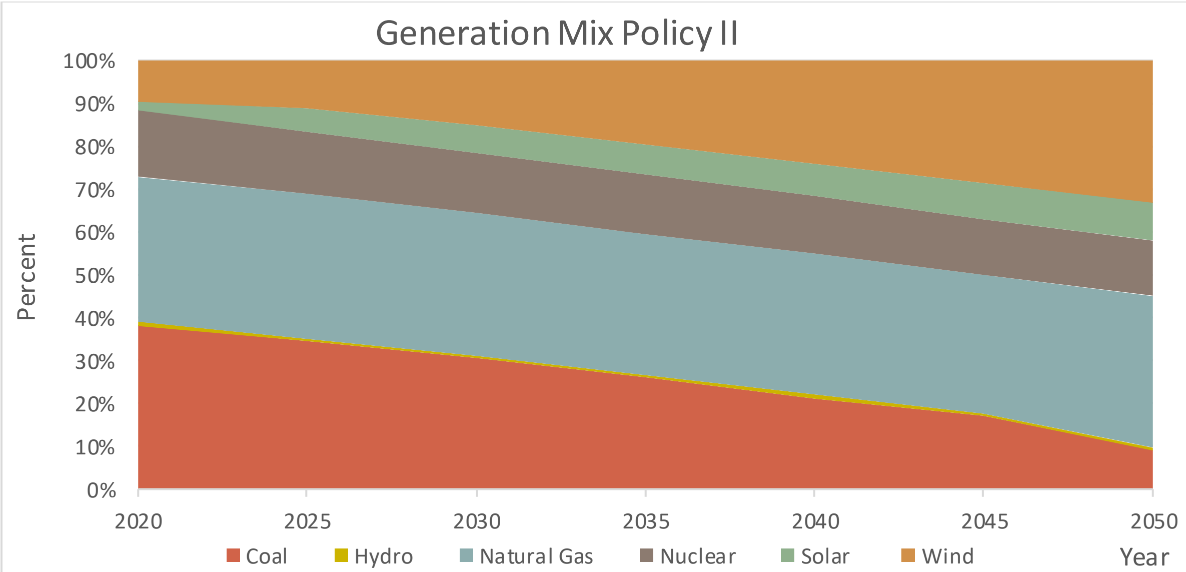

Figure 3.2. Generation Summary for Policy II

In 2020, there are 1416 PJ (34% of generation) of natural gas generation, and generation increases to 1706 PJ (35% of generation) in 2050. Even though there is an increase in natural gas generation, this increase slows over time. Similar to the previous scenario, nuclear generation goes from 661 PJ (16% of generation) in 2020, to 621 PJ (14% of generation) in 2050 and the generation remains the same until 2050. Hydro generation stays at a constant 35PJ (1% or less of generation) in all the time periods. There is no new investment in battery storage and the small of amount of existing battery storage capacity is used over time. In 2050, wind generation is 1600 PJ (17% of generation). In 2050, the solar generation is 422 PJ (7% of the generation). There is a larger share of wind and solar generation compared to Policy I. In Policy I, most of the emission reduction came from the decrease in coal, while wind and solar did not increase. In Policy II, wind and solar generation obviously increase due to the mandate. However, natural gas generation does not increase and while coal generation decreases.

3.5.2 Emissions Results

The emission results are displayed in Table 3.2. In the reference scenario, CO_2e emissions decrease over time with a 29% decrease of CO_2e from 2020 levels to 2050 levels. All the policies had a 35% decrease in CO_2e emissions from 2020 levels in the reference case. The emissions reduction within the time periods differ amongst the policies.

Table 3.2. CO_2e Emissions of the Different Scenarios

	CO_2e Emissions (kilo tons)	
	Policy I	**Policy II**
2020	968,076	951,578
2025	911,605	896,404
2030	855,134	842,921
2035	798,663	791,817
2040	742,192	755,030
2045	685,721	710,362
2050	629,249	642,528
Cumulative Emissions	**5,590,640**	**5,590,640**

3.5.3 Cost Results

LMCOE gives discounted value of generation for a year based on the generation weighted MCOE and gives the ability to compare across different scenarios. Table 3.33 shows the LMCOE for different scenarios. Policy I had the lower LMCOE, while Policy II had the higher LMCOE.

Table 3.3. Levelized Marginal Cost of Electricity for Different Scenarios

Policy	Levelized Marginal Cost of Electricity (¢/kWh)	Percent change from reference case
Reference	5.697	
Policy I	6.205	8.92%
Policy II	6.378	10.98%

Figure 3.4 shows the increases in total system cost from the different policies relative to the reference case. The incremental total system cost for the Policy I is 0.3% over the reference in 2020 and a 11.0% higher in 2050, and for Policy II there is a 4.6% increase over the reference case in 2020 and a 33.1% in 2050. The discounted total system cost for the Policy I is 3% and for Policy II it is 66%. Policy I and II have a lower percentage increase in total system cost than the LMCOE.

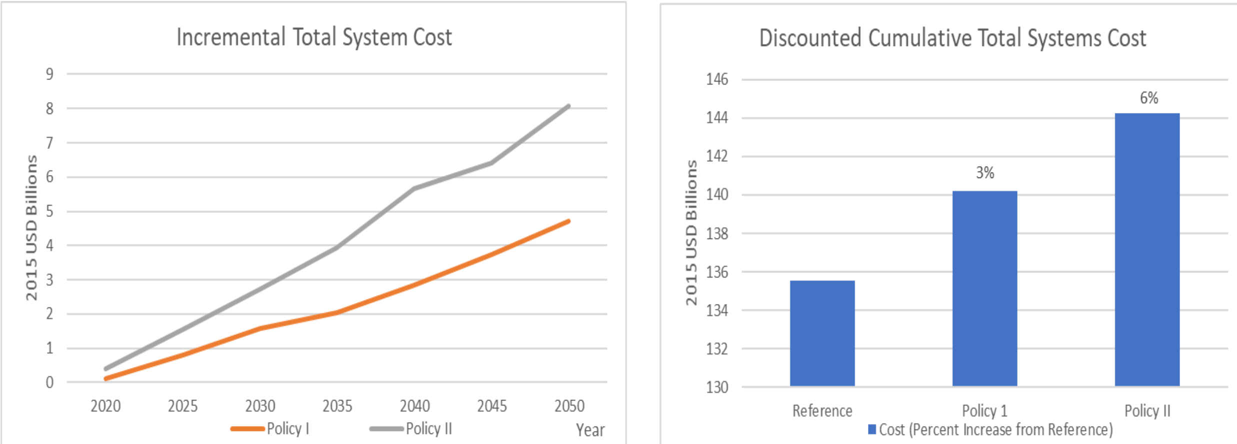

Figure 3.3 Incremental and Total Increase in Total System Costs Over Time Due to Different Policies Relative to the Reference Case

3.6 Conclusion

Policy II is a command and control policy, while Policy I is a market-based instrument. All policies hold the overall emission reductions constant where there 35% reduction of CO_2e emissions from 2020 levels by 2050 compared to the reference scenario. As such, different policies can be used to hold overall emissions constant. Wind and solar generator components such as solar panels and wind turbines generate emissions in the production process. The transport and installation of the generating systems also generate emissions. The emissions of the mentioned production, transportation and installation has not been considered in this chapter. However, on the fossil fuel side, there are the emissions from natural resource extraction has been considered.

Policy I led to a decrease of coal generation in the generation mix compared to the reference. Policy II did not decrease coal compared to the reference. In Policy I, wind and solar generation did not exceed the levels of the reference case. Natural gas generation increase in all the policies. Policy I had the lower LMCOE and Policy II had the higher LMCOE. Similarly, Policy I had the lower of discounted total system cost, and Policy II had the higher discounted total system cost.

CHAPTER 4. IMPLICATIONS OF THE CONSIDERING SHORT-TERM OPERATIONAL CONSTRAINTS ON HIGH PENETRATION OF INTERMITTENT RENEWABLE ENERGY POLICIES

4.1 Introduction

Important considerations in the assessment of the impacts of policies for substantially increasing penetration of renewable electricity generation include short-term operational constraints of power plants. Wind and solar generation fluctuate based on weather and therefore will impact the short-term operational constraints of other power plants in the system. Chapter 2 did not examine short-term operational constraints of power plants or generation fluctuations of wind and solar generation, with the 288 hourly time slices used. Wind and solar generation fluctuations occur at the sub-hourly time resolution and therefore an hourly time slice model cannot fully capture the costs associated with generation fluctuations. However, short-term operational constraints such as start-up times, minimum load, minimum up and down times and ramp limitations can be added to a capacity expansion model. For this chapter, short-term operational constraints are modeled on hourly time slices. As such, operational constraints operating at finer time scales are not reflected in the model. Typically, capacity expansion models with longer-term horizons examining periods of 30-50 years do not consider short-term operation constraints.

Studies such as Brouwer et al. (2014), Lantz, et al. (2016) and Frew et al. (2016) use production cost models to examine wind and solar generation, and these studies consider short-term operation constraints. However, production cost models are not typically used for addressing long-term issues such as capacity expansion. Capacity expansion models are used for planning the electricity infrastructure over a longer time horizon. Das et al. (2018) highlights that capacity expansion models that do not take into account short-term operational constraints tend to overestimate wind and solar integration capability as there is no consideration of the flexibility requirements associated with maintaining system reliability.

There has only been one instance where short-term operating constraints have been added to a TIMES model. Gaur et al. (2019) added short-term operation constraints to TIMES for a North Indian multiple region model. The study added ramp rates, start-up times, minimum up and minimum down times, start-up costs and maximum non-operational times to the model using the unit commitment and dispatch features of the TIMES model. All of this is done in the hourly time slice framework of TIMES; so operational constraints operating at finer time scales are not reflected. The study found that short-term operation constraints led to increased usage of existing capacity of coal and less new investment in coal and other conventional generation sources. Also, the addition of short-term operation constraints helped determine the how to use the non-renewable generation sources required in the system to allow for increased wind and solar generation compared to scenarios without short-term operation constraints.

The contributions of the study presented here are a more complete examination of emission savings and a more inclusive depiction of costs by examining system integration costs for policies that lead to high penetration of intermittent renewable generation with short-term operation constraints. The TIMES model contains technological detail that allows for the assessment of emissions savings related to increased penetration of intermittent renewable generation using a simplified unit commitment and dispatch formulation (Panos and Lehtilä, 2016). Using the 288 hourly time slices as used in Chapter 2, short-term operation constraints have been added to the model using the formulation of Panos and Lehtilä (2016) in TIMES. The time slice includes 24 hours for each day type, Weekdays, Saturdays, and Sundays and the four seasons to get total of 288 hourly time slices. Within the season and the week, hours of the day are treated as consecutive and wrapped around to the next day to facilitate formulation of the operational constraints for minimum up and down times, start-up and shut-down times. The short-term operation constraints and costs that have been added are start-up times and costs, partial load efficiency loss at the dispatching phase (when load is below a threshold, increased fuel consumption is needed to run the power plant), minimum load, minimum up time and down time and ramp rates. The updated costs provide a more complete understanding of system integration costs because they include different start-up costs. Details of the modifications made to the TIMES model are found in the methodology section and the details of the unit commitment and dispatch features are from Panos and Lehtilä (2016).

The research question that is being examined here is the following: what are the emissions and costs of policy mandates for high penetration of wind and solar electricity technologies for MISO when short-term operational constraints are considered?

4.2 Methodology

The short-term operational constraints in the version of the TIMES model due to Panos and & Lehtilä (2016), more realistically depict constraints on the electricity system, and is implemented through the use of several sets of binary and continuous variables. The short-term operation constraints and costs for start-ups, partial load efficiency losses at the dispatching phase, minimum load, minimum up and down times and ramp rate data are added as constraints and objective modifications to the optimization problem from Chapter 2 (Panos and Lehtilä, 2016). The optimization problem is solved as a Mixed Integer Problem (MIP). Individual power plants are not modeled. Instead the total capacity of a generation technology/fuel type such as coal or natural gas is divided into minimum semi-continuous unit size (Panos and Lehtilä, 2016). Table 4.1 shows the semi-continuous fossil fuel generators total capacity and unit size for which the operational constraints apply.

Table 4.1. Semi-continuous Fossil Fuel Generators Total Capacity and Unit Size

Classes of Generators	**2015 Capacity (GW)**	**Minimum Semi-continuous Unit Size (GW)**
Bituminous coal 1950s over 100 MW	2.459	0.5
Bituminous coal 1960s over 100 MW	5.377	0.5
Bituminous coal 1970s over 100 MW	11.509	0.5
Bituminous coal 1980s over 100 MW	6.907	0.5
Bituminous coal 1990s over 100 MW	1.505	0.5
Bituminous coal 2000s over 100 MW	2.968	0.5
Bituminous coal 1950s under 100 MW	0.099	0.5
Bituminous coal 1960s under 100 MW	0.311	0.5
Bituminous coal 1970s under 100 MW	0.095	0.5
Sub-Bituminous coal 1960s over 100 MW	0.336	0.5
Sub-Bituminous coal 1970s over 100 MW	1.052	0.5
Sub-Bituminous coal 1980s over 100 MW	2.034	0.5
Sub-Bituminous coal 1990s over 100 MW	0.000	0.5
Sub-Bituminous coal 1950s Under 100 MW	1.083	0.5
Sub-Bituminous coal 1960s Under 100 MW	0.075	0.5
Lignite coal 1950s over 100 MW	0.557	0.5
Lignite coal 1960s over 100 MW	2.125	0.5
Lignite coal 1970s over 100 MW	12.779	0.5
Lignite coal 1980s over 100 MW	13.486	0.5
Lignite coal 1990s over 100 MW	1.804	0.5
Lignite coal 2000s over 100 MW	3.848	0.5
Lignite coal 1950s under 100 MW	0.445	0.5
Lignite coal 1960s under 100 MW	0.451	0.5
Lignite coal 1970s under 100 MW	0.271	0.5
Lignite coal 1990s under 100 MW	0.532	0.5
Natural Gas Combined Cycle	28.38	0.4
Natural Gas Combustion Turbine	27.20	0.1

The different generator types have different technical specifications such as efficiency and availability factor. The minimum semi-continuous unit size is 0.4 GW for a combined cycle natural gas generator and 0.1 GW for a combustion turbine natural gas generator (Gaur et al., 2019). For all bituminous, sub-bituminous and lignite coal generators, the minimum semi-continuous unit size is 0.5 GW. All the semi-continuous units of a generation type have the same characteristics: start-up times and costs, partial load efficiency loss at the dispatching phase, minimum and maximum loads, minimum up and down times, and ramp rate. However, the offline and online status of the semi-continuous units differ from each.

The start-up time is the time in hours needed for a generator to synchronize to grid frequency to avoid thermal stress (Panos and Lehtilä, 2016). There are three different start-up times that vary according to the type of start-up. The three type of start-ups are hot, warm and cold start-ups. Each of the hot, warm and cold start-ups also has a different USD per MW cost associated with the start-up. The minimum load is the lowest level of generation at which a power plant can operate effectively (Panos and Lehtilä, 2016). The minimum load is expressed as a percentage of load.
There is a minimum number of hours that a power plant must be online (minimum up time) or a power plant must be offline (minimum down time) for a power plant to maintain electricity generation and avoid thermal stress (Panos and Lehtilä, 2016). Both minimum up time and minimum down time are measured in hours in this chapter. The ramp rate is the rate at which the power plant can increase or decrease generation within a specific time period (Panos and Lehtilä, 2016). The ramp rate has been measured in percent of online capacity. Power plants are more efficient at higher load levels, but when load is below 60%, there is increase in fuel consumption per unit of electricity generated called the partial load efficiency loss at the dispatching phase (Panos and Lehtilä, 2016). Partial load efficiency loss at the dispatching phase is measured as a percentage increase in fuel consumption. Table 4.2 gives the start-up times and costs, partial load efficiency loss at the dispatching phase, minimum load, minimum up time and down time and ramp rate data that has been model.

Table 4.2. Short-term Operational Data Added to Model

	Data Source	Coal Bituminous/Sub-bituminous	Coal Lignite	Natural Gas Combined Cycle	Natural Gas Combustion Turbine
Hot Start-up (Hours)	Schröder et al. (2013)	3	3	0.75	0.1
Warm Start-up (Hours)	Schröder et al. (2013)	4.67	3.5	2.67	0.2
Cold Start-up (Hours)	Schröder et al. (2013)	7.25	9.33	3	0.33
Hot Start-up Cost (USD/MW)	Schröder et al. (2013)	21.43	21.43	24.7	22.28
Warm Start-up Cost (USD/MW)	Schröder et al. (2013)	31.19	31.19	28.69	34.24
Cold Start-up Cost (USD/MW)	Schröder et al. (2013)	54.47	54.47	48.21	41.25
Minimum Load (% of online capacity)	Velástegui Andrade (2018)	31.67	45	40	40
Minimum Up Time (Hours)	Velástegui Andrade (2018)	6	6	4	2
Minimum Down Time (Hours)	Velástegui Andrade (2018)	4	4	2	2
Partial oad efficiency loss at the dispatching phase (%increase in fuel consumption when load is below 60%)	Schröder et al. (2013)	2	4.5	8	21
Maximum ramp rate (% of online capacity per hour)	Gaur et al. (2019)	40	40	100	100

For the classes of generators, binary status variables are defined that track whether any generators in a given class are currently online (Panos and Lehtilä 2016). Several binary variables indicate the status of the generating units and, in combination with logical conditions involving when the unit was turned on and when it will be turned off, define constraints that restrict the levels of associated generation variables that are distinguished by phase of operation (offline, starting up, dispatching and shutting down). This ensures that the operating characteristics such as heat rates and ramp rates reflect the phase for that technology (Panos and Lehtilä, 2016).

These classifications are implemented via disjunctive constraints. Disjunctive constraints can be implemented in different ways including big-M constraints or indicator constraints. Consider a constraint $atx < b$ which is imposed when a binary indicator variable, y, is 1, and if y is 0, the constraint is not imposed. (It is straightforward to adapt this approach for the case of equality constraints.) With the big-M formulation this constraint can be replaced by $atx < b + M(1 – y)$ where M is a large constant. When $y = 0$, the constraint is $atx < b + M$ where the constant M has been chosen to be large enough that this constraint will never bind, and when $y = 1$, the constraint is $atx < b$. Therefore, y turns on or off the indicator constraint. An alternative to the big-M constraint is the complementary formulation where the constraint is transformed to $(atx – b)y < 0$. Again, the binary variable, y, turns off this constraint when it is zero, and turns it on when it is one. The problem is that this constraint is non-convex. Global optimization techniques have been developed to implement indicator constraints (see Belotti et al., 2016), and IBM-CPLEX includes an implementation of solution procedures for the indicator constraints as part of the toolkit for problem solution from version 12.6.1 (IBM ILOG CPLEX V12.1, 2009).

Panos and Lehtilä (2016) have implemented dispatching and unit commitment features using the indicator constraint formulation to match generation characteristics for a unit to its phase classification. Thus, if y is the binary variable for a generating unit in a particular phase, and x is the level of generation for that unit with operational parameters associated with that phase, then the constraint $x(1 – y) < 0$ is imposed. With this constraint, if y is zero, then the unit is not in that phase, and the associated generation level cannot exceed zero, and if y is one, the zero upper bound is not imposed, and generation may be at a positive level.

All the other variables are continuous and the units are in GW for the hourly time slice. Separate continuous variables track the generation of units that are in alternative phases: offline, starting up, dispatching, and shutting down (Panos and Lehtilä 2016). The generation variables distinguished by phase are linked with binary variables via indicator constraints that enforce the logic that (a) each unit can be in only one phase, and (b) the associated phase is linked to when the unit was brought online and when it will go offline, as well as for how long the unit has been off line in order to distinguish the type of startup (hot, warm, or cold), which affects the operational performance of the unit during the starting up phase (Panos and Lehtilä 2016).

Additional logical constraints enforce minimum up and down time requirements (Panos and Lehtilä 2016). Generation by the units is managed by having separate continuous generation variables for each unit and phase (Panos and Lehtilä 2016). The technical coefficients defining efficiency are specific to the phase, reflecting the fact that operating characteristics differ by phase. Additional constraints and activities are used to implement the partial efficiency losses associated with operating a plant in the range of 0 percent to 60 percent (Panos and Lehtilä 2016). Taken together, these variables and constraints implement the logic of the short-term operational constraints.

Wind and solar variability have not been completely modeled. Figure 4.1 shows the wind availability factors of select candidate sites while Figure 4.2 shows solar availability factor of select candidate sites that has been used. Time slices 1-24 are Winter weekday time slices. Time slice 25-48 are Winter Saturday time slice and 49-72 are Winter Sunday time slices. Time slices 73-96 are Spring weekday time slices. Time slice 97-120 are Spring Saturday time slice and 121-144 are Spring Sunday time slices. Time slices 145-168 are Summer weekday time slices. Time slice 169-192 are Summer Saturday time slice and 193-216 are Summer Sunday time slices. Time slices 217-240 are Fall weekday time slices. Time slice 241-264 are Fall Saturday time slice and 265-288 are Fall Sunday time slices.

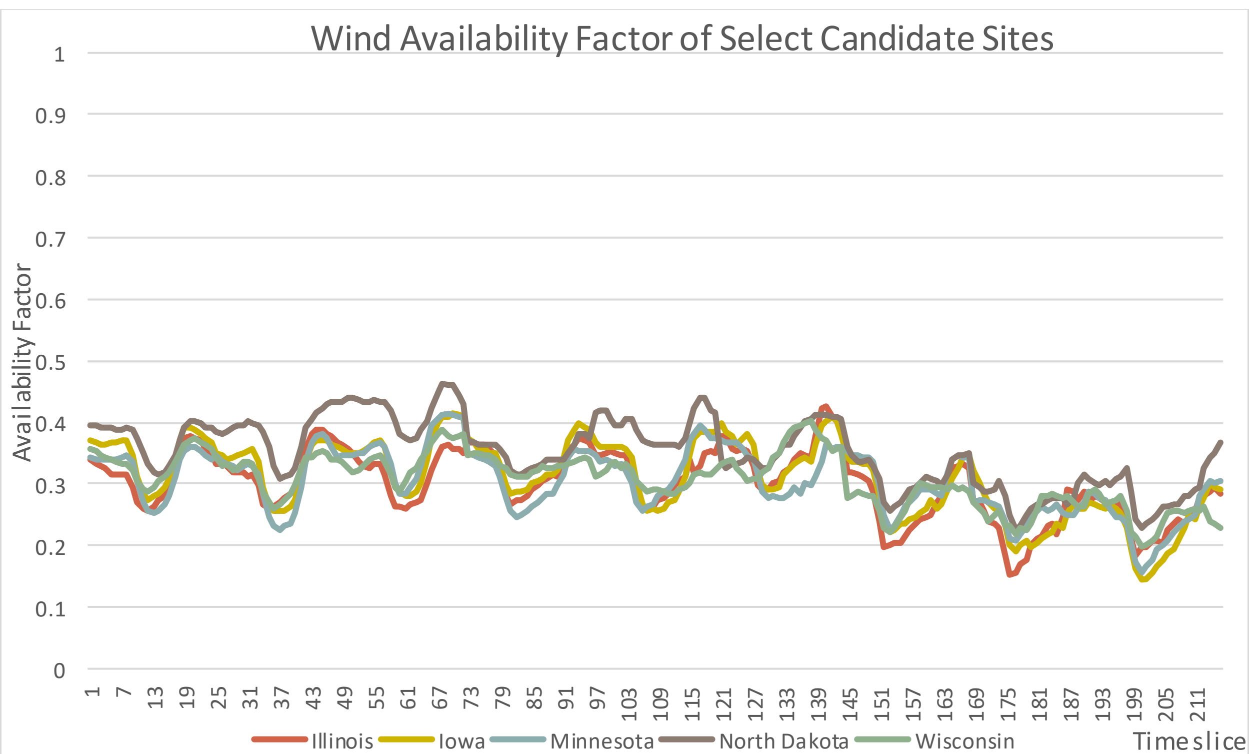

Figure 4.1. Wind Availability Factor of Select Candidate Sites

Figure 4.1 and Figure 4.2 show that the 288 hourly time slices have captured some of the variability associated with wind and solar generation. Although there are 288 hourly time slices, wind and solar generation fluctuations occur at the sub-hourly time resolution and therefore the model has not fully captured the generation fluctuations. The use of sub-hourly time slices maintaining temporal chronology would be needed to thoroughly capture wind and solar generation fluctuations. However, with the increase in the number of time slices there is also an increase in computational burden and larger data requirements. Therefore, there is a tradeoff between ability capture variability of wind and solar and increase in computational burden and larger data requirements. The principle loss of model fidelity is that the need for fast ramping capacity may be understated with hourly time slices.

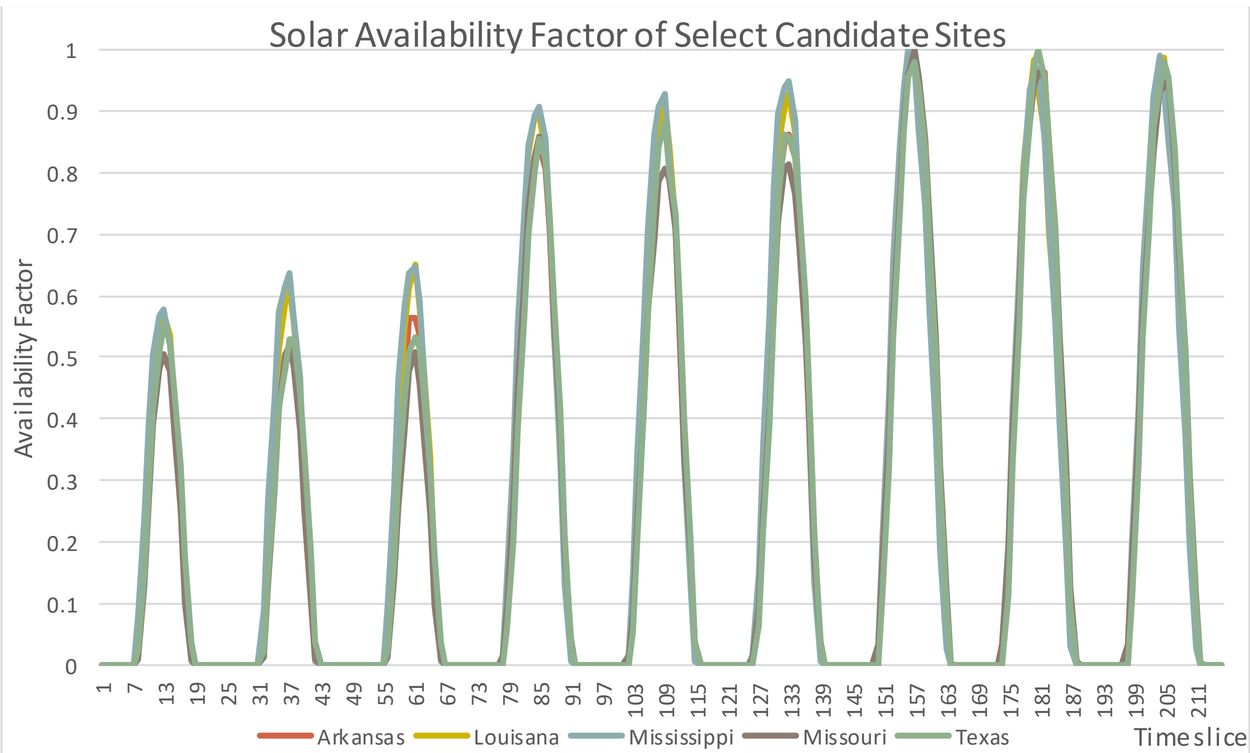

Figure 4.2. Solar Availability Factor of Select Candidate Sites

Without capturing all of the variability associated with wind and solar generation, it is not possible to model short-term operational constraints completely. Ideally, all the variability associated with wind and solar generation should be captured along with power plants of a generation type having all the same operating characteristics. Having individual power plant characteristics would give a more complete depiction of short-term operational constraints. There are short-term operational constraints that have not been added due to data limitations. These constraints include limits on very short-term ramping and the associated costs and partial efficiency loss at the start up and shut-down phase.

4.3 Policies

The policies and reference scenario are the same as in Chapter 2. The non-mandate scenario that does not include short-term operational constraints will be called the original reference scenario and the non-mandate scenario that includes short-term operational constraints will be called the updated reference scenario. For each mandate level, there are two scenarios. The first scenario comes from the first chapter where short-term operational constraints are not included and will be called the original scenario. The second scenario includes short-term operational constraints and will be called the updated scenario.

4.4 Results

4.4.1 Start-up and Shut-Down Results

Figure 4.3 shows 2020 natural gas generation during the different seasons for original reference scenario. Time slices 1-24 are weekday time slices. Time slice 25-48 are Saturday time slices, and 49-72 are Sunday time slices. The other years had a similar profile. The figure shows that particularly on Saturday and Sunday there are hours with no natural gas generation, but in the next hour there is natural gas generation, which is unrealistic. If start-up and shut-down times are considered, going from no generation to a high level of generation in an hour is not possible for some generators. The hours which have no natural gas generation differ by season for the original reference scenario.

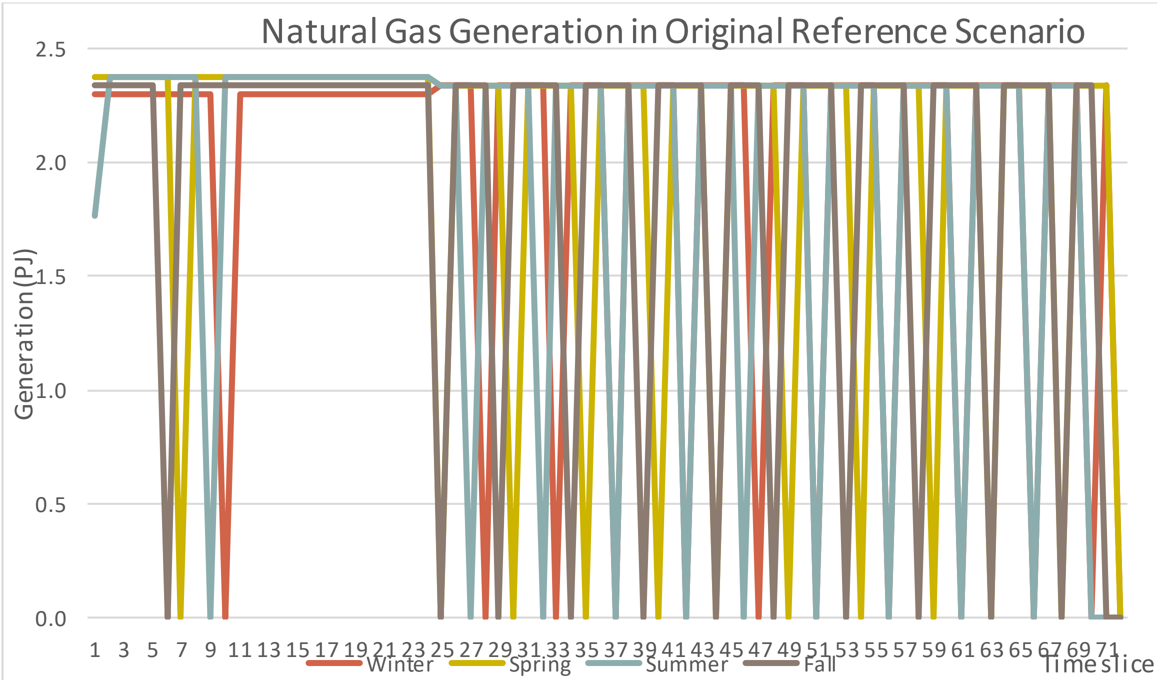

Figure 4.3. 2020 Natural Gas Generation during the Different seasons for Original Reference Scenario

Figure 4.4 shows 2020 natural gas generation during the different seasons with operational constraints. Time slices 1-24 are weekday time slices. Time slices 25-48 are Saturday time slice and 49-72 are Sunday time slices. The other years had a similar profile. The addition of constraints stops generation from going to 0. This arises because the differing semi-continuous power plant units have different online and offline schedules. The hour in which the lowest generation occurs differs by season. This shows that unrealistic generation profile of the original reference has been fixed.

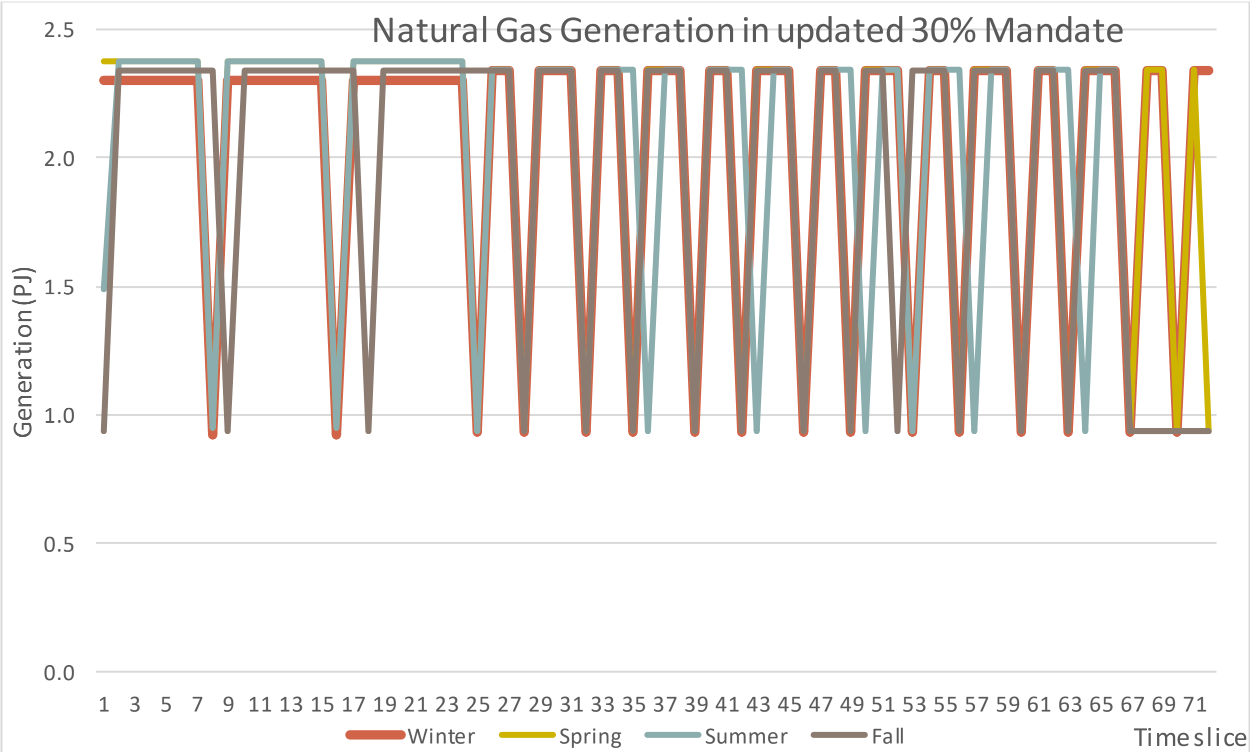

Figure 4.4. 2020 Natural Gas Generation during the Different Seasons with Operational Constraints

Figure 4.5 shows 2020 coal generation during the different seasons for the original reference scenario. Time slices 1-24 are weekday time slices. Time slices 25-48 are Saturday time slices and 49-72 are Sunday time slices. The other years had a similar profile. There are hours with no coal generation, but in the next hour there is coal generation, which is not realistic. If start-up and shut-down are considered, going from no generation to a high level of generation in an hour is not feasible when all the generators are considered. The hours which have low coal generation differ by season for the original reference scenario.

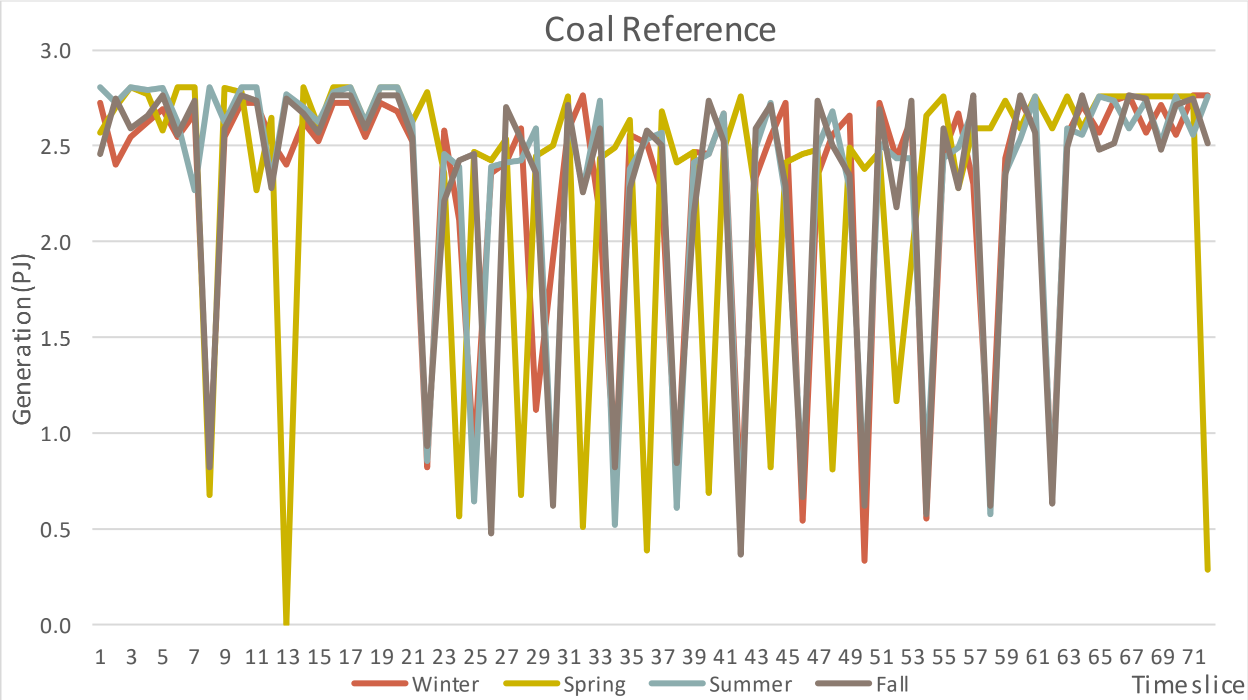

Figure 4.5. 2020 Coal Generation during the Different seasons for Original Reference Scenario

Figure 4.6 shows 2020 coal generation during the different seasons with operational constraints. Time slices 1-24 are weekday time slices. Time slices 25-48 are Saturday time slices and 49-72 are Sunday time slices. The other years had a similar profile. The addition of constraints seems to stop time slices from 0 generation. This shows that the unrealistic generation profile of the original reference has been fixed. Generation occurs in all time slices in a band between 1-3 PJ. There is a smaller standard deviation in generation with the addition of operational constraints. This arises from the differing semi-continuous power plant units have different online and offline schedules.

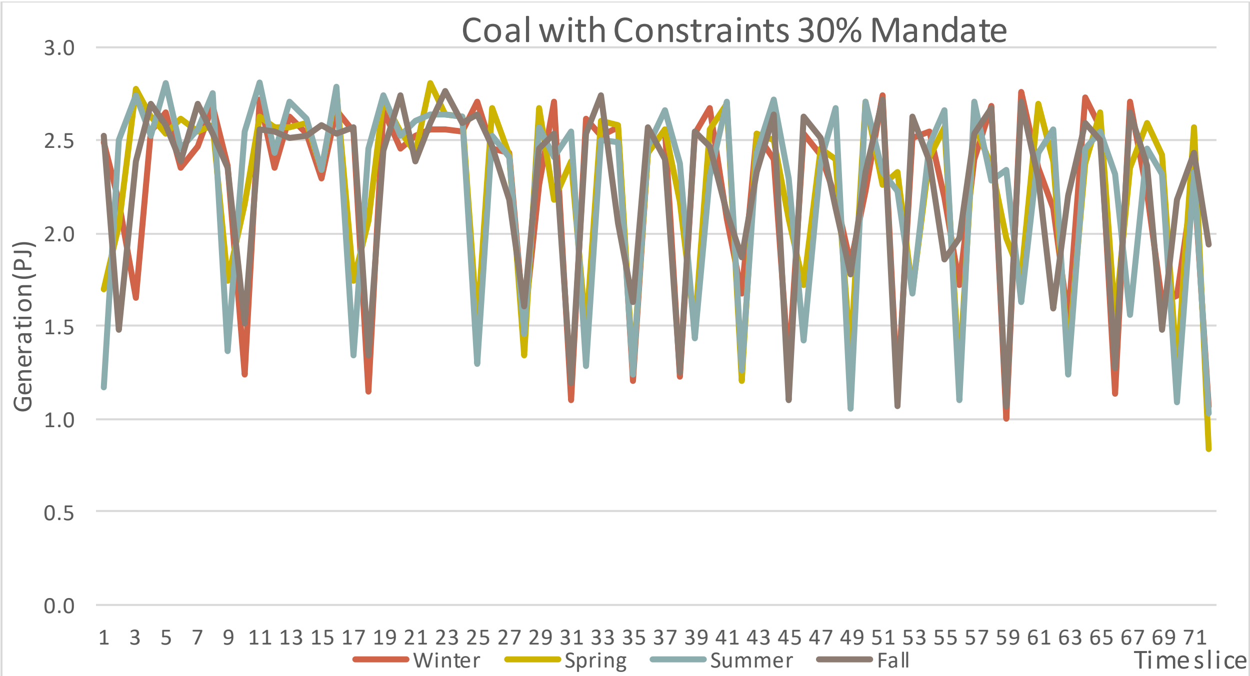

Figure 4.6. Coal Generation during the Different Seasons with Operational Constraints

4.4.2 Reference Scenario Results

The updated reference scenario looks similar to the original reference scenario. Figure 4.7 shows the generation mix for original reference scenario and updated reference scenario. Appendix Table B1 shows the original and updated reference generation mixes. For the updated reference scenario, coal generation goes from 1,597 PJ (38% of generation) in 2020 to 401 PJ (8% of generation) in 2050. For the updated scenario, coal generation is less than the original scenario in all years of the planning horizon. Given that coal generation has longer start up times, higher startup costs, longer minimum up times, longer minimum down times and lower ramp rates than other generation sources, there is decreased coal generation.

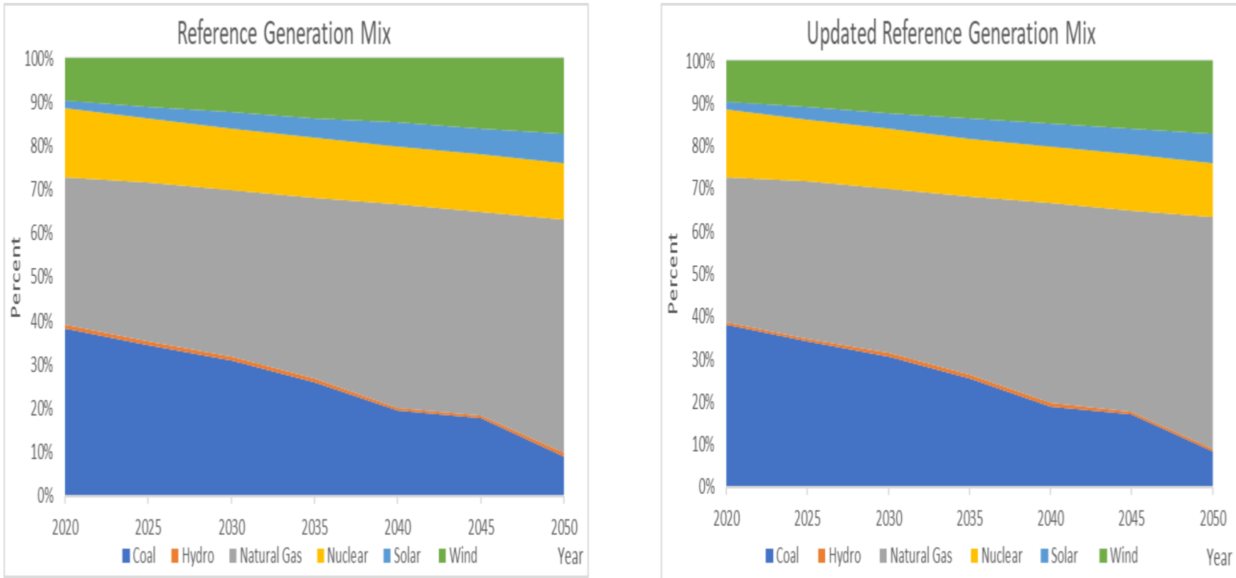

Figure 4.7. Generation Mix for Original Reference Scenario and Updated Reference Scenario

For the updated scenario, there are 1,431 PJ (34% of generation) in 2020 of natural gas generation and generation increases to 2,612 PJ (54% of generation) in 2050. Advanced combined cycle natural gas is more efficient, has shorter start-up times, lower start-up costs, shorter minimum up times, shorter minimum down times and higher ramp rates and replaces coal generation and the retiring combined cycle generation over time. For both scenarios, nuclear generation goes from 661 PJ (16% of generation) in 2015, but with planned retirements, generation decreases over time to 621 PJ (14% of generation) in 2020, and the generation amount remains the same until 2050. Hydro generation stays at 35PJ (1% or less of generation) in all the time periods. Although there is oil generation capacity, it is not used. Wind generation goes from 399 PJ (9% of generation) to 824 PJ (17% of generation) and solar generation goes from 83 PJ (2% of generation) to 326 PJ (7% of generation). For the reference scenario, the addition of short-term operational constraints did not make changes to nuclear, hydro, wind and solar generation. However, the addition of short-term operational constraints increased total system cost by 3.7% in 2020 and by 7.3% in 2050.

4.4.3 30% Mandate Results

With a 30% mandate for both the original and updated scenarios, coal generation is initially the largest generation source, but decreases over time. Even though there is coal capacity available, coal is used less for generation over time due to retrofitting and life extension costs. Figure 4.8 shows the generation mix for the 30% mandate scenario for original and updated cases. Appendix

Table B2 shows the generation breakdown of the generation mix for both original and updated scenarios with the 30% renewable generation mandate. In the original scenario, coal generation goes from 1,609 PJ (38% of generation) in 2020 to 435 PJ (9% of generation) in 2050. For the updated scenario, coal generation goes from 1,568 PJ (37% of generation) in 2020 to 193 PJ (4% of generation) in 2050. For the updated scenario, coal generation is less than the original scenario in all years of the planning horizon. Coal generation has longer start up times, higher startup costs, longer minimum up times, longer minimum down times and lower ramp rates than other generation sources. Therefore, when short-term operational constraints have been added to the model, there is less coal generation.

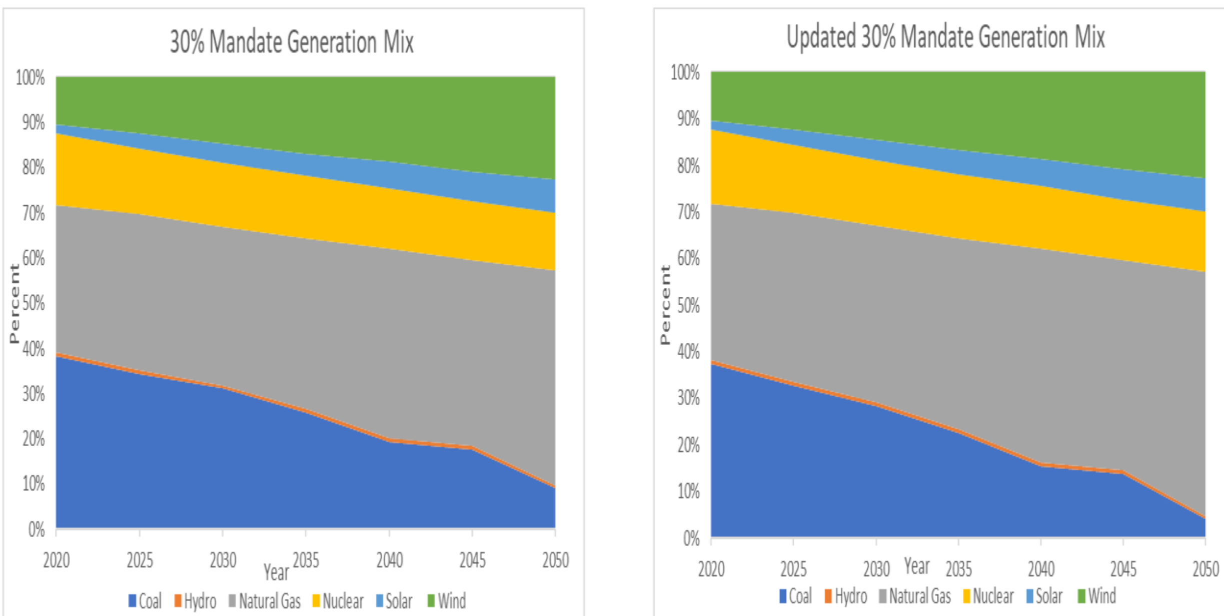

Figure 4.8. Generation Mix for 30% Mandate for Original and Updated Scenarios

In the original scenario, there are 1,378 PJ (33% of generation) in 2020 of natural gas generation and generation increases to 2,285 PJ (47% of generation) in 2050. For the updated scenario, there are 1,419 PJ (34% of generation) in 2020 of natural gas generation and generation increases to 2,526 PJ (52% of generation) in 2050. Advanced combined cycle natural gas generation begins to come online in 2025. Advanced combined cycle natural gas is more efficient and replaces coal generation and the retiring combined cycle generation over time. Natural gas prices are expected to stay low, and natural gas generation will increase over time (EIA 2019). Natural gas generation has shorter start-up times, lower start-up costs, shorter minimum up times, shorter minimum down times and higher ramp rate than other generation sources, in particular compared to coal generation. Therefore, when short-term operational constraints have been added to the model, there is more natural gas generation.

For both the original and updated scenario, nuclear generation goes from 661 PJ (16% of generation) in 2015, but with planned retirements, generation decreases over time to 621 PJ (14% of generation) in 2020. and the generation amount remains the same until 2050. Hydro generation stays at 35PJ (1% or less of generation) in all the time periods. Although there is oil generation capacity, it is not used. In 2050, wind generation is 1,095 PJ (23% of generation). In 2050, the solar generation is 349 PJ (7% of generation). Similar to the original scenario, there is no new investment in battery storage and a small of amount of the existing battery storage capacity is used over time. The addition of short-term operational constraints did not make changes to nuclear, hydro, wind and solar generation.

4.4.4 40% Mandate Results

With a 40% mandate for both the original and updated scenarios, coal generation is initially the largest generation source, but decreases over time. Even though there is coal capacity, coal is used less for generation over time due to retrofitting and life extension costs. Figure 4.9 shows the generation mix for the 40% mandate for original and updated scenarios. Appendix Table B3 shows the generation breakdown of the generation mix for both the 40% mandate original and updated scenarios. In the original scenario, coal generation goes from 1,609 PJ (38% of generation) in 2020 to 435 PJ (9% of generation) in 2050. For the updated scenario, coal generation goes from 1,500 PJ (36% of generation) in 2020 to 155 PJ (3% of generation) in 2050. For the updated scenario, coal generation is less than the original scenario in all of the years of the planning horizon. Coal generation has longer start-up times, higher start-up costs longer minimum up times, longer minimum down times and lower ramp rates than natural gas generation. When there is a larger percentage of wind and solar generation, short-term operational constraints are even more important. Thus, when short-term operational constraints have been added to the model, there is less coal generation.

With a 40% mandate for both the original and updated scenarios, coal generation is initially the largest generation source, but decreases over time. Even though there is coal capacity, coal is used less for generation over time due to retrofitting and life extension costs. Figure 4.9 shows the

generation mix for the 40% mandate for original and updated scenarios. In the original scenario, coal generation goes from 1,609 PJ (38% of generation) in 2020 to 435 PJ (9% of generation) in 2050. For the updated scenario, coal generation goes from 1,500 PJ (36% of generation) in 2020 to 155 PJ (3% of generation) in 2050. For the updated scenario, coal generation is less than the original scenario in all of the years of the planning horizon. Appendix Table B4 shows the generation breakdown of the generation mix for both the 40% mandate original and updated scenarios. Coal generation has longer start up times, higher startup costs longer minimum up times, longer minimum down times and lower ramp rates than natural gas generation. When there is a larger percentage of wind and solar generation, short-term operational constraints are even more important. Thus, when short-term operational constraints have been added to the model, there is less coal generation.

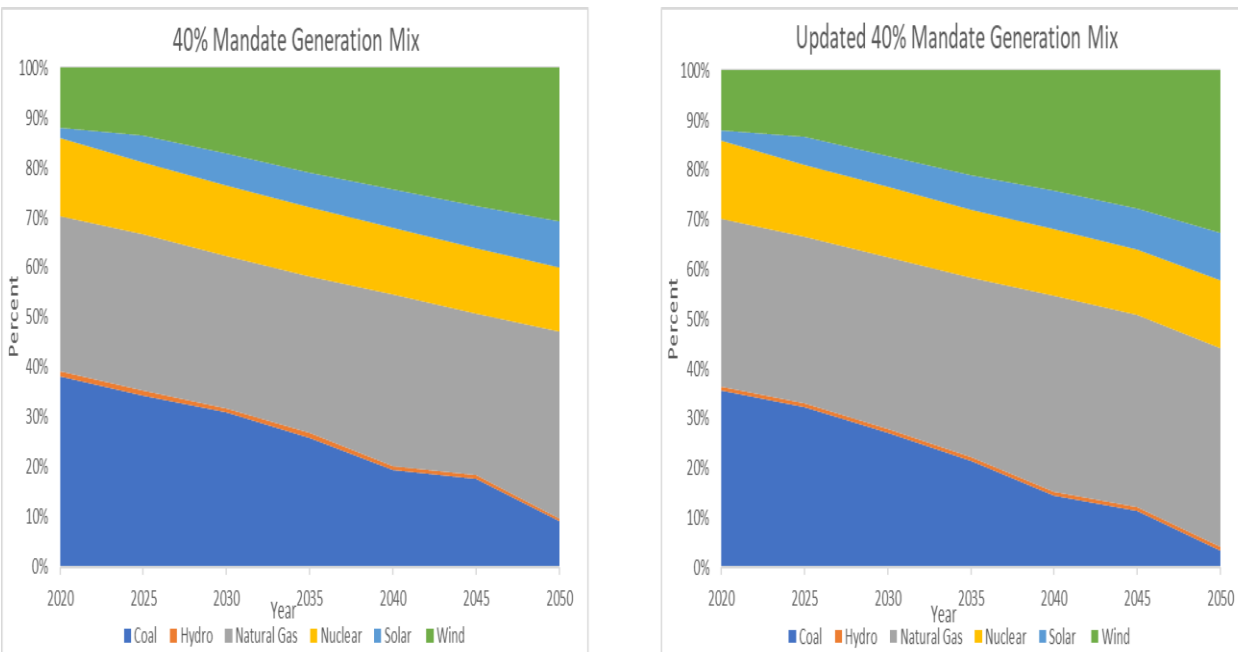

Figure 4.9. Generation Mix for 40% Mandate for Original and Updated Scenarios

In the original scenario, there are 1,309 PJ (31% of generation) in 2020 of natural gas generation and generation increases to 1,803 PJ (37% of generation) in 2050. For the updated scenario, there are 1,419 PJ (34% of generation) in 2020 of natural gas generation and generation increases to 1,819 PJ (38% of generation) in 2050. Advanced combined cycle natural gas is more efficient and replaces coal generation and the retiring combined cycle generation over time. Natural gas generation has shorter start-up times, lower start-up costs, shorter minimum up times, shorter minimum down times and higher ramp rate than other generation sources, in particular compared to coal generation. When there is a larger percentage of wind and solar generation, short-term operational constraints are even more important. Thus, when short-term operational constraints have been added to the model, there is more natural gas generation compared to the original scenario.

For both the original and updated scenarios, nuclear generation startsstarts at 661 PJ (16% of generation) in 2015, but with planned retirements, generation decreases over time to 621 PJ (14% of generation) in 2020 and the generation amount remains the same until 2050. Hydro generation stays at 35PJ (1% or less of generation) in all the time periods. Although there is oil generation capacity, it is not used. In 2050, wind generation is 1488 PJ (31% of generation). In 2050, solar generation is 438 PJ (9% of generation). Similar to the original scenario, there is no new investment in battery storage and the small of amount of the existing battery storage capacity is used over time. The addition of short-term operational constraints did not make changes to nuclear, hydro, wind and solar generation.

4.4.5 50% Mandate Results

With the 50% mandate for both the original and updated scenarios, coal generation is initially the largest generation source, but decreases over time. Even though there is coal capacity, coal is used less for generation over time due to retrofitting and life extension costs. Figure 4.10 shows the generation mix for a 50% mandate for original and updated scenarios. Appendix Table B7 shows the generation breakdown of the generation mix for both the 50% mandate original and updated scenarios. In the original scenario, coal generation goes from 1,609 PJ (38% of generation) in 2020 to 405 PJ (9% of generation) in 2050. For the updated scenario, coal generation goes from 1,431 PJ (34% of generation) in 2020 to 0 PJ (0% of generation) in 2050. For the updated scenario, coal generation is less than the original scenario in all of the years of the planning horizon. Coal generation has longer start up times, higher startup costs longer minimum up times, longer minimum down times and lower ramp rate than natural gas generation. When there is a larger percentage of wind and solar generation, short-term operational constraints become even more important. So, when short-term operational constraints have been added to the model, there is less coal generation. As the mandate level increases, there is a larger decrease in the coal generation.

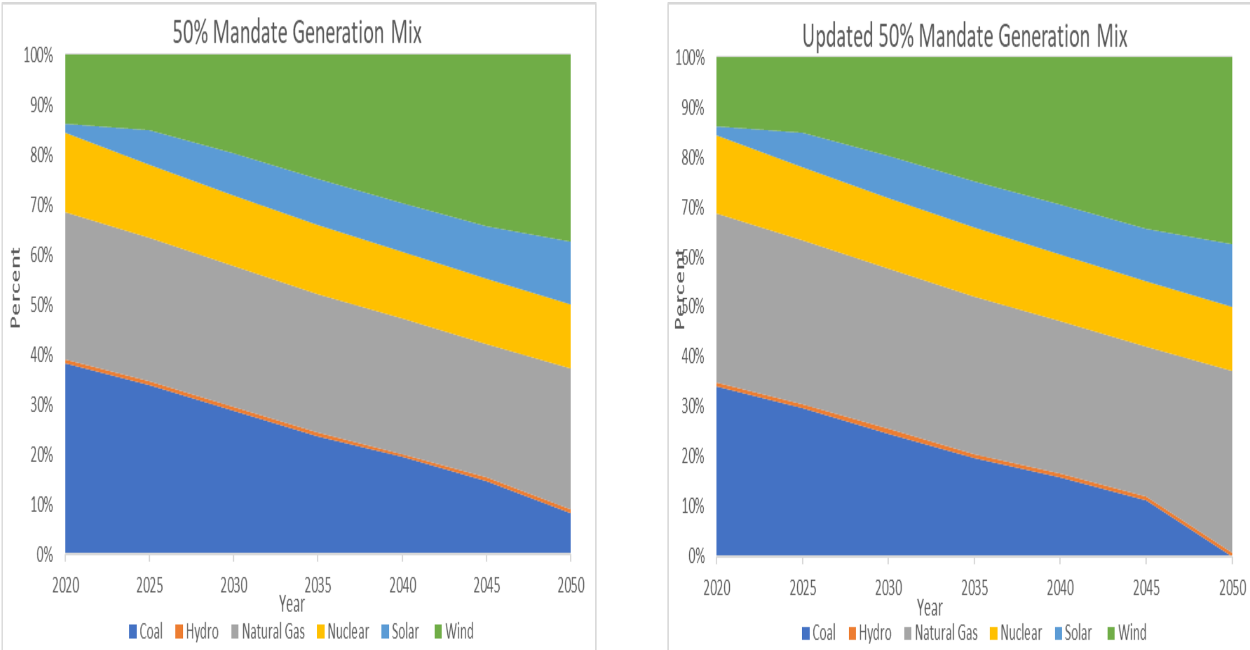

Figure 4.10. Generation Mix for 50% Mandate for Original and Updated Scenarios

In the original scenario, there are 1,240 PJ (29% of generation) in 2020 of natural gas generation and generation increases to 1,351 PJ (28% of generation) in 2050. For the updated scenario, there are 1,419 PJ (34% of generation) in 2020 of natural gas generation increasing to 1,756 PJ (36% of generation) in 2050. Natural gas generation has shorter start-up times, lower start-up costs, shorter minimum up times, shorter minimum down times and higher ramp rate than other generation sources, in particular compared to coal generation. When there is an even larger percentage of wind and solar generation, short-term operational constraints are even more important. Thus, when short-term operational constraints have been added to the model, there is more natural gas generation compared to the original scenario. As the mandate level increases, there is a larger increase in natural gas generation.

For both original and updated scenario, nuclear generation starts at 661 PJ (16% of generation) in 2015, but with planned retirements, generation decreases over time to 621 PJ (14% of generation) in 2020 and generation remains the same until 2050. Hydro generation stays at 35PJ (1% or less of generation) in all the time periods. Although there is oil generation capacity, it is not used. In 2050, wind generation is 1,803 PJ (37% of generation). In 2050, the solar generation is 606 PJ (13% of generation). Similar to the original scenario, there is no new investment in battery storage and a small of amount of the existing battery storage capacity is used over time.

The addition of short-term operational constraints did not make changes to nuclear, hydro, wind and solar generation.

4.4.6 Cost Results

The components of systems cost are fuel cost, investment cost, variable operating and maintenance cost and fixed operating and maintenance cost. Coal retrofit costs are included in fixed operating and maintenance cost. Commodity flow costs and salvage costs have not been considered in this definition.

Total system $\text{cost}_t = \Sigma_G \text{ Fuel cost}_{G,t} + \Sigma_G \text{ Fixed O\&M cost}_{G,t} + \Sigma_G \text{ Variable O\&M cost}_{G,t} + \Sigma_G \text{ Investment cost}_{G,t}$ **(1)**

Equation (1) gives the system cost for period t. Figure 4.11 shows the discounted increase in total system costs over time due to renewable generation mandates relative to the original reference case and updated reference case. In each of the years, the investment cost decreases slightly for the updated scenario compared to the original scenario. Similarly, the variable operating and maintenance costs and fuel costs decrease slightly for the updated scenario compared to the original scenario. However, there is an increase in fixed operating and maintenance costs in the updated scenario compared to the original scenario. The results indicate that with the addition of short-term operational constraints there is a between 12% and 28% increase in fixed operating and maintenance costs between the 30% original mandate and updated mandate, between 16% and 23% increase in fixed operating and maintenance costs between the 40% original mandate and updated mandate and between 16% and 20% increase in fixed operating and maintenance costs between the 50% original mandate and updated mandate. This arises from the short-term operating constraints that have been added to the model. The costs associated with short-term operating constraints had not been previously modeled in Chapter 2. Given that the short-term variation within hours of renewable generation sources have not been considered, the cost results are still more complete than the first chapter, but costs associated with the increased need for ramping capacity are likely underestimated.

As the mandate level increases, the total systems cost also increase. The undiscounted total system cost for the 30% mandate is a 2.0% increase over the reference in 2020 and a 5.2% increase in 2050; for the 40% mandate there is a 4.2% increase over the reference in 2020 and a 13.7% increase in 2050; and for the 50% mandate there is a 6.7% increase over the reference in 2020 and a 21.6% increase in 2050. A breakdown of total systems cost for the updated 30%, 40% and 50% mandates are shown in Appendix Table B5, B6 and B7 respectively. The increase appears to be linear, following the linear implementation of the mandates. The cost increases are mainly driven by start-up costs are investment and fixed operating and maintenance costs associated with maintaining the peaking reserve constraint.

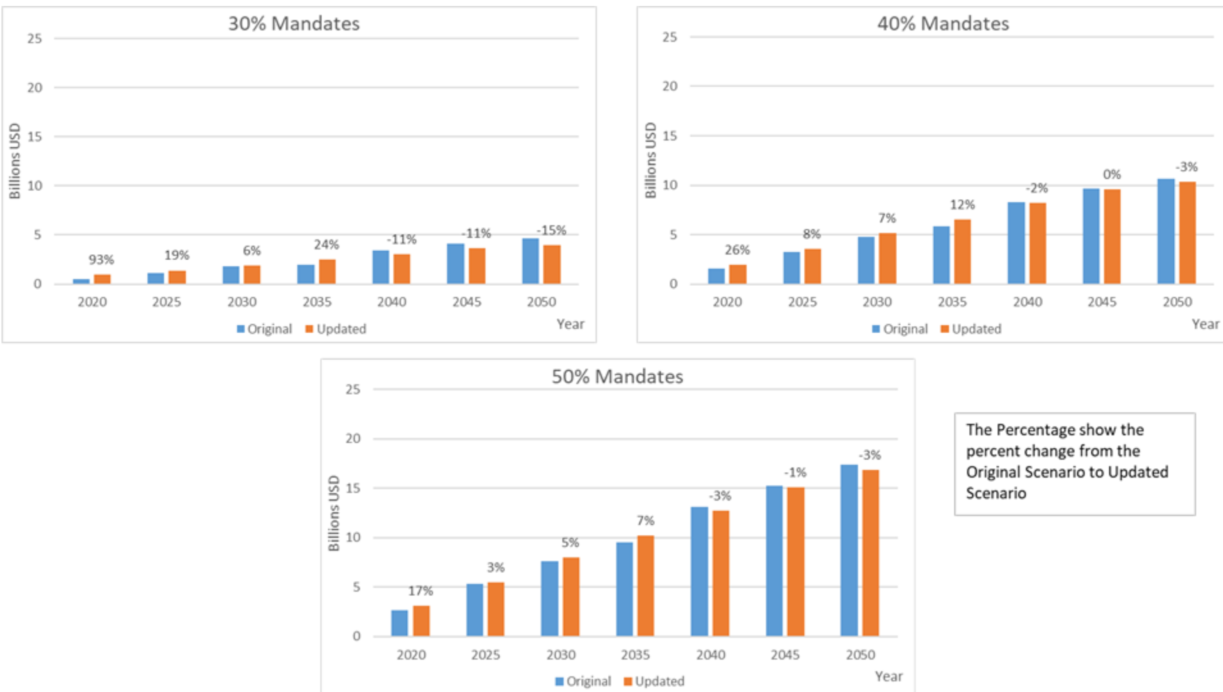

Figure 4.11. Incremental Increase in Total System Costs over Time Due to Renewable Generation Mandates Relative to the Original Reference Case and Updated Reference Case.*
*The percentage show the percentage increase in the total system cost of updated case from the reference case for specific year.

4.4.7 Emissions Results

Adding short-term operating constraints leads to changes in the generation mix. Therefore, it is also useful to examine the changes to the emissions. Figure 4.12 shows the increase in CO_2e kilotons saving over time due to the mandates relative to the original reference case and updated reference case. Appendix Table B8 and B9 show the breakdown of CO_2e kilotons saving from the original and updated reference, respectively, for different scenarios. Although CO_2e declines in the original reference scenario over time, the mandates lead to further emissions savings. CO_2e emissions savings follow a linear pattern consistent with the mandates. The 50% mandate in particular leads to large CO_2e emissions savings with a 23.1% reduction in 2050.

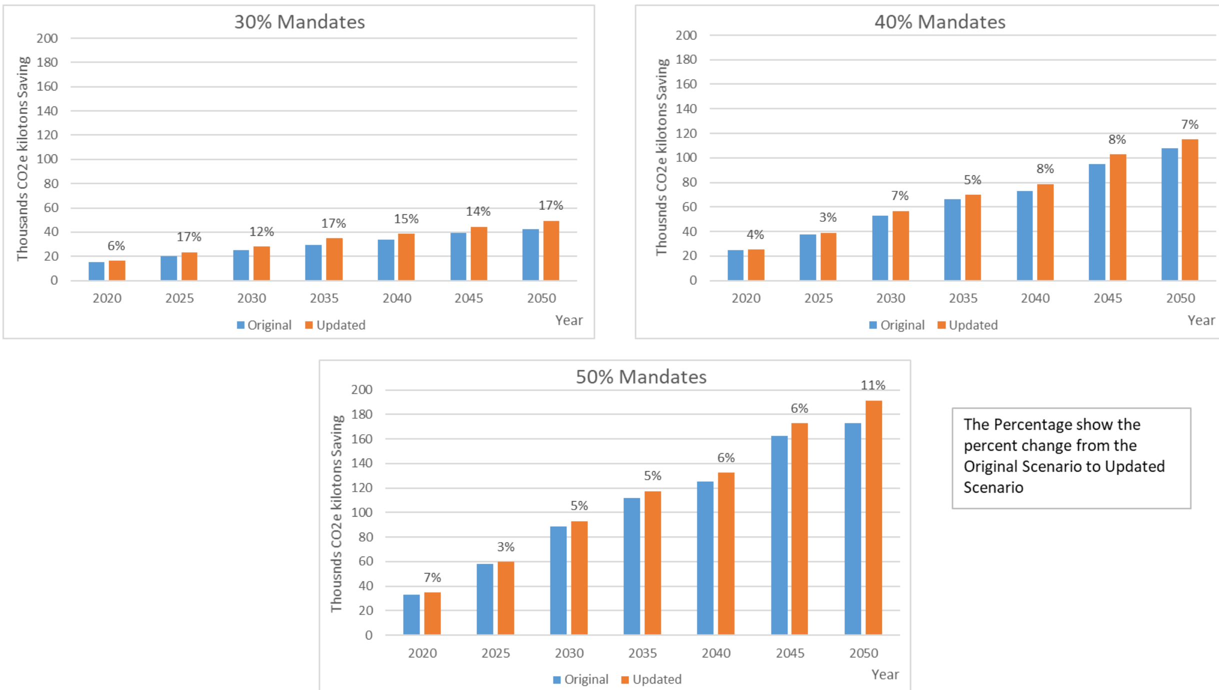

Figure 4.12. Increase in CO_2e kilotons saving Over Time due to Renewable Generation Mandates Relative to the Original Reference Case and Updated Reference Case. *
*The percentage show the percentage increase in CO_2e kilotons of updated case from the reference case for specific year.

It is now possible to distinguish between emissions reductions that come from the mandate policies versus the non-inclusion of short-term operating constraints in the original reference and mandate scenarios. Although CO_2e declines in the updated reference scenario over time, the mandates lead to further emissions savings. CO_2e emissions savings follow a linear pattern consistent with the mandates. The 50% mandate in particular leads to large CO_2e emissions saving with 25.6% in 2050.

The results show that adding short-term operating constraints on the generation system leads to larger CO_2e kilotons saving in each of the updated scenarios compared to the original scenario. The original reference and mandates scenarios did not include short-term operational constraints, which lead to underestimation of CO_2e kilotons saving. As the mandate level increases the CO_2e emissions saving increase. In particular, for the 50% updated mandate scenario has the highest CO_2e emissions saving difference to the 50% mandate original scenario. The results arise from the fact that coal generation decreases when short-term operating constraints are added, and therefore the emissions savings are larger. Coal generation is less flexible than other types of generation and therefore decreases. Natural gas generation increases when short-term operating constraints are added to the model, but natural gas generation is less CO_2e intensive than coal generation. Therefore, adding short-term operating constraints gives a more complete understanding of CO_2e emissions savings for the different scenarios.

It is also important to examine cost per ton of CO_2e reduced. Table 4.3 shows the cost per ton of CO_2e reduced for different original mandate scenarios. The cost per ton is calculated by dividing the CO_2e kilotons saving for each year of the mandate by the total system cost of the respective year. As the mandate level increases, there is a decrease in the cost per ton of CO_2e reduced.

Table 4.3. Cost per ton of CO_2e Reduced for Different Original Mandate Scenarios

Policy	**2015 USD per ton**						
	2020	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
30% Mandate original	25	43	58	52	83	85	88
40% Mandate original	54	77	81	80	102	91	90
50% Mandate original	70	85	80	79	97	87	90

Table 4.4 shows the cost per ton of CO_2e reduced for different original mandate scenarios shows. It is possible to see on the one hand the impact of the policy and on the other hand the consequences of not including some of the cost realities. Accounting for short-term operational constraints and costs increases estimates of the cost per ton of CO_2e reduced. As the original reference and mandate scenarios underestimated CO_2e kilotons saving due to the lack the short-term operational constraints, it is possible to see the consequences of ignoring some of the cost realities.

Table 4.4. Cost per ton of CO_2e Reduced for Different Updated Mandate Scenarios

Policy	**2015 USD per ton**						
	2020	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
30% Mandate updated	57	58	68	71	79	82	79
40% Mandate updated	76	91	90	93	104	94	89
50% Mandate updated	88	92	86	87	96	87	88

Studies in the literature find that considering short-term operational constraints in the form of Unit Commitment and Economic Dispatch (UCED) lead to increased emissions (Abdin and Zio, 2018). The results in this chapter seem to contradict the literature as the addition of short-term operational constraints lead to decreased emissions. Chiodi et al. (2011) examine the electricity sector for Ireland using a production cost model PLEXOS which contains UCED with and a capacity expansion TIMES model. The study found that increased emissions in the PLEXOS model compared to the TIMES model which did not contain short-term operational constraints. Production cost models examine the electricity sector at finer time resolutions and detail and therefore would better track emissions compared to a capacity expansion model and therefore would have higher emissions. Studies have added short-term operational constraints to long-term capacity expansion models such as Koltsaklis and Georgiadis (2015), who added short-term operational constraints to a capacity expansion model for Greece and Gaur et al. (2019) who added short-term operational constraints to a capacity expansion model for North India. Both studies find that the addition of short-term operational constraints lead to decreased emissions, which is similar to the results found in this study. Capacity expansion models that have short-term operational constraints have lower investment in fossil fuel-based generation sources by better optimizing the use of power plants without adding additional fossil fuel-based capacity than do models without short-term operational constraints. Therefore, capacity expansion models that have short-term operational constraints would have lower emissions than capacity expansion models without short-term operational constraints and production cost models. As such, the results of production cost models and capacity expansion models with short-term operational constraints cannot be directly compared.

4.5 Conclusion

Short-term operation constraints have been added to the model. The cost to society is underestimated when short-term operational constraints are ignored. The cost per ton of CO_2e reduced increases between 14% and 22% between the 30% original mandate and updated mandate, between 12% and 15% between the 40% original mandate and updated mandate and between 7% and 12% between the 50% original mandate and updated mandate. The addition of short-term operational constraints did change nuclear, hydro, wind and solar generation. However, the constraints lead to decreased coal generation and increased natural gas generation.

The variability of wind and solar generation fluctuations has not been fully captured due to hourly time slices and operational constraints operating at finer time scales that are not reflected in the model. Therefore, it is not possible to model all short-term operational constraints completely. Capturing wind and solar generation fluctuations and having individual power plants characteristics, and all short-term operational constraints would give a more complete understanding of integrating wind and solar into the system. The results of this chapter cannot be directly compared to a production cost model regarding wind and solar integration and the results of production cost model could differ from this chapter.

The addition of short-term operational constraints led to increased total systems cost. Although investment costs, fuel cost and fixed operating and maintenance costs decreased with the addition of short-term operational constraints, fixed operating and maintenance costs increased. The results indicate that with the addition of short-term operational constraints there is a 7% and 93% increase in the total system cost between the 30% original mandate and updated mandate, a 5% and 26% increase in the total system cost between the 40% original mandate and updated mandate and a 3% and 17% increase in the total system cost between the 50% original mandate and updated mandate. Investment costs, variable operating and maintenance cost and fuel cost decrease when comparing the original mandate and updated mandate. Fixed operating and maintenance costs increase and account for the whole increase in total systems cost. These originate from the start-up costs which were ignored in the original mandate scenarios. Therefore, there is a non-negligible increase in cost associated with the short-term operational constraints. Thus, adding short-term operating constraints gives a more complete understanding of CO_2e emissions savings for the different scenarios as the decrease in coal generation and increase in natural gas generation led to increased CO_2e emissions savings. The results indicate that with the addition of short-term operational constraints there is a 6% and 17% increase in CO_2e emissions savings between the 30% original mandate and updated mandate, a 4% and 8% increase in CO_2e emissions savings between the 40% original mandate and updated mandate and a 3% and 11% increase in CO_2e emissions savings between the 50% original mandate and updated mandate. Therefore, there is a non-negligible increase in CO_2e emissions savings associated with the short-term operational constraints. The results would better inform policymakers of costs and emissions impacts of polices that lead to a high penetration of intermittent renewable generation sources and would enable more informed future electricity generation choices.

CHAPTER 5. CONCLUSIONS

The overarching research problem was to evaluate different policies that lead to high penetration of intermittent renewable electricity sources. The first research question examined the emissions reduction benefits and system integration costs of policy mandates for high penetration of intermittent renewable electricity technologies for the Midcontinent Independent System Operator (MISO). As the level of the mandate for wind and solar generation increases from 30%, to 40% and 50%, there is both an increase in the LMCOE and discounted total systems costs as the mandate level increases. CO_2e, SO_2, PM 10 and PM 2.5 emissions saving from the mandates were converted to reductions in the SCE to do a cost-benefit analyses of the mandate policies. The calculation of monetary values of savings in emissions has been done using valuations for emissions that reflect the Social Costs of Emissions (SCE). The valuations for the different Social Costs of Emissions are widely debated in the literature and there is no consensus.

The reductions in the SCE increase as the level of the mandate increases. However, the reductions in the SCE do not justify the cost increases associated with the mandates. Mandates for renewable electricity reduce CO_2e emissions. As most of the emissions reduction come from coal generation reductions, the net impact depends on what gets substituted for coal. Generally, it is not possible to reduce one set of emissions relative to another given that the amount of electricity generation is fixed. Other emission reduction policies that target the specific emissions may be more effective methods to decrease emissions such as SO_2, PM 10 and PM 2.5.

The cost results should be considered a lower bound for potential cost increases as generation fluctuations, variations in future fuel costs and ramping, start-up and shut-down costs of other generation sources have not been considered. Having hourly time slices does not fully capture wind and solar generation fluctuations. Temporal chronology was not maintained for Chapter 2. Also, a downside of having fixed aggregate generation of the electricity commodities for the entire region is that substitution possibilities for satisfying end use demand from non-electricity commodities has been eliminated.

The second research question examined the total systems costs of mandates for renewable electricity generation and a carbon tax using a TIMES model for MISO. All policies implemented held the overall emission reductions constant where there 35% reduction of CO_2e emissions from 2020 levels by 2050 compared to the reference scenario. The renewable electricity mandate is a command and control policy (II), while the carbon tax is a market-based instrument (Policy I). As such, different policies can be used to achieve the same emissions goal.

Policy I led to a decrease coal generation in the generation mix compared to the reference. In Policy I, wind and solar generation did not exceed the levels of the reference, but wind and solar generation increased with the mandates. Natural gas generation increased with all of the policies. Policy I had the lower LMCOE while, while Policy II had the higher LMCOE. Similarly, Policy I had a lower discounted total system than Policy II.

There are issues of wind and solar generator components such as solar panels and wind turbines generating emissions in the production process. The transport and installation of the generating systems also generate emissions. The emissions of the mentioned production transportation and installation have not been considered in Chapter 3, but the emissions from natural resource extraction has been considered. Independent System Operator level implementation of mandates and carbon tax policies does no properly reflect the realities of state level implementation of renewable electricity policies.

The third research question examined the emissions and costs of policy mandates for high penetrations of wind and solar electricity technologies for MISO when short-term operational constraints are considered. The cost to society is underestimated when short-term operational constraints are ignored. The cost per ton of CO_2e reduced increases between 14% and 22% between the 30% original mandate and updated mandate, between 12% and 15% between the 40% original mandate and updated mandate and between 7% and 12% between the 50% original mandate and updated mandate. The addition of short-term operational constraints did not make changes to nuclear, hydro, wind and solar generation. However, the constraints lead to decreased coal generation and increased natural gas generation.

The addition of short-term operational constraints led to increased total systems cost. Although investment costs, fuel cost and fixed operating and maintenance costs were roughly equal with the addition of short-term operational constraints, variable operating and maintenance costs increased. The results indicate that with the addition of short-term operational constraints there is a 7% to 93% increase in the total system cost between the 30% original mandate and updated mandate, a 5% to 26% increase in the total system cost between the 40% original mandate and updated mandate and a 3% to 17% increase in the total system cost between the 50% original mandate and updated mandate. Investment costs, variable operating and maintenance cost and fuel cost decrease when comparing the original mandate and updated mandate. Fixed operating and maintenance cost increase and account for the whole increase in total systems cost and come from the start-up costs, which had been ignored in the original mandate scenarios. Therefore, there is a non-negligible increase in cost associated with the short-term operational constraints. Thus, adding short-term operating constraints gives a more complete understating of CO_2e emissions savings for the different scenarios as the decrease in coal generation and increase in natural gas generation led to increased CO_2e emissions savings. The results indicate that with the addition of short-term operational constraints there is a 6% to 17% increase in CO_2e emissions savings between the 30% original mandate and updated mandate, a 4% to 8% increase in CO_2e emissions savings between the 40% original mandate and updated mandate and a 3% to 11% increase in CO_2e emissions savings between the 50% original mandate and updated mandate. Therefore, there is a non-negligible increase in CO_2e emissions savings associated with the short-term operational constraints.

There are issues of the variability of wind and solar generation fluctuations that have not been fully captured due to hourly time slices, and therefore it is not possible to model all short-term operational constraints completely. Capturing wind and solar generation fluctuations and having individual power plants characteristics, and all short-term operational constraints would give a more complete understanding of the costs integrating wind and solar into the system. There are also some short-term constraints such as ramping costs that have not been added due to data constraints. Also, short-term operation constraints should ideally be examined at the sub-hourly time resolution along with wind and solar generation fluctuations, which has not occurred. The results of this chapter cannot be directly compared to a production cost model regarding wind and solar integration and the results of production cost model could differ from this chapter. Similarly, fixed aggregate generation of the electricity commodities for the entire region lead substitution possibilities for satisfying end use demand from non-electricity commodities has been eliminated.

There are possible extensions to the research reported here. Maintaining temporal chronology would improve depiction of battery storage and short-term operational constraints. To maintain temporal chronology, the number of hourly time slices would have to be increased from 288 to 8760. There are also increased data requirements and computation complexity associated with increased time slices. However, with better depiction of battery and improved short-term operational constraints, the results would improve. Other policies such as a coal tax could be examined. Having a tax on coal of the appropriate amount as deemed correct by the literature would also improve the results. There is a large emissions reduction associated with the decrease in coal generation. As such, a tax on coal could have important emission reduction benefits. It is also important to implement short-term operational constraints for all the policies including the carbon tax and not just mandates to stress the importance of short-term operational constraints and to see if a carbon tax is a more efficient policy.

Emission reduction policies that target specific emissions such as SO_2, PM 10 and PM 2.5 could also be examined. Having a tax on emissions such as SO_2, PM 10 and PM 2.5 of the appropriate amount as deemed correct by the literature would also improve the results as tax may be more effective methods to decrease emissions. It is also important to examine the velocity policy instruments. A rapidly implemented mandate or higher carbon tax would lead to different emissions outcomes. relative to policies that are implemented more slowly. A mandate that is implemented less rapidly would have lower emissions reduction benefits and lower costs. A carbon tax that is higher than the social cost of carbon would have higher emissions reduction benefits. A flat carbon tax would also lead to different emissions reduction outcomes. It is important to examine all the different possible velocity to understand the impact of velocity on emissions reduction outcomes.

Ultimately, the results would better inform policymakers of costs and emissions impacts of polices that lead to a high penetration of intermittent renewable generation sources and would enable more informed future electricity generation choices.

APPENDIX A. CHAPTER 2 APPENDIX

Appendix A contains tables and graphs that provide supplemental information for Chapter 2 used in the model. Unless another source is specified the data comes from Lennox (2019). The appendix is used to provide the supplemental information and data. Appendix Table A1 provides the duration of each time slice as a fraction of a year, while Appendix Table A2 shows the demand in each time slice. Appendix Tables A3, A4 and A5, A6 gives a breakdown of commercial, residential, transport and industrial sector demand respectively. Appendix Tables A7 and A8 give the candidate availability factor information for the hourly time slices for solar and wind generation respectively. Appendix Table A9 provides the total investment costs for new generation technologies, while Appendix Table A10 gives the operating and maintenance costs for new generation technologies. Appendix Table A11, A12 and A13 contain prices over the planning horizon for natural gas, coal and oil respectively. Appendix Table A14 provides the average emissions per PJ of electricity generation by generator type. Appendix Figure A1 shows the capacity projections for the different scenarios while Append Table A15 provides the total systems cost breakdown for the different scenarios. Appendix Tables A16, A17 and A18 gives the kilotons saving for SO_2, PM 10 and PM2.5 for the different scenarios respectively.

Appendix Table A1. Duration of each Time Slice as a Fraction of a Year

	Fall			Winter			Spring			Summer		
Hour	Weekday	Saturday	Sunday	Weekday	Saturday	Sunday	Weekday	Saturday	Sunday	Weekday	Saturday	Sunday
1	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
2	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
3	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
4	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
5	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
6	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
7	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
8	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
9	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
10	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
11	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
12	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
13	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
14	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
15	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
16	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
17	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
18	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
19	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
20	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
21	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
22	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
23	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015
24	0.0074	0.0015	0.0015	0.0073	0.0015	0.0015	0.0075	0.0015	0.0015	0.0075	0.0015	0.0015

Appendix Table A2. Demand in Each Time Slice as a Fraction of Maximum Demand

	Fall			Winter			Spring			Summer		
	Weekday	Saturday	Sunday	Weekday	Saturday	Sunday	Weekday	Saturday	Sunday	Weekday	Saturday	Sunday
1	0.63	0.60	0.58	0.69	0.70	0.68	0.61	0.61	0.59	0.73	0.73	0.69
2	0.61	0.60	0.58	0.67	0.68	0.66	0.60	0.59	0.57	0.69	0.70	0.66
3	0.60	0.58	0.57	0.66	0.66	0.65	0.59	0.58	0.56	0.67	0.68	0.64
4	0.59	0.58	0.56	0.65	0.66	0.64	0.59	0.57	0.55	0.66	0.66	0.63
5	0.60	0.58	0.56	0.66	0.66	0.64	0.60	0.57	0.55	0.67	0.66	0.62
6	0.63	0.59	0.56	0.67	0.66	0.64	0.63	0.58	0.56	0.70	0.66	0.62
7	0.68	0.60	0.58	0.71	0.68	0.65	0.68	0.60	0.57	0.73	0.67	0.62
8	0.72	0.62	0.59	0.77	0.71	0.67	0.71	0.62	0.59	0.77	0.70	0.64
9	0.73	0.65	0.62	0.79	0.73	0.69	0.72	0.64	0.61	0.81	0.74	0.69
10	0.75	0.68	0.64	0.79	0.74	0.71	0.73	0.66	0.63	0.85	0.79	0.74
11	0.76	0.69	0.66	0.79	0.75	0.71	0.74	0.67	0.64	0.89	0.84	0.78
12	0.77	0.71	0.68	0.78	0.74	0.71	0.74	0.67	0.65	0.93	0.87	0.82
13	0.78	0.71	0.69	0.77	0.73	0.71	0.74	0.67	0.65	0.95	0.90	0.85
14	0.79	0.72	0.70	0.76	0.72	0.70	0.75	0.67	0.65	0.98	0.91	0.87
15	0.80	0.72	0.70	0.76	0.71	0.70	0.74	0.67	0.65	0.99	0.93	0.89
16	0.80	0.72	0.71	0.75	0.70	0.69	0.74	0.67	0.66	1.00	0.94	0.90
17	0.80	0.72	0.71	0.75	0.70	0.69	0.74	0.67	0.66	1.00	0.95	0.92
18	0.80	0.72	0.72	0.76	0.72	0.71	0.74	0.67	0.67	0.99	0.94	0.92
19	0.80	0.73	0.74	0.79	0.75	0.75	0.73	0.67	0.68	0.97	0.92	0.91
20	0.80	0.73	0.75	0.81	0.76	0.76	0.74	0.68	0.69	0.94	0.90	0.88
21	0.78	0.71	0.73	0.80	0.75	0.76	0.74	0.68	0.69	0.92	0.88	0.87
22	0.75	0.69	0.70	0.78	0.74	0.75	0.72	0.67	0.68	0.89	0.85	0.84
23	0.70	0.66	0.66	0.76	0.73	0.72	0.68	0.64	0.64	0.83	0.80	0.79
24	0.66	0.62	0.63	0.72	0.70	0.69	0.64	0.61	0.61	0.77	0.75	0.74

Appendix Table A3. Breakdown of Commercial Sector Demand

Commercial Sector (PJ)	2015	2020	2025	2030	2035	2040	2045	2050
Cooking	20	20	21	21	20	19	19	19
Lighting	322	318	317	315	312	310	309	307
Miscellaneous	416	430	443	444	457	476	486	504
Office Equipment	72	74	77	79	81	83	86	91
Refrigeration	87	72	70	69	67	66	65	63
Cooling	147	139	134	126	127	128	129	130
Heating	85	78	73	73	70	69	68	67
Ventilation	118	120	120	122	123	126	128	129
Water Heating	61	60	59	58	56	55	55	53

*For commercial lighting, billion lumen per year has been converted to PJ.

Appendix Table A4. Breakdown of Residential Sector Demand

Residential Sector (PJ)	2015	2020	2025	2030	2035	2040	2045	2050
Freezing	20	18	17	16	16	16	15	15
Lighting*	132	123	109	106	103	99	80	69
Appliances	669	693	696	704	725	743	782	811
Refrigeration	98	89	84	81	78	74	71	68
Cooling	196	175	177	188	196	208	214	224
Heating	142	124	113	96	88	82	77	67
Water Heating	162	190	191	193	197	207	216	225

*For residential lighting, billion lumen per year has been converted to PJ.

Appendix Table A5. Breakdown of Transport Sector Demand

Transport Sector	2015	2020	2025	2030	2035	2040	2045	2050
Light Duty Vehicles	2	2	3	4	5	7	10	13
Trains	15	24	37	56	77	102	132	167

Note: The units for electric train are billion passenger miles has been converted to PJ. The units for electric light duty vehicles are vehicle miles traveled has been converted to PJ.

Appendix Table A6. Breakdown of Industry Sector Demand

Industry Sector (PJ)	2015	2020	2025	2030	2035	2040	2045	2050
Electricity	1134	1245	1336	1413	1443	1461	1472	1483
Asphalt	977	938	950	959	940	907	901	891
Liquefied Petroleum Gas	945	1175	1347	1403	1449	1475	1547	1603
Natural Gas	3072	3637	4224	4489	4798	5062	5270	5469
Petrochemical Feedstocks	684	758	792	831	864	886	927	959

Appendix Table A7. Solar Candidate Site Summary of Availability Factor Information for the Hourly Time Slices (Source: Habte et al., 2017)

Technology	**Mean**	**Minimum**	**Maximum**	**Standard Deviation across hourly time slices**
Arkansas High	0.239	0	1	0.31
Arkansas Low	0.237	0	1	0.31
Illinois High	0.226	0	1	0.29
Illinois Low	0.223	0	1	0.30
Indiana High	0.224	0	1	0.29
Indiana Low	0.221	0	1	0.30
Iowa	0.229	0	1	0.30
Kentucky	0.232	0	1	0.31
Louisiana High	0.251	0	1	0.32
Louisiana Low	0.244	0	1	0.32
Michigan	0.218	0	1	0.29
Minnesota	0.222	0	1	0.29
Mississippi High	0.255	0	1	0.33
Mississippi Low	0.249	0	1	0.32
Missouri	0.232	0	1	0.30
Montana	0.216	0	1	0.29
North Dakota High	0.213	0	1	0.28
North Dakota Low	0.206	0	1	0.28
South Dakota	0.220	0	1	0.29
Texas	0.239	0	1	0.31
Wisconsin High	0.222	0	1	0.30
Wisconsin Low	0.219	0	1	0.29

Appendix Table A8. Wind Candidate Site Summary of Availability Factor Information for the Hourly Time Slices (Source: Draxl et al., 2015)

Technology	Mean	Minimum	Maximum	Standard Deviation across hourly time slices
Arkansas High	0.364	0.209	0.489	0.067
Arkansas Low	0.287	0.143	0.418	0.069
Illinois High	0.305	0.153	0.426	0.051
Illinois Low	0.282	0.137	0.384	0.053
Indiana High	0.311	0.152	0.416	0.060
Indiana Low	0.286	0.128	0.397	0.053
Iowa High	0.316	0.145	0.415	0.059
Iowa Low	0.291	0.146	0.391	0.048
Kentucky	0.261	0.123	0.379	0.054
Louisiana	0.263	0.119	0.389	0.060
Michigan High	0.322	0.209	0.410	0.040
Michigan Low	0.295	0.179	0.386	0.040
Minnesota High	0.310	0.157	0.414	0.050
Minnesota Low	0.270	0.117	0.373	0.050
Mississippi	0.261	0.126	0.391	0.061
Missouri High	0.324	0.172	0.435	0.060
Missouri Low	0.275	0.140	0.384	0.053
Montana	0.357	0.233	0.479	0.052
North Dakota High	0.362	0.225	0.463	0.053
North Dakota Low	0.314	0.178	0.407	0.048
South Dakota	0.370	0.191	0.514	0.069
Texas	0.268	0.143	0.333	0.043
Wisconsin High	0.309	0.198	0.402	0.039
Wisconsin Low	0.286	0.161	0.362	0.043

Appendix Table A9. Total Investment Costs for New Generation Technologies (Overnight Capital Cost USD/kW)

	2015	2020	2025	2030	2035	2040	2045	2050
Coal Steam; Bituminous; Over 100 MW	2485	2423	2392	2392	2361	2361	2361	2361
Coal Steam; Subbituminous; Over 100 MW	2485	2423	2392	2392	2361	2361	2361	2361
Coal Steam; Lignite; Over 100 MW	2485	2423	2392	2392	2361	2361	2361	2361
Natural Gas - Combined-Cycle	828	828	828	828	828	828	828	828
Natural Gas - Advanced Combined-Cycle	2201	2168	2079	1991	1918	1847	1777	1697

Natural Gas - Combustion Turbine	553	542	542	531	531	531	531	531
Natural Gas - Advanced Combustion Turbine	3080	3017	3017	2955	2955	2955	2955	2955
Integrated Coal Gasification Combined Cycle		3080	3017	3017	2955	2955	2955	2955
Biomass - IGCC			3671	3671	3595	3595	3595	3595
Geothermal - Binary Cycle and Flashed Steam	2326	2210	2152	2152	2094	2094	2094	2094
Geothermal - Enhanced Geothermal System			3719	3624	3529	3434	3339	3245
Storage	4070	3840	3376	2992	2897	2881	2787	2700
Solar PV	2151	1498	1425	1384	1355	1327	1294	1262
Wind	1667	1824	1721	1416	1368	1342	1315	1289

Appendix Table A10. Operating and Maintenance Costs for new Generation Technologies

	Fixed O&M Costs (USD/kW)	**Variable O&M Costs (USD/kW)**
Coal Steam; Bituminous; Over 100 MW	28	1.13
Coal Steam; Subbituminous; Over 100 MW	28	1.13
Coal Steam; Lignite; Over 100 MW	28	1.13
Natural Gas - Combined-Cycle	10	0.86
Natural Gas - Advanced Combined-Cycle	9	0.49
Natural Gas - Combustion Turbine	16	0.86
Natural Gas - Advanced Combustion Turbine	6	2.64
Integrated Coal Gasification Combined Cycle	47	1.82
Biomass - IGCC	117	2.06
Geothermal - Binary Cycle and Flashed Steam	106	0.00
Geothermal - Enhanced Geothermal System	106	0.00
Storage	16	2.79
Solar PV	19.39	
Wind	66.53	

Appendix Table A11. Average Natural Gas Prices over the Planning Horizon

Million USD per PJ per year	2015	2020	2025	2030	2035	2040	2045	2050
Natural Gas prices	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82

Appendix Table A12. Average Coal Prices over the Planning Horizon

Million USD per PJ per year	2015	2020	2025	2030	2035	2040	2045	2050
Coal prices	0.24	0.68	0.69	0.69	0.70	0.70	0.70	0.70

Appendix Table A13. Average Oil Prices over the Planning Horizon

Million USD per PJ per year	2015	2020	2025	2030	2035	2040	2045	2050
Oil PADD 1 price	1.64	1.72	2.07	1.90	1.69	1.69	1.69	1.69
Oil PADD 2 price	2.66	3.01	3.45	3.16	3.01	3.01	3.01	3.01
Oil PADD 3 price	2.66	3.01	3.45	3.16	3.01	3.01	3.01	3.01
Oil PADD 4 price	1.64	1.72	2.07	1.90	1.69	1.69	1.69	1.69
Oil PADD 5 price	4.06	4.09	3.76	3.87	3.84	3.84	3.84	3.84

Appendix Table A14. Average Emissions per PJ of Electricity Generation by Generator Type

Emissions (kilo tons/PJ)	SO_2	NO_X	PM10	PM2.5	CO_2
Combined Cycle Natural Gas	0.001	0.008	0.007	0.006	117
Combustion Turbine Natural Gas	0.001	0.030	0.007	0.006	117
Bituminous Coal	0.958	0.378	0.081	0.015	205.3
Subbituminous Coal	0.883	0.303	0.081	0.015	211.9
Lignite Coal	0.958	0.378	0.081	0.015	205.3

CO_2 emissions data for bituminous coal, subbituminous coal and lignite coal comes from [1]. CO_2, SO_2 and NO_X emissions data for combined cycle natural gas and combustion turbine natural gas comes from [2]. SO_2, NO_X, PM10 and PM 2.5 emissions data for bituminous coal and subbituminous coal comes from [3]. SO_2, NO_X, PM10 and PM 2.5 emissions data for lignite coal comes from [4]. PM10 and PM 2.5 data for combined cycle natural gas and combustion turbine natural gas comes from [5].

Note: In the model, coal generators are divided into bituminous, subbituminous and lignite generation technologies. Each of the bituminous, subbituminous and lignite generation technologies is further divided by the decade of construction starting from 1950s. For natural gas, there is only combustion turbine natural gas and combined cycle natural gas generators.

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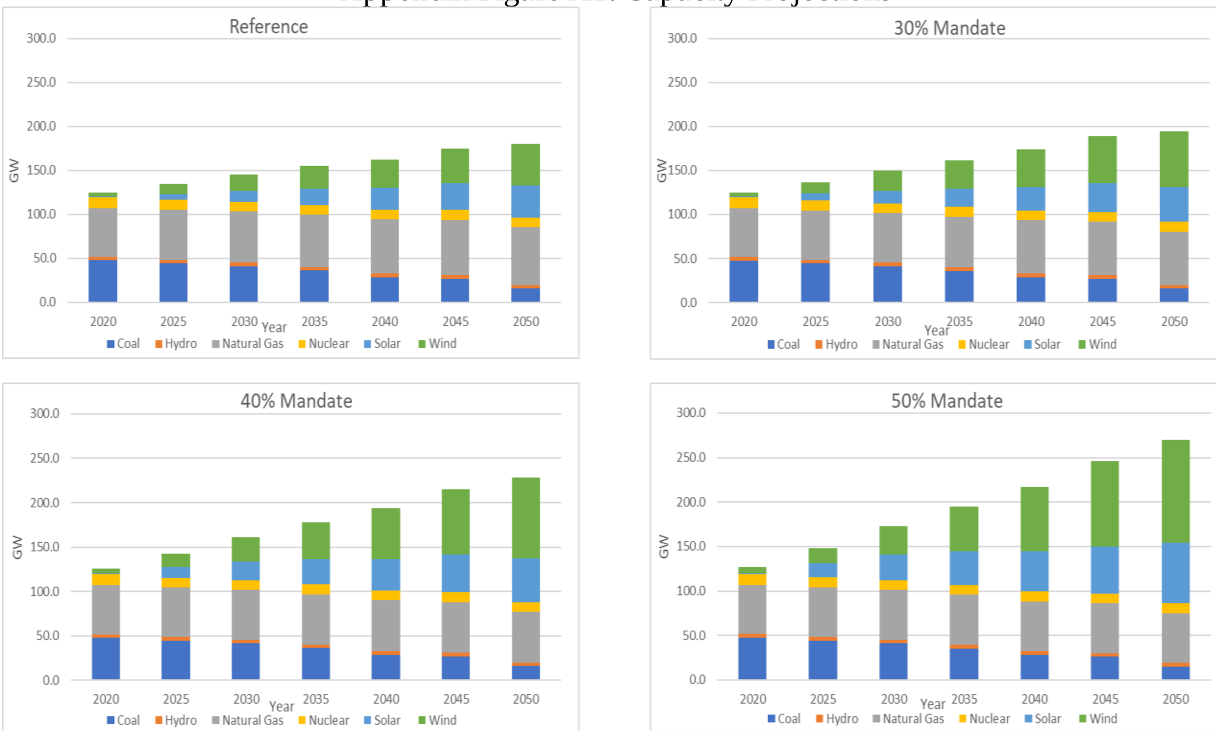
Appendix Figure A1. Capacity Projections



Append Table A15. Total Systems Cost Breakdown for the Different Scenarios

Scenario	Cost (USD Millions)	2020	2025	2030	2035	2040	2045	2050
Reference	Investment	15,970	16,922	16,213	15,700	15,043	14,476	12,195
	Fixed O&M	10,853	10,801	10,835	11,168	11,385	11,466	11,666
	Variable O&M	7,721	7,597	7,513	7,124	6,637	6,675	5,949
	Fuel	11,567	12,232	12,127	11,878	11,724	11,910	11,942
	Total	46,111	47,552	46,688	45,870	44,789	44,527	41,752
30% Mandate	Investment	16,480	18,036	17,845	17,797	17,593	17,479	15,495
	Fixed O&M	11,009	11,056	11,221	11,680	12,021	12,228	12,502
	Variable O&M	7,686	7,526	7,405	6,980	6,457	6,458	5,695
	Fuel	11,490	12,088	11,907	11,581	11,347	11,456	11,413
	Total	46,665	48,706	48,378	48,038	47,418	47,621	45,105
40% Mandate	Investment	17,439	20,120	20,796	21,556	22,208	22,847	21,400
	Fixed O&M	11,300	11,458	11,847	12,518	13,038	13,510	13,918
	Variable O&M	7,626	7,407	7,207	6,742	6,333	6,102	5,279

	Fuel	11,358	11,848	11,539	11,091	10,750	10,711	10,543
	Total	47,723	50,833	51,389	51,907	52,329	53,170	51,140
50% Mandate	Investment	18,444	22,183	23,770	25,370	26,972	28,501	28,017
	Fixed O&M	11,605	11,909	12,525	13,423	14,163	14,940	15,349
	Variable O&M	7,567	7,216	6,774	6,249	5,890	5,453	4,863
	Fuel	11,226	11,599	11,144	10,575	10,109	9,915	9,674
	Total	48,842	52,907	54,213	55,617	57,134	58,809	57,903

Appendix Table A16. SO_2 kilotons Saving for Different Scenarios

SO_2 kilotons Saving	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
30% Mandate	0 (0%)	0 (0%)	0 (0%)	1 (0%)	1 (0%)	1 (0%)	1 (0%)
40% Mandate	1 (0%)	1 (0%)	1 (0%)	1 (0%)	2 (0%)	3 (0%)	4 (0%)
50% Mandate	1 (0%)	1 (0%)	2 (0%)	2 (0%)	3(0%)	4 (0%)	5 (0%)

Appendix Table A17. PM 10 kilotons Saving for Different Scenarios

PM 10 kilotons Saving	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
30% Mandate	0.6 (0.4%)	1.2 (0.8%)	1.8 (1.3%)	2.4 (1.9%)	3.0 (2.4%)	3.7 (3.0%)	4.3 (3.6%)
40% Mandate	1.5 (1.0%)	2.9 (2.1%)	4.5 (3.4%)	6.2 (4.8%)	8.0 (6.3%)	9.7 (7.9%)	11 (9.6%)
50% Mandate	2.5 (1.7%)	4.4 (3.1%)	7.2 (5.4%)	10 (7.8%)	13 (10.2%)	16 (12.8%)	18 (15.5%)

Appendix Table A18. PM 2.5 kilotons Saving for Different Scenarios

PM 2.5 kilotons Saving	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
30% Mandate	0.5 (0.4%)	1.0 (0.7%)	1.6 (1.2%)	2.1 (1.7%)	2.7 (2.1%)	3.3 (2.7%)	3.8 (3.1%)
40% Mandate	1.3 (0.9%)	2.5 (1.8%)	4.0 (2.9%)	5.5 (4.3%)	7.0 (5.6%)	8.6 (7.0%)	10 (8.5%)
50% Mandate	2.1 (1.4%)	3.9 (2.7%)	6.3 (4.7%)	8.9 (6.8%)	11.4 (9.0%)	14.0 (11%)	16.3 (14%)

APPENDIX B. CHAPTER 4 APPENDIX

Appendix B contains tables and graphs that provide supplemental information for Chapter 4 used in the model. Unless another source is specified the data comes from Lennox (2019). The appendix is used to provide the supplemental information and data. B1, B2 and B3 presents the 30%, 40%, 50% mandate generation mix for original and updated scenarios respectively. Appendix Table B4 shows the reference cost breakdown for different scenarios. Appendix Table B8 shows CO_2e kilotons saving relative to original reference for different original mandate scenarios and B9 shows CO_2e kilotons saving relative to updated reference for different updated mandate scenarios.

Appendix Table B1. 30% Mandate Generation Mix for Original and Updated Scenarios

		2020 (PJ)	2025 (PJ)	2030 (PJ)	2035 (PJ)	2040 (PJ)	2045 (PJ)	2050 (PJ)
30% Mandate Original	Coal	1,609	1,481	1,369	1,167	900	834	435
	Hydro	35	35	35	35	35	35	35
	Natural Gas	1,378	1,489	1,550	1,691	1,940	1,941	2,285
	Nuclear	661	621	621	621	621	621	621
	Solar	83	146	187	228	268	309	349
	Wind	439	530	643	756	869	982	1095
30% Mandate updated	Coal	1568	1408	1245	1013	711	647	193
	Hydro	35	35	35	35	35	35	35
	Natural Gas	1,419	1,561	1,675	1,845	2,129	2,129	2,526
	Nuclear	661	621	621	621	621	621	621
	Solar	83	146	187	228	268	309	349
	Wind	439	530	643	756	869	982	1095

Appendix Table B2. 40% Mandate Generation Mix for Original and Updated Scenarios

		2020 (PJ)	2025 (PJ)	2030 (PJ)	2035 (PJ)	2040 (PJ)	2045 (PJ)	2050 (PJ)
40% Mandate Original	Coal	1609	1481	1362	1167	900	834	435
	Hydro	35	35	35	35	35	35	35
	Natural Gas	1,309	1,351	1,351	1,415	1,595	1,528	1,803
	Nuclear	661	621	621	621	621	621	621
	Solar	83	235	275	316	356	397	438

	Wind	508	579	761	943	1125	1306	1488
40% Mandate updated	Coal	1500	1393	1194	964	676	543	155
	Hydro	35	35	35	35	35	35	35
	Natural Gas	1,419	1,439	1,519	1,619	1,819	1,819	1,819
	Nuclear	661	621	621	621	621	621	621
	Solar	83	235	275	316	356	397	438
	Wind	508	579	761	943	1125	1306	1488

Appendix Table B3. 50% Mandate Generation Mix for Original and Updated Scenarios

		2020	2025	2030	2035	2040	2045	2050
50% Mandate Original	Coal	1,609	1,454	1,266	1,067	900	699	405
	Hydro	35	35	35	35	35	35	35
	Natural Gas	1,240	1,240	1,240	1,240	1,250	1,250	1,351
	Nuclear	661	621	621	621	621	621	621
	Solar	83	304	374	415	445	496	606
	Wind	577	648	868	1119	1380	1620	1802
50% Mandate updated	Coal	1,431	1,275	1,087	888	732	530	0
	Hydro	35	35	35	35	35	35	35
	Natural Gas	1,419	1,419	1,419	1,419	1,419	1,419	1,755
	Nuclear	661	621	621	621	621	621	621
	Solar	83	304	374	415	455	496	606
	Wind	577	648	868	1119	1370	1620	1802

Appendix Table B4. Reference Cost Breakdown for Original and Updated Scenarios

		Millions USD						
		2020	2025	2030	2035	2040	2045	2050
Original Reference	Investment	15,970	16,922	16,213	15,700	15,043	14,476	12,195
	Fixed O&M	10,892	10,838	10,876	10,910	10,977	11,017	10,994
	Variable O&M	7,743	7,611	7,499	7,770	6,555	6,519	5,803
	Fuel	11,579	12,180	11,995	11,666	11,432	11,521	11,496
Updated Reference	Investment	15,949	16,870	16,187	15,676	15,020	14,454	12,173
	Fixed O&M	11,964	11,877	11,971	12,720	13,295	13,383	14,056
	Variable O&M	8,631	8,633	8,563	8,043	7,532	7,621	6,892
	Fuel	10,921	11,999	11,768	11,591	11,382	11,400	11,353

Appendix Table B5. 30% Mandate Cost Breakdown for Original and Updated Scenarios

		Millions USD						
		2020	2025	2030	2035	2040	2045	2050
30% Mandate Original	Investment	16,480	18,036	17,845	17,797	17,593	17,479	15,495
	Fixed O&M	11,009	11,056	11,221	11,680	12,021	12,228	12,502
	Variable O&M	7,686	7,526	7,405	6,980	6,457	6,458	5,695
	Fuel	11,490	12,088	11,907	11,581	11,347	11,456	11,413
30% Mandate updated	Investment	16,442	17,967	17,722	17,659	17,429	17,306	15,288
	Fixed O&M	12,363	12,501	12,912	13,949	14,822	15,152	15,995
	Variable O&M	8,367	8,285	8,043	7,394	6,729	6,690	5,860
	Fuel	11,221	11,998	11,717	11,501	11,287	11,341	11,253

Appendix Table B6. 40% Mandate Cost Breakdown for Original and Updated Scenarios

		Millions USD						
		2020	2025	2030	2035	2040	2045	2050
40% Mandate Original	Investment	17,439	20,120	20,796	21,556	22,208	22,847	21,400
	Fixed O&M	11,300	11,458	11,847	12,518	13,038	13,510	13,918
	Variable O&M	7,626	7,407	7,207	6,742	6,333	6,102	5,279
	Fuel	11,358	11,848	11,539	11,091	10,750	10,711	10,543
40% Mandate updated	Investment	17,336	20,058	20,734	21,565	22,333	22,959	21,354
	Fixed O&M	13,153	13,414	14,231	14,890	15,978	16,550	17,105
	Variable O&M	7,775	7,657	7,190	7,116	6,489	6,348	5,844
	Fuel	11,138	11,796	11,456	10,999	10,623	10,599	10,483

Appendix Table B7. 50% Mandate Cost Breakdown for Original and Updated Scenarios

		Millions USD						
		2020	2025	2030	2035	2040	2045	2050
50% Mandate Original	Investment	18,444	22,183	23,770	25,370	26,972	28,501	28,017
	Fixed O&M	11,605	11,909	12,525	13,423	14,163	14,940	15,349
	Variable O&M	7,567	7,216	6,774	6,249	5,890	5,453	4,863
	Fuel	11,226	11,599	11,144	10,575	10,109	9,915	9,674
50 % M	Investment	18,277	22,016	23,603	25,234	26,835	28,355	27,836

	Fixed O&M	13,967	14,287	14,923	15,841	16,601	17,398	18,001
	Variable O&M	7,173	7,037	6,852	6,661	6,513	6,320	5,833
	Fuel	11,146	11,532	11,123	10,519	10,034	9,855	9,643

Appendix Table B8. CO_2e kilotons Saving Relative to Original Reference for Different Original Mandate Scenarios

CO_2e kilotons saving from original reference	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
30% Mandate original	15,400 (1.6%)	20,139 (2.2%)	24,990 (2.8%)	29,678 (3.5%)	33,479 (4.1%)	39,029 (4.9%)	42,343 (5.7%)
40% Mandate original	24,473 (2.5%)	37,810 (4.1%)	52,874 (5.9%)	66,460 (7.8%)	73,145 (8.9%)	94,958 (11.8%)	107,953 (14.4%)
50% Mandate original	32,803 (3.4%)	57,885 (6.2%)	88,517 (9.9%)	112,091 (13.1%)	125,091 (15.2%)	162,779 (20.2%)	172,843 (23.1%)

Appendix Table B9. CO_2e kilotons Saving Relative to Original Reference for Different Updated Mandate Scenarios

CO_2e kilotons saving from updated reference	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
30% Mandate updated	16,374 (1.7%)	23,527 (2.6%)	27,991 (3.2%)	34,845 (4.1%)	38,540 (4.7%)	44,491 (5.6%)	49,488 (6.6%)
40% Mandate updated	25,455 (2.6%)	38,991 (4.2%)	56,710 (6.4%)	70,041 (8.2%)	78,684 (9.6%)	102,604 (12.8%)	115,218 (15.5%)
50% Mandate updated	35,035 (3.6%)	59,875 (6.5%)	93,189 (10.5%)	117,501 (13.8%)	132,447 (16.1%)	172,601 (21.5%)	191,377 (25.6%)

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