Power Systems Optimization to Analyze Renewable Energy Policy and Resource Diversity

By

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Abstract

This thesis is organized into two chapters, which will be submitted separately for publication. The abstracts for each chapter are given below.

Chapter 1:

Many state-level Renewable Portfolio Standards (RPS) include preferences for solar generation, with goals of increasing the diversity of new renewable generation, driving down solar costs, and encouraging the development of local solar industries. Depending on their policy design, these preferences can impact the RPS program costs and emissions reduction. This study introduces a method to evaluate the impact of these policies on costs and emissions, coupling an economic dispatch model with optimized renewable site selection. Three policy designs of an increased RPS in Michigan are investigated: 1) 20% Solar Carve-Out, 2) 5% Distributed Generation Solar Carve-Out, and 3) 3x Solar Multiplier. The 20% Solar Carve-Out scenario was found to increase RPS costs 28%, while the 5% Distributed Generation Solar Carve-Out increased costs by 34%. Both of these solar preferences had minimal impact on total emissions. The 3x Solar Multiplier decreases total RPS program costs by 39%, but adds less than half of the total renewable generation of the other cases, significantly increasing emissions of CO_2, NO_x, and SO_2 relative to an RPS without the solar credit multiplier. Sensitivity analysis of the installed cost of solar and the natural gas price finds small changes in the results of the Carve-Out cases, with a larger impact on the 3x Solar Multiplier. Setting the correct level for a solar multiplier to achieve one's goals may prove difficult in light of changing costs associated with multiple technologies. The effective use of a credit multiplier can undermine objectives to increase renewable generation and decrease emissions, but do allow market forces to determine the level of solar development relative to other qualified renewable options. The Solar Carve-Out scenarios have a smaller impact on other non-solar related objectives, but may compel the development of high-cost solar, increasing the cost of implementing an RPS.

Chapter 2:

The variability of wind power introduces new challenges for the operation of the power system, including increased system ramping requirements. One method to reduce wind variability is to diversify the wind power resource by interconnecting diverse wind resources across a larger geography. This study uses a modified version of mean-variance portfolio optimization (MVP) to assess the potential for diverse wind to reduce the impacts of wind variability. To understand the value of the reduced variability to the power system, different portfolios of wind power are assessed using a unit commitment and economic dispatch model. Using MVP, diverse wind portfolios are shown to significantly reduce wind power variability, at the cost of increased installed wind capacity to meet the same level of wind generation of less diverse wind portfolios. However, the value of the reduced variability is complicated by complexities of the power system, including transmission constraints and the time of day of ramping need.

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Chapter 1 of this thesis focuses on impact of Renewable Portfolio Standard design variations. This chapter is part of a larger project investigating future Renewable Portfolio Standards for Michigan which was funded by the University of Michigan's Energy Institute (UMEI). During the project Dr. Mark Barteau, the Director of the UMEI, and Dr. Tom Lyon, the Associate Director for Social Science and Policy at the UMEI, provided valuable support and feedback during the completion of the Michigan RPS report.

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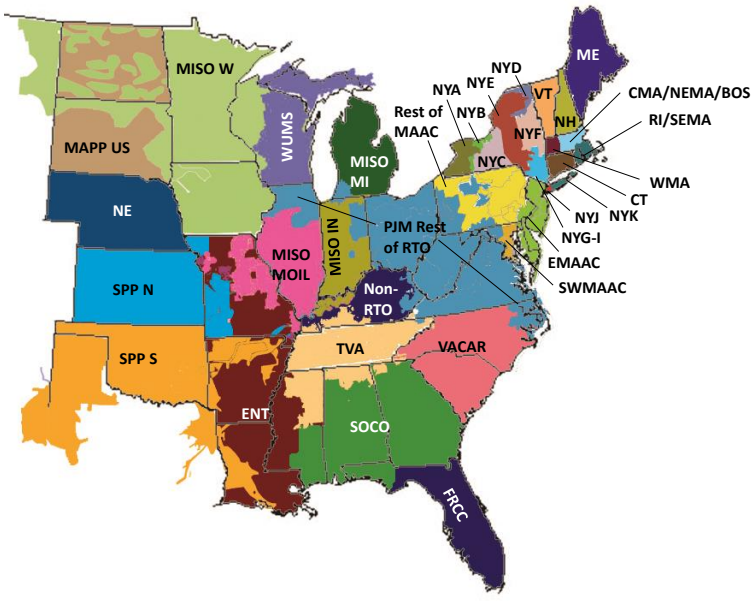
Preface

This thesis is organized into two chapters. The first investigates the impacts on emissions and costs of adding solar policy preferences into a Renewable Portfolio Standards (RPS). A variety of solar policy preferences exist, including credit multipliers and generation carve-outs, but are often implemented without a full understanding on their impacts on RPS implementation. This chapter will be submitted for publication in the near future.

The second chapter investigates the value of wind resource diversity to decrease some of the negative system impacts of integrating renewables into the grid. Wind diversity is shown to decrease wind power variability, however decreasing the variability does not always translate into reduced negative impact given some of the complexities introduced in a real power system. This chapter will also be submitted for publication in the near future.

The connection between the two chapters is the use of a unit commitment and economic dispatch model to analysis the change in power system behavior when variable renewables are added to the grid. The model is a full representation of the U.S. Eastern Interconnection, which spans from the Dakotas to Florida. A map of the EIC and the zonal boundaries defined in the model is shown below.



Chapter 1: The Environmental and Cost Implications of Solar Energy Preferences in Renewable Portfolio Standards

1.1 Introduction

Renewable Portfolio Standards (RPS) are a common policy tool used by state law makers to encourage the development of renewable energy generation. While each state's RPS varies in design and scope, most require that electric load serving entities, such as investor owned utilities and electric cooperatives, meet a set percentage of their demand with eligible renewable energy. RPS typically set a target year for the required amount of renewable energy to be met, with interim goals along the way. As of November 2014, 29 states have some form of a binding RPS in place .

A variety of motivations exist for implementing a RPS. Many see it as a tool to reduce emissions from the power sector, which, in 2012, accounted for about 38% of the CO_2 emissions in the United States (U.S. Environmental Protection Agency 2014a). The power sector also accounts for about 70% of SO_2 and 13% NO_x emissions (U.S. Environmental Protection Agency 2014b). Increasing the amount of local energy generation and manufacturing can be another reason for implementing a RPS, although these tend not to be a driving force to implement a RPS as found by Lyon and Yin (2010).

Beyond the target goals for renewable energy generation, there are many variations in RPS program designs. Eligibility requirements for renewable energy technologies can vary, including or excluding generation based vintage, size, and, for biomass generation, the fuel feedstock. Many policies incentivize specific technologies, with 14 states offering incentivizes or mandating contributions from solar within their RPS (Wiser, Barbose et al. 2011).

Policy makers see the benefits of solar development within their states in encouraging resource diversification within the renewables built to comply with the RPS and its potential to develop a local solar industry (Gaul and Carley 2012). Even though the installed cost of solar has decreased dramatically over the last decade, it is still often not the lowest cost renewable option as evidenced by its low contribution of capacity additions towards RPS compliance in the U.S., only 1.5%, compared to wind's 94% share (Wiser, Barbose et al. 2011). RPS mandates are met with the least cost technology and any policy variation incentivizing a more costly technology, such as solar, are methods for the RPS to indirectly subsidize the costly technology (Buckman 2011). Solar incentives within an RPS fall into two main categories: carve-outs and multipliers. A solar carve-out requires a certain percentage of the overall RPS be met with solar generation. New Mexico, for example, requires 20% of the renewable generation required by the RPS come from solar generation (Heeter, Barbose et al. 2014). A solar multiplier gives additional credit toward RPS compliance for every unit of energy from solar. Michigan has a 3x multiplier for solar, allowing every megawatt-hour generated from solar to count as three megawatt-hours towards RPS compliance (Quackenbush, White et al. 2014).

Some RPS policies provide incentives or mandates for distributed generation (DG) or customer-sited systems, with limitations on the size of the generators. While DG incentives are not typically limited to solar, it is expected that solar will be the primary benefactor (Gaul and Carley 2012). DG incentives take the form of both carve-outs and multipliers: Massachusetts requires 456 GWh of customer-sited solar PV, while Washington gives a 2x multiplier for DG (Wiser, Barbose et al. 2011).

Technology-specific multipliers and carve-outs can impact the costs and emissions reduction potential of the RPS. Carve-outs may add binding constraints to compliance if the required technology displaces more cost effective renewable options. On the other hand, credit multipliers may cause the actual renewable generation to be less than the required amount in the RPS, as incentive credits that do not represent actual generation can be used towards compliance.

This study proposes an approach to quantifying the impacts of RPS solar policy preferences on emissions and program costs. A solar energy multiplier, a solar energy carve-out, and a distributed generation solar carve-out are all compared to a "pure" RPS (i.e., an RPS without any specific technology incentives or mandates). Renewable energy projects are chosen to minimize the cost of RPS compliance subject to any constraints imposed by the solar preference. An economic dispatch model is used to measure the impacts on the power system from the introduction of new, typically variable, renewables on to the system. The economic benefits, including the offset production costs of conventional generation and displaced capacity requirements, can be compared to the costs of building the renewables projects to determine the net cost of the RPS to rate payers within the state/region. The environmental benefits arise from the reduction in the emissions from the combustion of fossil fuels, such as CO_2, NO_x, and SO_2.

This methodology to assessing the environmental and cost impacts of solar preferences in a RPS is tested on future potential designs for Michigan's RPS. Currently Michigan has a 10% by 2015 RPS, which is expected to be met (Quackenbush, White et al. 2014). At this point, no expansion of the RPS beyond 2015 has been put in place, although discussion of increasing the RPS is ongoing.

The results of this study demonstrate the value and applicability of this method to assess the impact of RPS policy design on costs and emissions. While the quantitative results will vary by region, the methods proposed by this study could be applied to any state.

Several studies have employed economic and power systems models to analyze the impacts of RPS policies, ranging from detailed and complex models to simple grid averages. Johnson (2014) uses an analysis of renewable generation price elasticity to calculate the cost of carbon emissions reductions in the U.S. Northeast through RPS policies. To capture CO_2 mitigation potential, the analysis tests different assumptions for the type of fuel the RPS will displace. Considine and Manderson (2014) develop an econometric forecast to determine the impact of California's RPS on cost and emissions, in the light of efficiency efforts and varying natural gas prices. This study is limited by assuming fixed operating hours for generators, with imports serving the role as the

"swing fuel." A recent comprehensive report by the National Renewable Energy Laboratory (NREL) and Lawrence Berkeley National Laboratory (LBNL) measured the retrospective costs and benefits of existing RPS policies throughout the U.S. (Heeter, Barbose et al. 2014).

Other analyses of RPS include robust power systems representations to understand the generator responses to the introduction of renewable generation. Multiple studies (Sullivan, Logan et al. 2009; Bird, Chapman et al. 2011; Palmer, Paul et al. 2011) from NREL deploy the Regional Energy Deployment System (ReEDS) model, a capacity and transmission expansion model, to understand the impact of RPS and other policies aimed at introducing renewables to the grid. Bird, Chapman et al. (2011) analyzed a federal cap and trade policy and RPS policies, in isolation and in tandem. Palmer, Paul et al. (2011) also relies on the ReEDS to examine various renewable energy policies, including a federal RPS. While both of these studies provide a rigorous examination of the impacts of RPS policies, neither focus on the specific impacts associated with solar preferences within an RPS.

Johnson and Novacheck (2015) coupled an economic dispatch model with a method to optimize renewable site selection to determine least cost RPS compliance and emissions reductions. The study presented in this article builds off of this previous work by quantifying the environmental and cost impacts of solar policy preferences in an RPS. This study presents new methods to more fully capture the impacts of RPS policy variations.

1.2 Methods

To analyze the cost and environmental impact of an increased RPS in Michigan, two models are used iteratively: an economic dispatch model to simulate the behavior of dispatchable generators and a renewable site selection model to select the renewable projects that meet the RPS targets. The economic dispatch model captures generators' responses to the introduction of renewables and determines the energy costs displaced by the introduction of various renewable projects. The renewable site selection model takes the market energy prices produced by the economic dispatch model and determines renewable projects that meet the RPS target at least cost to rate payers. The generation profile of the selected renewable projects are then added to the power system representation used by the economic dispatch model. The two models are run iteratively in five year increments from 2015 to 2035 to fully capture the impact of adding renewables to the grid. The introduction of a renewable project with low variable costs (e.g., wind and solar) will put downward pressure on the market energy prices in hours when that renewable project is generating. This will impact the economic competitiveness of future projects and the least cost renewable build plan to comply with the RPS. The methodology presented in this study builds off of previous work to optimize renewable site selection in the context of varying RPS targets (Johnson and Novacheck 2015), expanding the approach to capture the impacts of technology preferences in the RPS design.

1.2.1 Renewable Site Selection

The renewable site selection model determines the renewable build plan that complies with the RPS mandate, as identified by four factors: (1) the cost of the renewable power purchase agreement (PPA), (2) the avoided variable costs of conventional generators including fuel costs, (3) the avoided costs of firm capacity to maintain the peak reserve margin, and (4) the change in the net electricity import costs (i.e., increased export revenue and decreased import costs). The system of equations that determine the selection of renewable projects under different solar policy variations are detailed in Equations 1-10.

The renewable PPA costs equal the revenue requirement that renewable projects need to be financially viable. The revenue requirement is calculated using the method described in Johnson, De Kleine et al. (2014), but expanded to other renewable projects in addition to wind. The costs included in the revenue requirement for renewable project i, denoted as $C_{PPA,i}$ in the below equations, are the installed cost of the project and the associated financing, fixed operations and maintenance costs, taxes, and any fuel costs (for biomass, municipal solid waste, and landfill gas projects) (Johnson, De Kleine et al. 2014). This study did not assume any extension of the investment tax credit (ITC) or production tax credit (PTC), but if relevant tax incentives existed they would be accounted for in the revenue requirement as well.

The offset variable costs of conventional generators and the change in the net import cost caused by a renewable project are estimated by determining the energy market revenue a project expects to receive. The calculation of energy market revenue, $C_{e,i}$, for renewable project i is shown in Equation 1,

$$C_{e,i} = \frac{\sum_{t=1}^{8,760}(P_{i,t} \times E_t)}{P_i} \quad (eq. 1)$$

where P_i is the annual generation for project i, $P_{i,t}$ is the power output at hour t of site i, and E_t is the market energy price at hour t. Multiplying the energy market price by the associated generation from the renewable project and summing the products over time determines the avoided energy costs that reflect the time-of-day value of the renewable generation. The introduction of wind and solar, which are assumed to have $0/MWh dispatch cost, are assumed to displace the most expensive conventional generators that are operating at that time. Biomass, municipal solid waste, and landfill gas have non-zero dispatch costs because of fuel and other variable costs associated with their operation. However, they will operate when the market energy price is above its dispatch cost, at which point it will displace the most expensive conventional generators that would have operated in the absence of the biomass generation. The energy market revenue expected by a renewable project can therefore be used to estimate the amount variable costs of conventional generators and net import costs will decrease if that renewable project is integrated into the grid.

In addition to avoiding energy costs, the introduction of renewables also displaces the need for some firm capacity. NERC, in cooperation with state public utility commissions and independent

system operators (ISO), develops targets for the amount of firm capacity above the peak load in the region a balancing area (BA) must have in place (North American Electric Reliability Corporation 2013). MISO's target, for example, is to have 14.2% more capacity than the peak load throughout the region (North American Electric Reliability Corporation 2013). Variable renewables, even though they cannot be called on to increase their generation, do receive some capacity credit to be used towards meeting the reserve margin. The capacity value of project i, $C_{cap,i}$ ($/MWh), is based on the capacity credit, γ, which is a percentage of the installed capacity and a fixed value for firm capacity, C_{NE} ($/kW-yr). As shown in Equation 2, the product of γ and C_{NE} is divided by the project's capacity factor, CF_i, which normalizes the capacity credit to the total generation of the project. The value of γ is typically based on analysis to determine the probability a type of variable generation will be available on peak. Wind and solar capacity credits are determined separately. In this study, γ is assumed to be 14.1% for wind (Midcontinent Independent System Operator 2013), 38% for solar (PJM 2014), and 80% for biomass to reflect its value as a dispatchable resource. The total capacity value the renewable projects provide an estimate of the cost of the displaced firm capacity that would have needed to be built to meet the reserve margin requirements for the BA had the renewable projects not been built.

$$C_{cap,i} = \frac{C_{NE} * \gamma_i * 10^3 \frac{kW}{MW}}{CF_i * 8760 hr/yr} \quad (eq.2)$$

The list of projects and the size of the projects are selected to minimize the above market cost, β, which represents the net cost impact of a renewable project, the sum of which represents the total RPS program cost. Equations 3 through 6 determine the renewable project selection.

$$Min\ \beta = \sum_{i=1}^{n}[(C_{PPA,i} - C_{e,i} - C_{cap,i}) * P_i] \quad (eq.3)$$

$$s.t., \quad \sum_{i=1}^{n} P_i \geq \varphi \quad (eq.4)$$

$$P_i \leq CF_i * Cap_{max,i} * 8760 \frac{hrs}{year} \quad (eq.5)$$

$$P_i \geq 0 \quad (eq.6)$$

The decision variables in the linear optimization problem are the amount of renewable generation, P_i, to be provided by site i to comply with the RPS mandate. Equation 4 requires the sum of all the decision variables be at least the incremental addition of renewable generation, φ, required by the RPS. Equation 5 sets the upper bound for generation from each site, set by the assumed capacity limit for each site. The optimization is run each year of the study to determine the set of projects to be built in that year.

The RPS solar policy variations add or alter constraints. First, the decision variables that represent solar generation must be distinguished from the other variables. Equation 7 shows how the decision variables are broken into three subsets of all of the possible projects. P_{ns} are the non-solar

decision variables, P_{Us} are the utility scale solar decision variables, and P_{DGs} are DG solar decision variables.

$$P_{ns}, P_{Us}, P_{DGs} \subset P \quad (eq.7)$$

In the case of the 20% Solar Carve-Out and the 5% DG Solar Carve-Out, a constraint is added to require the addition of the appropriate type of solar. In the Solar Carve-Out, Equation 8 is added in order to require that all of the generation from solar is some proportion, ω_{Us+DGs}, of the total incremental renewable generation required by the RPS. In the case of the DG Solar Carve-Out, Equation 9 replaces Equation 8 to require some proportion, ω_{DGs}, of the total incremental renewable generation to come from DG solar.

$$\sum_{j=1}^{n_{Us}} P_{Us,j} + \sum_{k=1}^{n_{DGs}} P_{DGs,k} \geq \omega_{Us+DGs} * \varphi \quad (eq.8)$$

$$\sum_{k=1}^{n_{DGs}} P_{DGs,k} \geq \omega_{DGs} * \varphi \quad (eq.9)$$

The solar multiplier does not add any constraints, rather it modifies the constraint in Equation 4. Any solar generation is multiplied by α, as can be seen in Equation 10, allowing it to count extra towards meeting the incremental renewable generation constraint relative to non-solar generation.

$$\sum_{l=1}^{n_l} P_l + \alpha \left[\sum_{j=1}^{n_{Us}} P_{Us,j} + \sum_{k=1}^{n_{DGs}} P_{DGs,k} \right] \geq \varphi \quad (eq.10)$$

1.2.2 Economic Dispatch Model

Renewable generation will displace certain conventional generation based on cost and operational constraints. Due to the variable nature of both wind and solar, conventional generators will also incur more start-ups and shut-downs in order to balance the supply and demand of power. The unit commitment and economic dispatch model captures these changes in generator behavior and their impacts on costs and emissions of the power system.

Plexos for Power Systems by Energy Exemplar is the unit commitment and economic dispatch model used in this study. Plexos employs linear programing to determine the least cost operations for the entire system. The optimization problem is solved using an interior algorithm with mixed integer programming used to determine unit commitment. The problem is solved chronologically in hourly intervals. The economic dispatch model minimizes the cost of generation over time, as influenced by generator operating conditions and the fuel price. These include generator heat rate curves (efficiency of fuel use), cost of variable operations and maintenance, start costs, and the level of generation. Constraints to the optimization include, matching supply and demand in real time (unless over constrained), generator output range (minimum/maximum load), generator

availability (impacted by forced outage rate), generator ramp rate (rate at which a generator can change load point), and transmission limits between zones.

This model begins as a full representation of the synchronous U.S. Eastern Interconnection (EIC), segmented into 35 zones. Major inputs to this model include transmission constraints between zones, load profiles, generators reflective of their operational constraints, and zonal fuel prices. Key assumptions used in the test case are provided in Section 2.4, as well as the Supporting Information.

1.2.3 Michigan Test Case

The methods described in this study can be applied to any state and the system characteristics of the examined area will determine the emissions and costs impacts of solar preferences in an RPS. This study presents a case study, using Michigan as a demonstration of the use of the methods to analyze the impact of RPS policy variation. The majority of Michigan is part of the Midcontinent Independent System Operator's (MISO) footprint, with a small portion of the southwest corner of the state belonging to PJM. Michigan and MISO as a whole is heavily dependent on coal for power generation. In 2013 coal accounted for 54% of all generation in Michigan (U.S. Energy Information Agency 2013a).

Michigan's current RPS calls for 10% renewables by 2015. This study assumes that the RPS target is increased to 25% by 2025 and maintained thereafter. The four scenarios assessed include: a Pure RPS (no solar policy variation), a 20% Solar Carve-Out (20% of the new renewable generation must be solar, ω_{Us+DGs} = 0.2 in Equation 8), a 5% DG Solar Carve-Out (5% of new renewable generation must be DG solar, ω_{DG} = 0.05 in Equation 9), and a 3x Solar Multiplier (solar receives 3 times the credit towards RPS compliance, α = 3 in Equation 10). The changes in costs and emissions are determined by comparing the scenarios to a scenario with no expansion of the RPS, details of which are provided in (Johnson and Novacheck 2015). Sensitivity of the results to natural gas price and the installed cost of solar are considered.

The full Eastern Interconnection model is run in 2015. The geography is then reduced for subsequent years reduce modeling time. The reduced geography includes the northern portion of MISO and the Western portion of PJM, which borders Michigan directly. Using the power flow results from full 2015 run, imports and exports into and out of reduced geography (MISO and Western PJM) are held constant for all subsequent runs to capture the influence of the rest of the Eastern Interconnection on the reduced geography, while still allowing flows into and out of Michigan to be optimized throughout the study period.

Qualified renewable technologies considered in this study include wind, utility scale solar, DG scale solar, biomass (six feedstock options), municipal solid waste (MSW), and landfill gas (LFG). The renewable project location, size, and generation profile are specific to Michigan. Wind data are from NREL's Eastern Wind Dataset, solar data from seven sites using TMY2 weather data and NREL's System Advisory Model (National Renewable Energy Lab 2014) to determine generation

profiles. Single axis tracking systems are assumed for utility-scale projects, while DG projects are fixed axis. The resource assumptions for biomass and MSW are from "A Geographic Perspective on Current Biomass Resource Availability in the United States" (Milbrant 2005) while landfill gas data are from the EPA's Landfill Methane Outreach Program (U.S. Environmental Protection Agency 2014cc).

The installed cost of renewables may also change over the study horizon, particularly the cost of solar. Assumptions for the costs of renewables are shown in Table 1. The installed cost of wind, biomass, MSW, and LFG generators are assumed to remain constant (in terms of real dollars) over the study period. According to data from quarterly reports published by the Solar Energy Industries Association (Solar Energy Industries Association 2014), utility scale solar has shown a 15.1% year over year decrease in the installed cost of projects since 2012 (using quarterly weighted averages). DG PV has seen a 9% decrease over the same time period. This study assumes this rate of decline will continue until it hits a floor of $1/W-AC for utility scale solar and $1.5/W-AC for distributed solar, is consistent with the DOE SunShot target. Under our assumptions, utility scale solar reaches this target in 2021, while DG scale projects reach their target in 2027.

Table 1: 2014 Renewable Assumptions

Technology	Wind	Utility Solar	DG Solar	Biomass	Landfill Gas
Installed cost ($/kW)	1,940[a]	2,453[b]	4,734[b]	4,505[c]	1,816[d]
Annual change in installed cost (real $)	0%	15%[b]	9%[b]	0%	0%
Fixed O&M ($/kW-yr)	25[c]	23[c]	20[c]	106[c]	174[d]
Variable O&M ($/MWh)	-	-	-	5[c]	5[c]
Fuel cost ($/MMBtu)	-	-	-	1.90 – 4.12	2.20

Sources: a) Wiser and Bolinger (2013), b) Solar Energy Industries Association (2014), c) U.S. Energy Information Agency (2013b), d) U.S. Environmental Protection Agency (2012)

The base zonal fuel prices were calculated using the EIA 923 database based on the generation weighted average of the fuel costs reported by all generators within the same zone. The method captures geographic diversity of fuel costs seen in the real power system. The fossil fuel price forecast used in the economic dispatch model comes from the EIA's 2014 Annual Energy Outlook (AEO). The AEO assumes a 1.0% growth rate in the price of coal, and a 3.1% growth rate in the price of natural gas between 2012 and 2040.

Sensitivity analysis is performed on the assumed floor for the installed cost of solar and the price of natural gas. For the installed cost of solar, the low sensitivity sets the floor prices at $0.5/W-AC and $0.75/W-AC for utility and DG scales respectively. The high floor is assumed to be $1.25/W-AC and

$2/W-AC. For the natural gas price sensitivity, the low gas scenario assumes prices will be 50% lower than the forecasted value, while the high scenario assumes prices will be 50% higher.

Coal retirements were assumed to include announced retirements (1.2 GW) and units for which compliance with Mercury and Air Toxics Standard would exceed the cost of a new natural gas combined cycle (750 MW).

1.3 Results

The economic dispatch model and renewable site selection model were executed iteratively to determine the generation mix, costs, and emissions with each scenario over the 20 year study horizon (i.e., 2015 to 2035). The results show the impact of three solar policy variations on an assumed expansion of Michigan's RPS: 20% Solar Carve-Out, 5% DG Solar Carve-Out, and 3x Solar Multiplier. Each policy variation is compared to a Pure RPS case with no incentives or preferences for any technology. In Section 3.1, the impacts of RPS solar preferences on the generation mix are presented; Section 3.2 details changes in emissions; Section 3.3 presents the impact on the cost of the RPS. In Section 3.4, we present the results of the sensitivity analysis, in which we test the importance of assumptions for the installed cost of solar (high and low) and natural gas price (high and low).

1.3.1 Generation Mix

Figure 1 shows the changing generation profile over the 20 year study period for the three solar policy preferences and the Pure RPS case. Note that all scenarios experience an increase in total generation, due partly to load growth within Michigan and partly to an increase in net exports. By adding low variable cost renewable generation, Michigan increases its electricity exports to neighbor states. Therefore, renewables added to meet Michigan's RPS displace conventional generation within the state, as well as generation in neighboring states including Indiana, Ohio, and Wisconsin.

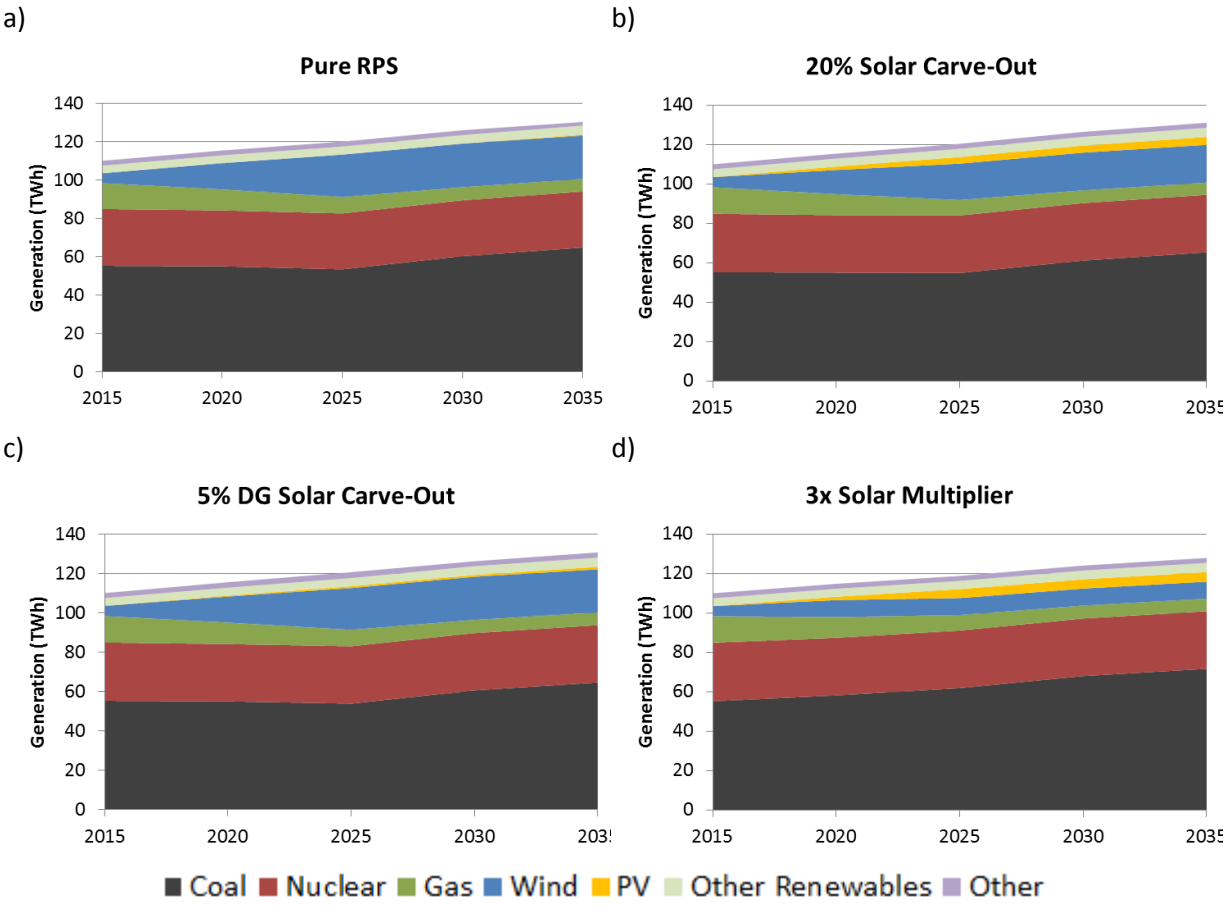


Figure 1 Generation mix by fuel type for each RPS policy variation: (a) Pure RPS; (b) 20% Solar Carve-Out; (c) 5% DG Solar Carve-Out; (d) 3x Solar Multiplier

Even under an expanded RPS, Michigan's power sector remains dominated by coal. In the Pure RPS case, coal accounts for nearly half of all generation throughout the study period. Without any extra incentive or mandate for solar in this case, nearly all new renewable generation comes from wind, making up 98% of all new renewable generation in the final year of the study. Solar is only added after 2030 to maintain the RPS target as load grows between 2025 and 2035. The total renewable generation over the study period, and the share of generation for the different renewable technologies are shown in Figure 2.

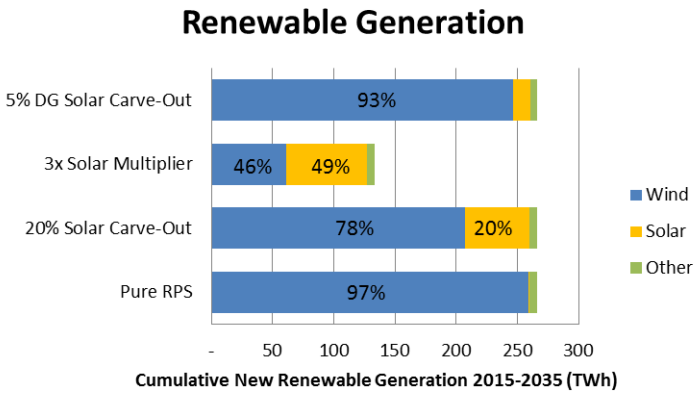


Figure 2 Total renewable generation between 2015 and 2035, by type. Without solar preferences embedded in the RPS, wind dominates new renewable generation.

In the 20% Solar Carve-Out and the 5% DG Solar Carve-Out cases, the amount of solar generation meets the solar requirement stated in the RPS, but nothing more, until the study year 2030 when new solar becomes preferable to new wind. The 3x Solar Multiplier case yields the highest solar penetration, both in terms of the share of new renewable generation and absolute generation. Over the study period, 49% of all new renewable generation comes from solar in the 3x Solar Multiplier case compared to only 20% in the 20% Solar Carve-out. By 2035, solar contributes 4.8 TWh annually, representing over 4% of Michigan's load.

While the solar multiplier proved to be most effective in increasing the amount of solar generation on the system, it comes at the expense of wind generation and the total penetration of renewables. By incentivizing solar through a credit multiplier, every megawatt-hour of solar generation is counted as three megawatt-hours towards RPS compliance. With this multiplier, solar becomes competitive with wind by 2018 and after this date only solar is built to comply with the RPS. Each of the other three scenarios (i.e., Pure RPS, 20% Solar Carve-Out, 5% DG Solar Carve-Out) reach the target penetration of renewables, which is 24.3% of load. (n.b., Renewable penetration does not hit 25% due to historical workforce incentives in Michigan's original 10% by 2015 RPS, which were assumed to be grandfathered in across all cases.) The 3x Solar Multiplier case, however, only achieves a renewable penetration of 15.9% of load, adding 52% less new renewable generation relative to the other three scenarios.

Due to the reduction in total renewable generation under the 3x Solar Multiplier, there is a significant increase in coal generation over the Pure RPS: 15.9% more coal generation in 2025 and 10.6% more in 2035. The 20% Solar Carve-Out also increases coal generation, but has a smaller impact relative to the 3x Solar Multiplier. In the Carve-Out cases, solar projects take the place of wind. This swap increases coal generation because solar generates on peak and is more likely to displace natural gas, while wind may generate at any hour of the day, increasing the likelihood of displacing coal in off peak hours. Compared to the Pure RPS case, coal generation is 2.7% greater

for the 20% Solar Carve-Out in 2025, decreasing to 0.8% greater in 2035. The 5% DG Solar Carve-Out mandates less solar, allowing more wind on the system, leading to a similar amount of coal generation to the Pure RPS.

1.3.2 Emissions

Adding solar preferences to an RPS changes the type of renewable capacity added to the power system. Different renewable generation profiles for as available generators such as wind and solar impact the type of generation that is displaced by the renewables, and in turn the reduction in emissions of pollutants such as CO_2, SO_2, and NO_x.

In a previous study using a comparable methodology, we determined that, without an expanded RPS, Michigan's CO_2 emissions rate increases from 0.60 lbs/MWh in 2015 to 0.70 lbs/MWh in 2035, due to an increase in the capacity factor of coal plants within the state to meet load growth (Johnson and Novacheck 2015). By increasing Michigan's RPS to 25% by 2025 (a 15% increase over the current 10% mandate), the Pure RPS case decreases the CO_2 emission intensity to 0.52 lbs/MWh in 2025 and 0.57 lbs/MWh in 2035 relative to no RPS expansion. Renewable capacity is only built between 2025 and 2035 to maintain the RPS target under load growth, which is insufficient to prevent an increase in coal generation, accounting for the increase in the CO_2 emissions rate. The Pure RPS also decreases the emissions rate of SO_2 and NO_x by 19.5% and 17.4% relative to no RPS expansion, respectively, in 2035.

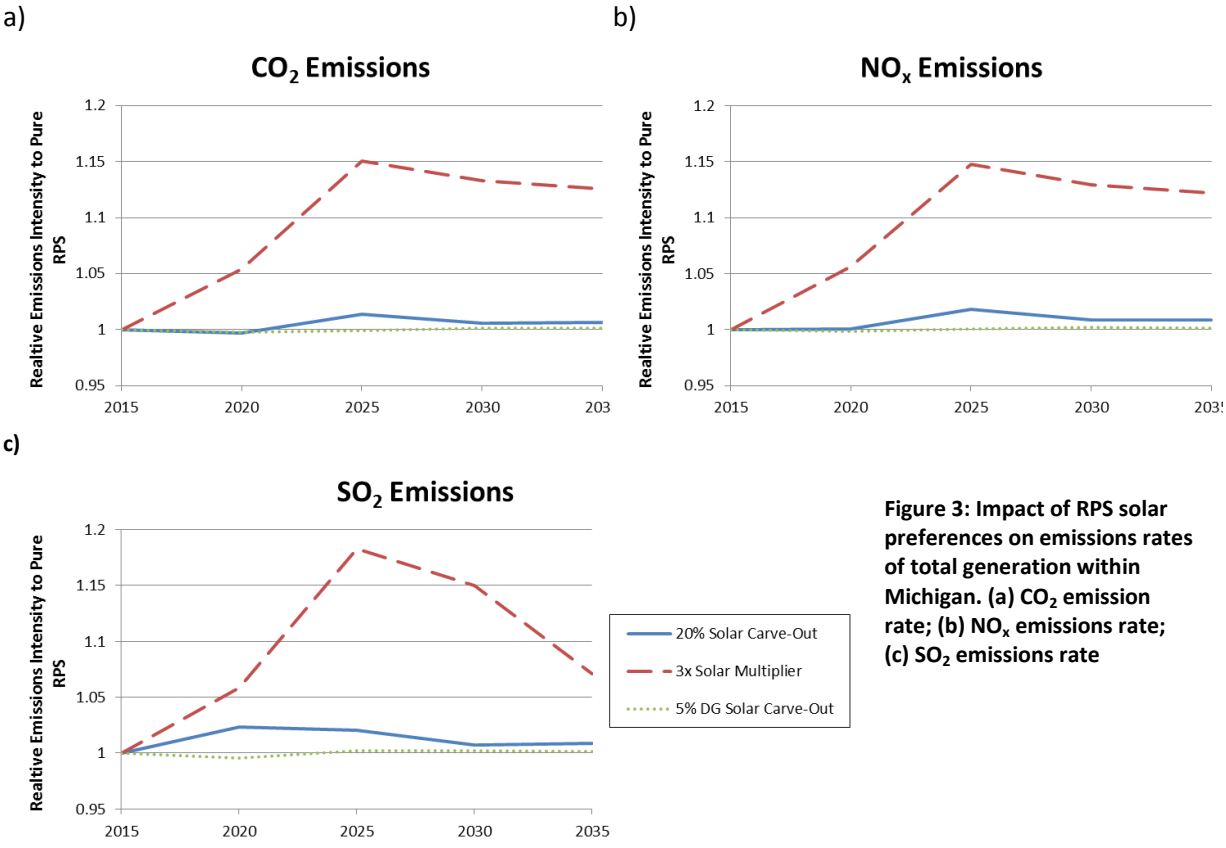


Figure 3: Impact of RPS solar preferences on emissions rates of total generation within Michigan. (a) CO_2 emission rate; (b) NO_x emissions rate; (c) SO_2 emissions rate

Figure 3 shows the relative emissions rate impact of adding a solar policy preference to the Pure RPS within Michigan for CO_2, SO_2, and NO_x. In general, the 3x Solar Multiplier case increases the emissions rate because less renewable capacity is added, requiring more fossil generation. The 20% Solar Carve-Out increases the CO_2, NO_x, SO_2 emissions rate slightly as there is more coal generation relative to the Pure RPS. The 5% DG Solar Carve-Out shows very little change from the Pure RPS.

Figure 4 shows the cumulative change in CO_2 over the 20 year study period between the solar policy variations and the Pure RPS. The CO_2 emissions in this figure reflect region-wide emissions, not just Michigan, since some of Michigan's added renewables displace out of state generation. The 3x Solar Multiplier increases CO_2 emissions dramatically over the study period, while the two Solar Carve-Out scenarios have little impact on total emissions reductions.

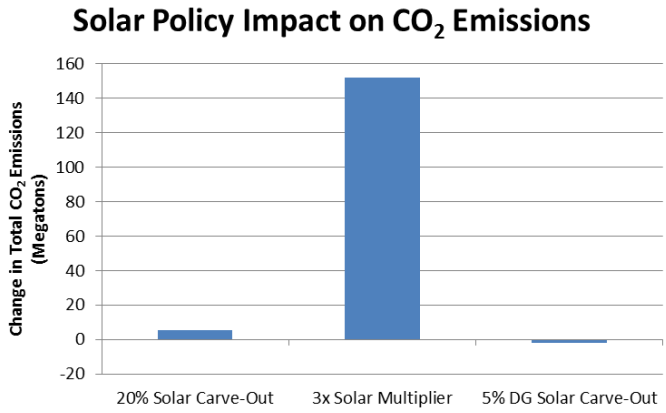


Figure 4 Change in CO_2 emissions over the study period due to solar policy preferences.

1.3.3 RPS Program Cost

We have characterized four cost categories that are attributable to the implementation of an RPS. The four categories are:

1) **New renewable power purchase agreements:** We assume new generation is achieved through renewable power purchase agreements (PPAs), with contract terms that meet the project's revenue requirement discussed in the methods section.

2) **Displaced variable cost of conventional generation:** These PPA costs can be offset by displacing dipatchable generation. By turning down (or off) coal and gas units, the production costs associated with generation decrease.

3) **Reduced need for capacity:** By awarding some fractional credit for the value of renewable capacity, the need to expand conventional capacity to maintain the peak load reserve margin decreases, further reducing costs to rate payers.

4) **Change in net imports:** New renewable generation can increase exports out of the state and decrease imports into it. This decreases electricity import expenses, while increasing electricity export revenue to in-state rate payers.

Adding solar preferences to the RPS impacts all four of these cost categories, as well as the total program cost. Figure 5 displays how each of these components change relative to the Pure RPS for each solar policy variation over the 20 year time horizon. Using a discount rate of 7%, the net present value (NPV) of the RPS program costs of the Pure RPS is $3.6 billion over the 20 year study period. The 20% Solar Carve-Out and the 5% DG Solar Carve-Out policy scenarios increase the NPV by $1.0 billion (+28%) and $1.2 billion (+34%) respectively. The 3x Solar Multiplier case decreases total NPV by $1.4 billion (-39%), due to less renewable generation being added in this scenario.

Driven by our assumptions on installed costs for each technology, solar does not become a lower cost alternative to wind in Michigan until after 2030 under the base case assumptions. Therefore, the two solar carve outs mandate a more expensive technology be built, increasing the total renewable PPA portion of the RPS program cost. Over the 20 year study period, the Pure RPS adds $8.5 billion in NPV PPA costs. Incorporating a 20% Solar Carve-Out increases the renewable NPV PPA cost of the RPS by 16.0%, while the 5% DG Solar Carve-Out increases the NPV PPA cost by 15.5%. Even though less solar capacity is added in the 5% DG Solar Carve-Out, the increase in the PPA cost is similar because DG solar projects are more expensive than utility scale projects, which are exclusively chosen in the 20% Solar Carve-Out case. The Solar Carve-Out cases also decrease the cost of capacity expansion to maintain the reserve margin relative to the Pure RPS. Because solar operates on peak, it is given a larger credit towards meeting the reserve margin. However, capacity expansion accounts for the smallest portion of the four components of the RPS program cost, as can be seen in Figure 3.

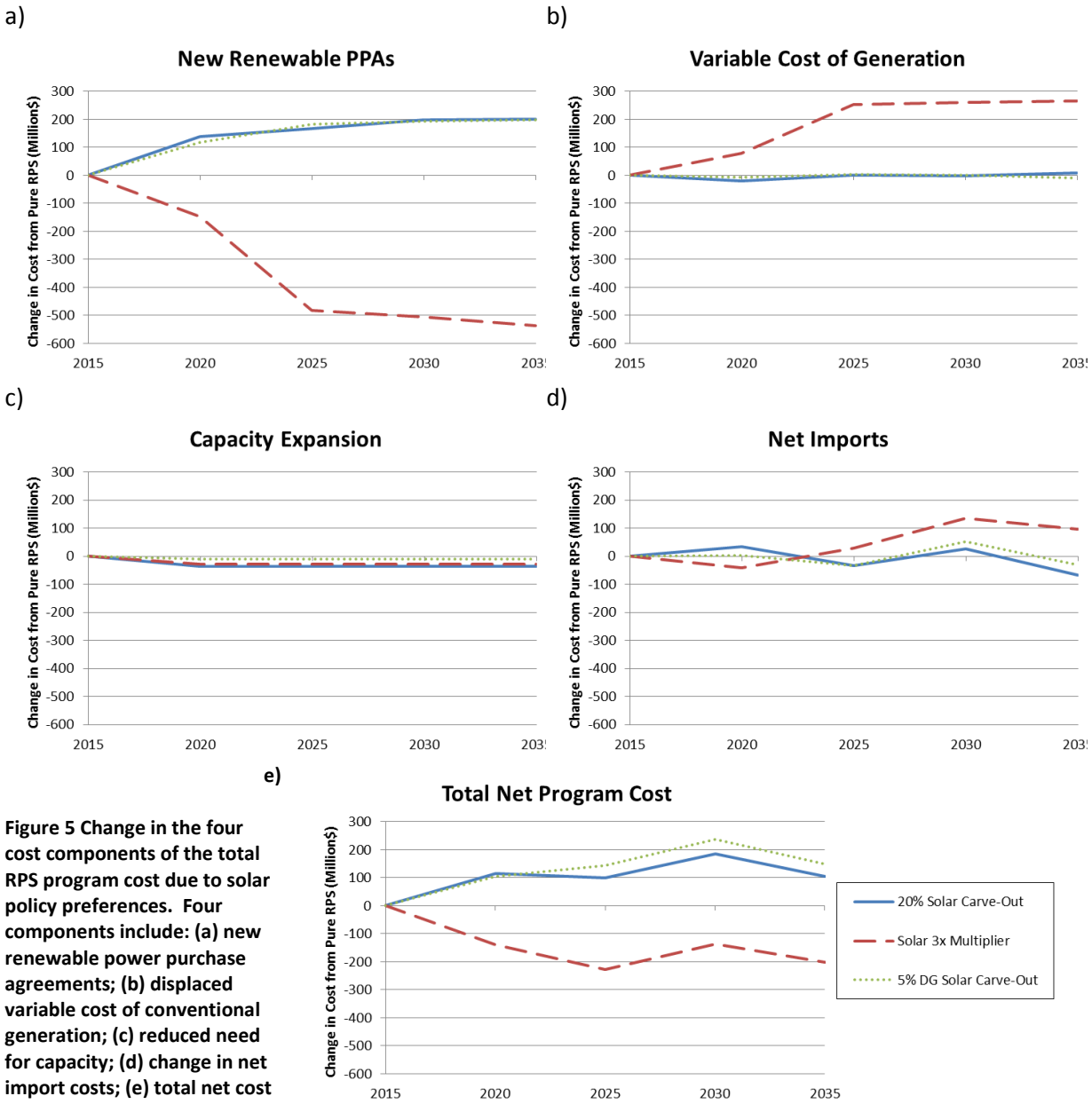


Figure 5 Change in the four cost components of the total RPS program cost due to solar policy preferences. Four components include: (a) new renewable power purchase agreements; (b) displaced variable cost of conventional generation; (c) reduced need for capacity; (d) change in net import costs; (e) total net cost

The 3x Solar Multiplier case shows a larger change in three of the four cost components. Even though the most solar is built in the solar multiplier case, the total renewable PPA cost is less than that of the Pure RPS because less renewable capacity is built overall (i.e., there is far less wind in this case). The smaller contribution of renewables causes both the variable cost of conventional generation and the net import costs to increase in the 3x Solar Multiplier case.

1.3.4 Sensitivity

In light of the uncertainties in key assumptions, over the 20 year study period, sensitivity of results to natural gas prices and solar installed costs were tested. For the installed cost of solar, the low sensitivity sets the floor prices at $0.5/W-AC and $0.75/W-AC for utility and DG scales, respectively.

The high floor is assumed to be $1.25/W-AC and $2/W-AC, respectively. The sensitivity of the natural gas fuel price forecast sets the low gas prices 50% lower than the forecasted value, while the high scenario assumes prices will be 50% higher. The program cost, CO_2 emissions rate, and coal generation sensitivity to the base assumptions are considered. The sensitivity results are only discussed for the year 2025.

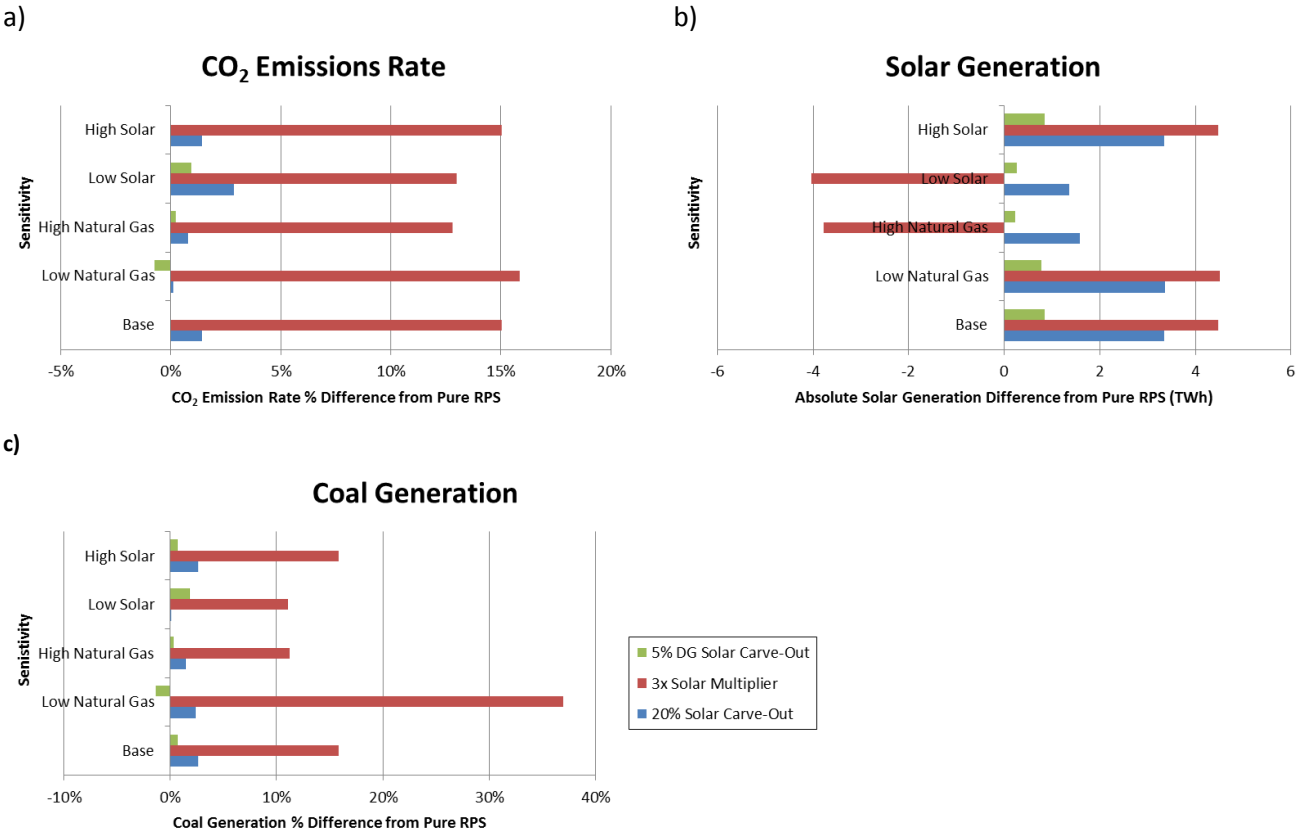


Figure 6: Assumption sensitivity on results of CO_2 emissions, coal generation, and solar generation. The percent difference is shown for CO_2 and coal, while the absolute difference for solar due to the low amount of solar added in the Pure RPS with base assumptions.

Figure 6 shows how CO_2 emissions rate, coal generation, and solar generation change under different assumptions for the natural gas fuel price and the floor installed cost for solar in 2025, while Figure 7 shows the different components of the total RPS program cost change. In both figures, the solar policy variations are compared to the Pure RPS under the same sensitivity assumption. For example, for the high gas sensitivity, the solar policy variations, and the Pure RPS scenarios used the high gas sensitivity assumption. The only impact of the higher floor cost of solar is an increase in total PPA costs. In the two Solar Carve-out base cases, the carve-out constraint (Equations 8 and 9) remains binding until 2030 (no additional solar is built beyond what is required by the carve-out). A higher floor for the installed cost of solar only increases the costs to meet the carve-out constraint, without impacting the renewable build plan. The renewable build plan also does not change in the 3x Solar Multiplier case, as the higher floor for the installed cost of solar

does not change the year when solar, with the multiplier, becomes competitive with wind. The only difference being solar is more expensive. Because the renewable build plan is not impacted by the high floor for the installed cost of solar, there is no impact on emissions, coal generation, or solar generation relative to the base assumptions.

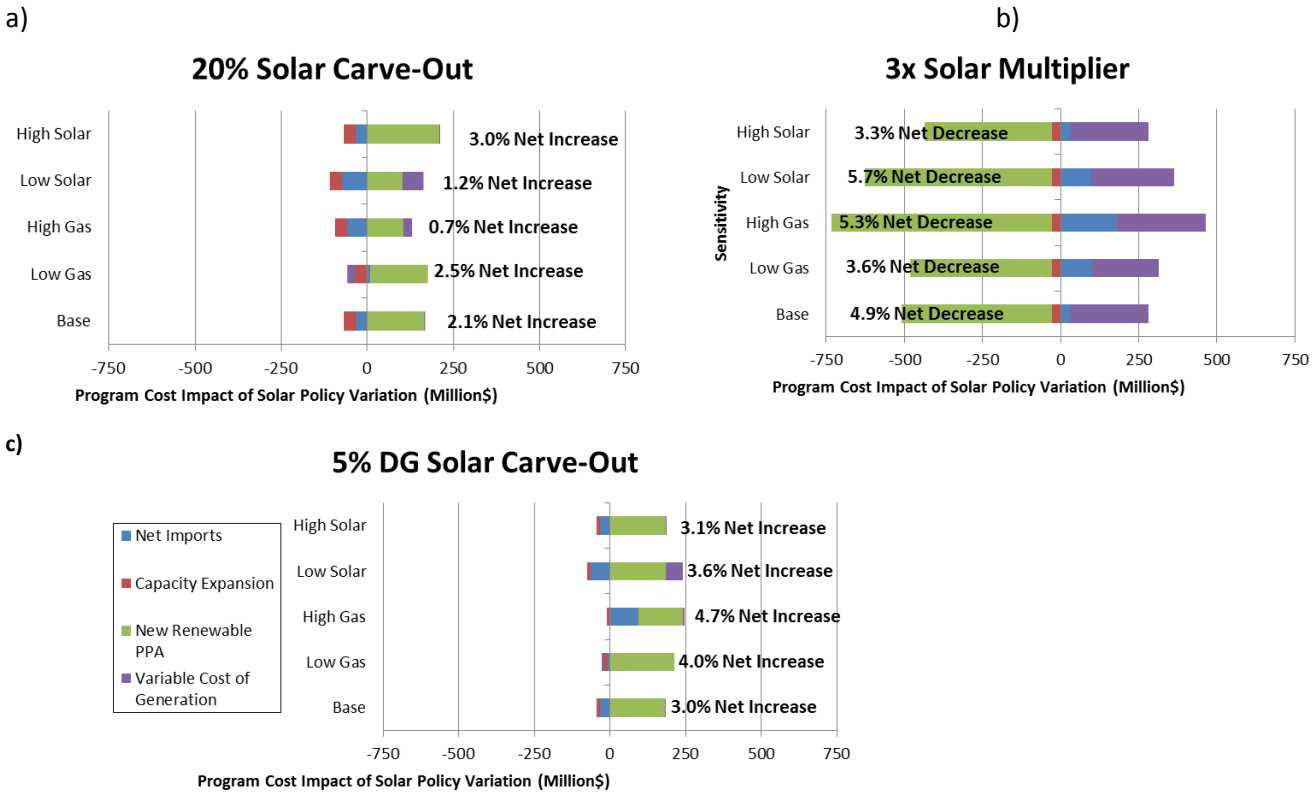


Figure 7: Sensitivity analysis on the cost of solar preferences in RPS, relative to Pure RPS case. The percent difference in the net total cost for each sensitivity is also shown.

The low solar cost, on the other hand, does impact the renewable build plan. With a lower floor for the installed cost of solar, the carve-out constraint in the 20% Solar Carve-Out case becomes non-binding after 2021, and utility scale solar replaces wind to meet the RPS target after that date in all cases (Pure RPS and solar policy variations). The solar preference impact on renewable PPA costs decrease relative to the base assumptions in all scenarios except the DG Carve-Out. PPA costs increase slightly as the DG solar constraint remains binding even as utility scale solar becomes competitive with wind. The location of the utility scale solar changes in the Carve-Outs compared to the Pure RPS. The location of the utility scale projects in the Carve-Out scenarios tends to export the solar generation out of Michigan rather than displacing generation in the state. This results in an increase in the variable cost of generation for the Carve-Outs, while the net imports decrease. Low solar cost decreases the impact has on CO_2 emissions, while increasing the emissions rate impact in the Carve-Outs. This is again due to where the solar is located in the Carve-Out scenarios. This is due to the emissions rate increasing in the Pure RPS under low solar conditions. Coal generation also increases in the low solar case in the Pure RPS scenario, decreasing the impact the

solar policy variations have on coal generation. For cost, solar and coal generation, and CO_2 emissions, the decreased impact of the solar policy variations in the low solar sensitivity is primarily due to increased solar generation in the Pure RPS. The increased solar generation in the Pure RPS in effect, nullifies the need of the solar preferences to achieve the objectives they were put in place to address.

High natural gas fuel price has a similar impact to the low solar installed cost floor. Natural gas is used primarily during peak hours, therefore a higher natural gas price increases the energy market price differential between peak times and off-peak times. Since solar only generates on peak, it will displace higher cost conventional generation than wind. Therefore, after 2021 the above market cost (β in equation 3) is minimized by choosing utility scale solar in all cases. Again, the carve-out constraint in the 20% Solar Carve-Out scenario becomes non-binding. Both the 20% Solar Carve-Out and the 3x Solar Multiplier decrease the RPS program cost impact of solar policy variations. However, the 5% DG Solar Carve-Out case is most expensive under high natural gas prices. The DG solar added to the system is both small and expensive relative to the utility scale solar leading to little benefit of a 5% DG Solar Carve-Out in the presence of high gas prices. The impact of high natural gas prices on CO_2 emissions, solar generation, and coal generation is similar to the low solar installed cost floor due to large amounts of solar generation added in the Pure RPS case under high natural gas prices.

Low natural gas prices make solar less attractive, as the differential between peak and off-peak energy market prices decrease. For all solar policy variations, the low natural gas prices case look similar to the base case assumptions, but slightly more expensive as the low natural gas price removes some of the value of solar to displace expensive on-peak generation in the base case.

In general, the sensitivity of the RPS program cost results on the floor for the installed cost and the natural gas fuel price forecast is low. In the 20% Solar Carve-out case, the percent increase in the RPS program cost over the Pure RPS range from 0.7% increase to 3.0% increase, with a 2.1% increase found in with the base assumptions. The range is small for the 5% DG Solar Carve-Out as well, spanning a 3.0% to 4.7% increase in program cost. The 3x Solar Multiplier ranges from a 3.6% to a 5.7% decrease in total cost.

1.4 Discussion

RPS policies have been touted to meet a variety of objectives, including reducing local air pollution and greenhouse gas emissions, as well as increasing employment through “green jobs.” Without any specific technology incentives, the RPS drives the market to meet the mandate for renewables with the least cost generation technology available (Buckman 2011). In Michigan’s case, and in many other states in the US, the dominant technology used for RPS compliance is wind (Gaul and Carley 2012). Increasingly, states are broadening the objectives of RPS policy to include resource diversification and encouragement of new local industries, such as the solar industry (Gaul and Carley 2012). This has led states to include solar policy preferences in the form of credit multipliers and carve outs. However, due to the higher cost of solar, these solar policy variations do not offer

the lowest short term cost of RPS compliance. This study introduces a method for evaluating the impacts of such solar preferences on three key outcomes: the generation mix, emissions, and RPS program costs. When testing this method on the potential expansions to Michigan's RPS, the effectiveness and impacts of the solar policy preferences at achieving the various RPS objectives can be examined.

The most direct objective of all RPS is to add renewable energy generation to the grid. Not surprisingly, the most cost effective policy to add renewables to the grid is the Pure RPS with no solar preferences, as shown in Table 2. Of the solar policy variations, the solar multiplier has lowest cost per addition of new renewable generation. However, this metric can be misleading because the solar multiplier adds 52% fewer renewables than the Pure RPS and the two solar carve-out cases. Because the best resources are chosen first, every incremental renewable project will be more expensive than the earlier projects.

	RPS Cost Metrics (NPV Discount Rate = 7%)			HHI Index Generation Diversity Index	
	Renewable Energy ($/MWh of New Renewables)	Solar Energy (Solar PPA$/MWh of New Solar)	CO_2 Mitigation ($/ton of CO_2 Reduction)	All Generation	Within All Renewable Generation
Pure RPS	31.0	NA	29.6	3,312	6,732
20% Solar Carve-Out	39.7	117	38.5	3,234	5,032
3x Solar Multiplier	36.7	106	38.5	3,751	3,161
5% DG Solar Carve-Out	41.5	367	39.3	3,253	6,301

Table 1: Impacts of solar preferences on RPS outcomes

A key objective of an RPS with solar preferences is to increase the amount of solar generation. Solar generates on-peak, helping to reduce the most expensive conventional generation and reducing the required capacity to maintain the peak load reserve margin more than wind.

Of the three solar policy variations, the solar multiplier adds the most solar at the lowest RPS program cost. In this case, there is no mandate to build solar. For that reason, solar is only chosen once the three times multiplier makes it cost competitive with wind, which in this case is 2018. The 20% Solar Carve-Out is second most cost effective option to increase solar generation. The 5% DG Solar Carve-Out is the most expensive of the solar preferences. Even with the smaller carve out mandate, DG solar is more expensive than utility scale. However, the 5% DG Solar Carve-Out is the only scenario where distributed generation is chosen over utility scale solar. If increasing the decentralized nature of the power system is one of the objectives of the RPS, then the 5% DG Solar Carve-Out is the only RPS solar policy option to achieve this goal.

It is important to note the only reason the 3x Solar Multiplier is the most cost effective option to add solar is because the multiplier makes solar more completive to wind during the study period. Michigan's current RPS (10% by 2015) has a 3x Solar Multiplier in the policy. However, only 28 MW have been approved in the state (Quackenbush, White et al. 2014) because the multiplier has not made solar competitive with wind to this point. Therefore, the multiplier in the current RPS is not a cost effective method if the objective to add solar, while a carve-out would have mandated solar be built regardless of the cost.

Additionally, a multiplier for solar is inherently "under-designed" (i.e., encourages no solar development) in the years before it makes solar competitive, but "over-designed" (i.e., only encourages solar development) after solar with the multiplier is chosen over any other renewable project. Before it becomes competitive, the multiplier is essentially useless as no solar is added. After it makes solar competitive, it dramatically reduces the amount of total renewables added to the system as there is no incentive to build any renewable project besides solar with the multiplier benefit.

Another reason adding solar generation is an objective of recent RPS designs is to increase generation source diversity. The Herfindahl Index (HHI) is used to quantify competiveness of a market by accounting for market share among the different players in the market. HHI has also been deployed outside of economic markets, including to measure power capacity diversity within a region (Wang, Shahidehpour et al.). In this analysis, we deployed it to assess the RPS's ability to introduce diversity to the generation mix. The equation for HHI is given in Equation 11,

$$HHI = \frac{\sum_{i=1}^{n} {g_i}^2}{\left(\sum_{i=1}^{n} g_i\right)^2} * 100^2 \qquad (eq. 11)$$

where g_i is the annual generation from generation type i (i.e., coal, wind, solar, etc.). A lower index indicates more a more diverse generation mix. Table 2 shows the HHI results for generation diversity in Michigan. In the context of markets, an HHI <1000 is considered a competitive market, while higher values indicate large portions of the market are dominated by a small number of players.

When considering all of Michigan's generation, the two solar carve-outs slightly decrease the index slightly relative to the Pure RPS because they add solar generation not present in the Pure RPS. The solar multiplier actual increases the index by 13.2% because, even though the most solar is introduced in this case, new renewable generation is less than half of what is added in the Pure RPS. From this perspective, adding more renewables, even if they are predominately from one source, has the largest impact on increasing generation diversity given Michigan's heavy reliance on coal.

When considering the diversity within all renewable generation, the solar policy preferences do have a large impact on the HHI. All three solar policy variations decrease the index, with the

multiplier decreasing the index the most (-53% from the Pure RPS). Again, much less renewable generation is added in this scenario and in particular much less wind generation is added. The 20% Solar Carve-Out also significantly reduces the HHI (-25.3%), while adding the same amount of total renewable generation as the Pure RPS.

Finally, one of the primary objectives of many RPS is to reduce the carbon emissions from the power sector. The three solar policy variations all increase mitigation costs in roughly comparable amounts, increasing the cost per unit of CO_2 reduction between 30 – 33%. Each of the carve-out policies minimally impact CO_2 emissions relative to the Pure RPS, but both increase the RPS program cost, reducing the cost effectiveness of CO_2 mitigation. The 3x Solar Multiplier scenario is the least expensive program to implement, but also adds the least renewable generation and therefore mitigates significantly less carbon. If the region of interest was relied predominately on natural gas instead of coal, solar policy preferences may prove to reduce the cost of carbon mitigation of an RPS. In this case, solar would most likely displace the least efficient natural gas generators, as they would be the most expensive generators and would only be called on to generate on peak. Wind would also displace off peak generation, which in a natural gas system would most likely be efficient combined cycle generators, and therefore wind's CO_2 emission reduction potential would be reduced relative to solar.

1.5 Conclusions and Policy Implications

The number of objectives imbedded in an RPS are numerous and growing. Introducing solar policy variations has been one method to broaden an RPS's impact on a variety of objectives, including increasing renewable resource diversity and spurring local solar industry development. However, these solar policies impact the cost of the RPS and two of the primary objectives of RPS: increase renewable generation and reduce emissions from the power sector. The tradeoff from introducing solar policy preferences must be considered carefully; this study proposes a method to analyze these impacts in order to better inform RPS policy design.

Because the solar carve-outs mandate a certain amount of solar be added to the system no matter the cost, the RPS program cost can only increase with these designs, although, total renewable generation remains the same as the RPS with no solar preferences, assuming that no alternative compliance payments are triggered. The 5% DG Solar-Carve-Out, even though adding less solar generation, is more expensive than the 20% Solar Carve-Out because of the significant increase in cost when going from utility scale solar to DG solar. In both solar carve-out scenarios, emissions increase slightly due to Michigan's reliance on coal generation. In systems more reliant on natural gas, the solar carve-outs would have a smaller impact on emissions and may even decrease emissions compared to an RPS with no solar preferences.

The introduction of a 3x Solar Multiplier significantly changed the results of increasing the RPS in Michigan. By the third year of the study, solar was consistently chosen over wind, leading to solar providing over half of all new renewable generation. This also meant the 3x Solar Multiplier case

added less than half of the total renewables than the other scenarios, which reduce the total RPS program costs at the expense of increased coal generation and increased emissions.

The changing cost of solar makes the multiplier a difficult policy tool to use. It ensures the technology will not be built until the cost decreases sufficiently, unlike carve-outs, making it a more cost effective method to introduce solar in an RPS. However, once the cost decreases enough for the multiplier to make solar the least cost option, a multiplier dramatically changes the results of the RPS, inhibiting its ability to increase renewable generation in general and its emissions reduction potential.

An ideal solar policy preference in an RPS would encourage solar development, but not until costs have reduced sufficiently, while ensuring the primary objectives are not undermined by the "under-design" of a multiplier. One policy option to achieve these objectives could be to constrain the amount of solar that is eligible to receive the multiplier credit. For example, solar generation up to 20% of all new renewable generation is eligible for multiplier credits, while any additional generation does not receive any multiplier credits. Another possible design could have a decreasing multiplier, setting its value as a function of total solar generation on the system. As solar generation increases, the multiplier for the next incremental solar generation receives fewer incentive credits. This would limit the number of incentive credits awarded, while still incentivizing solar development.

An explicit recognition of objectives when introducing or modifying an RPS would assist in the assessment of the tradeoffs associated with a solar policy preference. Given the potential impacts on program costs and emissions reductions, the introduction of a solar policy preference should be carefully considered.

Chapter 2: Value of Wind Diversity to Decrease Variability Induced Ramping in the Presence of Transmission Constraints

2.1 Introduction

Wind power variability is one of the pressing challenges of integrating large quantities of wind power into the grid. The fast ramping up or down of wind power can have negative consequences on grid operations, including increased costs, inefficient operation of conventional generators, and the need for additional ancillary services (Kirby and Milligan 2006; Milligan and Kirby 2008; Katzenstein, Fertig et al. 2010). One method to deal with the variability of power output from individual wind farms is to develop and interconnect other wind farms that are subject to different wind patterns, essentially diversifying the wind power portfolio. If proper wind power portfolios are chosen, the cumulative power output of the portfolio will be smoother relative to the output from individual wind farms. However, reduced variability through wind portfolio diversification may require the development of lower quality wind sites, resulting in a tradeoff between output variability and the average power output of the entire portfolio. Wind diversification will also spread the wind farms out geographically, potentially reducing the need for extensive transmission capacity expansion in the regions of highest quality wind (high capacity factors). However, transmission congestion across the region spanned by the wind farms will reduce the ability of the wind farms to counteract each other's variability. The goal of this research is to further investigate optimization techniques used to examine diversified wind power systems and offer new understanding on the impact that transmission constraints have on the value of diverse wind in reducing wind power variability and its negative system impacts.

To evaluate the impact of wind diversity, a modified version of the multi-objective optimization method called Mean-Variance Portfolio optimization (MVP) is implemented. The two objectives of the optimization are to minimize the ramp rate variability of the wind power output and to maximize the average power output of the cumulative wind farms, where ramp rate variability is defined as the change of the cumulative wind power output from time step to time step. MVP has been used before to analyze wind power diversity. Hansen (2005) investigated its use to provide additional capacity credit for interconnected wind farms. Using three wind farms, Hansen (2005) demonstrates how using MVP can guide strategies to allow for more economical wind power development. The study minimizes the deviation from average output given the objective of increased capacity credit, rather than decreased wind power variability.

Degeilh and Singh (2011) also laid out an approach to optimize the siting of wind farms using MVP. Similar to Hansen (2005), the study minimized the deviation from the mean output, rather than minimizing ramping amplitude from one time step to the next. Using power output data from the National Renewable Energy Laboratory (NREL) wind dataset from their interconnection studies

(National Renewable Energy Laboratory 2013), the optimal portfolios are evaluated using loss of load probability (LOLP) to determine the capacity credit of a wind portfolio that is less variable.

Roques, Hiroux et al. (2010) applies MVP theory to find optimal wind power portfolios in Europe using wind power data from Spain, France, Germany, Denmark, and Austria. They used two methods: one that minimized wind ramping variability and another that minimized variance from average output during peak hours. In all cases, the study found that the current wind power portfolio and projected portfolios could achieve significant reductions in variability at the same power output by using MVP to better plan wind projects. While the authors went through multiple iterations of the optimization to add additional realism to the results (including adding cross border transmission constraints and inter-country wind resource potential), the assumption that all wind power within a country was perfectly correlated failed to put value on diversified wind resources within an individual country. In addition, their treatment of transmission constraints does not account for power from other sources also using the transmission lines to deliver power from one country to the next.

Rombauts, Delarue et al. (2011) further explored the issue of transmission capacity constraints when using MVP to determine the efficient wind farm build out. While they tackled the issue of transmission in greater depth than Roques, Hiroux et al. (2010), the optimization model still relies on the assumption that the use of the transmission capacity will be limited to wind, which is not representative of many wind integration designs. Unlike the earlier studies, Rombauts, Delarue et al. (2011) chooses wind sites to minimize ramp rate variability rather than the deviation from the average.

Liu, Jian et al. (2013) expanded the work done with MVP to develop a robust optimization of diverse wind power given MVP's sensitivity to the covariance matrix and average power output. The optimization technique is primarily constructed to ensure the wind portfolio's output remains above a particular threshold rather than dealing with wind power variability.

Other studies have also investigated wind power diversity without the use of MVP. Katzenstein, Fertig et al. (2010) used wind speed data from weather stations and existing wind farms throughout the Midwest and examined how the interconnection of multiple wind farms impacted the overall variability of power output. They found that the majority of reductions in power output variability (ramping up or down) were achieved by connecting only a few of the closest wind farms, and only small gains were achieved by connecting more sites from farther away. Katzenstein and Apt (2012) investigated a method to account for the cost of sub-hourly ramping of wind farms, both individual and interconnected. The method includes an optimization technique that minimizes the services required by the wind power output. The study found that higher capacity factor sites and interconnected sites reduced the cost of wind power variability. Reichenberg, Johnsson et al. (2014) used sequential optimization to investigate optimized placement of wind power to decrease variability. However, the study only discussed decreases in variability and not the impact on the rest of the power system. Schmidt, Lehecka et al. (2013) demonstrated how a premium based

feed-in tariff incentivize wind diversification and therefore decreases wind power variability of the system.

This study is novel because it uses a power systems model to assess the value of wind diversity, focuses on minimizing the wind power portfolio's ramp rate variance rather than minimize its deviation from the average, and restructures the MVP framework to meet particular wind penetration levels. After using MVP to create different wind power portfolios, ranging in level of diversity, this study directly measures the ramping impacts the different portfolios induce on the power system. Using a unit commitment and economic dispatch model, the change in behavior of the power system to different portfolios can be quantified. Multiple studies have used power system models to quantify impacts of integrating variable renewables into the grid. Some of these studies used such models to better understand the impact and efficacy of renewable energy policies (Sullivan, Logan et al. 2009; Bird, Chapman et al. 2011; Palmer, Paul et al. 2011), while others focused on operational changes and the emissions implications of the general integration of wind power (Valentino, Valenzuela et al. 2012; Oates and Jaramillo 2013; Turconi, O'Dwyer et al. 2014). However, none of these studies have attempted to model the impacts of resource diversification on power system behavior, as this study proposes.

MVP does not capture transmission constraints, when the transmission is not only used for wind, failing to capture much of the complexity of the power system operation when considering wind power portfolios. This study will also focus on the how transmission constraints impact the ability of a diverse wind power portfolio to decrease the impacts of system ramping. Diverse wind tends to spread out the wind resources geographically, reducing the potential for wind power curtailment induced by transmission congestion. Also, MVP assumes the variability of one wind farm can be cancelled by any combination of wind farms that have equal variability in the opposite direction. However, if the transmission within the region is congested either from wind power or other sources, the variability will be offset.

Similar to Rombauts, Delarue et al. (2011), this study minimizes ramp rate variability of the overall portfolio rather than the deviation from the average power output as most past studies using MVP have done. To reduce system ramping requirements, it is important to decrease the magnitude and frequency of large ramps (up or down) in the wind power output. This will generally minimize the negative system level impacts of wind power variability, which is not necessarily true when the deviation from the portfolio's average output is reduced. Minimizing the deviation from the average also penalizes solutions with periods of high power output. Typical average power output from wind farms ranges from 35-40% (National Renewable Energy Laboratory 2013). Therefore, in hours when the portfolio operates close to 100% of its capacity, the power output variance increases, thereby penalizing the portfolio. By minimizing the ramp rate variance instead, the portfolio is not penalized for operating well above its average power output, as long as the change in output was gradual to reach the high output.

Finally, to assess the impact of diversification in the power system, this study creates portfolios using MVP that have constant wind generation, unlike other MVP studies which maintain constant wind power capacity. Therefore, the system of equations presented in past work is modified. The decision variables have units of installed capacity, rather than the share of capacity a wind farm contributes to the overall portfolio. The modification allows for better comparison of results from the unit commitment and economic dispatch model and is analogous to Renewable Portfolio Standards (RPS) policies in place in many states in the US, which require that electric utilities meet a particular percentage of their retail sales (load) from renewable energy, such as wind energy.

2.2 Methods

This study employs MVP and power systems modeling to analyze the value of diverse wind to reduce wind power variability and the negative system impacts that the variability causes. MVP is first used to develop a set of wind power portfolios, ranging from heavily concentrated in regions with high quality wind to widely spread across the geography considered. The different wind power portfolios are then evaluated using a unit commitment and economic dispatch model to measure the system's response to the integration of the different wind power portfolios. This power systems model is first run assuming no transmission constraints (i.e., "copper sheet"), and then again with inter-zonal transmission constraints. This isolates the impact of MVP's inability to capture transmission constraints and help elucidate the ability of wind diversity to decrease the system impacts of wind variability in a real system.

2.2.1 Optimizing Diverse Wind Portfolios

The two objectives of this application for MVP are: 1. Minimize the installed capacity of wind power, and 2. Minimize the ramp rate variability from time step to time step. The first objective is simply the sum of the installed capacity at each site, as shown below,

$$Min \ \sum_{i=1}^{n} x_i \tag{1}$$

where x_i is the installed capacity in MW at site i and n is the number of wind sites in the system being considered for wind power development. Equation 1 is analogous to maximizing the average power output used in most MVP frameworks. To minimize installed capacity while meeting the wind penetration constraint (described later) requires the highest average power output sites be developed first.

The second objective is more complex and involves minimizing the entire portfolio's ramp rate variance. The variance is a statistical measure (square of the standard deviation) and quantifies the spread in the ramp rates. By minimizing the ramp rate variance of the interconnected wind farms, the frequency and magnitude of large ramps up and down in cumulative wind power output will decrease. The ramp rate variance of a portfolio *P* is given by,

$$\sigma_P{}^2 = \sum_{i=1}^{n} x_i{}^2 \, \sigma_i{}^2 + 2 \sum_{i<j}^{n} x_i \, x_j \sigma_{ij} \tag{2}$$

where ${\sigma_i}^2$ is the variance in the ramp rate of site *i*, and σ_{ij} is the ramp rate covariance between sites *i* and *j*. The ramp rate variance is a quadratic equation that can be can be simplified into matrix form.

$$Min\ \boldsymbol{x}^T \boldsymbol{\Pi} \boldsymbol{x} \tag{3}$$

where $\boldsymbol{x}$ is vector of all x_i, and $\boldsymbol{\Pi}$ is the covariance matrix. The covariance matrix is a symmetric matrix where each entry is the covariance in the ramp rate from one site to another site. The matrix is shown below,

$$\boldsymbol{\Pi} = \begin{bmatrix} {\sigma_1}^2 & \cdots & \sigma_{1n} \\ \vdots & \ddots & \vdots \\ \sigma_{n1} & \cdots & {\sigma_n}^2 \end{bmatrix}. \tag{4}$$

where σ_{ij} is the covariance between the ramp rate of site i and site j. The variances in the ramp rates at each individual site are along the diagonal of the covariance matrix. Each covariance is calculated by comparing the ramp rates of wind sites within the study region. The Hessian of the ramp rate variance is simply $2 * \boldsymbol{\Pi}$. The covariance matrix is by definition positive semi-definite, and therefore the ramp rate variance is convex (Degeilh and Singh 2011).

The first constraint in the optimization is the requirement that a minimum amount wind energy be delivered from the portfolio's wind farms over one year,

$$\left(8766\ \frac{hrs}{year}\right) * \sum x_i\ CF_i\ \geq \alpha * E_{Load}\ [MWh/year] \tag{5}$$

where CF_i is the capacity factor (average power output as a percentage of total installed capacity) of site i, E_{load} is the region's annual electricity demand, and α is the percentage of the demand that must be met by wind. The left hand side is multiplied by 8766, the average number of hours in a year accounting for leap years. In this study, the optimization is solved with two different values for α (10% and 20%) to test the impact of wind diversity under different wind energy penetrations.

Another constraint deals with the individual size constraints of each wind farm in the portfolio,

$$0 \leq x_i\ \leq\ x_{i,max} \tag{6}$$

where $x_{i,max}$ is the maximum installed capacity allowed at site i. The decision variables in this system are the installed capacity at each wind farm site x_i. The wind sites data is from the NREL Eastern Wind Dataset (National Renewable Energy Laboratory 2013), which defines wind power outputs for each site in ten-minute time intervals for three representative years, as well as the maximum installed capacity.

The chosen geography to investigate is the Midcontinent Independent System Operator (MISO) and MAPP US (the non-MISO areas of North and South Dakota). The recently added southern portion of MISO's service territory is excluded from the system geography. As the system operator of the

region, MISO must manage the system in a manner that effectively deals with wind power variability. Given this responsibility, we consider this entire interconnected geography for wind power diversification. Within the region there are 572 wind farm sites in the NREL database, yielding 572 decision variables in the optimization problem.

The results of the optimization will produce a Pareto frontier for each minimum energy constraint. The Pareto frontier represents changing the importance of each objective from 100% weight on minimizing the installed capacity (least diverse portfolio) to 100% weight on minimizing the ramp rate variance of the portfolio (most diverse). The optimization is solved using Matlab's linear programming functionality to solve the minimum installed capacity objective, while quadratic programming algorithms are used to solve the minimum for the ramp rate variance. To develop the Pareto frontier between the optimal points for each objective, the minimum installed capacity objective is changed to a constraint, setting a limit to the total installed wind power capacity. The optimization problem is then solved with the single objective of minimizing ramp rate variance. The maximum value of the capacity constraint is changed in equal increments and the optimization resolved such that the Pareto frontier is defined by twenty points including the optimal points at either end of the frontier.

2.2.2 Power Systems Model

A power systems model is then used to analyze the impact of diverse wind portfolios on grid operations. Plexos for Power Systems by Energy Exemplar is used to solve the unit commitment and economic dispatch problem by finding the least cost method for generation to meet demand. The model determines which generators should run and how much power each should be producing at every time step. The cost of generation is determined by fuel prices, efficiency of power generation (heat rate curves), variable operations and maintenance costs, and generator start-up costs. In addition, the model must meet a set of system constraints, including generator min/max output, generator forced outages, generator ramp rates (speed at which generator can change output), and transmission limits between zones. To investigate the impact of wind power variability, the model is solved in 10-minute intervals.

As mentioned earlier, the geography in this study is the northern MISO region and MAPP US, which are part of the synchronous U.S. Eastern Interconnection (EIC). To quantify expected imports/exports into and out of the MISO region to the rest of the EIC, the model first considers a representation of the entire EIC. The model splits the EIC into 35 zones. Each zone has a unique assumption of hourly load profile and maximum import/export transmission capacity between neighbor zones. The transmission capacity between zones was determined from data presented in the Eastern Interconnection Planning Collaborative (EIPC) and other studies done by various Independent System Operators (ISOs) in the EIC (ISO-NE ; MISO ; NYISO). Fuel prices are defined uniquely for each zone and were calculated using fuel receipts information from the 2013 EIA 923 database (U.S. Energy Information Agency 2013a). The size of the model is then reduced to only the northern MISO zones and MAPP US to reduce modeling time. Imports/exports to and MISO and the rest of the EIC, that were calculated using the full EIC model, are held constant in the

reduced geography. Existing wind capacity was removed from the model to test the impact of wind power diversity.

Particularly important model assumptions for quantifying impacts of wind diversity include the ramp rates of conventional generators (how quickly can the generator change power output), generator start costs, and transmission expansion methodology. The ramp rate assumptions are given in table 1 (Black & Veatch 2012). The ramp rates are given in terms of percent of capacity available to ramp per minute. Combustion turbines, typically natural gas fired, have the most ramping flexibility, able to react quickly to changes in load or wind power output, while coal steam generators have the least ramping flexibility. It was assumed nuclear generators do not ramp, only operating at full capacity when operational.

Table 1: Ramp Rate Assumptions

Generator Type	Ramp Rate (% of Capacity / Minute)
Coal/Other Steam	2.0%
Combustion Turbine	8.3%
Combined Cycle	5.0%

The cost to start a generator also impacts the how the power system reacts to variable wind generation. Kumar, Besuner et al. (2012), a report by Intertek APTECH for NREL and the Western Electricity Coordinating Council, studied the true costs of generator starts as a function of the time the generator has been turned off, with costs tending to increase as time increases. However, Oates and Jaramillo (2013) found these start costs were significantly higher than those actually bid in to the market generators. Therefore, start costs bids from PJM's market were used in the model to allow realistic dispatch.

Finally, under some circumstances transmission in the model was expanded to accommodate wind development in remote locations with low load and little transmission capacity to export wind. If a zone's export transmission capacity was less than the maximum difference between a zone's wind generation and the zone's load at any given time, then transmission capacity was added to the model to allow the excess wind to be delivered outside of the zone. However, the transmission expansion did not include a full system transmission optimization.

The four different wind power portfolios, ranging from no emphasis on wind diversity to all emphasis on diversity, are assessed in the unit commitment and economic dispatch model for each of the wind penetration levels (10% of load and 20% of load). Additionally, each portfolio is considered under a "copper sheet" (no transmission constraints) assumption and with the transmission constraints intact. The four wind power portfolios are chosen from the Pareto frontiers. Both of the optimal solutions (minimum installed capacity and minimum ramp rate

variance) are tested along with the portfolio one step away from minimum installed capacity and the portfolio that increases the minimum ramp rate variance by only 10%.

2.3 Results

The results are provided in two sections. First, the results from the multi-objective optimization are presented. Points along the Pareto frontier define wind power portfolios, of which a subset is used as input into the power systems model. Then, the power system modeling results are shown to illustrate the value of wind power diversity to decrease the system impact of wind power variability in the presence of transmission constraints.

2.3.1 Optimization Results

Figure 1 shows the Pareto frontiers for the two different minimum wind energy penetrations, normalized to the minimum installed capacity portfolio for each Pareto frontier. The normalized view reveals the difference between the 10% and 20% wind generation targets. With increased wind penetrations, decreasing the ramp rate variance of the minimum installed capacity case requires more incremental capacity. To halve the variance, the 20% case requires a 4% increase in capacity, while the 10% only requires a 2% increase in capacity. Under higher wind penetrations, more wind farm sites are needed to meet the wind generation target, due to the maximum capacity constraints at the highest quality wind sites. The increase in number of wind farms used to minimize the installed capacity adds some "natural" diversity to the minimum installed capacity.

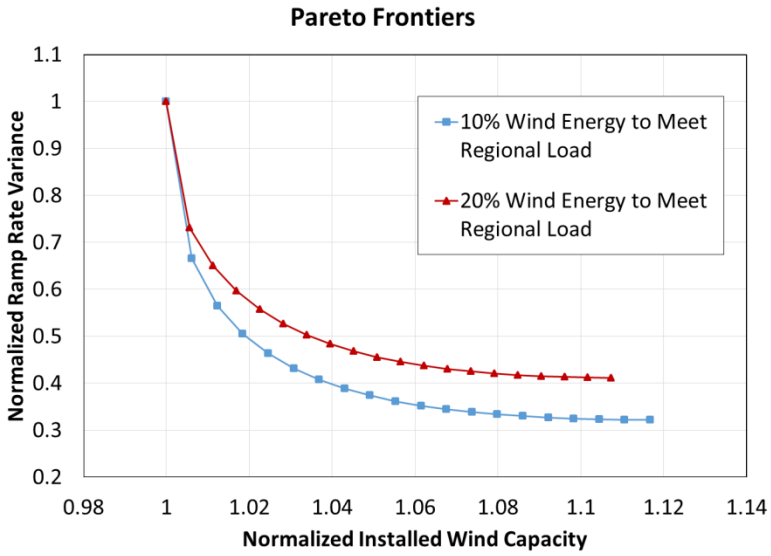


Figure 1 Pareto frontiers normalized to the wind power portfolio with the smallest installed capacity

The slope at different points can be interpreted as the tradeoff between the two objectives. On the far left end of the Pareto frontier, the largest reductions in ramp rate variance come with only a minimal increase in the installed capacity. The Pareto frontiers quickly flatten out. Therefore, to achieve the last feasible reductions in the ramp rate variance requires significant increases in the installed capacity.

The values for the decision variables (installed capacity at each wind farm) change significantly across the Pareto frontier. Figure 2 shows how they change for both of the minimum energy requirements. Each horizontal line represents one of the wind farm decision variables. The decision variables are sorted with the highest capacity factor sites (highest wind power potential) on top and the lowest capacity factor sites on the bottom. Moving from left to right on the x-axis represents moving along the Pareto frontier from minimum installed capacity to minimum ramp rate variance. The darker the line, the larger the share of that wind farm's contribution to the total wind installed capacity. These figures show there is a gradual dispersal of the installed capacity across decision variables as ramp rate variance is reduced. The darkest region of the plot, in the upper left-hand corner, demonstrates the importance of building at the high capacity factor sites when the primary objective is to minimize the total installed capacity.

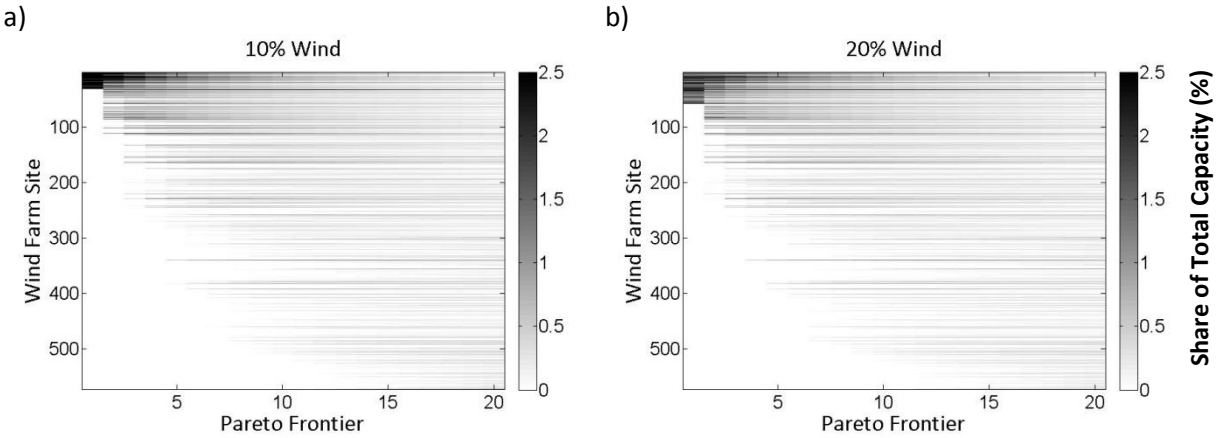


Figure 2 Change in the decision variable values along the Pareto frontier as a percentage of each variable's contribution to the total. The first profile only builds at the highest capacity factor sites, which are constrained by a maximum installed capacity each site can accommodate. (a) Wind penetration equivalent to 10% region load; (b) Wind penetration equivalent to 10% region load.

The figures also show that there are sites that consistently make up relatively large portions of the total installed capacity along the Pareto frontier. There are two types or sites that are favored along the Pareto frontier: sites with high capacity factors, and sites with low ramp rate covariance relative to the rest of the portfolio. Sites with consistently dark lines can be considered the most important decision variables towards one or both objectives.

The primary motivation to minimize the ramp rate variance of a cumulative wind power portfolio is to reduce the frequency and magnitude of large ramping events, in either direction. Figure 3 assesses how well-diversified wind achieves this objective. For both wind penetrations, figure 3 shows the cumulative frequency of the absolute ramp rates (ramp up and down combined) of four wind power portfolios along the Pareto frontiers. Both extremes of the Pareto frontier are shown, along with two portfolios in between the optimal points. One of the portfolios is one step from the from the minimum installed capacity point (Portfolio 2), this represents the largest decrease in ramp rate variance between points on the Pareto frontier. The other portfolio has a 10% higher

ramp rate variance than the minimum variance (Portfolio 10). As the ramp rate variance of a portfolio decreases, the cumulative frequency in Figure 3 shifts closer to the y-axis.

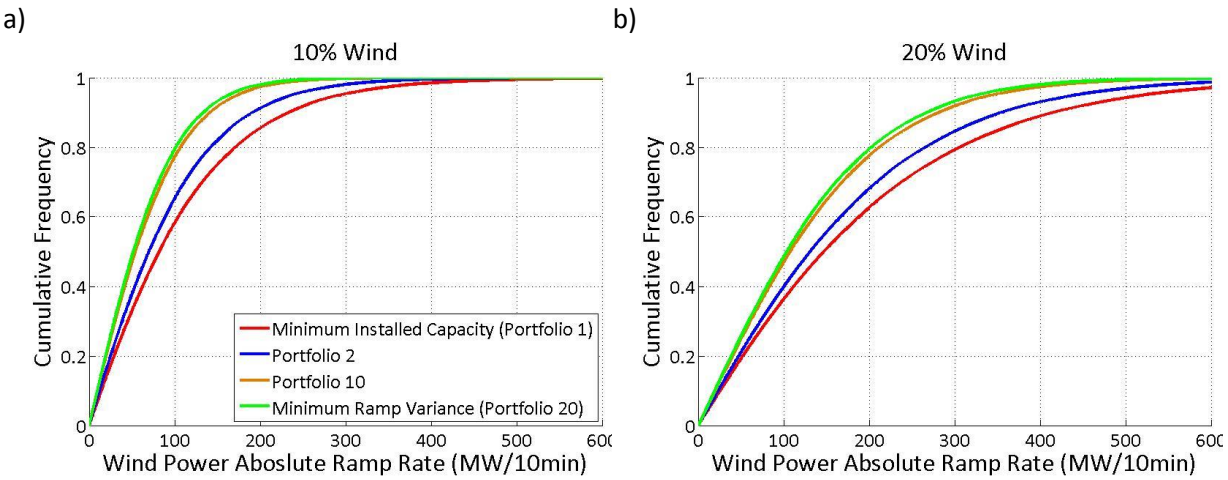


Figure 3 Cumulative frequency distribution of the absolute ramp rate for different points along the Pareto frontier for (a) 10% wind; (b) 20% wind.

Figure 3 shows that minimizing the ramp rate variance decreases the frequency and magnitude of large ramping events relative to the Minimum Installed Capacity portfolio. In the 10% wind case, ramps of 250 MW or more in a period of 10 minutes is expected about 10% of the time for the minimum installed capacity portfolio. Portfolio 10 and the Minimum Ramp Rate Variance portfolio nearly eliminate ramps that magnitude or greater. Ramps of 250 MW or more are expected more often in the 20% wind cases. However, the Minimum Ramp Rate Variance portfolio of the 20% wind case reduces the frequency of such ramps significantly, nearly matching the frequency of 250 MW or greater ramps in 10% wind Minimum Installed Capacity portfolio. In both wind penetration levels, reducing the ramp rate variance of the wind power portfolio to within 10% of the minimum achievable variance has nearly an identical impact on the reduction of large ramping events. Unless all possible improvement in ramp rate proves to be valuable, the cumulative frequency distribution suggests it is not worth the doubling of wind power capacity required to reduce the ramp rate variance between Portfolio 10 and the Minimum Variance portfolio.

2.3.2 Power Systems Modeling Results

The optimization results demonstrate that wind portfolio diversification can reduce the cumulative wind power output's variability. To understand the system impacts of the reduced wind power variability, four different wind power portfolios along the Pareto frontier were assessed using a unit commitment and economic dispatch model. The portfolios included, the minimum installed capacity ("Portfolio 1"), the portfolio one step along the Pareto frontier from the minimum capacity ("Portfolio 2"), the portfolio with a ramp rate variance 10% greater than the minimum variance ("Portfolio 10"), and the portfolio with minimum ramp rate variance ("Portfolio 20"). For each portfolio, the model is run without transmission constraints ("Copper Sheet"), and with transmission constraints ("Tx Constrained") to capture the impact of transmission on the ability of

wind diversity to reduce variability impacts. Finally, a case without wind is assessed in both a Copper Sheet and Tx Constrained model to differentiate between ramping caused by wind variability and ramping caused by other parts of the power system.

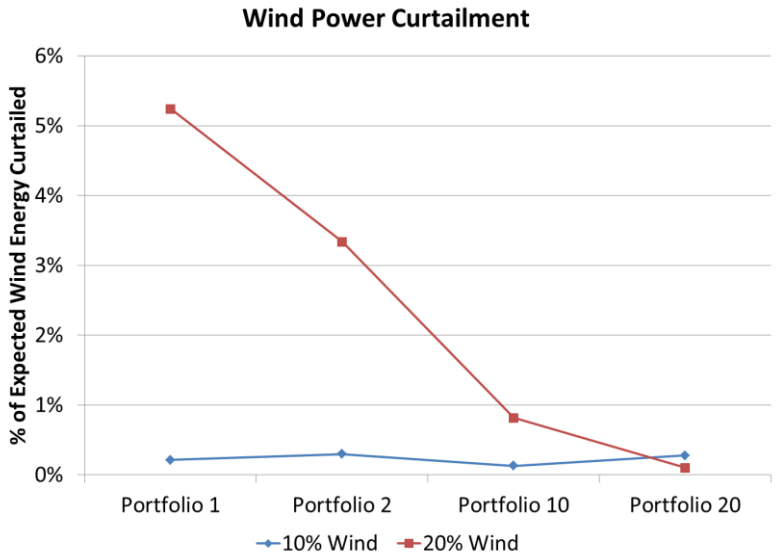


Figure 4 Percent of wind generation curtailed relative to the expected wind generation. Curtailment results are only shown from the Tx Constrained models as curtailment is insignificant in the Copper Sheet models.

Figure 4 shows how wind diversity changes wind power curtailment in the Tx Constrained models. At 10% and 20% wind, curtailment nearly exclusively occurs due to transmission congestion and not because of other factors. Wind is not curtailed due to wind generation being greater than system wide load of or turn down constraints of conventional generators. Therefore, there is nearly no curtailment in the Copper Sheet models.

In the less diverse portfolios, wind is added in locations with limited transmission capacity availability to deliver wind to other regions. To realistically represent transmission expansion associated with the development of remote wind resources, transmission capacity was added when zonal export capacity was too small to deliver excess wind to the rest of the system (as discussed in Section 2.2). Therefore, curtailment in the 20% case is caused by transmission congestion throughout the system, and is not due to an inability for the wind to be delivered outside of its zone. In Portfolio 1, more than 5% of the expected wind generation must be curtailed. As the wind capacity is spread out across the model geography, the system wide transmission congestion is reduced, steadily decreasing the amount of curtailed wind generation. Portfolio 10 decreases wind power curtailment to less than 1% and Portfolio 20 eliminates nearly all curtailment. The 10% wind cases show approximately constant curtailment. The total wind generation added in these cases is insufficient to cause enough system wide transmission congestion to curtail wind. Wind is only curtailed in situations where conventional generators are unable to turn down generation sufficiently to accommodate wind generation.

Wind that is not curtailed forces the rest of the system to react to its variability. To quantify the wind induced ramping requirements we define a "Ramping Ratio". The Ramping Ratio takes the total energy devoted to ramping and divides it by the sum of all the conventional generation. The ramping energy is based on time interval used (10 minutes for this study) and the change in the power output over the time interval. The Ramping Ratio therefore represents the share of total conventional generation over the year used for ramping purposes. Figure 5 shows the increase in the Ramping Ratio of the wind portfolios over the system without wind, isolating variable wind's impact on ramping. Note that the Copper Sheet results with wind are subtracted from the Copper Sheet results without wind, and Tx Constrained results with wind are subtracted from the Tx Constrained results without wind.

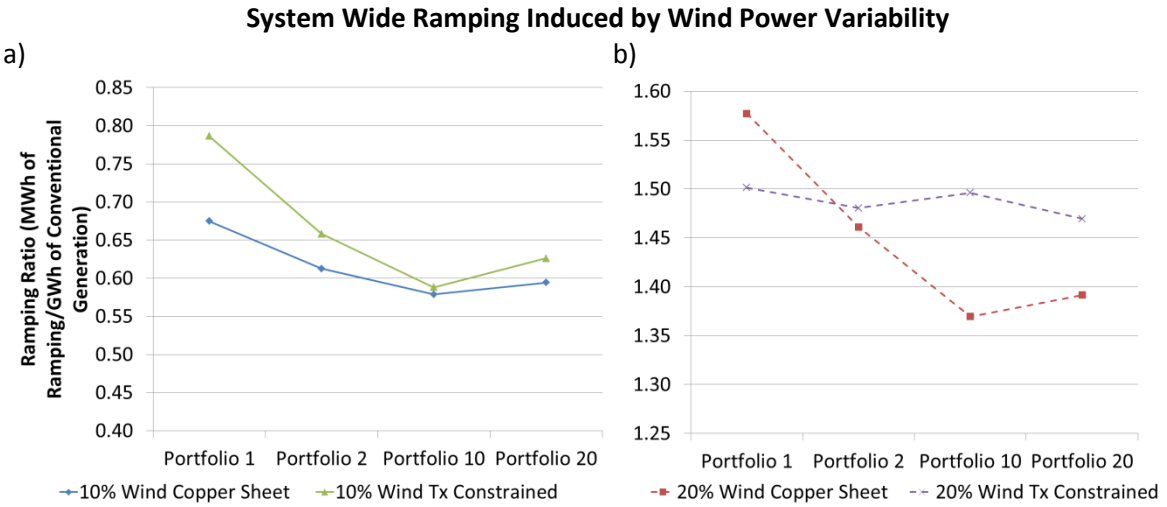


Figure 5 The increase of the Ramping Ratio by adding variable wind generation to the system relative to the associated no wind model. The Ramping Ratio is defined as the proportion of conventional generation used for ramping up or down throughout the year. The units of the figure are MWh of ramping energy per GWh of total conventional generation. Figure 5a) shows the results for the Copper Sheet and Tx Constrained models for 10% wind, and figure 5b) shows the results for 20% wind.

With the exception of the 20% Wind Tx Constrained cases, the results show the general reduction in wind variability induced ramping as the wind portfolio is diversified, the intent of the MVP optimization. However, in these cases, the Ramping Ratio increases slightly between Portfolio 10 and Portfolio 20. As was shown in the cumulative frequency distributions in figure 3, the intensity of the wind variability is nearly identical between the Portfolio 10 and Portfolio 20, with only a slight improvement from complete diversification in Portfolio 20. Even so, a decrease in the Ramping Ratio would be expected between Portfolios 10 and 20. This demonstrates how MVP does not capture all of the factors impacting ramping in the real system. These factors will be discussed more in the next section.

The gap between the Copper Sheet and the Tx Constrained lines in Figure 5 shows how transmission constraints impact the amount of system ramping caused by wind variability and how that impact changes based on the diversity of the wind portfolio. For 10% wind, transmission

constraints increases the proportion of generation used for ramping to deal with wind power variability of Portfolio 1 by 17%. As the portfolio becomes more diverse, the gap between the lines shrinks, reaching a minimum increase of 2% in the Ramping Ratio caused by wind variability at Portfolio 10. This demonstrates wind diversity's ability to reduce transmission congestion, allowing the system to operate more often as a copper sheet.

On the other hand, at 20% wind, Portfolio 1 decreases the wind power variability's contribution to the Ramping Ratio in the presence of transmission constraints, while Portfolio 2 only increases the ratio by 1.3%. The contradictory results relative to 10% wind is due to increased frequency of wind curtailment at the 20% wind penetration level. Curtailing the wind removes variability from the system, decreasing the system wind ramping relative to the Copper Sheet, which experiences no curtailment. As the Portfolios become more diverse, curtailment decreases and therefore increases wind power variability and the system ramping needed to react to the variability. Diversity therefore lowers the Ramp Ratio after considering curtailment.

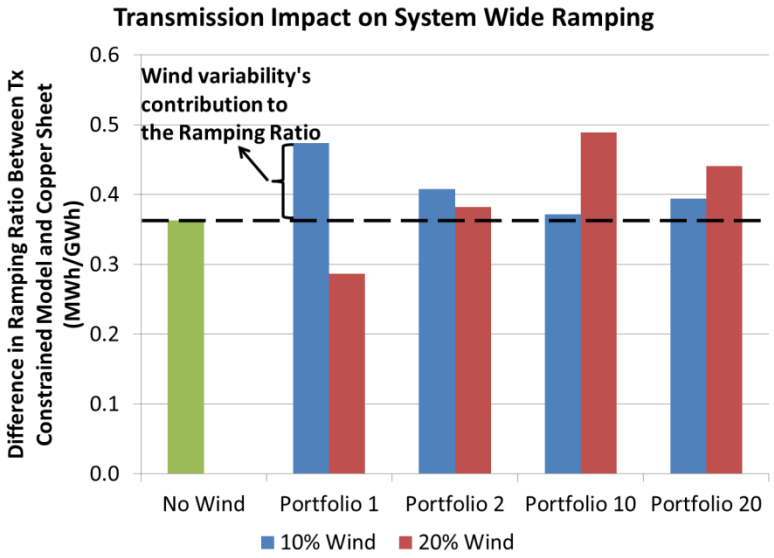


Figure 6 Difference between the Ramping Ratio of the Tx Constrained model and the Copper Sheet model. In all cases, including when no wind is added to the system, the introduction of transmission constraints increases ramping. Wind variability's contribution to the increased Ramping Ratio is the difference between the height of the bar and the dashed line (height of green bar).

The full impact of transmission constraints on system ramping is shown in figure 6. The figure compares the difference in the entire Ramping Ratio of portfolios in the Tx Constrained and Copper Sheet model (i.e., the difference between Portfolio 1 in the Tx Constrained model and Portfolio 1 in the Copper Sheet model). In all cases, transmission constraints increase ramping requirements as congestion limits the ability to share ramping flexibility. The dashed line represents the increase in the Ramping Ratio by adding transmission constraints to the no wind case. The difference between the height of the wind portfolio bars and the dashed line account for the segment of the increase linked to wind variability.

The figure shows that the increase in ramping associated with wind variability when transmission constraints are introduced is only a small portion of the total increase in the ratio. The share of the increase in the Ramping Ratio caused by wind variability is largest for Portfolio 1 with 10% wind and Portfolio 10 for 20% wind, both responsible for about a quarter of the increase. In the absence of curtailment, diversity decreases the portion of the increased Ramping Ratio induced by wind variability, as can be seen in the 10% wind portfolios. Portfolio 1 for 20% wind actual decreases Ramping Ratio relative to the No Wind case with the introduction of transmission constraints. This is again due to the increased frequency of wind curtailment in the 20% cases.

2.4 Discussion

In the optimization results section, MVP demonstrates how wind diversity can significantly decrease wind power variability. Figure 3 shows the reduction in both frequency and magnitudes of large changes in the cumulative wind power output. However, as shown in figure 5, complexities of power system operations can impact system wind ramping trends, leading to unintuitive results as less variable portfolios are integrated into the system. This demonstrates MVP's inability to capture all of the factors impacting ramping in the real system. The most important factors impacting MVP's ability to reduce system wide ramping are the system's transmission constraints and the time of day of the wind power variability.

Transmission congestion can lead to wind power curtailment, as shown in figure 4, with curtailment being more likely when wind capacity is concentrated in a small area with limited transmission capacity. Even though transmission capacity was expanded in the model to allow excess zonal wind generation (generation not consumed by internal zonal load) to be exported, transmission congestion in neighboring zones forced curtailment. This impact of transmission increases wind diversity's value, even though it is not directly related to decreased system ramping. MVP dispersed the location of wind capacity, decreasing congestion and therefore curtailment. Additionally, by spreading the share of wind capacity across the different zones, less transmission expansion was needed to export excess wind from individual zones, decreasing costs of transmission expansion.

Even when curtailment is not an issue, the value of wind diversity can also be increased by reducing transmission congestion relative to less diverse portfolios. Since less diverse portfolios are more likely to cause transmission congestion in parts of the system, they limit how much wind from different zones can counter-act each other's variability. A diverse wind portfolio tends to be less likely to cause transmission congestion, allowing the system to act more like a copper sheet and wind to counter-act its own variability. Therefore wind diversity can be of even more value in a transmission constrained system relative to the copper sheet as can be seen from 10% wind results in figure 5. Portfolio 10 reduces the Ramping Ratio caused by wind variability by 25% in the presence of transmission constraints, while only achieving a 14% decrease without them, compared to Portfolio 1. In this case, even though MVP does not account for transmission constraints, there is added benefit to diversifying the wind capacity.

Another power system complication not considered by MVP is the time of day of wind power variability, which can impact the system's ability to provide the appropriate ramping response. During peak times, more generation will be online and operating at maximum capacity in order to meet load. This may reduce the number of generators with ramping flexibility, especially if wind power output decreases rapidly requiring an increase in generation from the rest of the system. Also, transmission is more likely to be congested during on-peak hours, forcing individual zones to deal with wind power variability without the benefit of using neighboring regions flexibility. Off-peak hours may also have limited ramping flexibility if much of the generation capacity is offline, leaving mostly baseload plants to provide ramping. Baseload plants tend to be the most constrained in their ramping ability, causing more total ramping to be needed in the face of significant wind variability, particularly if the baseload plants are forced to ramp down to deal with increasing wind power output.

Time of day's impact can be seen in figure 5 and figure 6. In both cases, Portfolio 20 for both 10% wind models and the 20% Copper Sheet model increases wind variability's share of the Ramping Ratio relative to the less diverse Portfolio 10. The two portfolios have very similar ramp rate variances according to the MVP optimization, although Portfolio 20 is the minimum achievable ramp rate variance portfolio. But contradictory to the MVP results, Portfolio 20 increases the share of wind variability's contribution to the Ramping Ratio relative to Portfolio 10. Portfolio 20 changes the time of day of wind generation, requiring ramping at times with low ramping flexibility more often than Portfolio 10. Additionally, adding transmission constraints to the 10% wind case increases the Ramping Ratio between Portfolio 10 and Portfolio 20 more than the Copper Sheet, suggesting transmission congestion also plays a role in reducing Portfolio 20's value to decrease wind variability's system impacts.

Table 2: Impacts of Wind Diversification. All values are from Tx Constrained results relative to Portfolio 1.

	10% Wind			20% Wind		
	Portfolio 2	Portfolio 10	Portfolio 20	Portfolio 2	Portfolio 10	Portfolio 20
Transmission Capacity Expansion (MW)	-1,893	-4,674	-5,114	-2,306	-6,598	-7,609
Installed Wind Capacity (MW)	84	751	1,587	154	1,392	2,939
Production Cost ($000)	95,801	18,495	-182,511	-40,402	-225,771	-293,217
CO_2 Emissions (10^6 tons)	-2.24	-3.56	0.67	-3.4	-10.4	-11.7

The complications introduced by transmission constraints and time of day of generation make valuing wind diversity challenging. Table 2 summarizes some of the main impacts from wind power diversification for the Tx Constrained models. The reported values are relative to Portfolio 1 (the most variable wind portfolio). The transmission expansion and installed wind capacity follow intuitive trends. As the wind is diversified, the share of the capacity located in remote zones with

little transmission capacity decreases, reducing the need for major upgrades in transmission capacity. However, this also comes at the cost of increasing the total wind capacity to meet the required wind energy levels.

The trends in production costs (cost to operate the power system) and CO_2 emissions associated with power generation are not as clear. Due to complications of time of day of generation and transmission constraints, a less variable portfolio with less required ramping does not necessarily result in production cost savings. The contribution of Portfolio 10's wind variability to the Ramping Ratio in the 10% wind case is the smallest of all 10% wind portfolios. However, the total annual production costs increase by $18.5 million compared to Portfolio 1. Portfolio 20 on the other hand, increased the Ramping Ratio relative to Portfolio 10, but the system is over $200 million less expensive to operate. CO_2 emissions follow the opposite trend; Portfolio 10 decreases emissions while Portfolio 20 increases emission relative to Portfolio 1. The two trends emphasize the importance of considering the time of day of wind variability. The results suggest Portfolio 20 was more variable during off-peak hours, requiring ramping constrained baseload generators to react to its variability. Even though ramping ability is limited during these hours, it is also the cheapest given the low cost of baseload generation. But coal accounts for most of the baseload generation in MISO. Therefore ramping during off-peak hours is the most CO_2 intensive ramping in the geography considered in this study. Conversely, Portfolio 10 is more variable at intermediate or on-peak times. During these times natural gas fired generators are more likely to ramp in response to variable wind, which are more costly to operate but are less CO_2 intensive than coal generators.

The 20% wind results shows a more obvious trend of decreasing production costs and CO_2 emissions with more diverse wind portfolios. This is due to the reduction in wind power curtailment in the diverse portfolios, allowing wind to reduce the amount of conventional generation. Displacing conventional generation with wind power decreases costs to run the system and the associated emissions.

2.5 Conclusion

MVP optimization or some modification to it has been used by multiple studies to investigate wind power diversity (Hansen 2005; Roques, Hiroux et al. 2010; Degeilh and Singh 2011; Rombauts, Delarue et al. 2011). This study combines MVP with a power systems model to investigate the value of wind power diversity to decrease system wide ramping. The results of the power systems model demonstrate how the complications of the real power system can unpredictably impact expected results when using MVP to diversify wind power portfolios. Transmission constraints can cause wind power curtailment, and transmission congestion can limit a portfolio's ability to counter act its own variability by interconnecting wind from different locations. Wind diversification can significantly reduce wind curtailment and transmission congestion, increasing diversification's value above what was predicted from the MVP results. However, the time of day of wind variability can also impact the value of diversification. Even in diverse wind power portfolio, variability at times of low ramping flexibility (on-peak and off-peak times) can cause increased system ramping not predicted from the MVP results.

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Appendix

Supplemental Info

This section gives more detail to the unit commitment and economic dispatch model used in the two papers.

Zonal Definition

The below figure shows the zonal boundaries used in the model. Zonal boundaries were primarily defined to be consistent with by ISO definitions.

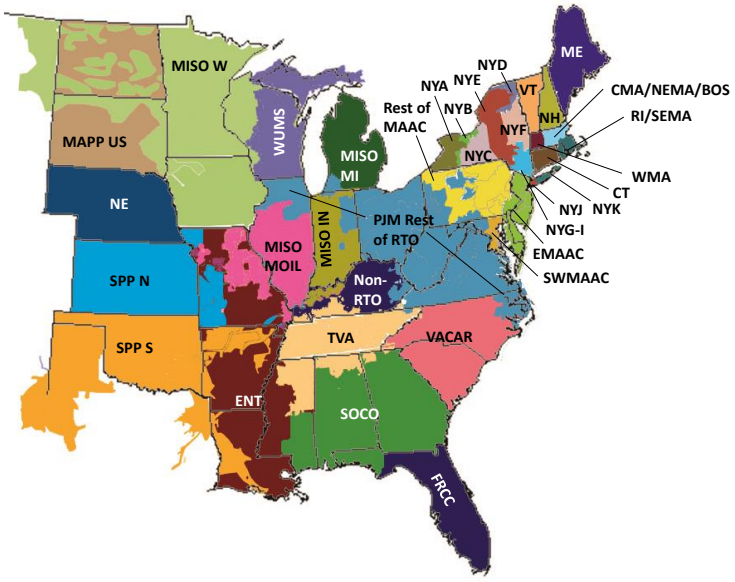

Figure 1: Geographic boundaries of model zones

Existing Generator Heat Rate

Max load heat rates were calculated using hourly data from the EPA's CEMS database (U.S. Environmental Protection Agency 2013a). When unavailable, average heat rate from EPA's eGrid dataset was used (U.S. Environmental Protection Agency 2013b). When both were unavailable, the median heat rate (or 75th percentile heat rate if generator was observed to be an "inefficient" and infrequently used generator) from similar generator types was used. Table 2 gives the average full load heat rate for different generator types.

Table 2: Average full load heat rates by generator type

Generator Type	Average Full Load Heat Rate (Btu/kWh)
Bituminous Coal	11213
Subbituminous Coal	10872
Lignite Coal	11081
Natural Gas Combustion Turbine	14639
Natural Gas Combined Cycle	8069
Municipal Solid Waste	21098
Landfill Gas Internal Combustion Engine	16057

Partial load heat rate is also captured in the model. The generators are assumed to operate most efficiently at 100% output, with their heat rate increasing as their output drops. Figure 2 shows the heat rate as a function of generator output.

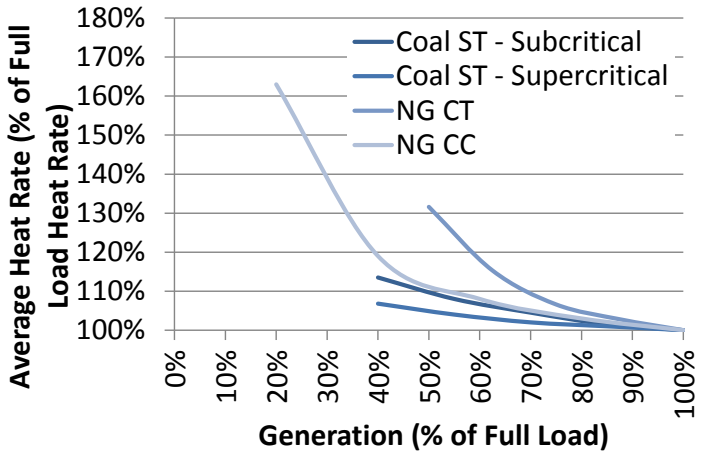

Figure 2: Heat rate penalty of partial load operation by generator type

Variable O&M

Assumptions for variable O&M change by generator type and region (U.S. Energy Information Agency 2013b).

Table 3: Variable O&M costs by generator type (U.S. Energy Information Agency 2013b)

Generator Type	Variable O&M Range ($/MWh)
Coal Steam	3.89 – 6.62
Nuclear	1.87 – 3.18
Natural Gas GT	4.74 – 13.02
Natural Gas CC	1.49 – 4.10
Biomass Steam	4.58 – 7.79

Fuel Price

Base fuel costs were obtained from using a fuel weighted average of fuel receipts reported in EIA 923 database (U.S. Energy Information Agency 2013a) for all generators within each zone. For Chapter 1 fuel prices were then escalated based on EIA AEO fuel forecasts. Chapter 2 only uses on 2013 fuel prices. Table 4 shows the calculated base fuel price for the entire EIC.

Fuel	Bituminous Coal	Subbituminous Coal	Lignite Coal	Distillate Fuel Oil	Natural Gas	Residual Fuel Oil
Price ($/MMBTU)	2.804	1.983	1.996	23.533	4.502	19.029

Table 4: Base EIC Fuel Cost in 2013 (U.S. Energy Information Agency 2013a)

Emissions

Emissions rates for CO_2 and SO2 are shown in table 5. NO_x is shown separately in table 6 as it is expressed in terms of electricity generation rather than fuel use, given NO_x emissions are more influenced on generator operation than the others.

Table 5: CO_2 and SO_2 emissions

Fuel Type	CO_2 (lb/MMBtu)	Average Post Control SO_2 (lb/MMBtu)
Coal		
Bituminous	205.9	1.11
Subbituminous	212.9	0.54
Lignite	215.2	0.46
Natural Gas	117.1	0
Diesel	161.4	0
MSW	91.9	0.35

Table 6: NO_x emissions rate (U.S. Environmental Protection Agency 2013b)

Generator Type	Median NOx Rate (lb/MWh)
Coal Steam	
Bituminous	3.53
Subbituminous	2.60
Natural Gas Turbine	1.03
Natural Gas Combined Cycle	0.20
Natural Gas Steam	2.48
DFO IC	25
DFO Gas Turbine	4.80