Title
Application of Power Systems Economics to Wind and Solar Power Integration

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Publication Date
2015

Peer reviewed|Thesis/dissertation

Application of Power Systems Economics to Wind and Solar Power Integration

by

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A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Energy and Resources

in the

Graduate Division

of the

University of California, Berkeley

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Summer 2015

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Abstract

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The focus of this dissertation is the economic implications of the technical challenges of integrating variable generation, namely wind and solar, into the electric power system. The research is organized around three topics: short-term variability of wind and solar generation, changes in the economic value of wind and solar with increasing penetration, and the effectiveness of different measures at mitigating changes in economic value with increasing penetration levels. Early studies of PV grid impacts suggested that short-term variability could be a potential limiting factor in deploying PV. Many of these early studies, however, lacked high-quality data from multiple sites to assess the costs and impacts of increasing PV penetration. As is well known for wind, this research demonstrates that accounting for the potential for geographic diversity can significantly reduce the magnitude of extreme changes in aggregated PV output, the resources required to accommodate that variability, and the potential costs of managing variability. Still, the economic value of wind and PV is found to drop as the penetration increases in a case study of California that uses a long-run investment model with significant detail on the operational constraints in the power system. The drop is primarily due to a drop in the capacity value (particularly for solar) and energy value. Day-ahead forecast error and ancillary service costs, although not insignificant, do not change as dramatically with increasing penetration. The same model and data is then used to evaluate several options to stem the decline in value of these technologies. The largest increase in the value of wind at high penetration levels comes from increased geographic diversity. The largest increase in the value of PV at high penetration levels comes from assuming that low-cost bulk power storage is an investment option. Other attractive options, particularly at more modest penetration levels, include real-time pricing and technology diversity.

To: Ryan Wiser

Thank you for you support, mentoring, and confidence.

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Acknowledgments

Foremost, I thank Ryan Wiser (Berkeley Lab) for enabling me to pursue this body of research. Ryan significantly shaped my thinking and co-authored the reports and papers derived from this research. Ryan also worked closely with the U.S. Department of Energy to fund this research through the the Office of Electricity Delivery and Energy Reliability (Research & Development Division and Permitting, Siting and Analysis Division) and the Office of Energy Efficiency and Renewable Energy (Wind and Hydropower Technologies Program and Solar Energy Technologies Program). In particular, I thank Lawrence Mansueti, Patrick Gilman, Venkat Banunarayanan, and Kevin Lynn of the DOE for their support. At UC Berkeley I substantially advanced with advising from Duncan Callaway, Severin Borenstein, Shmuel Oren, and Daniel Kammen. I also greatly benefited from guidance, feedback, support, and comments from Debbie Lew (NREL), Michael Milligan (NREL), Galen Barbose (Berkeley Lab), Mark Bolinger (Berkeley Lab), Naïm Darghouth (Berkeley Lab), Joe Eto (Berkeley Lab), Paul Denholm (NREL), Marco Nicolosi (Connect Energy Economics), Meredith Fowlie (UC Berkeley), Udi Helman (Helman Analytics), Alan Lamont (Lawrence Livermore National Laboratory), J. Charles Smith (Utility Variable Generation Integration Group), Anthony Papavasiliou (Catholic University of Louvain), Arne Olson (Energy and Environmental Economics), Thomas Hoff (Clean Power Research), Abraham Ellis (Sandia National Laboratory), Dave Renne (NREL), Ray George (NREL), Benjamin Kroposki (NREL), Mark O'Malley (University College Dublin), Michael Goggin (American Wind Energy Association), and Mark Ahlstrom (WindLogics). Content in Chapter 4 was improved with editing assistance of Jarett Zuboy (consultant). Of course, any remaining omissions or inaccuracies are my own. Finally, I would not have made it through this process without the support of my family.

Chapter 1

Introduction

The past two decades have seen tremendous growth in the deployment of renewable energy resources worldwide. In 2012, renewable resources grew at an average rate of 15%/yr and contributed nearly 5% of the global power generation (BP, 2013).[1] Accompanying this rapid growth is a rapid decrease in the installed cost, particularly in wind and photovoltaic (PV) generators. The installed cost of wind in the U.S. declined from over $5,000/kW in 1982 to less than $2,000/kW in 2012 (Wiser and Bolinger, 2013). The installed cost of PV in the U.S. was greater than $8,000/kW in 2002 (Barbose et al., 2012) while utility-scale PV projects had an installed cost as low as $2,270/kW at the end of 2012 (GTM and SEIA, 2013). The International Energy Agency (IEA) expects continued growth in renewables across three different scenarios in the World Energy Outlook (IEA, 2012). In those scenarios, non-hydro renewables provides between 11% and 28% of the global power generation by 2035.

Sustaining or accelerating past growth rates in order to supply large shares of electricity from renewable energy requires that challenges are addressed. Various challenges have at time impeded the rate of deployment of wind and solar generation. These challenges include cost, institutional barriers, regulatory complications, and the need to gain public acceptance (IPCC, 2011a). In most regions of the world, the challenge of the cost of renewables is primarily addressed through policy support for deployment (e.g., renewables portfolio standards, tax incentives, feed-in-tariffs). Maintaining growth of renewables as policy support phases out requires the economic value of renewables to be in line with the costs of renewables.

While all of the challenges are important, the focus of this dissertation is on the economic value of renewable energy, in particular wind and solar, two variable renewable resources. The primary foundation for the analysis of the economic value of wind and solar in this dissertation is the power system economics literature. An important aspect of the research is the close attention to literature on the technical feasibility and challenges of integrating variable generation into the electric power system. This research highlights the economic implications of these technical challenges.

[1] Renewable resources in this case includes wind, geothermal, solar, biomass and waste.

1.1 Primary Themes

The overarching question that drives the research in this dissertation is: when variable renewable resources are delivered to loads, what resources are displaced and what costs can therefore be avoided? In this dissertation, these costs that are avoided when variable renewables are delivered to loads are referred to as the economic value. Given this focus, the analysis in this dissertation does not focus on the costs of building and operating renewable energy facilities (sometimes referred to as the "bus-bar" costs), and it does not focus on the cost of delivering that power to loads over transmission networks. The bus-bar and transmission costs, along with the factors affecting those costs, are significant (Mills et al., 2011, 2012) and they should be accounted for in the overall consideration of the economics of variable renewables. An implicit assumption in this analysis is that sufficient transmission is built to deliver renewable energy to loads and that transmission capacity is then available to help balance the system over a large footprint.

Relative to conventional generation, the key challenge in understanding the economic value of wind and solar energy is the variable and uncertain nature of their output. Individual wind and solar power plants exhibit significant variability over both short (sub-hourly) and long time scales (multiple hours, diurnal, and seasonal). As not all of this variability can be forecast ahead of time wind and solar also introduce additional sources of uncertainty into power systems. While loads are also variable and uncertain to some degree, the characteristics of the variability and uncertainty of wind and solar differ from that of load. This dissertation accounts for these characteristics of wind and solar in economic terms.

Academic literature and technical reports regarding the economic value of wind is increasingly deep. In a comprehensive review of literature on the cost of intermittency by the UK Energy Research Center (UKERC), Gross et al. (2006) identify contributions reaching back to the late 1970's. In the 1990's they identify methodological developments followed by a "renaissance" in studies starting at the turn of the century. Some of the literature loosely refers to variable generation and, as a result, lumps wind and solar together when discussing findings. While the literature describing the economic value of wind is increasingly deep, there are more gaps in the understanding of the economic value of solar generation. As a consequence, it is not obvious as to how much of the insight and recommendations learned from the analysis of wind necessarily applies to solar too.

The analysis in this dissertation is structured in a way that provides similar settings for exploring questions about the economic value of wind and solar. Whenever a question is analyzed for a solar technology, a similar analysis is conducted for wind. In this way similarities and differences between the two technologies can be clearly identified. When wind and solar are found to be similar, it is expected that the deep literature on the economic value of wind can provide insight into understanding solar. Where the technologies differ, however, some of the conclusions and rules-of-thumb that apply to wind may need to be separately evaluated for solar.

The research in this dissertation is organized into three main chapters that focus on the following topics:

1. Short-term variability: variations in wind and solar production on time-scales of hours or shorter.
2. Changes in the economic value of wind and solar with increasing penetration.
3. Effectiveness of different measures at mitigating changes in economic value with increasing penetration levels.

1.2 Short-term variability

Based on the literature and increasing experience operating systems with large amounts of wind, it is relatively well-understood that short-term variability is not a major technical or economic barrier to increasing wind penetration. This is largely due to the impact of aggregation: short-term changes in wind power from individual wind plants (or even wind turbines) are largely uncorrelated, which implies that the aggregate generation is relatively much smoother than the variable generation from a single turbine. This aggregation effect is less and less effective over longer time scales because changes in wind power are relatively more correlated. Achieving smoothing over longer time scales requires larger and larger distances between wind plants.

Although this effect is relatively well known for wind, several different sources (both in the academic literature and practitioners) point to observations of extreme short-term variability in photovoltaic (PV) plants as a potential barrier to increased deployment. Examples of such extreme variability include observations of large ramps in PV production (>50% of nameplate capacity) in less than 1-minute from a single PV plant. Photovoltaic cells have no inherent inertia so a change in incident insolation caused by a passing cloud can lead to a near instantaneous change in the power output of an individual PV cell.[2] Empirical assessments of short-term variability of PV from the aggregate of many different PV plants is hampered by the relative paucity of datsets that measure output from many sites with high time resolution over a long time frame.

Chapter 2 addresses the concern that short-term variability of PV output could be a barrier to increased deployment by applying early lessons from wind research about the smoothing effects of aggregation to PV. The research uses a year of time-synchronized solar insolation data with 1-minute time resolution from more than twenty sites to demonstrate the smoothing benefits of aggregation for solar. Simply confirming the benefits of aggregation is not unique: other researchers had made the same point using the same insolation dataset (Hoff and Perez, 2009) and PV data from Germany (Wiemken et al., 2001) and Japan (Murata et al., 2009). The unique contribution of this research was to answer three remaining questions:

[2] Short-term variability of concentrating solar thermal plants (CSP) was less of a concern in part due to the inherent thermal inertia of the fluid that transfers heat from solar collectors to a steam generator (often a high-temperature oil).

1. How far apart do PV sites need to be in order to obtain the benefits of smoothing?
2. How does the short-term variability of PV compare to the variability of wind and how do the distances required to obtain the benefits of smoothing compare?
3. What are the economic implications of accounting for (or ignoring) the smoothing that occurs when aggregating PV sites? Is short-term variability likely to be a barrier to achieving high PV penetration levels?

The results show that the distance between PV sites required to achieve the benefits of smoothing are short for fluctuations on a time scale of about 15 minutes or shorter. None of the sites in the 23-site network showed discernible correlation in fluctuations on time-scales shorter than 15 minutes, even for sites that were only 10 km apart (the closest pair of sites in the network). Longer time-scale fluctuations on the order of 60 minutes are more clearly correlated for nearby sites. The correlation of 60 minute fluctuations was found to be above about 0.2 for pairs of sites closer together than about 75 km. Obtaining the smoothing benefits of aggregation for these longer time-scale fluctuations requires further separation than for the very short time-scale fluctuations.

The same network of solar insolation sites also had time-synchronized wind speed measurements with 1-minute time resolution. Ten of these wind sites would be suitable for development of wind plants.[3] Analysis of the short-term variability of wind power output found comparable, but slightly lower variability as compared to the PV variability over short time-scales. Assessment of the distances between wind sites required to obtain the smoothing benefits of aggregation found that wind sites needed to be slightly further apart than PV sites. Overall, the smoothing benefit from aggregating similarly sited wind and PV was found to be similar.

A back-of-the-envelope estimate of the cost of managing short-term variability shows that ignoring the benefits of smoothing can lead to very high costs associated with managing short-term variability (almost $40/MWh). But accounting for the smoothing benefits of aggregation reduces the estimate of the cost of managing the aggregate variability to $2–3/MWh, similar to the cost of managing short-term variability of similarly sited wind. In this case, the early lessons learned about the smoothing benefits from aggregation of wind also apply to PV.

1.3 Changes in the economic value with increased penetration

Aside from short-term variability, there are still many other characteristics that drive the economic value of wind and solar power. Among others, these include:

[3] The wind site was considered suitable if its projected capacity factor exceeded 20%.

- Reduction in generation from other power plants: What fuels are being displaced by wind and solar generation?
- Reduction in need to build other power plants: How much capacity can be avoided when adding wind and solar to the system? How valuable is it to avoid this capacity?
- Uncertainty: How certain are forecasts over the time-horizons required to commit or decommit power plants? What are the economic consequences of these forecast errors?

For low penetration levels, these characteristics of wind and solar generation have been considered in estimates of the value of wind and, more recently, solar power. Wholesale power prices in competitive power markets reflect the marginal value of additional generation at any particular time (or the marginal cost of meeting an additional unit of demand). Wholesale power prices and wind and solar generation profiles can be used to estimate the current economic value of wind and solar, accounting for many of these factors (Joskow, 2011).[4]

Current wholesale power prices cannot inform questions regarding how the economic value of wind and solar might change with increasing penetration levels. In the long-run, increasing the amount of wind and solar available in power markets will change the investment patterns and dispatch of other generation sources. Wholesale prices with increased wind and PV, particularly the timing of when prices tend to be high or low, will be different compared to a situation with low wind or PV penetration.

Understanding changes in the value of wind and solar with increasing penetration levels requires simulations of future scenarios that account for these broader changes in the structure of the power system in response to increased wind and solar. While some literature examines these long-run changes in economic value with increasing penetration, particularly for wind, relatively little of that literature also accounts for the operational constraints that affect power plant operations. In fact, the literature is sparse when it comes to understanding what factors contribute to changes in the value of wind and solar with increasing penetration.

Chapter 3 describes an investment and dispatch model that was developed to explore the changes in the long-run economic value of wind, PV, CSP, and CSP with thermal storage with increasing penetration levels. The model is used in a case study that is loosely based on California in 2030. The economic value of wind and solar in this case study accounts for avoided fuel, avoided capacity, uncertainty in wind and solar forecasts during the commitment of generation, and the need for increased ancillary services (in this case regulation reserves) to manage short-term variability of wind and solar. The dispatch model, using a number of simplifications also used elsewhere (Müsgens, 2006), accounts for operational constraints on conventional power plants including ramp-rates, minimum generation limits,

[4]The degree to which the avoided cost of capacity is reflected in wholesale power prices depends on whether the wholesale power market is an “energy-only” market where energy prices are used to signal the need for new capacity or if the market has a separate capacity obligation that requires a certain level of generation capacity to be built. In the latter case the economic value of wind and solar would need to also account for any revenues earned from contributing to the capacity obligation.

inefficiencies associated with part-loading, and start-up costs. This dispatch model uses a full year of hourly load, wind, and solar data.

Since many thermal power plants take multiple hours to start and stop, many wholesale power markets include a day-ahead (DA) wholesale power market that aids the process of deciding which units to turn on or off during the operating day. Due to the lead time, these decisions are made with imperfect forecasts of load, wind, and solar generation and imperfect predictions of which thermal units will be available (among other uncertainties). Numerous techniques are used in academic studies and in practice to capture the impact of DA forecast errors in operational studies of wind and solar. Commonly, an imperfect DA forecast is used for wind and solar generation in deciding which units to commit in the DA market. The commitment of those units that cannot be started or shutdown in real-time is then fixed and the system dispatch is simulated using the actual wind and solar generation. Had the actual generation of wind and solar been known in the DA, a better (lower cost) commitment of thermal generation would have been used. The resulting inefficiency is referred to as the DA forecast error cost or the unit-commitment cost of wind and solar.

A unique contribution of this research is to develop and implement a method to endogenously estimate this DA forecast error cost of wind and solar in a long-run investment model. The approach used in this model is to split the problem of determining the long-run investment and dispatch into two separate problems, the master "investment problem" and the slave "dispatch problem". An iterative procedure is then used to search for a set of generation investments that earn just enough revenue in the wholesale power market (simulated in the dispatch problem) to cover their fixed investment costs. At that point, the market is in a long-run equilibrium where no additional new generation would have an incentive to enter the market and all new generation that is built is able to cover its investment costs. For each iteration, the dispatch problem is solved as described above: commitment decisions, DA schedules, and DA wholesale prices are based on imperfect DA forecasts of wind and solar while RT dispatch and RT wholesale prices are based on actual wind and solar generation. The approach of splitting the problem into an investment problem and dispatch problem then iteratively searching for a final investment portfolio is based on insight from the Benders Decomposition method (Conejo et al., 2006). The complications introduced from having imperfect commitment decisions in the dispatch problem, however, lead to the method deviating from the exact Benders method. In the end, this sometimes led to challenges in getting the model to converge to the long-run equilibrium. In these cases, alternative methods were required to find a final long-run equilibrium set of investments. While the approach served its purpose of simulating a system in long-run equilibrium for different penetration levels, the algorithm should be improved before being used in more general applications.

The long-run model is used to generate wholesale power prices with increasing penetration of one of the variable generation (VG) technologies at a time. The marginal value of additional VG is then estimated at each of these penetration levels using the resulting wholesale prices. The marginal value is separated into four separate components: the capacity value (based on revenues earned from the wholesale power market during periods of scarcity[5]), energy value (based on revenues in non-scarcity periods assuming perfect forecasts), DA forecast error costs, and ancillary service costs.

At low penetration levels, the marginal value of solar is found to exceed the marginal value of wind. The high value of solar at low penetration is primarily driven by its high capacity value. With increasing penetration levels the value of wind decreases, primarily due to a combination of a small decrease in the capacity value and a small decrease in the energy value. In contrast, the value of PV and CSP without thermal storage (CSP_0) decline much more rapidly. Up to about 10–15% penetration, the decline is almost entirely due to a decrease in the capacity value. Whereas at low penetration periods of scarcity were found to occur in the late afternoon (coinciding with times having some PV and CSP_0 generation), at higher penetration the periods of scarcity shift into the early evening after the sun goes down. At penetration levels above about 15%, the continued decrease in marginal value of PV and CSP_0 is due to a decrease in energy value. Eventually PV and CSP_0 begin to displace lower cost fuels, like coal, or to be curtailed when it is not possible to absorb the generation. This surplus solar generation first occurs on relatively low load days with high solar insolation (e.g., spring weekends). The addition of six hours of thermal storage to CSP (CSP_6) maintains the higher capacity value and energy value through about 15% penetration. Even the value of CSP_6 was found to decline after about 15% penetration due to a decreasing capacity value.

Even though the magnitude of the capacity value and the rate of change of the capacity value and energy value with increasing penetration are very different between wind and solar, there are some similarities between the technologies. In both the case of wind and solar, the change in the value with increasing penetration levels was not driven by changes in the cost of DA forecast errors or ancillary services. The cost of DA forecast errors was not negligible, but it was not found to exceed $6/MWh even at very high penetration levels. The ancillary service costs were found to be $1.1/MWh or less and generally decreased with increasing penetration in $/MWh terms.

The primary theme from this chapter is that understanding the changes in the value of wind and solar with increasing penetration levels requires a focus on the changes in the capacity value and energy value. While the costs of DA forecast errors and ancillary services should not be ignored, they were not found to change as much with penetration levels. Furthermore, ancillary service costs were found to be second order costs.

1.4 Mitigation of changes in economic value with increasing penetration

Understanding what drives changes in the economic value of wind and solar with increasing penetration also helps to identify which measures might be most effective in mitigating

[5]Periods of scarcity are identified as periods when the DA wholesale price exceeds $500/MWh.

declines in the economic value at high penetration levels. Chapter 4 uses the same model, methods, and data to evaluate the effectiveness of several measures to mitigate the decline in value of wind and solar. Since CSP_0 and PV were found to have similar behavior with increasing penetration and thermal storage was found to be an effective method to maintain the value of CSP with increasing penetration, Chapter 4 only considers wind and PV.

The commonly discussed mitigation measures evaluated in Chapter 4 include increased geographic diversity, technological diversity (through combinations of variable generation technologies), more flexible conventional generation, low cost bulk power storage, and price responsive demand subject to real-time prices (RTP). While these mitigation measures have been discussed extensively in the literature, the contribution of this chapter is a quantitative comparison of all of these different mitigation measures for both wind and PV using the same case study and model. Furthermore, the chapter evaluates the change in economic attractiveness of each of the mitigation measures with increasing penetration of wind and PV.

The mitigation measures that led to the greatest increase in value at high penetration were found to be different between wind and PV. For wind, increased geographic diversity led to the largest increase in the value of wind at very high penetration levels (40% of the annual energy met by wind). Wind patterns vary in different parts of the Western Interconnection, offering diversity in generation profiles even over multiple hour and longer time scales. The increased diversity increased both the capacity value and energy value of wind relative to a case without as much geographic diversity. Increased geographic diversity did not appear to be as effective as a mitigation measure for PV. The value of PV with increased penetration primarily declined due to periods of scarcity shifting into the early evening and surplus PV production on relatively low load, high solar days; factors not related to short-term variability or extended periods of cloud cover. Increased geographic diversity of PV minimizes the latter effects, but does not address the factors that primarily lead to decreases in the value of PV with high penetration.

Instead the mitigation measure that led to the largest increase in the value of PV at high penetration was the availability of low-cost storage. Assuming that low-cost storage is available as an investment option leads to an increasing amount of storage capacity in the system as PV penetration is increased. In turn, the energy value of PV increases relative to its energy value without low-cost storage. Notably, even treating this storage as a system asset (and not coupling its usage to a particular PV plant) leads to an increase in the value of PV.

Though RTP did not lead to the largest increase in the value of wind or PV at very high penetration levels, it did increase the value of both wind and PV by the largest amount at more modest penetration levels (10% penetration of PV or 30% penetration of wind). With RTP, reductions in demand relative to historical demand patterns (referred to here as the demand response) become negatively correlated with wind and PV generation patterns. In other words demand response tends to increase (larger reductions in demand relative to historical demand patterns) when renewable production is low. Demand response tends to decrease (smaller reductions in demand) or even become negative (increases in demand relative to historical demand patterns) when renewable production is high.

Not only did implementing these mitigation measures increase the economic value wind and PV, the mitigation measures themselves became more economically attractive with increasing penetration of wind and PV. The economic attractiveness of implementing a mitigation measure would need to be compared to the cost of the mitigation measure. This step was not done here, as the focus of this analysis was on quantifying the change in the value of wind and PV with and without the mitigation measures, not the costs of implementing these measures. In the case of increased geographic diversity for wind, this means that the revenues that could be earned by wind at diverse sites (per unit of wind production) would increase relative to the revenues earned by wind near existing wind plants. That increase in revenues would need to be compared to any potential increase in transmission costs or decrease in wind quality for diverse sites.

Finally, one interesting finding from the analysis of mitigation options relates to technological diversity (combinations of wind and solar technologies). At modest penetration levels, wind and solar did not appear to interfere with one another, in the sense that increasing the penetration of wind did not decrease the value of PV or vise versa. In particular, the value of wind at 10% penetration or 20% penetration was no lower if there was also 10% penetration of PV. In fact, the value of additional PV at 10% PV penetration was found to *increase* with 10% of demand also met by wind. Specific targets of 20% or 30% penetration of aggregate renewables would potentially be easier to meet with combinations of renewables rather than one renewable technology alone.

The analysis of short-term variability of solar, changes in the value of variable renewables, and mitigation options all raise additional questions or point to areas where additional detailed analysis might be useful. The final chapter, Chapter 5 briefly summarizes these recommendations for future research.

Chapter 2

Short-Term Variability of Solar Power

2.1 Introduction

Worldwide interest in the deployment of photovoltaic generation (PV), both distributed throughout the urban landscape and in large-scale plants, is rapidly increasing. PV plants as large as 60 MW are operating in Europe, while 500 MW PV plants are in various stages of development in the United States. Operating experience with large PV plants, however, demonstrates that large, rapid changes in the output of PV plants are possible. The output of multi-MW PV plants in the Southwest U.S., for example, are reported to change by more than 70% in five to ten minutes on partly-cloudy days (NERC, 2009). The reliable integration of generating plants with variable and uncertain output requires that power system operators have adequate resources to ensure a balance between the load and generation. The variability of PV output may create some concern about the ability of system operators to maintain this balance.

Early studies of the power system impacts of PV highlighted the rapid ramping of PV plants due to clouds, and the commensurate increased need for balancing resources, as a potential limiting factor in the grid penetration of PV. Many of these early studies, however, lacked high-quality data from multiple sites to assess the costs and impacts of increasing PV penetration. Similar concerns were raised some years ago regarding the variability of wind energy in studies that were often based on scaling the output of single wind turbines or anemometers to hypothetical large scale deployment (Wan and Parsons, 1993). More recent state-of-the-art studies of wind energy integration into the electric power system, however, have demonstrated the significant smoothing effect of geographic diversity, particularly with regards to rapid changes in the output of several interconnected wind plants. The lack of correlation between rapid changes in the output of different wind turbines reduces the variability of the aggregated wind output relative to the variability projected from simple scaling of the output of a single turbine (Beyer et al., 1990; Ernst et al., 1999; Farmer et al., 1980; Grubb, 1991; Holttinen, 2005; Holttinen et al., 2009; McNerney and Richardson, 1992; Nanahara et al., 2004; Persaud et al., 2000; Sorensen et al., 2007; Wan, 2005; Wan et al., 2003). A large body of experience with and analysis of wind energy demonstrates that this geographic smoothing over short time scales results in only a modest increase in balancing reserves required to manage the short-term variability of wind energy (Gross et al., 2006; Holttinen et al., 2009; Smith et al., 2007; Wiser and Bolinger, 2010).

The objective of this study is to assess the potential impact of the short-term variability of PV plants by exploring the short-term variability of PV output, the spatial and temporal scales of geographic diversity of PV, and the implications for the cost of managing the short time-scale, stochastic variability in the power system. Aside from the short-term variability impacts of PV, there are additional important considerations that we do not consider in the limited scope of this study. We do not evaluate the very-short time scale variability (<1-min) of PV which may affect power quality and may require careful evaluation in interconnection standards for PV. We do not consider the forecastability of PV and wind over multiple hours to days ahead and therefore do not include an assessment of the unit-commitment costs of PV and wind in this study (EnerNex Corp., 2009; Tuohy et al., 2009). We do not consider the avoided energy costs of PV (or the *energy value* of PV) and the contribution of PV to long-term planning reliability or resource adequacy (or the *capacity value* of PV). We also do not consider the flexibility of the conventional generation system over multiple hour periods. We therefore do not assess the potential for curtailment of PV at high penetrations due to minimum generation constraints (Denholm and Margolis, 2007b) or for operational cost implications of large multiple hour ramps with systems that have inflexible conventional generators. Finally we do not consider the potential value of PV for transmission expansion deferral or the potential need to increase investments in transmission/distribution infrastructure in areas where PV production exceeds the local load. These broader issues are discussed in more detail elsewhere (DOE, Forthcoming).

To asses the potential impact of short-term variability of PV, the characteristics of short-term variability of PV are compared to the characteristics of wind in a specific region of the United States. As explained in further detail in the chapter, the data used in this analysis are measured 1-min solar insolation and estimated 1-min clear sky insolation for 23 time-synchronized sites in the Southern Great Plains network of the Atmospheric Radiation Measurement program. Wind speed data from 10 of the sites in the same network are converted into estimated wind power output to compare the variability of PV and wind. Variability across different time scales is analyzed by calculating the step changes from one averaging interval to the next over different averaging intervals from 1-min to three hours. Diversity across these different time scales is measured by the degree of correlation of variability as a function of distance between sites. The results of this analysis demonstrate that, at individual sites, PV is more variable than wind for sub-hourly time scales, but that the distances between sites required to obtain diversity and therefore smooth the output for sub-hourly variability are slightly less for PV than for wind. Overall, for similarly sited PV and wind plants sited in a 5×5 grid with 50 km spacing, we find that the variability of PV is slightly more than wind, particularly for variability on time scales of 5-15 min. Finally, we use a simple approximation method to estimate the cost of carrying additional reserves to manage short-term variability. We conclude that the costs of managing the short-term variability of geographically distributed PV plants are not substantially different from the modest costs to manage the short-term variability of similarly sited and geographically distributed wind in this region.

The remainder of this chapter is organized as follows:

- Section 2 provides an overview of the short-term variability impacts of PV plants and the potential economic consequences of measures to maintain the same level of reliability with and without PV.
- Section 3 reviews the methods used to quantify the variability of PV and wind while accounting for the impacts of geographic diversity and the methods used to estimate the costs of managing this variability.
- Section 4 summarizes the data sources used to quantify the short-term variability of PV and wind using time-synchronized data from multiple sites in the same region.
- Section 5 presents the results from the examination of the variability of PV on different time scales and at different levels of geographic diversity.
- Section 6 summarizes a simple analysis of the potential cost implications of the variability of PV compared to wind.
- Section 7 presents our conclusion that for a particular arrangement of similarly sited PV and wind, the variability of PV is only slightly greater than the variability of wind for sub-hourly time scales. We therefore expect that the costs to manage short-term variability of PV will not be substantially different from the costs to manage the short-term variability of wind energy in this region.

2.2 Power System Impacts Due to Short-term Variability of PV Plants

The short-term variability of PV generation will impact the power system in a variety of ways. Our analysis focuses only on the operational integration impacts of stochastic (i.e. cloud-induced rather than deterministic changes due to the movement of the sun) PV variability over short time scales. Namely, our analysis is focused on the need for power system operators to maintain a short-term balance between generation and loads.

The additional variability and uncertainty introduced by PV plants will, to some degree, increase the use of these resources and methods to maintain balance, which will impose costs to the power system. Additional uncertainty and variability over time scales shorter than the time it takes to start and synchronize fast-start units, for instance, must be met by balancing reserves from spinning resources. An increase in spinning resources held in reserve leads to more units dispatched to "part load" levels, which leads to an efficiency penalty and higher costs than dispatching units to optimal set points (Mills et al., 2009b). Increased ramps in the net-load over the time scale of the economic dispatch may also require out-of-merit order dispatch whereby a fast ramping, but higher cost, unit is dispatched to produce more power while a slow ramping, but lower cost, unit is slowly moved to its higher set point (Kirby and Milligan, 2008).

To some extent, previous studies have evaluated the balancing resources required to accommodate the short-term variability of PV. Unlike the extensive body of work on the operational integration impacts of wind, however, these (often-dated) studies generally lack high-time resolution PV data from multiple sites. Many of the conclusions are instead based on scaling PV data from single sites or simple cloud models (Table 2.1). These studies often conclude that the economic value of PV is significantly reduced at increasing levels of PV penetration due to the additional need for reserves or that the high variability of PV and the limited ramp rates of conventional generation limit the feasible penetration of PV. The conclusions of these studies are questionable due to the lack of high time-resolution data from multiple PV sites. Studies that have evaluated sub-hourly PV data from multiple sites, on the other hand, do not separate the impacts of PV from the impacts of much larger quantities of wind and solar thermal plants (Piwko et al., 2010; Piwko et al., 2007b).

System operators only need to balance the variability of the load net the aggregated output of PV sites in the balancing area (while respecting transmission capacity limits). The degree to which PV increases the demand for resources to balance the net load therefore depends on the amount of smoothing offered by geographic diversity.

Previous research demonstrates that smoothing from geographic diversity for solar does occur. Jewell and Ramakumar (1987) and Kern and Russell (1988) develop cloud models to estimate the smoothing effect of geographic diversity. Jewell and Ramakumar (1987) consider regions ranging from 10 km^2 to 100,000 km^2, while Kern and Russell (1988) consider an area of 0.2 km^2 (50-acres). Wiemken et al. (2001) use data from actual PV sites in Germany to demonstrate that 5-min ramps in normalized PV power[1] at one site may exceed +/-50% but that 5-min ramps in the normalized PV power from 100 PV sites spread throughout the country[2] never exceed +/- 5%. Results from Curtright and Apt (2008) based on three PV sites in Arizona indicate that 10-min step-changes in output can exceed 60% of PV capacity at individual sites, but that the maximum of the aggregate of three sites is reduced.[3] Otani et

[1]Normalized PV power is measured PV power divided by the installed capacity of PV.

[2]The area covered by the sites is about 600 km $\times$ 750 km, or about 450,000 km^2.

[3]In contrast to the other studies reviewed in this paragraph, Curtright and Apt (2008) state that their PV data "imply that site diversity over a $\sim$280 km range does not dampen PV intermittency sufficiently to eliminate the need for substantial firm power or dispatchable demand response. The high correlation between geographically dispersed arrays may indicate that high, widespread clouds are responsible for a portion of the intermittency." These results do not agree with the conclusions from the other literature cited in this paragraph because Curtright and Apt (2008) (1) consider only a limited number of sites (three) and (2) their calculation of correlation coefficients between the three sites uses the full time-series across all time scales rather than isolating the variability across particular shorter time scales. The high correlation coefficients (0.5-0.73) they find between distant sites (110 km to 290 km apart) are in part due to the correlated, deterministic change in the position of the sun at the three sites and changes in insolation over multiple hour time scales. Our results, presented in later sections, find diversity over multiple sites within a

Table 2.1: Sample of PV operational integration studies that focus on short-term variability[a]

Reference	PV Variability	Conclusions
Lee and Yamayee, 1981	100% change in 10-min assumed for PV	Dispatch and operating reserve penalties for PV can eliminate economic value.
Chalmers et al., 1985	Simple uniform cloud model generates worst case ramps	Variability exceeds ramp-rate capability of on-line generation at low PV penetration.
Chowdhury and Rahman, 1988	Simulated 10-min data for single, 750 MW PV plant	Out-of-merit order dispatch due to limited ramp rates of thermal units can eliminate economic value of PV.
Jewell and Unruh, 1990	Cumulus cloud model and synthetic 1-min PV data assumed to have different magnitude fluctuations	PV penetration limited by ramp-rates of dispatchable generation. Limit is relaxed as PV is increasingly dispersed.
Bouzguenda and Rahman, 1993	Scaled 10-min data from single 20 kW PV plant	PV penetration limited by ramp-rates of dispatchable generation.
Asano et al., 1996	Scaled 10-sec data from a single location	PV increases required capacity and ramp-rates of units used to balance 5-30 min variability.
Piwko et al., 2007b	15-min PV production data from multiple sites overlaid with synthesized short-term data assumed to be uncorrelated between sites	Operational integration impacts are modest.[b]
Piwko et al., 2010	Hourly satellite-derived PV production overlaid with synthesized 10-min PV production data from multiple sites	Operational integration impacts are modest.[b]

a - EnerNex Corp. (2009) evaluates unit commitment costs but does not address short-term variability
b - Impacts of PV were not separately identified in scenarios with much more wind and solar thermal

al. (1997) demonstrate that the variability of sub-hourly irradiance even within a small area of 4 km $\times$ 4 km can be reduced from geographic diversity. Kawasaki et al. (2006) similarly analyze the smoothing effect within a small 4 km $\times$ 4 km network of irradiance sensors and conclude that the smoothing effect is most effective during times when the irradiance variability is most severe—particularly days characterized as partly cloudy. Murata et al. (2009) develop and validate a method for estimating the variability of PV plants dispersed over a wide area[4] that is very similar to the methods we use in the next section (and to methods used for wind by Ilex Energy Consulting Ltd et al. (2004) and Holttinen (2005)). Their analysis shows that the aggregate variability of PV plants sited over a wide area depends on the correlation of the variability between plants. The correlation of variability, in turn, is a function both of the time scale and distance between plants. Variability is less correlated for plants that are further apart and for variability over shorter time scales.[5] Interestingly, Murata et al. (2009) find nearly zero correlation between 1-min and 5-min fluctuations at all distances between sites, even distances as close as 2 and 9 km apart, respectively. Even different inverters within a single 13.2 MW PV plant in Nevada can have very low correlations in 1-min changes on a highly variable day (Mills et al., 2009a). Hoff and Perez (2010) develop a simple model to predict the relative variability of a fleet of PV plants to the variability of individual plants using the number of plants and a parameter they define as the dispersion factor. The dispersion factor is based on the ratio of the time required for a cloud to pass over the entire fleet of PV plants to the time scale of interest. The average variability of the fleet over the time scale of interest is estimated to equal only $1/\sqrt{N}$ of the variability of a single site if the dispersion factor is larger than the number of plants in the fleet, but approaches the variability at a single site as the dispersion factor decreases to one. Hoff and Perez (2010) predict that the average variability of the fleet reaches a minimum when the dispersion factor is equal to the number of plants in the fleet.

Overall, the clear conclusion from this body of previous research is that with "enough" geographic diversity the sub-hourly variability due to passing clouds can be reduced to the point that it is negligible relative to the more deterministic variability due to the changing position of the sun in the sky. It is not necessarily clear how dispersed PV will be in the future, however. Siting considerations including available land or rooftop area or available transmission capacity may naturally lead to a high degree of dispersion. On the other hand, if plants would naturally be more densely sited, obtaining more geographic diversity will introduce additional costs. Increasing the spacing between PV plants may require additional

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$\sim$280 km range can dramatically reduce variability over sub-hourly time scales.

[4] They consider 52 sites across the country of Japan from 2 km to 923 km apart.

[5] The results of the study by Murata et al. (2009) are unfortunately not directly comparable to our results, however, because they do not separate changes in PV output that occur from clouds from the deterministic changes that occur due to changes in the position of the sun. As a result, variability over time scales longer than 20-min or so in their results do not drop to zero with increasing distance due in part to the deterministic changes in the position of the sun. As explained in the next section, our analysis separates this deterministic component from the stochastic component due to the movement of clouds through the use of the clear sky index.

transmission capacity or increased transmission losses. Similarly, increasing the spacing between plants may require moving some plants out of the highest quality solar resource areas. Since the quality of the solar resource dictates the capacity factor of a PV plant, a reduction in the quality of the solar resource will increase the generation cost of the repositioned PV. Also breaking up a large PV plant into smaller dispersed PV plants may forgo economies of scale available to the larger PV plant.

The tradeoff between the costs to increase geographic dispersion and the benefits of the reduced variability seen by the system operators is a complex problem that will generally be site and system specific. Instead of determining the best deployment of PV plants, we therefore only focus on understanding key drivers of this tradeoff for both PV and wind: the characteristics of variability and the spatial and temporal scales of geographic diversity. Specifically, we investigate the short-term variability of similarly sited PV and wind plants.

2.3 Methodology

Estimation of the Variability from Dispersed Photovoltaic Plants

The operational integration impacts of PV plants will depend on the characteristics of the variability over various time scales. Variability over short time scales, for example a rapid change in the net-load that must be met by conventional generation, is relatively more challenging and more expensive to accommodate than similar sized changes over longer time periods.

A common method for characterizing the variability of a resource over different time scales is to calculate the "deltas" or "step changes", which refers to the difference in the output of a plant from one averaging interval to another. The duration of the averaging interval is $\bar{t}$. Given minute by minute output data at a single site, P_1, a step change at a single site with a sixty minute averaging interval, for example, is calculated as:

$$\Delta P_1^{\overline{60}}(t) = P_1^{\overline{60}}(t) - P_1^{\overline{60}}(t-60) = \left(\frac{1}{60}\sum_{i=0}^{59} P_1(t+i)\right) - \left(\frac{1}{60}\sum_{i=-60}^{-1} P_1(t+i)\right) \tag{2.1}$$

The overall average variability of the resource at a single point over an averaging interval can then be characterized by the standard deviation of the step changes over a long observation period or by some percentile of the step changes. A common metric is the 99.7^{th} percentile (Holttinen et al., 2008), which corresponds to three standard deviations from the mean for a normally distributed random variable.[6] The standard deviation of the step

[6]There are, of course, a multitude of different ways to characterize variability over different time scales. We choose to use the standard deviation and 99.7^{th} percentile of step changes from data averaged over different time-averaging periods because this method is commonly used in wind integration studies. Murata et al. (2009) apply a slightly different metric based on the ramps generated using different lag times (rather

changes with a sixty minute averaging interval at a single site, $\sigma_{\Delta P_1}^{\overline{60}}$ is:

$$\sigma_{\Delta P_1}^{\overline{60}} = \sqrt{\mathrm{Var}\left(\Delta P_1^{\overline{60}}\right)} \tag{2.2}$$

The 99.7th percentile may be more or less than three standard deviations from the mean depending on the shape of the distribution of the step changes. A distribution with relatively "fat tails" will have a 99.7th percentile that exceeds three standard deviations. We follow nomenclature and definitions slightly different from Murata et al. (2009) and refer to the ratio of the 99.7th percentile to the standard deviation of the step changes over different averaging intervals as $\kappa_{3\sigma}$:

$$\kappa_{3\sigma}^{\bar{t}} = \frac{99.7^{\mathrm{th}} \text{ percentile of } |\Delta P_1^{\bar{t}}|}{\sigma_{\Delta P_1}^{\bar{t}}} \tag{2.3}$$

For maintaining compliance with NERC reliability standards, however, system operators need only to balance the load net of all generation rather than the output of individual plants. More important than the variability of a single variable generation plant, therefore, is the variability of the sum of all variable generation plants. N plants each with an output of $P_i(t)$ leads to an aggregate output, $P(t)$, of:

$$P(t) = P_1(t) + P_2(t) + P_3(t) + P_4(t) + ... + P_n(t) \tag{2.4}$$

Using the standard deviation of the step changes metric, the total variability of the aggregate of all PV plants for a particular averaging interval, $\sigma_{\Delta P}^{\bar{t}}$, is:

$$\sigma_{\Delta P}^{\bar{t}} = \sqrt{\mathrm{Var}\left(\Delta P^{\bar{t}}\right)} = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N}\mathrm{Cov}\left(\Delta P_i^{\bar{t}}, \Delta P_j^{\bar{t}}\right)} \tag{2.5}$$

The role of geographic diversity is to reduce the variability of the aggregate of multiple plants relative to scaling the output of a single plant (even though the absolute level of variability of N plants in aggregate will be larger than the absolute level of variability at an individual site). This benefit is called a "diversity factor" (Farmer et al., 1980), a "space filter" (Healey, 1984), an "equivalent filter" (Nanahara et al., 2004), or as we call it, a "diversity filter." As mentioned in the introduction, the benefit of geographic diversity has

than data averaging times). Woyte et al. (2007) characterize variability over different time scales using a localized spectral analysis based on wavelets. This method isolates the magnitude of the fluctuations that occur according to their persistence time scale. Both of these methods are perhaps more mathematically accurate and concise relative to the manner used in the present study, but the method used here is often used in practice. Curtright and Apt (2008) use spectral analysis to characterize the variability of PV over different time scales. In contrast to the localized spectral analysis employed by Woyte et al. (2007), however, the approach used by Curtright and Apt (2008) implicitly assumes that fluctuations across all time scales are periodic. A comprehensive review of methods used to characterize variations in solar insolation at a single site is available from Tovar-Pescador (2008).

been analyzed in detail for wind energy. For our purposes, we define a diversity filter as a process that changes the variability of multiple sites relative to summing the variability of each site independently. The impact of diversity is demonstrated by the ratio of the aggregated variability of all sites to the sum of the variability of each individual site.

$$\text{Diversity Filter} = D^{\bar{t}} = \frac{\sigma^{\bar{t}}_{\Delta P}}{\sum_{i=1}^{N} \sigma^{\bar{t}}_{\Delta P_i}} \tag{2.6}$$

For purposes of simplification, if it is assumed that all N plants are similar in that they have the same variability, then the diversity filter over different time scales reduces to:

$$D^{\bar{t}} = \frac{\left(\sigma^{\bar{t}}_{\Delta P}/N\right)}{\sigma^{\bar{t}}_{\Delta P_1}} = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} \rho^{\bar{t}}\left(\Delta P_i^{\bar{t}}, \Delta P_j^{\bar{t}}\right)} \tag{2.7}$$

Where $\rho^{\bar{t}}\left(\Delta P_i^{\bar{t}}, \Delta P_j^{\bar{t}}\right)$ is the correlation coefficient of the $\bar{t}$-min step changes between sites i and j. The diversity filter (the ratio of the variability of PV at the system level to the variability of PV at all sites individually) therefore depends on the correlation of the step changes for each time scale, which is a function of both the spatial and temporal scales. For sites located very close to each other, such that they are perfectly correlated over a time scale of $\bar{t}$ (and therefore $\rho^{\bar{t}} = 1$), the diversity filter is equal to 1: the variability at the system level is equivalent to the sum of the variability of PV at all sites individually. When plants are sited such that they are perfectly uncorrelated over a time scale of $\bar{t}$ (and therefore $\rho^{\bar{t}} = 0$) the diversity filter is equal to $\frac{1}{\sqrt{N}}$: the variability at the system level is $\sqrt{N}$ times the variability at a single site (again assuming all sites have similar size and variability characteristics).

Based on relationships developed by Nanahara et al. (2004) and Glasbey et al. (2001), and results from Murata et al. (2009), it is expected that the correlation of deltas between two sites will decrease exponentially with increasing distance, d_{ij}, and will similarly decrease with shorter averaging intervals, $\bar{t}$. A functional form that captures both this spatial and temporal behavior of correlation is:

$$\rho^{\bar{t}}\left(\Delta P_i^{\bar{t}}, \Delta P_j^{\bar{t}}\right) = \frac{1}{2}\left(e^{-\frac{C_1}{\bar{t}} d_{ij}^{b_1}} + e^{-\frac{C_2}{\bar{t}} d_{ij}^{b_2}}\right) \tag{2.8}$$

Where C_1, C_2, b_1 and b_2 are constant parameters that can be estimated from a fit to solar data in a particular region. At zero distance the correlation is one and as the distance between sites increases the correlation reduces to zero. Similarly, for very long time scales the correlation increases to one and over very short time scales falls to zero.

Assuming this particular functional form and that all plants are similar in their ramping characteristics and size allows the diversity filter to be specified in terms of the distance between PV plants and two model constants.

$$D_{\Delta}^{\bar{t}} = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N}\left(\frac{1}{2}\left(e^{-\frac{C_1}{\bar{t}}d_{ij}^{b_1}} + e^{-\frac{C_2}{\bar{t}}d_{ij}^{b_2}}\right)\right)} \tag{2.9}$$

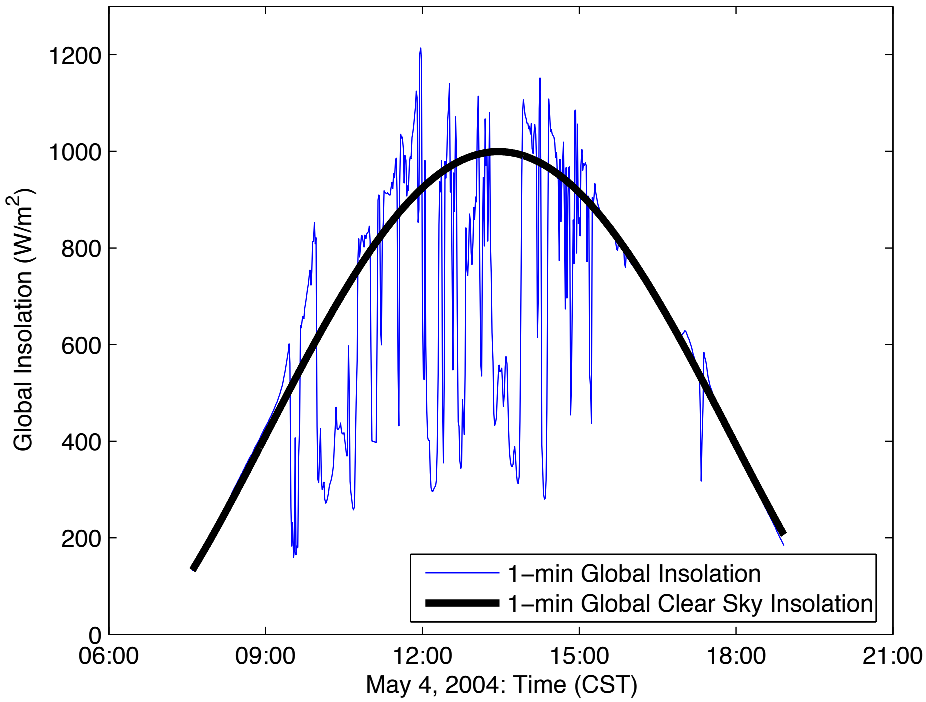
According to this formula and the assumption that all plants are similarly sized and have similar variability characteristics, the variability of all plants aggregated to the system level can be determined based on the variability of a PV plant at a single site, the model constants, and the location of each PV plant.

For PV, rapid output changes are largely driven by fast moving clouds. PV output also changes based on diurnal cycles of the sun, but this variability can be perfectly forecasted. The variability due to changes in the position of the sun can therefore be evaluated by system operators without consideration of geographic diversity. Because of the relative lack of understanding of the short-term variability due to fast moving clouds we focus on the stochastic component of the variability of PV output. This stochastic component due to cloud movement can be separated from the deterministic component due to changes in the position of the sun in the sky by focusing only on the clear sky index, $k(t)$, in place of the overall change in power output, $P(t)$. The clear sky index is the ratio of the actual global insolation measured at the site to the global insolation expected if the sky were clear (Figure 2.1). Since PV plant output is generally proportional to solar insolation, the variability of the clear sky index is similar to the variability of the ratio of actual PV plant output to PV plant output if the sky were clear. The stochastic variability in solar insolation is not exactly equivalent to the stochastic variability in actual PV plants due to "within-plant" smoothing that can occur relative to variability of insolation at a point (Mills et al., 2009a), changes in PV plant efficiency with temperature, PV tracking systems, and diverse PV panel orientations other than horizontal for non-tracking PV systems.[7] We focus on the variability of the clear sky index from insolation measurements rather than the variability of the clear sky index from actual PV plants for the bulk of this study because of the relative higher quality of the insolation dataset available at the time of this study. The variability, particularly over shorter time scales, in our results will most likely provide an upper bound to the stochastic variability expected from actual PV plants.

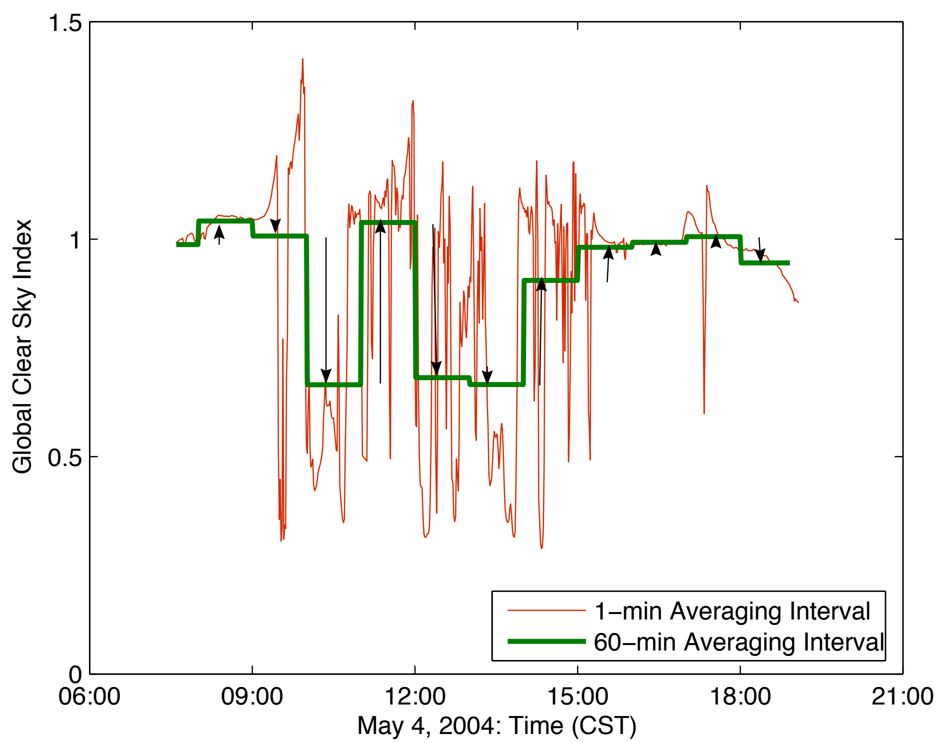
Estimation of the Cost to Manage Short-Term Variability at the System Level

Determining the cost of managing sub-hourly variability is a complex problem that is generally evaluated through detailed integration studies. Without performing a detailed integration study we still want to understand in general terms the relative difference in cost between

[7]Mills et al. (2009a) summarize comparisons between variability of point insolation measurements and PV plant output. Within-plant smoothing reduces variability on time scales shorter than about 10-min for a 13.2 MW PV plant.



(a) Example of 1-min global insolation and global clear sky insolation on a partly cloudy day



(b) Example of 1-min global clear sky index, 60-min average of the clear sky index, and arrows representing magnitude and direction of 60-min deltas

Figure 2.1

managing variability at a single site and variability estimated for an aggregate of multiple sites. Similarly, we want to understand the cost of managing short-term variability of PV relative to the more-well-known cost of managing the stochastic short-term variability of wind. Based on these broad objectives, we provide a simple estimate of the costs to manage short-term variability that is largely based on methods and assumptions from Farmer et al. (1980), Grubb (1991), Milborrow (2001), Wan (2005), and EnerNex Corp. and Windlogics Inc. (2006). These simple estimates are only meant to illustrate relative changes in costs; the cost impact of short-term variability should in the future be evaluated with more detailed methods.

To estimate the costs of managing sub-hourly variability we make the following simplifying assumptions:

- Only the net of the variability of load and variable generation is managed by the system operator.
- The incremental variability above the variability of the load is managed with additional balancing reserves.
- The capacity of the variable generation added is assumed to have a nameplate total that is 10% of the peak load.
- As a proxy for resources required to maintain a balance between load and generation, we characterize the additional variability on different time scales using the following deltas:
  - As a proxy for the NERC CPS1 standard, we use the 1-min deltas
  - As a proxy for the NERC CPS2 standard, we use the 10-min deltas
  - As a proxy for the imbalance or hour ahead forecast error we use the 60-min deltas[8]

[8]Our use of the deltas as a proxy for the requirements to manage variability on different time scales follows approaches used in other detailed integration studies. The authors of the 2006 Minnesota Wind Integration Study estimate the increase in sub-hourly reserves for wind based on the 1-min deltas (regulation requirement), the 5-min deltas (load following requirement), and the 60-min deltas (operating reserve margin to cover forecast error using persistence forecast) (EnerNex Corp. and Windlogics Inc., 2006). The wind deltas are combined with the deltas from load to estimate the increase in the total balancing reserves in high wind scenarios relative to a base scenario. The authors of a 2004 study of the balancing reserves required to manage wind in the Irish system (Ilex Energy Consulting Ltd et al., 2004) based reserve requirements on the 1.25 min deltas (fast reserves), 30-min deltas (slow reserves), and 1-hour deltas (replacement reserves). The wind deltas are combined with the deltas from the load to estimate the increase in total balancing reserves at various levels of wind penetration using an algorithm similar to one presented by Doherty and O'Malley (2005). An earlier study of the costs of accommodating renewables in the UK used 30-min deltas (response) and 4-hour deltas (reserve) to estimate the balancing costs for wind. The 4-hour reserve was assumed to be met with a combination of standing reserve and spinning reserve, depending on the cost tradeoffs between part-load efficiencies for spinning reserve and start-up costs for standing reserve (Ilex Energy Consulting Ltd and Strbac, 2002).

- Over these short time scales we assume that load deltas are uncorrelated with the deltas from the variable generators. The variance of the net load deltas is therefore assumed to be the sum of the variance of the load deltas and the variance of the variable generator deltas.[9]

- We assume that the variability from the 1-min and 10-min deltas can only be met with resources that are spinning, or on-line and synchronized with the grid.

- The amount of spinning reserves required to manage the 1-min and 10-min deltas is assumed to equal three times the standard deviation of the net load deltas. While we explore the shape of the non-normal distributions of the deltas, the general form of Eq. 2.7 does not provide information of how the shape of the distribution changes with the aggregation of multiple sites. In addition, without actual 1-min time-synchronized load data we do not know how the shape of the distribution of the net-load deltas will compare to the shape of the distribution of the variable generation deltas and load deltas. We therefore ignore the potential non-normal distributions of the net-load for the purpose of a simple estimation of costs. Future work in specific regions should directly evaluate the shape of the distribution of the net-load deltas.

- We assume that the variability from the 60-min deltas can be met with a combination of spinning and non-spinning resources. The amount of spinning reserves to manage the 60-min deltas is assumed to be half of the standard deviation of the 60-min deltas. Deltas larger than half of the standard deviation of the 60-min deltas are assumed to be met by deploying non-spinning resources.

- We assume that resources required to manage the 1-min, 10-min, and 60-min deltas are held in reserve and therefore cannot simultaneously also be used to meet the peak net load. The additional reserve requirement is therefore met with resources that cannot also provide capacity. We therefore assume that there is an opportunity cost of capacity associated with increasing these reserves.[10]

- The standard deviation of the deltas is assumed to be constant throughout the year for load and wind deltas. For PV deltas we examine two cases:

[9] The 60-min variable generation and load deltas are likely to be correlated to some degree. The stochastic changes in insolation due to clouds, as captured by the clear sky index, however, are less likely to be correlated with changes in load than the changes in total solar insolation and load. Either way, we do not use time-synchronized load and variable generation data to account for correlation between generation and load deltas in our simple estimates. More detailed evaluations of the costs of managing short-term variability for a specific load should account for the potential correlation of generation and load over the 60-min time-scale, but the correlation is not expected to be significant.

[10] Note that the assumption that resources are held in reserve to meet 60-min deltas and that there is an opportunity cost of capacity for these resources is driven by hourly scheduling periods between BAs. The opportunity cost of capacity would be reduced if the solar and wind resources were integrated into BAs that have shorter scheduling periods (Kirby and Milligan, 2008, 2009).

  - The standard deviation of the PV deltas is assumed to be constant and proportional to the standard deviation of the deltas from the clear sky index. For example, if the standard deviation of the clear sky index deltas is 0.1 then the standard deviation of the PV deltas is assumed to be 0.1 times the nameplate capacity of the installed PV.
  - The standard deviation of the PV deltas is assumed to change throughout the year in proportion to the clear sky insolation expected for any hour. Following the previous example, if the standard deviation of the clear sky index deltas is 0.1 then the standard deviation of the PV deltas is assumed to be 0.1 times the amount of power that would be produced by the PV plants if the sky were clear in any particular hour. This assumption allows the amount of reserves procured to manage PV variability to change with the position of the sun.[11]
  - In either case, the opportunity cost of capacity is based on the peak reserve requirement and is not assumed to change depending on whether reserves are constant throughout the year or if they change with the position of the sun.

- The cost of spinning reserves is assumed to be based on an efficiency penalty for the marginal plant that is part-loaded to provide spinning reserves.

- The cost of non-spinning reserves is assumed to be based on the higher cost of energy from a quick starting plant that provides non-spinning reserve relative to the cost of energy from the marginal plant that would have otherwise been used.

Additional details and the equations used to estimate the additional cost of managing reserves are included in Appendix A.1.

Numerical Assumptions

In addition to the methodological assumptions, several numerical assumptions are required to estimate the cost of additional reserves to manage additional short-term variability. The assumptions used are listed in Table 2.2.

In the following sections we start by exploring the variability of PV at individual sites. We then evaluate the correlation of deltas between geographically dispersed sites and use real 1-min insolation data from multiple time-synchronized sites to develop the constants for Eq. 2.8. We then demonstrate the effectiveness of the diversity filter for an array of sites, and use a similar approach to compare the variability of an array of similarly sited solar and wind sites. Finally, we estimate the increased costs associated with managing the sub-hourly

[11] In this case no reserves are held to manage short-term variability of solar in the middle of the night when the clear sky insolation is zero. Similarly, fewer reserves are held during winter mornings with low clear sky insolation than the reserves held in during summer afternoons when the clear sky insolation is at its peak. For the same type of clouds, the aggregate variability will be less if the clouds pass on a winter morning than if they pass during a summer afternoon.

Table 2.2: Numerical assumptions to estimate cost of additional reserves

Assumption	Value
Efficiency penalty of part loaded marginal plant, η	15%
Full-load variable cost of marginal plant, c_m	\$55/MWh
Variable cost of standing plant, c_g	\$85/MWh
Fixed cost of capacity, FC_p	\$100/kW-yr
Standard deviation of 1-min load deltas[a]	0.3% of peak
Standard deviation of 10-min load deltas	0.8% of peak
Standard deviation of 60-min load deltas	3.7% of peak
Multiple of st. dev. of deltas kept in reserve, κ	3
Multiple of st. dev. of 1-10 min deltas from spinning resources, $\gamma_{1,10}$	3
Multiple of st. dev. of 60 min deltas from spinning resources, γ_{60}	0.5
Capacity factor of solar, CF_S	20%
Capacity factor of wind, CF_W	30%

a - The load deltas are illustrative values from a Minnesota utility with a peak load of 6,000 MW (Wan, 2005)

variability of solar and wind. Before presenting these results, however, Section 2.4 discusses the data used in this analysis.

2.4 Data

We explore the short-term variability of PV across multiple time scales at a single site by calculating the deltas in the clear sky index across an entire year. Variability is characterized by the standard deviation of the deltas, the shape of the distribution of the deltas, and the magnitude of the 99.7^{th} percentile of the deltas. Then, using time-synchronized data from multiple sites we examine the correlation of deltas between sites that are at varying distances from one another.

The primary data required for this analysis are high time resolution solar and wind data for multiple time-synchronized sites covering a broad geographic region. The only readily available U.S. dataset that fit this need was one that contains historic data from the Atmospheric Radiation Measurement (ARM) Program at the Southern Great Plains (SGP) network.[12] The solar data are 1-min averaged global, direct, and clear sky insolation from 23

[12]Gaps in the time-series data were filled using tools provided by the ARM program. The data collected from the SGP site was run through a program called "nc fill" as part of the ARM NetCDF Tool Suite. The option was set to use linear interpolation to fill gaps in the data sets. We synchronized the 23 datasets by removing any data points that did not simultaneously occur at all sites in the network. Aside from the

instrument sites[13] from 2004. The sites are located 20 km to 440 km apart and are located in the states of Oklahoma and Kansas. Data on clear sky insolation and the cosine of the solar zenith angle data are provided with the SGP dataset. We use these data to calculate the clear sky index at each point measurement, $k_i(t)$, as the ratio of the measured insolation to the clear sky insolation. To avoid potential problems with calculating the clear sky index when the sun is near the horizon and clear sky insolation is very low, we only calculate the clear sky index for periods when the cosine of the solar zenith angle exceeds 0.15.

The SGP dataset also includes 1-min averaged wind speed data at 10 m from 15 instrument sites[14] in the SGP network. The wind speed data were extrapolated to the typical hub height of wind turbines, 80 m, using a simple $1/7^{th}$ power law extrapolation.[15] The wind speed data were then converted into wind power output using a multi-turbine power curve,[16] recreated in Figure 2.2 (Holttinen, 2005). Wind speed data from five of the 15 sites showed very low annual capacity factors (below 20%) and were therefore excluded from our assessment of wind variability.[17]

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quality control provided by the ARM Program, no other additional cleaning or error checking procedures were performed on the data.

[13]The 23 sites with solar data are C1,E1-13, E15, E16, E18-22, E24, and E27.

[14]The 15 sites with wind data are E1, E3-9, E11, E13, E15, E20, E21, E24, and E27.

[15]The power law extrapolation is $u_{80} = u_{10}(80m/10m)^{\frac{1}{7}}$ where u_{80} is the extrapolated wind speed at 80 m above the ground and u_{10} is the measured wind speed 10 m above the ground. Wind variability over short time scales may be greater at 10m than it is at 80m due to turbulence. We do not correct for potential changes in variability with height and our results may therefore overestimate the variability of wind, particularly over time-scales shorter than 10-min.

[16]Our conversion from wind speed to wind power using a multi-turbine curve only accounts for the reduction of the slope of the power curve at wind speeds lower than the rated wind speed and wind speeds around the cut-out speed of a single turbine. Had we used only a single turbine power curve, small changes in wind speed at wind speeds near the cut-out wind speed of the turbine would cause the wind power output data to include changes from the full output to zero. The multi-turbine power curve is a better representation of how the output of entire wind plants change at wind speeds around the cut-out wind speed. Aside from this conversion of 1-min wind speed data into 1-min wind power data our analysis does not account for the smoothing of wind power variability that occurs within a wind plant from geographic diversity. We also do not apply any alterations to the 1-min data due to the inertia of the wind turbine. Multiple sources indicate that wind turbine inertial dampening of wind speed variability impacts time-scales on the order of 20 seconds or less, but not 1-min variability (Apt, 2007; Sorensen et al., 2007).

[17]The sites where wind speeds were too low for development of wind power were E4, E7, E20, E21, and E27. Capacity factors, based on the wind speed extrapolation and power curve conversion method outlined in this section, for the excluded sites ranged from 4% to 19%. The remaining sites had estimated capacity factors that ranged from 21% to 30%. The average capacity factor across the included sites was 25%. The average wind speed and capacity factor results are included in the appendix.

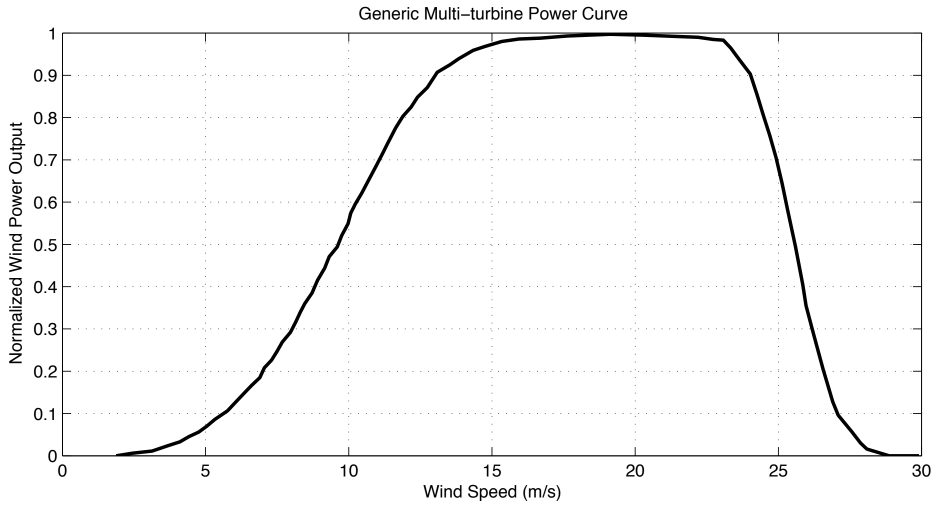


Figure 2.2: Generic multi-turbine power curve used to convert hub-height wind speed to wind power from Holttinen (2005).

2.5 Results

Deltas at Individual Sites

The anecdotes of extreme deltas from PV plants and the conclusions from many of the previous solar integration studies described in Table 2.1 are based, in large measure, on data from single sites. In this section we examine the deltas at individual sites within the SGP network.

Consistent with previous anecdotes and literature, severe deltas are apparent in the point insolation measurements from the SGP data. Deltas greater than +/- 0.6 in the global clear sky index were observed in one minute at individual sites. Similarly, deltas greater than +/- 0.6 were observed based on 10-min and 60-min averaging intervals (Figure 2.3). Figure 2.3 is a cumulative probability distribution plot of the deltas from the individual sites where the magnitude of the deltas are smaller than the value on the x-axis for the percent of the deltas shown on the y-axis. For reference cumulative distribution functions of normal or "bell curve" distributions with the same standard deviations as the actual 1-min, 10-min, and 60-min deltas are included as thin lines in the figure. This chart shows that extreme deltas occur very infrequently, but the shape of the distribution, particularly for the 1-min deltas, shows a higher probability of extreme deltas than would be expected for a normal distribution with a similar standard deviation. In other words, the distribution of the deltas exhibits "fat tails" relative to a normal distribution.

The standard deviation of the deltas in the global clear sky index increase with longer time scales from 1-min to 180-min (Figure 2.4a). The 180-min deltas have nearly double the standard deviation of the 1-min deltas. Figure 2.4a shows the standard deviation and 99.7^{th} percentile of the deltas averaged (but not aggregated) across the 23 sites in the SGP

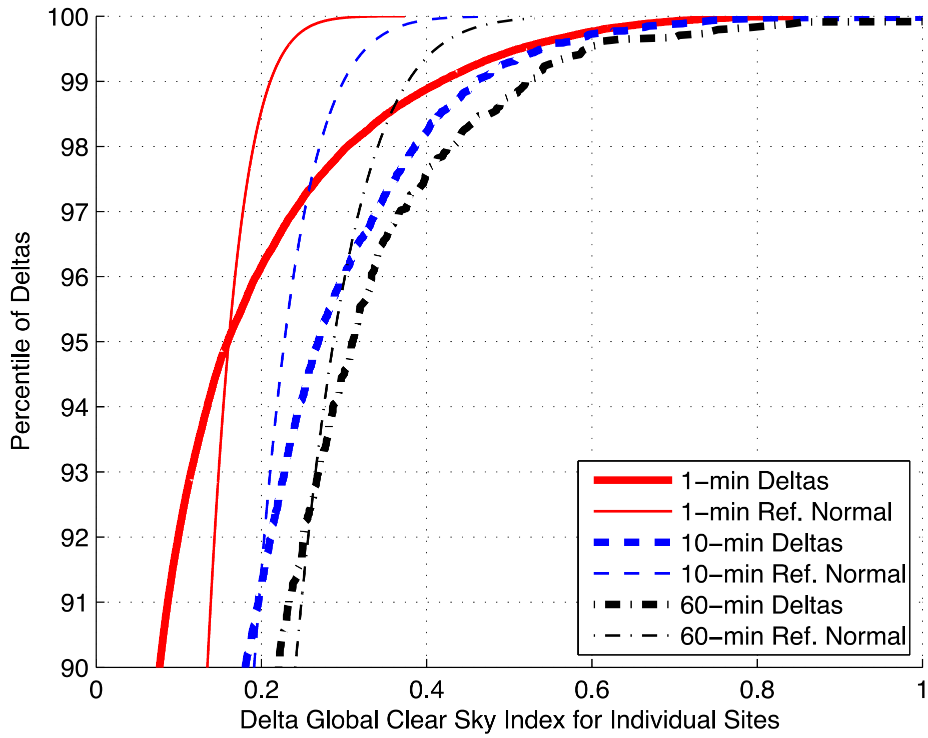
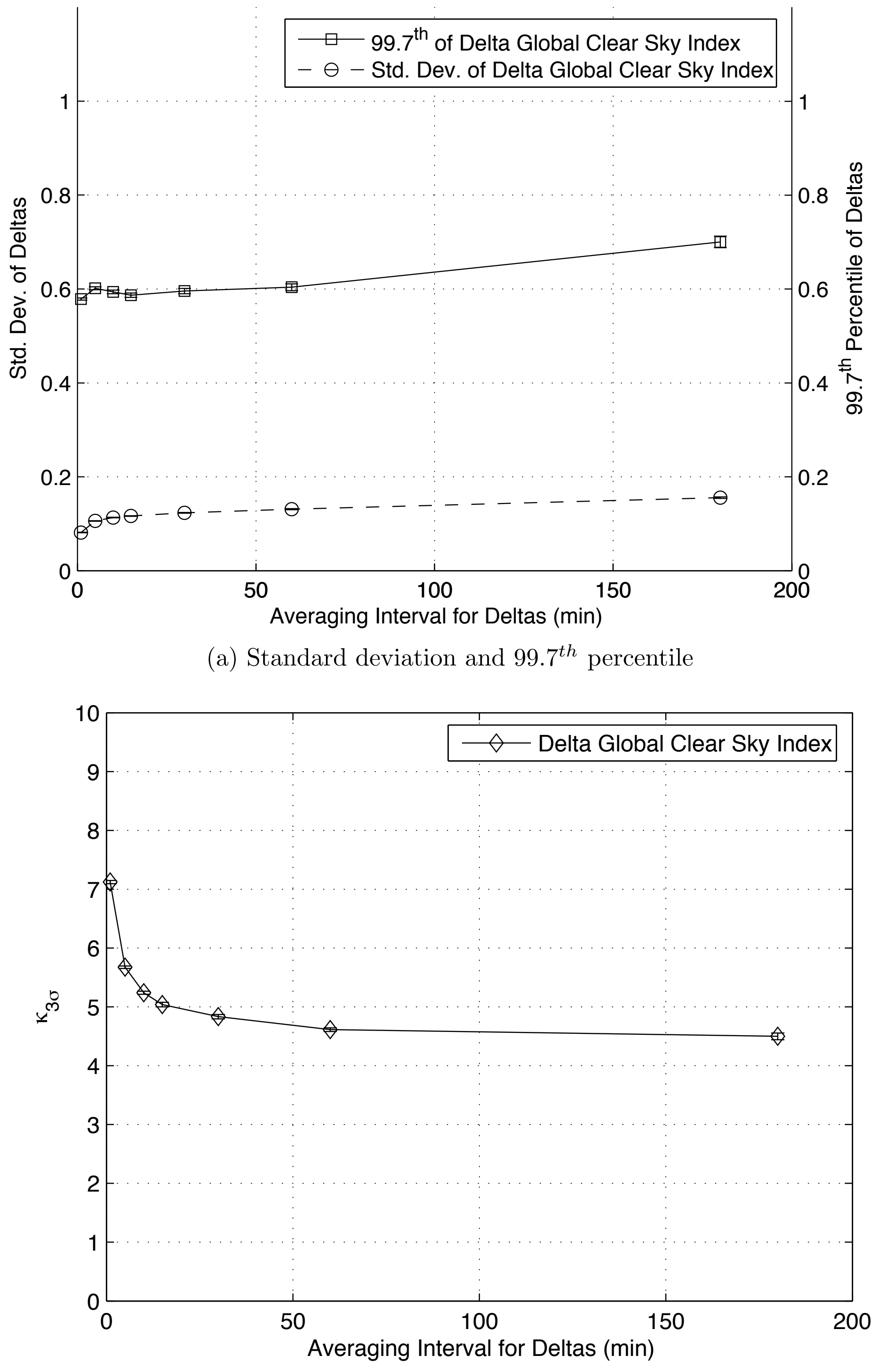


Figure 2.3: Cumulative probability distribution of 1-min, 10-min, and 60-min deltas of the global clear sky index at individual sites in the SGP network. The thin lines show the shape of normal distributions with similar standard deviations as the actual data.

network. The error bars represent +/- one standard error, but are small enough to fit within the markers. The figure shows that 99.7% of the deltas are consistently below about 0.6 for 60-min and shorter deltas. For these time scales, deltas larger than 0.6 are therefore likely to occur less than 0.3% of the year. Another way to interpret these results is that for a single site, the average clear sky index over a 60-min period only has a probability of 0.3% of being 0.6 larger or smaller than the average clear sky index in the next 60-min period.

If the distribution of deltas was normally distributed, 99.7% of deltas would be within three standard deviations. The "fat tails" evident in Figure 2.3, however, lead to the 99.7^{th} percentile being much larger than three standard deviations (Figure 2.4b). The 99.7^{th} percentile of the 1-min deltas, for example, is seven standard deviations. The ratio is reduced for deltas over longer time scales, but even the 99.7^{th} percentile of the 180-min deltas remain more than four standard deviations, demonstrating that the distribution of the deltas with averaging intervals of 1-min to 180-min all have "fat tails" relative to a normal distribution.

The deltas at individual sites therefore demonstrate that severe changes are possible and that they occur more frequently than expected if the deltas were assumed to have the same standard deviation but be normally distributed. The balancing resources required to accommodate 99.7% of the deltas therefore exceeds that which would be required were one



(a) Standard deviation and 99.7^{th} percentile

(b) Ratio of 99.7^{th} percentile and standard deviation

Figure 2.4: (a) Standard deviation and 99.7^{th} percentile of deltas in global clear sky index over different averaging intervals for the individual sites within the SGP network. (b) The ratio of 99.7^{th} percentile and standard deviation of deltas in global clear sky index at individual sites. Error bars represent +/- one standard error from the mean (N = 23).

instead trying to manage variability based on three standard deviations. These deltas for individual sites reflect behavior similar to the assumptions used in many of the previous studies on PV integration. Jewell and Unruh (1990), for instance, simulated up to 50% changes in 1-min output from PV. The electric system modeled in that study was shown to incur inadvertent interchanges with other balancing areas if the penetration of PV was just 2% of the peak system load on a capacity basis. Assuming that the highest deltas in the SGP dataset occurred while the clear sky radiation is sufficient for a PV system to be at its rated capacity, the 1-min deltas in the SGP data could be as severe as 80% of the PV capacity were there no smoothing in the PV plant itself. Deltas above 60% of the rated capacity would be expected 0.3% time, again assuming no smoothing within the PV plant. Changes of this magnitude are found to exist over all averaging intervals from 1-min to 60-min. Such severe changes in PV output would be technically challenging and expensive to accommodate if they did in fact occur with large scale PV deployment.

Correlation of Deltas with Distance

We now turn to a consideration of the correlation of deltas in the clear sky index across a region in order to understand the impact of aggregating the output of several PV sites. Figure 2.5 shows the correlation of deltas across the time-scales of 1-min to 180-min for pairs of sites at different distances from one another. In addition, the figure includes the line of best fit to Eq. 2.8. As shown in the figure, we find nearly zero correlation of 1-min deltas between all 23 sites in the SGP network. Even the closest sites in the network, separated by 20.5 km, demonstrate zero correlation in 1-min deltas. Similar zero correlation for 1-min deltas was found for sites as close as 2 km in Japan by Murata et al. (2009), and nearly zero correlation was found for 1-min deltas on a highly variable day for different inverters within a single 13.2 MW PV plant in the U.S. (Mills et al., 2009a). Clearly, even within a very small region 1-min deltas are nearly uncorrelated.

The near zero correlation for sites as close as 20 km was similarly found for 5-min deltas in the clear sky index. For 10-min deltas, however, a slight increase in the correlation between deltas at the closest sites becomes apparent. Hourly deltas exhibit clearer correlation between sites especially for sites that are closer than about 75 km apart. Three hour deltas are correlated for sites that are even farther apart.

Our use of the clear sky index in this case avoids an issue that is apparent in the analysis of the data used by Murata et al. (2009). Because Murata et al. (2009) use insolation or PV production data to examine the correlation of ramps with distance, the correlation between sites due to the deterministic component of the movement of the sun's position in the sky leads to correlation of ramps longer than about 15-min even for sites that are very far apart.[18] The same problem is apparent in the correlations presented by Curtright and Apt (2008).

[18] For deltas 15-min and longer, the results from Murata et al. (2009) show non-zero correlation for sites as far as 923 km apart. This is because Murata et al. (2009) include the deterministic portion of the PV output in the data used for estimating correlations.

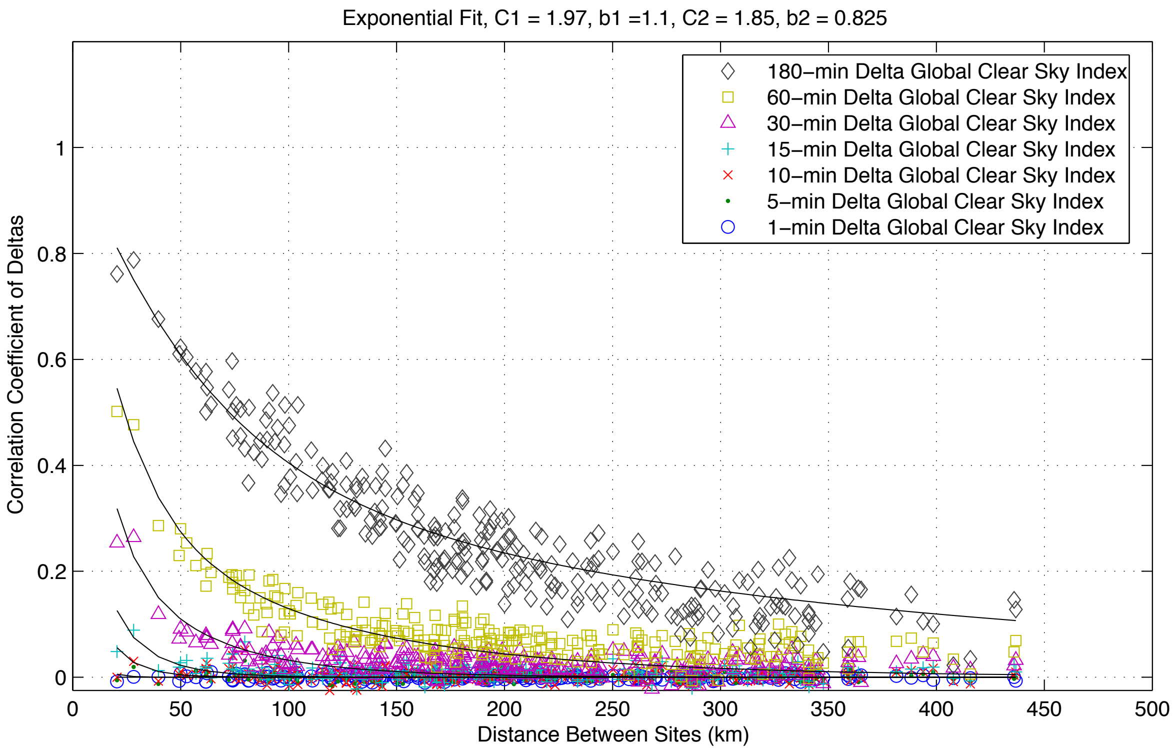


Figure 2.5: Correlation of changes in global clear sky index between 23 geographically dispersed solar insolation measurement sites in the SGP network. (—) Fit to the correlation data to the relationship in Eq. 2.8.

Because the clear sky index removes the influence of this deterministic portion of the data, the correlations we present in Figure 2.5 approach zero with increasing distance.

The near zero correlation for 1-min and 5-min deltas implies that aggregating output from PV sites at least 20 km apart[19] will smooth, as measured by the standard deviation, the 1-min and 5-min deltas by a factor of $\frac{1}{\sqrt{N}}$. Aggregating the output from sites 20 km apart will smooth deltas over longer time scales to a lesser degree than the deltas for shorter time scales due to the greater correlation of deltas with larger averaging intervals.

Aggregate Deltas from Geographically Dispersed Sites

In this section we consider the impact of aggregating geographically dispersed sites. We begin by aggregating the actual point measurements of the clear sky index from the SGP sites and then project the smoothing that would occur from a denser array of PV sites.

[19] Or at least 2 km apart for 1-min deltas and 9 km apart for 5-min deltas, according to the data from Murata et al. (2009).

Smoothing from Aggregating SGP Sites

We first aggregate clear sky data from five close sites[20] within the SGP network and then aggregate the data from all 23 sites within the SGP network.[21] Figure 2.6 shows an example of smoothing from averaging of the global insolation across multiple sites on a partly cloudy day. As expected, the aggregation of the simultaneous output of sites within the SGP network leads to a reduction in the *relative* magnitude of the deltas for all time scales compared to scaling the output of a single site across the entire year. This reduction in the relative magnitude of the deltas is more pronounced for all sites (Figure 2.8) than for five close sites (Figure 2.7). The distribution of the 1-min deltas from the aggregation of sites also appears to be more normal in that the tails of the distribution are less pronounced than the tails of the distribution of 1-min deltas from a single site (Figure 2.3). Aggregating the output from 5 close sites in the SGP network, for example, reduces the magnitude of the most extreme 1-min deltas to below +/- 0.4 from the observed +/-0.8 deltas shown for a single site in the previous section. Aggregating all 23 sites further reduces the most extreme 1-min deltas to below +/-0.2. Assuming that such a severe delta occurred while PV plants were at their rated capacity would lead to a maximum 20% change in the output of all PV plants in 1-min, far below the 80% change that could occur at a single site in 1-min under the same assumptions. Because the reduction in the relative magnitude of the deltas with aggregation is a key result of this analysis, we summarize the cumulative distribution of deltas from individual sites and aggregated sites for convenience in Figure 2.9.

The 99.7^{th} percentile and the standard deviation of the deltas for different averaging intervals is also significantly lower for the five and 23 aggregated sites (Figure 2.10a) than for individual sites (Figure 2.4a). For example, if all of the sites in the SGP network were to be aggregated, the balancing resources required to manage 99.7% of the 1-min deltas of the clear sky index would be only 16% of the resources required to manage 99.7% of the 1-min deltas if the same level of PV capacity were developed at an individual site. This compares to a 22% reduction of the standard deviation of the 1-min deltas when moving from an individual site to 23 aggregated sites.[22] The reduction in the 99.7^{th} percentile is larger than the reduction in the standard deviation due to the tightening of the distribution that also occurred when aggregating the 1-min deltas (Figure 2.10b). While the ratio of the 99.7^{th} percentile to the standard deviation of 1-min deltas at an individual site is 7.1, the ratio of the same parameters for the aggregated sites falls to 4.9 (see Table 2.3). Comparison of the ratio of the 99.7^{th} percentile to the standard deviation shows that reductions in this

[20] The sites are E9, E11-13, and E15. The closest two sites are about 50 km apart. The furthest two sites are about 170 km apart. The area between the five sites is about 7,000 km^2, just larger than the state of Delaware.

[21] The 23 sites with solar data are C1,E1-13, E15, E16, E18-22, E24, and E27. The closest sites are 20 km apart and the furthest sites are 440 km apart. The area of the SGP network is around 143,000 km^2, similar in area to the states of Wisconsin, Iowa, or Illinois.

[22] As described in Section 2.3, the ratio of the standard deviation of the deltas from the aggregate of N uncorrelated sites to the standard deviation of the deltas from a single site is expected to be about $\frac{1}{\sqrt{N}} = \frac{1}{\sqrt{23}} = 21\%$.

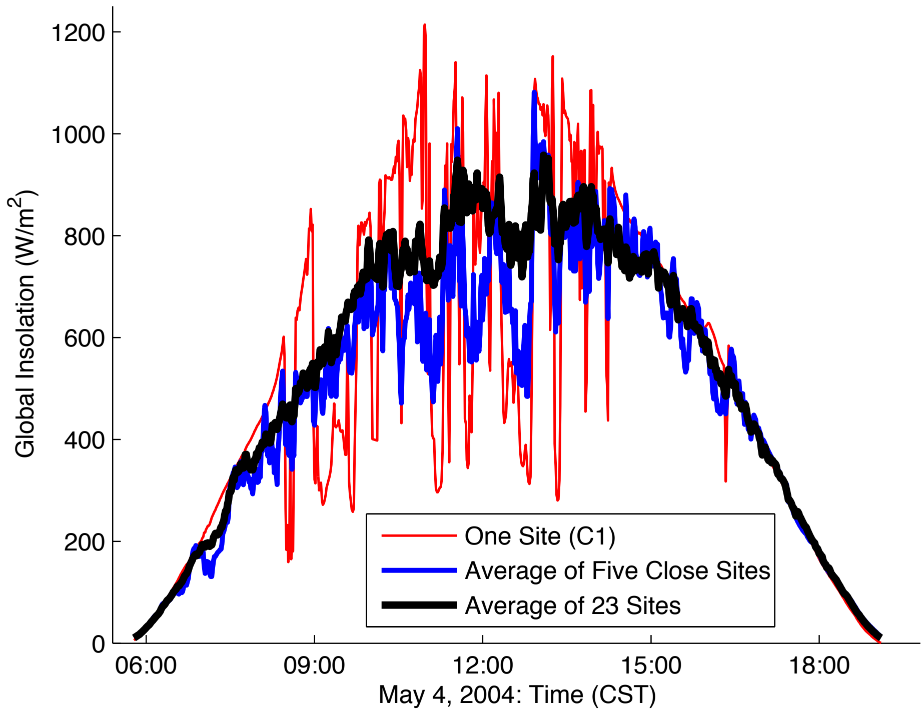


Figure 2.6: Example of 1-min global insolation from one site, the average of five close sites, and the average of all 23 sites in the SGP network on a partly cloudy day.

ratio are apparent for all deltas, especially for those 60-min or shorter. The distributions remain slightly "fat-tailed" relative to a normal distribution, but are much less so than for individual sites.[23]

Whereas the deltas are uncorrelated between all sites in the SGP network for time scales shorter than 5-min, Figure 2.5 shows that there is positive correlation for both 60-min and 180-min deltas between sites in the SGP network. Aggregating the sites that are positively correlated therefore leads to a slightly lesser benefit of geographic diversity than if all of the sites were uncorrelated. The balancing resources required to manage 99.7% of deltas from the 23 aggregated SGP sites would be 31% and 54% of the resources required to manage 99.7% of the 60-min and 180-min deltas, respectively, from an individual site (this compares to 16% for 1-min deltas, as reported earlier).

Smoothing from a Denser Array

The area covered by the SGP network is sizable. Aggregating sites over 400 km apart to achieve the benefits of geographic diversity may not always be feasible, either because individual balancing areas are smaller than this size or because solar resource conditions

[23]Slightly "fat-tailed" distributions for wind variability have also been noted (e.g. Holttinen et al., 2008).

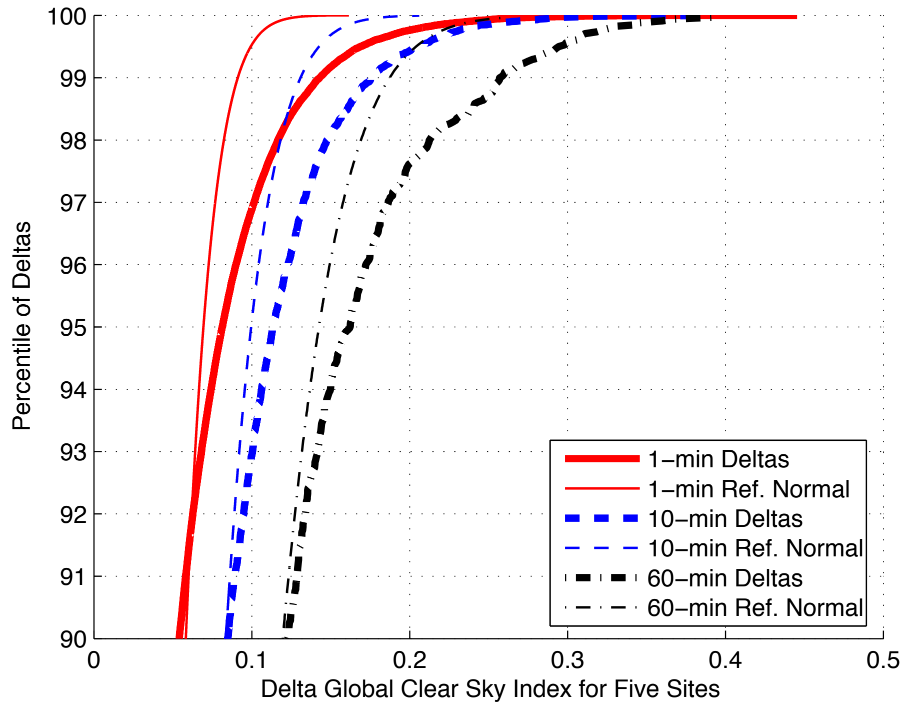


Figure 2.7: Cumulative probability distribution of 1-min, 10-min, and 60-min deltas of the global clear sky index for five close sites in the SGP network aggregated together (N = 5). The thin lines show the shape of normal distributions with similar standard deviations.

Table 2.3: Summary of standard deviation and 99.7^{th} percentile of global clear sky index for individual, 5 close sites, and all 23 sites in the SGP network.

Deltas	$\sigma^{\bar{t}}_{\Delta k}$			99.7^{th} percentile			$\kappa_{3\sigma}$		
	1-min	10-min	60-min	1-min	10-min	60-min	1-min	10-min	60-min
Individual Sites	0.08	0.11	0.13	0.58	0.59	0.60	7.1	5.2	4.6
5 Close Sites	0.03	0.05	0.07	0.19	0.23	0.31	5.5	4.5	4.3
All 23 Sites	0.02	0.03	0.05	0.09	0.10	0.19	4.9	3.9	4.0

or transmission costs support dense spacing of solar plants. In this section we use the fit to the correlation of deltas with distance (Eq. 2.8) the deltas observed at individual sites (Figure 2.4a) and the “diversity filter” (Eq. 2.7) to predict the deltas that would be observed from aggregating a much more dense array of sites. We estimate the maximum of the 99.7^{th} percentile of deltas by conservatively assuming that the ratio of the 99.7^{th} percentile to the standard deviation of the deltas does not change relative to an individual site (see Figure

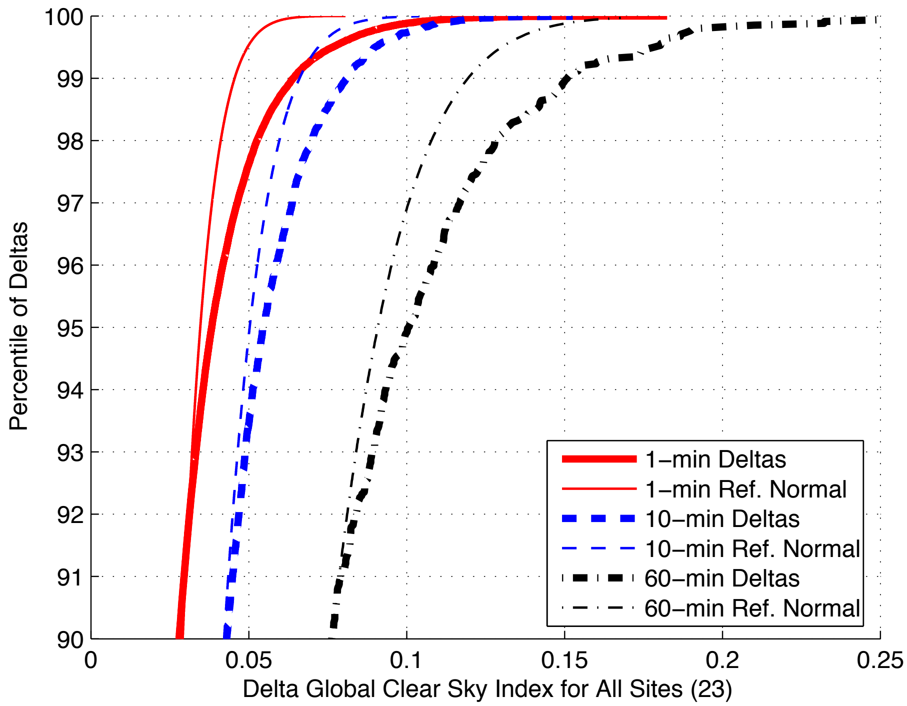


Figure 2.8: Cumulative probability distribution of 1-min, 10-min, and 60-min deltas of the global clear sky index for all sites in the SGP network aggregated together (N = 23). The thin lines show the shape of normal distributions with similar standard deviations.

2.4b). This assumption is conservative since the analysis of the SGP data did show a degree of reduction in this ratio (Figure 2.10b) especially for shorter averaging intervals. We do not know with certainty, however, how the ratio of the 99.7^{th} percentile to the standard deviation would change for a more dense array that includes sites with deltas that are more correlated than the deltas from the sites in the more sparse SGP array.

The array that we simulate is purely to illustrate the potential broader use of the data analyzed from the SGP network. We therefore restrict the array to sites spaced by at least 20 km so that we do not need to extrapolate from the fit in Figure 2.5. Specifically, we use a 10×10 site square array of 100 sites spaced by 20 km on a grid.[24] As shown in Figure 2.11, for an array with these characteristics, we find that the maximum expected 99.7^{th} percentile of the 30-min or shorter deltas would be smaller than the deltas observed from the aggregate of the 23 sites in the SGP network. The relative aggregate variability is reduced because of the increase in the number of sites that are uncorrelated. For longer time scales, however, the close sites within the dense array are more correlated than the sites in SGP network. Over these time scales, therefore, the benefit of the greater number of sites in the dense array is balanced by the fact that the deltas of the sites are more correlated over time scales of

[24]The total area of the dense array would be 40,000 km^2, smaller than the 52,000 km^2 area of San Bernardino County, an area in Southern California with a high solar resource potential.

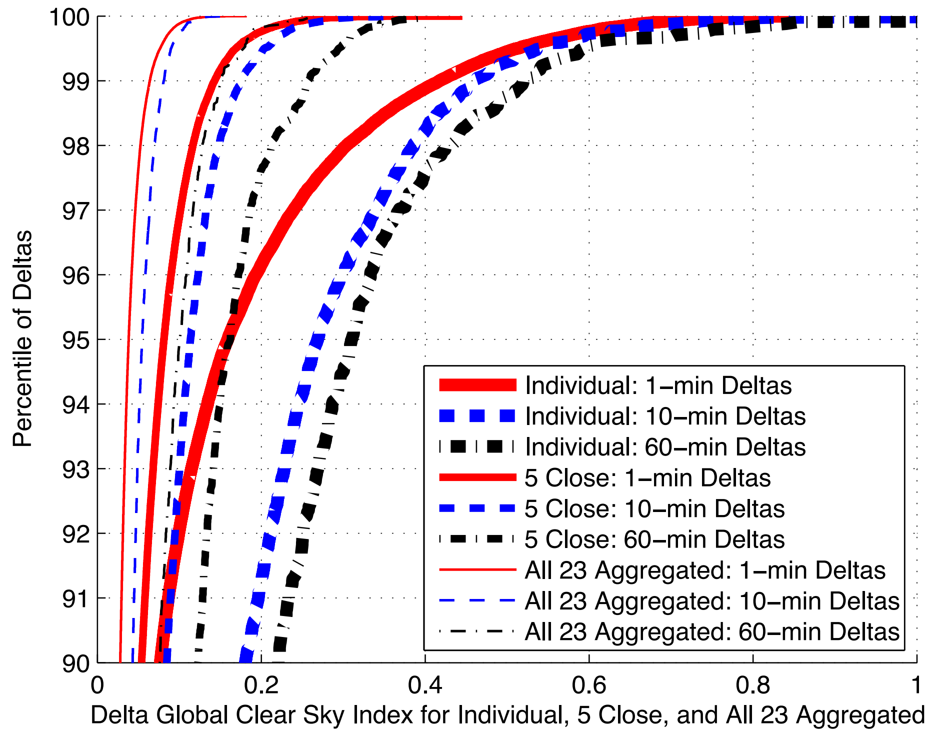


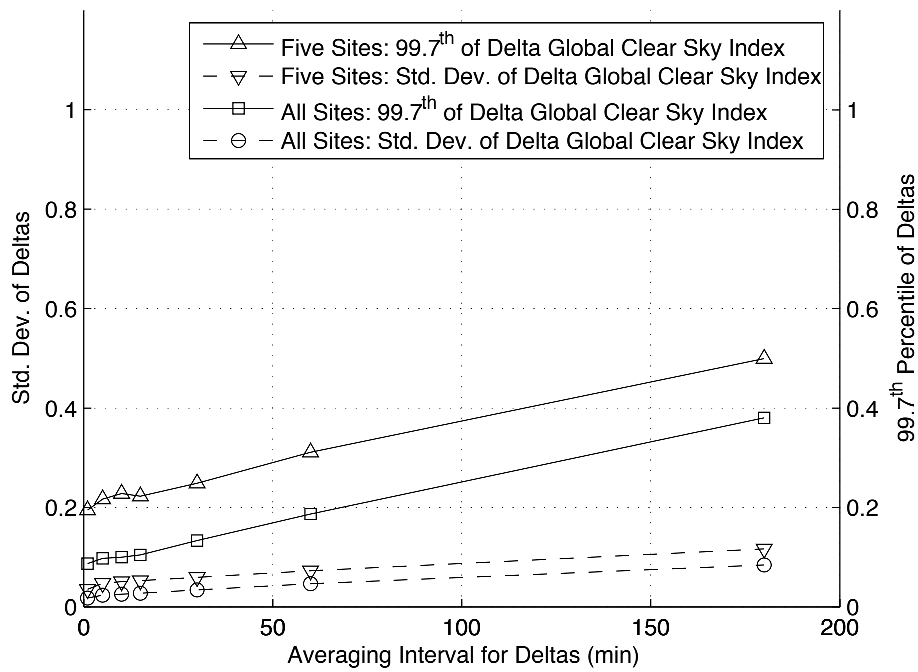
Figure 2.9: Cumulative probability distribution of 1-min, 10-min, and 60-min deltas of the global clear sky index for individual sites, five close sites, and all 23 sites in the SGP network aggregated together.

60-min and 180-min. As a result of the counteracting trends, Figure 2.11 (in comparison to Figure 2.4a) shows that the aggregate variability of the dense array with 100 sites is similar to the aggregate variability of the sparse SGP network with 23 sites for longer time scales.

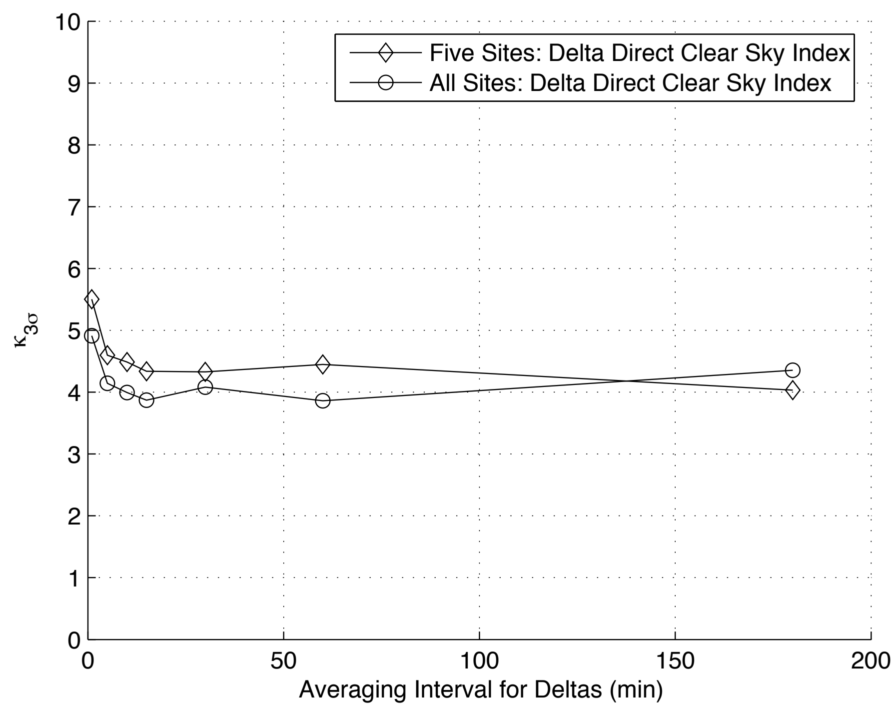
Across all time scales, the simulated dense array requires far fewer resources to manage the aggregate variability than if the same amount of PV were to be installed at a single site with no benefit of geographic diversity. The resources required to manage 99.7% of the deltas for the dense array for time scales of 15-min and shorter are predicted to be less than 10% of the clear sky insolation, six times less than the resources required to manage the variability of the same amount of PV if all solar were to be located at a single site. The resources to manage 99.7% of the 60-min deltas for the dense array is 20% of the clear sky insolation—three times less than if the same amount of PV were based at a single site.

Comparison of Solar and Wind Deltas from Similarly Sited Plants

One way to put these results into perspective is to compare the expected variability from an array of PV sites to a similarly spaced array of wind sites. We performed a similar analysis for 1-min normalized wind power data estimated from 10 wind speed measurement sites



(a) Standard deviation and 99.7^{th} percentile



(b) Ratio of 99.7^{th} percentile and standard deviation

Figure 2.10: (a) Average standard deviation and 99.7^{th} percentile of deltas in global clear sky index from five close sites and all sites aggregated together in the SGP network over different averaging intervals. (b) The ratio of 99.7^{th} percentile and standard deviation of deltas in global clear sky index from five close sites and all sites aggregated together in the SGP network.

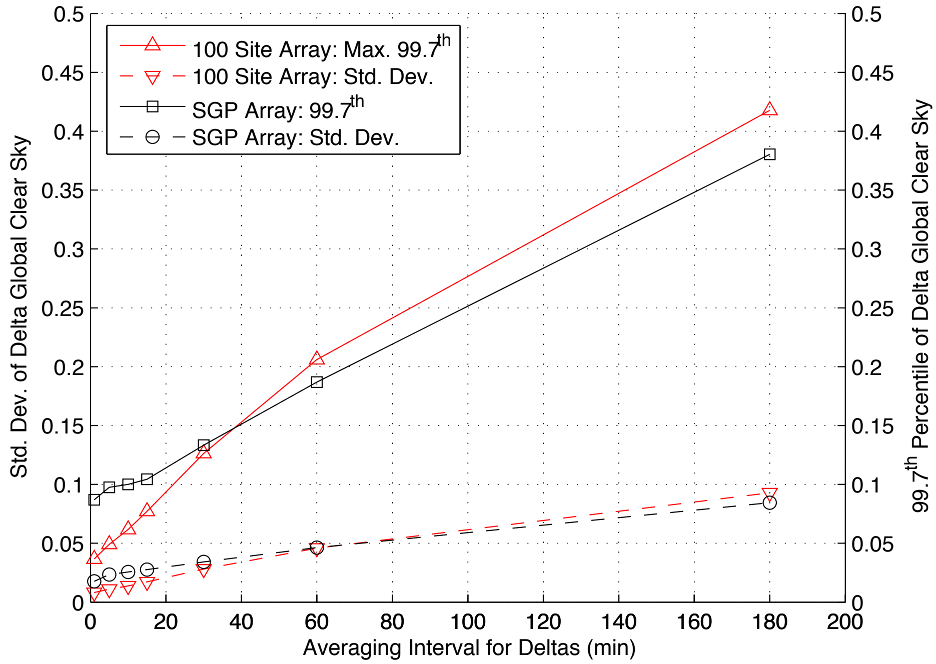
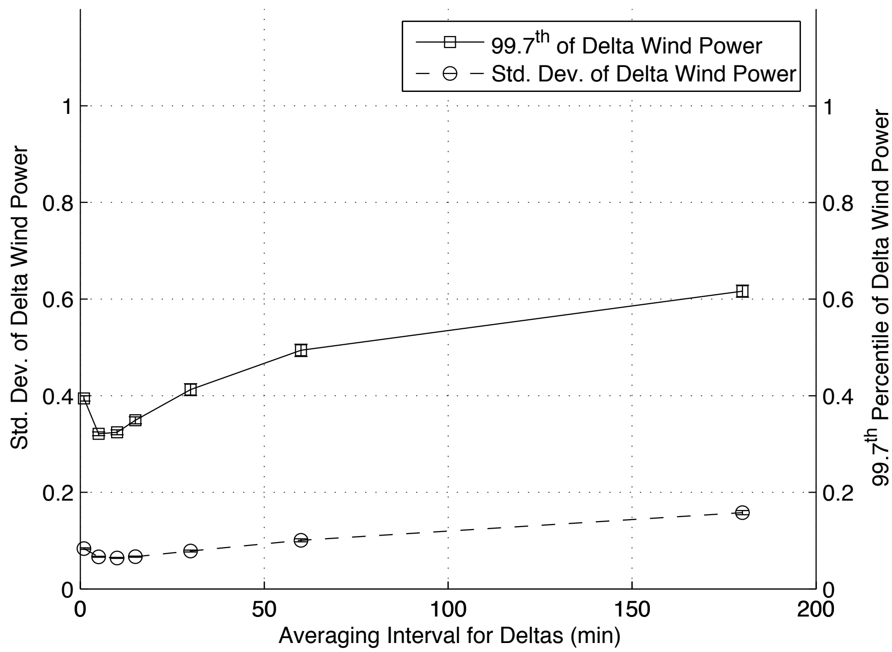


Figure 2.11: Comparison of the standard deviation and 99.7^{th} percentile of deltas in global clear sky index for the individual sites within the SGP network compared to the same for a simulated array of 100 sites arranged in a more dense 10×10 grid with 20 km spacing between sites.

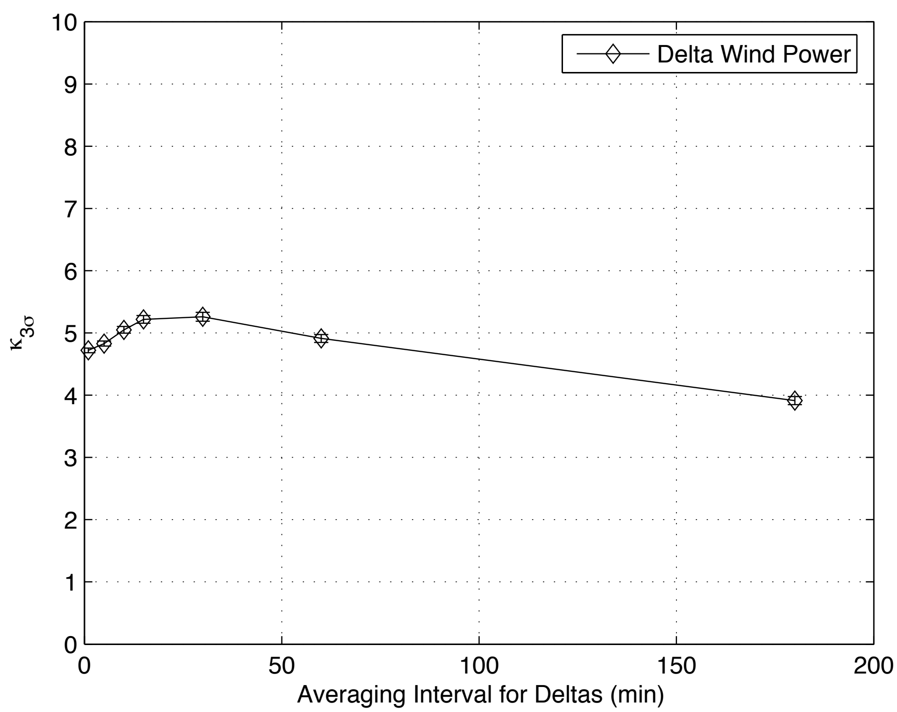
within the SGP network. Namely, we estimated the deltas of the normalized wind power at individual sites (Figure 2.12a) the ratio of the 99.7^{th} percentile to the standard deviation of the deltas (Figure 2.12b) and the correlation of deltas as a function of the distance between sites and the time scale of the deltas (Figure 2.13).

The standard deviation of 1-min deltas at individual wind sites was comparable to the 1-min deltas of the clear sky index at individual sites, but the standard deviation of deltas over longer time scales were somewhat less for the wind sites. The 99.7^{th} percentile was significantly less for wind than for solar, especially for 60-min and shorter averaging intervals. The tails of the 1-min and 5-min delta distributions were slightly less "fat" for wind than for solar (Figure 2.12b). The correlation of wind deltas for dispersed sites in the SGP network demonstrated similar behavior as found for solar and previous studies using actual wind turbine output in Germany (Ernst et al., 1999). Overall, however, deltas for wind were slightly more correlated than deltas for solar (the non-deterministic component measured by the clear sky index) for any given distance, particularly for deltas longer than 30-min (Figure 2.13). This comparison of the correlation with distance and variability at individual sites suggests that wind is less variable than solar at individual sites, but wind in this region benefits slightly less from geographic diversity than does solar.

Next we use the fit to the correlations in Figure 2.13 based on Eq. 2.8, the deltas observed



(a) Standard deviation and 99.7^{th} percentile



(b) Ratio of 99.7^{th} percentile and standard deviation

Figure 2.12: (a) Standard deviation and 99.7^{th} percentile of deltas in normalized wind power over different averaging intervals for the individual sites within the SGP network. (b) The ratio of 99.7^{th} percentile and standard deviation of deltas in normalized wind power at individual sites. Error bars represent +/- one standard error from the mean (N = 10).

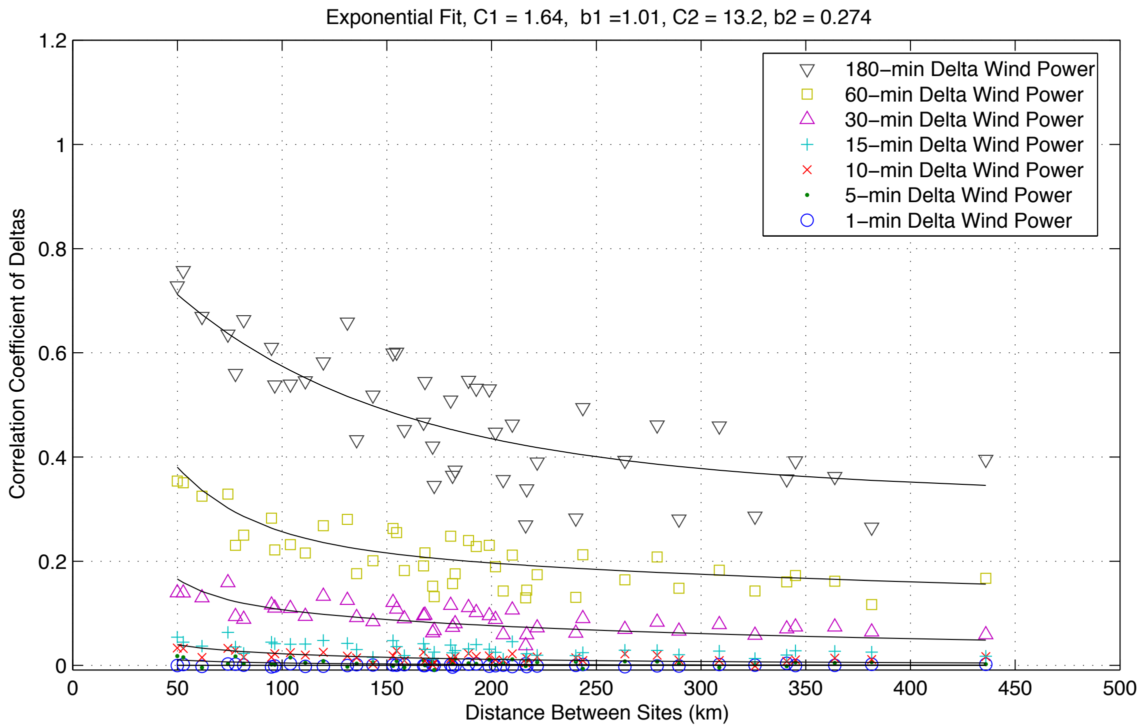


Figure 2.13: Correlation of changes in wind power between 10 geographically dispersed wind speed measurement sites in the SGP network. (—) Fit to the correlation data to the relationship in Eq. 2.8.

at individual sites (Figure 2.12a) and the "diversity filter" (described by Eq. 2.7) to predict the deltas that would be observed from aggregating an array of wind sites for comparison to a similarly arranged array of solar sites. The array we chose for this section was again based on the constraint that we did not want to extrapolate from the data obtained from the SGP network. Since the closest wind measurement sites were 50 km apart, we simulate a 5 × 5 site square array of 25 sites spaced by 50 km on a grid for both solar and wind (see Figure 2.14 and note that the solar array included here is a different arrangement of sites than the arrays evaluated in Section 2.5). The 99.7^{th} percentile is again estimated for both solar and wind by assuming that the ratio of the 99.7^{th} percentile to the standard deviation for the array is equivalent to the ratio for a single site.

The results of this simulation demonstrate that the standard deviation of the deltas of similarly sited solar and wind plants in the 5 × 5 array are reasonably comparable, particularly for 30-min and longer deltas. The 99.7^{th} percentile of the 5 to 15-min deltas are notably smaller for wind, however. If balancing resources were procured based on the 99.7^{th} percentile, for example, the 10-min deltas for solar would require nearly double the balancing resources that wind requires.[25] The results also show for both the aggregated solar and wind,

[25]We tested a variety of different spacings for the array of sites to determine if these conclusions depended

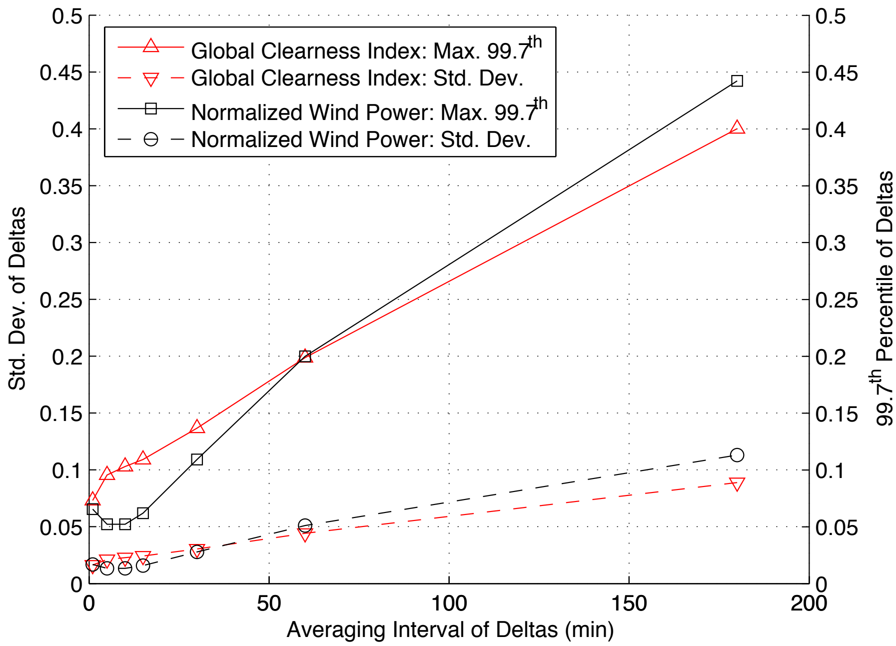


Figure 2.14: Comparison of the simulated standard deviation and 99.7^{th} percentile of deltas in global clear sky index to normalized wind power from similarly arranged array of 5×5 grid with 50 km spacing between sites.

the longer time scale deltas are expected to be much larger in magnitude than the shorter time scale deltas. The 60-min deltas, for instance, are double or greater the magnitude of the 15-min and shorter deltas.

Potential Cost Impacts

Detailed studies of the changes in power system operations required to manage the short time-scale variability of PV are required to fully understand the cost implications of short-term PV variability. As a first approximation, however, we can use a simple method and set of assumptions to estimate the cost of managing the short time-scale variability of solar. With this simple method, we examine the relative difference in cost of managing solar all based at a single site, solar dispersed over multiple sites, and similarly sited solar and wind. Our comparison lacks any consideration of within-plant smoothing based on geographic diversity, which may be relatively more important for short time scales (1-10 min) for wind

on our choice of array spacing. Although the overall shape of Figure 2.14 changes, the primary conclusions still hold with other array orientations.

in comparison to solar due to the lower areal density of wind plants.[26] Regardless, we rely on a simple method to estimate the additional cost of holding spinning or utilizing non-spinning reserves to accommodate the short-term variability of PV and wind assuming a 10% penetration of wind or solar (on a capacity basis). These costs only address the short-term variability and do not address other costs (e.g., unit commitment costs due to day-ahead forecast errors) or benefits (e.g., capacity value and energy value) of PV.

Estimated Cost of Reserves

The estimated increase in the cost of balancing reserves per unit of variable generation relative to the cost of balancing reserves without variable generation is summarized in Table 2.4. The costs for a single site and five close sites of solar are based on the standard deviation of the deltas for the different time scales observed in Figure 2.4a and Figure 2.10a, respectively. The costs for a 25 site grid of solar and wind are based on the standard deviation of the deltas for the different time scales projected in Figure 2.14. Again, the standard deviation is used because we do not use 1-min time synchronized load data from the same region to determine the shape of the distribution of the net load deltas. The results in the four leftmost columns of Table 2.4 shows the cost of balancing reserves assuming that to accommodate the increase in solar or wind system operators conservatively increase reserves at a constant level throughout the year ("Reserves Constant Throughout Year"). The column on the right shows the increase in the cost of balancing reserves for the 25 site grid of solar assuming, instead, that system operators set the additional reserves knowing that the variability of the solar output will change with clear sky insolation ("Reserves Change with Position of the Sun"). This captures the fact that system operators do not need to maintain reserves for solar at night and fewer reserves are required when clear sky insolation is low. The opportunity cost of capacity, however, is assumed to be based on only the peak net-load hours of the year and therefore does not change from hour-to-hour.

Placing all of the solar at a single point and holding reserves constant throughout the year leads to an increase in the cost of balancing reserves that is large enough to substantially erode any value of adding solar to the power system. Adding the same quantity of solar to the grid at the five locations that correspond to the five closest sites in the SGP network, however, increases the cost of balancing reserves relative to load alone by only about a quarter of the increase in costs from adding the solar at a single point. Further spreading the same quantity of solar to 25 sites in a 5 × 5 grid leads to an increase in the cost of balancing reserves that is only about 7% of the cost of adding the solar at a single site. Clearly, the number and orientation of the solar systems added to the grid will have a substantial impact on the overall increase in balancing reserves and the associated cost to manage the sub-hourly variability of PV. The earlier studies listed in Table 2.1 that scaled the output of single sites

[26] Assuming a solar plant density of 20 W/m^2 (Denholm and Margolis, 2008), a 100 MW plant would cover an area of 5 km^2 or a square 2.2 km long on a side. Wind plant density, on the other hand, is around 5W/m^2 due to the spacing between turbines within a plant (U.S. Department of Energy (DOE), 2008, p. 156). A 100 MW wind plant would cover an area of 20 km^2 or a square 4.4 km on a side.

and found limits to the penetration of PV based on short-term variability may have come to dramatically different conclusions had they accounted for the potential smoothing effects of geographic diversity.

The cost of balancing reserves for geographically diverse solar sites is also not expected to be substantially different than the cost for similarly sited wind. The slightly greater variability of solar than similarly sited wind for time scales shorter than 60-min projected in Figure 2.14 leads to a slightly greater increase in the cost of balancing reserves for solar than for wind if the increase in balancing reserves is constant throughout the year. If the required increase in balancing reserves is in proportion to clear sky insolation, however, the cost of balancing reserves for solar can be nearly identical to the cost of balancing reserves for wind. The decrease in the cost of balancing reserves when reserves are held in proportion to clear sky insolation is due to the fact that no reserves are needed for solar at night. The increased costs of balancing reserves for similarly sited solar and wind in a 5 $\times$ 5 grid are modest, but these results should be verified with more detailed solar and wind integration studies.

Table 2.4: Estimated unit cost of reserves to manage short-term variability

Time Scale	Increased Reserve Costs ($/MWh)				
	Reserves Constant Throughout Year				Reserves Change with Position of Sun
	Solar			Wind	Solar
	1 Site	5 Sites	25 Site Grid		
1-min Deltas	$16.7	$4.8	$1.2	$0.9	$0.8
10-min Deltas	$17.3	$4.4	$1.0	$0.2	$0.7
60-min Deltas	$5.0	$1.6	$0.6	$0.5	$0.5
Total Cost	$39.0	$10.8	$2.7	$1.6	$1.9

2.6 Conclusions

Our analysis demonstrates that step-changes or deltas in solar insolation at individual points can be severe. Infrequent step changes from one averaging interval to the next with averaging times from 1-min to 180-min can exceed 60% of the clear sky insolation. The distributions of sub-hourly deltas at individual sites are fat-tailed relative to a normal distribution. The 99.7^{th} percentile of the deltas, therefore, is much larger than three standard deviations.

Previous studies of the integration of PV into the electric power system demonstrate that scaling the output from an individual solar site leads to limits of the penetration of PV on the grid. The limit is due to the additional balancing resources required to accommodate the variability of PV plants, and the variability over short time scales (sub-hourly) is found to be particularly challenging to accommodate. Increasing balancing reserves to accommodate the variability of solar located at a single point is estimated to lead to a significant increase in costs and, as suggested by earlier studies, could limit the amount of solar that can be added to the power system.

As is well known for wind, however, accounting for the potential for geographic diversity can significantly reduce the magnitude of extreme deltas, the resources required to accommodate variability, and the potential increase in balancing reserve costs. The aggregate of just five close sites in the SGP network show that 99.7% of the 15-min and shorter deltas are no larger than 25% of the expected clear sky output of the aggregated sites. Furthermore, we estimate that 99.7% of the 15-min and shorter deltas from 100 sites in a 10 $\times$ 10 grid with 20 km spacing would be no larger than 10% of the clear sky output of the aggregated sites (this compares to 60% for an individual site). We also find that the sub-hourly deltas from similarly sited solar and wind are expected to be within the same order of magnitude, though deltas in the 5-15 min range are expected to be somewhat more severe for solar than for wind.

The cost of accommodating the short-term variability of similarly sited solar and wind plants is expected to be comparable in this region, but further research is required to understand the costs of managing the variability and the within-plant smoothing for solar that can occur on shorter time scales. Moreover, the non-normal distribution of deltas indicate that more detailed studies may wish to focus on managing variability for a target maximum percentile (i.e., directly estimate reserves to manage the 99.7^{th} percentile events rather than assume that the distribution is normal and three standard deviations is equivalent to the 99.7^{th} percentile). Consideration of variability on time-scales of about 15-minutes or longer, meanwhile, should be careful to account for the deterministic changes in PV plant output due to changes of the position of the sun. Future studies should evaluate the spatial and temporal scales of geographic diversity in regions where PV is expected to be deployed in large quantities, particularly the desert Southwest. High time resolution (1-min or less), time-synchronized data for multiple sites separated by a distances of 2km to 200 km is required for such future work. Finally, although it was not considered in this study, studies of regions that expect both PV and wind deployment should evaluate the potential for the same balancing reserves to accommodate variability of both PV and wind.

Chapter 3

Changes in the Value of Variable Generation

3.1 Introduction

Long term decisions regarding how much renewable energy to procure, what type of renewable energy to procure, and what supporting infrastructure to build are made difficult by the variable and unpredictable nature of some renewable resources, in particular wind and solar. In order for decisions to be made on an economic basis, the costs of procuring variable renewables needs to be compared to the benefits of those renewables. The costs side of the equation considers metrics like the levelized cost of energy (LCOE) or the cost of a power purchase agreement (PPA) (Barbose et al., 2011; Fischedick et al., 2011; Wiser and Bolinger, 2011). The costs can also include the contribution of renewables in expanding the need for infrastructure, like the bulk transmission network, to deliver renewables supply to electric loads (Holttinen et al., 2011; Mills et al., 2011, 2012). The benefits side, also called the "avoided costs", can include a wide range of factors including hedging against fossil fuel price fluctuation, reducing environmental impacts from other sources of electricity, and avoiding fuel, operations and capital cost expenditures from operating other power plants (Angeliki, 2008). Renewable resources that are sited on the distribution system near electric loads have further potential benefits of reducing electrical losses and avoiding expenditures related to transmission and distribution (T&D) system infrastructure. The potential benefits depend on a wide range of factors including penetration level, generation profile, and network characteristics (Cossent et al., 2011; Passey et al., 2011).

This chapter only focuses on quantifying the benefits side of this equation and it further only focuses on a subset of the benefits. The objective of the research is to quantitatively examine the marginal economic benefits of additional variable renewables in avoiding the capital investment cost and variable fuel and operations and maintenance (O&M) costs from other power plants in a power system while including operational constraints on conventional generators and the increased need for ancillary services from additional variable renewables.

This subset of the benefits of renewables will be referred to as the "marginal economic value" in this paper, though it is recognized that this narrow definition of marginal economic value focuses only on certain direct cost savings of renewable energy in wholesale electricity markets and does not include many other impacts that renewable energy sellers, purchasers, and policymakers might and do consider. The analysis does not include impacts to the transmission and distribution system so the potential benefits or costs of distributed generation are excluded from this chapter. This chapter also does not consider externalities, public benefits, or renewable energy costs in evaluating the narrowly defined economic value.

The primary focus of this research is in determining how the economic value of variable renewables changes with increasing penetration levels. The economic value with increasing penetration levels is compared between four renewable technologies: wind, single-axis tracking photovoltaics (PV),[1] concentrating solar power (CSP) without thermal storage (CSP_0), and CSP with 6 hours of thermal storage (CSP_6).[2]

The purpose of comparing four different technologies at many different penetration levels is to highlight the drivers of changes and differences in the value of variable renewables along with areas where further research is warranted. In addition to examining the changes in the value of variable renewables with increasing penetration, a case where the penetration of a flat block of power that delivers electricity on a 24×7 basis is increased in a manner similar to the variable generation cases for comparison purposes.

This chapter loosely uses California as a case study to explore these impacts, and relies on an investment and dispatch model that simultaneously considers long-run investment decisions and short-run operational constraints using hourly data over a full year. The dispatch model does not include transmission constraints nor does it consider the potential for generation outside of the case study area (California in this chapter) to be displaced or to provide flexibility in managing increased variable generation. Variable generation that is sited outside of California, however, is assumed to be able to be dynamically scheduled into California, such that all of the variability and uncertainty is managed within California. The

[1]

Deployment of PV is currently a mix of fixed PV with various orientations, single-axis tracking PV, dual axis tracking PV, and concentrating PV. This chapter only evaluates single-axis tracking PV tilted at an angle equivalent to the latitude of the PV site. Though the exact numerical results will likely differ across the different PV technologies or combinations of PV technologies, analysis of the value of PV at low penetration demonstrates that the value of PV differs by less than \$10/MWh between fixed PV tilted at the latitude and oriented toward the south and tracking PV. Between single-axis tracking at zero tilt, single-axis tracking at latitude tilt, and dual axis tracking the differences in the marginal economic value at low penetration are less than \$3/MWh.

[2] This chapter does not consider the potential for natural gas firing in the steam generator of a CSP plant nor does it consider hybrid solar-conventional plants where steam from the solar field is injected into the feedwater system of a conventional thermal plant (e.g. the steam cycle of a CCGT or a coal plant). Furthermore, thermal storage for CSP, which is dispatched based on system needs within the dispatch model, is limited to 6 hours in the majority of the scenarios except one test of the economic value of CSP with 10 hours of thermal storage at 20% penetration. These potential mitigation options for CSP could be considered in future research.

model was designed to quickly evaluate the economic value of variable renewable resources over a wide range of penetration levels and a variety of sensitivity scenarios.

Absent from this analysis is an evaluation of several strategies that might be available to reduce any decline in economic value of variable renewables with increasing penetration. These strategies, including technology diversity (i.e., combinations of VG technologies), more flexible thermal generation, price responsive demand through real-time pricing programs, and low cost bulk power storage, may increase in value with increasing penetration of variable renewables and in turn, may increase the economic value of variable renewables at higher penetration levels. The next chapter will use the same framework presented here to evaluate the impact of these strategies in more detail. In addition, assumptions regarding the interaction of California with generation and loads in the rest of the Western Electricity Coordinating Council (WECC) could be examined in the future since excluding the rest of WECC from this analysis is potentially an important assumption.[3]

The remainder of this chapter begins by reviewing the existing literature regarding the economic value of variable renewables and changes in that value with increasing penetration levels. The review focuses on describing the importance of the long-run economic value of variable energy generation while also considering operational constraints in conventional power systems. The following section outlines the methodology used in this chapter to evaluate the economic value of variable generation (VG) with increasing penetration levels, including a description of how investment decisions in non-VG resources are made in the model, how those resources are dispatched, and how long-run wholesale electricity prices are calculated. The methodology section also explains the implied capacity credit of variable generation and how the economic value of variable generation is decomposed into several different components. The data and assumptions section provides further detail on the

[3]Regarding the marginal economic value of variable generation the assumption that the rest of WECC is ignored may understate the value at high penetration levels for the following reasons:

- If the rest of WECC has low VG penetration then the effective penetration considering all of WECC will be lower than the effective penetration considering only California.
- The rest of WECC has additional incumbent sources of flexibility including large hydro resources and additional pumped hydro storage that are not included. Furthermore additional thermal generation may be able to help manage variability and uncertainty so that California generators do not need to provide as much flexibility.
- Some loads in the rest of WECC have peak periods that correspond with heating loads in the winter evening which may increase the capacity value of wind.

This assumption may also overstate the value at high penetration levels for the following reasons:

- WECC has additional generation with low variable costs or limited flexibility, including incumbent coal and nuclear generation. Expanding the analysis footprint to all of WECC would increase the overall proportion of these resources thereby decreasing the energy value and increasing the curtailment of variable generation.

Without more detailed analysis it is not possible to say with certainty which of these factors would have the biggest impact on the marginal value of variable generation at high penetration levels.

quantitative input values used in the case study presented in this chapter of increasing penetration of variable generation for 2030 in California. The results section then summarizes the long-run dispatch and investment results for different penetration levels of variable generation to help understand the long-run economic value of variable generation. The long-run value of wind, PV, and CSP with and without thermal storage are then compared with increasing penetration and that value is then decomposed into several constituent parts. Sensitivity cases that include relaxing thermal and hydro operational constraints, adding a carbon tax, reducing the cost of resources that primarily provide capacity (i.e., combustion turbine peaker plants), and assuming that no thermal plants retire for technical life reasons by 2030 are then used to better understand the factors that impact the economic value of variable generation. Key findings from the results are then summarized in the final concluding section. The appendices provide an overview and detailed description of the model developed for and used in this chapter, numeric values for parameters used to characterize thermal and hydro generation, and additional results from the sensitivity scenarios.

3.2 Background

Before describing the methodology used to evaluate the economic value of variable generation with increasing penetration levels in Section 3.3, this section first provides motivation for the detailed focus on the economic value of variable renewables, outlines approaches for estimating long-run economic value, and identifies previous studies of the economic value of variable renewables. The majority of the existing literature that covers the economic value of variable generation focuses on wind, though more recent studies have begun to evaluate the economic value of solar. This section again only focuses on literature that covers the limited definition of economic value used in this chapter, which covers direct investment costs, fuel costs, O&M costs for conventional generators and excludes investment costs for variable generators, T&D impacts, and other public benefits. This narrow focus does not provide a full cost/benefit analysis of variable generation, but it does allow clear exploration of a subset of the issues that would drive a full cost/benefit analysis.

Role of Economic Value in Renewable Procurement Decisions

The need to better understand the economic value of variable renewables was recently highlighted by Joskow (2011) and Borenstein (2012). Joskow argues that it is inappropriate to make economic comparisons of variable generation resources based only on life cycle costs or LCOE metrics. The reason that comparisons based on LCOE alone are inappropriate is that the economic value of a unit of energy depends on the time when the energy is generated, or more specifically, the conditions of the power market during that time. The value of energy, as captured by wholesale power market prices, can vary by orders of magnitude depending on whether the power system has ample low cost generation available or little generation of any sort available. Energy that is generated during times when prices are high is much more valuable than energy generated during times when prices are low. Economic comparisons between different generating technologies need to therefore account for how well correlated generation is with these times. Since LCOE comparisons do not account for differences in value depending on when energy is generated, these comparisons do not reflect differences in the value of a resource to a power system.

An alternative to comparing resources simply based on LCOE metrics or PPA prices is to compare them based on their relative total net benefits. The total net benefit in this case might be estimated by subtracting the total costs of a resource from the total revenues it would earn by selling its power into a wholesale power market with time varying prices, a "market test". Analogously, this test can be restated as: does the short-run profit of a resource exceed its fixed costs of investment and operations, where the short-run profit is the difference between the total revenues earned if power were sold at prevailing wholesale market prices and the generator's variable costs (i.e., fuel, wear & tear, and O&M).[4] As noted by Borenstein (2012), there is active debate regarding the extent to which variable renewables impose costs that cannot be reflected in energy market prices because the costs are due to actions that power system operators take outside of the normal market timelines. In particular, system operators may need to add additional operating reserves or some other form of non-energy market product (e.g. a "ramping product") to accommodate variability and uncertainty that is not resolved within the timelines of the power market (e.g., reserves to manage sub-hourly variability and uncertainty in a market where the shortest scheduling interval is hourly). In this case, the market test can be modified by further subtracting any estimated share of additional costs due to the variable generators from the short-run profit.

This comparison can be carried out for any potential generation investment. Those resources whose short-run profits exceed fixed costs are the resources that are economic, not considering the other factors that might impact decisions mentioned earlier. Those resources whose short-run profits fall short of fixed costs require additional sources of revenue or a reduction in costs in order to also be economic. The required increase in revenue or decrease in costs depends on the size of the gap between the short-run profit and the fixed costs. The idea of "grid parity" for any resource could similarly be interpreted as the point where the fixed cost of the resource equals the short-run profit of that resource in a power market.

Previous analysis of the sensitivity of renewable resource procurement decisions and transmission expansion in the Western Interconnection (Mills et al., 2011) used a similar framework to the approach advocated by Joskow and Borenstein. The analysis used a simplified framework where different renewable resource options were compared based on the delivered cost of the renewables net the market value of these renewables to load zones throughout the western United States. The analysis found that resource procurement and transmission

[4] Often individual renewable energy plants sell their output directly to a load serving entity through a long-term contract based on a fixed price per unit of energy. In this case, the net benefit can be calculated from the perspective of the purchaser where the total cost is represented by the price paid for the power (the PPA price) and benefits are the time-varying avoided costs from not needing to buy the same amount of power from the wholesale power market at that time. In this fashion the perspective shifts from the resource owner to the resource purchaser, but the net benefits of the resource remain quantitatively similar.

expansion decisions in the Southwest were sensitive to factors affecting the cost of generating renewable energy (the bus-bar costs), the costs of delivering renewable resources to loads (the transmission costs), and the economic value of the renewables to loads (the market value). Depending on the scenario, resources would shift between wind and solar and transmission needs would similarly shift between high quality solar resource regions in the Southwest and various high quality wind resource locations throughout the West. The base solar technology assessed in the previous analysis was CSP_6; PV and CSP_0 were included in sensitivity cases. For a 33% renewable energy target, the solar penetration, in terms of the total amount of energy generated by solar as a percentage of the annual demand,[5] was found to vary between 4–13% and the wind penetration was found to vary between 12–21% depending on the scenario.

One of the simplifying assumptions in the screening tools used in that study was that the economic value of the renewables did not change with penetration level. Part of the motivation of the present chapter was to develop a better understanding of how the economic value of variable renewables changes at increasing penetration levels. To develop this understanding a much more detailed investment and dispatch model was required to evaluate the economic value component with increasing penetration levels. As will be explained, one of the main findings of this analysis is that the marginal economic value of variable renewables does change between low penetration and high penetration, particularly for PV and CSP_0.

Projections of high future penetration levels of variable renewables are common. Contributing to these projections in the U.S. are the 29 states in the U.S. with renewable energy standards, including California which is set at 33% renewables by 2020 (Wiser and Bolinger, 2011). In addition, the U.S. Congress has in the past considered further supporting clean energy with federal standards. The European Union set an overall binding share of gross final energy consumption of 20% renewables by 2020 (IEA, 2010). As a result of this binding target, renewable electricity is expected to provide 37% of Europe's electrcity in 2020 with wind and solar both making substantial contributions (European Commission, 2011). Combined with interest in variable renewables in other countries and operating experience in countries with high penetration of wind energy, it is clear that there is strong interest in understanding the impacts of high penetration of renewable energy.

There is also interest in high penetration of variable renewables in studies that focus on mitigating climate change. In one assessment of 162 different climate mitigation and future energy scenarios, the percentage of electricity from wind energy in aggressive mitigation scenarios by 2030 was around 10% in the median scenario with the 75^{th} percentile approaching 25% wind penetration. The percentage of electricity from PV in the aggressive mitigation scenarios by 2030 reached only around 1% in the median scenario and 7% in the 75^{th} percentile scenario though with more-sizable growth after 2030 (Krey and Clarke, 2011). Given the range of variable renewable penetration levels that are being considered in these and other studies, as well as the high levels of VG already experienced in some regions and to increasingly be expected in other regions it is important to understand how the economic

[5] All penetration levels in this chapter similarly refer to penetration on an energy basis.

value of variable renewables might change over a wide range of penetration levels.

Modeling the Long-Run Impact of Variable Renewables at Varying Penetration Levels

One of the challenges of using wholesale power market prices to evaluate the economic value of variable generation (to then compare to the fixed cost or PPA price of those technologies) is that wholesale prices will change over the lifetime of a power plant. The current prices in this year or the prices in previous years may not reflect trends that can affect future prices like fuel changes, increased emissions controls or other environmental restrictions, and changes in the capital costs of new power plants. More importantly for the focus of this chapter, wholesale power prices change with increasing penetration of variable generation (Jacobsen and Zvingilaite, 2010; Podewils, 2011; Woo et al., 2011).[6] The recommendation that wholesale power market prices be used to estimate the economic value of variable generation from Joskow and Borenstein therefore requires the use of models to estimate future wholesale prices, particularly in the case of evaluating the economic value of variable generation with increased penetration levels.

There are several options available for creating models of future wholesale prices with increasing penetration of variable generation. As one approach, a number of studies have estimated the impact of variable renewables on power system operations by simply adding increased variable generation to a static mix of other generation capacity. In particular, a significant body of literature specifically evaluates the flexibility of the conventional generation system and the technical feasibility of integrating wind energy into existing power systems (Gross et al., 2007; Gransson and Johnsson, 2009; Holttinen et al., 2011; Klobasa and Obersteiner, 2006; Maddaloni et al., 2009; Smith et al., 2007; Strbac et al., 2007; Ummels et al., 2007; Wiser and Bolinger, 2011). The focus of this literature has primarily been based on the operations of the power system with increased wind and has therefore generally assumed that existing conventional generation is dispatched differently but that the installed capacity of that generation does not change with increased wind. The prices generated by models used in this literature therefore reflect only the short-run economic value of wind and not the long-run economic value of wind.

A short-run analysis, as used in these studies, is useful for a conservative assessment of operational integration issues, such as evaluating the technical feasibility of managing variable generation. A short-run analysis may be particularly useful for analyzing low levels

[6] Jacobsen and Zvingilaite (2010) reports lower prices and higher volatility with increasing wind in Denmark, while Woo et al. (2011) reports the same for wind in ERCOT. Morthorst (2003) reports a relatively weak relationship between wholesale market prices and wind, but a stronger relationship between wind generation and prices in imbalance markets. Jónsson et al. (2010) shows that a stronger relationship exists between wholesale prices in the day-ahead market and day-ahead *predictions* of wind power rather than day-ahead prices and actual wind generation. Podewils (2011) reports that mid-day day-ahead prices in Germany are decreasing due to the addition of large amounts of photovoltaic generation.

of wind or solar penetration since low levels of penetration would not significantly affect wholesale power market prices or the mix of generation resources.

Scenarios of high wind and solar penetration over a period long enough to make investments in (or retirements of) other generating technologies, however, are better dealt with using a long-run analysis that can allow for changes in the generation mix due to new investments and plant retirements. In addition, answering questions about the impact of VG on investment incentives for conventional generation, investment incentives for measures to better manage wind or solar energy variability and uncertainty like storage, or impacts on consumer electricity prices all require understanding long-run dynamics. Some previous analyses of these latter questions have instead used a short-run framework where wind penetration is changed significantly and all other investments in the power system are kept the same irrespective of the wind penetration level (Green and Vasilakos, 2010; Hirst and Hild, 2004; Olsina et al., 2007; Sensfuß et al., 2008; Sioshansi and Short, 2009; Sioshansi, 2011a; Traber and Kemfert, 2011): as a result, the conclusions from these studies only reflect short-run impacts and do not address important questions about the long-term impact of variable generation.

In the long run, generation can retire for technical or economic reasons, load can grow necessitating increased generation capacity, or new investments can be made based on the expected economic attractiveness of building new generation. The nature of some of these changes can be impacted by the amount of VG penetration. These long-run changes are therefore relevant for modeling future prices and for understanding the value of variable generation over the lifetime of a power plant, especially at higher VG penetration levels.

As described in more detail later, the model used in this chapter for estimating the value of variable generation is based on a long-run modeling framework that addresses investment and retirement decisions while also accommodating important operating constraints for conventional generation, Text Box 1. A product of the long-run modeling framework are hourly prices for energy and ancillary services that reflect the long-run cost of meeting an additional unit of demand in any particular hour. These long-run hourly prices in combination with generation profiles are used to estimate the economic impact of adding additional variable generation resources.

Text Box 1. Framework for evaluating long-run equilibrium

When a power system is in equilibrium, meaning that there is no economic incentive for existing units to leave the market and no economic incentive for additional units to be built, and only small changes in the system are investigated, short-run prices and long-run prices are similar. Major changes to a system, such as the addition of large amounts of wind or solar energy, however, can lead to a significant divergence between short-run prices and long-run prices. The long life of variable generation assets (>20 years) leaves time for changes in the other generation resources (e.g., retirement and new investment) and makes long-run prices more relevant for understanding the overall economic value of variable generation.

Stoft (2002) presents a simple framework for understanding the long-run dynamic response to changes in power systems, Figure 3.1. The operation of generating resources in a power market impacts short-run profits (again, defined as the difference between the total revenues earned from selling power in the market and the variable costs from generating power). Potential new generators then determine whether they should enter a market based on the expectation of the short-run profits the generation could earn in the market. If the short-run profits are high enough to cover the fixed cost of investment in new capacity then new generation will enter the market and add to the resources that can be dispatched.

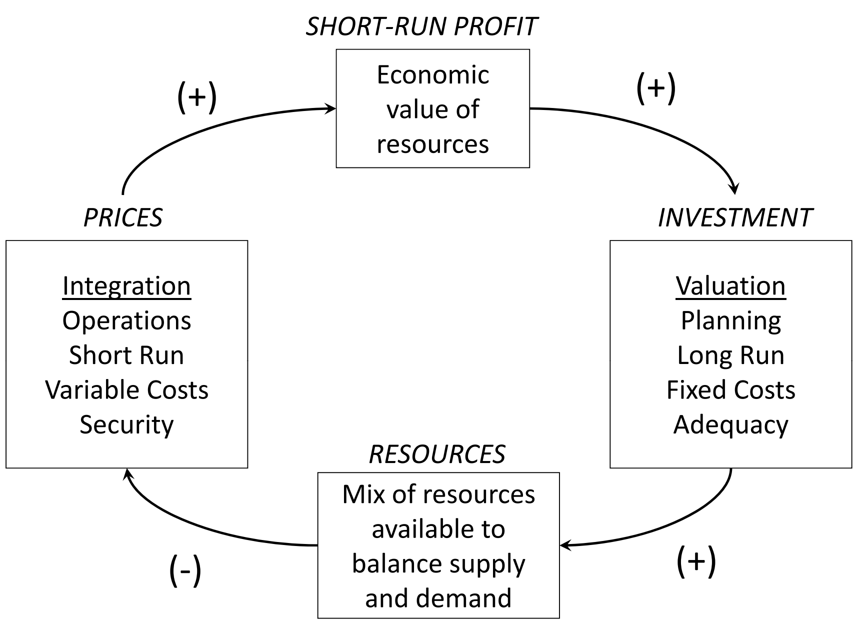


Figure 3.1: Framework for evaluating long-run economic value (adapted from Stoft (2002))

The positive and negative symbols in Figure 3.1 indicate whether each step reinforces or dampens the next step. High prices, for instance, lead to an increase in short-run profits (positive), which increases the incentives to invest in new generation (positive) and can increase the amount of resources available in the market (positive). An increase in the amount of resources in a market, however, will **decrease** the prices in that market (negative). Overall, this feedback loop tends to be stable, meaning that it will push investments and prices to an equilibrium point where there is no economic motivation for additional new investments and no generator would retire for economic reasons. It also indicates that long-run equilibrium prices depend in part on the capital cost of investment options. The long-run impact of adding variable generation or any other resource to a power market depends on the impact the resource has on market prices, the change in the short-run profits for generators, and the change in investments because of the addition of the resource. Additional details of the long-run modeling approach used in this chapter are provided in Section 3.3.

Existing Studies of the Economic Value of Variable Renewables

Beyond the studies focused on operational integration challenges and studies of the economic value of VG at high penetration that use a short-run analysis framework cited earlier, a number of studies have examined the economic value of variable generation using either current prices or long-run prices generated in a scenario with no or low amounts of variable generation. Borenstein (2008) used historic real-time prices and simulated long-run equilibrium prices to estimate the economic value of PV in California at zero penetration. He showed that the long-run value of PV can exceed the value estimated using only flat-rate retail tariffs by up to 30–50% if fixed-axis PV panels were oriented toward the southwest. Mills et al. (2011) estimated market value adjustment factors for a variety of renewable resources in the western U.S. and found that the per unit of energy market value of solar technologies, particularly CSP_6, generally exceeded the per unit of energy market value of generation resources that were assumed to have flat generation profiles (e.g., biomass). The market value of wind was found to be lower than the market value of biomass, depending on the combination of wind generation profile and load center where the wind generation was delivered. Sioshansi and Denholm (2010) used current wholesale power prices in the Southwestern U.S to evaluate the economic profitability of CSP with and without thermal energy storage over a wide range of thermal storage and solar field size combinations. Fripp and Wiser (2008) found relatively little correlation between historic wholesale prices and different wind generation profiles in the western U.S. At low penetration the wholesale value of wind power was found to be similar to or up to around 10% less than the value of a flat block of power, depending on the wind site.

A growing body of literature provides significant insights into the long-run economic value of variable generation considering long-term investment and retirement decisions with increasing penetration levels, though with varying levels of temporal and geographic resolution. The models used in these studies are not necessarily designed to just quantify the economic value of renewables with increasing penetration, but the economic value of these resources is implicitly estimated in these models. In the U.S., the National Energy Modeling System (NEMS) is used by the Energy Information Administration to create energy forecasts in the Annual Energy Outlook. NEMS includes wind and solar energy in the mix of potential resources in their long-run assessment of future energy markets. The temporal resolution of NEMS, however, allows for only nine time periods per year and the geographic resolution is limited to thirteen supply regions (Energy Information Administration (EIA), 2010).

The contribution of CSP to energy supply was investigated by Zhang et al. (2010) in the GCAM integrated assessment model, a model used for assessing future climate change mitigation scenarios. The GCAM model only used ten time slices over the year. Even with this low time resolution, Zhang et al. (2010) found decreasing economic incentives to build additional CSP with increasing penetration, though higher penetration levels were still attractive with the addition of a few hours of thermal storage.

The Renewable Energy Deployment System (ReEDS) model developed by the National Renewable Energy Laboratory greatly increases the geographic resolution of load and renewable energy data, but still uses relatively low temporal resolution of 17 time-periods per year. Several additional statistical correction factors are included in ReEDS to address the relatively low temporal resolution.[7] The ReEDS model has been used to evaluate investments in scenarios with 20% wind energy (DOE, 2008) and 20% solar (Brinkman et al., 2011).[8]

Comparison of dispatch and investment results depending on the level of temporal resolution used in modeling high wind penetration scenarios indicates that temporal resolution can significantly impact estimates of the long-run economic value of wind (Ludig et al., 2011; Nicolosi et al., 2010). As a result, when practical computing constraints can be overcome, studies of the long-run economic value of VG are increasingly seeking higher levels of temporal resolution, up to hourly with a full year or more of wind, solar and load data. These studies often highlight the importance of geographic diversity, changes in the value of variable renewables between high and low penetration, changes in the long-run mix of conventional generation due to increased variable renewables, and the lower economic value for wind than an energy-equivalent flat block of power (Bushnell, 2010; DeCarolis and Keith, 2006; Fripp, 2008; Grubb, 1991; Lamont, 2008; Miera et al., 2008).

Instead of focusing on the long-run value of wind, Swider and Weber (2007) use a long-run model with several "day types" (12 day types, each day with 12 time segments) to demonstrate the difference in total system costs when wind is variable and unpredictable compared to the costs if wind were to have a flat generation profile across the entire year. Somewhat unique amongst the studies that consider longer term impacts, their model includes more of the detailed operational constraints that impact the dispatch of thermal power plants. De Jonghe et al. (2011) compare the long- run investments that would be made in a power system with increasing penetration of wind energy using a method that includes several operational constraints for thermal generation to those investments that would be made if a more simple method that uses traditional screening curves without operational constraints were applied. Though they do not include uncertainty in wind generation in the analysis, they find that the inclusion of operational constraints in investment decisions leads to more

[7] `http://www.nrel.gov/analysis/reeds/`

[8] In addition to developing generation investment decisions using 17 time-periods per year using the ReEDS model, Brinkman et al. (2011) verify that the system built by ReEDS can be operated using an hourly production cost model. The results of the hourly production cost model, however, are not fed back into the build-out and design of the system in ReEDS.

baseload capacity being replaced by flexible mid-load generation in scenarios with significant wind.

Aside from these latter two studies, much of the existing literature on the economic value and operational integration of variable generation with increasing penetration tends to either (1) focus on longer term value but lack high temporal resolution and/or consideration of the operational constraints of conventional resources in the power system or (2) have high temporal resolution and pay significant attention to operational constraints but assume a static mix of conventional generation even at high penetration levels thereby focusing on short-run impacts and ignoring long-run dynamics.

3.3 Methodology

This chapter seeks to bridge the divide in the literature by incorporating hourly generation and load profiles, unpredictability of variable generation and some of the important limitations of conventional thermal generators including part-load inefficiencies, minimum generation limits, ramp-rate limits, and start-up costs. This detail is then used to calculate the long-run value of wind, PV, and CSP generation with increasing penetration levels considering long-run dynamics of retirements and new investment decisions. While the limitations of many of the earlier studies do not necessarily take away from the importance of their findings, including both operational constraints and hourly time resolution in a long-run analysis framework allows concerns about the uncertainty of variable generation and the limitations of thermal plant flexibility for managing variability and uncertainty to be more directly addressed in the estimations of the long-run economic value of variable generation.

The marginal economic value evaluated in this analysis is based on the avoided costs from conventional generators including avoided fuel costs, start-up costs, O&M costs, and capital investment costs for an additional increment of VG from a particular VG penetration level. In calculating the marginal economic value, factors such as the ability of variable generation to reduce investment in conventional generation capacity, the ability of VG to reduce consumption of different fuels at different times depending on current system conditions, the impact of day-ahead forecast errors from VG, and the need to increase ancillary services are all addressed to varying degrees. The new investment options in non-VG resources include CTs, CCGTs, coal, nuclear, and pumped hydro storage.

The analysis does not consider many other costs and impacts that may be important in some cases. The costs and impacts that are not considered in this analysis include environmental impacts, transmission and distribution costs or benefits, effects related to the lumpiness and irreversibility of investment decisions, and uncertainty in future fuel and investment capital costs. Similarly, the present analysis does not consider the investment cost in VG resources. These costs and factors are excluded in order to provide clarity in the drivers of the results of this analysis and to avoid the results being driven by specific local factors such as distribution system design or time lags in transmission investments. Of course, actual investment and policy decisions might reasonably consider these and other elements as well.

In each of the scenarios considered in this analysis, one VG technology is increased from a base case with almost no VG (the 0% case)[9] to increasingly high penetration levels measured on an energy basis. The amount of VG included in each case is defined by the scenario and is not a result of an economic optimization. In other words, the VG is "forced in" to the market without consideration of the investment or operating cost of the VG. The scenarios are set up in this way to observe how the marginal economic value of VG, as narrowly defined in this chapter, changes with increasing penetration across a wide range of penetration levels. The results provide a survey of the potential range of the marginal economic value of different VG technologies and how it changes with increasing penetration. As is described in Section 3.4, the generation profiles with increasing penetration to some degree capture the impact of geographic diversity by aggregating additional sites with unique generation profiles. No scaling of variable generation profiles was used to model higher penetration levels.

In this analysis the penetration of VG is increased for only one VG technology at a time. Combinations of VG technologies, like wind and PV or PV and CSP with thermal storage, are not considered here. Combinations of VG technologies will be addressed in a future paper as a form of "technological diversity" that might stem the decrease in the economic value of VG at high penetration when only one technology is deployed along with other strategies such as price responsive demand, more flexible thermal generation, and low-cost bulk-power storage.

The high penetration cases include solar penetration levels that approach 30% of electricity. In the case of wind energy it was decided to push the penetration even higher to just over 40% on an energy basis due to the relatively smaller change in the marginal economic value of wind between 10% and 30% penetration relative to solar, as will be described in the later sections.[10] There were no fundamental barriers that prevented further increases in the penetration level beyond the levels examined here, although, as is shown later, VG curtailment and decreased marginal economic value at high penetration reduce the incentives for increasing penetration to higher levels.

The marginal economic value derived from each of these cases can be interpreted as the maximum marginal investment and fixed O&M cost that a VG technology would need to have to justify additional investment beyond the amount of VG considered in the case. In a case where the marginal value of VG is, for instance, $70/MWh at 10% penetration then

[9] Every case includes at least 100 MW of wind, PV, and CSP in order to observe how the value of these technologies change when the value of the other VG is increased to high penetration levels.

[10] Note that the exact penetration level used to describe each of the cases varies from the case title. For example, the actual penetration of PV in the "30% PV" case is 31.5%. The reason for the discrepancy is differences between the amount of annual energy production across individual renewable energy project sites that are aggregated to create the overall VG generation profile relative to the estimated amount of energy that would be generated by a typical site. The number of sites used to generate the profiles for the different penetration levels was based on typical estimates of annual energy production rather than site specific estimates. As a result the number of sites used in the "30% PV" case slightly exceeded the number of sites that were needed to generate exactly 30% of the annual electricity in the study year.

the marginal investment and fixed O&M cost of the VG would need to be below $70/MWh to economically justify investment in additional VG. This interpretation, of course, ignores the many factors that are excluded from this analysis that could change the absolute level of the marginal value. The relative changes from low penetration to high penetration and the comparisons across VG technologies are therefore the more relevant indicators of the drivers of the marginal economic value rather than the absolute magnitudes.

California is chosen for this particular case study as an example of the application of the model and framework used to estimate marginal economic value of VG with increasing penetration, though this study is not designed or intended to exactly mimic all of the laws, policies, and various other factors that impact the electricity market in California. That being said, California is chosen due to the recent aggressive Renewables Portfolio Standard (RPS) of 33% by 2020 that was signed into law[11] and the diversity of renewable resources that are actively being considered in renewable procurement in the state, including wind, PV, CSP with and without thermal energy storage (TES), and some geothermal and biomass. Decisions that renewable project developers, utilities, regulators, and system operators are making or will need to make in the near future somewhat depend on the relative cost and benefits of these different renewable resources. Of particular importance has been the recent rapid decline in the cost of photovoltaics (Barbose et al., 2011). In California this reduction in PV costs, among other factors, has led to a number of proposed renewable projects shifting from CSP technology (often based on solar trough or parabolic dish technology) to PV as well as the addition of thermal energy storage to some proposed CSP plants in order to boost their value to the power system. Wind resources located in and out of California will also continue to compete with these solar technologies in renewable procurement decisions. It is therefore important to quantitatively understand how the benefits, including the economic value, compare across technologies and change with increasing penetration. Similar questions regarding the relative economic value of renewable resources occur in many different regions, but the marginal economic value of VG with increasing penetration may vary to some degree depending on the characteristics of the conventional generation, VG resources, and electric loads.

The remainder of this section summarises the framework and model that is used to estimate the marginal economic value of VG with increasing penetration, considering both long-run retirement of and investment in non-VG generation resources as well as commitment and dispatch decisions that occur during operations while accounting for the constraints that limit dispatch of conventional plants. The section first describes how power plants are committed and dispatched in the model, and then describes how the decision to invest in new non-renewable power plants is made. The method used for calculating the capacity credit of the VG based on the change in total investments in new power plants is also described. The marginal economic value of VG can then be calculated based on the dispatch results (i.e., wholesale power and ancillary service prices) from the non-VG power plant investments that

[11] `http://www.leginfo.ca.gov/pub/11-12/bill/sen/sb_0001-0050/sbx1_2_bill_20110412_chaptered.pdf`

were previously found to lead to a market equilibrium in the year 2030. The model itself is formulated for the purpose of this analysis in the mathematical programming language called AMPL and is solved using the IBM ILOG CPLEX Optimizer. Additional details of the model can be found starting in Appendix B.1.

Dispatch

The commitment and dispatch portion of the model used in this analysis (called the dispatch model) determines schedules and dispatch for thermal generation, hydropower, pumped hydro storage, variable generation, and load using hourly data over a full year. The dispatch decisions are co-optimized with decisions regarding which resources will provide ancillary services to meet reserve targets in each hour. The ancillary service requirements include non-spinning, spinning, and regulation reserves which are differentiated primarily by whether or not a resource must be online in order to provide reserves and by the time by which the reserve must be able to be fully deployed. The thermal generation constraints and parameters include variable O&M costs, the cost of fuel consumed just to have the plant online (called the no-load cost), the marginal variable fuel cost associated with producing energy, start-up costs, limits on how much generation can ramp from one hour to the next, and the minimum generation limit for online generation. The source of the numerical values used for these parameters is discussed later in Section 3.4. Hydropower is limited based on a monthly hydropower generation budget and an hourly minimum generation limit. Pumped hydro storage is limited by the capacity of the storage converter and by the reservoir capacity. All variable generation is assumed to be able to provide regulation-down, but CSP_6 is the only VG technology that can provide regulation-up and spinning reserves. Transmission constraints are not included in the dispatch and commitment decisions.[12]

The dispatch model focuses on two primary time horizons, the day-ahead (DA) and real-time (RT). These two time horizons correspond to the market time-lines used in many of the organized markets in the United States, including the California Independent System Operator (CAISO).

In the DA process used in this model, forecasts of output from variable generation are used to determine schedules for all generation that will maximize social welfare (consumer surplus plus supplier surplus) based on the characteristics, constraints, and operating costs of generators, the availability of hydro generation, electricity demand, and the DA forecast of VG. The DA market prices for energy and ancillary services (AS) in each hour are based on the shadow value or dual value of constraints that require generation and load to be in

[12]There is nothing inherent in this framework that requires transmission constraints to be excluded from the dispatch and commitment model. With a more detailed dispatch model transmission constraints could explicitly be modeled. In the long-run, however, transmission investments can also be made which would require including transmission investment options and decisions regarding where to site new generation investment. These decisions are possible to include in the investment model but would begin to rapidly increase the complexity of the model. For this pilot case study of California options relating to transmission were ignored.

balance in each hour and ancillary service targets to be met, respectively. The shadow value of an ancillary service target constraint, for example, represents the marginal change in the social welfare that would occur if the ancillary service requirement were to change by a small amount in that hour. The DA schedules and market prices contribute to the total revenues earned by any generation resource, as shown later.

In the RT process used in this model, generators are dispatched to maximize social welfare given the actual amount of VG that occurs in RT (considering forecast errors that occur in the DA). For generators that are not classified as quick-start generation, the commitment decision from the DA process is binding in the RT, thus limiting the options for maintaining a balance in RT. The combined-cycle vintage (CCGT) modeled in this analysis, for instance, is assumed to not be able to start within the hour and therefore does not have quick-start ability. If in the DA process CCGT resources are required to be on-line to meet the DA schedule, then in RT the CCGT resources can only be dispatched between the maximum capacity of CCGT generation that is online and the minimum generation limits of the online CCGT resources, while also considering ramp-rate limits. The CCGT cannot change to off-line in RT. On the other hand, simple-cycle combustion turbines (CT) are assumed to have quick-start ability. Even if CT resources are provided with a DA schedule that would leave the CT generation off-line, the CT resources can still be used in RT to balance the system if changes in system conditions require additional generation capacity.

Commitment Approach

The details of the dispatch model can be found in Appendix B.3. Overall the dispatch model is similar to the model outlined by Sioshansi and Short (2009). A key simplification in the approach used in this analysis, however, is that individual conventional generation plants are grouped into vintages that have similar generation characteristics. Each vintage is then dispatched as a combined resource rather than directly committing and dispatching individual units.

Instead of committing individual units, the commitment process in this simplified dispatch model determines how much capacity within a vintage will be online in each hour of the next day (and the current day in the case of quick-start vintages). The decision to increase or decrease the amount of on-line generation considers that any increase in the amount of vintage that is on-line causes an increase in the total startup cost.[13] The commitment process also determines how much of the on-line fraction of the vintage will be used to generate energy or, alternatively, to provide reserves from spinning resources. The minimum

[13]The simplification further only focuses on start-up costs and does not include a minimum run time constraint. The start-up costs are somewhat high which makes it unattractive to start generation if it is only going to be used for a short time. Furthermore, it would not make sense to apply the average minimum run time for individual units to the entire fleet of generation within the same vintage. It doesn't make sense because staggering individual unit start-up times can make the minimum time that a certain amount of the fleet is online much shorter than the individual run times for each unit that makes up the fleet.

generation and ramp-rate constraints and part-load impacts are then based on the amount of online generation in any hour.

Grouping plants into vintages results in a simplification that treats generators as a continuous resource (i.e. linear dispatch of capacity) rather than a discrete resource (i.e. stepwise dispatch of capacity). This simplification allows the problem to remain linear and therefore results in more reasonable solution times relative to a model that commits each unit individually (which would make the dispatch model a mixed-integer linear program rather than a linear program). Overall the impact of this simplification on the results is somewhat ambiguous: linear commitment and dispatch constraints would tend to overstate the flexibility of the system while aggregating all existing units and using average plant characteristics understates the flexibility of some units.

A similar vintage-based commitment and dispatch approach was used by Müsgens (2006) to model market power in Germany and by Müsgens and Neuhoff (2006) to model the dispatch of a power system with wind generation. Additional details of this approach are available in Kuntz and Müsgens (2007). Advantages and disadvantages of the linear “ready-to-operate” approach used by Müsgens (2006) relative to integer unit-commitment models are quantitatively evaluated by Abrell et al. (2008).[14]

Storage and Hydro Resource Dispatch

Modeling resources with storage, including hydro, bulk power storage, and thermal storage for CSP resources, can add significant complexity due to uncertainty over time periods relevant to the scheduling and dispatch of the storage. Modeling hydro and storage resources in dispatch models is particularly challenging due to the opportunity cost associated with discharging energy from a resource that is not then availabe at a later time that might be more valueable. Several of the challenges with modeling hydro generation in studies with significant variable generation levels are discussed by Acker (2011).

In this analysis, the complexity is significantly reduced by assuming that the DA schedules for the storage and hydro resources are set based on the DA forecasts of VG and the RT schedules are adjusted with perfect foresight to respond to the actual VG generation and system needs in RT. Based on these assumptions the dispatch of the hydro and storage resources is then co-optimized with the dispatch of the thermal generation in each individual case. This approximation somewhat overstates the ability of storage and hydro resources to respond in RT to system needs that differ from the DA schedules, but not unduly so. Though there is clearly room for improvement, the overall approach used in this analysis does not differ significantly from the manner that hydro is modeled in previous variable generation integration studies. Additional details regarding the specific hydro and storage modeling assumptions for this study are described in Section 3.4.

As a check to ensure that these resources were not earning extremely high revenues, the revenue earned by hydro in the model was compared to the revenue that a hydro resource

[14] Another promising option for simplifying commitment decisions in long-term planning studies, but is not used here, is outlined by Palmintier and Webster (2011).

would earn for the same scenario using a hydro dispatch algorithm based only on the net load (without any consideration of forecast errors, other generation, or reserves) and a simple peak shaving algorithm. At 30% penetration of PV or CSP_0 or 40% penetration of wind, hydro dispatched using the simple peak shaving algorithm earned only 4-8% less than the revenues earned with the optimized hydro dispatch from the dispatch model.

Scarcity Prices

Scarcity pricing is used in this model to signal periods where it is difficult to maintain balance between supply and demand.[15] In most hours of the year the market price for energy is based on the marginal cost of the most expensive vintage that is on-line, but not bound by minimum or maximum generation limits or ramping limits. In some cases the price is set based on the opportunity cost for dispatching hydro or storage in that hour (and therefore not being able to dispatch the hydro or storage in later hours). In cases where there is insufficient available capacity from on-line generation or vintages that are quick-start, the prices can rise even higher and thereby signal scarcity in the available generation resources. When insufficient generation is available to meet demand and AS targets the prices in this model rise to predefined scarcity price levels that can be interpreted as the assumed loss of social welfare for missing AS targets and eventually for involuntary load shedding.

The scarcity price levels for missing AS targets are set following the scarcity prices used at the CAISO (CAISO, 2009). The scarcity price levels for the different reserves ensure that non-spinning reserve targets are missed before the higher quality spinning and regulation reserve targets are missed. The assumed loss of social welfare for involuntary load shedding is a value that falls within the wide range ($1,000/MWh to $100,000/MWh) of commonly cited estimates of the value of lost load (VOLL) (Stoft, 2002).[16]

[15] Price responsive demand could also be used to balance supply and demand. However, in this chapter the elasticity of demand is assumed to be quite inelastic (with a constant elasticity of -0.001 up to the VOLL). In the next chapter demand is assumed to be more elastic in a scenario that investigates the long-run impact of real-time pricing with high VG penetration.

[16] The choice of the loss of social welfare associated with involuntary load shedding and missing reserve targets impacts the number of hours of the year where the available generation is less than the demand (leading to hours with scarcity prices) which in a reliability based study would impact the loss of load expectation (LOLE). If a low value is chosen for the VOLL then the number of hours with scarcity prices and the LOLE will increase. A high VOLL, on the other hand, causes the number of hours with scarcity prices and the LOLE to decrease. As described later in Section 3.5 the choice of these scarcity prices leads to scarcity prices occurring approximately 0.8% of the year (about 70 hours per year) or less. If planners were to desire fewer hours with scarcity prices, the VOLL estimates would need to be increased or some other mechanism would need to be used to ensure adequate generation capacity were available (i.e. resource adequacy obligations). We note that controlling the number of hours where demand exceeds generation (the level of reliability) is important from a system planning/reliability perspective, but for the purposes of examining how the marginal economic value of variable generation changes with increasing penetration it is less important to identify the generation capacity needed to meet a absolute target level of reliability. Instead, what is important in this analysis is ensuring that the relative level of reliability remains similar across scenarios even with changes in the amount of variable generation. By maintaining the same scarcity

- Non-spinning reserves: \$500/MWh
- Spinning reserves: \$1,000/MWh
- Regulation reserves: \$2,000/MWh
- Involuntary load shedding: \$10,000/MWh

Revenues

All generation resources are assumed to participate in the DA market (and to be paid accordingly at a rate of $p_{DA}Q_{DA}$), but also to pay for (or to be compensated for) RT deviations from the DA schedule ($Q_{RT} - Q_{DA}$) at the RT price (p_{RT}). The total revenue (TR) earned by each resource in each hour is:

$$TR = p_{DA}Q_{DA} + p_{RT}\left(Q_{RT} - Q_{DA}\right) \tag{3.1}$$

Though not shown here for clarity, and explained more in Appendix B.3, the revenues also include sales of ancillary services in the RT and DA market by conventional generation and CSP_6 at the corresponding RT and DA prices for AS (including regulation, spinning, and non-spinning reserves). The other VG technologies can only sell the regulation down AS and are further charged for increasing the AS requirements. The cost of the additional AS for the other VG technologies is subtracted from the revenues earned by the VG technologies based on the hourly contribution to the additional AS requirements and the hourly AS price.[17]

As can be seen from the formulation of the total revenues in Equation 3.1, generation that does not deviate from the DA schedule in RT will be compensated for all of the generation at the DA price. Generators that are not needed in the DA but then are required in RT are compensated for all of their generation at the RT price.

Variable generators that have a DA forecast that exceeds the actual RT generation are assumed to "buy" power equivalent to the deviations in RT at the RT price. If the lower amount of generation than expected causes the system to dispatch more expensive generators than would otherwise be needed in RT (e.g., a quick start CT is needed in RT but was not needed DA) then the cost of buying the power in RT at the RT price can exceed the payment that the variable generator earned in the DA for the overforecast of variable generation.

Conversely, variable generators with a DA forecast that is lower than the RT generation are assumed to "sell" power equivalent to the deviations at the RT price. If the greater

prices and keeping the system in long-run equilibrium at all penetration levels of VG we maintain the relative level of reliability.

[17] There is some controversy regarding how to estimate the costs of ancillary services due to variable generation and much more controversy regarding how to allocate those costs between different generators or loads (e.g., Milligan et al., 2011). The simple method used here to estimate the short-run profits accounting for contribution to AS requirements is one of many options. The focus of this chapter is to examine the relative economic impact of these different requirements, not to examine in detail methods for allocating these costs.

amount of generation than expected causes RT prices to be lower than the DA price then the revenues earned from selling the deviations in RT can be lower than the revenues the variable generator could have earned if the DA VG forecast was correct and power equivalent to the deviations were sold at the DA price.

Finally, variable generators can in some hours earn more than what they would have earned if perfectly forecast. This occurs any time that a RT deviation from the DA happens to be in the direction of system need (e.g., if the RT generation exceeds the DA forecast generation at a time when the system needs more power than expected in the RT, then the variable generator can earn additional revenue due to the deviations). The overall difference in the revenue earned by variable generation that cannot be perfectly forecast from the revenue that could have been earned if RT generation always exactly matched the DA schedule makes up the cost of DA forecast errors for variable generation that is discussed later in Section 3.3.

Using Equation 3.1 to estimate the revenues for variable generators reasonably follows the approach used in most organized wholesale markets (i.e., ISO/RTO markets) in the U.S. (ISO/RTO Council, 2010). Some organized markets have programs, such as the California ISO Participating Intermittent Resource Program, that help minimize costs associated with RT deviations. On the other hand, many transmission system operators outside of ISO/RTO markets apply punitive imbalance charges for deviations from scheduled generation (Rogers and Porter, 2011). In keeping with the approach used in most ISO/RTO markets, VG RT deviations in this model are settled at RT prices without any consideration of punitive imbalance charges.

The revenues in Equation 3.1 do not include any sort of capacity payment, instead all revenues earned by resources in the power market are earned through sales of power and ancillary services, similar to an “energy-only” market. This is just a modeling choice: it would be possible to obtain the same results by replacing the revenues that are earned during hours with scarcity prices by an equivalent “capacity payment” that depends on the contribution of generation resources during periods where generation capacity is limited. For example, the energy and ancillary service prices could be capped at $500/MWh and capacity payments would equal the difference in revenue if the capacity prices were not capped at that low level. While the choice of capacity payments or reliance on an “energy-only” market design is a simple choice for a model, the choice of mechanism to ensure adequate investment is much more important in real-world conditions due to issues like market power and risk associated with investment with long-term uncertainty (Stoft, 2002).

Low Price Periods and Curtailment

During some periods of the year too much generation in the DA or RT market can cause prices to drop to very low levels. During times with very low prices, variable generators, which have very low or zero marginal generation costs, may become indifferent between generating power and being compensated at the very low wholesale price for power or not generating at all. In this analysis, we assume (both for simplicity and so as to not forecast policy outcomes for 2030) that production-related incentives that are used today are no longer available for variable generation (e.g., the production tax credit (PTC) and renewable energy credits (RECs) are not used). Without these production incentives there is no opportunity cost associated with curtailment of VG when the wholesale power price drops to zero. VG is also indifferent to curtailment when the DA price is positive yet the RT price drops toward zero since, as shown by Equation 3.1, when the RT price is zero the RT generation can deviate from the DA schedule by any amount without penalty. In the case where the DA price is positive and the RT price is zero, VGs earn the same revenue whether curtailed in RT or not. To account for this situation, the dispatch model only curtails VG when the system cannot economically absorb additional VG and the price for power is zero.

The curtailment that is calculated in this analysis is only due to system flexibility issues and does not reflect curtailment that would occur due to insufficient transmission capacity between variable generation and loads. Current wind curtailment in U.S. power systems is due to a mixture of flexibility and transmission related factors, but transmission is the primary cause of curtailment (Wiser and Bolinger, 2011). The results from this analysis will not capture curtailment related to transmission.

In addition, since no production related incentives are included for VG in this analysis prices do not become negative in times of high VG generation. Had production incentives been included in the analysis there would be an opportunity cost associated with being curtailed. VG would then only be indifferent between curtailment and continuing to generate and earn the production related incentive if the wholesale power prices were to become negative.

Virtual Load

Virtual load bids were added to the DA process when average DA prices were found to differ from average RT prices. Ideally DA and RT prices should be approximately equal when averaged over a long period because an arbitrage opportunity exists between the DA and RT market when average prices are not equal. A generator that expects that average RT prices will be consistently greater than the average of DA prices would have the incentive to not participate in the DA market (or bid a very high cost so that they receive a DA schedule that has them not generate) but then make the generation available in the RT to capture the higher RT prices. Many organized markets allow market participants to use virtual bids to arbitrage between DA and RT markets to reduce these systematic deviations between DA and RT prices and therefore increase the overall efficiency of the power market (Isemonger, 2006).

A virtual load in the DA would appear to increase the DA load and increase the amount of generation that would be scheduled in the DA market. The actual RT load would be lower than the DA load since the virtual load from the DA would not show up in RT. This lower load in RT would tend to decrease RT prices. A market participant would find it profitable to bid virtual load in the DA as long as the RT price is greater than the DA price on average. The virtual load would "buy" a quantity of load (L_{vl}) at a price of p_{DA} and, since the load would not show up in RT, it would "sell" a RT deviation from the DA schedule of L_{vl} at the RT price (p_{RT}). Since the revenues from selling the virtual power in RT ($L_{vl}p_{RT}$) exceed the cost from buying the virtual power DA ($L_{vl}p_{DA}$) when the RT price exceeds the DA price ($p_{RT} > p_{DA}$) the virtual load bid is profitable. If too much virtual load is bid in the DA, however, the DA price will increase and eventually exceed the RT price. Virtual load bids would then be unprofitable since power would be bought DA at a price greater than the power was sold in RT.

Without the virtual load bids, the average DA and RT prices in our analysis were found to differ because, in general, there is an asymmetry associated with the cost of managing under-forecasts versus over-forecasts of variable generation. When the DA forecast of VG exceeds the actual RT VG the cost associated with backing down on-line generation, changing the dispatch of hydro or storage, or in extreme cases curtailing VG were not too high. On the other hand, when the DA commitment is made with the expectation that the DA forecast of VG will contribute in RT, and when actual VG in RT is lower than the DA forecast, there are often periods where the costs of dealing with under-forecasts were fairly high. After dispatching upward any available on-line capacity, for example, the remaining options for dealing with a shortage of generation in RT involved dispatching hydro and storage away from what would otherwise have been more profitable periods, starting any available quick-start CTs, missing reserve targets at the predefined social welfare cost (as described earlier in this section), or involuntary load shedding at the VOLL. The higher recourse cost associated with managing under-forecasts relative to the costs associated with over-forecasts leads average RT prices to exceed average DA prices when DA commitment decisions are based strictly on forecasted VG. Such an asymmetry in balancing costs has also been reported for real power markets (Morthorst, 2003; Skytte, 1999).

One solution to reduce the difference between average DA and RT price, as noted earlier, is to over-commit resources in the DA through the use of virtual load. A small amount of virtual load in hours with VG would increase the other generation resources available to be dispatched up when the RT VG is below the DA forecast. The right amount of virtual load to include, however, is not an easy task to determine. Methods like stochastic unit-commitment use several scenarios to determine the optimal DA commitment given uncertainty in RT generation (Bouffard and Galiana, 2008; Meibom et al., 2010; Papavasiliou et al., 2011; Ruiz et al., 2009; Tuohy et al., 2009; Wang et al., 2011). In this study, however, only one DA forecast scenario was used. As a result, in this study, the amount of virtual load included in each case was empirically found by increasing virtual load bids up to the point that there was near zero average profit (or losses) associated with virtual load bids over the course of a one-year simulation period (indicating that the systematic arbitrage opportunity was largely eliminated).

The shape of the hourly virtual load bids were a fraction of the DA forecast for VG (in the case of wind, PV, and CSP_0) or historic hourly load (in the case of CSP_6). The decision to use a fraction of the historic hourly load in the case of CSP_6 was based on early experimentation with the model. As an example from the model used in this chapter, in the case with 15% PV the average DA price exceeded the average RT price by \$11/MWh if no virtual load was included in the DA. When 14% of the DA forecast of PV generation was included as virtual load in the DA the difference between the average DA price and the average RT price decreased to \$2/MWh. This overall approach appeared to mitigate obvious issues with differences in average DA and RT prices, but this is an area where additional work should be focused in order to improve power market simulation methods with significant penetrations of VG.

Investment

An important feature of this analysis is that the detailed operational impacts of VG are always based on a system that is in long-run equilibrium for the given amount of VG. As described in Section 4.2, other studies have often examined the operational impacts of VG by adding VG to a system that was originally designed to meet future load but without consideration of the potential for significant additions of VG to the system. Or, conversely, studies that have examined the long-run impact of VG have ignored or downplayed the operational constraints of conventional power plants and therefore at least partially ignored integration concerns.

In this study, the system is considered to be in long-run equilibrium when the conventional power generation that has not reached the end of its technical life (the incumbent generation) is either able to earn enough revenue to justify staying in the market, or the generation retires for economic reasons, and any new conventional generation that enters the market is able to cover its annualized fixed cost of investment. In other words, the short-run profit of incumbent generation that stays in the market must exceed its fixed O&M cost and the short-run profit of new generation must equal the fixed investment and O&M cost of that generation. The short-run profit (SR_π) is defined as the difference between the total revenues (TR) from selling power (and ancillary services) in the power market and the variable cost ($VC(Q_{RT})$) of producing that power (including fuel costs, start-up costs, emissions costs, and variable O&M costs).

$$SR_\pi = \sum_{t \in T} \left(TR_t - VC_t \left(Q_{RT} \right) \right) \tag{3.2}$$

With these conditions met, the non-VG system is in long-run equilibrium because all incumbent generation that stays in the market has an economic incentive to remain in the market, no additional new generation would find it profitable to enter the market (because then prices would decrease and the generation would not be able to cover its investment costs), and no already added new generation has an economic incentive to leave the market (because those plants can cover their costs in the market and if these generators exited then prices would go up and some other generation would take its place in the market).

Simulating a system in long-run equilibrium is insightful because it indicates how power market rules and operational practices influence prices and investment decisions in the long term. It is also important to understand, however, that real power markets are never exactly in long-run equilibrium. Real investments are lumpy and power plants take time to build, fuel prices and investment costs change in unpredictable ways, market participants sometimes exercise market power, and regulatory interventions often affect prices and investment decisions. More detailed, dynamic models have been developed to explore these factors (absent the complicating contribution of high penetrations of variable generation) (e.g., Botterud et al., 2005; Hobbs et al., 2007; Murphy and Smeers, 2005; Olsina et al., 2006).

Any model of a power system makes certain simplifying assumptions in order to investigate the interactions between variables and parameters in the model. In this study the long-run investment model is simulating a world where long-run non-VG investments are made in a competitive manner based on the average performance of the investments over a year with a particular level of VG penetration. The dispatch over the year is simulated with a candidate set of investment generation. With each set of candidate generation capacity the same year of hourly load, hourly VG generation, VG forecast errors, and monthly hydro power generation budget are simulated.

When insufficient generation exists in the candidate portfolio the prices spike to high levels many times per year. The high prices signal the need for more generation in the candidate portfolio. When too much generation is in the candidate portfolio the prices collapse such that there are few if any scarcity pricing events within the year. The low prices signal too much generation in the candidate portfolio. In this way the long-run equilibrium is found based on repeated deterministic simulations of data that is inherently uncertain (including the load, VG production, VG forecast errors, and monthly hydro budget). The only uncertainty that is captured in this model, then, is with regards to day-ahead commitment decisions based on inaccurate day-ahead forecasts.

In reality, investment decisions must be made with significantly more uncertainty than is captured here (including fuel price uncertainty and capital cost uncertainty), and may be affected by regulatory interventions that are not modeled in the present analysis. Nonetheless, the simulations presented in the chapter indicate what could happen if market participants use the outcome of generation investment decisions in the previous year to adjust investment decisions for the next year. With repeated opportunities to adjust investment decisions, coupled with relatively stable load and amounts of VG installed capacity, the simulation results should mimic investment decisions that would be made by market participants within the economic framework considered.

To illustrate the operation of the model in one case, the performance of generation in terms of short-run profit earned over a year with different candidate sets of generation and for two different levels of PV penetration is shown in Figure 3.2. The short-run profit of new CCGT generation is shown on the vertical axis and the total non-PV nameplate capacity is shown on the horizontal axis (which includes incumbent pumped hydro storage, hydro, nuclear, geothermal, CCGTs, natural gas steam turbines, and CTs along with varying amounts of new CCGTs). The annualized investment and fixed O&M cost of new CCGT resources is approximately \$200/kW-yr in this case.

When too little generation is available in the candidate set, the high short-run profits of CCGT resources, well above \$200/kW-yr, show that additional new CCGT generation

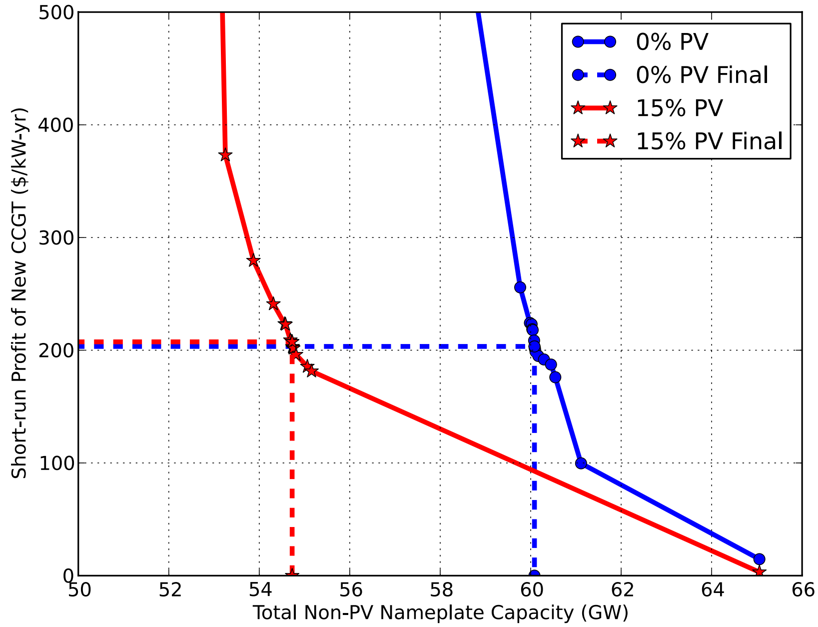


Figure 3.2: Relationship between short-run profit of new CCGT generation and total non-VG nameplate capacity with 0% and 15% PV.

investments are profitable. When too much generation is available in the candidate set, the low short-run profits, below $200/kW-yr, mean that some of the generation in the candidate set is not able to cover its investment cost and should not be built. The final candidate set of generation is such that the short-run profit of the new CCGTs that are in the portfolio is equivalent to $200/kW-yr.

With the final candidate set of generation resources in this specific case, the other new investment options, including new CT, new coal, new nuclear, and new storage resources, all had short-run profits that were lower than their respective annualized investment and fixed O&M cost. These other options were therefore not included in the final set of generation resources. All of the incumbent generation, on the other hand, were able to cover their fixed O&M cost and therefore were also included in the final set of generation resources. Note that in other scenarios, however, combinations of different resource options can be and are added. Additional detail regarding how the investment algorithm decides which generation resources to include in the candidate sets of generation, including how the algorithm deals with combinations of multiple new investment options, is provided in Appendix B.2.

The effect of adding VG to a system, in this case PV, is that it makes some of the generation capacity that would be built if there were no PV (i.e. the investment decisions for 0% penetration) unable to cover the cost of new investment. This is shown in Figure 3.2 by the lower short-run profit of the new CCGT resources with 15% PV relative to the short-run profit of the same amount of generation in a case with 0% PV. As a result, with the additional PV generation, less CCGT is added to the final candidate portfolio of generation. If too little CCGT generation is added in the case with 15% PV penetration, however, the prices will again rise and increase the short-run profit of new CCGT resources. In the end, the short-run profit of the CCGT generation in the final candidate set of generation with 15% PV is the same as the short-run profit of the new CCGT in the final candidate set of generation with 0% PV.

Implied Capacity Credit

The change in the total amount of non-VG capacity that is included in the final candidate set of generation resources relative to cases with less VG represents the amount of generation capacity that VG displaces. In traditional planning studies with VG, the amount of conventional generation that can be displaced without reducing the level of reliability relative to what it would have been without the VG is sometimes called the capacity credit or the capacity value of the VG (Amelin, 2009; Billinton et al., 1996; Garver, 1966; Hasche et al., 2011; Kahn, 2004; Keane et al., 2010; Madaeni et al., 2012; Milligan and Porter, 2006; Milligan, 2000).

In this study, the implied capacity credit is a result of the investment decisions and the impact of those decisions on dispatch rather than a detailed reliability analysis. The use of scarcity pricing during periods with insufficient generation capacity to meet loads, as described earlier in Section 3.3, is a proxy for indicating periods with high loss of load probability (LOLP), a common metric used in reliability studies. In a reliability study the sum of the loss of load probability over a period drives the loss of load expectation (LOLE) in a similar way that the sum of the scarcity prices over a period drive the short-run profits of a peaking plant. In a reliability study the LOLE is kept constant across cases that are meant to have the same level of reliability whereas in this study the short-run profits of generation that is built to meet peak loads is kept constant at the annualized fixed cost of investment across many scenarios. While investment decisions in this study are based on a fundamentally different approach than an explicit LOLP-based reliability analysis, it is clear that the relationship between displaced conventional generation capacity and additional VG follow similar drivers. This relationship is illustrated in more detail using a model of a simple power market that is much more simple than the power market modeled in this chapter in Appendix B.6.

In fact, one analysis that explicitly draws a link between investment decisions in a system where insufficient generation in periods leads to outage costs equal to the value of lost load (VOLL) and reliability based on LOLP is a paper by (Chao, 1983). The investment decisions in the model used in our analysis are built on similar intuition. The implied capacity credit of VG estimated in this analysis should therefore follow similar trends as what would be found with a detailed reliability analysis. However, for actual planning purposes a detailed reliability analysis that accounts for forced outages, required maintenance, and time to repair should be carried out.

Estimation of Long-run Value

In each case once the long-run equilibrium of non-VG resources has been determined, the system is dispatched a final time over the full year of hourly data using the final candidate portfolio of generation resources. Because the final non-VG portfolio is in long-run equilibrium, the prices for energy and ancillary services in the final dispatch represent the long-run marginal value of energy and reserves in each hour for the given level of VG penetration. The short-run profit earned by any resource that generates power when the system is in long-run equilibrium is therefore defined in this chapter as the marginal long-run economic value of that resource. For any new investments in non-VG resources that are part of the portfolio, the "market test" mentioned earlier in Section 3.2 results in the short-run profit being approximately equivalent to the fixed cost of investment and fixed O&M cost. Similarly, the short-run profit of VG resources can be compared to the fixed cost of investment to determine if it would be economically valuable to build more of that VG resource using the same "market test". In the case of VG, the short-run profit earned in this final dispatch represents the marginal economic value of that VG resource.

Since the prices that result from the dispatch of the system reflect the marginal value in that hour, the long-run marginal economic value calculated in any scenario indicates the value of adding a small increment of power with the same hourly generation profile. The marginal value does not, however, indicate the average value of all power that is produced by VG resources. For example, as will be shown in Section 3.5, the marginal value of most VG resources is lower when the system is at 10% penetration of VG than it is when at 0% penetration of VG. The marginal value of VG at 10% penetration indicates the value of increasing penetration beyond 10% while the greater marginal value at lower penetration levels indicates that the average value of all VG added to get to 10% penetration is greater than the marginal value at 10% penetration. The average value is useful for comparisons of average costs and benefits while the marginal value is useful for determining if there would be economic value to increasing the penetration from the predefined penetration level.

Because the marginal economic value of power is based on prices that result from a system that is in long-run equilibrium, the marginal economic value reflects both the value of displacing fossil fuel and the value of displacing the need for new conventional generation capacity. In contrast, a study that simply adds significant VG to a power system that is in equilibrium without VG is only reflecting the short-run economic value. In that case, the prices will fall below equilibrium levels and generators that were built to provide services to the system in a case with no VG will no longer be able to justify their investment costs in a system with high VG penetration. The system, in that case, would be far from equilibrium. Over the long life of a VG power plant, the long-run value is more useful for evaluating the benefits of VG because the short-run value reflects the temporary conditions of an out-of-balance system.

Decomposition of Marginal Economic Value

In addition to exploring how the marginal economic value of VG changes across technologies and with increasing penetration, it is important to understand what factors contribute to changes in the marginal economic value with penetration. Understanding what drives changes in the marginal economic value can help inform a search for market reforms or technological changes that can help mitigate decreases in economic value with increasing penetration, as will be discussed in a future paper.

In this study we choose to decompose the marginal value of VG into four separate and additive components: capacity value, energy value, day-ahead forecast error, and ancillary services. The definition of these components and the methods used to estimate each component differ from approaches sometimes used in other studies, particularly regarding the AS cost and DA forecast error cost. The values found in this chapter using this decomposition approach, however, do not appear to be out of line with values available in the other studies.

- Capacity Value ($/MWh): The portion of short-run profit earned during hours with scarcity prices (defined to be equal to or greater than $500/MWh).
- Energy Value ($/MWh): The portion of short-run profit earned in hours without scarcity prices, assuming the DA forecast exactly matches the RT generation.
- Day-ahead Forecast Error ($/MWh): The net earnings from RT deviations from the DA schedule.
- Ancillary Services ($/MWh): The net earnings from selling AS in the market from VG and paying for increased AS due to increased short-term variability and uncertainty from VG.

The capacity value reflects the contribution of VG to balancing supply and demand when generation is scarce. In particular, the periods with scarcity are defined to be periods where the price of energy rises to or above $500/MWh, the lowest scarcity price level for missing AS targets.[18] As will be described more in Section 3.5, periods with scarcity prices are infrequent with the final candidate portfolios: less than 1% of the year has scarcity prices in all cases considered in this analysis.

Even though scarcity prices are infrequent, they play an extremely important role in determining the short-run profit of new investments. The short-run profit earned by new CCGT resources during periods with scarcity prices, for example, is equivalent to 85–95% of the total short-run profit earned over the year in most cases.[19] During periods with scarcity

[18] The choice of the price level that differentiates between prices that are categorized as scarcity prices and non-scarcity prices impacts the decomposition of the marginal economic value into “capacity value” and “energy value”, but the choice does not impact the overall total marginal economic value.

[19] The exception to this are cases with high penetrations of CSP with 6 hours of thermal storage. In these cases the normal peak-load pricing model no longer applies since the system becomes increasingly energy-limited rather than capacity-limited. As will be described later, this is an area that is worth additional research.

prices the price of energy far exceeds the variable cost for CCGT plants, leading to high short-run profit in these hours. In addition, in some hours CCGT resources are operating while more expensive CT resources are at the margin, leading to additional short-run profit.

In contrast, for most of the rest of the year the price of energy is found to be nearly equivalent to the marginal variable cost of the CCGT (and the CCGT is on the margin) or the price is found to be below the marginal cost of production (meaning that the CCGT resources will typically be off-line or at minimum generation). In these hours the CCGT resource earns almost no short-run profit. Note that in a sensitivity case with no retirements, presented later in Section 3.5, additional low efficiency natural gas steam turbine plants remain in the power market which makes the short-run profit of CCGTs less dependent on scarcity prices compared to the reference scenarios. Furthermore, across all scenarios, the short-run profit of VG are less dependent on scarcity prices than CCGTs in part because VG technologies have zero variable costs.

The energy value is the remainder of the short-run profit earned by VG assuming perfect DA forecasts. Additional generation by VG would displace energy from the marginal resource in these hours, and the energy value then reflects the avoided fuel, emissions, and variable O&M costs from the generation that is displaced by VG, again based on an assumed perfect DA forecast of VG.

Day-ahead forecast error cost is the cost of deviations from the DA schedule paid at the RT price. This cost reflects the impact of RT deviations from the DA schedule in each hour. If the value is positive then the RT deviations contribute to meeting system needs and this is an additional value (e.g. solar thermal storage being re-dispatched in RT can help mitigate system conditions). If the value is negative, then the day ahead forecast error represents the cost that the RT deviations impose (i.e. wind forecast errors on average increase cost).

The ancillary service component reflects the net value from a resource providing AS to the system (e.g., regulation down provided by wind or solar) and the additional burden of a resource in requiring an increase in the procurement of AS (e.g., regulation) to manage intra-hour variability. A negative value indicates a net cost: the expense of procuring additional AS due to the variability of VG exceeding any revenue earned by VG for selling AS. The costs that are attributed to VG reflect the assumption that AS requirements change in proportion to the DA schedule for VG. The amount of AS added to compensate for the additional short-term variability and uncertainty of VG is described in Section 3.4.

3.4 Data and Assumptions

This chapter focuses on a case study of adding increasing amounts of VG to a power system based on load, VG profile, and capacities of incumbent generation that loosely correspond to California in 2030. We are only using selected data from California primarily based on existing generation and historical load profiles. We are not attempting to exactly model many elements that impact California including the detailed CAISO market rules, imports, procurement and contracting policies, and emissions regulations, among other factors. The results reflect these assumptions which mean that not only would these results be different in other regions, they are not meant to exactly model California either.

The only load and conventional generation resources that are considered are for the California NERC sub-region; load and conventional generation resources defined by NERC as outside of the California NERC sub-region are ignored.[20] The generation profiles for VG, however, include some resources that are located outside of California based on the site selection process described in the next section. These resources are assumed to be dynamically scheduled into California such that all of the variability and uncertainty, including within-hour, is managed within the state.

Variable Generation

The VG profiles and DA forecasts are based on hourly data corresponding to the historical generation profile estimated for the year 2004. Other choices of the historical generation years for VG and load were not tested in this study. Future research could examine the sensitivity of the results to the choice of historical year or the number of years chosen for analysis. The wind generation profiles and forecasts for each 30 MW wind site used to reach the target wind penetration level are based on the dataset derived for the Western Wind and Solar Integration Study (WWSIS) (Potter et al., 2008).

The solar generation profiles are based on hourly satellite derived insolation data from the National Solar Radiation Database (NSRDB).[21]

Each solar site used to reach the target penetration level is located at one of the 10 km × 10 km grid points included in the NSRDB. Each PV site is assumed to have a 100 MW nameplate capacity (AC) and each CSP site is assumed to have a 110 MW nameplate capacity. For PV the insolation data are converted into PV generation profiles using the NREL System Advisor Model (SAM). The PV data are based on single-axis tracking PV that is tilted at an angle of the PV site latitude. For CSP the insolation data are converted

[20]In reality California is a net-importer of power from other regions in the WECC from power plants that are not considered by NERC to be part of the California sub-region. Imports in 2010 included renewable power, coal power, large hydro power, natural gas power, nuclear power, and unspecified sources of power (`http://energyalmanac.ca.gov/electricity/total_system_power.html`). Estimating the role of imports in 2030 in California would require assessing plant retirements in 2030, modeling transmission between California and the rest-of-WECC in 2030, and projecting renewable penetration levels for the rest of WECC. This level of detail was not included in the model. Depending on how much of the out-of-state coal retires by 2030, access to more out-of-state coal would tend to lower the economic value of variable generation at high penetration since coal would be displaced instead of more expensive natural gas. Access to more out-of-state nuclear would also lower the economic value of variable generation at high penetration levels. Access to out-of-state large hydro in the Pacific Northwest and along the Colorado River would potentially increase the resources available to manage variability and uncertainty in some hours but it could also reduce flexibility in low load hours depending on the minimum flow constraints of out-of-state hydro. Access to out-of-state natural gas would raise or lower the economic value of variable generation depending on the heat-rate and flexibility of the out-of-state natural gas relative to the heat-rate and flexibility of the in-state natural gas.

[21]`ftp://ftp.ncdc.noaa.gov/pub/data/nsrdb-solar/`

into thermal heat generation in the solar field using SAM. The solar plant is then dispatched within the dispatch model based on a method similar to (Sioshansi and Denholm, 2010).[22] The solar field multiplier (the ratio of the peak power output of the solar field relative to the nameplate capacity of the solar plant power block) is assumed to be 1.25 for CSP_0 and 2.5 for CSP_6. DA forecasts of solar insolation from the WWSIS are also converted into DA forecasts of generation for PV and solar field heat for CSP resources. DA solar forecasts were only generated on a 20 km $\times$ 20 km grid in the WWSIS. Individual solar sites on a 10 km $\times$ 10 km are then assigned forecasts from a nearby site on the 20 km $\times$ 20 km grid. This approximation will tend to overstate the correlation of DA forecast errors and potentially the DA forecast error costs for solar.

Note that the solar and wind DA forecasts are point forecasts developed in the WWSIS using numerical weather models. Increasingly studies of unit-commitment and scheduling with variable generation are using stochastic unit-commitment methods that rely on several different forecasts in order to represent the uncertainty inherent in day-ahead forecasts rather than relying on one point forecast, as discussed in Section 3.3. Evaluating the impact of stochastic unit-commitment on the long-run value of VG is left for future research.

The actual generation profiles for the VG resources that were modeled in each of the scenarios were selected from the resources identified in the Western Renewable Energy Zone Initiative (WREZ) (Pletka and Finn, 2009). The resources were picked by ranking all of the WREZ resources by their relative economic attractiveness[23] to load zones in California[24] and then selecting the most attractive resources of the type of VG being considered up to the desired penetration level. As a result of this procedure, solar resources were all selected from high-quality solar resource hubs in California with some additional solar from Arizona hubs in cases with more than 20% solar penetration. Wind resources were similarly selected from California hubs at low wind penetration levels. At 10% penetration additional wind resources were selected from hubs in Oregon, Arizona, Nevada, and Utah. At 20% penetration additional wind resources were selected from Washington, Wyoming and Idaho, and for 30% penetration and above wind resources were selected from New Mexico as well.

[22] The key difference with the CSP dispatch approach used in this chapter is that the CSP sites are grouped together into a CSP vintage and decisions regarding how much CSP to bring on-line are linearized rather than the binary on/off decisions modeled for an individual CSP plant in (Sioshansi and Denholm, 2010). The linearization used in this chapter is a simplification that is used to maintain reasonable dispatch solution times at the expense of more accurate representation of individual power plant decisions.

[23] Specifically, the resources were ranked by the adjusted delivered cost estimated in the WREZ Peer Analysis Tool (`http://www.westgov.org/rtep/220-wrez-transmission-model-page`). This metric includes the bus-bar cost of the resource, a pro-rata share of a new 500 kV transmission line between the resource hub and the load zone, and a simplified estimate of the market value of the power to the load zone.

[24] The California load zones included in the WREZ Peer Analysis Tool included Sacramento, San Francisco Bay Area, Los Angeles, and San Diego.

Load

Historical hourly demand data for 2004 (in order to match the solar and wind data) are based on the aggregated demand reported for all of the transmission zones that are assigned to the California NERC sub-region.[25] The historical load profile for 2004 is increased to estimate demand in 2030 by applying a constant growth factor of 1.16 to all hours of the historic year.[26] The peak load in 2030 based on scaling the historical California load shape from 2004 is 63 GW. Demand is treated as nearly inelastic in this case study with an assumed constant elasticity of demand of -0.001 up to the assumed value of lost load ($10,000/MWh).

Hydropower and Pumped Hydro Storage

Hydropower is challenging to model accurately due to the many non-economic constraints on river flows downstream of the plant and the variable river flows upstream of the plant. Furthermore, detailed historical hydro data showing constraints and hydro plant parameters are rarely available in the public domain. In this analysis hydro is dispatched between the total nameplate capacity of hydro in the California NERC sub-region and a minimum generation constraint that varies by month as described below. The current nameplate capacity of hydro generation in California is 13.3 GW. All of this hydro capacity is assumed to be available in 2030. Additional investments in hydro are not considered in the investment model.

The amount of total hydro generation in California that is assumed possible each month (the hydro generation budget) is based on the total actual hydropower generation within the California NERC sub-region during the same calendar month from the median hydropower generation year for the years of 1990 through 2008.[27] The historical hydropower generation data were collected from Ventyx. The minimum hourly hydro-flow constraint each month is based on the average hourly generation rate that would lead to the lowest monhtly total hydro generation measured between 1990 and 2008 in that same calendar month.

The reasonableness of the hydro assumptions were checked by comparing hydropower generation duration curves for a modeled case (with no variable generation) to a short hourly record of aggregated hydropower production in the CAISO.[28] The shape of the modeled hydropower generation shows more time at maximum generation and minimum generation relative to the time spent at minimum and maximum for the actual hydropower generation. This could partly be explained by 2010-2011 being higher than median hydro years, but it may also be due to hydro constraints that are not captured in this analysis.

[25] The demand data were collected from Ventyx Velocity Suite, hereafter referred to as Ventyx.

[26] The growth factor is based on an extrapolation of the annual growth rate between 2015-2020 estimated by WECC (which adjusts load forecasts for expected energy efficiency measures) to the period between 2005-2030.

[27] The median hydropower generation was used in this study but data were collected to be able to examine the impact of high hydro or low hydro years on the estimated economic value of variable generation.

[28] The available hourly hydro generation data between 2010 and the end of 2011 were extracted from the CAISO website at `www.caiso.com/green/renewableswatch.html`

The 3.5 GW of existing pumped hydro storage (PHS) capacity in California is assumed to be available in 2030. The reservoir capacity is assumed to be equivalent to 10 hours of storage capacity at full power (35 GWh). The round-trip efficiency of the pumped hydro is assumed to be 81%. Inflow into the pumped hydro storage from direct precipitation onto the reservoir or runoff from area surrounding the pumped hydro storage reservoir is assumed to be negligible.

Both hydropower and pumped hydro storage are assumed to be able to provide ancillary services and both can earn high revenue during hours with scarcity prices as long as sufficient energy is available.

Thermal Generation Vintages and Technical Life

The existing WECC thermal generation fleet was grouped into several different vintages based on factors including fuel, plant size, and age. The thermal plant vintages were then used to derive average performance characteristics that are used in the dispatch model. The amount of incumbent generation within each vintage is based on the amount of generation that would still be operating in 2030 assuming typical plant technical lifetimes.[29] Generation that is older than the technical life in 2030 is assumed to be retired for technical reasons, while economic retirement decisions are based on whether or not the short-run profit of incumbent generation is sufficient to cover its fixed O&M cost, as described earlier in Section 3.3. A sensitivity scenario, presented in Section 3.5, examines the impact of the technical life assumptions by assuming that no existing generation is retired by 2030 for technical reasons.

Incumbent Generation Capacity

The resulting total incumbent generation in California in 2030 is 45.5 GW of nameplate capacity. In addition to the incumbent hydropower and pumped hydro storage, the incumbent thermal generation is grouped into two coal vintages, three CCGT vintages, one CT vintage, one natural gas steam turbine vintage, geothermal, and nuclear. Based on the assumed technical life, 5% of the incumbent generation capacity is coal, 35% is CCGT, 9% is CT, 0.2% is natural gas steam turbine (almost all of the existing natural gas steam turbine fleet is assumed to reach the end of its technical life by 2030), 10% is nuclear, 4% is geothermal, 29% is conventional hydropower, and 8% is existing PHS. Additional older vintages are included

[29] The technical life assumptions were as follows: 60 years for nuclear plants, 50 years for coal, natural gas steam plants and geothermal, and 30 years for CT and CCGT plants. The technical life of coal and natural gas steam plants is based on an analysis of historical plant retirement ages in North America using the Ventyx Velocity Suite database of plant ages and retirement dates; similar assumptions are used in other studies ((IEA), 2010; Sims et al., 2007). Fewer retirements of CTs and CCGTs were available from the historical Ventyx data, and instead a technical life of 30 years was assumed based on the technical life presented by International Energy Agency (IEA) (2011). The technical life for nuclear plants is based on an original license life of 40 years with a single 20-year license renewal. A similar assumption was used in the 2010 EIA Annual Energy Outlook Alternative Nuclear Retirement Case (Energy Information Administration (EIA), 2010).

for the incumbent generation in a sensitivity case where there are no assumed retirements from the existing generation. These additional vintages are described in Appendix B.4. The appendix also provides more details on the data and assumptions used to model pumped hydro storage, and thermal and hydropower generation.[30]

Generation Operational Parameters

Standard thermal generation performance parameters[31] (including maximum and minimum generation, ramp-rates, part-load heat rates and emissions curves, and start-up heat) were derived based in large measure on the average historical performance of WECC thermal generators within the same plant vintage based on figures reported in the Ventyx Velocity Suite, as described in further detail in Appendix B.4.[32] The Ventyx data largely derive from actual historical plant performance measured hourly through the Continuous Emissions Monitoring System (CEMS) from the EPA. The Ventyx dataset does not quantify NO_x or SO_2 emissions during start-up that are in addition to normal emissions at part-load.[33] The NO_x and SO_2 emissions during start-up were therefore approximated as a ratio of the emissions at full load using the ratios reported by initial analysis of Lew et al. (2011).[34]

Ramp-rates for the CT vintage were found to be very low when using hourly data from the Ventyx dataset. In addition the Ventyx dataset does not include ramp-rates for hydro nor does Ventyx report non-fuel start-up costs. The ramp-rates for the CT vintage and for hydropower[35] along with the non-fuel start-up costs related to wear & tear for all thermal

[30] No existing wind or solar were included in the incumbent generation in order to be able to examine the marginal economic value of VG across a full range of VG penetration levels starting from nearly zero penetration. Existing biomass and combined-heat and power generation in California were also excluded from the analysis for simplicity. Biomass generation is similar to thermal generation in that there is often a non-negligible variable cost associated with generating energy. It differs from conventional generation however due to variability in resource availability and in demand for energy to satisfy policies external to the power market like the state RPS.

[31] A minimum run-time limit was not included since thermal generation is dispatched as a fleet in this analysis. The minimum run-time for an individual plant does not limit the minimum time a fleet of generation can operate with a given amount of generation online as the timing of when individual units were started and stopped could be staggered.

[32] The thermal generator parameters used in this study are intended to be used in similar case studies of other WECC regions. Characteristics of all WECC generators were therefore used rather than focusing only on the characteristics of generation in California.

[33] CO_2 emissions during start-up can be estimated from the Ventyx data since Ventyx reports fuel combustion during start-up and CO_2 emissions are proportional to fuel combustion.

[34] The ratio of the start-up NO_x emissions to the full-load hourly NO_x emissions was 9.5 for a CCGT, 6.7 for a CT, and 2.9 for coal based on the analysis by Lew et al. (2011). The ratio of the start-up SO_2 emissions to the full-load hourly SO_2 emissions was only reported for coal by Lew et al. (2011). The ratio reported for the SO_2 emissions for coal, 2.7, was assumed to be the same for CCGTs and CTs in this analysis.

[35] The ramp-rates used here are more conservative than the ramp-rates that are reported for CTs and aggregated hydropower plants by Makarov et al. (2008). This lower bound on ramp rate capabilities helps to reduce any bias that would otherwise be introduced by the fact that this study does not include any costs associated with ramping plants.

plants are therefore derived from the assumptions used in WECC transmission modeling (WECC, 2011). The non-fuel start-up costs for coal plants derived from the WECC assumptions are similar to the warm start costs (i.e., the plant is not down for longer than 120 hours) for coal plants reported by Gray (2001). More recent preliminary research on average "lower-bound" start-up costs for coal, natural gas steam turbines, CCGT, and CT plants by Intertek Aptech shows high variability depending on the way that plants are designed to operate and the degree to which investments are made to reduce start-up costs (Lefton, 2011). The Aptech research also indicates that the range of start-up costs from actual plants may be somewhat higher for coal plant and lower for CT plants than the assumed average costs used in this analysis. As non-fuel start-up costs are an area of ongoing research, this is an area where assumptions should be revisited as more detailed estimates become available.

The incumbent geothermal and nuclear plants were assumed to be inflexible and therefore not able to reduce their output from their nameplate capacity. Although there are examples showing that it is technically possible to ramp and cycle both some nuclear and geothermal plants,[36] it is assumed for simplicity that regulatory, policy, and practical restrictions prevent flexible operation. Even if these plants were modeled as being flexible, they would rarely be cycled due to the very low variable cost of the nuclear and geothermal resources; the wholesale price of power would have to drop below the low variable cost of these plants for there to be any economic benefit to cycling the plants.

The variable O&M costs for each vintage were based on averaging the Ventyx estimates for variable O&M cost for each WECC plant across the vintages. Where estimates were not available from Ventyx, estimates from WECC transmission modeling were used instead.

No consideration was made of planned and forced outage rates of generation in this analysis. This assumption is not expected to impact the relative changes in the marginal economic value of variable generation with increasing penetration. It will, however, tend to understate the capacity and energy value of VG. Irrespective of the VG penetration level this assumption will also tend to understate the absolute amount of conventional generation that is required to reach long-run equilibrium and low percentages of periods with scarcity prices and involuntary load shedding. Determining the actual amount of generation to build in 2030 will require the use of a reliability model that accounts for factors like conventional generation forced and planned outages.

[36] Nuclear examples: A survey of cycling capabilities of steam plants concluded that limited nuclear cycling was a valid assumption (Fenton, 1982). The survey did report 6 nuclear power units, however, that were being turned down at night. The units could be turned down to as low as 50% of their capacity. Various occasions of the Columbia Generating Station, a nuclear power plant in the northwestern U.S., being turned down for economic dispatch have been reported (Rudolph and Ernst, 2010). There are also examples of geothermal plants being operated in a more flexible manner than strictly baseload (Brown, 1996; Grande et al., 2004).

Fuel Costs

Fuel costs for gas, coal, and uranium in 2030 are based on projections from the EIA in the Annual Energy Outlook, 2011 (EIA, 2011). The EIA gas price projection reflects recent reductions in expected gas prices due to the rapid growth of shale gas. While no sensitivity cases are used in this chapter to directly explore the impact of different gas prices on the economic value of variable generation, it should be recognized that uncertainty in future natural gas prices is a major source of uncertainty in estimating the absolute level of the marginal economic value of variable generation.

New Investments

This model allows for new investments in coal, CCGT, CT, nuclear, and PHS. The operating characteristics of the new investments (e.g., minimum generation, ramp rate, heat rates, emission rates, variable O&M costs, start-up costs, etc.) are assumed to be equivalent to the characteristics of recent vintages of incumbent plants that use the same fuel. The annualized capital cost and fixed O&M costs for all technologies except the PHS are based on a pro-forma financial model developed by E3 for WECC transmission modeling (WECC, 2010). The PHS annualized capital cost is based on EIA Annual Energy Outlook assumptions (EIA, 2010). No capital cost assumptions are made for wind and solar since these resources are forced in at different penetration levels. The variable O&M cost of wind and solar is assumed to be zero.

Ancillary Service Requirements

As described in Section 3.3, AS targets are included in the dispatch of the system in addition to energy demand.

Market rules and operating procedures impact AS requirements and differ among power markets. Rather than explicitly modeling the AS requirements for a particular region or set of market rules, in this chapter the AS targets are based largely on the rules of thumb developed in the WWSIS (Piwko et al., 2010), with some minor adjustments made based on an examination of 1-min solar, wind, and load data synthesized for the CAISO 33% RPS analysis.[37] The rules of thumb developed in the WWSIS are largely based on examining the

[37] Data are available on the CAISO website under 33% Trajectory Case: Preliminary New Scenarios, One-Minute Data for Load, Wind and Solar. `http://www1.caiso.com/23bb/23bbc01d7bd0.html` The changes between the AS requirements used here and the rules of thumb developed in the WWSIS include (1) the WWSIS suggested an increase of reserves equivalent to 5% of the VG that would be split between spinning reserves and regulation reserves while this study allocates the full increase to regulation reserves and (2) the total amount of regulation and spinning reserves for hourly load was 3% of hourly load in the WWSIS while here it is 2% for regulation and 2% for spinning reserves. These adjustments were made in order to ensure that the regulation reserve requirement rules used in this model would be sufficient to cover the majority of the 1-min deviations of the 1-min data from interpolated 1-min data between hourly averages. Since this model uses only hourly average data, and does not explicitly model sub-hourly dispatch, these changes to

amount of reserves that would be required to meet three times the standard deviation of ten-minute changes in the net load. Implicitly, this reserve method assumes that sub-hourly dispatch is available and that day-ahead forecast errors dominate the uncertainty. Different reserve requirements would be needed for situations with different practices for scheduling and dispatching generation resources.

Hourly spinning and non-spinning reserves requirements are based only on the hourly load while hourly regulation reserve requirements are based on load and DA forecasts of VG. Similar AS requirements are applied for wind and solar (PV and CSP_0); a reasonable assumption based on previous analysis of 1-min data for wind and solar (Mills and Wiser, 2010a). The AS targets are as follows:

- Non-Spinning Reserve: 4% of hourly load
- Spinning-Reserve: 2% of hourly load
- Regulation: 2% of hourly load plus 5% of day-ahead forecast of wind, PV, or CSP_0

The non-spinning reserves can be met by quick-start CT's that are off-line or by other resources that are on-line. The non-spinning reserves are assumed to be needed within 30-minutes. The amount of non-spinning reserve that a resource can offer is then based on how much it can increase its output in 30-minutes given the ramp-rate limits of the resource. The spinning reserves can only be met by on-line resources and are assumed to be needed within 10-minutes.[38]

Regulation reserves are required in both the up and down direction, whereas spinning and non-spinning reserves are only required in the up direction. The regulation reserves can only be met by on-line resources and need to be fully deployable within 5-min. Additional details on how AS requirements are co-optimized with energy demand in the dispatch of generation resources are provided in Appendix B.3.

3.5 Results

The marginal economic value of wind, PV and CSP with increasing penetration of each variable energy resource in California is first explored by showing the total non-VG investment and the dispatch results for both VG and non-VG resources, including the implied capacity credit, changes in energy generation, emissions and curtailment. Variable generation profiles and the hourly prices for energy and ancillary services are then used to estimate the

the reserve rules act somewhat as a proxy to the resources that would be needed in sub-hourly dispatch.

[38] We were not exactly attempting to match AS requirements for the WECC region. To be in compliance with current WECC requirements, the spinning reserves would need to be equivalent to half of the total contingency reserves. This would imply that the spinning reserve would be increased to 3% of the load and the non-spinning reserve would be decreased to 3%. Since these requirements do not change with changes in the penetration of variable generation, this change in contingency reserve allocation would not be expected to have a noticeable impact on the marginal economic value of variable generation.

marginal economic value of variable generation. This marginal economic value is decomposed into capacity value, energy value, day-ahead forecast error, and ancillary service costs to show which factors contribute the most to changes in the marginal economic value with increasing penetration. Finally, sensitivity cases are used to explore how the marginal economic value would change for a system without flexibility constraints, with higher energy costs (by adding a carbon price), with lower capacity costs, and without retirement of currently existing generation. Future research will consider strategies to stem the decrease in the economic value of VG at high penetration such as price responsive demand, more flexible thermal generation, and lower-cost bulk-power storage (lower cost than the assumed cost of PHS in this chapter).

Investment and Dispatch Impacts

Nameplate Capacity of Generation

As described in Section 3.3, adding VG to a power system decreases the amount of new non-VG capacity that is economic to add in 2030 relative to a scenario with no VG capacity. The amount of non-VG capacity that is built in the present framework is based on economic considerations: new generation resources are only added if the short-run profits earned by the resource can cover the annualized investment cost and fixed O&M cost. The resulting investments, however, are coupled with indicators of the reliability of the system. Across all of the penetration scenarios and VG technologies, for example, the percentage of time with wholesale power prices that equal or exceed $500/MWh[39] is always below 1% of the year, Table 3.1.[40] If too little generation were built to cover peak demand and AS in cases with high penetration of VG then the percentage of time with price spikes would increase and, as illustrated earlier in Figure 3.2, the short-run profits of conventional generation would increase. The fact that the amount of time with price spikes stays relatively constant with increasing VG, suggests that just as sufficient generation capacity is being added in the case without VG as is being added in the cases with increasing VG penetration. [41]

Interestingly, the frequency of price spikes decreases with very high penetrations of CSP_6 presumably because the overall system shifts towards being energy constrained rather than capacity constrained as is explained throughout the Results section.

[39] $500/MWh is the lowest scarcity price level that indicates that AS targets are not being met.

[40] The percentage of time that wholesale prices equal or exceed $500/MWh is based on load and generation data from only one year. In a reliability focused planning study where it is important to ensure an absolute level of reliability (rather than maintaining a relative level of reliability in this study) it would be important to include more years of data with different load and generation shapes. In addition, factors like scheduled maintenance and forced outage rates would need to be considered. These issues are less important for this study since the results are driven primarily by maintaining a relative level of reliability rather than reaching an absolute reliability target.

[41] Following the arguments in Appendix B.6, a relatively constant number of hours with scarcity prices across the year, as expected for a system that maintains a long-run equilibrium, is an indicator that a reliability-based loss of load expectation analysis (LOLE) would similarly find a constant LOLE across the

Text Box 2. Comparison of variable generation to flat block of power

Irrespective of the generation profile, adding significant amounts of any type of new generation to a power system to some degree changes dispatch and investment decisions in the rest of the power system. A case was run using a resource that has a flat generation profile over the entire year in order to better highlight changes in the marginal economic value of variable generation that are due in part to factors like temporal generation profiles, variability, and uncertainty in contrast to changes that are associated with simply adding significant amounts of generation from a new resource. This resource is referred to as a flat block throughout the Results section. The flat block is only meant to provide an idealized comparison; it is not meant to characterize any particular alternative resource.

The total nameplate capacity and the total annual energy production from the resources in the power market with increasing penetration of a flat block are shown in Figure 3.3. From 0% to 30% penetration adding a unit of nameplate capacity from the flat block offsets the need to build new combined cycle natural gas plants. At 40% penetration of a flat block, however, no new combined cycle plants need to be built and none of the existing thermal generation finds it economically attractive to retire for economic reasons. At this penetration, then, the total nameplate capacity slightly exceeds the total nameplate capacity between 0% to 30% penetration of the flat block.

Increasing penetration of the flat block offsets energy generated by combined cycle natural gas plants. Even at high penetration adding power from a flat block does not displace any generation from the small amount of incumbent coal in this market in 2030.

Additional results based on increasing the penetration of a flat block are included throughout the Results section along with comparable results for the four variable generation technologies.

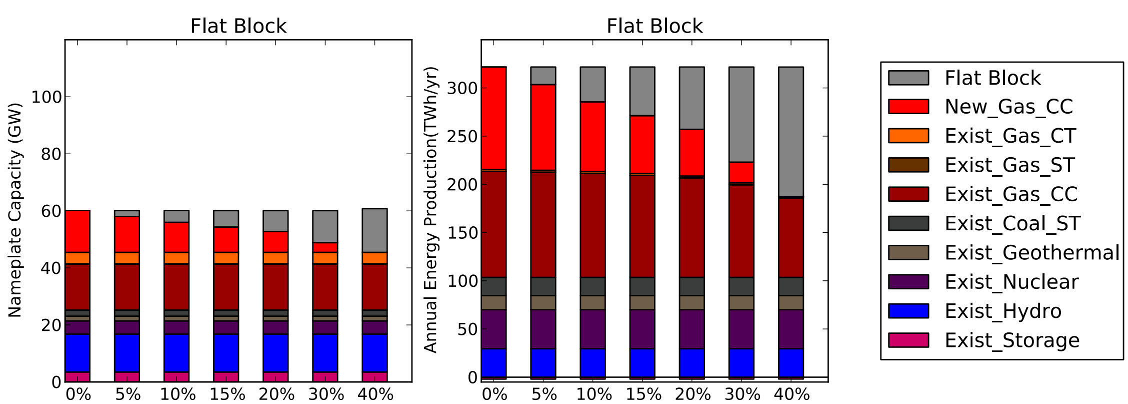


Figure 3.3: Total nameplate capacity and total energy generation from different resources with increasing penetration of a flat block of power.

Table 3.1: Percentage of the year with energy prices that equal or exceed $500/MWh with increasing penetration of VG.

	Penetration of VG							
VG Technology	0%	2.5%	5%	10%	15%	20%	30%	40%
Flat Block	0.8%	n/a	0.8%	0.8%	0.8%	0.8%	0.8%	0.7%
Wind	0.8%	n/a	0.7%	0.7%	0.7%	0.8%	0.8%	0.8%
PV	0.8%	0.8%	0.8%	0.8%	0.8%	0.7%	0.7%	n/a
CSP0	0.8%	0.8%	0.8%	0.8%	0.7%	0.6%	0.6%	n/a
CSP6	0.8%	0.8%	0.7%	0.6%	0.6%	0.3%	0.0%	n/a

Additionally, the amount of involuntary load shedding as a percentage of the total load remains below 0.01% with increasing penetration of VG, Table 3.2. If too little generation were built or if the system did not have sufficient flexibility to manage higher penetrations of VG then the amount of involuntary load shedding would substantially increase. That the amount of involuntary load shedding remains below 0.01% even with high VG penetration also demonstrates that sufficient generation is being built by the model and that the system has sufficient flexibility to manage VG. The amount that the involuntary load shedding does increase in cases with high VG penetration, particularly high wind, can be explained in part due to the steeper net-load duration curve at the very high net-load levels with high VG penetration relative to the steepness of the load duration curve at very high load levels without VG. When the cost of new capacity is roughly $200/kW-yr and the value of lost load is assumed to be $10,000/MWh, it is more economic to involuntarily shed load for any net-load level that occurs less than roughly 20 hours per year than it is to build new capacity just to meet those very infrequent high net-load events. Because the net-load duration curve is slightly steeper more of the net-load occurs for less than 20 hours per year than the amount of load that occurs for less than 20 hours per year without VG.[42]

At 40% penetration of a flat block the amount of involuntary load shedding falls because new capacity no longer needs to be built and therefore the periods with prices high enough to trigger involuntary load shedding are not needed to induce new investments. Instead, the prices only need to rise high enough to ensure that incumbent generation does not retire for economic reasons. As with the frequency of high prices, the amount of involuntary load shedding decreases with high CSP_6 penetration as the overall system shifts towards being energy constrained rather than capacity constrained.

scenarios (other than the high CSP_6 cases).

[42]Whereas the number of hours of the year with price spikes in Table 3.1 is a proxy for the loss of load expectation (LOLE) that would be estimated in a reliability analysis, the percentage of unmet load in Table 3.2 is a proxy for the expected unserved energy (EUE), a different reliability metric. As a result, these results suggest that even if the LOLE calculated in a reliability study were expected to remain constant across these scenarios, the EUE calculated in a reliability study would be expected to slightly increase with increasing penetration of variable generation.

Table 3.2: Percentage of the total annual load that is not met during periods with prices that exceed the value of lost load ($10,000/MWh).

	Penetration of VG							
VG Technology	0%	2.5%	5%	10%	15%	20%	30%	40%
Flat Block	0.004%	n/a	0.004%	0.004%	0.004%	0.004%	0.004%	0.002%
Wind	0.004%	n/a	0.005%	0.004%	0.005%	0.006%	0.008%	0.009%
PV	0.004%	0.002%	0.003%	0.004%	0.006%	0.007%	0.006%	n/a
CSP_0	0.004%	0.002%	0.003%	0.005%	0.006%	0.006%	0.006%	n/a
CSP_6	0.004%	0.004%	0.003%	0.002%	0.001%	0.000%	0.000%	n/a

The resulting amount of new conventional generation that is built, the amount of incumbent conventional capacity, and the nameplate capacity of VG are shown for each penetration level in Figure 3.4.

In all cases (excluding the sensitivity cases explored later) the only new non-VG investments are in new CCGT resources under the assumptions used in this study. While the short-run profit of new CCGT resources was approximately equal to the investment cost of new CCGTs, the short-run profits of new coal, new nuclear, and new PHS resources were far below their annualized investment cost, Table 3.3. Major changes to fuel costs or investment costs would likely be needed to increase investments in these other technologies.

Similarly, no new CTs were built in addition to the existing incumbent CTs. The short-run profit of the CTs however, was commonly close to or above 90% of the annualized fixed investment cost of new CTs, or only $20/kW-yr or less below the assumed annualized investment cost of CTs. Even though the CCGTs were assumed to have fixed investment and O&M costs that were $10/kW-yr more than that of the CTs, the CCGTs were slightly more economically attractive because the CCGTs earned greater short-run profit in non-scarcity hours due to their relatively high efficiency in comparison to the CTs (they both earned roughly the same amount during scarcity hours). That being said, CTs become increasingly more attractive with increasing penetration of VG (except in the case of increasing CSP_6) due to the decreased amount of energy needed from CCGTs and the increased value of CT flexibility. Relatively modest reductions in the assumed investment cost of CTs relative to CCGTs would therefore lead to new CTs substituting for a portion of the CCGTs that are built, as is found in the sensitivity studies in Section 3.5. Similarly, consideration of factors such as the shorter lead time for construction and smaller size of individual units, factors not considered in this analysis, would tend to favor new CTs instead of new CCGTs. Furthermore, the relatively high amount of flexibility from the incumbent CTs, hydro, and pumped hydro storage in California all contribute significant flexibility to the system that would otherwise require new CTs in regions that lack substantial flexibility in the incumbent generation. Given the relatively small difference in the gap between the short-run profit and fixed cost of CTs relative to the gap for CCGTs it is important that CTs are considered in more detail in studies that would guide actual procurement processes.

Table 3.3: Short-run profit of investment options as a percentage of annualized fixed cost with and without 20% penetration of VG in 2030.

Investment Option	CCGT	CT	Coal	Nuclear	PHS
Fixed Cost ($/kW-r)	203	194	494	950	706
VG Technology	Short-run Profit as Percentage of Fixed Cost (%)				
0% VG	100%	88%	76%	51%	28%
20% Flat Block	100%	88%	76%	51%	28%
20% Wind	100%	94%	76%	51%	31%
20% PV	100%	95%	76%	51%	34%
20% CSP_0	100%	98%	74%	49%	36%
20% CSP_6	99%	68%	75%	51%	8%

As VG penetration increases, the total nameplate capacity of the combintation non-VG and VG resources increases above the nameplate capacity of non-VG resources alone in the 0% VG case. The increase in total nameplate capacity of the combintation of non-VG and VG resources is particularly evident in the cases with wind, PV, and CSP_0. This reflects the relatively low capacity factor of these resources and their relatively low ability to offset new investments in non-VG capacity especially at high penetration levels. Despite the increase in the combination of VG and non-VG nameplate capacity, in all cases the amount of non-VG capacity alone actually decreases with increasing VG penetration due to reductions in the amount of new CCGTs that are built. No penetration levels showed an increase in the nameplate capacity of non-VG capacity relative to the 0% VG case, indicating that VG at all penetration levels had some ability to offset new investments in non-VG capacity. In addition, all incumbent capacity in 2030 that was not retired for technical reasons found it to be economically attractive to stay in the power market in 2030. In other words, the short-run profit of incumbent generation always exceeded the assumed fixed O&M cost required to continue to operate the incumbent resources.

The effectiveness of VG in reducing the amount of non-VG capacity that is needed with increasing penetration differed between technologies. PV and CSP_0 were more effective at reducing the non-VG capacity at low penetration, but lost effectiveness at higher penetration levels. Wind only slightly reduces the amount of non-VG capacity that is built, but wind continues to displace a small amount of non-VG capacity even at higher wind penetrations. CSP_6 was very effective at reducing non-VG capacity at both high and low penetration levels.

The effectiveness of VG in reducing the amount of new non-VG nameplate capacity that is built can be more easily observed through calculating the implied marginal capacity credit of VG. As described in Section 3.3, the implied marginal capacity credit (hereafter called the capacity credit) is calculated as the incremental reduction in non-VG nameplate capacity per

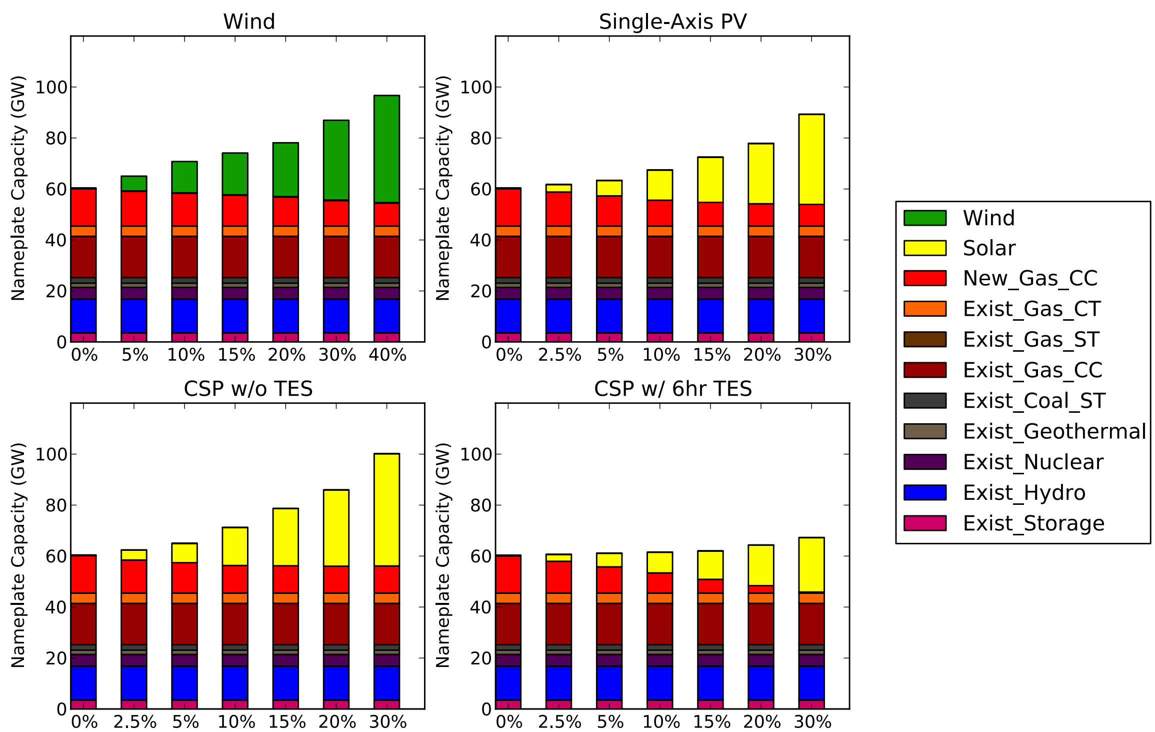


Figure 3.4: Total nameplate capacity of generation with increasing penetration of variable generation.

unit of additional VG nameplate capacity added between two different penetration levels. The capacity credit between two low penetration cases (0% and 5% penetration) and between two high penetration cases (15% and 20% penetration) is shown in Table 3.4. The increase in total (VG and non-VG) nameplate capacity with increasing penetration for each VG technology shown in Figure 3.4 can be explained by the fact that the capacity credit of the VG resources is in most cases far below 100% of the nameplate capacity and is therefore also far below the capacity credit of new CCGT resources or of a flat block of power. Since the capacity credit of VG is less than the capacity credit of new CCGT resources that are used to meet system needs in the 0% VG case, the total nameplate capacity of all generation increases.

There are also important differences between the various VG technologies in terms of their capacity credit. At low penetration, the capacity credit of the solar technologies is highest. This high capacity credit is due to the coincidence of solar production and scarcity prices, which at low penetration occur during times with peak demand. The capacity credit of PV and CSP_0 calculated in this model is within a similar range estimated for low penetrations of solar using more detailed probabilistic methods (Madaeni et al., 2012; Pelland and Abboud, 2008; Shiu et al., 2006).[43] The ability of TES to shift production from mid-day into the later afternoon hours results in a significantly higher capacity credit for CSP_6 relative to CSP_0 and PV. The coincidence of wind production and scarcity prices is lower, which leads to a lower capacity credit for wind.

At high penetration, the capacity credit of PV and CSP_0 drop by a considerable amount while the capacity credit of wind only decreases by a small amount from its already low level. In fact, the marginal capacity credit of wind at high penetration is slightly greater than the capacity credit of PV and CSP_0 at high penetration. The steep decline in the capacity credit of PV and CSP_0 indicates that the addition of more PV or CSP_0 when the penetration of those technologies is already high does not offset as much conventional capacity as they did at low penetration levels. Intuitively, this is because with high PV and CSP_0 penetration the net load peaks during early evening hours, and no increase in PV or CSP_0 capacity can help meet demand during that time. More specifically, as will be described in Section 3.5, the decreasing capacity credit of these solar technologies is a result of prices decreasing during times with higher solar production (i.e. scarcity prices stop occurring in the afternoon on summer days) and scarcity prices shifting to early evening hours in the summer when there is little or no solar production from PV and CSP_0 yet demand is still high. The decreased capacity credit for PV or CSP_0 with increasing penetration has been noted before (Kahn, 1979; Perez et al., 2008).

With thermal storage, however, the TES is dispatched such that a CSP_6 resource continues to produce power into the early evening and even later evening hours until the normal diurnal demand is considerably lower. The capacity credit of CSP_6 is therefore relatively high both at low penetration and high penetration.

Energy Production

Irrespective of the ability of VG to reduce the amount of conventional capacity that is built in future years, it is clear that all VG resources reduce the amount of electricity that is generated by conventional generation. Similar to the impact of adding a flat block of power, generation from natural gas fired CCGTs is found to be particularly affected with increasing

[43] It is not clear exactly why the effective incremental capacity credit of single-axis tracking PV is slightly greater than the capacity credit of CSP_0. The result appears to be very sensitive to the generation profile at the end of the day. In some days with price spikes PV generated slightly more energy per unit of nameplate capacity in early evening hours relative to CSP_0 at low penetration levels, which would contribute to a slightly larger capacity credit for PV relative to CSP_0. This finding is not only due to the assumed latitude tilt of the single-axis tracking PV because similar differences in the generation profile in the few days with price spikes were observed at low penetration using a PV generation profile based on single-axis tracking PV that was not tilted at the latitude of the PV site. One potential reason for the small difference in capacity credit is due to the minimum generation constraint on CSP_0 of 25% of the nameplate capacity which would potentially cause CSP_0 to generate less energy in the early evening hours relative to a PV plant without a similar minimum generation constraint. Nevertheless it is clear that the relatively small differences in the capacity credit are extremely sensitive to early evening generation profiles and further detailed analysis of the capacity credit would be needed to determine if there is a significant difference between the capacity credit of single-axis tracking PV and CSP_0.

Table 3.4: Effective incremental capacity credit of VG at low and high penetration levels.

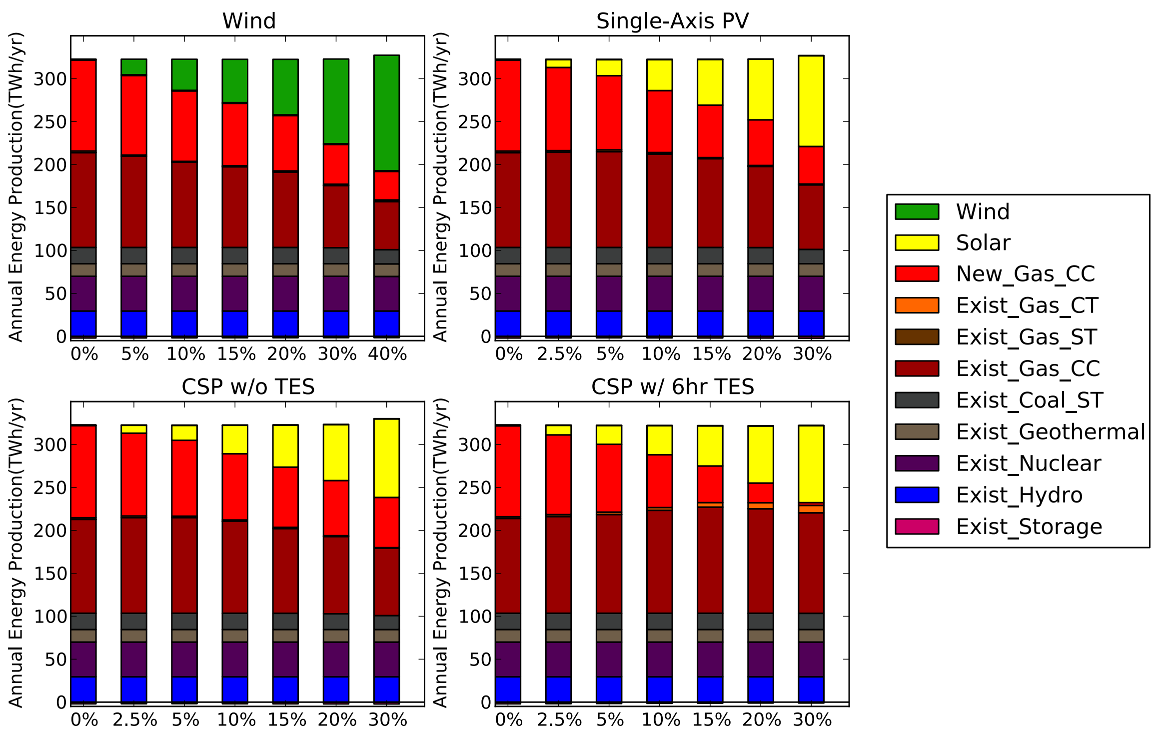
	Low Penetration of VG 0% → 5%			High Penetration of VG 15% → 20%		
Technology	Incremental Reduction in Non-VG Capacity (GW)	Incremental Increase in VG Capacity (GW)	Effective Marginal Capacity Credit	Incremental Reduction in Non-VG Capacity (GW)	Incremental Increase in VG Capacity (GW)	Effective Marginal Capacity Credit
Flat Block	2.1	2.1	100%	1.6	1.6	100%
Wind	1.0	5.7	18%	0.7	4.7	15%
PV	2.8	5.8	48%	0.4	5.9	7%
CSP_0	2.7	7.3	37%	0.2	7.4	2%
CSP_6	4.3	5.1	84%	2.5	4.8	52%

penetration of VG as shown in Figure 3.5. The slight increase in total energy production with increasing VG penetration in Figure 3.5, as opposed to constant energy production across all scenarios, is due to the energy that is available from VG but is curtailed. Curtailment is examined in more detail later in this section.

The amount of energy from incumbent CT resources remains a small fraction of total generation. Only in the high penetration cases with CSP_6 does the generation from CT resources increase a noticeable amount.

Further investigation shows that the increase in energy from CT resources in high CSP_6 penetration scenarios is due to a lack of sufficient energy generation in winter months. One interesting trend noted earlier in Table 3.1 is that power prices are less likely to rise to high levels in the cases with increasing penetration of CSP_6. This lack of high price periods coupled with new generation investment in CCGT resources and an increase in CT production indicates that the system is increasingly "energy-constrained" rather than "capacity-constrained" in these scenarios. In these high CSP_6 cases, new CCGT resources are built, in part, to provide energy in winter months. In December, in particular, sufficient capacity is available to meet demand between the capacity of the thermal plants, hydropower generation, storage, and CSP_6 resources. However, in order to meet demand, during this month the capacity factor of CT resources rises to 98% when in a case with no VG the CTs would normally be off for the entire month. While the thermal generation is dispatched near to its maximum capacity for the month of December, the amount of energy that can be produced over the month by hydropower and the amount of energy that can be produced by CSP_6 resources is limited due to resource constraints (limited water supply for the hydro resources and extended cloudy periods for the CSP_6). The addition of new CCGT plants provides additional energy in December in addition to capacity in other high load months.

The incumbent PHS is represented as a net consumer of energy on the system in Figure 3.5 because storage consumes more electricity during the storage cycle than it can discharge



Note: Energy for existing storage (Exist_Storage) is a negative value that represents the net energy consumed by pumped hydro storage.

Figure 3.5: Total energy generation from different resources with increasing penetration of variable generation in 2030.

during the generation cycle. The net energy consumption of storage is very small, usually less than 2 TWh/yr, and does not change noticeably between the high and low penetration cases for most VG technologies. With high penetrations of CSP_6 the net energy consumption of PHS decreases. The decrease indicates that incumbent PHS is used less frequently in the high CSP_6 cases than it is used in cases without VG. This is presumably because the system has access to considerable amounts of TES and arbitrage opportunities between low and high price periods are less prevalent.

At high penetration levels a small amount of incumbent coal generation is also displaced by VG. Since the variable cost of coal is much lower than the variable cost of CCGT resources, natural gas plants will generally be dispatched to their lower limits before coal plants are dispatched down. The slight reduction in energy generation from incumbent coal plants indicates that coal plants will be the marginal plant more often in cases with high VG than in cases without VG. In regions of the country with more incumbent coal than California the displacement of coal is expected to occur at a lower penetration of VG than observed in this case study.

Even before displacing energy from coal plants, however, cases with VG increasingly decrease the energy production from natural gas CCGTs. The ratio of the energy produced by incumbent natural gas CCGTs to the energy that could be produced if the CCGT were at full output all year, also known as the CCGT capacity factor, decreases with increasing penetration of VG, Table 3.5. Even increasing the penetration of a flat block of power, however, causes incumbent CCGTs to have a lower capacity factor. The increased energy available from the flat block of power effectively pushes the supply curve out, increasing the frequency by which incumbent CCGTs are marginal generation resources, at minimum generation, or offline.[44] Relative to the impact of a flat block, adding wind, PV, or CSP_0 further decreases the capacity factor of incumbent CCGTs with increasing penetration. The capacity factor of incumbent CCGTs increases with increasing CSP_6 relative to the same amount of energy with a flat block of power.

Table 3.5: Capacity factor of mid-size incumbent CCGT resources with increasing penetration of VG in 2030.

	Capacity Factor (%) Penetration of VG							
VG Technology	0%	2.5%	5%	10%	15%	20%	30%	40%
Flat Block	81%	n/a	80%	79%	77%	75%	69%	58%
Wind	81%	n/a	78%	72%	68%	63%	52%	40%
PV	81%	82%	82%	80%	76%	70%	59%	n/a
CSP0	80%	82%	82%	79%	74%	68%	61%	n/a
CSP6	81%	83%	85%	89%	91%	89%	85%	n/a

Though the capacity factor of incumbent CCGTs decreases substantially with increasing penetration of most VG technologies, the load factor of the CCGTs does not necessarily decrease at the same rate with increasing VG penetration. The load factor for a CCGT vintage is the energy-weighted average of the ratio of the actual generation from the CCGT vintage relative to the amount of the CCGT vintage that was on-line. The load factor in a particular hour where the new CCGT vintage was generating at 800 MW when 1000 MW of the new CCGT vintage was online would be 80%. Since CCGT plants are most efficient when operated at their full capacity, the most efficient dispatch, assuming there were no AS requirements, no forecast errors and no start-up costs, would always ensure that the amount of on-line generation exactly matched the amount of energy that would be needed from the generation vintage in each hour. The new CCGT vintage would therefore only have 800 MW online when it was generating at 800 MW, such that the load factor was 100% (i.e., at full-load).

[44] This reduction in capacity factors for incumbent resources with increasing penetration of a flat block of power is similar to the observation by Milligan et al. (2011) that increasing penetrations of a flat block could lead to increased cycling of incumbent coal plants.

Constantly matching the amount of power generated by the vintage to the amount of the vintage that is online would require frequent start-ups and shutdowns of the generation resources. The dispatch model used in this chapter is formulated to account for AS requirements, DA forecast errors and start-up costs which means the load factor can and will be less than 100% (i.e., part-loaded) in any hour. The load factor of a vintage is less than 100% in some hours due to some combination of (1) contributions toward meeting the AS targets, (2) redispatch to manage forecast errors between the DA and RT and (3) avoiding start-up costs associated with bringing CCGT capacity on-line. The latter factor can also decrease the load factor of CCGTs in a case with an increasing penetration of a flat block of power. Hence, cases with high VG penetration and even the case with high penetrations of a flat block of power increasingly require natural gas CCGTs to be operated at part-load. Increased operation at part-load will decrease the overall efficiency of CCGT plants.[45]

The decrease in efficiency at part-load means that the actual reduction in fuel consumption and emissions measured by the dispatch model is less than the reduction that would be expected if the efficiency of CCGTs remained at the full-load efficiency level even while part-loaded. The increase in part-loading of CCGT plants is quantified by examining the load factor of CCGT resources with increasing penetration in Table 3.6.

Table 3.6: Energy-weighted average load factor of mid-size incumbent CCGT resources with increasing penetration of VG in 2030.

	Load Factor (%) Penetration of VG							
VG Technology	0%	2.5%	5%	10%	15%	20%	30%	40%
Flat Block	97%	n/a	96%	96%	96%	95%	94%	93%
Wind	97%	n/a	96%	95%	94%	93%	92%	91%
PV	97%	97%	98%	97%	94%	91%	91%	n/a
CSP_0	96%	97%	98%	97%	94%	93%	92%	n/a
CSP_6	97%	98%	98%	99%	99%	99%	98%	n/a

The results in Table 3.6 indicate that mid-size incumbent CCGT resources operate at part-load (a load factor less than 100%) more frequently with high penetration of a flat block, but even more so with high VG penetration, except with CSP_6 where the TES helps the mid-size incumbent CCGT be dispatched more efficiently. Even with high VG penetration, however, the load factor remains above 90%. A mitigating factor that helps keep the load factor from dropping too low with VG penetration, even though the capacity factor of the same vintage drops at a much faster rate, is the ability to shut-down CCGT resources during low load or high VG generation periods rather than always part-loading the resource. The

[45]The heat rate curves and the no-load heat rate for each vintage are described in more detail in Appendix B.4.

Table 3.7: Average heat rate of mid-size incumbent CCGT resources with increasing penetration of VG in 2030.

	Average Heat Rate (MMBTU/MWh) Penetration of VG							
VG Technology	0%	2.5%	5%	10%	15%	20%	30%	40%
Flat Block	7.2	n/a	7.2	7.2	7.2	7.2	7.3	7.3
Wind	7.2	n/a	7.2	7.2	7.3	7.3	7.3	7.4
PV	7.2	7.2	7.2	7.2	7.3	7.4	7.6	n/a
CSP_0	7.2	7.2	7.2	7.2	7.3	7.4	7.5	n/a
CSP_6	7.2	7.2	7.2	7.2	7.2	7.2	7.2	n/a

tradeoff is the increase in start-up costs to bring the generation offline and then back online at a later point.

Increased part-load operation, more frequent start ups, and increased provision of reserves from on-line resources will reduce the overall average efficiency of thermal plants in converting fuel into electricity. The reduction in efficiency can be observed through an increase in the ratio of annual fuel consumption to annual energy production, or the average heat rate of a resource. The average heat rate of a particular vintage of thermal generation, incumbent mid sized CCGT resources, is shown to slightly increase with increasing penetration of a flat block and increase even more with increasing penetration of VG in Table 3.7, with CSP_6 again being an exception due to the thermal energy storage. For the other VG technologies, this reduction in efficiency of thermal generation also leads to a reduction in the avoided emissions from adding VG than otherwise would be the case were efficiency degradation not to occur.

Avoided Emissions

A byproduct of the investment and dispatch decisions is the pollution emissions from the thermal generation with increasing penetration of VG.[46] Since the addition of VG is found to primarily displace electricity generated by incumbent and new natural gas fired CCGT plants in the cases evaluated here, the reduction in emissions relative to a case without VG are also primarily from avoiding emissions from CCGT resources. The avoided CO_2 emissions are proportional to the avoided fuel combustion in thermal resources. The avoided NO_x and SO_2 emissions, however, are not proportional to fuel consumption due to emissions during

[46] Similar to the decision to not model regulations and policies like the California RPS, we do not include any existing emissions related policies that would impact the cost and quantity of power plant emissions in California, such as a SO_2 cap-and-trade program. Actual emissions will be impacted by technology characteristics (which are modeled in this chapter) as well as regulations (which are not considered here). Moreover, NO_x and SO_2 are regional pollutants where the damage of the pollutant depends on factors including where pollution is emitted from, when the pollutant is emitted, and prevailing weather conditions, not just the quantity of pollutant emitted. These factors are not considered in this analysis.

start-up and part-load that are greater than would be expected based on the fuel burned during those times. NO_x emissions during start-up and part-load operation are reported to be particularly high (Denny and O'Malley, 2006; Katzenstein and Apt, 2009; Suess et al., 2009).

The formulation of the dispatch model, described in Section 3.3, accounts for the increase in emissions during start-up and due to part loading of thermal plants, though the same caveats regarding the simplification of the commitment and dispatch based on vintages applies equally to estimating the avoided emissions. The total emissions of CO_2, NO_x, and SO_2 all decrease with increasing VG penetration relative to the case with 0% VG penetration, Figures 3.6–3.8. The decrease in emissions with increasing penetration of all VG indicates that the start-up and part-load emission impacts are secondary to the overall reduction in electricity production from thermal generation, the main driver of the decrease in emissions. CO_2 emissions decline with increasing VG penetration to a greater degree in percentage terms than NO_x and SO_2 because NO_x and SO_2 are found to be dominated by the relatively small amount of incumbent coal resources that are not, until very high penetration, displaced by VG.

At very high penetration (greater than 20% penetration) VG begins to reduce the energy generated from incumbent coal resources. The emissions from incumbent coal resources are higher per unit of electricity than the emissions from natural gas resources, with over two orders of magnitude difference in the emissions rate per unit of electricity in the case of SO_2. The reduction of electricity from coal resources at high penetration overwhelms any effects due to start-up and part-loading of natural gas resources for NO_x and SO_2 emissions. Though this is less evident for CSP_6, the overall impact of very high VG penetration, therefore, is to displace more emissions per unit of electricity from VG than at low penetration, at least under the assumptions used in the present analysis. The penetration level at which VG start to displace incumbent coal is of course dependent on the amount of incumbent coal capacity in the region. Regions with more incumbent coal will experience reductions in coal plant output and emissions at lower VG penetration levels than found here.

Another way to examine the avoided emissions from adding VG is to show the ratio of the incremental reduction in emissions between two cases and the incremental increase in VG generation between those two cases. This incremental avoided emissions rate is shown for CO_2 in Table 3.8, NO_x in Table 3.9, and SO_2 in Table 3.10. The avoided emissions rate is similar to the rate of emissions of a fully-loaded CCGT plant at high and low penetration levels (385 kg CO_2/MWh, 28 g NO_x/MWh, and 2 g SO_2/MWh for a mid-sized incumbent CCGT), except when VG starts displacing generation from coal resources. The reduction in efficiency due to part-loading and start-up of thermal generation ends up leading to a small reduction in the overall incremental avoided CO_2 emissions rate at high penetration relative to the incremental avoided CO_2 emissions rate at low penetration, as shown in Table 3.8, particularly for PV and CSP_0. The somewhat greater degradation in CO_2 emissions benefits for PV and CSP_0 are presumably caused by the relatively higher part loading and start up required to manage these resources relative to wind and CSP_6. On the other hand, Table 3.9 shows a reduction in the incremental avoided NO_x emissions rate for wind and CSP_6 when

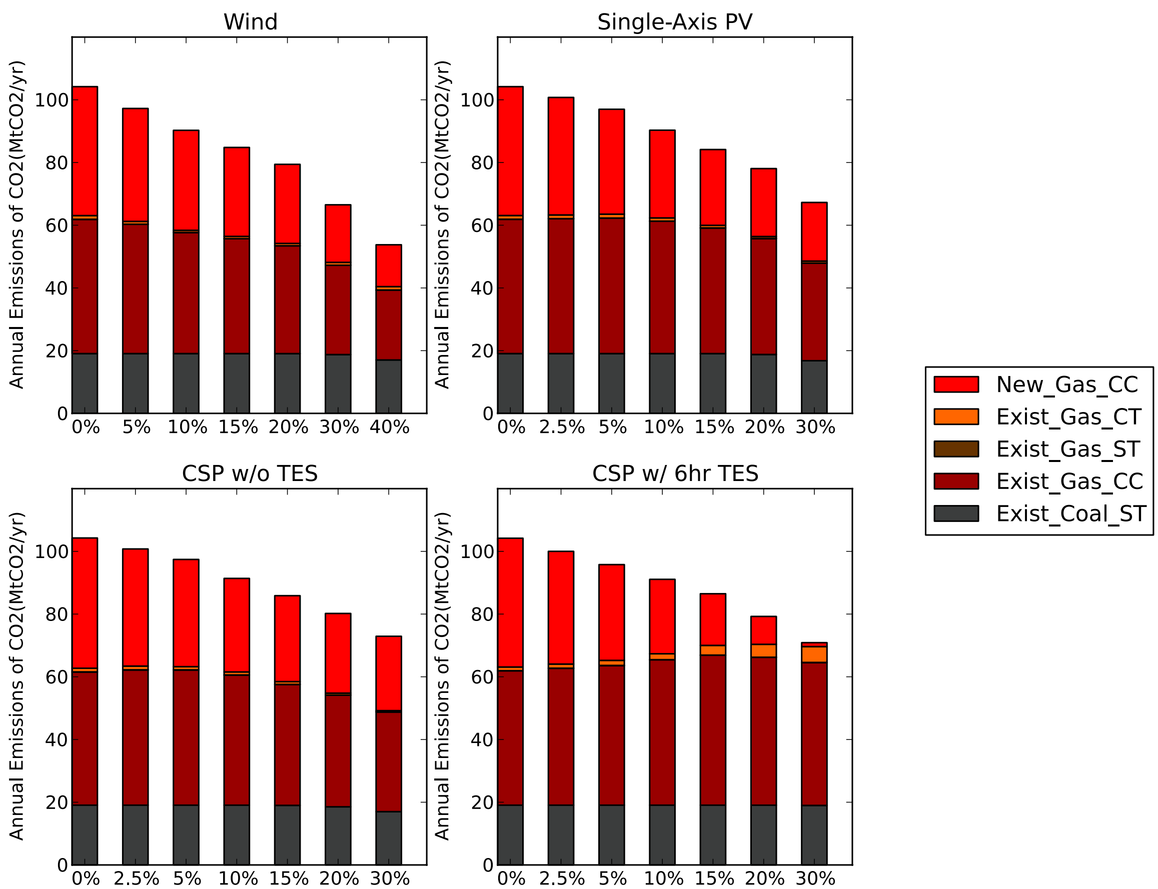


Figure 3.6: Total CO_2 emissions from different resources with increasing penetration of variable generation in 2030.

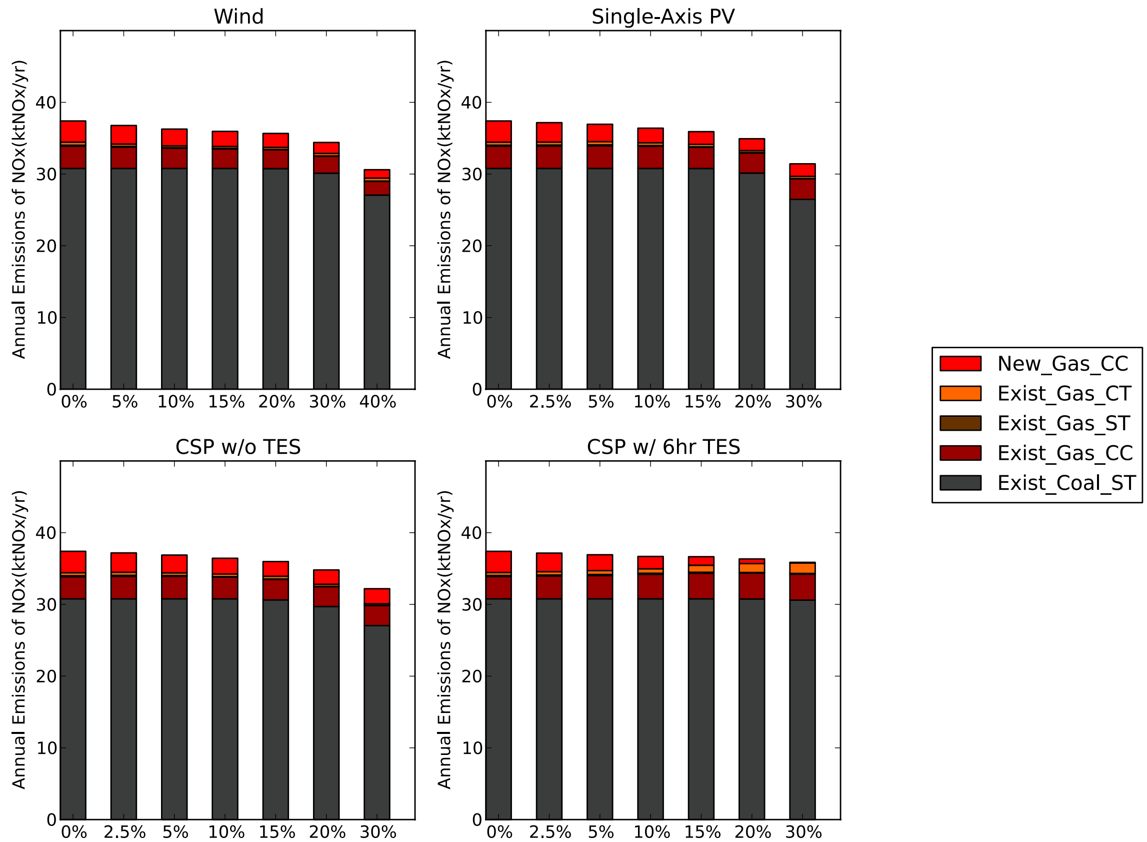


Figure 3.7: Total NO_x emissions from different resources with increasing penetration of variable generation in 2030.

comparing 0-5% penetration to 15–20% penetration at the same time that the incremental avoided NO_x emissions rate for PV and CSP_0 increases. The incremental avoided SO_2 emission rate also increases for PV and CSP_0, Table 3.10. The increase in the incremental avoided NO_x and SO_2 emissions rate for PV and CSP_0 is due to the small displacement of coal between 15–20%. When VG displaces generation from incumbent coal, as is the case with high PV and CSP_0 penetration, the incremental avoided emissions from VG increase since coal produces significantly higher emissions (for NO_x, and SO_2) than CCGT resources. While coal also produces higher CO_2 emissions per unit of electricity, the difference between the emissions rate of coal and natural gas is not as high as it is for NO_x and SO_2. As can be seen in Figures 3.7 and 3.8, the incremental avoided NO_x and SO_2 emissions rate for wind also begins to climb at very high penetration levels as wind displaces incumbent coal.

These avoided emissions results are dependent on the particular mix of generation and

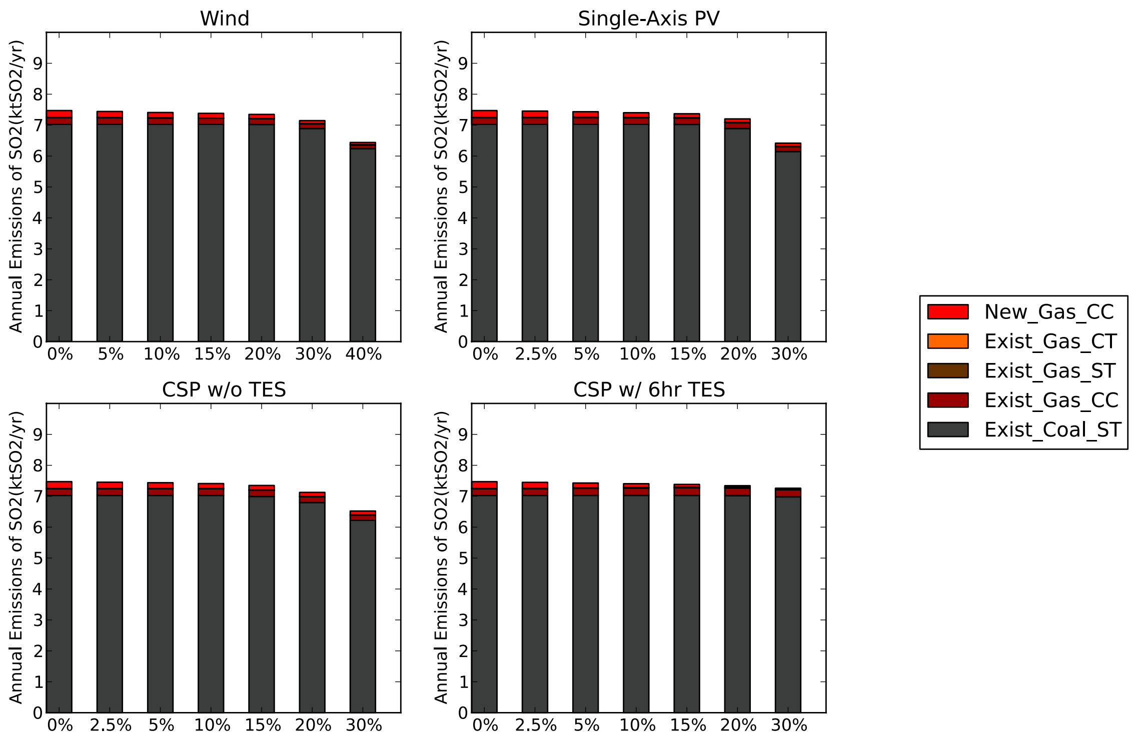


Figure 3.8: Total SO_2 emissions from different resources with increasing penetration of variable generation in 2030.

assumptions regarding retirement. In particular, regions with more incumbent coal than California would have emissions from coal plants displaced by VG at lower penetration levels than found in this case study. Nonetheless, the main conclusion from these results is that adding VG avoids emissions, even when part-load and start up emissions are accounted for. The magnitude of avoided emissions depends on the mix of generation (including retirements), the type of generation that will be built in future years, and the generation profile of VG.

Curtailment

At higher penetration levels, VG will sometimes produce power when the system has limited flexibility to manage the additional VG (i.e., the system has limited ability to reduce the output of other generation), as described earlier in Section 3.3. During these hours the wholesale price for electricity will decrease to very low levels (approaching $0/MWh) which may make VG indifferent to curtailing (and earning no revenue) or generating (and earning almost no revenue). When even more VG is available during these constrained times cur-

Table 3.8: Incremental avoided CO_2 emissions rate of VG at low and high penetration level in 2030.

Technology	Low Penetration of VG 0% → 5%			High Penetration of VG 15% → 20%		
	Incremental Reduction in CO_2 Emissions (10^9 kg/yr)	Incremental Increase in VG Generation (TWh/yr)	Marginal Rate of Avoided Emissions (kg/MWh)	Incremental Reduction in CO_2 Emissions (10^9 kg/yr)	Incremental Increase in VG Generation (TWh/yr)	Marginal Rate of Avoided Emissions (kg/MWh)
Flat Block	7.0	18	390	5.5	14	390
Wind	7.0	18	390	5.4	14	380
PV	7.2	18	400	6.1	17	350
CSP_0	6.8	17	410	5.7	16	350
CSP_6	8.4	21	400	7.2	20	370

Table 3.9: Incremental avoided NO_x emissions rate of VG at low and high penetration level in 2030.

Technology	Low Penetration of VG 0% → 5%			High Penetration of VG 15% → 20%		
	Incremental Reduction in NO_x Emissions (10^3 kg/yr)	Incremental Increase in VG Generation (TWh/yr)	Marginal Rate of Avoided Emissions (g/MWh)	Incremental Reduction in NO_x Emissions (10^3 kg/yr)	Incremental Increase in VG Generation (TWh/yr)	Marginal Rate of Avoided Emissions (g/MWh)
Flat Block	510	18	28	380	14	27
Wind	630	18	35	290	14	20
PV	460	18	26	990	17	57
CSP_0	520	17	31	1,170	16	72
CSP_6	480	21	23	310	20	16

Table 3.10: Incremental avoided SO_2 emissions rate of VG at low and high penetration level in 2030.

	Low Penetration of VG 0% → 5%			High Penetration of VG 15% → 20%		
Technology	Incremental Reduction in SO_2 Emissions (10^3 kg/yr)	Incremental Increase in VG Generation (TWh/yr)	Marginal Rate of Avoided Emissions (g/MWh)	Incremental Reduction in SO_2 Emissions (10^3 kg/yr)	Incremental Increase in VG Generation (TWh/yr)	Marginal Rate of Avoided Emissions (g/MWh)
Flat Block	35	18	1.9	27	14	1.9
Wind	30	18	1.7	34	14	2.4
PV	37	18	2.1	170	17	9.6
CSP_0	34	17	2.1	220	16	14
CSP_6	44	21	2.1	41	20	2.1

tailment of VG will be required. In contrast to VG, curtailment did not occur for increasing penetrations of the flat block of power.

The challenges of accommodating higher penetrations of VG can therefore be illustrated in two ways: (1) by examining the amount of VG that is sold at low prices and (2) by examining the amount of VG that has to be curtailed, Figure 3.9. The amount of energy that is sold at low prices is based on summing the amount of VG scheduled in the DA that occurs when the DA price is below \$1/MWh with the amount of RT deviations from the DA schedule that is sold when the RT price is below \$1/MWh. The amount of curtailment is based on the difference between the amount of energy that is used in the market relative to what could have been used if there were no curtailment. Note that CSP resources have solar fields that are sized larger than the power block (i.e., a solar field multiplier that is greater than 1) in this model. The curtailment that is due to this oversizing was excluded from the curtailment reported here by only focusing on curtailment of CSP that occurs during periods with very low prices (<\$1/MWh). This curtailment reflects power system flexibility constraints rather than factors related to the design of CSP plant for cost minimization.

The amount of energy that is sold at low prices increases at a much faster rate with increasing penetration than the amount of VG curtailment. The reason is that when curtailment occurs, only the fraction of the VG generation that exceeds what the system can economically accommodate is curtailed whereas all of the DA scheduled energy is sold at low prices when the DA prices are low. For example, if in a particular hour the DA forecast of VG was 1000 MW but the system could only economically accommodate 950 MW of VG in the DA scheduling process, then 50 MW of VG generation would be curtailed but the remaining 950 MW of generation would be sold at a price of \$0/MWh.

Changes in curtailment and the amount of energy sold at low prices with increasing penetration differ substantially across VG technologies. For wind and CSP_6, the amount

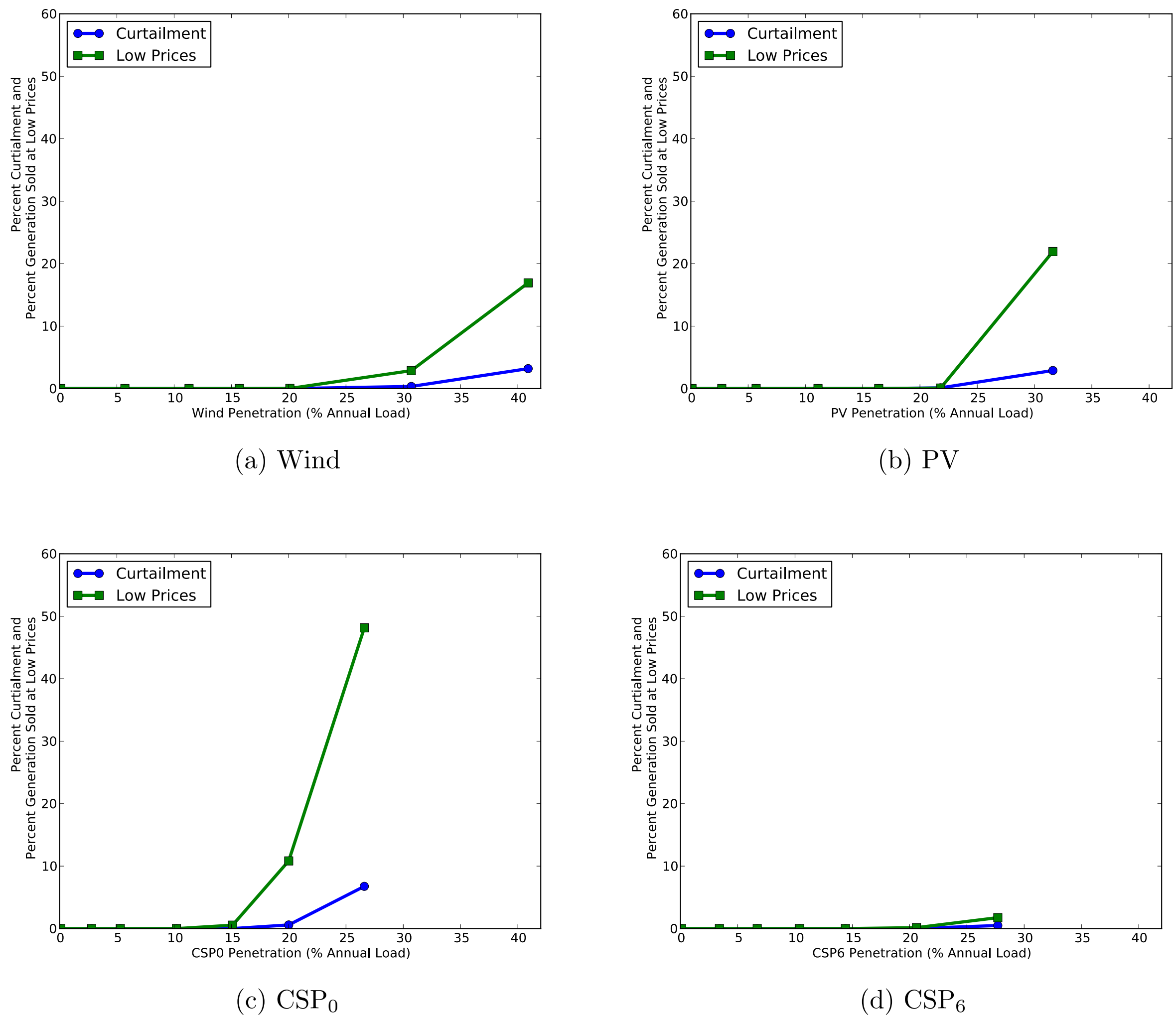


Figure 3.9: Curtailment of variable generation and percentage of variable generation that is sold during periods where wholesale power prices are very low (<\$1/MWh) in 2030.

of energy that is curtailed in the 30% penetration case is less than 1% of the annual available energy. At 40% penetration of wind, curtailment is around 2.5%. At 30% and 40% penetration of wind the amount of energy that is sold at low prices is around 3% and 18% of the annual available wind, respectively. For CSP_6, thermal energy storage helps reduce the amount of energy sold at low prices, less than 2% at 30% penetration. PV and CSP_0 experience substantially greater curtailment and amount of energy sold during low price periods than do CSP_6 and wind, especially at penetrations above 15–20%. The curtailment and amount of energy sold at low prices for CSP_0 at 30% penetration, for example, is 7% and 48%, respectively, more than double the curtailment and amount of energy sold at low prices for wind at 40% penetration. The curtailment and amount of energy sold at low prices for PV follows a similar path as CSP_0. Though not shown here, incremental curtailment rates (incremental curtailment per unit of incremental VG energy) when increasing penetration from 20% penetration to 30% penetration are much higher than average curtailment rates (total curtailment per unit of total VG energy). In the case of CSP_0 the incremental curtailment rate between 20% and 30% penetration is approximately 22%.

The curtailment and amount of energy sold at low prices has an impact on the marginal economic value of VG at high penetration, impacting PV and CSP_0 to a greater extent than wind and CSP_6 (see Sections 3.5 and 3.5). Curtailment was highlighted by Denholm and Margolis (2007b) as a potential limit to PV penetration. This chapter adds further insight by highlighting the portion of VG that is sold at low prices. The curtailment of VG is relatively low compared to other studies and the current curtailment that is observed for wind at relatively low penetration rates for three reasons. First, California is a relatively flexible system with significant hydro resources and substantial gas-fired generation. Analysis of curtailment with increasing PV penetration by Denholm and Margolis (2007b) highlighted the important role of the overall system flexibility in mitigating PV curtailment at increasing penetration levels. Second, in long-run equilibrium in 2030 no plants with high fixed costs and low variable costs, such as nuclear generation, are found to be built. If these plants were built the total amount of inflexible baseload generation would increase and curtailment of variable generation would similarly increase. Third, this analysis does not consider curtailment due to insufficient transmission capacity. As mentioned in Section 3.3, curtailment due to insufficient transmission capacity between generation and loads is one of the largest contributors to wind curtailment that is currently occurring in the U.S.

Marginal Economic Value

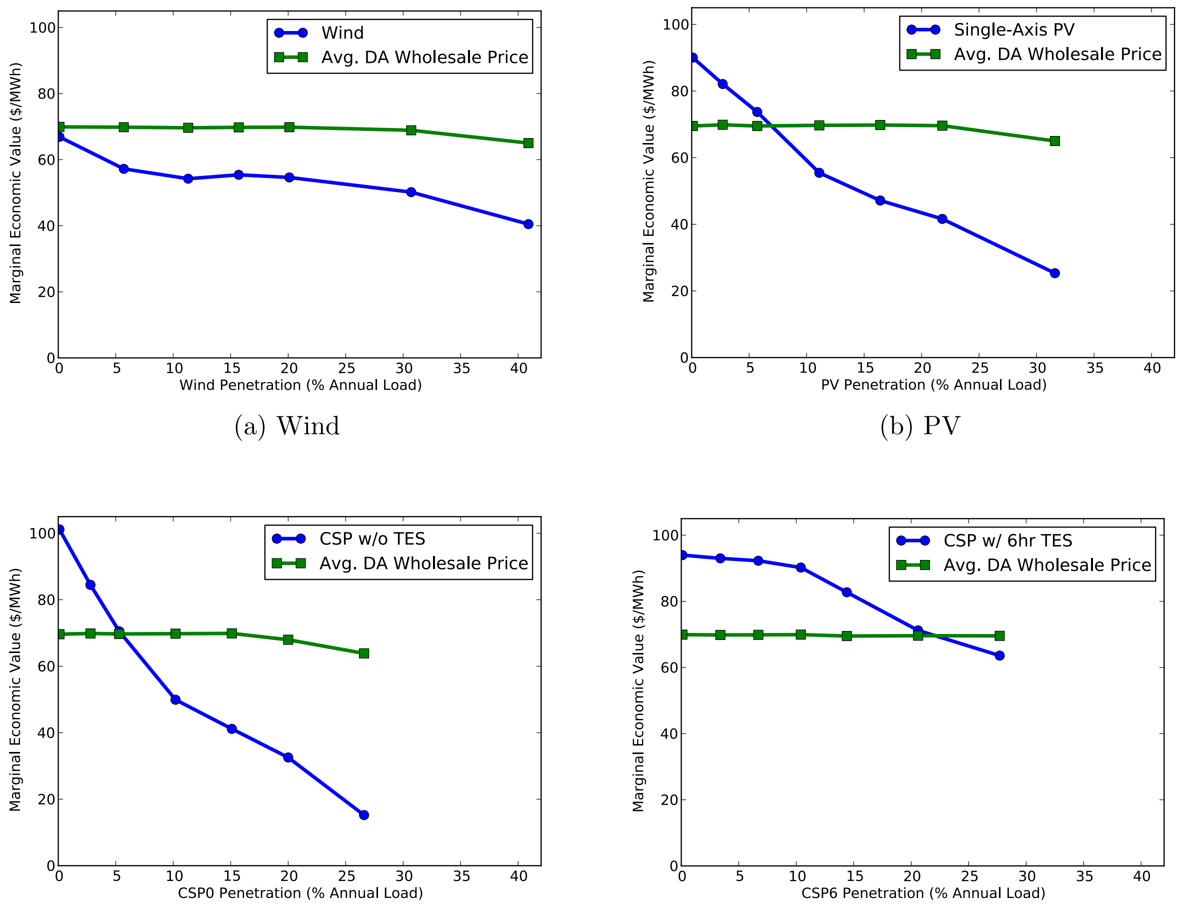
The preceding dispatch and investment results point to a number of important differences between VG technologies and highlight the impact of increasing VG penetration. At low penetration, solar has a much greater capacity credit than wind. Both wind and solar primarily displace electricity, fuel, and emissions from natural gas CCGT resources at low penetration, under the assumptions used in this chapter. At high penetration, the marginal capacity credit of wind declines but neither the capacity credit nor the resources that are being displaced by wind generation change dramatically. For solar at high penetration, however, the marginal capacity credit of PV and CSP_0 decrease substantially from the capacity credit at low penetration and these resources begin to displace energy from coal plants. At high penetration more curtailment and energy sales at low energy prices is expected for PV and CSP_0 than for wind. Due to thermal energy storage, CSP_6 maintains a higher marginal capacity credit even at high penetration and avoids substantial curtailment and energy sales during times with low energy prices.

This section explores the impact of these trends on the relative differences in the marginal economic value of wind and solar and how the marginal economic value changes with increased penetration. The marginal economic value, as described in more detail in Section 3.3, is based on the DA and RT prices calculated with the equilibrium set of generation investments and the VG generation less any additional costs due to increased AS requirements for VG.

The calculated marginal economic value of wind, PV, CSP_0, and CSP_6 with increasing penetration of each VG technology is shown in Figure 3.10. For comparison purposes, the time-weighted average wholesale DA price in each case is also shown. The average wholesale price is relatively constant with increasing penetration of VG until high VG penetration levels. This relatively constant wholesale price with increasing VG is largely a result of the assumption that the rest of the non-VG system remains in long-run equilibrium. In particular, this assumption of long-run equilibrium requires prices to rise high enough and frequently enough to cover the fixed cost of any new non-VG investment. Since all cases require some new non-VG capacity to be built the prices must be sufficiently high to cover the fixed cost of that new non-VG generation. Only at very high penetration levels (>20% energy penetration) does the time-weighted average wholesale price begin to decrease, though the non-VG system remains in long-run equilibrium.

The marginal economic value of wind is found to be similar to (but slightly lower than) the average wholesale price at low penetration levels. As the penetration of wind increases to 20%, the marginal value of adding additional wind decreases by approximately $12/MWh relative to the case without wind even though the average wholesale price does not change. At very high penetrations of 30% and 40% the marginal value of wind decreases further. At 40% wind penetration the time-weighted average wholesale price also begins to decrease.

Based on the “market test” from Borenstein described earlier in Section 3.2, the marginal economic value of wind can be used to indicate the “grid-parity” cost where the economic value of the wind plant would equal the fixed cost of the wind plant. If the annualized fixed cost of wind is above the marginal economic value of wind, then no additional wind would be built based on this “market test” (of course more might be built based on other non-market factors including an RPS requirement or because of other factors not modeled here). If, on the other hand, the annualized fixed cost of wind were less than the marginal economic value of wind then it would be economically attractive to add more wind assuming again that no other factors are at play. The declining marginal economic value of wind with increasing penetration indicates that the cost of wind needs to be continuously driven lower to justify adding more wind strictly on economic grounds, particularly for adding additional wind beyond 20% penetration. Related, the value to a utility of adding more wind decreases



(a) Wind (b) PV

(c) CSP_0 (d) CSP_6

Figure 3.10: Marginal economic value of variable generation and an annual flat-block of power with increasing penetration of variable generation in 2030.

when there is already significant wind penetration.

As shown in Figure 3.10, the marginal economic value of solar exceeds the time-weighted average wholesale DA price of power as well as the marginal value of wind at low penetration levels. The high value of solar, \$20–30/MWh higher than the average wholesale power price and the marginal economic value of wind, is due largely to the high degree of coincidence of solar generation and times of peak load and scarcity prices when using a demand profile based on California loads. This high degree of coincidence is also what led to the high capacity credit estimated earlier in Section 3.5. The high marginal economic value of solar resources at low penetration has been highlighted in several recent studies (e.g., Borenstein, 2008; Lamont, 2008; Sioshansi and Denholm, 2010). Of course, when comparing wind and solar resources in procurement decisions the higher marginal economic value of solar at low penetration must also be weighed against the relative levelized cost of wind and solar supply.

One particularly interesting result at low penetration levels is that the marginal economic value of PV, CSP_0, and CSP_6 are all relatively similar on a $/MWh basis. This shows that there is not a strong economic signal at low penetration levels that would indicate that CSP with TES would be more valuable than a plant without TES on a per unit of energy basis. It might be possible to justify the addition of TES to a CSP plant based on the fact that TES can increase the capacity factor of a CSP power block. Depending on the cost of TES and the cost of increasing the solar field size, adding TES may actually decrease the levelized cost of a CSP plant (Herrmann et al., 2004; Turchi et al., 2010). At low penetration, the cost reduction benefits would need to be the primary motivation for adding TES since there is not a clear increase in the value of CSP with TES relative to the value of CSP without TES. This finding supports the relatively sparse market interest in CSP with TES in markets that currently have low solar penetration.

As the penetration of solar is increased to 10% the marginal value of adding additional PV and CSP_0 drops significantly relative to the marginal economic value of adding additional CSP_6. At 10% penetration, the marginal economic value of adding additional CSP_6 is about $4/MWh less than the value at 0% penetration. For solar without TES, in contrast, the marginal economic value of adding more solar at 10% penetration is $35/MWh and $50/MWh less than the value of adding solar at 0% penetration for PV and CSP_0, respectively. Also at about 10% penetration, the marginal economic value of PV and CSP_0 reach and then drop below the economic value of wind. The marginal economic value of CSP_6, on the other hand, remains above that of wind at all penetration levels considered here.

This relative difference in value at high penetration indicates that solar resources with TES can be substantially more valuable than resources without TES. Of course, the decision to procure CSP with TES relative to other solar technologies would also need to consider the relative cost of these options. If the recent rapid decrease in the price of PV is sustained and the cost of CSP with TES does not follow the same trajectory, then PV could still be a more attractive option for increasing solar penetration even with 10% PV penetration and despite the lower marginal economic value.

At higher penetrations of VG, the marginal economic value of adding additional PV or CSP_0 is below the marginal economic value of wind. While the economic value of wind starts lower than the value of the three solar technologies at low penetration, its value does not drop as fast as the marginal economic value of PV and CSP_0. In this particular case, the wind resources that are procured at high penetration levels increasingly come from diverse wind regions that are out-of-state. The diversity in the wind generation patterns and forecast errors are part of the reason for the slower decline in the value of wind with high penetration. Solar generation profiles, on the other hand, are largely dictated by the position of the sun. Geographic diversity can help mitigate short term variability issues due to clouds, but it does not impact the overall daily solar generation profile.

Decomposition of Marginal Economic Value

The marginal economic value of VG and the flat block of power can be decomposed into several components in order to better pinpoint the causes of the high economic value of solar at low penetration, the relatively slow decline in the value of wind with increasing penetration, the drivers for the steeper decrease in the value of PV and CSP_0 with higher penetration, and the reasons for the substantially higher value of CSP_6 relative to the other VG at high penetrations. Without this decomposition step it is not clear if these trends are due to changes in capacity credit, changes in thermal generation that is being displaced, imperfect forecastability, or AS impacts.

Specifically, using the method that is described in Section 3.3, in this section the marginal economic value of VG is decomposed into capacity value, energy value, DA forecast error, and AS impacts. All of these components are presented in terms of $/MWh-of-VG such that the values can be easily compared.

Decomposing the marginal economic value in this way helps to understand the causes for changes in the value of VG and, perhaps more importantly, can help identify promising strategies for mitigating decreases in the marginal economic value of VG with increasing penetration. The results of the decomposition are shown in Table 3.11. For comparison, the marginal economic value of a flat block of power that is assumed to have no variable fuel or O&M cost is equivalent to the time-averaged wholesale DA price of power, which at low penetration levels is about $70/MWh. The capacity value of a flat block between 0% to 30% penetration is found to be about $20/MWh (or about $170–180/kW-yr) and the energy value is about $50/MWh.[47] Only at 40% penetration does the energy value and capacity value of the flat block of power begin to decrease.

Up to 30% penetration the decomposition for wind shows that the marginal economic value of wind is less than the marginal value of a flat block due primarily to the lower capacity value of wind. As the penetration of wind increases from 0% to 20% penetration, for example, the marginal capacity value of wind decreases by $8/MWh. The energy value of wind at 0% penetration is found to be similar to the energy value of a flat block of power. Moreover, the energy value only drops by $2.5/MWh when the penetration of wind increases from 0% to 20%. At still higher penetration levels the capacity value of wind is relatively stable while the energy value begins to fall more noticeably between 30% and 40% penetration.

DA forecast error costs are found to be meaningful, though these costs do not impact the marginal economic value of wind as much as the declining capacity value and energy value in this particular region. In addition, while the absolute $/year cost of forecast errors steadily increases with increasing wind penetration, the changes in the DA forecast error cost per unit of wind energy are somewhat ambiguous with increasing penetration. At

[47] The capacity value of a flat block is similar to the cost of capacity in this market, which corresponds to the fixed cost of new CCGT resources ($200/kW-yr = $23/MW-h). The energy value of a flat block is similar to the fuel and variable O&M cost of a fully loaded CCGT ($46–52/MWh in the model used here, depending on the vintage).

Table 3.11: Decomposition of the marginal economic value of variable generation in 2030 with increasing penetration.

Component	Penetration of a Flat Block						
($/MWh)	0%	5%	10%	15%	20%	30%	40%
Capacity Value[a]	(170) 20	(180) 20	(170) 20	(180) 20	(180) 20	(180) 20	(140) 16
Energy Value	50	50	50	50	50	50	49
DA Forecast Error	0	0	0	0	0	0	0
Ancillary Services	0	0	0	0	0	0	0
Marginal Economic Value	70	70	70	70	70	70	65

Component	Penetration of Wind						
($/MWh)	0%	5%	10%	15%	20%	30%	40%
Capacity Value[a]	(69) 17	(37) 12	(30) 10	(30) 10	(28) 9	(25) 8	(25) 8
Energy Value	50	49	48	48	48	46	39
DA Forecast Error	-0.2	-3	-4	-2	-2	-3	-6
Ancillary Services	-0.4	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2
Marginal Economic Value	67	57	54	55	54	50	40

Component	Penetration of PV						
($/MWh)	0%	2.5%	5%	10%	15%	20%	30%
Capacity Value[a]	(120) 37	(110) 34	(82) 27	(39) 13	(24) 8	(11) 4	(4) 1
Energy Value	54	53	52	49	45	41	27
DA Forecast Error	-0.2	-5	-4	-6	-5	-4	-3
Ancillary Services	-0.9	-0.8	-0.7	-0.4	-0.2	-0.1	-0.0
Marginal Economic Value	89	81	73	55	47	41	25

Component	Penetration of CSP_0						
($/MWh)	0%	2.5%	5%	10%	15%	20%	30%
Capacity Value[a]	(110) 47	(84) 36	(54) 24	(22) 10	(11) 5	(6) 3	(5) 2
Energy Value	56	54	52	46	41	33	16
DA Forecast Error	-2	-5	-5	-6	-5	-4	-4
Ancillary Services	-1.1	-0.8	-0.5	-0.2	-0.1	-0.1	-0.1
Marginal Economic Value	100	84	70	50	41	32	14

Component	Penetration of CSP_6						
($/MWh)	0%	2.5%	5%	10%	15%	20%	30%
Capacity Value[a]	(150) 37	(160) 37	(150) 37	(150) 35	(100) 24	(85) 20	(61) 15
Energy Value	55	55	55	55	58	53	52
DA Forecast Error	-0.1	-1	-1	-1	-1	-2	-3
Ancillary Services	1.4	1.4	1.3	1.2	1.0	0.7	0.1
Marginal Economic Value	94	93	92	90	83	71	64

a - Capacity value in parentheses is reported in $/kW-yr terms and reported to two significant digits.

first, as wind penetration grows from 0% to 10% the DA forecast error cost increases up to $4/MWh. Between 10% to 20%, however, the DA forecast error cost declines to $2/MWh and then begins to increase again at 30% penetration up to a cost of $6/MWh at 40% penetration. There are three primary factors of the DA forecast error cost that can contribute to the variation: (1) the difficulty associated with managing DA forecast errors (measured by the standard deviation of the difference between the DA and RT price), (2) the relative magnitude of the DA forecast errors (measured by the standard deviation of the difference between the RT generation and the DA forecast for wind normalized by the annual wind generation), and (3) the correlation between DA and RT differences in prices and wind generation.

Each of these factors are examined in turn to better understand the causes of the variation in the DA forecast error cost. With increasing penetration of wind the relative magnitude of wind forecast errors decreases between 0% and 30% penetration due to increasing geographic diversity in wind sites and only slightly increases between 30% and 40% wind penetration. The correlation between DA and RT wind deviations and price deviations steadily increases with increasing penetration. The remaining factor, the difficulty with managing DA forecast errors, is therefore the main contributor to the variability of the DA forecast error cost with increasing penetration. Between 0% and 10% penetration the difficulty with managing DA wind forecast errors steadily increases. Between 10% and 20% penetration, however, the spread of differences between DA and RT prices decreases. This indicates that the cost of "purchasing" power in RT to make up for a generation shortfall between DA and RT or the discount for "selling" power in RT that exceeds the DA scheduled generation are lower between 10% to 20% penetration than between 0% to 10% penetration. Beyond 20% penetration the cost of purchasing power in RT or the discount for selling power in RT increases to levels beyond those at 10% penetration resulting in an overall increase in the DA forecast error cost at 40% penetration.

The ancillary service costs for wind are found to be low, less than $1/MWh, and do not increase with increasing penetration. The large amount of hydropower in California helps to maintain low AS costs even with increasing AS targets. In all cases the time-weighted average price for regulation up remains in the range of $8–10/MW-h. Hydropower does not entirely drive the AS costs, however, since similarly low AS costs and AS prices were observed during prior analysis by the authors of a region with significantly less hydropower (namely the Rocky Mountain Power Area) using the same model and similar assumptions. In addition, this price range for regulation up reserves is similar to the prices for regulation in recent years for several centralized markets in the U.S. (CAISO, MISO, and ISO-NE) but lower than regulation prices in other markets. Regulation prices in ERCOT, NYISO, and the CAISO prior to the recent market technology upgrade and redesign have been in the range of $20–60/MW-h (Milligan and Kirby, 2010). Increases in the prices for ancillary services would potentially lead to higher costs for ancillary services for wind.

Interestingly, rather than AS costs increasing with increasing wind penetration, the AS costs actually slightly decrease with increasing penetration per unit of wind energy. The modeling assumptions in this analysis lead to AS targets increasing in proportion to the increase in energy generated by wind. As a result, if the AS prices (and their correlation with wind generation) did not change with increasing wind penetration then the cost of AS for wind would remain relatively constant with increasing wind production. In fact, the slight decrease in the cost of AS for wind with increasing penetrations shown in Table 3.11 and the relatively stable time-averaged AS prices indicates two potential changes that may occur as the penetration of wind increases. First, the AS prices could become lower specifically during times when wind power is generating and higher at other times as the penetration of wind increases from 0%. Second, wind could be selling more AS in the form of regulation down with increasing penetration. Examination of regulation down from wind shows that it does increase with increasing wind penetration, but the impact is negligible (less than $0.003/MWh at 40% penetration). Thus the price of AS must decrease during hours with high wind penetration. Previous analysis of modeled regulation prices with increasing wind production in ERCOT noticed a similar trend. In a previous study by GE, regulation prices were found to decrease with increasing wind penetration even though the total regulation requirement increased (GE Energy, 2008).[48]

Though the findings are specific to the cases analyzed, overall, the decomposition of the value of wind shows that:

- The primary value of wind is the energy value. The energy value of wind at low penetration is similar to the variable cost of energy from a fully loaded CCGT. At high penetration, the energy value starts to decline as wind displaces energy from incumbent coal plants.
- The capacity value of wind is slightly less than the capacity value of a flat block of power at zero penetration. The capacity value of wind drops as penetration increases, but is relatively stable at a low value at medium to high penetration.
- The cost of day-ahead forecast errors is impacted by the degree of the wind site diversity, but remains below $5/MWh except at very high penetration.
- Ancillary service costs are modest, less than $1/MWh, and do not significantly increase at high penetration levels at least for the cases analyzed here.

These conclusions are broadly consistent with findings of the many detailed operational and valuation studies that have explored the impacts of higher levels of wind penetration. In particular, the ancillary service cost and day-ahead forecast error cost for wind are within

[48] This is explained by GE as follows: "In general, with increasing wind generation capacity, the unit price per MWh of spinning reserve decreases due to several factors. First, the balance of generation is provided by units with lower variable costs as wind generation capacity is increased. Second, because of the daily variability of wind generation, thermal units with long start-up times and minimum-run times tend to be scheduled for hours where their dispatch levels are reduced by wind output. This provides regulating range with virtually no opportunity cost for these high-wind hours. Third, the accuracy of wind forecasting used in the day-ahead unit scheduling plays a role. If wind generation forecasts are not considered at all, or are heavily discounted, the balance of generation will tend to be over-committed" (GE Energy, 2008).

the range, though on the lower end, of "integration costs" found in various operational integration studies of wind (DeCesaro et al., 2009). It should be recognized that there is some controversy regarding how these costs should be calculated and interpreted (Milligan et al., 2011).

The decomposition of the value of the three solar technologies shows that at low penetration, the primary reason that the value is greater than that of a flat block and of wind is due to the substantially greater capacity value. At 0% penetration, the capacity value of solar is \$17–27/MWh greater than the capacity value of a flat block (and more so when compared to wind).

Based on the earlier finding that the effective capacity credit of CSP_6 at low penetration was greater than the capacity credit of the other solar technologies, it is somewhat counter-intuitive that the capacity value of CSP_6 is not greater in dollars per unit of energy (\$/MWh) terms, though it is greater in dollars per unit of nameplate capacity (\$/kW-yr) terms. The reason is that the CSP_6 technology produces more energy per unit of nameplate capacity than the other solar technologies. As an illustration, consider two different 100 MW power plants that both earn the same \$8 million/yr revenue during hours with scarcity prices (or \$80/kW-yr), but one plant generates 200 GWh/yr and the other generates 400 GWh/yr. The plant that produces more energy over the year will have a lower capacity value of \$20/MWh while the plant that produces less energy over the year will have a higher capacity value of \$40/MWh. Along the same lines, consider the same two 100 MW plants but the plant that generates 400 GWh/yr earns the full \$8 million/yr revenue during hours with scarcity prices whereas the generation profile of the plant that generates 200 GWh/yr is such that it earns only \$4 million/yr during hours with scarcity prices (or \$40/kW-yr). The capacity value of both plants would be equal to \$20/MWh, notwithstanding the high capacity credit and the high capacity value in \$/kW-yr terms associated with the former.

Similarly, even though the CSP_6 technology is more likely to be producing power during scarcity hours and has a higher capacity value in \$/kW-yr terms it produces more energy per unit of capacity and therefore has a similar capacity value, in \$/MWh terms, to the other solar technologies. This also explains how the capacity value of CSP_0 can be greater than the capacity value of PV at zero penetration level in \$/MWh terms even though the capacity value in \$/kW-yr terms of CSP_0 is slightly lower than the capacity value of PV in \$/kW-yr terms. The difference between the capacity value of PV and CSP_0 in \$/MWh terms is due to the lower amount of energy per unit of nameplate capacity for CSP_0 relative to PV.

The energy value of solar at 0% penetration is found to be \$4–6/MWh greater than the energy value of a flat block because it displaces relatively less efficient, and therefore higher cost, gas plants during periods of high demand in summer. At 0% penetration the energy value of solar is similarly \$4–6/MWh greater than the energy value of wind.

The AS and DA forecast error cost for PV and CSP_0 are small in magnitude relative to the energy value and capacity value, and are also similar in magnitude to the AS and DA forecast error cost for wind. Variations in AS and DA forecast error costs for PV and CSP_0 with increasing penetration are driven by similar factors as for wind, discussed earlier. Similar to what was found for wind, the DA forecast error cost increases in absolute \$/year terms with increasing penetration, but the marginal DA forecast error cost per unit of solar energy does not monotonically increase with increasing penetration. Detailed analysis of the factors driving the DA forecast error cost similarly shows that the relative magnitude of forecast errors decreases with increasing penetration and that variations in the DA forecast error cost are primarily related to variations in the difficulty of managing DA forecast errors at different penetration levels.

One important difference with wind, however, is that further examination of the AS costs for PV and CSP_0 at high penetration levels shows that the sales of regulation down begin to become relatively more important in keeping the cost of ancillary services at the very low level at high penetration. At 0% penetration, for example, the cost of purchasing AS for CSP_0 is about \$1.1/MWh and the revenues from selling regulation down from CSP_0 is zero, leading to a net cost of AS for CSP_0 at 0% penetration of about \$1.1/MWh, as reported in Table 3.11. At 30% penetration, on the other hand, the cost of purchasing AS for CSP_0 is about \$1.5/MWh and the revenues from selling regulation down from CSP_0 increases to about \$1.4/MWh, leading to the reported net cost of AS of only \$0.1/MWh. Revenues from the sale of regulation down only begins to exceed \$0.05/MWh for CSP_0 penetration levels above 10%, indicating that provision of regulation down by CSP_0 plants is only found to be useful at higher penetration levels. Similar behavior is observed for the sale of regulation down by PV at high penetration levels.

The net AS portion is positive for CSP_6 indicating that CSP_6 resources are earning revenue from selling AS whereas the other VG technologies are net buyers of AS at all penetration levels. Regardless, because AS prices are found to be low (in the range of \$8–10/MW-h for regulation up), the AS revenue earned by CSP_6 is found to be relatively low, under \$2/MWh. As mentioned earlier in this section, if the AS prices were to be higher (as they are in some organized markets within the U.S.) the AS revenue for CSP_6 could potentially be higher. Though AS costs are relatively small, the provision of regulation down by PV and CSP_0 at high penetration levels and provision of AS by CSP_6 appears to be an area where further research and demonstration of technical capabilities might be of interest. Similar research is being conducted for wind (e.g., Kirby et al., 2010). Additional research specifically on the impact of ancillary service revenues for CSP with TES based on historical energy and AS prices is available from Sioshansi and Denholm (2010).

In all penetration levels the DA forecast error costs are found to be substantially larger than AS costs. Although DA forecast errors caused a decrease in the value of CSP_0 of up to \$6/MWh, the same type of DA forecast errors were managed by the CSP_6 resource at a cost of at most \$2/MWh. This may represent an upper bound to the value of TES in managing DA forecast errors, however, since perfect foresight is assumed in RT for the management of DA forecast errors.

The most dramatic change in the marginal value of VG resources is the decrease in capacity value of PV and CSP_0 with increasing penetration levels. By the time the penetration reaches 10% on an energy basis, the marginal capacity value decreases by \$24/MWh and \$37/MWh from the marginal capacity value at 0% penetration for PV and CSP_0, respectively. While at low penetration the marginal capacity value of PV and CSP_0 are considerably greater than the capacity value of wind and of a flat block of power, at 10% penetration the marginal capacity value from adding additional PV or CSP_0 is comparable to the marginal capacity value from adding additional wind. Beyond 10% penetration the capacity value of PV and CSP_0 continues to drop steeply relative to that for wind.

The change in capacity value with increasing penetration of PV and CSP_0 is explained in Figure 3.11. The figure shows the historical hourly load shape scaled up to 2030 and the net load (historical load less hourly solar generation) on three days of the year where high load leads to scarcity pricing. The net load is shown for increasing penetrations of PV. The log of the hourly wholesale price is also shown in the figure to illustrate the coincidence of times of high system need with times of solar generation. PV generates significant amounts of power during the scarcity period at low penetration levels, but as the penetration of PV increases, times with high net load and high prices shift towards the early evening, when PV production has dropped off. As similarly found in Section 3.5, PV generation clearly reduces the need for new capacity at low penetration, but with increasing penetration PV is less effective at reducing that need.

A similar net-load curve and pricing is shown with increasing levels of CSP_6 on the same three days, Figure 3.12. The addition of TES allows solar generation during the day to be shifted into the early evening and reduce the peak net load at higher penetration levels. As a result, the times with scarcity prices do not shift as much as in the PV case and solar generation remains high during times with scarcity prices. The end result is that the capacity value of CSP_6 remains relatively high over all penetration levels considered and only begins to meaningfully decline above 10% penetration.

In contrast to the steeply declining capacity value of PV and CSP_0 at high penetration levels, the capacity value of wind is relatively stable with increasing penetration for two reasons: first, the low capacity credit of wind means that even as wind is added, the times with the peak loads and scarcity prices largely remain the same times even as penetration increases. Second, while wind is not producing a significant amount during times with peak loads and scarcity prices, many wind sites are producing a small amount. Adding more wind sites that have a small probability of producing power during these times keeps lowering the total peak net load slightly with increasing penetration. As a result the small capacity credit of wind is maintained even with high wind penetrations.

The marginal energy value of PV and CSP_0 also decline at a faster rate than the marginal energy value of wind. As a result, at 15% penetration, the energy value of PV and CSP_0 is less than the energy value of wind. The lower energy value for PV and CSP_0 at 15% penetration can be explained in part by the fact that in some hours of the year (<2% of the hours in a year) incumbent coal resources are dispatched to less than their nameplate capacity, while incumbent coal is found to be always at its full capacity with 15% wind. In particular, as PV and CSP_0 increases, incumbent coal tends to be dispatched down in winter and spring months during early morning hours on weekends when solar generation increases faster than the morning load picks up. The displacement of coal increases further

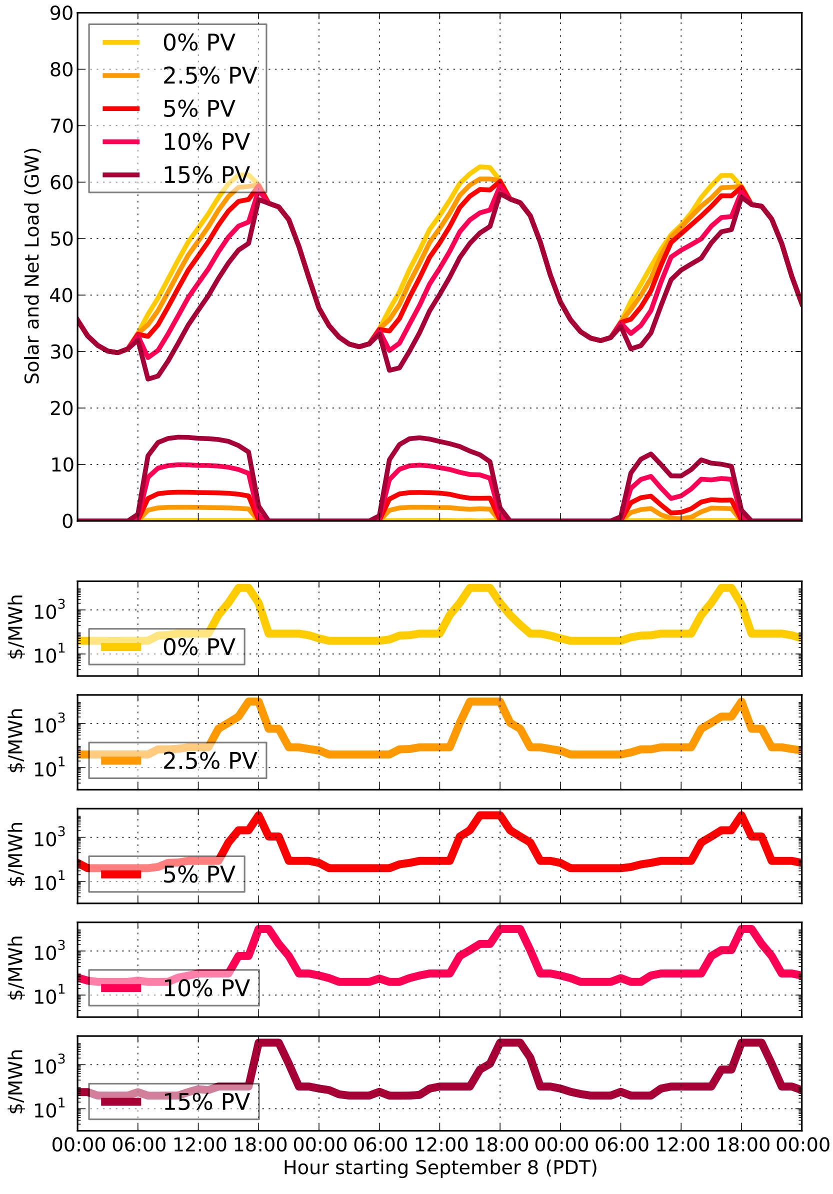


Figure 3.11: Historical load less the generation from PV and hourly energy prices on three peak load days with increasing PV penetration.

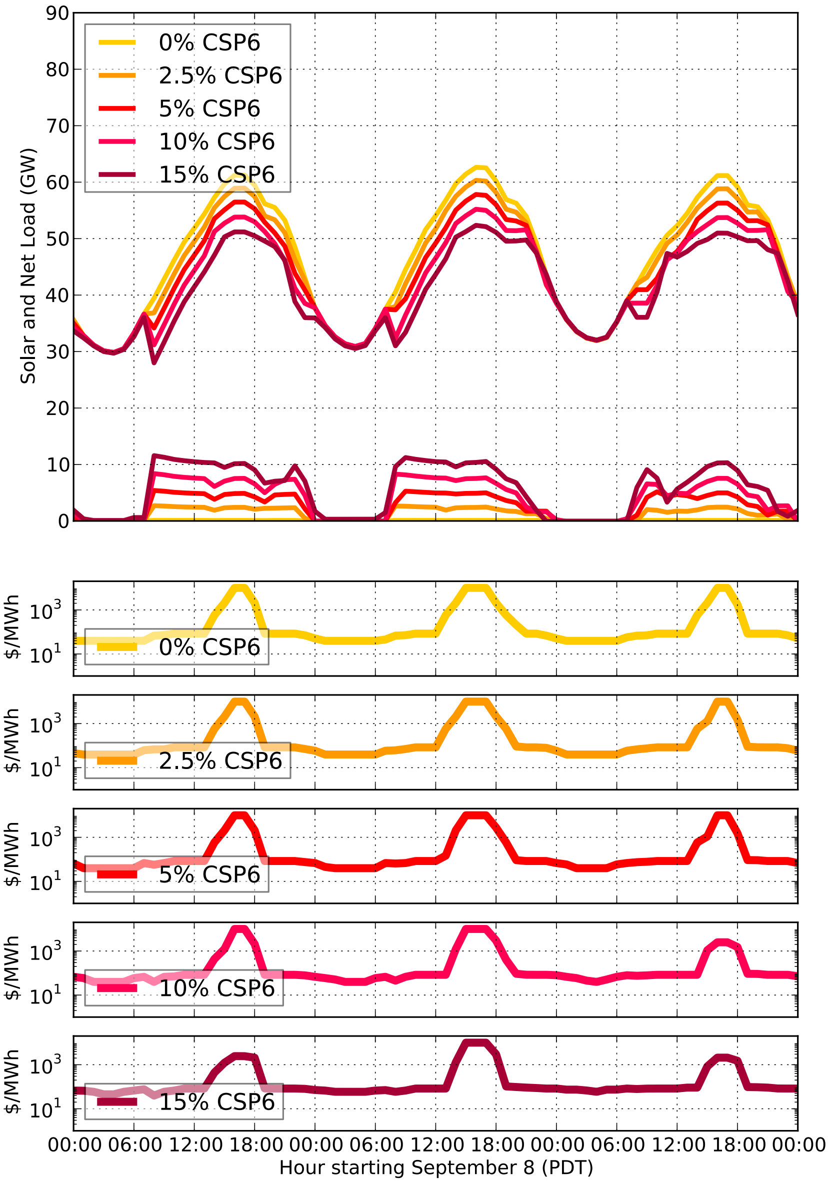


Figure 3.12: Historical load less the generation from CSP_6 and hourly energy prices on three peak load days with increasing CSP_6 penetration.

with higher PV and CSP_0 penetration, and coal begins to be dispatched down with wind at 20% penetration. By 30% penetration, the incumbent coal is found to be dispatched below their nameplate capacity 5% of the year with wind and over 25% of the year with PV and CSP_0. The energy value of VG decreases when coal is displaced due to the lower full load variable cost of energy from coal ($27/MWh) relative to the full load variable cost of energy from CCGT resources ($46–52/MWh).

The energy value of CSP_6 on the other hand, remains greater than or equal to the fully loaded cost of energy from a CCGT resource even at 30% penetration. The decrease in the total marginal value of CSP_6 with increasing penetration is due to the declining capacity value after a penetration of 10%. As described earlier in Section 3.5, increasing penetrations of CSP_6 begin to reduce price spikes and involuntary load shedding as the penetration increases above 10%. This decreases the need to build new conventional capacity to meet peak loads in the summer. At the same time, reducing the amount of new generation capacity that is built starts to lead to a situation where the lower conventional capacity and the lower solar production in the winter months becomes the most constrained time for the power market. The constraints are not due to insufficient generation capacity but due to insufficient energy. Either way new conventional capacity is needed to balance the available generation and demand. This particular result depends on how much energy is available from hydropower and the CSP_6 in winter months, factors that would not normally be considered in reliability based studies that focus primarily on periods with peak loads. As the penetration of CSP_6 increases, the shift from a capacity-constrained to an energy-constrained system causes the capacity value to begin to decrease at these high penetration levels.[49] Eventually the value of CSP_6 is found to be lower than the average DA wholesale price.[50] Even at 30% penetration, however, the marginal economic value of CSP_6 is found to be well above that of wind (+$14/MWh) and of PV and CSP_0 (+$45/MWh and +$50/MWh).

In sum, the main contributor to the decline in the marginal economic value of wind, PV, and CSP_0 are changes in the capacity value for penetrations between 0% and 10% and changes in the energy value with greater penetration. The change in capacity value at low penetration can lead to a decrease on the order of $24–37/MWh in the value of PV and CSP_0 and a decrease on the order of $7/MWh for wind. The change in the energy value between 10% penetration and 20% penetration can decrease the value of PV and CSP_0 by

[49]The changing dispatch of the incumbent generation capacity, including the increasing capacity factor of CTs in the winter months described in Section 3.5, may in part explain the slight increase in the energy value of CSP_6 at 15% penetration.

[50]We tested whether there is notable value in increasing the size of the thermal storage at higher penetration levels. We found that increasing the thermal storage from 6 hours to 10 hours of thermal storage with the same sized solar field as used in the CSP_6 cases (a solar field multiplier of 2.5) only increased the value by $1–2/MWh relative to CSP_6 at 20% penetration. In contrast, increasing the thermal storage to 10 hours and simultaneously increasing the solar field size (a solar field multiplier of 3) increased the value by about $8/MWh relative to CSP_6 at 20% penetration. The increase in value was due to an increase in capacity value and energy value and a small decrease in the DA forecast error cost. Additional research on how the optimal thermal storage and solar field multiplier change depending on penetration (and deployment of other VG resources) is an area where additional research should be conducted.

\$8–13/MWh, while the change in the energy value between 10% and 40% can decrease the value of wind by \$8/MWh. The cost of DA forecast errors do not dramatically increase with increasing penetration, but they are not negligible at \$2–6/MWh. The cost of ancillary services, given the assumed AS procurement rule, are consistently less than \$2/MWh for wind, PV, and CSP_0. Because of TES, CSP_6 is able to avoid—to some degree—many of these factors that otherwise drive down the marginal economic value of VG. As a result, especially at high penetration, the marginal economic value of CSP_6 is considerably higher than for the other resources considered.

Sensitivity Cases

To explore the sensitivity of these results to a small subset of important parameters, four sensitivity cases were developed:

- **No operational constraints:** Relax major operational constraints in the dispatch model to quantify the impact of operational constraints on the marginal economic value of VG.
- **Carbon cost:** Increase the cost of energy through a price on carbon to illustrate the sensitivity of the marginal value of VG to inclusion of one type of externality.
- **Cost of capacity:** Reduce the cost of capacity from conventional resources to demonstrate the impact of lower capital costs for CTs and the shifting of new investments toward CTs instead of CCGTs.
- **No retirements:** Assume that plants do not have a technical life and therefore that no plants that exist today will retire by 2030 for technical reasons. This tests the sensitivity of the marginal economic value to the assumption about the technical life of incumbent plants.

Key results from the four sensitivity cases are described below.

No Operational Constraints

In order to determine how much of the decline in the economic value of VG was due to operational constraints on conventional generation and hydropower, a sensitivity case was run where major operational constraints were relaxed.

The dispatch in this case resembled a pure-merit order dispatch because power plants were assumed to be able to startup and shutdown without cost, ramp between zero output and full generation at any rate, and not experience part-load efficiency penalties related to low output levels. Furthermore any unit was assumed capable of providing each type of reserves. Hydropower was assumed to no longer be restricted by a minimum flow constraint.[51]

[51] More specifically, the operational constraints that were relaxed include the following:

Though this unconstrained case is not a realistic representation of the power system, the difference in the marginal economic value of VG between the un-constrained sensitivity case and the case with the operational constraints indicates the importance of modeling such constraints, Figure 3.13. The difference in the value of wind with and without operational constraints considered, for example, at up to $5/MWh, is similar to the size of the day-ahead forecast error cost for wind. Furthermore, decomposition of the value of wind without operational constraints[52] shows that the capacity and energy value of wind do not change significantly with and without operational constraints in California. This leads to the conclusion that the factors affecting the day-ahead forecast error costs (e.g., DA commitment of non-quick-start generation and costs and capacity of quick-start generation) are some of the most important constraints to model for wind in this case study in addition to the merit-order dispatch.

At low penetration levels, the operational constraint sensitivity case demonstrates that the initial decrease in the marginal value of PV and CSP_0 would still occur even if the system were perfectly flexible. The no constraints scenario only modestly increases the value of PV and CSP_0.

On the other hand, at high penetration levels the relative difference in the marginal economic value for PV and CSP_0 between the no constraint and reference case is large and far exceeds the cost of the day-ahead forecast errors. As shown in the Appendix B.5, removal of operating constraints substantially increases the energy value at high penetration relative to the energy value in the reference scenario, suggesting that said removal allows the system to not dispatch down coal. This suggests that operational constraints that might impact energy value, such as the thermal generator ramp rate limits and minimum generation constraints, may be more important for understanding the decline in the value of PV and CSP_0 at very high penetration levels (>20% penetration or so). The difference in the value of CSP_6 with and without the operational constraints shows no strong trend, suggesting that increasing CSP_6, as modeled in this study, does not push the limits of power system operations in the same way as PV, CSP_0, and wind.

Carbon Cost

Adding a carbon cost in the model increases the variable cost of thermal generation and therefore increases the energy value of variable generation. The increase in the marginal

- Conventional thermal generation: start-up costs removed from objective function and short-run profit calculation, minimum generation constraint relaxed, all plants able to offer non-spinning reserves even if offline, ramp rate limits removed for non-spinning, spinning, and regulation reserves and for hour to hour changes in energy, no day-ahead commitment decisions are binding in real time. Removing these constraints allows generation vintages to always operate at full load and therefore results in no part-load efficiency losses.

- Hydropower generation: relaxed minimum flow constraint, removed ramp rate limits for reserves and hour to hour changes in energy production.

[52]See Table B.14 in Appendix B.5.

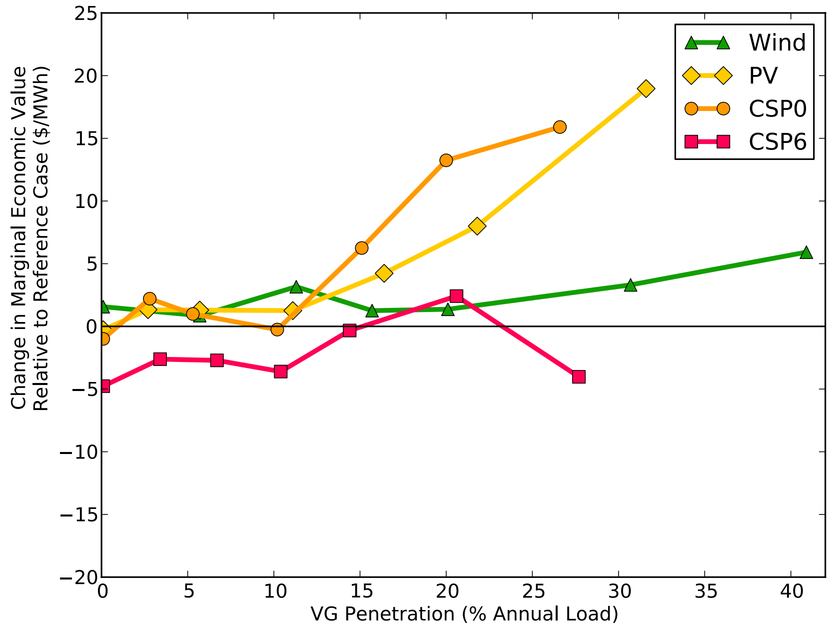


Figure 3.13: Difference in marginal economic value of variable generation between a case where the operational constraints for thermal and hydropower generation are ignored and the reference case.

economic value of VG with a carbon cost relative to the reference case which had no carbon cost is shown in Figure 3.14.

With a carbon cost of \$32/tonne CO_2,[53] the value of a flat block of power increases from about \$70/MWh (\$20/MWh capacity value and \$50/MWh energy value) to just over \$80/MWh (\$20/MWh capacity value and \$63/MWh energy value).

The only noticeable change in the value of wind in the carbon cost case comes in the form of an increase in the energy value of wind across all penetration levels of \$11–13/MWh. This increase in the energy value is expected since wind was shown to have an avoided emissions rate in the range of 380–390 kg CO_2/MWh in Table 3.8. At this rate of avoided emissions, wind would decrease carbon costs by \$12/MWh when the cost of carbon is \$32/tonne CO_2. The capacity value, DA forecast error, and AS cost of wind do not noticeably change under the carbon cost scenario.

Similar to wind, the addition of a carbon cost to the solar cases only has a noticable impact on the energy value. Furthermore, the increase in energy value from the higher carbon cost is also similar to the increase in energy value that would be expected based on the avoided emission rates reported in Table 3.8. At low penetration levels, the avoided CO_2

[53]The carbon cost is similar to the cost used in economic evaluations of generation resources in transmission planning studies at WECC (Western Electricty Coordinating Council (WECC), 2010).

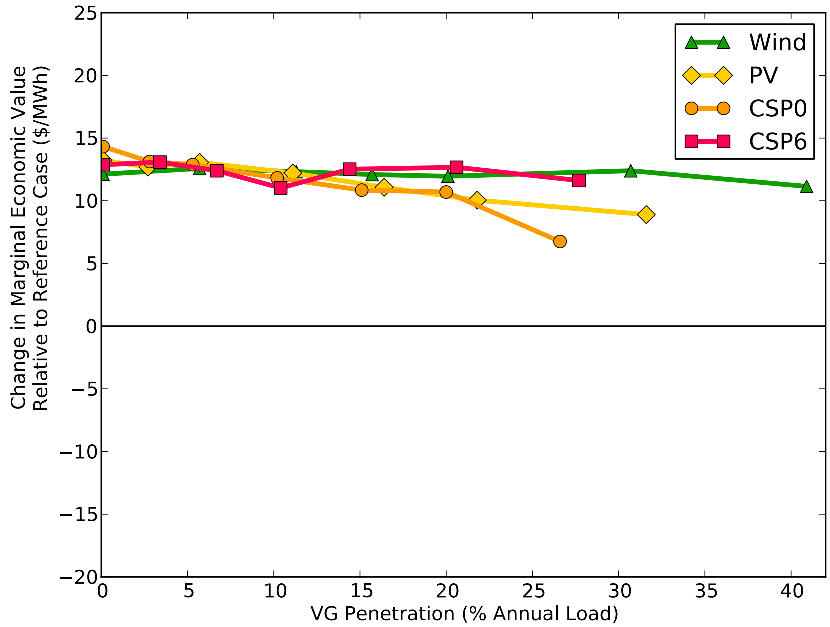


Figure 3.14: Difference in marginal economic value of variable generation between a case with a $32/tonne CO_2 carbon cost and the reference case without a carbon cost.

emissions rate for PV and CSP_0 is 400–410 kg CO_2/MWh leading to an expected increase in energy value with a carbon cost of $32/tonne CO_2 of $13/MWh. At high penetration levels the avoided CO_2 emissions rate for PV and CSP_0 is 350 kg CO_2/MWh leading to an expected increase in energy value with a carbon cost of $32/tonne CO_2 of $11/MWh. The actual increase in the energy value is about $13/MWh at low penetration and $10/MWh at high penetration.

Cost of Capacity

The cost of capacity is an important driver of the capacity value of variable generation. Reducing the cost of new gas-fired CTs from $194/kW-yr in the reference scenario to $139/kW-yr[54] in the sensitivity scenario results in a change in investments from only CCGTs in the reference case to a mixture of new CTs and new CCGTs in this sensitivity scenario. Without VG about 32% of the new capacity that is built is from CTs and the rest of the new capacity remains CCGTs. At low penetration levels of PV and CSP_0 the proportion of CTs slightly declines. At 10% PV penetration and above, however, the proportion of CTs increases with

[54] The lower cost of capacity is based on the benchmark "cost of new entry" (CONE) levelized revenue requirement for the 2014-15 period in the PJM forward capacity market: `http://www.pjm.com/markets-and-operations/rpm/rpm-auction-user-info.aspx`. The CONE for this period is $139/kW-yr.

increasing penetration. The proportion of CTs steadily increases with increasing wind penetration. In contrast to the other VG technologies, the proportion of CTs steadily declines with increasing penetration of CSP_6 and at 15% penetration and above CTs are no longer built even with the reduced capital cost of CTs.

Reducing the cost of CTs also results in shorter periods with scarcity prices and therefore a lower capacity value for both a flat block and for variable generation. The capacity value of a flat block decreases from $20/MWh in the reference case to $16/MWh in the case with the lower cost of capacity. The capacity value of solar at low penetration, specifically 0% penetration, decreases by $7–8/MWh and the capacity value of wind at low penetration decreases by $4/MWh.[55] At 20% penetration, the capacity credit is lower for VG leading to less sensitivity in the capacity value to changes in the cost of capacity.

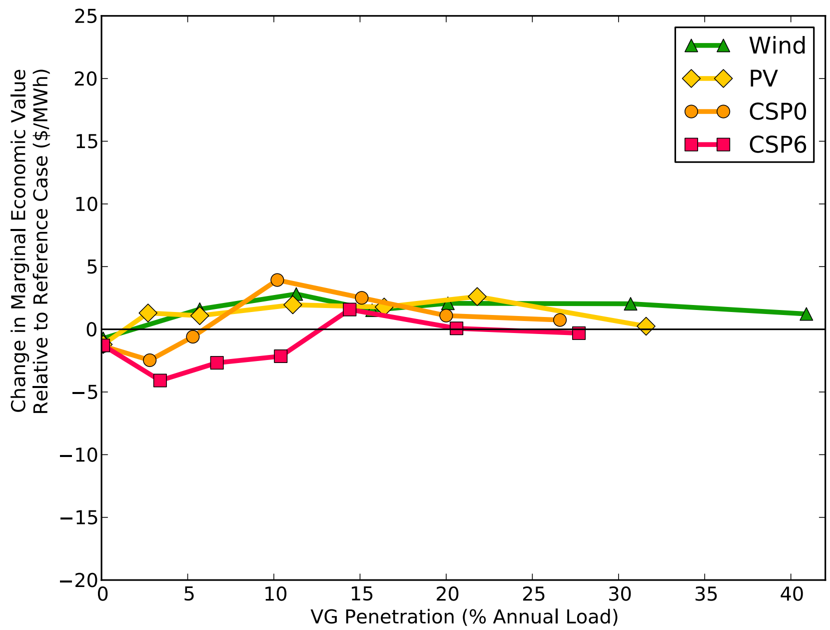


Figure 3.15: Difference in marginal economic value of variable generation between a case with a lower cost of combustion turbines and the reference case.

Overall, the impact of the lower cost of capacity on the marginal economic value of VG is somewhat ambiguous. CT resources have a worse heat rate than CCGTs, which leads to higher energy costs during the increasing times when CTs are dispatched. Therefore, although the reduction in the cost of capacity decreases capacity value, the increase in the dispatch of less efficient generation increases the energy value of a flat block and of VG. The energy value of a flat block in the low cost of capacity case, for example, is $54/MWh,

[55] see Table B.16 in the Appendix for the decomposition of the marginal economic value of VG in this sensitivity case.

\$4/MWh greater than the energy value of a flat block in the reference case. At low penetration, the energy value of wind is \$4/MWh higher and the energy value of solar is \$5–6/MWh higher in the low cost of capacity case than the energy value in the reference case. At high penetration, the energy value of wind remains about \$4/MWh higher while the energy value of solar is \$1–2/MWh higher in the low cost of capacity case relative to the energy value in the reference case. In sum, even though the lower cost of capacity decreases the capacity value of VG, the overall change in the marginal economic value is small due to the opposing increase in the energy value, Figure 3.15.

No Retirements

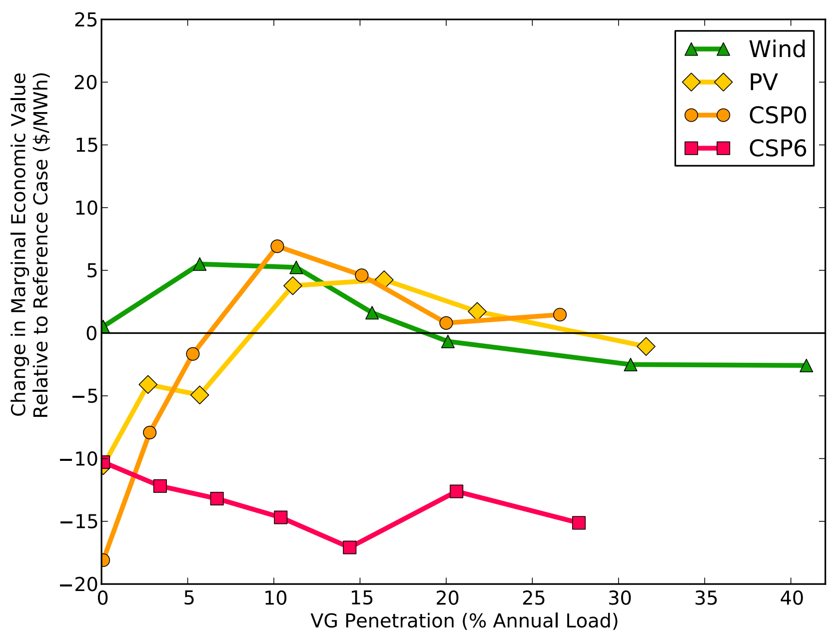


Figure 3.16: Difference in marginal economic value of variable generation between a case without retirements of existing generation and the reference case where generation is retired after a technical life.

Without retirements of existing generation due to plants reaching the end of their technical life, significantly more incumbent natural gas steam turbines along with additional older CT and CCGT generation is available in 2030 than in the reference scenario. The total incumbent non-VG capacity is 69.4GW in the no retirements scenario in comparison to 45.5 GW in the reference scenario. Even without VG, however, in the no retirements scenario a portion of this incumbent capacity, about 9.2 GW, was found by the model to retire for economic reasons because the short-run profits of these incumbent generators were insufficient to cover their assumed fixed O&M cost; in the reference scenario, no economic retirements were found to occur. A small amount of new CCGT (1.5 GW) were also built in the no retirement scenario without VG. A large portion of the short-run profit for these new CCGTs was found to be derived from hours where less efficient plants with higher variable costs were setting the energy price. In the reference case, on the other hand, hours with scarcity prices provided the majority of the short-run profit of new CCGTs. In total, the nameplate capacity of generation in the no retirements scenario without VG was 61.8 GW, slightly greater than the 60.1 GW of nameplate capacity of generation in the reference scenario without VG. The greater amount of total generation in the no retirements scenario can be explained by the lower cost of capacity: in the no retirements scenario the cost of capacity is simply the assumed fixed O&M cost of the natural gas steam turbines that retire for economic reasons (about $66/kW-yr) whereas in the reference scenario the cost of capacity is similar to the cost of the new CCGTs (about $200/kW-yr). With a cost of capacity of around $200/kW-yr in the reference case it is economically more attractive to shed load for load levels that occur less than 20 hours a year whereas with the lower cost of capacity it is more economically attractive to shed loads that occur only 6–7 hours per year. Hence, without VG the total nameplate capacity in the no retirements scenario is found to be greater than the total nameplate capacity in the reference scenario.

One of the impacts of these changes is that, at low penetration levels, the capacity value of solar and wind resources is lower in the no retirements case than it is in the reference case. The energy value, on the other hand, is somewhat higher since VG displaces less efficient plants. How these two opposing trends impacts the total value of VG depends on the technology and the penetration level. At low penetration levels for solar, the net result is that the value of solar in the no retirements case is lower than it is in the reference case, Figure 3.16. At 10% and 15% penetration, however, the higher energy value of PV and CSP_0 leads to a net greater value than the reference case. At 20% and 30% penetration the value of PV and CSP_0 in the no retirements case is about the same as the value in the reference case. The value of CSP_6 in the no retirements case remains below the value in the reference case at all penetration levels. The reason is that although the energy value of CSP_6 increases relative to the reference scenario, the capacity value of CSP_6 decreases by a larger amount across all penetration levels. The value of wind is greater in the no retirements case for penetration levels of 15% and below but becomes slightly less valuable at higher penetration levels. Overall, these results suggest that the value of VG can be relatively sensitive to assumptions about retirements.

3.6 Conclusions

Understanding the economic value of variable generation is important for making long-term decisions about renewable procurement and supporting infrastructure. This paper uses a unique modeling framework that captures both long-run investment decisions as well as dispatch and operational constraints in order to understand the long-run marginal economic value of wind, PV, and CSP with and without thermal energy storage and how that value changes with increasing penetration levels. Though the model only captures a subset of the benefits and costs of renewable energy, it provides unique insight into how the value of that subset changes with technology and penetration level. Pollution emissions were not the focus of this analysis, and as such we did not include the impact of many emissions related policies, though emissions were estimated as a byproduct of the investment and dispatch decisions. The decrease in emissions of CO_2, NO_x, and SO_2 with increasing penetration of variable generation illustrates that there are additional benefits of variable generation that were not monetized in this analysis.

The results from this case study implementation of the model demonstrate that the narrowly-defined economic value and changes in economic value with increasing penetration differ among variable renewable technologies. Not only does the economic value vary by renewable energy technology and penetration but the ordering of renewable energy technologies based on marginal economic value also change with penetration. The magnitude of these variations suggests that investors, resource planners, and policy makers should carefully consider the economic value and relative differences in the economic value among renewable energy technologies when conducting broader analyses of the costs and benefits of renewable energy. Nor should these evaluations be static—as renewable energy penetration increases new analysis will be needed. Also important is identifying ways to minimize the decline in value of variable renewable energy with penetration. Though that has not been the focus of the present work, by decomposing changes in economic value into capacity value, energy value, day-ahead forecast error and AS costs the present work can inform future analysis of these mitigation options. This analysis can also inform the design of simplified renewable procurement and transmission planning tools, like the WREZ model or other simple screening tools, by illustrating the relative importance of changes in the economic value of VG with increasing penetration to other factors that would be included in the simplified tools. The change in the value of PV and CSP_0 with increasing penetration should be given particular attention in such tools. More specifically, the key conclusions from this case study assessment of California include the following:

- *Solar has high value at low penetration:*

  The marginal economic value of solar at low penetration levels is high in California. This high value at low penetration is largely due to the ability of solar resources to reduce the amount of new non-VG capacity that is built, leading to a high capacity value. The magnitude of the capacity value of solar resources depends on the coincidence of solar generation with times of high system need, the cost of generation resources that would otherwise be built, and decisions regarding retirement of older, less efficient conventional generation.

- *There is little apparent value to thermal storage at low solar penetration:*

  At low penetration levels in California, we find that there is no strong increase in value per unit of electricity associated with adding TES to CSP plants. TES may be justified for minimizing the levelized cost of CSP plants, but there is no clear evidence in the present analysis that it is required to maximize economic value at low solar penetration.

- *The value of PV and CSP without thermal storage drop considerably with high penetration:*

  Without any mitigation strategies to stem the decline in the value of solar, the value of PV and CSP_0 drop considerably with increasing penetration. For penetrations of 0% to 10% the primary driver of the decline is the decrease in capacity value with increasing solar generation. Additional PV and CSP_0 are less effective at avoiding new non-VG capacity at high penetration than at low penetration. For penetrations of 10% and higher the primary driver of the decline is the decrease in the energy value. At these higher penetration levels additional PV and CSP_0 start to displace generation with lower variable costs. The operational constraints of thermal generation and hydropower contribute to the declining energy value of PV and CSP_0 at high penetration levels. At 20% solar penetration and above, there are increasingly hours where the price for power drops to very low levels, reducing the economic incentive for adding additional PV or CSP_0, and eventually there is curtailment of a portion of the energy generated by those solar technologies. The decline in the value is not driven by the cost of increasing AS requirements and is not strongly linked to changes in the cost of DA forecast errors.

- *At medium to high penetration CSP with thermal storage is considerably more valuable relative to PV and CSP without thermal storage:.*

  The value of CSP_6 also decreases at higher penetration levels but not to the extent that the value of PV and CSP_0 decline. As a result, at higher penetration levels the value of CSP with thermal storage is considerably greater than the value of PV or CSP_0 at the same high penetration level. The capacity value of CSP_6 remains high up to penetration levels of 15% and beyond because the thermal energy storage is able to reduce the peak net load even at higher CSP_6 penetration levels. Power system operational constraints are less severe for high penetrations of CSP_6 due to the ability to use thermal energy storage, as modeled in this analysis, to avoid pushing against any such constraints.

- *The value of wind is largely driven by energy value and is lower than solar at low penetration:*

  The value of wind is found to be significantly lower than solar at low penetration due to the lack of correlation or slightly negative correlation between wind and demand or wind and high prices. This lower value of wind is largely due to the lower capacity value of wind and at least for low to medium penetrations of wind the decline in the total marginal economic value of wind with increasing penetration is found to be largely a result of further reductions in capacity value. The energy value of wind is found to be roughly similar to the energy value of a flat block of power (and similar to the fuel and variable O&M cost of natural gas CCGT resources operating at full load). Only at very high penetration levels does the energy value of wind start to drop in the California case study presented here. Operational constraints cause some of the decline in the value of wind, but a large part of the decline in the value of wind is due to the merit-order impact of wind. The DA forecast error costs have little influence on the value of wind at low penetration and remain fairly manageable, on average less than $7/MWh, even at high penetration levels. AS costs are not found to have a large impact on the economic value of wind as modeled in this analysis.

- *At high penetration, the value of wind can exceed the value of PV and CSP without thermal storage:*

  While the marginal economic value of solar exceeds the value of wind at low penetration, at around 10% penetration the capacity value of PV and CSP_0 is found to be substantially reduced leading to the total marginal economic value of PV and CSP_0 being similar to the value of wind. At still higher penetrations, the energy value of PV and CSP_0 fall faster than the energy value of wind leading wind to have a higher marginal economic value than PV and CSP_0. CSP_6 on the other hand, is found to have a considerably higher value than wind at all penetration levels.

These results may, to a degree, be influenced by the fact that the analysis has loosely focused on California. In California, a region characterized by considerable natural gas fired generation, substantial hydropower generation, and diversity in potential wind resource sites, the dominant factors in understanding the economic value of wind and solar with increasing penetration levels are changes in the energy and capacity value of these sources. Analysis tools and methods for understanding economic value must therefore be able to adequately represent factors affecting resource adequacy and the merit-order stack of resources. Analysis, especially at high penetration, should also characterize conventional plant operational constraints like ramp-rates and start up costs. In regions outside of California that lack as much flexible gas and hydropower, consideration of operational constraints will be even more important.

Characterizing the impact of DA forecast errors and ancillary service requirements adds significant complexity to the analysis. Though the model used in this analysis relied on several simplifications, including commitment and dispatch decisions based on vintages rather than individual units and perfect foresight in the RT, the overall results indicate that the economic impact of DA forecast errors and AS requirements do not change as dramatically with increasing penetration and are a second order cost in the case of AS. That said, the actual amount of AS and the amount of flexibility required to manage DA forecast errors do increase with increasing VG penetration. Even though the economic impact may not be very large per unit of renewable energy, managing DA forecast errors and procuring adequate AS are both extremely important for ensuring system reliability and should continue to receive significant attention in studies of the steps necessary to ensure the technical feasibility of increasing variable generation penetrations.

One of the most important results from this work is the high capacity value of solar at low penetration and the decline in that capacity value (with the exception of CSP_6) with penetration levels around 10% on an energy basis. Given the importance of capacity value to the value of solar, areas of research that should be explored further include the ability of solar to contribute to resource adequacy, how that contribution changes with increasing penetration, and the economic implications of the decreasing contribution with increasing penetration. The capacity credit of PV and CSP_0 at increasing penetration levels should be investigated in more detail using detailed LOLP models to complement the less detailed, economic-focused analysis used here. In addition, as flexibility of generation resources becomes more important with increasing penetration of variable generation, methods to incorporate measures of flexibility into adequacy studies may also need to be developed. The capacity credit for CSP_6 should also be investigated further at high penetration levels. Based on the results presented here, however, energy constraints appear to impact the ability of CSP_6 to reduce the need for new generation capacity suggesting that methods used to evaluate the capacity credit of CSP_6 should be based on those suited to evaluating the capacity credit of resources in energy-constrained systems (e.g., methods used to evaluate resource adequacy in a system dominated by hydropower).

Another important finding of the present work is that the long-term value of adding TES to CSP is only obvious at higher penetration levels where the energy and capacity value of CSP_0 and PV fall off much faster than the value of CSP_6. Based on these results, TES should be especially considered by resource planners, solar manufacturers, and project developers for regions where the penetration of solar is expected to become substantial. Additional research is needed to assess whether this finding holds for power systems that differ from the one studied here. Research to explore the value of thermal storage in helping to manage DA forecast errors and AS increases caused by other VG technologies is also warranted.

Though this study focused on California and just one variable generation technology at a time, the same framework can be used to understand the economic value of variable generation in other regions and with different combinations of renewable energy. In the next chapter, the same framework is used to evaluate how changes in the power system, like price responsive demand, more flexible thermal generation, and lower cost bulk power storage, might impact the value of variable generation. Each of these "mitigation strategies" might help slow the decline in the marginal economic value of variable generation found in this chapter. Ultimately, it is not possible to precisely know the long-run value of variable generation due to numerous sources of uncertainty, including future regulatory policies, future fuel prices, and future investment costs of conventional technologies. Analysis models like the one presented in this chapter, however, can help identify promising routes forward and inform decisions.

Chapter 4

Strategies to Mitigate Changes in Value

4.1 Introduction

The addition of significant quantities of variable generation (VG) to a power market will face technical, economic, and institutional challenges. A large body of research and actual operating experience with large shares of VG indicate that integrating VG[1] into the grid is technically feasible (e.g., IPCC, 2011b). As far as economic challenges, costs of renewables are still declining, and a growing body of literature examines the economic value of VG and how it changes with increasing penetration (e.g., Hirth, 2013). Increasingly these economic studies attempt to incorporate the economic implications of technical challenges associated with VG. For instance, the share of studies that account for the detailed operational constraints of conventional generation when estimating the economic value of VG is growing.

In the previous chapter, we explored how the long-run marginal economic value of VG changed with increasing penetration levels. The analysis used a long-run economic framework that accounted for changes in the mix of generation resources due to new generation investments and plant retirements while also incorporating significant detail important to power system operations and dispatch with VG. Economic value of VG was primarily based on the avoided costs form other non-renewable power plants in the power system including capital investment cost, variable fuel, and variable operations and maintenance (O&M). In that chapter, the "valuation chapter," we examined how the marginal economic value of individual VG technologies changed as penetrations increased. This was carried out for wind, single-axis-tracking photovoltaics (PV), and concentrating solar power (CSP) with and without 6 hours of thermal energy storage (CSP_6 and CSP_0, respectively). Only one VG technology was deployed at a time. The analysis in the valuation chapter further assumed demand was very inelastic, that new conventional generation plants had similar operating

[1]Variable generation is sometimes called variable energy resources (VER) in other literature.

constraints as incumbent generation resources, VG siting was not optimized for geographic diversity, and that the cost of new bulk power storage was relatively high.[2]

The valuation chapter highlighted a number of important conclusions. The marginal value of wind was found to be largely based on the energy value (with lower capacity value) and therefore slightly lower than the value of a flat block of power at low penetration. The marginal value of wind was found to decline with increasing penetration, particularly at penetration levels above 30%.[3] The marginal value of wind decreased by 40% when going from 0% wind to 40% wind penetration. The marginal value of solar, on the other hand, was found to be relatively high at low penetration levels, particularly due to the high capacity value. As the penetration increased, the values of PV and CSP without thermal storage declined due to an initial steep drop in the capacity value followed by a decline in the energy value. The marginal value of PV decreased by 72% when going from 0% to 30% PV penetration. The value of CSP with thermal storage dropped much less with increasing penetration and had a distinctly higher marginal value at high penetration relative to the other solar technologies and wind. The marginal values of wind, PV, and CSP with thermal storage in the Reference scenario of the valuation chapter are reproduced in Figure 4.1.[4] A number of these conclusions for wind and solar are supported by results from other studies and from empirical evidence in other regions (e.g., Hirth, 2013).

The objective of our current chapter, the "mitigation chapter," is to evaluate several different mitigation measures[5] that may increase the value of VG at high penetration levels relative to the results found in the valuation chapter. The specific measures include increased geographic diversity, technological diversity (through simultaneous combinations of VG technologies), more-flexible new conventional generation, lower-cost bulk power storage, and price-elastic demand subject to real-time pricing (RTP). Although this is not a comprehensive list of available mitigation measures, these measures span a broad range of simplified representations of options to address challenges identified in the valuation chapter. Whereas the valuation chapter assessed wind, PV, CSP_0, and CSP_6 in detail, in this chapter we focus primarily on measures to mitigate changes in the value of wind and PV. CSP technologies receive less attention because the values of PV and CSP_0 were found to follow similar trends, and changes in the value of CSP_6 were already mitigated in part by the addition of thermal storage.

The primary question in evaluating each mitigation strategy is: If this mitigation strategy were to be implemented, how would it change the value of VG relative to an unmitigated case? We determine the change in the marginal value of VG after implementing the mitigation measure relative to the marginal value of VG at the same penetration level without the mitigation measure (i.e., the value in the Reference scenario from the valuation chapter), as

[2]The cost of storage in the Reference scenario, \$700/kW-yr, was based on the cost of new pumped-hydro storage from EIA [2011].

[3]Throughout this document, all penetration levels refer to the share of annual energy demand that is met by renewables (i.e., penetration on an energy basis).

[4]The change in the value of CSP without thermal storage was similar to that of PV.

[5]Mitigation measures are sometimes referred to as integration options in other literature.

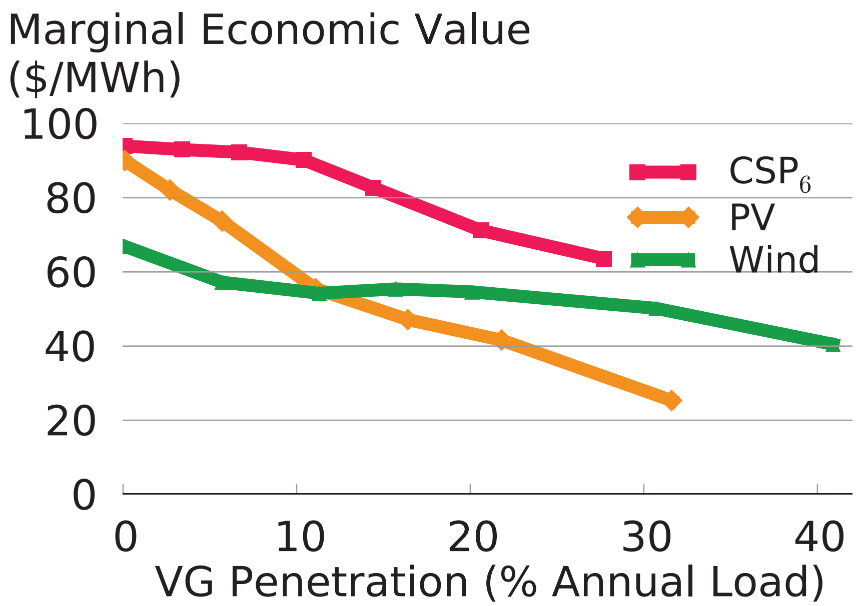


Figure 4.1: Marginal economic value of wind, PV, and CSP with thermal storage found in the Reference scenario of the valuation chapter.

illustrated in Figure 4.2. To make this comparison, we use new scenarios in which a mitigation measure is implemented, find new long-run equilibrium investments and wholesale prices with that mitigation measure, and then recalculate the value of VG in that new long-run equilibrium. For example, we decrease the investment cost for new pumped-hydro storage (PHS) from the high level in the Reference scenario, in which no new storage is built, to a much lower level that causes new storage to be built in the model. We then compare the value of VG in the Low-cost Storage scenario to the value of VG at the same penetration level in the Reference scenario. An increase in the value of VG with the mitigation measure relative to the case without the mitigation measure signals that the mitigation measure can help moderate the decline in the value of VG with increasing penetration found in the valuation chapter.[6]

An obvious related question is whether it makes economic sense to pursue these mitigation measures. We cannot answer that question directly in this analysis, because it requires understanding both the cost and the economic value of implementing the mitigation mea-

[6] We do not consider uncertainties in parameters (e.g., uncertain natural gas or carbon prices) that will impact the absolute level of the value of VG. We are primarily interested in the difference in value between the case with the mitigation measure and the Reference scenario, a metric that is less sensitive to these uncertainties.

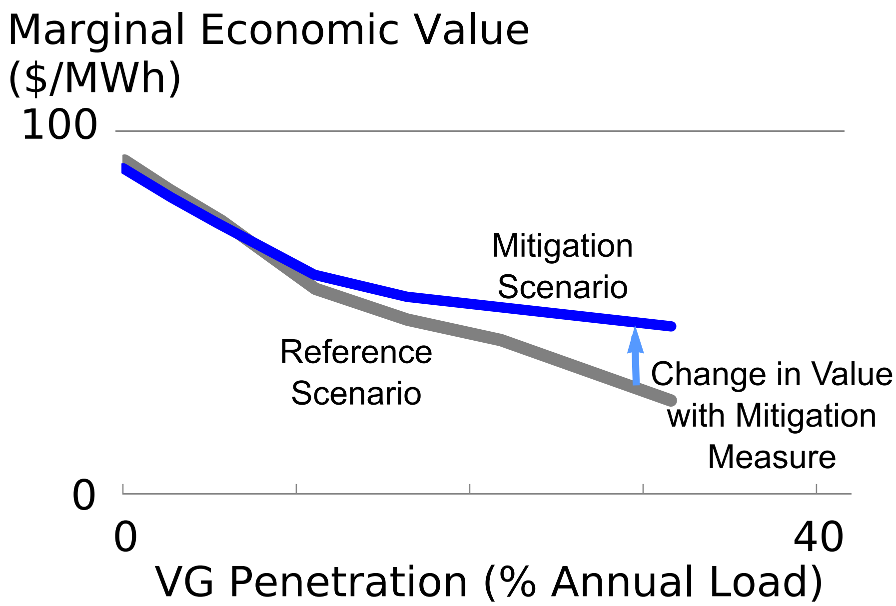


Figure 4.2: As shown here, change in the value of VG after implementation of a mitigation measure is defined in relation to the value in the Reference scenario from the valuation chapter.

sures. We do not address the cost, primarily owing to a lack of comparable data; some measures are relatively new and have not yet been deployed at scale, while others require data and analysis tools that are beyond the scope of this chapter. In addition, many of the measures that might mitigate the decline in the value of VG are driven by factors other than renewables. RTP, for example, is usually justified on the basis of reductions in peak demand. Other measures, such as increased flexibility in conventional generation, are driven by a need for reliability, not necessarily economics. It is helpful to determine whether these measures make economic sense, but economic considerations are not necessarily the main justification for pursuing them. Likewise, any benefit of RTP or flexible generation in increasing the economic value of VG is, in many cases, an ancillary one relative to the larger value proposition from these resources.

We do, however, provide insight into a related question: Does the marginal economic value of a mitigation measure increase with larger shares of VG? While we do not determine if mitigation measures produce a net gain, because we do not consider the cost of the measures, we do use the modeling framework to determine if the marginal economic value of mitigation measures increases with increasing VG. If the value increases, then the overall economic attractiveness of the mitigation measures could be greater with increased VG than without.

Conversely, if there was no strong reason to implement a mitigation measure without VG and the value of the measure does not increase with increasing VG penetration, then there would be no apparent reason to implement the measure with VG. In the best case, the marginal value of a mitigation measure would increase with increasing VG, and implementing that measure would increase the marginal value of VG relative to a case without the measure. Again, however, showing an increase in marginal value due to a mitigation measure does not on its own indicate that the measure should be implemented; a full analysis of VG and mitigation-measure values and costs would be required to evaluate their net economic impacts.

The remainder of the chapter is organized as follows. Section 4.2 provides an overview of several studies that have examined various mitigation measures with increasing penetrations of VG. Previous studies have often not evaluated the long-run marginal value of VG or of mitigation measures while considering more detailed operational constraints on conventional generation. Our chapter contributes to filling this gap in the literature. Section 4.3 outlines the methodology used in this chapter to compare the marginal economic value of VG with and without mitigation measures.[7] This section also describes how we estimate the change in the marginal economic value of the mitigation measures with increasing VG penetration levels. Section 4.4 covers the impact of each mitigation measure on the value of VG. Additional details on the methodology specific to each mitigation measure are described in the subsection specific to the measure. Section 4.5 examines whether the marginal values of the mitigation measures increase with increased penetration of VG. Section 4.6 summarizes key findings.

4.2 Background

Most of the mitigation measures assessed in this chapter have been described elsewhere, although that literature is primarily focused on wind. Many of these previous studies identify non-economic advantages of these mitigation measures. For example, assessments of geographic diversity might demonstrate the reduced aggregate variability of wind without quantifying the increase in the economic value of geographically diverse wind. Other studies not only explore these non-economic advantages, but also quantify the increase in economic value. Grubb (1991) is an early example of a study that considers the change in the economic value of wind with geographic diversity, more-flexible conventional generation, and improved forecasting in the United Kingdom. Hirth and Ueckerdt (2013) is a very recent example that estimates the value of wind with more-flexible provision of ancillary services (AS), more-flexible combined heat and power plants, increased transmission capacity between neighboring regions, and increased storage capacity in Germany. They find that these mitigation measures can increase the value of wind relative to an unmitigated case but do not prevent a drop in the value of wind with increasing penetration. Like these papers, our analysis compares the benefits of several mitigation measures over a wide range of pene-

[7] Details of the overall long-run economic framework and the basic assumptions used in the model remain the same as in the valuation chapter and thus are not repeated here.

tration levels for both wind and PV. The remainder of this section summarizes literature relevant to specific mitigation measures.

Geographic diversity is perhaps the most widely studied mitigation measure for wind. DeCarolis and Keith (2006) find total costs to be lowered by building transmission to multiple remote wind locations rather than limiting the increase in wind penetration to one site. Milligan and Factor (2000) similarly find benefits of geographic diversity in wind locations, although wind-resource quality is a more important factor. They show that the overall least-cost portfolio of wind locations exclude sites with low wind speeds, even if those low-quality sites are further away from others. Kempton et al. (2010) demonstrate clear differences in off-shore wind patterns along the U.S. Atlantic coast. They find that if these off-shore sites were to be connected by transmission, the aggregate wind generation would rarely approach zero power generation, even though zero output is common at individual wind sites. Similar results were found in the Midwestern United States by Archer and Jacobson (2007). Obersteiner and Saguan (2011) highlight the increase in the economic value of wind with increased geographic diversity in central Europe.

Less analysis has been done on the geographic-diversity benefits of solar. Mills and Wiser (2010b) and Hoff and Perez (2010) find clear benefits from geographic diversity in reducing short-term variability of PV caused by clouds but do not assess longer-timescale issues like day-ahead (DA) forecast errors. Denholm and Margolis (2007b) point to the challenges with diversifying PV production over longer hourly timescales given that production will be dictated largely by whether the sun is up, which is not substantially affected by geographic diversity.

Technological diversity in terms of the complementary profiles of wind and solar is highlighted in the California Intermittency Analysis Project by Piwko et al. (2007a). Nikolakakis and Fthenakis (2011), Denholm and Hand (2011), and Lew et al. (2013) find less curtailment for combinations of wind and solar compared to similar penetrations of one technology alone. Denholm and Hand find that the ratio of wind to PV that leads to the lowest curtailment with high aggregate renewable penetrations is 30% PV to 70% wind in the Electric Reliability Council of Texas (ERCOT) region. Vick and Moss (2013) find better matching to load for combinations of wind and solar compared to wind alone. Budischak et al. (2013) find that combinations of PV and wind have lower costs than wind alone for all-renewable systems. Lamont (2008) examines the change in the value of wind and PV with increasing penetration using data from California, including a sensitivity analysis of the cross impacts between wind and PV. Lamont finds that increasing PV penetration to 10% increases the marginal value of wind by about $6/MWh, but increasing wind penetration only slightly increases the marginal value of PV. Denholm and Mehos (2011) consider the possibility of synergies between PV and CSP with thermal storage. By assuming that CSP with thermal storage can reduce the overall system minimum generation level, they find that curtailment of PV at 25% penetration is reduced to below the curtailment level for 15% PV in a scenario without the "flexibility benefits" from CSP. Key to this result is the assumption that conventional generation with high minimum generation levels would be required if CSP with thermal storage were not available and that adding CSP with thermal storage displaces those resources with high minimum generation levels.

The advantages of more-flexible thermal generation are frequently discussed both in terms of increasing the profitability of thermal generators and in terms of integrating wind and solar. Ma et al. (2012) evaluate the profitability of flexible and inflexible plants with increasing wind based on a case study of an IEEE test system. They find the profitability of flexible plants depends in part on the magnitude of wind forecast errors. Several papers illustrate the difference in profitability of power plants that are modeled as perfectly flexible or modeled accounting for realistic operating constraints (e.g., Deng and Oren, 2003; Gardner and Zhuang, 2000; Tseng and Barz, 2002). These results can be used to estimate the potential upper bound on how much profits can be increased by increasing the flexibility of power plants. Denholm and Margolis (2007b) estimate the reduction in PV curtailment that can be achieved with reductions in the minimum generation limits of conventional power plants. In contrast to a relatively large increase in the value of wind in the United Kingdom that was found with more-flexible generation by Grubb (1991), EnerNex Corp. (2008) finds that adding more-flexible generation led to only a slight reduction in wind-integration costs with 20% wind penetration in the Public Service of Colorado service territory.

Storage is frequently suggested as a potential measure to mitigate impacts of wind and solar, although the cost of storage is often prohibitive. Sioshansi (2011b) provides a thorough review of the wind and storage literature, then examines the increase in the value of wind with storage in a system where generators exercise market power. Sioshansi et al. (2009) estimate the value of storage based on wholesale power prices in the PJM region. They find that the increase in the value of storage with increasing storage capacity slows when the storage reservoir capacity reaches about 8 hours. Denholm and Margolis (2007a) find that 8–12 hr of bulk power storage capacity can greatly reduce PV curtailment with PV penetrations exceeding 20%. Rasmussen et al. (2012) find large benefits to adding 6-hr bulk power storage in scenarios with over 50% renewables penetration but only marginal benefits for adding low-efficiency, seasonal storage. Hirth (2013) estimates the change in the value of wind and PV with assumptions of low or high amounts of PHS in Germany. Hirth finds that increases in storage increase the value of PV more than wind at high penetration levels, because the diurnal generation pattern of PV is well suited to storage with 6–8 hours of reservoir capacity, whereas periods of especially high and especially low wind generation occur over longer timescales. Garcia-Gonzalez et al. (2008) develop a method to determine optimal DA bids for wind and storage given uncertainty in wind and wholesale power prices. They find joint operation of storage and wind to be more profitable than separate, uncoordinated operation due to assumed penalties for deviations of actual generation from DA schedules. In Ireland, Tuohy and OMalley (2011) find that the capital cost of PHS is prohibitive until wind penetrations exceed about 42%. Steffen and Weber (2013) derive a straightforward method to estimate the optimal storage capacity in a system with and without variable renewables based on a load duration curve and modified screening curve approach. This approach has the disadvantage of ignoring operational constraints on thermal power plants and potential reservoir capacity limits. On the other hand, it provides the distinct advantage of a clear, transparent, and quick method for estimating optimal storage capacities under a wide range of scenarios. Lamont (2013) develops a theoretical framework to evaluate the marginal value of storage and to characterize the impact of storage on wholesale power prices. One particularly relevant finding is that storage tends to moderately increase off-peak prices, which are not sensitive to increased demand from charging storage, and greatly reduce peak prices, which are very sensitive to increased generation from discharging storage. Lamont indicates that storage could provide a relatively small benefit to wind (which tends to generate during off-peak times) while having a negative impact on solar (which tends to generate during peak times).

Finally, RTP as a mitigation measure for wind is explored in detail by Sioshansi and Short (2009) based on a case study of the ERCOT region in Texas. They consider detailed operational constraints of thermal generation and transmission limits between wind-rich regions and load centers using a short-term framework (i.e., they do not consider retirement or investments in conventional generation). The introduction of RTP is estimated to increase the value of wind by \$6–10/MWh, depending on the assumed price elasticity of demand. De Jonghe et al. (2012) consider wind and RTP in a long-run investment framework that accounts for own-price (prices in the same hour) and cross-price (prices in different hours) elasticities of demand and some thermal plant operational constraints like ramp rates. They find a slight increase in the optimal amount of installed wind with RTP compared to the optimal amount of wind without RTP. Including cross-price elasticities increases the optimal installed wind by more than it is increased when cross-price elasticities are ignored. Denholm and Margolis (2007a) estimate the reduction in PV curtailment that is possible when assuming that up to 10% of each day's normal demand can be shifted to other hours of the day to absorb PV generation. Callaway (2009) develops new methods to control a population of thermostatically controlled loads to produce grid-balancing services that will be required more often with increased wind and solar generation. An advantage of this approach is that services can be provided without large (or even noticeable) impacts to customer comfort levels. A potential disadvantage is that the timescale of the response provided may be shorter than multiple hours. Qualitative evaluation of renewable integration needs and various demand response programs by Cappers et al. (2012) suggests that balancing services over these longer timescales may be especially important for renewable integration. However, RTP programs that may provide response across longer timescales have far less regulatory and stakeholder support, particularly at the residential level, than incentive-based demand-response programs. Klobasa and Obersteiner (2006) survey the demand-response potential of different sectors in Germany then estimate the reduction in balancing costs in scenarios with high wind if that demand response were available. They identify several sources of demand response that could be activated 20–200 times per year with short notice (within the operating day) and could maintain that response for several hours. Accessing this demand-response potential would require suitable tariffs, communication infrastructure, and in some cases aggregators for small customers.

Other mitigation measures are discussed in the literature but are not considered in our analysis. The model used in this chapter, as in the valuation chapter, does not consider market trades with nearby regions over transmission interties (although variable renewable generators are located outside of California). Nicolosi (2012) identifies the level of policy support needed to supplement revenue renewable generators earn from the wholesale power market to cover the investment cost of wind and PV and achieve target deployment levels in Germany. Nicolosi finds that increased grid capacity between Germany and neighboring regions increases the value of wind and PV, thereby lowering the support costs. Hirth and Ueckerdt (2013) find a similar increase in the value of wind in Germany with increased grid capacity to other regions.

4.3 Methodology

Modeling Framework

The methods used in this chapter are based on the same model and framework used in the valuation chapter. In that model, the marginal economic value of VG at increasing penetration levels is calculated by adding VG to a competitive, "energy-only" power market[8] then determining hourly prices (for DA energy, real-time [RT] energy, and AS) over a year when the rest of the market reaches long-run equilibrium given the VG penetration. The long-run equilibrium accounts for changes in the mix of generation resources due to new generation investments and plant retirements for both technical reasons (i.e., when generators reach the end of an assumed technical service life) or for economic reasons (i.e., when generation is not profitable enough to cover its ongoing, fixed operations and maintenance [O&M] costs).

The new non-VG investment options include natural gas combined cycle gas turbine (CCGT) and combustion turbine (CT) plants as well as coal, nuclear, and PHS. The investment framework is based largely on the idea that new investments in conventional generation will occur up to the point that the short-run profits of that new generation (revenues less variable costs) are equal to the fixed investment and fixed O&M costs of the generation.

For new generation to fully cover its fixed investment and O&M costs through the power market, wholesale prices must periodically exceed the marginal fuel cost of generation. In some hours, generation will be at its full capacity and unable to meet all of the AS targets, and eventually load will need to be shed involuntarily. The wholesale prices in those hours rise to predefined, administratively set scarcity prices that reflect the need for additional generation at those times. [9] In other hours, excess generation can lead to curtailment of

[8] In an "energy-only" market, no capacity obligation is placed on load-serving entities, and prices are allowed to spike to high levels to indicate periods of scarcity. In contrast, many organized wholesale markets impose a capacity obligation on load-serving entities or operate an auction for capacity payments to meet a target level of installed capacity. Energy and AS prices in markets with capacity obligations are not expected to rise to high levels to indicate periods of scarcity (unlike the "energy-only" market modeled in this analysis). The energy and AS prices in markets with capacity obligations do not, on their own, signal the contribution of a generating resource to meeting system needs in critical periods.

[9] Many of the results in this chapter reflect the assumption of a system in long-run equilibrium. Other studies that add VG to a static mix of conventional generation reflect the short-run assumption that generation investments do not change in response to large increases in new VG generation. Those studies are

generation. There are no additional penalties or costs associated with curtailment, so prices periodically fall to zero but do not become negative.

Marginal Economic Value

The marginal value of VG is based on the revenue variable generators earn when selling power into such a power market in long-run equilibrium. The total revenue is calculated as the sum of the revenue earned by selling forecasted generation into the DA market at the DA price and the revenue earned (or lost) by selling any deviations from the DA forecast in the RT market at the RT price. No punitive imbalance penalties are levied on VG for RT generation that differs from the DA forecast. Instead, deviations from the DA forecast are generally sold at an RT price that is lower than the DA price, or shortfalls in RT generation from the DA forecast are purchased at RT prices that exceed the DA price. In addition, VG is allowed to sell AS. In the case of PV and wind, the AS that they can sell is regulation in the downward direction. Wind and solar are also charged for any assumed increase in the hourly AS requirements due to short-term variability and uncertainty. Following the assumptions in the valuation chapter, the regulation reserve requirement is assumed to increase by an amount equivalent to 5% of the DA forecast of wind and PV in each hour.

To better understand the source of value and the causes of changes in value, we decompose the value into four categories:

- Capacity Value ($/MWh): The portion of net revenue earned during hours with scarcity prices (defined to be greater than $500/MWh).
- Energy Value ($/MWh): The portion of net revenue earned in hours without scarcity prices, assuming the DA schedule exactly matches the RT generation.
- Day-ahead Forecast Error ($/MWh): The net earnings from RT deviations from the DA schedule.
- Ancillary Services ($/MWh): The net earnings from selling AS in the market from wind or PV and paying for increased AS due to increased short-term variability and uncertainty from wind or PV.

Similar to the valuation chapter, the resulting estimate of the marginal economic value is based only on a subset of the benefits related to implementing mitigation measures or adding VG. The subset of the benefits examined in this analysis is primarily based on avoiding the capital investment cost and variable fuel and O&M costs from other (fossil-fuel-based) power plants in the power system. These avoided costs are calculated while accounting

more likely to see overall decreases in wholesale prices with increasing VG compared to the behavior of long-run equilibrium prices with increasing VG penetration. In long-run equilibrium, prices need to remain high enough to cover the fixed cost of any new investments. The timing of high prices is likely to shift with increased VG prices, but the overall level is less likely to decrease.

for operational constraints on conventional generators and the increased need for AS when adding VG. As in the valuation chapter, the economic value reported here is the marginal economic value based on the change in benefits for a small change related to the mitigation measure (e.g., a small change in the amount of bulk power storage) or in the amount of VG at a particular penetration level. The analysis similarly does not consider many other costs and impacts that may be important, including environmental impacts, transmission and distribution costs or benefits, effects related to the "lumpiness" and irreversibility of investment decisions, and uncertainty in future fuel and investment capital costs.

For the most part, the analysis also does not consider the cost of VG nor the cost to implement mitigation measures. Instead we focus on the economic value of VG and mitigation measures; a full comparison among generation technologies and mitigation measures would need to account for both the value and the cost. One exception is the low-cost storage mitigation measure. In this case, the mitigation measure is implemented by lowering the assumed investment cost for PHS then allowing the model to find the amount of new PHS that would be built in long-run equilibrium for the given VG penetration. If the true cost of PHS were to fall to this level, which is much lower than the cost assumed by the U.S. Energy Information Administration (EIA) in its *Annual Energy Outlook 2011* (EIA, 2011), then the cost of implementing the bulk power storage mitigation measure would be fully accounted for. On the other hand, if an external policy measure (e.g., a storage subsidy or a utility requirement to invest in a certain amount of storage) were used to lower the market cost of storage, then this analysis would similarly be ignoring the cost of that subsidy or investment mandate.

Note that the methods used to calculate marginal values in the main sections of this chapter—Section 4.4 (Change in the Value of VG after Implementing Mitigation Measures) and Section 4.5 (Change in the Value of Mitigation Measures with Increasing VG)—are substantially different. Briefly, in Section 4.4, two separate scenarios are modeled through long-run equilibrium for each mitigation measure: the valuation chapter's Reference scenario without the mitigation measure and a scenario in which the mitigation measure is fully implemented; the marginal values of VG between the two scenarios are then compared at each VG penetration level. In Section 4.5, the scenarios analyzed are all based on the long-run equilibrium prices in the Reference scenario with no mitigation measures implemented; the marginal value of a mitigation measure in one of these scenarios thus represents the potential short-run profit of implementing the measure for the first time. More detail on the methods used in Sections 4.4 and 4.5 are included in the introductions to each section.

Case Study of California in 2030

The mitigation analysis is based on the same case study used in the valuation chapter. The case study loosely matches characteristics of California projected to 2030. These characteristics of California include generation profiles for VG, existing generation capacity, and the hourly load profile. Thermal generation parameters and constraints (e.g., variable O&M costs, the cost of fuel consumed just to have the plant online, the marginal variable fuel cost associated with producing energy, start-up costs, limits on how much generation can ramp from one hour to the next, and minimum generation limits of generation that is online) are largely derived from observed operational characteristics of thermal generation in the Western Electricity Coordinating Council (WECC) region, averaged over generators within the same vintage. Aside from fossil-fuel-fired generation, the existing generation modeled in California includes geothermal, hydropower, and PHS. California load and conventional generation is treated in isolation from any other load or conventional generation in the rest of WECC. In other words, we do not consider existing or future transmission capacity between California and the rest of WECC, except for imports of VG to serve California loads. Fossil-fuel prices are based on the fuel prices in 2030 in the EIA's *Annual Energy Outlook 2011* reference case forecast (EIA, 2011).

4.4 Change in the Marginal Value of VG after Implementing Mitigation Measures

The primary question of this chapter is: How much does the marginal economic value of VG change when a mitigation measure is implemented relative to the value without the mitigation measure? To answer this question, we estimate the marginal economic value of VG in a case with the mitigation measure and compare it to the marginal economic value of the same VG technology at the same penetration level in the Reference scenario from the valuation chapter. Implementing the mitigation measure requires re-running the model to determine a new long-run equilibrium with the measure implemented. For example, in the case of price-responsive demand with RTP, the marginal value of VG is estimated where the price elasticity of demand is changed from very inelastic (with a constant elasticity of -0.001) in the Reference scenario to an elasticity of -0.1 in the RTP mitigation scenario. Relative to the Reference scenario, the new long-run equilibrium with price-responsive demand and RTP results in less investment in conventional generation capacity irrespective of the VG penetration. The reduction in conventional capacity is a result of consumer willingness to reduce demand during hours with high prices (rather than needing to build new generation capacity to meet demand in those hours). The resulting long-run equilibrium prices in a scenario with RTP are used to estimate the marginal value of VG. This economic value is then compared to the economic value in the Reference scenario at the same penetration level to determine how well the mitigation strategy is able to moderate the decline in the marginal value of VG with increasing penetration.

We start by describing the change in the marginal value of VG with geographic diversity, then address technological diversity. Next we examine the impact of assuming that new CCGTs are more flexible than existing CCGTs. We then describe the impact of lowering the cost of new storage in terms of the amount of storage that is built with different VG penetration levels, the dispatch of storage, and the change in the value of VG with low cost storage. Finally, we simulate the impact of RTP by changing the elasticity of demand.

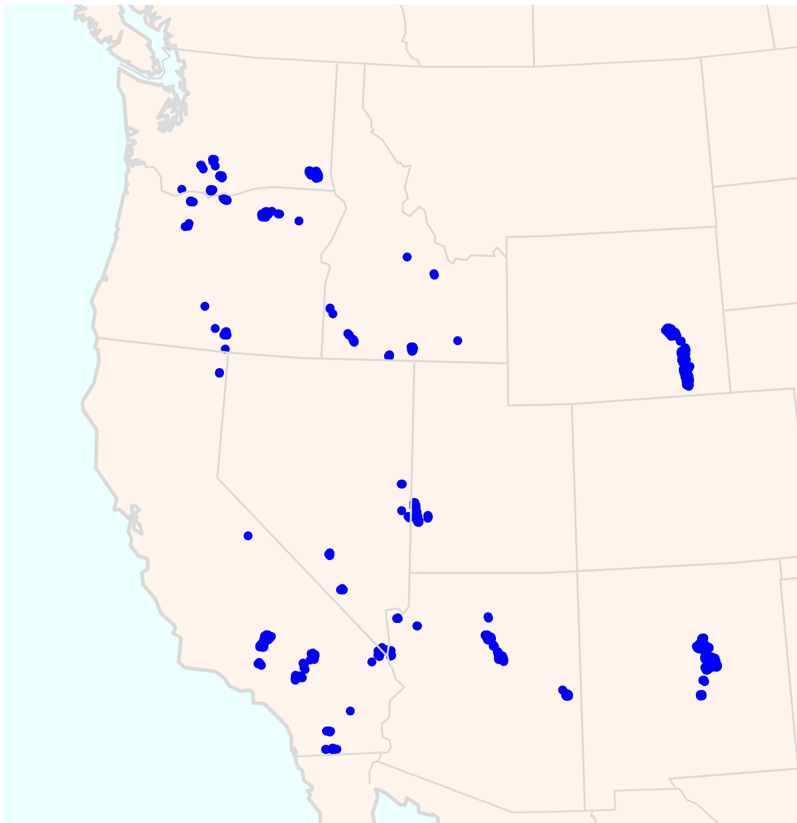


Figure 4.3: Location of wind sites in the Reference scenario with 40% wind penetration.

Change In the Marginal Value of VG with Geographic Diversity

Wind sites in the Reference scenario were selected from resource hubs identified in the Western Renewable Energy Zone (WREZ) Initiative (Pletka and Finn, 2009). These resource hubs are assumed to have a finite capacity available for building wind plants. As the penetration of wind was increased in the Reference scenario, wind sites from additional WREZ hubs were included in the wind portfolio. As a consequence, a certain amount of geographic diversity is already reflected in the Reference scenario, Figure 4.3.

In this mitigation analysis, we develop an alternative wind portfolio in which wind sites are selected using only the criteria that the sites are geographically diverse. We use increasing wind penetration at these high-diversity sites to find new investment and dispatch decisions and long-run equilibrium power prices. We then compare the marginal value of wind in this Diverse scenario to the marginal value of wind in the Reference scenario. For illustration purposes, we similarly find the change in the marginal value of wind in a scenario that concentrates all of the wind sites in one region. In this Concentrated scenario, the wind sites are located at WREZ hubs in and around Southern California.[10]

Again, it is important to remember that this analysis estimates the magnitude of the change in the value of wind with more diversity. It does not determine whether an increase in diversity should be pursued, as the analysis does not consider the cost of increased diversity.

We chose the high-diversity wind sites by identifying a combination of potential wind sites that has the lowest aggregate variability over the year while still generating adequate annual energy to meet a desired target. In more formal terms, a mathematical program was used to determine which wind sites should be selected to satisfy Eq. 4.1, following a similar approach described by Palmintier et al. (2008). This approach is one of many ways that could be used to identify a portfolio with high wind diversity.

$$\begin{aligned} \min_{(u_i \ldots u_m)} \quad & \text{Variance} = \sum_{i \in I} \sum_{j \in I} u_i u_j \mathrm{Cov}(W_i, W_j) \\ \text{s.t.} \quad & \sum_{i \in I} u_i E_i \geq \text{Total wind energy target} \end{aligned} \tag{4.1}$$

Where W is the hourly production of the wind site over a year, E is the annual total energy generated by that site, and u is a binary decision variable to determine whether the site should be included or not.

In practice, solving this problem is very computationally intensive, so several simplifying approximations were used. First, only a subset of all possible sites were used. The Western Wind and Solar Integration Study (WWSIS) wind dataset used in this analysis includes wind generation profiles for more than 30,000 30-MW wind sites in WECC (Potter et al., 2008). Instead of evaluating all of those sites, we randomly selected 1,000 representative sites that had annual capacity factors above 20%. Scaling parameters were used so that a particular site evaluated in Eq. 4.1 could represent up to 600 MW of wind (or 20 individual sites that are actually 30 MW in the WWSIS dataset). The variable u, which is used to determine whether a site should be part of the diverse wind portfolio, was split into two variables: one that determines whether a representative site should be included or not and a second that estimates how many of the nearest 20 sites should also be included in the final diverse portfolio. In addition, a supplementary parameter was added to the model to set the maximum number of sites that the program would evaluate (as suggested by Palmintier et al. (2008)).

[10] In the Concentrated scenario, we ignore constraints identified in the WREZ Initiative in terms of how much wind could be sited in a particular region. We still use individual 30-MW wind sites from the WWSIS dataset to build the wind profiles, so we do capture some geographic diversity within the WREZ hubs even when all wind is located in and around Southern California.

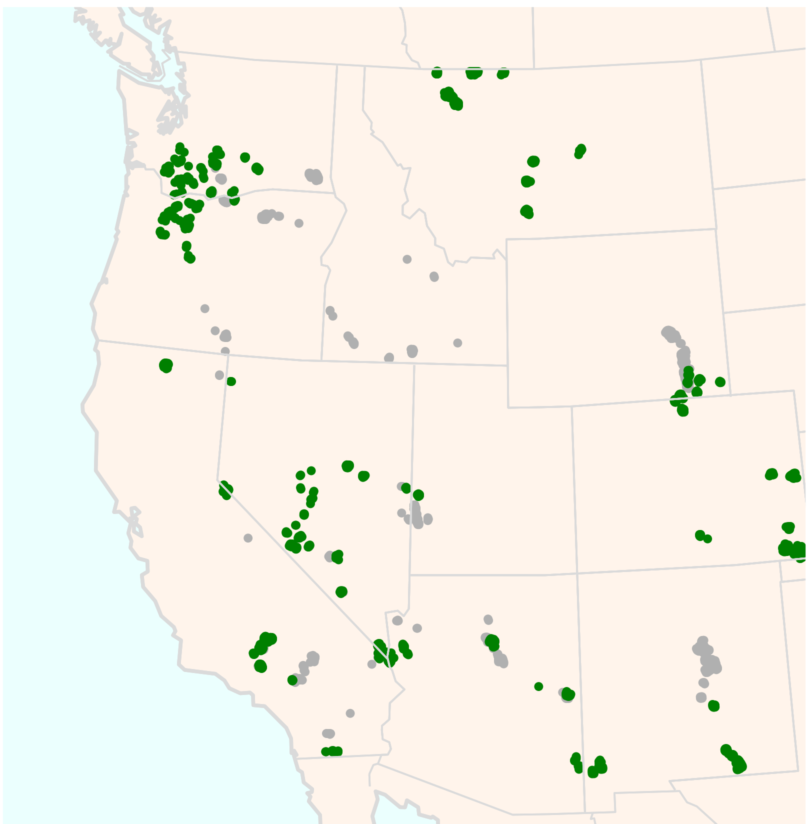


Figure 4.4: Location of wind sites in the Diverse scenario with 40% wind penetration (locations in the Reference scenario are shown in gray).

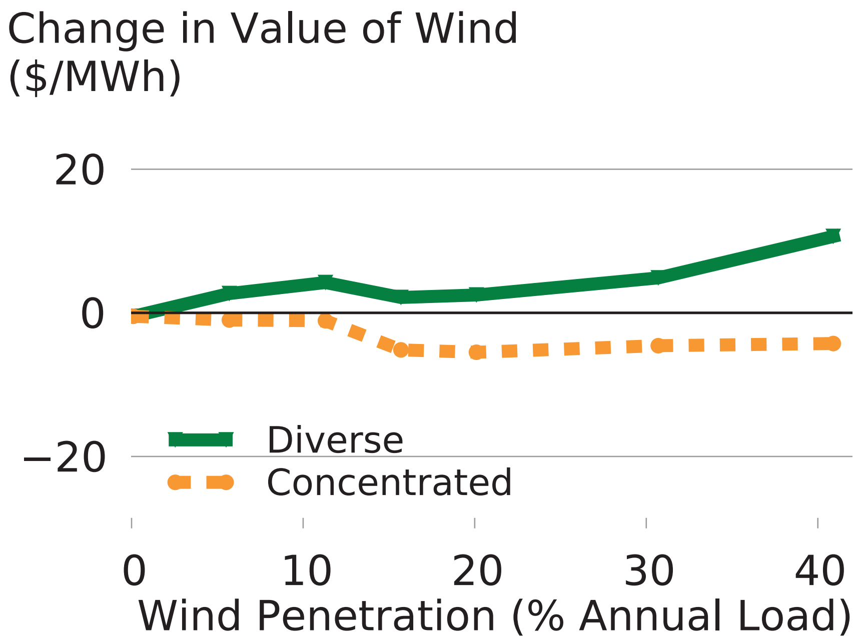


Figure 4.5: Change in the marginal economic value of wind with geographically concentrated or diverse wind sites relative to the Reference scenario.

The modified program was written in AMPL and solved using the CPLEX solver. For a particular wind-penetration level, the model identified which of the possible 1,000 sites should be selected to minimize total variance while generating the desired annual energy. The output also indicated how many of the nearest 20 wind sites should also be included in the final diverse wind portfolio. The number of nearby sites was rounded to the nearest integer between 1 and 20. These results were then used to generate a new high-wind-diversity portfolio for each wind-penetration level, e.g., Figure 4.4, which shows the portfolio at 40% wind penetration.

Using the Diverse scenario's wind portfolios instead of the Reference scenario's portfolios increases the marginal value of additional wind by about $5/MWh at moderate penetration (10%) and high penetration (30%). At very high penetration, the Diverse scenario's portfolio increases the marginal value of additional wind by more than $10/MWh, Figure 4.5. Detailed analysis of the Diverse scenario's wind portfolios indicates that the increase in value relative to the Reference scenario is primarily based on an increase in the capacity value for penetrations below 30%. At 40% penetration, the increase in the value of wind for the Diverse scenario's portfolio is due to an increase in energy value followed by a smaller increase in the capacity value and a small decrease in the DA forecast error cost. The increase in energy value is in part due to a reduction in curtailment in the Diverse scenario. Over 3%

Figure 4.6: Location of wind sites in the Concentrated scenario with 40% wind penetration (locations in the Reference scenario are shown in gray).

of the annual wind is curtailed at 40% wind penetration in the Reference scenario, but less than 0.1% is curtailed in the Diverse scenario.

A portfolio with high geographic diversity leads to a higher value of wind due to a reduction in extremes: fewer hours have significant amounts of wind from all wind sites in the portfolio (reducing over-generation and curtailment), and more hours have at least a small amount of wind generation from some sites. The benefit of increased geographic diversity is more pronounced with high wind penetration levels since wind is more likely to affect wholesale prices at high penetration levels.

In contrast, concentrating the wind sites in one geographic region (Figure 4.6) decreases the value of wind relative to the Reference scenario. Concentrating wind in one region tends to increase the frequency of extremes, where all wind is generating or no wind is generating. Increases in wind generation tend to occur simultaneously in areas where wind speeds are already high and thus while wholesale prices are already low (due to the surplus wind generation). Similarly, wind forecast errors tend to be correlated when wind sites are concentrated. In this case, concentrating wind sites decreases the value of additional wind by around \$6/MWh, with wind penetration up to 40%, as shown in Figure 4.5. The lower value in the Concentrated scenario is driven primarily by an increase in the DA forecast error cost. Since large forecast errors can be technically challenging to manage, concentrated wind also raises concerns about secure system operations.

We do not implement a scenario with a high geographic diversity of PV sites. As explained in a later section, the decline in the value of PV at high penetration levels is due to PV production decreasing when the sun sets and high-price periods shifting into the early evening. Since geographic diversity can do little to affect the timing of the sunset, geographic diversity appears unattractive for stemming the decline in the marginal value of PV found in the Reference scenario.

Change in the Marginal Value of VG with Technological Diversity

The value of one VG technology can depend on the amount of other VG technologies included in a scenario. In the Reference scenario, only one VG technology was added at a time. In this section, we explore how the value of VG changes when the penetration of a different VG technology is increased. First, we estimate the change in the value of wind when the system has 10% PV penetration relative to the value of wind without PV. Next, we examine the change in the value of wind with 10% penetration of CSP with thermal storage (CSP_6). Finally, we look at the change in the value of PV with 10% wind penetration.

To what degree can adding 10% PV penetration mitigate the decline in the value of wind found in the Reference scenario? To evaluate this question, we created a new set of investment, dispatch, and wholesale prices in a scenario with 10% PV and increasing penetration of wind. The resulting marginal value of wind in this new 10% PV mitigation scenario is compared to the value of wind in the Reference scenario in Figure 4.7.

The marginal value of additional wind when 10% of the energy is served by PV is greater than without 10% PV for wind penetration levels between 0% and 20%. At 0% wind penetration, the marginal value of wind is just over \$7/MWh greater with 10% PV than without it; this positive value steadily decreases until it is only slightly greater at 20% wind penetration. Beyond 20% wind penetration, the value of additional wind with 10% PV begins to decrease relative to its value without 10% PV. For wind penetrations above 20%, adding 10% PV is not an effective mitigation measure and instead can reduce the value of additional wind.

The increase in the value of 10% wind with 10% PV is largely due to an increase in the capacity value of wind and a slight increase in the energy value of wind. Since the system is in long-run equilibrium with or without the 10% PV, the average wholesale power prices over the whole year remain at around \$70/MWh (sufficient to cover the investment cost of the

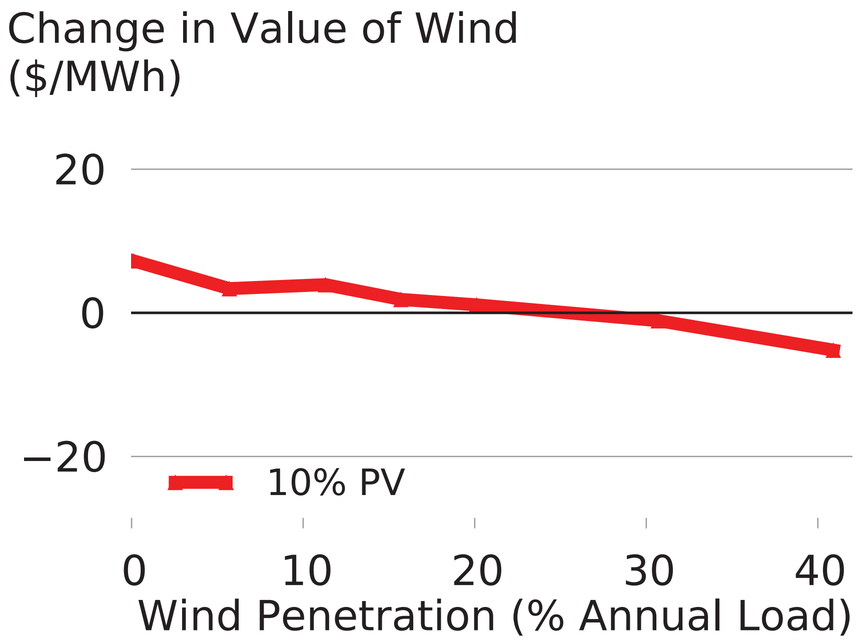


Figure 4.7: Change in the marginal economic value of wind with 10% penetration of PV relative to the Reference scenario.

new CCGT generation). The main difference in the wholesale prices between scenarios with or without 10% PV is the timing of high or low prices. The increase in the capacity value of wind with 10% PV is due to PV shifting the timing of the peak prices into the early evening, when wind generation is somewhat stronger. To illustrate this point, Figure 4.8 shows load, net load, wind generation, and real-time prices on three days with high loads and scarcity prices (indicating a need for additional generation in those hours). With 10% wind and 0% PV, the net load peaks and prices spike between roughly 1 pm and 6 pm. The addition of 10% PV pushes the peak net load closer to 6 pm, and prices spike later between roughly 2 pm and 8 pm. With 10% wind, these later price spikes happen to line up better with wind production on these particular days. While wind is not operating at its full capacity during these price spikes, it is generating more during the early evening, on average, thus the value of wind increases with 10% PV.

To what degree can adding 10% penetration of CSP_6 mitigate the decline in the value of wind found in the Reference scenario? We created a new set of investment decisions, dispatch, and wholesale prices with 10% CSP_6 penetration and increasing penetration of wind. The marginal values of wind in this 10% CSP_6 scenario are nearly identical to the values in the Reference scenario for most wind-penetration levels, Figure 4.9. Only around 40% wind and 10% CSP_6 does the value of wind begin to decline relative to the value at

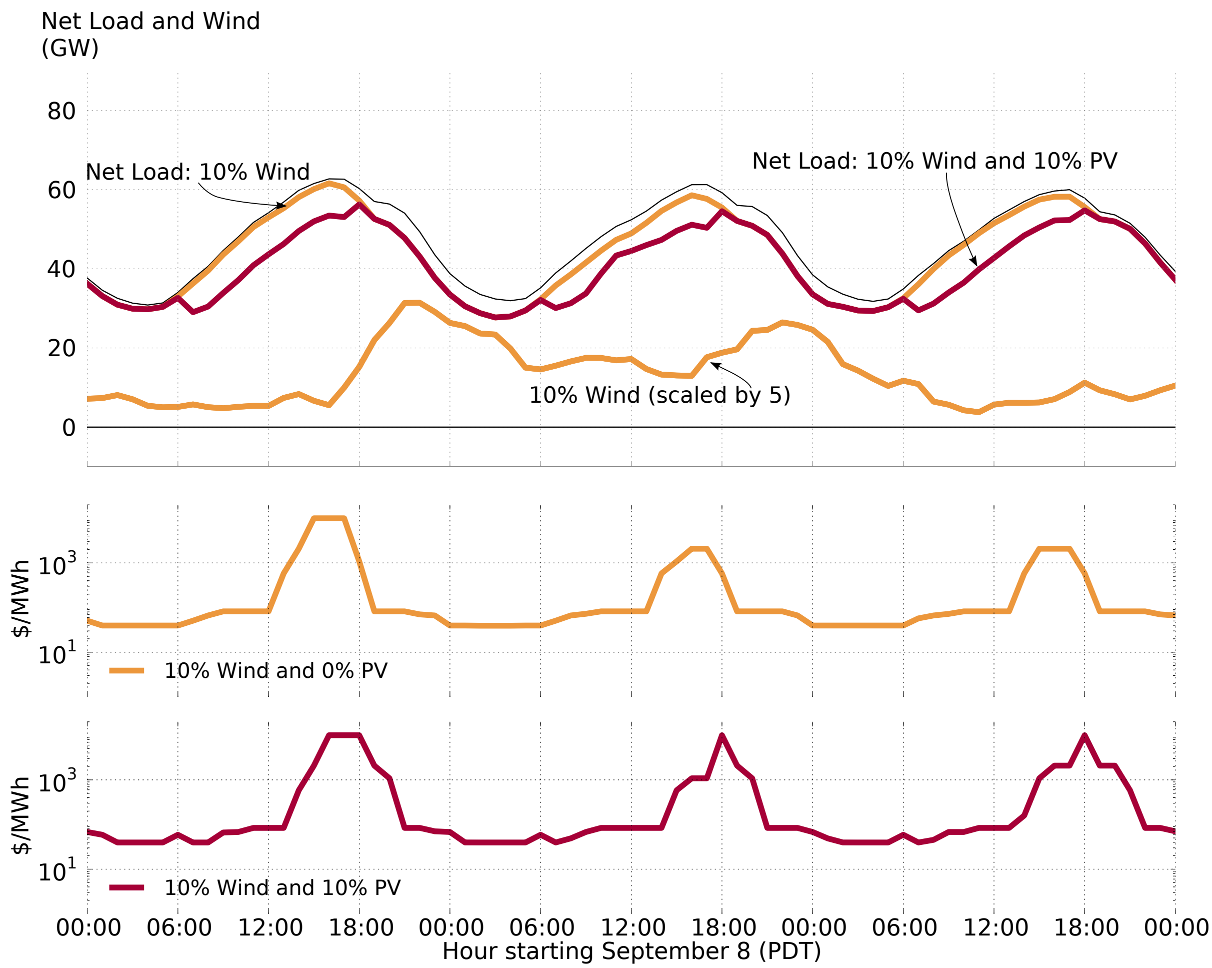


Figure 4.8: Historical load (thin line), net load, wind generation profile (scaled by a factor of 5 for clarity), and resulting RT price on three peak load days with and without 10% PV penetration.

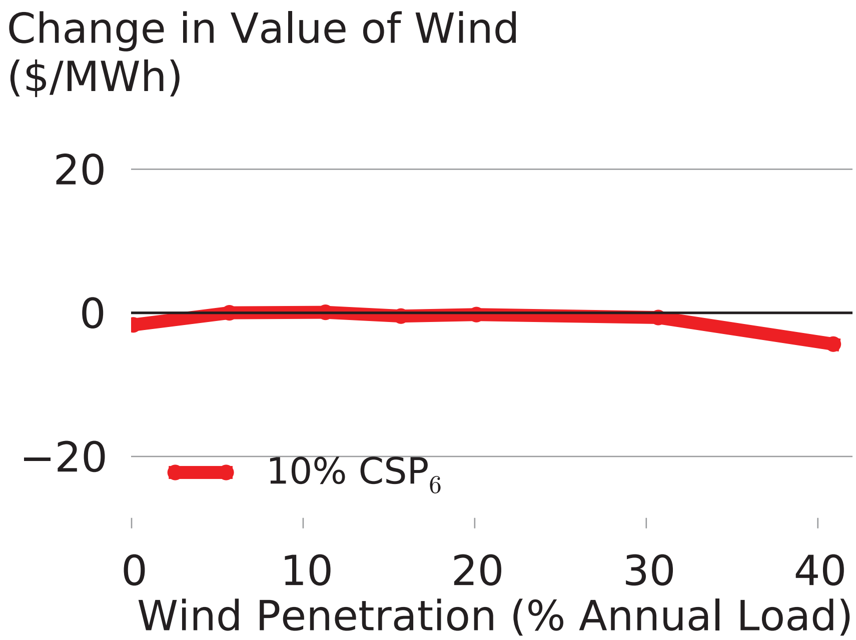


Figure 4.9: Change in the marginal economic value of wind with 10% penetration of CSP with 6 hours of thermal energy storage relative to the Reference scenario.

40% wind without CSP_6.

Two points help explain why adding CSP_6 does not increase the value of wind. First, the addition of 10% CSP_6 does not shift the timing of scarcity prices. Analysis in the valuation chapter demonstrates that scarcity prices continue to occur at the same time of day with or without 10% CSP_6, unlike in the case with 10% PV, where scarcity prices shift into the early evening. This is because the addition of thermal storage allows CSP to continue to reduce the net load in the early evening after the sun goes down. Since CSP_6 does not shift the timing of scarcity prices, the value of wind does not increase. Second, wind and CSP_6 generation are not closely related. The timing of wind generation and CSP_6 generation is uncorrelated at 10% penetration of wind and 10% penetration of CSP_6. With increasing wind penetration, the two technologies become more and more negatively correlated, meaning that when wind is generating CSP_6 is less and less likely to be also generating. CSP_6 starts operating in a way to avoid periods with wind, but this does not increase the value of wind. Eventually at 40% wind penetration CSP_6 cannot avoid generating at the same time as wind which lowers prices during periods with wind and decreases the marginal value of wind. Opportunities for CSP_6 to provide system services that might mitigate the impact of wind are rare because times with wind generation are not tied to times with CSP_6 generation.

These results indicate that CSP_6 is not an effective strategy for mitigating the decline in

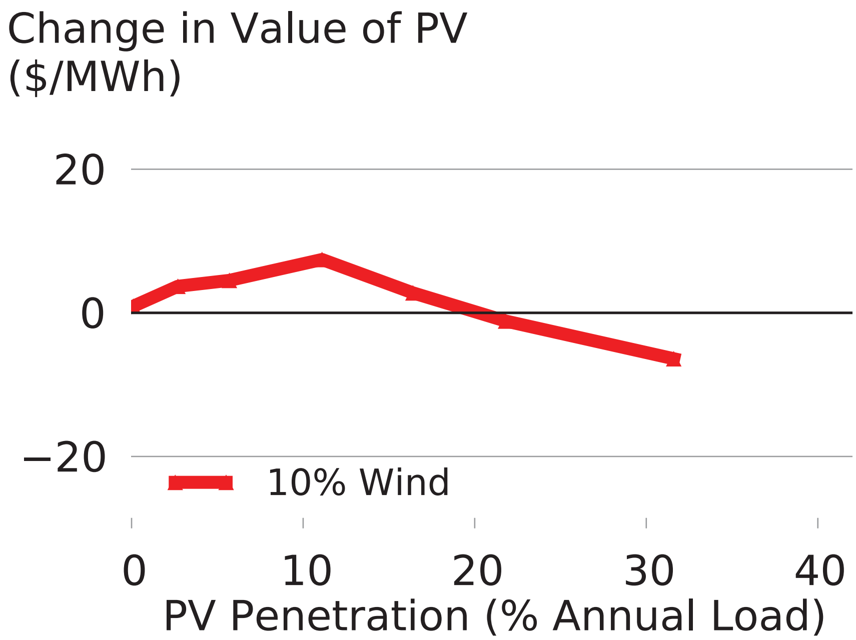


Figure 4.10: Change in the marginal economic value of PV with 10% penetration of wind relative to the Reference scenario.

the marginal value of wind with increasing wind-penetration levels. That said, we also find that the addition of 10% CSP_6 does not diminish the value of wind over wind-penetration levels of 0% to 30%.

To what degree can adding 10% penetration of wind mitigate the decline in the value of PV found in the Reference scenario? We created a new set of investment decisions, dispatch, and wholesale prices with 10% wind penetration and increasing penetration of PV. As shown in Figure 4.10, at very low PV penetration ($\tilde{0}$ %) the value with or without 10% wind is similar. The high value of PV at low penetration is due to the coincidence of PV generation and scarcity prices in the late afternoon on peak-load days. Wind does not generate much power in the late afternoon, so adding 10% wind does not substantially affect the timing of scarcity prices and the marginal value of PV. However, as PV penetrations increase, adding 10% wind increases the marginal value of PV substantially relative to the Reference scenario, reaching roughly $7/MWh higher at 10% PV penetration. This increase in the value of PV is almost entirely due to an increase in the capacity value of PV with 10% wind versus the capacity value with no wind. The increase in the capacity value is tied in part to wind generation occurring in early evening (as described earlier) and thus slowing the shift of high-price hours into the early evening with increasing PV.

Above about 10% penetration of PV, the value of PV with 10% wind starts declining toward the value of PV without wind. At 20% PV penetration, the value of PV is again similar with or without 10% wind. At 30% penetration of PV, the marginal value of PV with 10% wind is $6/MWh lower than the value of PV without wind. Wind can, therefore, reduce the decline in the value of PV at moderate PV-penetration levels, but not at 20% or greater PV-penetration levels.

In some cases CSP_6 is thought of as a mitigation measure for PV in the sense that energy from CSP_6 could be substituted for energy from PV while keeping the same penetration level of solar (e.g., Denholm and Mehos, 2011). In effect, that approach increases the value of solar by decreasing the penetration of PV. In our approach we treat technological diversity in a different manner. Instead of increasing the value of solar by decreasing the penetration of PV, we are interested in measures that mitigate the decline the n value of PV for the same penetration level of PV. CSP_6 is not often thought of as a method to mitigate the decline in the value of PV in this manner, since both technologies generate power during sunny periods. We did not examine a full set of PV-penetration levels with 10% CSP_6, but we did perform a spot check by adding 10% CSP_6 to a scenario with 20% PV then comparing the value of PV to the value in the Reference scenario without CSP_6. The value of PV at 20% penetration is $4.5/MWh lower with 10% CSP_6 than without CSP_6. The decrease in the value of PV when there is also CSP_6 is due to a decrease in the energy value and a smaller decrease in the capacity value of PV. The thermal storage enables CSP_6 to shift much of its generation into hours when PV is not generating (mostly to the early evening hours), but there remain hours when both CSP_6 and PV are generating at the same time, effectively lowering prices during those hours relative to what they would have been with only PV. The cost of AS and DA forecast errors do not change substantially with or without CSP_6.

For moderate penetration levels, technological diversity can increase the value of wind or PV relative to a scenario with just one VG technology. Just as importantly, we find a range of penetration levels where wind and solar technologies do not interfere with each other. The value of additional wind at 20% penetration and 10% PV or 10% CSP_6 (a total VG penetration of 30%) is similar to the value of additional wind at 20% penetration of wind alone. In other words, there is no reduction in economic value of wind at 20% wind penetration with or without 10% penetration of PV or CSP_6. At 30% wind penetration, wind is only slightly less valuable with 10% PV or 10% CSP_6 (a total VG penetration of 40%) than without it. Similarly, the value of additional PV at 20% PV penetration and 10% wind (a total VG penetration of 30%) is almost equal to the value of additional PV at 20% PV penetration alone. This suggests that analysts can evaluate the value of wind or PV at up to 20% penetration with only one technology at a time, knowing that the value of that technology will not decrease if up to a 10% penetration of the other variable technology is added.

Taken together, these scenarios indicate that relatively high penetrations of total VG can be achieved using combinations of wind and solar technologies while maintaining or even enhancing the value of the wind/solar generation compared with the value of using single wind and solar technologies in isolation. However, determining whether to pursue technological diversity as a mitigation measure would require comparing the anticipated

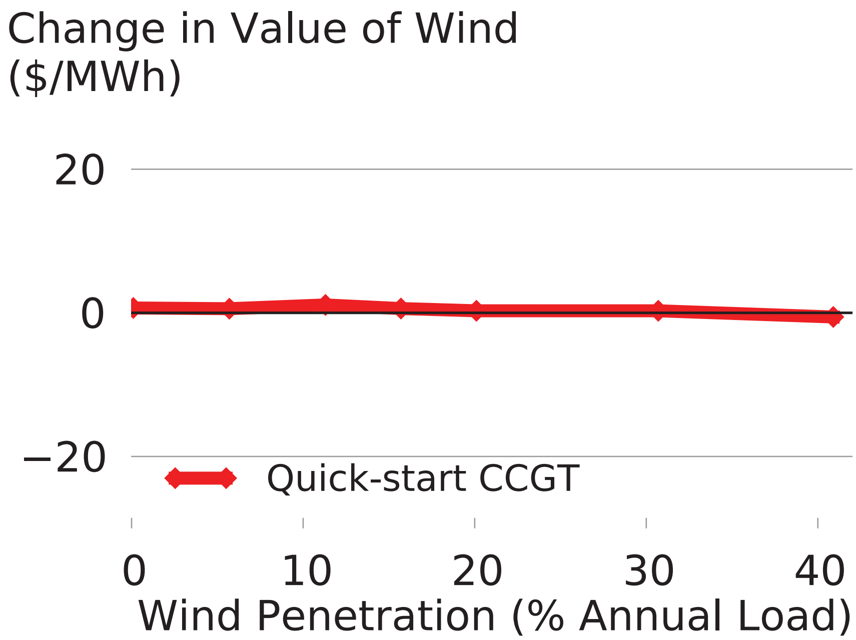


Figure 4.11: Change in the marginal economic value of wind with all new CCGTs having quick-start capabilities relative to the Reference scenario.

increase in value against the potential higher cost of building combinations of technologies to achieve the target penetration level. For example, even though the value of 20% wind may be lower than the value of 10% wind and 10% PV, PV might be more expensive than wind, leading to an overall higher cost. The value changes illustrated in this chapter are an important part of this full consideration.

Change in the Marginal Value of VG with More-Flexible Generation

The characteristics of the conventional generation fleet can impact the value of VG. In this section, we examine whether making new CCGT plants more flexible mitigates the decline in the value of wind and solar with increasing penetration. We do this by assuming that new CCGTs, like CTs, have quick-start capability and can be committed and decommitted in real time (in the Reference case we assume that the commitment decisions of all CCGTs are made day-ahead and cannot be changed).[11] The quick-start CCGTs are assumed to

[11]Other options not considered here include rolling-unit commitment (e.g., Tuohy et al., 2007), plant improvements to minimize start-up damages and resulting costs (e.g., Kumar et al., 2012), and retrofits of existing plants to enable quick start or faster ramp rates (e.g., Puga, 2010).

maintain the same ramp rate as assumed in the Reference scenario once online. We find new investment decisions, dispatch, and wholesale prices with increasing penetrations of wind and PV assuming that all new CCGTs have quick-start capability, and then we compare the value of wind and PV to the value in the Reference scenario.

For both wind and PV, the change in the value with quick-start CCGTs relative to the value in the Reference scenario is negligible, Figures 4.11 and 4.12. This can most likely be explained by the relatively low DA forecast error cost for wind and PV even with CCGTs that need to be committed in the DA (as in the Reference scenario) and the fact that new CCGTs only make up a portion of the total generation mix in California. It could also be due to the way wholesale prices in this model allocate costs and benefits to VG. For example, Figure 4.12 shows a slight decrease in the value of PV with new quick-start CCGTs relative to the value in the Reference scenario, but further examination of the "social surplus"[12] with or without quick-start CCGTs always shows a positive (but very small) increase in the social surplus with quick-start CCGTs. This small discrepancy shows that the formulation of wholesale prices can impact the effectiveness of allocating costs and benefits between different market participants. Actual prices used in wholesale markets may produce different results.

Based on the modeling approach used in this chapter, making new CCGTs more flexible by allowing commitment in real-time does not appear to be a promising mitigation measure to stem the decline in the value of wind and PV in this region. Perhaps a more promising strategy would be to focus on increasing the flexibility of existing generation or reducing the cost of starting and stopping new and existing thermal power plants. These options are left as suggestions for future research. In addition, the impact of more-flexible generation will depend on the degree of flexibility in the existing generation mix. California has significant amounts of CTs, PHS capacity, and hydropower. In comparison, we found in an earlier analysis of highly concentrated wind in the Rocky Mountain Power Area (Mills and Wiser, 2013) that assuming all new CCGTs had quick-start capability increased the value of wind by up to $6/MWh at 30% wind penetration. The Rocky Mountain Power Area has much less flexible incumbent generation relative to California. As such, results shown in the present paper should not be used to suggest a negligible benefit to generation flexibility overall, and this is an area where future research is recommended.

Change in the Marginal Value of VG with Low-Cost Storage

In this section we quantify how much more valuable wind and PV are when low-cost storage is added to the system. Bulk power storage in this section refers specifically to any storage resource that charges using power from the grid and discharges when providing power to the grid. Storage is modeled as PHS that has a round-trip efficiency of 81%. Storage dispatch is optimized concurrently with the dispatch from all other generation options (including conventional generation and hydro). Storage can be charged or discharged and can also provide

[12]Social surplus is the estimate of the total economic benefit to consumers of consuming electricity less the long-run cost of producing electricity.

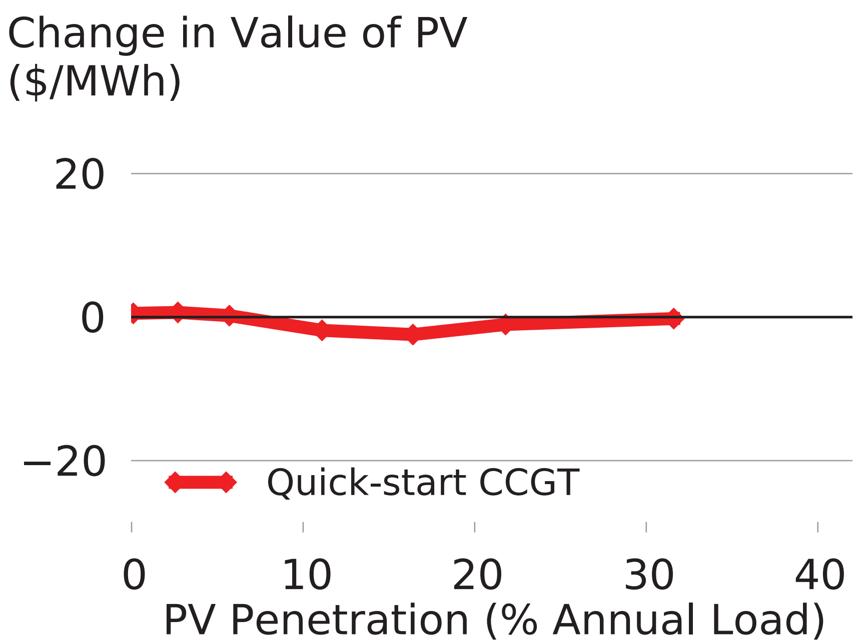


Figure 4.12: Change in the marginal economic value of PV with all new CCGTs having quick-start capabilities relative to the Reference scenario.

AS, specifically, regulation (up or down), spinning reserve, and non-spinning reserve. Additional details on the dispatch of storage are provided in Mills and Wiser (2012b). The size of the assumed storage reservoir is sufficient to provide power for 10 hours at full nameplate capacity.

In the Low-cost Storage scenario, new investment decisions, dispatch, and wholesale prices are found assuming that new PHS could be built with a much lower investment cost than assumed in the Reference scenario. PHS storage was an investment option in the Reference scenario, but the high cost of new PHS storage in the Reference scenario prevented any new additions.[13]

The Low-cost Storage scenario assumes a lower annualized investment cost and fixed O&M cost equivalent to $140/kW-yr, approximately 20% of the cost used in the Reference scenario.[14] Since the cost of storage in the Low-cost Storage scenario is even lower than the annualized fixed cost of a CCGT or CT and new capacity is needed, storage automatically

[13]Both the Reference scenario and the Low-cost Storage scenario include 3.5 GW of existing PHS storage capacity.

[14]This low investment cost is based on the cost estimate for a proposed PHS facility that uses two existing mine pits for the upper and lower reservoirs (Eagle Crest Energy, 2008). Such a unique situation means that this cost likely represents an extreme lower bound to the cost of PHS.

Table 4.1: Investment in new PHS storage capacity with increasing penetration of wind and PV in the Low-cost Storage scenario.

New PHS	VG Penetration						
(GW)	0%	5%	10%	15%	20%	30%	40%
Wind	4.4	4.4	4.8	5.4	5.3	5.7	6.9
PV	4.4	3.3	3.5	4.7	6.2	9.8	N/A

becomes one of the investment options selected in the model. The additions of new PHS capacity chosen by the model with increasing penetrations of wind and PV are shown in Table B.13.[15]

With the assumption of low storage-investment costs, 4.4 GW of new storage capacity are built even in the no wind and PV cases. The amount of new storage capacity grows by 57% with 40% wind.[16] The amount of energy that can be stored in the bulk power storage reservoir becomes increasingly important with higher penetrations of wind. Whereas the storage reservoir capacity is only a binding constraint 22 times during the year with 0% wind penetration, the reservoir capacity is a binding constraint 64 times with 30% wind. We only allow storage reservoir capacity to increase in proportion to storage generating capacity (with the proportion fixed at 10 hours of reservoir capacity at full generating capacity). The increase in the number of times that the storage reservoir is a binding constraint indicates that wind might benefit more from proportionally larger storage reservoirs. The relatively small increase in the value of wind with low-cost storage (discussed below) may also be due to the limited storage reservoir capacity.

The increase in new storage capacity is largest with 30% penetration of PV: 122% higher than the case with no PV.[17] At lower PV penetrations (<15%), however, the capacity contribution of PV displaces the need for new storage capacity, thereby lowering the amount of new storage relative to a case with 0% PV penetration. By 15% PV penetration, the situation changes, and the amount of new storage capacity increases above what was built in the no PV case. In contrast to wind, the amount of energy that can be stored in the bulk power storage becomes less important with higher penetrations of PV. The reservoir capacity is only a binding constraint 13 times during the year with 30% PV (compared to 22 times at 0% PV). This suggests that PV requires proportionally smaller reservoirs than the 10 hours of storage capacity assumed here and smaller reservoirs than would be ideal for wind. This is likely due to the diurnal profile of solar where storage would need to be

[15]This new storage is built only after assuming large reductions in the capital cost of storage. Without those cost reductions, no new storage would be built.

[16]At 40% wind penetration, the total new and existing storage capacity is 25% of the nameplate capacity of wind.

[17]At 30% PV penetration, the total new and existing storage capacity is 38% of the nameplate capacity of PV.

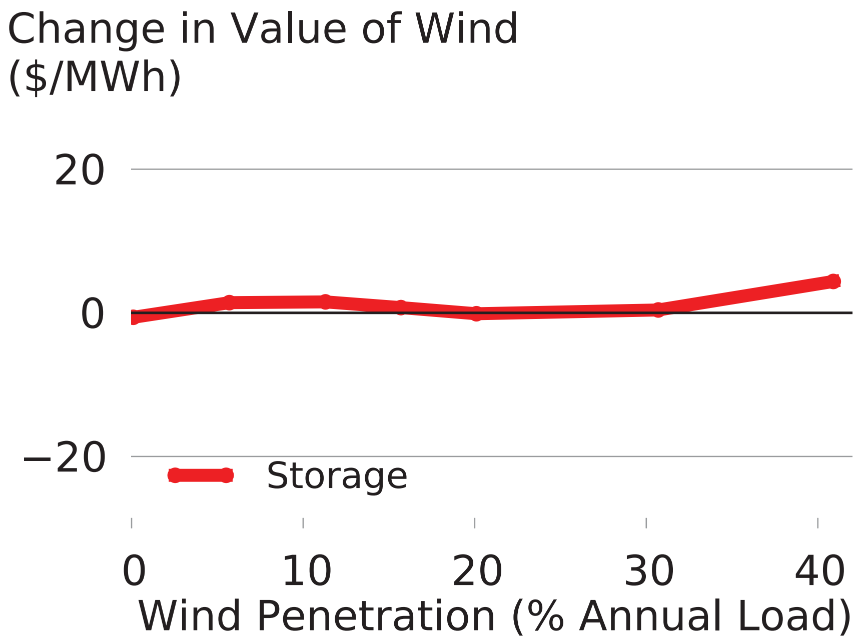


Figure 4.13: Change in the marginal economic value of wind with low-cost PHS.

charging for at most half of the day with high solar penetrations. In contrast wind is more variable over longer periods: high wind periods can last for multiple days, leading to a larger benefit from more storage reservoir capacity.

The investments in new storage change the value of wind relative to the Reference scenario with no new storage. Although additional storage increases the value of wind at nearly all penetration levels, the increase is negligible until 40% wind penetration, Figure 4.13.

A relatively weak negative correlation between wind generation and generation from storage (existing and new) indicates that storage tends to be charging when wind is generating, and storage tends to be generating when the wind is not blowing, as shown in Table 4.2, although this relationship does not always hold. This leads to an increase in the energy value of wind due to increases in wholesale prices when storage is charging and wind is generating. Additionally, the energy value of wind increases in part due to a reduction in wind curtailment from 3.2% with 40% wind in the Reference scenario to 0.2% in the Low-cost Storage scenario.

At the same time, the assumed low cost of storage capacity reduces the capacity value of wind. Since storage is now the option with the lowest investment cost, it becomes the new capacity resource. Fewer hours with scarcity prices are required to cover the fixed cost of investment in storage compared to the number of hours required to cover the cost of a CCGT. This in turn lowers the capacity value of wind, since wind now generates less power

Table 4.2: Correlation between VG and the net generation from new and existing storage.

Correlation	VG Penetration						
	0%	5%	10%	15%	20%	30%	40%
Wind	-0.00	-0.11	-0.14	-0.16	-0.18	-0.22	-0.30
PV	0.41	0.12	-0.28	-0.58	-0.74	-0.86	N/A

during periods with scarcity prices.

At most penetration levels, the reduction in capacity value is similar to the increase in energy value, leading to only minor changes in the marginal value of wind. At 40% wind penetration, the increase in the energy value with storage is distinctly larger than the reduction in the capacity value. As a result, the marginal value of wind increases by about $4/MWh with storage relative to the Reference scenario.

At low PV penetration, the value of PV declines modestly with low-cost storage relative to the value of PV in the Reference scenario, Figure 4.14, owing to a decrease in capacity value. Since the capacity value is a large source of PV value at low penetration levels, a decrease in the number of hours with scarcity prices, as seen with the introduction of low-cost storage, has a negative impact on the value of PV at low penetration. Furthermore, at low PV penetration, storage and PV tend to generate power at similar times, as corroborated by the positive correlation between PV generation and storage discharge in Table 4.2, resulting in lower wholesale prices at these times and potentially lower energy value.

The results are different at higher PV penetrations, where low-cost storage substantially increases the value of PV. Low-cost storage begins to increase PV value relative to the value without low-cost storage at greater than 5% PV penetration. By 30% PV penetration, the marginal value of additional PV is $20/MWh greater with low-cost storage than without.

The increase in the value of PV with low-cost storage is almost entirely due to the increase in the energy value of PV relative to the Reference scenario. The only other contributor to the increase in PV value is a decrease in the cost of DA forecast errors of less than $2/MWh. The energy value of PV increases in part due to a reduction in PV curtailment from 2.9% with 30% PV in the Reference scenario to less than 0.1% in the Low-cost Storage scenario. The strong negative correlation between PV generation and generation from storage (existing and new) at high PV penetrations indicates storage is consistently charging when PV is generating and discharging otherwise, Table 4.2. The transition from storage and PV generating power at the same time to storage charging when PV is generating and discharging otherwise is apparent during peak-load days in Figure 4.15. The load on these three days is the highest during the year. On these particular days, storage switches from charging late at night and discharging in the late-afternoon and early evening to charging in the early morning after the sun rises and discharging in the early evening with increasing PV penetration. Charging the storage during the early morning increases power prices in those hours relative to what

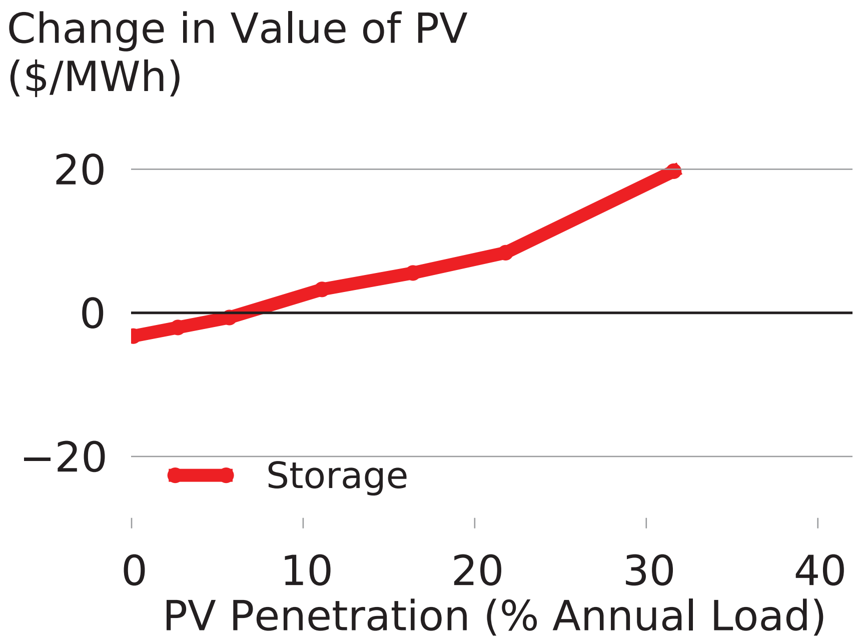


Figure 4.14: Change in the marginal economic value of PV with low-cost PHS relative to the Reference scenario.

they would have been without new storage capacity. The increase in prices during this time increases the energy value of PV.

Change in the Marginal Value of VG with RTP

In the Reference scenario, all electricity demand is assumed to be indifferent to the DA and RT wholesale market price. This is the situation in much of the United States, where customers pay retail rates that do not vary depending on actual conditions in the DA and RT markets. Increasingly, however, retail rates are including pricing signals to retail customers to indicate periods when electricity consumption is particularly expensive. Large industrial and commercial customers already participate in programs that subject them to prices in wholesale markets in some parts of the United States. Furthermore, the roll-out of smart meters that record demand at 15-minute intervals will enable small commercial and residential customers to transition to retail prices reflecting conditions in the wholesale market.

If retail prices shift from static to dynamic, or RTP, customer demand is also likely to change relative to historical demand patterns. Studies indicate a wide range of estimates of the elasticity of customer demand to changes in power prices (e.g., Allcott, 2011; Boisvert et al., 2007; Lijesen, 2007; Taylor et al., 2005; Zarnikau and Hallett, 2008). In the RTP

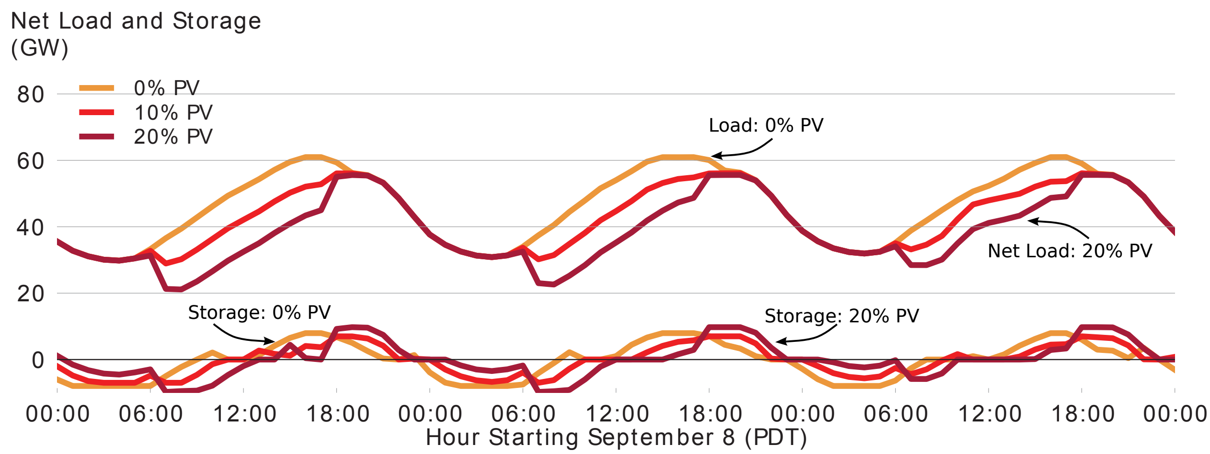


Figure 4.15: Net load (load less PV) and storage generation on peak days with increasing PV penetration.

scenario, electricity demand is assumed to have a constant own-price elasticity of -0.1,[18] such that a 10% increase in wholesale prices leads to a 1% reduction in demand relative to the historical demand in the same hour of the year.

The RTP program is implemented in the model by making demand price elastic and then finding new investment decisions, generation dispatch, and wholesale power prices with price-responsive demand. In the model, both DA and RT demand are price responsive. If DA prices are near average levels, then the price-responsive demand will be close to historical demand when DA commitments of thermal generation are made. If RT prices then rise due to unexpected shortfalls in VG, then the price-responsive demand will be lower than historical demand levels. To be clear, active participation of the demand side in wholesale power markets through RTP, as modeled in this chapter, does not match tariffs or programs used in practice.[19] The first program to expose residential customers to RTP, for instance, uses the DA market price to set the RTP price for customers prior to the operating day, but does not update that price based on real-time conditions (Allcott, 2011). The demand response offered by RTP as modeled in this chapter is a simplified representation of the "idealized" demand-side participation that might be achieved through new designs of RTP programs or combinations of other existing demand-response programs.

One notable feature of implementing RTP is that price spikes become less severe (prices no

[18]A constant elasticity of -0.1 is within the range of assumptions used in other studies on the impact of RTP (e.g., Borenstein and Holland, 2005; De Jonghe et al., 2012; Sioshansi and Short, 2009). In particular Borenstein and Holland (2005) test the impact of RTP assuming a constant elasticity between -0.1 and -0.5 and participation of between 33% and 99% of the load in RTP.

[19] The closest analogue would be a large industrial customer that buys electricity from a retail service provider including a direct pass through of the spot market price. The customer would then actively monitor the wholesale price on a RT basis to decide how much power to consume at any time (e.g., Zarnikau, 2010).

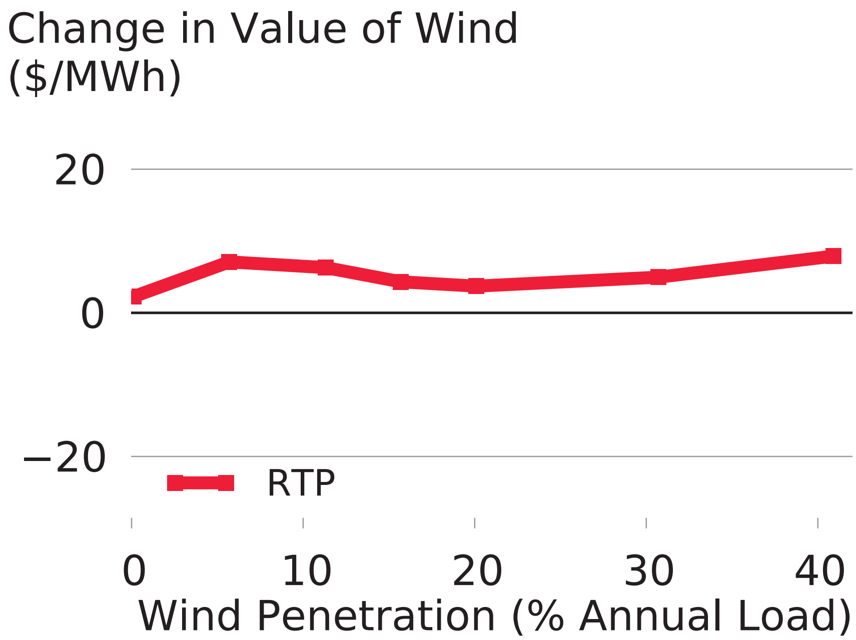


Figure 4.16: Change in the marginal economic value of wind with RTP and price-responsive demand relative to Reference scenario.

longer rise to $10,000/MWh) but prices above $500/MWh increase in frequency. A related outcome is that less conventional generation capacity is built in the RTP scenario, since reductions in demand relative to historical levels at time of system need enable a balance between demand and generation rather than relying on new conventional capacity (similar to the results from Borenstein and Holland (2005)). The new wholesale prices with RTP are used to estimate the change in the value of wind and PV relative to the value in the Reference scenario with inelastic demand.

Implementing the RTP program increases the value of wind at all penetration levels, Figure 4.16. The largest increase in the value of wind relative to the Reference scenario is $7–8/MWh, which occurs both at 5% wind and 40% wind. Less than $2/MWh of this increase in value is due to decreases in the DA forecast error cost with RTP. The remainder of the increase in wind value with RTP is due to an increase in the sum of the energy and capacity values. The capacity value of wind increases because the increase in the number of hours with prices above $500/MWh happens to cover more hours with some wind generation. The energy value increases because price-responsive demand increases relative to historical levels during times with increased wind generation (due to wind's impact on depressing wholesale prices at these times leading to higher load and therefore and increase in wholesale prices).

Table 4.3: Correlation between VG and demand response provided by RTP.

Correlation	VG Penetration						
	0%	5%	10%	15%	20%	30%	40%
Wind	-0.03	-0.17	-0.31	-0.39	-0.44	-0.54	-0.69
PV	0.27	0.09	-0.16	-0.42	-0.59	-0.79	N/A

Tracking the correlation between demand response and wind generation illustrates the degree to which demand-side decisions are influenced by wind. Demand response in this context is defined as the difference between the historical load profile assuming that demand is not influenced by wholesale power prices and the price-responsive load profile. Positive correlation between demand response and wind generation indicates that price-responsive demand leads to lower demand at the same time that wind is generating electricity, while negative correlation indicates that price-responsive demand leads to higher demand when wind is generating. The correlation between demand response and wind at different penetration levels, Table 4.3, indicates that wind and demand response are largely uncorrelated at very low wind penetration, but that price-responsive demand increases during times with high wind at higher penetration. Contrary to most demand-response programs that have historically been designed to decrease demand, these results indicate that the value of wind is increased by shifting demand to, or even increasing demand during, times when wind is generating power.

As with wind, implementing the RTP program increases the value of PV at high penetration levels; in contrast to wind, the RTP program decreases the value of PV at low penetration levels (<5%), Figure 4.17. The reason for the decrease in PV value with RTP at low penetration is similar to the reason for the decrease in PV value with low-cost storage. Implementing RTP reduces the cost of capacity and the duration of very high price spikes. At low PV penetration, this decrease in high prices lowers the revenue earned by PV. At 10% PV penetration, however, implementing RTP increases the value of PV by up to $10/MWh. At even higher penetration levels, the increase in PV value from RTP is closer to $7–8/MWh.

At low PV penetration, PV and the demand response from RTP are positively correlated, as shown in Table 4.3, indicating that RTP decreases demand at the same time that PV is generating power. Lower demand leads to lower wholesale prices and therefore lowers the marginal value of PV at low penetration. At 10% PV penetration and above, PV and demand response are negatively correlated, indicating an increase in demand when PV is generating. At 30% penetration, the correlation between PV and demand response is almost -0.8, substantially more negatively correlated than wind and demand response at 30% penetration. On average over the entire year, RTP increases the total demand by only 0.1% at 10% PV penetration but by 3.2% at 30% PV penetration. Nearly all of the increase in demand occurs during daytime hours when PV is producing power, particularly in spring months. Such changes in consumption patterns may require end-use control technologies or

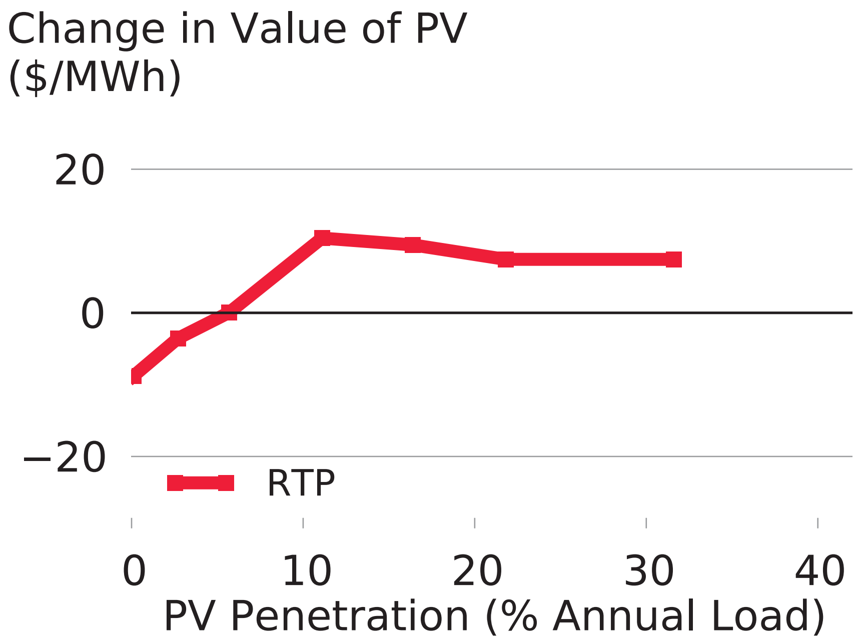


Figure 4.17: Change in the marginal economic value of PV with RTP and price-responsive demand relative to the Reference scenario.

customer behaviors that differ from those in traditional demand-response programs, which primarily reduce demand during summer afternoons. Midday electric vehicle charging might be well suited to increasing customer demand during times with high PV production.

The characteristics of the modeled demand response provided by RTP on peak-load days with increasing PV penetration can be illuminated further by examining a time series of the historical load, the remaining load after implementing RTP, and the difference between historical load and the load with RTP (i.e., the demand response), Figure 4.18. Implementing RTP without PV leads to demand response that is greatest in the late afternoon and effectively levels the peak demand on all three days. Increasing PV penetration shifts the demand response provided by RTP from late afternoon into early evening. The demand response does not entirely disappear during the daylight hours—times when PV is generating. Thus, even though the hours with highest prices shift into the early evening, high prices still occur during times with PV generation, thereby helping to maintain the value of PV with increasing penetration.

Demand-response strategies for peak-load days, such as pre-cooling, which shifts cooling loads away from the peak to earlier in the day, may need to be adjusted in scenarios with high PV penetration. At 0% PV penetration, a pre-cooling strategy would aim to reduce demand before around 6 pm on peak-load days. With high PV penetration, the pre-cooling would

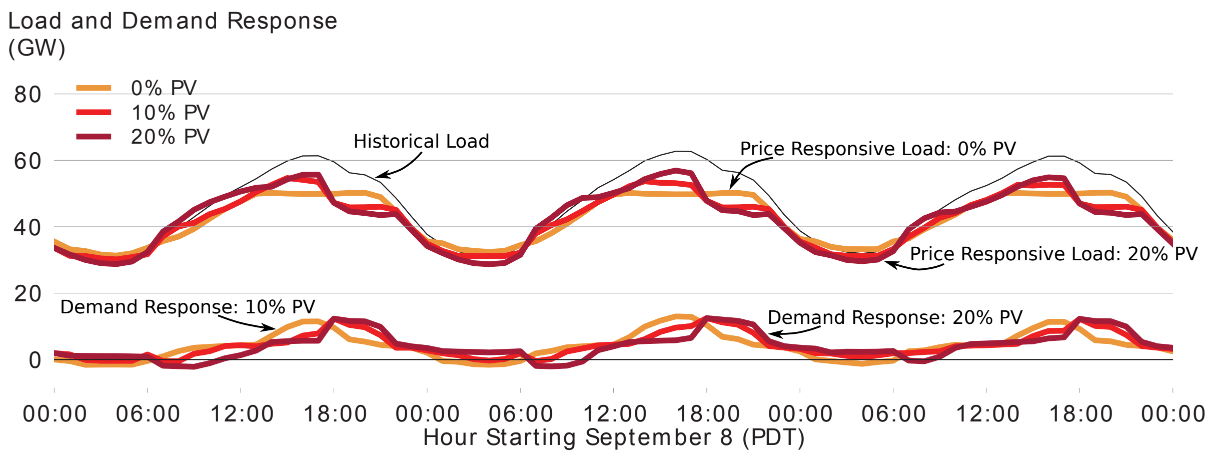


Figure 4.18: Historical load (thin line), price-responsive load, and effective demand response on peak days with increasing PV penetration.

need to reduce demand between about 6 pm and 9 pm. High PV penetrations may also shift the focus from one customer class to another, depending on the load profiles of different customer classes. In some regions, commercial loads tend to peak earlier in the day while residential loads peak later in the evening. In that case, demand-response programs could target commercial customers at low PV penetration but shift to residential customers at high PV penetrations. Many other factors go into the design of demand-response and retail-pricing programs, but this analysis suggests that expectations for future PV penetration levels might be an important consideration.

4.5 Change in the Value of Mitigation Measures with Increasing VG

Now that we have examined the impact of mitigation measures on the value of VG, a related question is whether it makes economic sense to implement these mitigation measures. We do not fully address that question, mostly due to a lack of comparable data on mitigation-measure costs. However, we indirectly provide insights by asking: How much does the marginal economic value of mitigation measures change with increasing penetration of VG? An increase in the economic value of mitigation measures with increasing VG penetrations indicates that a mitigation measure may become more economically attractive with increased VG. The more a mitigation measure's marginal value increases, the higher the cost of implementing it can be while still being economically attractive (or the lower the subsidy would need to be to incentivize the measure).

We develop a metric for each mitigation measure showing the change in the measure's marginal economic value with increasing VG penetration before mitigation is implemented. The marginal value metrics are all based on the long-run equilibrium prices from the unmitigated Reference scenario in the valuation chapter.

The general principle for developing these metrics is consistent across all mitigation measures: each metric is based on estimating the short-run profit that a resource with the same hourly profile would have assuming that the resource does not impact wholesale prices in the Reference scenario (i.e., the resource is a price-taker). However, the specific metric used for each scenario differs based on the characteristics of the mitigation measure. In the case of bulk power storage, for example, the metric is the short-run profit that storage would earn based on the prices from the Reference scenario at a particular level of VG penetration. First, the DA energy prices, RT energy prices, and AS prices from the Reference scenario are used to create a DA schedule and RT dispatch for storage. The marginal economic value of storage is then estimated as the short-run profit of storage based on those schedules and prices. The change in the value of storage with increasing penetration of VG is estimated by calculating the short-run profit of storage using prices and schedules from scenarios with different VG-penetration levels. This metric only reflects the marginal economic value of a mitigation measure before it is implemented, since the prices used in this analysis are derived from the unmitigated Reference scenario.

Similar to the presentation in the previous section, we start by describing the change in the value of geographic diversity with increasing penetration of VG, then address the change in the value of technological diversity. Next we examine the value of more flexible generation, specifically CCGTs that can be started in real-time and CCGTs with a fast ramp rate. We then examine the change in the value of storage and real-time pricing with increasing penetration of VG.

Change in the Marginal Value of Geographic Diversity

Consider a situation in which wind is increasingly added to the power system based on the wind-site locations used in the Reference scenario. As this wind is added, we want to know if the marginal value of wind from the high-diversity sites described earlier (Diverse sites) would appear greater than the marginal value of wind at the Reference scenario sites and how this changes with penetration. To answer this question, we estimate the marginal value of wind at the diverse sites using the DA, RT, and AS prices from the Reference scenario. We then compare the marginal value of wind from the diverse sites to the marginal value of wind from the Reference scenario sites, Figure 4.19. The marginal value of wind at the diverse sites is estimated using wholesale prices from the Reference scenario and the generation profiles at the diverse sites.

As wind is added from the sites in the Reference scenario, the marginal value of wind from the diverse sites becomes increasingly greater than the marginal value of wind from the sites in the Reference scenario. This indicates that, if a wind developer were to consider two sites, one with a generation profile similar to the wind sites in the Reference scenario and one with a profile similar to the diverse sites, then the diverse site would have a higher marginal

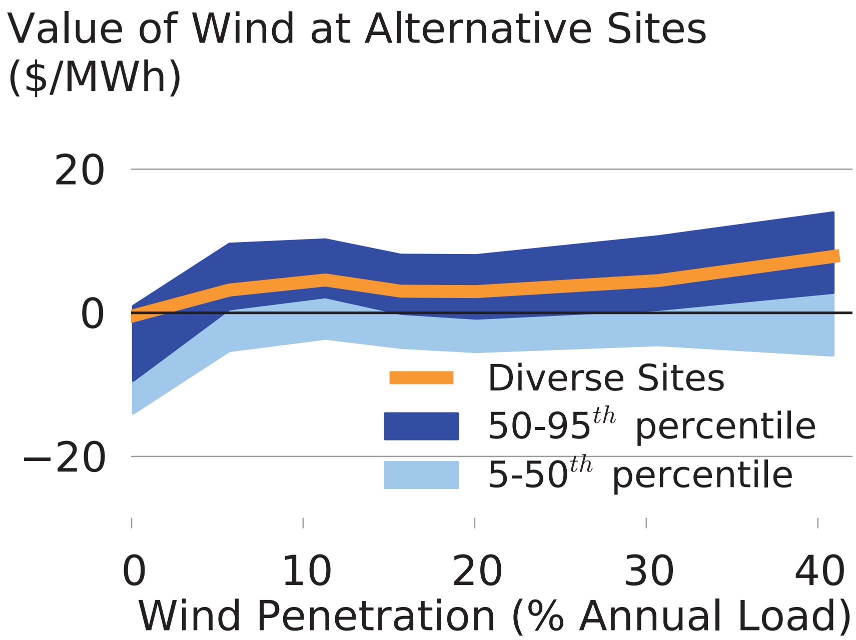


Figure 4.19: Difference between the marginal value of wind at alternative wind sites relative to the value of wind at sites used in the Reference scenario.

value per unit of energy generated (assuming the wind output is sold into a power market with the long-run equilibrium prices identified in the Reference scenario). This greater value increases with increasing penetration of wind from the Reference scenario sites to the point that diverse sites see a premium of $7–8/MWh. A developer could then compare this premium for siting at a higher-value location to the potential costs of that location. These potential costs could include increased transmission costs (if the site is further from California loads) or lower annual wind production, both of which could be larger than the value premium. Only when the value premium exceeds any increase in costs to access the diverse sites would the developer choose the diverse site on economic grounds.

In addition to the diverse sites, which were selected to minimize the aggregate variability of a portfolio of wind sites, many other potential wind sites are available in the Western United States. We selected 10,000 wind sites at random from the list of potential sites in WECC from the WWSIS data set and calculated the marginal value of wind at each of these alternative sites. The difference between the marginal economic value of wind from the alternative sites and the value of wind in the Reference scenario at each wind-penetration level is shown in Figure 4.19. We show the value of wind from the 50^{th} to the 95^{th} percentile of sites relative to the value of wind in the Reference scenario as the dark blue region; in other words, the top of the dark blue range indicates the marginal value of the 500 highest-value wind sites out of the 10,000 alternative sites. The value of wind from the 5^{th} to the 50^{th} percentile is shown in light blue.

The choice of wind sites becomes more important at higher penetration levels. If a wind developer could choose from any of these potential 10,000 sites, then at low wind penetration the range in value between sites would be about \$15/MWh (5^{th} to 95^{th} percentile or top of the dark blue to bottom of the light blue). At 40% wind penetration, this range increases to \$20/MWh. This indicates that high-value sites become more valuable relative to low-value sites at high wind penetration. At 40% wind penetration, the developer would find it economically attractive to build at a high-value site (in the 95^{th} percentile) instead of a low-value site (in the 5^{th} percentile) as long as any reduction in annual production or increase in transmission costs (or any other site-specific differences in costs) did not exceed \$20/MWh. Given the potential wide variation in wind quality and access to transmission capacity, considerations about geographic diversity are not likely to dominate siting decisions at present. Wind resource quality and transmission availability are likely to be more important factors.

In contrast to the wind findings, the difference in the value of PV at alternative sites appears to decrease with increased PV penetration. We calculated the marginal value of PV from 2,000 sites pulled at random from various southwest WREZ hubs using the prices from the Reference scenario. Figure 4.20 plots the range of the marginal value between the 5^{th} and 95^{th} percentile of these alternative sites.

At low penetration, the difference in value between low-value sites and high -value sites (5^{th} to 95^{th} percentile) is around \$21/MWh. At low PV penetration, different choices of PV sites will lead to different values of PV. A site that is cloudy during summer afternoon peak-load times, for example, might have a substantially lower value than a site that is clear during summer afternoons.

At high PV penetrations, in contrast, the marginal value of PV from any of the potential sites is similar to the marginal value of PV at the sites chosen for the Reference scenario. The difference in value between low-value and high-value sites is only \$6-7/MWh (5^{th} to 95^{th} percentile). This indicates that no matter what site is chosen for the next increment of PV—near or far from other PV sites—the marginal value of that site will be similar to the value found in the Reference scenario.

The narrowing of the value of PV from different sites with high PV penetration is due to wholesale prices consistently dropping in most hours with PV production and high prices shifting to hours after the sun has gone down. Since geographic diversity does not change the timing of sunrise and sunset (and situating plants further east of California only shifts the timing of sunset for those PV locations to earlier hours), geographic diversity provides little opportunity to mitigate the decline in the value of PV. Furthermore, while geographic diversity can mitigate costs associated with DA forecast errors and short-term variability that affects the need for AS, these costs do not strongly increase with increasing PV penetration. As such, these shorter-timescale issues are not a major contributor to the decline in the value of PV, hence mitigating them through additional geographic diversity will not address the root cause of the changes in PV value with increasing penetration.

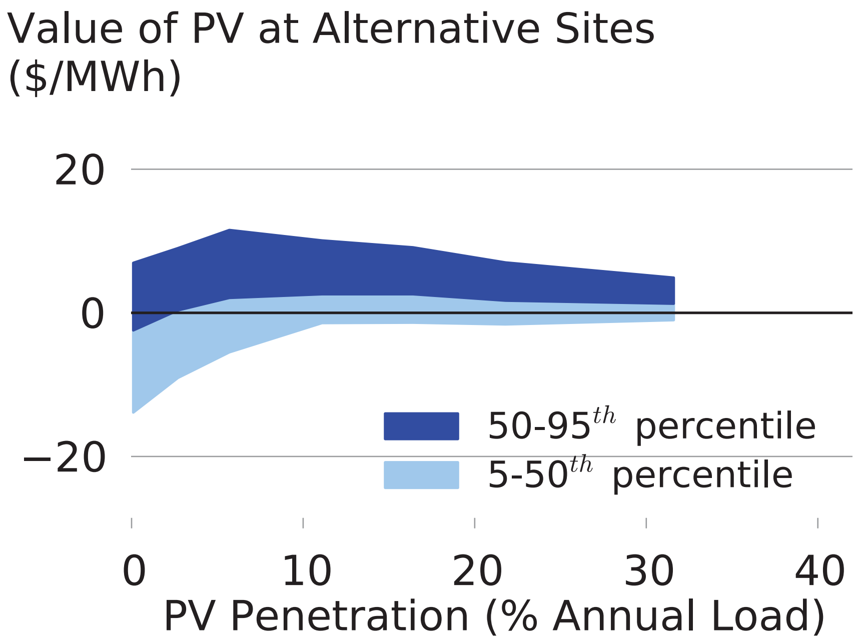


Figure 4.20: Difference between the marginal value of PV at alternative PV sites relative to the value of PV at sites used in the Reference scenario.

Change in the Marginal Value of Technological Diversity

In the case of technological diversity, we use the wholesale power prices from the Reference scenario to examine the change in the economic value of the first increment of one technology as the penetration of another is increased. For example, we explore how the value of the first increment of wind changes when there is no PV compared to when there is increasing PV on the system. An increase in the value of wind as PV penetration increases indicates that technological diversity becomes more attractive with higher VG penetration than with low VG penetration.

The value of the first increment of wind with increasing penetrations of PV is found based on the wholesale prices from the Reference scenario, Figure 4.21. The value of the first increment of wind increases as more PV is added to the system, similar to the findings from Lamont (2008).[20] Intuitively this increase in the value of wind with PV is due to the addition of PV shifting the high-price periods into the early evening. In this particular case, wind tends to be stronger in the early evening than it is earlier in the day.

[20]Lamont (2008) uses 2001 weather data for load, wind, and PV. This analysis uses 2004 weather data. The similar findings between the two papers suggest the results are not unique to one particular weather year.

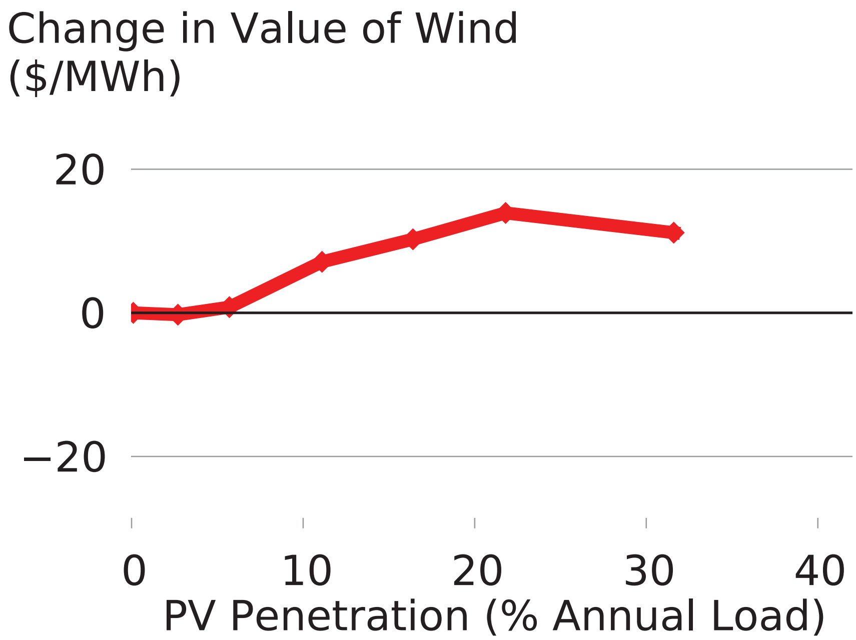


Figure 4.21: Change in the marginal economic value of wind at 0% penetration with increasing penetration of PV.

In particular, Figure 4.21 shows that the value of wind at 0% penetration as more PV is added increases beyond what it would have been without PV by about $5/MWh at medium PV penetration (10% penetration) and about $10/MWh at high PV penetration (20% penetration). At 30% PV penetration, the value of the first increment of wind is still higher than it would be without PV but lower than the value at 20% PV penetration.

Again using the wholesale power prices from the Reference scenario, the value of the first increment of wind is found with increasing penetration levels of CSP_6, Figure 4.22. The value of the first increment of wind does not change significantly at any penetration level of CSP_6.

Next we examine the value of the first increment of PV as more wind is added to the system, Figure 4.23. The value of the first increment of PV does not change significantly with increasing wind penetration, again matching the findings from Lamont (2008).

In the Reference scenario, the high value of PV at low penetration is primarily due to the high capacity value and energy value of PV. These results demonstrate that PV continues to have a high value at low penetration, even with large increases in the penetration of wind. The value of the first increment of PV does not, however, notably increase due to the addition of wind, whereas this was the case for the first increment of wind due to the addition of PV.

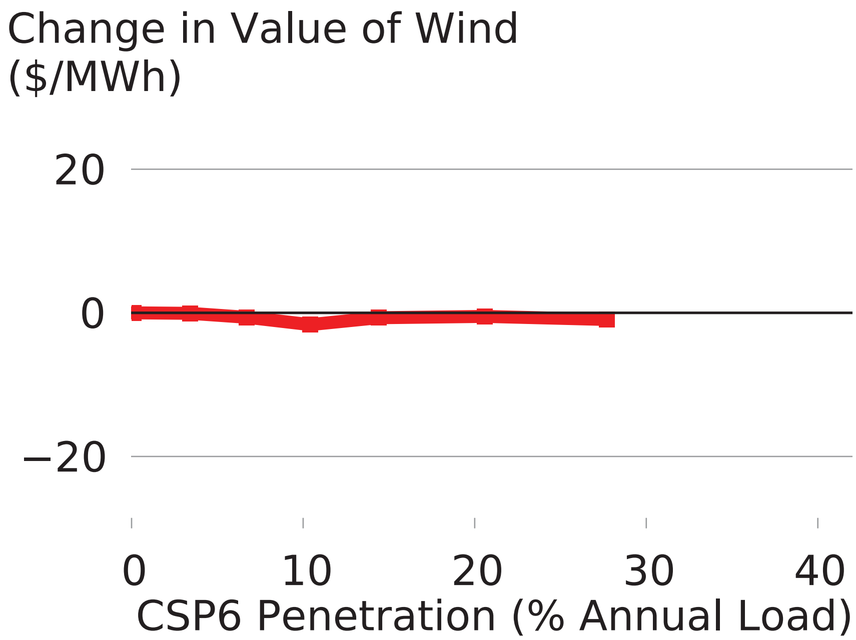


Figure 4.22: Change in the marginal economic value of wind at 0% penetration with increasing penetration of CSP with 6 hours of thermal energy storage.

The value of the first increment of PV decreases with increasing penetration of CSP_6, particularly with CSP_6 penetrations above 10%. The wholesale prices from the Reference scenario with increasing CSP_6 penetration begin to decrease during the middle of the day in the summer, thereby also decreasing the value of the first increment of PV, Figure 4.24. By 30% CSP_6 penetration, the decrease in the value of PV is nearly $30/MWh lower than found without CSP_6. This decrease in value is primarily due to a decrease in PV capacity value. The capacity value of PV at 0% penetration is only $11/MWh with 30% penetration of CSP_6, whereas the capacity value of PV at 0% penetration without CSP_6 is $37/MWh. The energy value of PV also decreases as more CSP_6 is added. The decrease in the value of the first increment of PV with increasing penetrations of CSP_6 suggests that these two solar technologies can "crowd" each other out of the market.

Change in the Marginal Value of More-Flexible Generation

Here, we examine the degree to which more-flexible generation increases in value with increasing penetration of wind and solar. Two separate options are considered in order to make new CCGT investments more flexible. One option assumes that new CCGTs have very high ramp rates when they are online, while maintaining the assumption that they

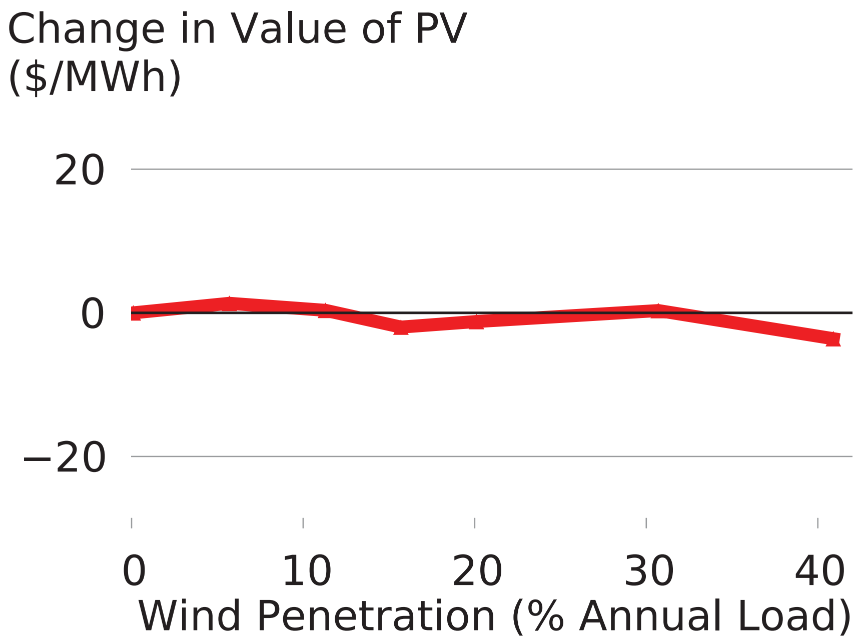


Figure 4.23: Change in the marginal economic value of PV at 0% penetration with increasing penetration of wind.

must be committed in the DA.[21] The second option assumes new CCGTs have quick-start capability and can be committed and decommitted in real time. The quick-start CCGTs are assumed to maintain the same ramp rate as assumed in the Reference scenario once online.

The wholesale prices and the dispatch of the fast-ramping CCGT are used to estimate the short-run profit in the Reference scenario with increasing wind and PV, Figure 4.25. Increasing the ramp rate of new CCGTs moderately increases the value of the CCGTs, as reflected in the short-run profit of those plants, but only for high penetrations of wind and PV.

With near-zero or low penetrations of wind and PV, enabling new CCGTs to ramp more quickly does not increase the value relative to the normal CCGT. As the penetration of PV increases beyond 20%, the premium for the fast-ramping CCGT increases by less than $10/kW-yr or roughly 5% of the annualized fixed cost of the new CCGT. The premium for the fast-ramping CCGT is roughly half that value for 40% penetration of wind.

In contrast, the quick-start CCGT has about a $5/kW-yr premium in value relative to the normal new CCGT even without wind or PV added to the system. This premium for a quick-start CCGT increases with increasing penetrations of wind and PV, Figure 4.26. At

[21]The ramp rate for new CCGTs was 39%/hour in the Reference scenario and 100%/hour for the fast-ramping CCGTs.

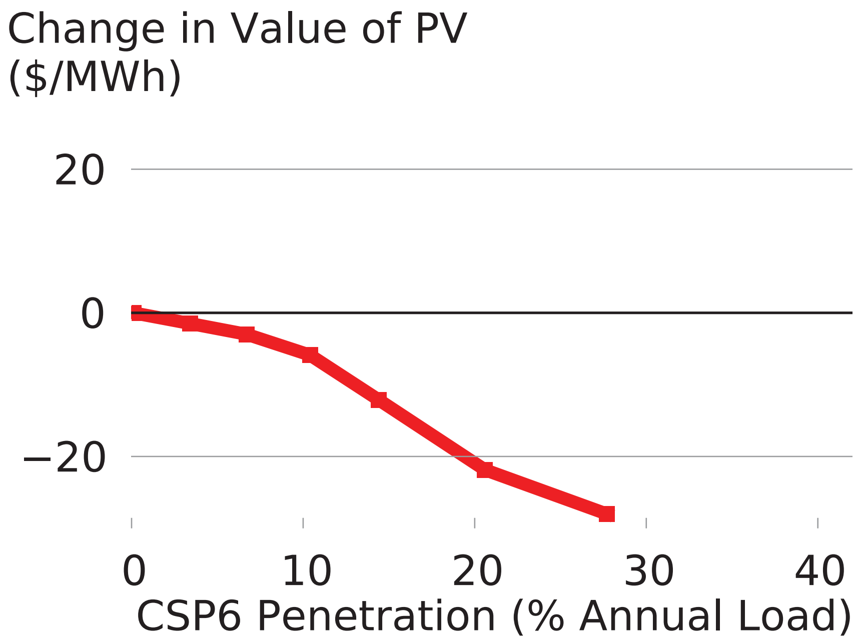


Figure 4.24: Change in the marginal economic value of PV at 0% penetration with increasing penetration of CSP with 6 hours of thermal storage.

30% penetration of wind or PV, the quick-start CCGT is worth approximately $20/kW-yr more than a normal CCGT. The premium increases to roughly $33/kW-yr, or 16% of the annualized fixed cost of a CCGT, by 40% wind penetration.

A portion of this increase in the premium, particularly with 40% wind, is due to the ability of quick-start CCGTs to take advantage of scarcity prices during events that were unforeseen in the DA. For example, with 30% wind there are seven times in the year when prices are below $100/MWh in the DA market (suggesting adequate generation capacity) while prices in the RT market for the same hour rise above $500/MWh (suggesting scarcity in the RT market). A quick-start CCGT can start in the RT to earn high revenues even if it were not committed in the DA. With 40% wind, there are 16 such unforeseen events. A larger number of events indicates more opportunity for a quick-start CCGT to earn a premium over a CCGT whose commitment is fixed in the DA market.

Both the quick-start and fast-ramping capabilities increase the value of CCGTs relative to the value of the normal CCGT. Both of these forms of increased flexibility increase in value with increasing wind and PV. This indicates that wholesale market prices, at least as they are modeled in this analysis, reflect a premium that is paid to more-flexible generation, and the premium increases with penetrations of wind and PV. Based on these results, the wholesale market prices reflect a higher premium for quick-start CCGTs than the premium

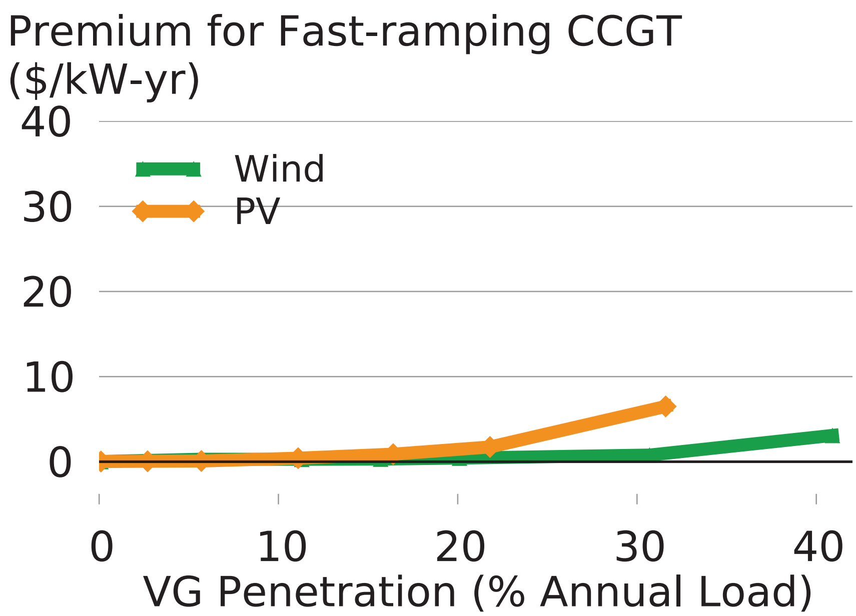


Figure 4.25: Change in the short-run profit premium for a fast-ramping CCGT relative to a CCGT without fast ramping.

for fast-ramping CCGTs with or without increased wind and PV penetration. Overall these results imply that more-flexible CCGTs will become more competitive than less-flexible CCGTs with increasing penetration of wind and PV. Additional research is warranted to determine if such a premium exists with power plants and wholesale prices in actual power markets, particularly markets that are not designed to be "energy only" markets as modeled in this analysis.

Change in the Marginal Value of Bulk Power Storage

In this section, we quantify the degree to which bulk power storage becomes more economically attractive with increasing wind and PV. To examine the change in the value of storage, we use the wholesale prices from the Reference scenario to calculate the short-run profit storage would earn for different levels of wind and PV penetration. Storage is assumed to buy and sell power at the wholesale power price in the DA and RT markets. Storage can also provide regulation, spinning reserves, and non-spinning reserves. We make the simplifying assumption that storage has perfect foresight from one hour to the next within the DA

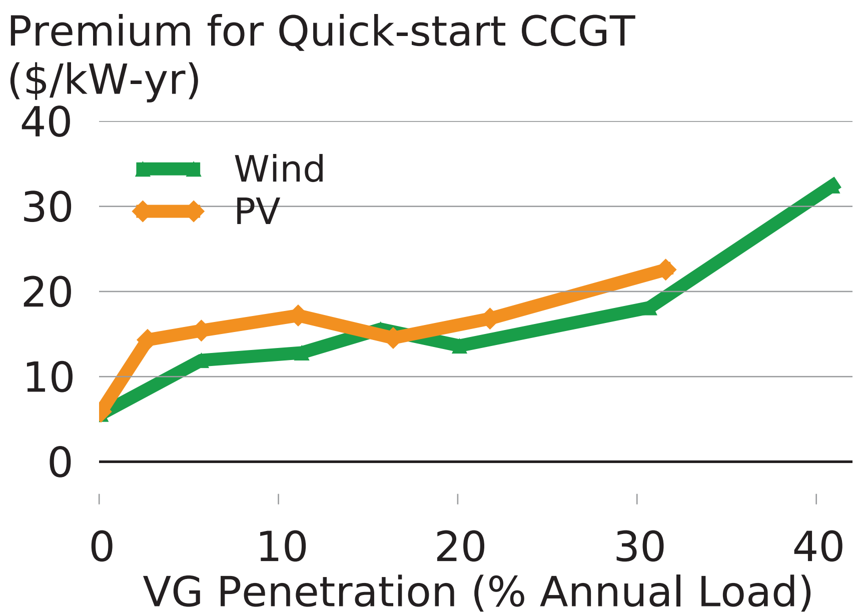


Figure 4.26: Change in the short-run profit premium for a quick-start CCGT relative to a CCGT without quick start.

market (or from one hour to the next within the RT market).[22] This simplifying assumption tends to overstate the short-run profit of real storage, which has imperfect foresight from one hour to the next in the DA or RT market. In the Reference case, no new storage is built due to its high investment cost. The value of storage reported here, therefore, represents the marginal value before any new storage is added to the system.

Even without the addition of wind or PV, storage has substantial value, about $198/kW-yr, in the Reference scenario. Almost 85% of the value is from the capacity value of storage. The remaining 15% of the value of storage is split between energy value (2/3) and AS (1/3). The value of storage increases with increasing penetrations of wind and PV, Figure 4.27. At 30% penetration of PV, the value of storage increases by over $100/kW-yr relative to the value with 0% PV, while at the same penetration of wind the value of storage increases by slightly less than half that value.

The increase in the value of storage with increasing PV is predominantly driven by an increase in the energy value of storage (e.g., energy arbitrage between different hours of the day).[23] Wholesale prices decrease to $0/MWh in nearly 10% of the hours of the year

[22]On the other hand, we assume that storage does not know how prices will change between one particular hour in the DA market and that same hour in the RT market.

[23]These arbitrage opportunities should be relatively predictable with increasing PV due to the regular

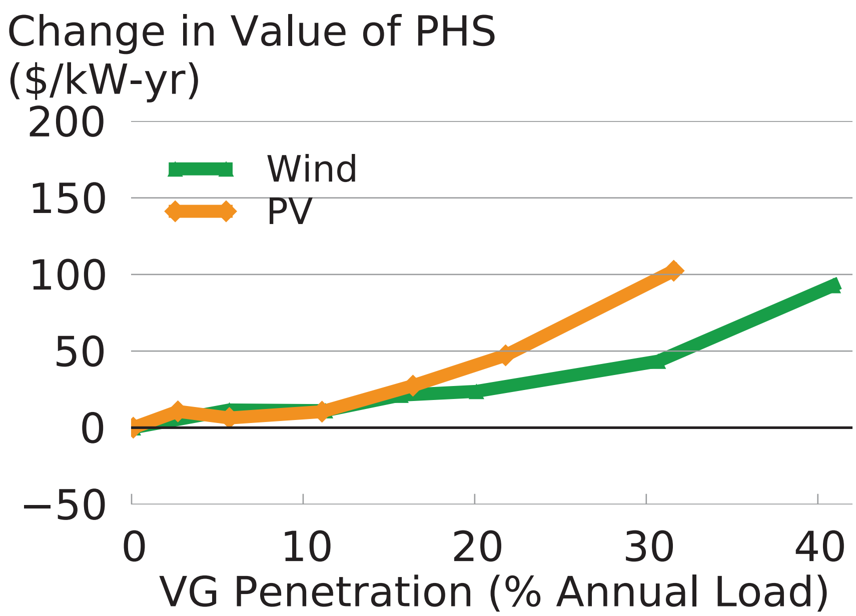


Figure 4.27: Change in the short-run profit of PHS with increasing VG.

with 30% PV penetration, while prices never go to $0/MWh with 0% PV. Increases in the number of hours with very low prices increase opportunities for profitable arbitrage with storage. The capacity value remains high but does not increase much with increasing PV penetration.

The increase in the value of storage with wind is primarily driven by an increase in the value of managing DA forecast errors (e.g., arbitraging between the DA and RT markets).[24] With 30% wind, wholesale prices approach $0/MWh much less frequently than they do with 30% PV. The situation does change at 40% wind, where the frequency of low prices increases to the point that they occur as often as with 30% PV (roughly 10% of the hours of the year). At these very high wind penetration levels the value of storage is further increased by energy value derived from the arbitrage opportunities between high and low priced hours in the DA market.

These results suggest that increasing wind and PV penetration make investment in storage more attractive than it is without high wind and PV penetration. However, at least in the Reference scenario, this higher value is not sufficient to make up for the high investment cost of storage.

diurnal PV generation pattern.

[24]Capturing this value with storage will be more challenging due to the uncertainty in DA forecasting.

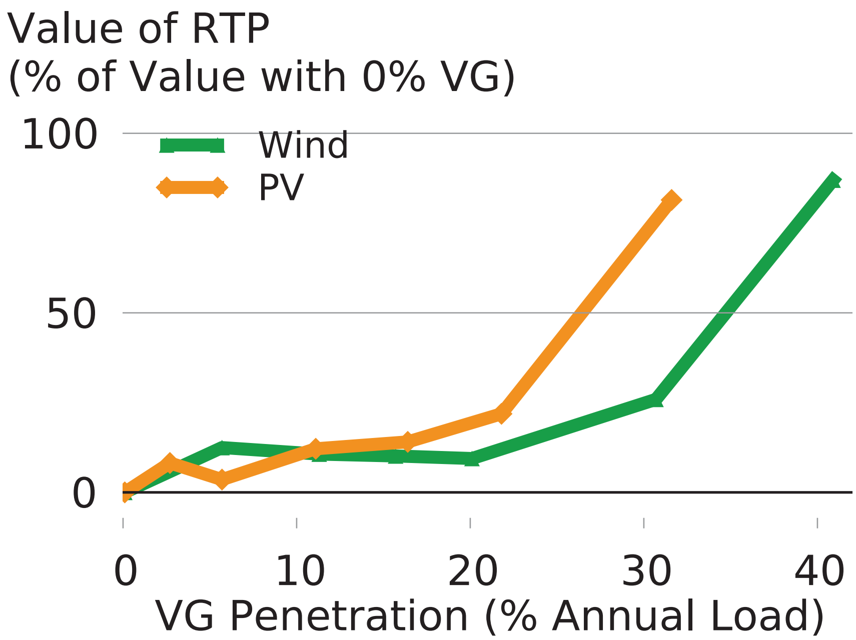


Figure 4.28: Change in the benefit of RTP with increasing VG as a percentage of the benefit of RTP at 0% VG.

Change in the Marginal Value of RTP

Here we estimate how attractive RTP would be with and without increasing penetration of wind and PV. It is not clear how to estimate the economic value of an RTP program and then how the value of RTP changes with increasing penetration of wind and PV. To avoid a detailed exploration of this question, we instead develop a simple metric and quantify the percentage change in that metric with increasing wind and PV. The metric used to quantify the value of RTP is the short-run profit that would be earned by a demand-response resource that participates in both the DA and RT markets. The demand response is the difference in the historical demand and the price-elastic demand assuming a constant price elasticity of -0.1. This demand response is then multiplied by the DA market price in the Reference scenario. RT demand response is any further change in the demand response based on the wholesale prices in the RT market. Any increase in value based on RT deviations of demand response from the DA schedule are based on the RT prices. This short-run profit of demand response is used as a proxy for the value of RTP for any wind and PV penetration level in the Reference scenario.

The value of RTP with increasing wind and PV as a percentage of the value of RTP with 0% VG penetration increases dramatically for VG penetrations greater than 20%, Figure 4.28. At 30% penetration of PV and 40% penetration of wind, the marginal value of RTP is 80–90% more than the value without wind or PV. The majority of the increase in the value of RTP at high penetrations of wind and PV comes from the additional flexibility in RT (i.e., value derived from helping to manage forecast errors between RT and DA). Up to 5% PV penetration or 20% wind penetration, the additional flexibility of RTP between RT and DA markets contributes less than about 6% of the value of RTP. At higher penetrations, the RT contribution eventually increases to around 40% of the value of RTP. Such heavy reliance on rapid and flexible responses to needs that were unforeseen in the DA is a large departure from many current U.S. RTP and demand-response programs. Additional research into the design of programs, technologies, and policies that would provide such flexibility from the demand side may be warranted.

4.6 Conclusions

Our earlier work found declines in the marginal economic value of wind and PV with increasing penetration (Mills and Wiser, 2012b). As was found in Germany by Hirth and Ueckerdt (2013), a number of mitigation measures can moderate, but not eliminate, these reductions in value.

The largest increases in the value of wind relative to the unmitigated Reference scenario at penetration levels above 20% occur with increased geographic diversity in wind sites, implementation of RTP for retail sales, and the availability of low-cost bulk power storage. The largest increases in the value of PV above 10% penetration occur with the availability of low-cost bulk power storage and RTP. One challenge is that interactions between bulk power storage, RTP, and PV will change depending on PV penetration levels. Both low-cost bulk storage and RTP reduce the cost of meeting peak loads on summer afternoons. This reduces the value of PV at penetrations below 5%, even though the same mitigation measures are found to increase the value of PV relative to an unmitigated case at higher penetration levels.

For both wind and PV, deployment of RTP programs will be driven by myriad factors, but the attractiveness of RTP increases substantially with high ($> 5\%$) wind and PV penetration relative to the attractiveness without wind and PV. That said, the character of the ideal demand response provided by RTP in high wind and PV penetration scenarios does not look the same as the demand response provided without wind and PV. For both wind and PV, the ideal demand response provided by RTP increases demand during times when wind and PV are generating power. Moreover, on peak-load days, the reduction in demand from RTP shifts from the afternoon into the early evening as PV penetration increases. The increase in attractiveness of RTP and the increase in the value of wind and PV found in this analysis will require that demand response has the flexibility to provide response depending on when wind and PV are available. Customers that are considering switching to RTP programs or designers of RTP programs should similarly consider the benefits of this flexibility. Additional research in this area would be valuable.

Low-cost storage is also promising for increasing the value of wind and PV at high penetration, although the increase in PV value is substantially larger than the increase in wind value. This analysis only considered one type of storage: PHS with 10 hours of reservoir capacity. Therefore, the estimated changes in the value of wind and PV assume this type of storage is somehow made available with a low investment cost. The increase in the value of PV with storage is driven by an increase in the energy value, suggesting that multiple hours of storage capacity will be needed to do diurnal shifts to achieve a similar increase in the value of PV. For wind, the analysis suggests that more than 10 hours of storage would be beneficial. Future research on the right amount of storage capacity and ways to reduce storage cost would be beneficial. The cost of storage must be greatly reduced from EIA's current estimate of PHS cost to justify investment in new storage capacity.

Increased geographic diversity produces a large increase in the value of wind. With increasing penetration, wind at geographically diverse sites could earn higher revenue than wind sited closer to existing wind. This increase in the value of wind will need to be weighed against any increased costs due to additional transmission or lower wind quality associated with these alternative sites. In contrast, increasing the geographic diversity of PV beyond the degree of diversity already represented in the Reference scenario does not appear to have the potential to substantially increase the value of PV at high penetration levels.

This analysis identified some apparently unpromising measures for increasing the marginal value of wind and PV relative to the Reference scenario without those measures. The premium for more-flexible new CCGTs increases with wind and PV penetration. On the other hand, assuming that all new CCGTs could be started in RT does not significantly increase the value of wind or PV. The valuation chapter, on the other hand, found that relaxing all operational constraints on new and existing generation capacity increases the value of wind and PV. In combination, these results suggest that the focus should be on increasing the flexibility of existing conventional generation, not just new generation. The relatively high amount of flexibility in California is important to note, the impact of more flexible generation will be different in other regions.

We found interesting interactions between different VG technologies in the technological diversity cases. At 10% penetration of wind and 10% penetration of PV, the marginal value of PV increases by as much as \$7/MWh relative to the Reference scenario. Different combinations of wind and solar do not produce similar increases in the value of wind or PV. More importantly, however, various combinations of VG technologies were found that do not decrease the value of wind or PV relative to the Reference scenario, even though the aggregate proportion of annual demand met by VG technologies is higher. Specifically, combinations of 10–20% wind and 10% PV or 10% CSP_6 have no lower value than wind alone. Similarly, combinations of 10–20% PV with 10% wind have no lower value than PV alone. These results suggest that if 10–20% wind or PV penetrations can be economically justified on their own, then 30% penetration from combinations of wind and solar technologies would be similarly justified.

Throughout this analysis, only one mitigation measure is implemented at a time. In some cases, the benefits of different mitigation measures are caused by similar factors (e.g., increases in the value of wind at high penetration with RTP and storage are both linked to an increase in demand during times when wind is generating). As such, the change in the value of wind or PV from simultaneously implementing multiple mitigation measures is not expected to be the same as the sum of the change in value from each mitigation measure implemented in isolation. Interactions between mitigation measures is an area for future research.

Chapter 5

Conclusions

The research presented in this thesis covers three important questions related to the economic value of variable wind and solar generation:

- To what degree is short-term variability smoothed through aggregation, and how does this smoothing impact the economic costs of managing short-term variability?
- How does the marginal economic value of wind and solar change with increasing penetration levels and what factors contribute to those changes?
- How effective are commonly discussed mitigation measures at stemming the decline in marginal value with increasing penetration levels?

Decades of research and growing experience has produced an expansive literature addressing these questions for wind, but comparatively little addresses these questions for solar. The research in this thesis always examines wind and solar in similar settings with similar assumptions in order to identify similarities and differences between the two technologies. Where wind and solar are found to be similar, much of the expansive literature for wind can provide a useful foundation for understanding the impacts of solar. Where wind and solar are found to be different, additional research specific to solar will be useful and lessons learned for wind may not always apply to solar.

The research in this thesis shows that the greatest similarities between wind and solar relate to short-term issues including the costs and challenges of managing day-ahead forecast errors when scheduling wind and solar along with sub-hourly variability. Sub-hourly variability of wind and PV can be severe at individual points, but aggregation of multiple facilities over the geographic footprint of a balancing area provides significant smoothing. This smoothing greatly reduces the costs of managing sub-hourly variability relative to what the cost would be if all plants were perfectly correlated. Day-ahead forecast errors lead to economic inefficiencies due to incorrect commitment of conventional power plants relative to the commitment with better forecasts. The economic costs of these day-ahead forecast errors were found to be relatively modest—below $6/MWh even with high penetrations of wind and solar. The economic costs of short-term variability and day-ahead forecast errors were similar between wind and solar and did not dramatically increase over the penetration levels considered in the case studies.

There are more marked differences between wind and PV over longer time scales. One important difference is that solar production tends to be relatively well correlated with load, at least in areas where peak load is dominated by summer cooling loads, whereas wind production is often poorly correlated with loads. This difference leads to a high capacity value of solar at low penetration levels in contrast to the low capacity value of wind. The economic consequence of this difference alone can make solar \$20–30/MWh more valuable than wind at low penetration levels. The tendency for summer cooling loads to extend into the early evening, after the sun sets, leads to a relatively rapid decline in the marginal capacity value of PV and CSP without thermal storage. Adding thermal storage to a CSP plant is a relatively straight forward way to continue to produce power into the early evening and to mitigate this decline. Since the capacity contribution of wind is small to begin with, it does not see as large of a change in its capacity value with penetration. Similarly, the concentration of sunny hours in only part of the day leads to a relatively narrow production profile for solar. On days with high sun and relatively mild loads (e.g., spring days or weekends), significant solar production can displace a large portion of the thermal fleet, even to the point of needing to curtail solar production. Consequently, the energy value of solar can also decline faster than the energy value of wind for similar penetration levels. In the case studies presented in this thesis, the marginal value of PV at 15% PV penetration was lower than the marginal value of wind at 15% wind penetration, the opposite of the relative ranking at low penetration levels.

From a technical perspective, the longer-time scale issues of capacity value and energy value are easier to manage than the shorter-term issues, but the economic consequences of changes in the capacity value and energy value with penetration are larger. The economic impacts of the shorter time-scale issues of day-ahead forecast errors and sub-hourly variability are relatively modest, but from a operational perspective they present new challenges that should not be taken lightly. System operators and power markets will need to be prepared to manage these technical challenges.

From an economic perspective, the challenges that need to be mitigated with increasing penetration of wind and solar are primarily the change in capacity value and energy value. Of the mitigation measures examined in this thesis, the ones with the greatest impact on capacity value and energy value tended to be the most effective at stemming the decline in the value of wind and solar with increased penetration. Since wind and solar are different over the longer time scales that affect capacity value and energy value, the most effective mitigation measures are also different between wind and solar.

The largest increase in the value of wind with the implementation of a mitigation measure was with increased geographic diversity. Broader distribution of wind sites accesses different wind regimes and different timing of weather systems. This diversity reduces the frequency of extreme periods with high wind or low wind production at all sites, increasing the value of wind. With high penetrations of PV, however, the timing of solar production is dominated by the location of the sun in the sky. Geographic diversity can mitigate short-term variability due to clouds but it does little to address the timing of sunrise and sunset. Therefore, geographic diversity is not as promising of a mitigation measure for stemming the decline in the value of solar with increasing penetration.

The largest increase in the value of PV at high penetration levels was with the availability of low cost storage. Assuming that storage had a low cost led to significant investments in new pumped hydro storage. The optimal dispatch of that new storage with high PV penetration was such that storage was charging during times with PV generation and storage was discharging at times with little or no PV. On peak load days the storage charged primarily in the morning then discharged after sunset. The increased demand from charging storage during times when PV was generating primarily increased the energy value of PV. Investments in new storage also increased the value of wind at high penetration levels, but not to the degree it increased the value of PV. Part of the reason for the smaller increase in the value of wind was that the assumed amount of storage reservoir capacity (10 hours at full discharge) was increasingly a binding constraint with a large increase in wind penetration. This suggests that a proportionally larger storage reservoir is required for high wind penetrations relative to the size of storage with high PV penetration.

Assuming that demand was price responsive and subject to real-time pricing also increased the value of wind and PV. At modest penetration levels (10% PV or 20% wind) assuming RTP was used led to the largest increase in the value of wind and PV. Similar to storage, a portion of the increase in the value of wind and PV is due to an increase in demand during hours with high wind or PV generation. The response from RTP or the ideal response from a demand response program will look different with wind versus PV (and different from a scenario with no wind or PV). The design of future demand-side programs should take expectations of future renewable deployment into account.

One interesting finding from the analysis of mitigation options was that wind and solar did not interfere with each other at penetrations of 20-30% aggregate renewable penetration levels. The marginal value of wind with 20% wind penetration would be no lower with or without 10% penetration of PV or CSP with six hours of thermal storage. This indicates that achieving high renewable penetration levels may be easier with combinations of technologies rather than trying to achieve the same penetration with one technology alone.

In some sense this research merely provides direction for future, more refined research. The results have mapped out areas of differences between wind, with an extensive body of research and operating experience, and solar which is relatively less understood. The remainder of this section will describe some of the possible future refinements to research on the economics of variable generation and potential avenues for applying the lessons learned from this research in practice.

Modeling complex systems like the power system always requires significant simplifications and approximations. One area of refinement of this research would be validation of the models and the economic framework. A few anecdotes from empirical evidence suggests that power markets with variable generation behave similar to the way they are modeled in this research. These examples could be expanded in the future to develop a more robust

Table 5.1: Empirical estimate of the value of wind and solar in the CAISO based on 2012 data.

$/MWh	Flat Block	Wind	Solar
NP-15			
Energy Value	28.1	26.0	33.3
DA Forecast Error		-2.1	-0.5
Marginal Value	28.1	23.9	32.8
SP-15			
Energy Value	30.0	27.4	40.6
DA Forecast Error		-1.5	-0.8
Marginal Value	30.0	26.0	39.7

validation of the model and assumptions used in this thesis.

One point of comparison is from analysis of wind and PV in Germany. Analysis of actual market data shows that the market value of PV at low penetration is greater than the market value of wind, but the market value of PV declines at a faster rate with increased penetration (Hirth, 2013).

A second point is from a full year of hourly wind and solar production and day-ahead forecasts recently released by The California ISO.[1] I used this data in conjunction with wholesale power prices from the DA and RT market in the CAISO to estimate the energy value and day-ahead forecast error cost of wind and solar. The California market is such that the major loads are required to procure sufficient capacity to meet a planning reserve margin. Since these transactions occur outside of the wholesale power market, the capacity value of wind and solar are not reflected in these prices. It is also not clear how much the CAISO has increased ancillary service requirements in response to wind and solar. The only components of the value of wind and solar that are reflected in this empirical analysis are the energy value and DA forecast errors, Table 5.1. As was found in the research in this thesis, the value of solar exceeds the value of a flat block and of wind, the value of wind is slightly less than the value of a flat block of power, and the cost of day-ahead forecast errors is modest. This comparison provides some insight, though additional work is needed to ensure that the CAISO pricing reflects the true energy and day-ahead forecast error costs given operational constraints on conventional generators.

A third comparison to empirical data is from an assessment of the increased need for ancillary services for wind in ERCOT and the cost of procuring these services from the wholesale power market (Maggio, 2012). The increased need for ancillary services in the form of non-spinning reserves and regulation cost roughly $1.2/MWh with 8.5% penetration of wind (Wiser and Bolinger, 2013). I estimated the cost of ancillary services for wind to be only $0.2/MWh in California. This lower cost could potentially be explained by the large fraction of hydropower in California. In either case, the cost of ancillary services is only a small fraction of the value of wind.

[1] Available at: http://www.caiso.com/Documents/2012Report-Wind-SolarResources.xls

Hydropower is one area where further refinements in modeling is warranted. Hydro plays an important role in being able to respond to changes in the system between the day-ahead and real-time, but that response is limited by the size of the hydro reservoir. More realistic approaches for modeling optimal dispatch of hydro with uncertainty are available (Pereira et al., 1998). If more detailed data on hydro inflows, reservoirs, and operating constraints were also available then an interesting analysis would compare the role of hydro as modeled with the simplifications in this thesis compared to the role of hydro with more advanced methods. Similarly, accounting for uncertainty in the dispatch of storage would be an interesting area for additional research and model validation.

One of the major challenges in modeling the change in the value of variable generation with increasing penetration and with mitigation measures was inclusion of operational constraints on conventional generation in a long-run equilibrium analysis. In particular, capturing the impact of imperfect commitment of thermal generation based on imperfect day-ahead forecasting presented many difficulties. The approach used in this research was to develop a method to search for a long-run equilibrium set of generation using insight from the Benders decomposition method. The performance of a candidate set of generation was simulated over a full year with day-ahead commitments based on imperfect forecasts followed by real-time dispatch with actual wind and solar generation. The performance of a candidate generator was then based on the short-run profit of the generator over the year. This performance was used to develop a refined candidate set of generation in a separate optimization run. The optimization utilized information about the performance of the current candidate set of generation plus information about past candidate sets of generation to try to find an improved set of generators.

In practice, this search method often came very close to finding a set of generators that were in long-run equilibrium (all new generators could cover their cost of investment but no additional generation could be supported). But the method was not completely reliable and would sometimes require additional steps to find a set of generation in long-run equilibrium. Additional research could undoubtedly develop better, more reliable methods, though the question of whether such improvements are worthwhile hinges in part on the degree that capturing imperfect day-ahead commitments or costs of ancillary services within the model is necessary. For the most part, the results indicate that the impact of imperfect day-ahead forecast errors on the value of variable generation is somewhat modest and does not strongly change with penetration levels. In some cases, it may be sufficient to simply approximate the impact of imperfect forecastability through other means (e.g., simulation of a system that is not necessarily in long-run equilibrium to develop an adjustment factor that would be added to a simplified long-run model). Other potential methods include:

- Identify a peak capacity resource then mimic long-run equilibrium by adding or subtracting capacity to maintain a constant loss-of-load expectation for any level of renewables penetration (Tuohy and OMalley, 2011).

- Develop adjusted screening curves for conventional generation options based on start-up costs, then utilize these adjusted curves to find a long-run equilibrium portfolio

(Staffell and Green, 2012).

- Separately analyze and estimate individual components of the value of renewables, then aggregate those separate value streams to estimate the total value of renewables (Olson and Jones, 2012).

Incorporation of transmission into the modeling of economic value was largely ignored in this analysis and should be considered in future work. Given the cost of transmission and the long time needed to build transmission, one challenge is in demonstrating that the value of transmission in the future will exceed the costs. Earlier research highlighted the important role of transmission capacity in mitigating market power (Borenstein et al., 2000): when transmission capacity is limited, relatively small investments in capacity may create significant value through increased competition. Similar analysis of the role of transmission capacity in mitigating uncertainty and variability of variable generation may also find significant benefits with small increases in transmission capacity. Where the transmission network cannot be expanded, the challenges of integrating variable generation may become more severe than found here. Strategies for mitigating changes in the value of variable generation in severely transmission constrained networks is another area of potential research.

Another important research direction is to determine how to incorporate lessons learned from detailed evaluation of the value of variable renewables and mitigation options into routine decision making processes. Integrated resource planning (IRP) by utilities, for example, requires comparison of the costs and benefits of different resource options (implicitly or explicitly). The models and methods used in practice, however, often do not have substantial detail on the impacts and benefits of variable renewables and mitigation options (Bolinger and Wiser, 2005; Mills and Wiser, 2012a). Additional research could identify the degree to which additional refinements in IRP methods and models are required or correction factors that could be used to adjust existing model inputs to approximate behaviors identified in more detailed models. Similar research would be useful for evaluating methods to compare bids for resource procurement from resources with different generation profiles or degrees of dispatchability. Some utilities simply rank all potential generating resources by the expected cost while others utilize more granular comparisons based on the temporal generation profile and geographic location (e.g., the least-cost, best-fit method used by California IOUs in renewable resource procurement). Improvements or refinements to these methods could be based on lessons learned from more detailed analysis as presented in this thesis.

A more general, but related, research direction is ways to reform institutional practices that if not changed may lead to increasingly adverse outcomes with increasing penetrations of renewables. One clear example of this is related to retail rate design. Research by Darghouth et al. shows that increasing penetrations of variable renewables can increase the customer bill savings of distributed PV if retail rates remain flat and allow for net metering (Darghouth et al., 2013). Shifting retail rates to time-of-use rates or real-time pricing that better reflect the cost of consuming power (or the value of customer-sited generation) depending on the timing, on the other hand, lead to declining bill savings of distributed PV if the system-level penetration of PV is also very high. Rising customer bill savings with flat rates and increasing system level penetration could encourage more customers to switch to PV at the same time as the system-level value decreases, thus exacerbating the issue. Detailed evaluation of the value of variable renewables with increasing penetration can be useful for highlighting these challenges and identifying mitigation options or solutions through reform of institutional practices.

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Appendix A

Short-term Variability

A.1 Approximating the Cost of Balancing Reserves

In this appendix we provide details of how our estimates of the cost of balancing reserves were derived. The basic method follows an approach first described by Farmer et al., 1980, then simplified by Grubb, 1991, and then applied in practice by Milborrow, 2001. The objective of the analysis is to estimate the cost of providing additional balancing reserves to manage the variability of wind or solar generators at the system level per unit of variable energy generation, URC ($/MWh). The total cost of balancing reserves is assumed to be the sum of the reserves required over various time scales. Following EnerNex Corp. and Windlogics Inc., 2006, for instance, this would be the reserves based on the 1-min deltas (regulation), 5-min deltas (load following),[1] and 60-min deltas (operating reserve margin). In this appendix, we simplify the notation for the deltas by simply referring to the standard deviation of the deltas normalized by the peak as σ. Therefore, σ_L is the standard deviation of the load deltas over a particular averaging interval divided by the peak load. Similarly, σ_V is the standard deviation of the deltas of a variable generator over a particular averaging interval divided by the nameplate capacity of the variable generator. The standard deviation of the deltas from the load net variable generation normalized by the peak load (without variable generation) is σ_{L-V}.

Unit Reserve Costs of Variable Generation

For all time scales, we assume that the increase in the unit reserve costs per MWh of variable generation (URC) is the difference in the annual reserve costs for managing the net-load with variable generation (ARC_{L-V}) relative to the annual reserve costs for load alone (ARC_L)

[1] We use the 10-min deltas in place of the 5-min deltas since the NERC CPS2 reliability performance standard focuses on 10-min averages of the area control error (ACE).

per unit of energy produced by the variable generator (E_V).

$$URC = \frac{ARC_{L-V} - ARC_L}{E_V} \tag{A.1}$$

The annual energy produced by the variable generator (E_V) depends on the capacity factor of the variable generator (CF_V) and can be written relative to the penetration of the variable generator on a capacity basis ($\alpha = \frac{K_V}{K_L}$) and the peak load (K_L).

$$E_V = K_L \alpha CF_V 8760 \tag{A.2}$$

Reserve Costs for 1-10 min Deltas

For 1-min and 10-min variability, we assume that only on-line and synchronized resources (or spinning balancing reserves) can be used to manage variability and that there is an opportunity cost of capacity that accompanies these reserves. The opportunity cost of capacity for the reserves is the unit cost of capacity, FC_p (in units of \$/MW-h), multiplied by the amount of balancing reserve during peak net-load hours. We assume that the amount balancing reserve is a multiple, κ, times the standard deviation of the load or net load deltas. The multiple κ is assumed to be three for both the load and the net-load, corresponding to 99.7% of the deltas if the load and net-load deltas were normally distributed.[2] While the amount of reserve procured in any hour ($\sigma_L K_L$ for load) can vary, the opportunity cost of capacity is fixed throughout the year and only depends on the amount of reserve procured during peak load periods. We always assume that even if the reserve procurement changes throughout the year, the peak reserve requirement will correspond to the peak load requirement.

The hourly cost of keeping units positioned to provide spinning balancing reserve is the product of the variable cost of the marginal unit (c_m) and the part-load efficiency penalty (η) times the amount of required spinning reserve in each hour. The part-load efficiency penalty represents the increase in the variable costs for the rest of the energy that the spinning unit generates relative to the variable cost if the plant were at its most efficient set point (generally full capacity) (see Mills et al., 2009b for additional discussion). The amount of spinning balancing reserve in each hour is a multiple (γ) of the standard deviation of the load or net load deltas in each hour. The multiple γ is also assumed to be three for both the

[2] We know from the earlier analysis that the deltas of solar and wind are not normally distributed, but we do not know how the distribution of the load deltas will compare to the distribution of the net-load deltas. The shape of the distribution of net-load deltas may become closer or further from normally distributed than the distribution of the load deltas alone or the variable generation deltas alone. Since we do not have 1-min time-synchronized load data that corresponds to the 1-min time-synchronized solar and wind data, we cannot directly estimate the shape of the distribution of the net-load deltas. Instead, we rely on this simplifying assumption, explicitly acknowledging that this is a simple analysis and is not meant to guarantee that the result will be an accurate estimate of the cost to manage 99.7% of the deltas for the different time scales.

load and net load. The annual reserve costs to manage the 1-min or 10-min deltas for the load is then:

$$ARC_L = \sum_{8760} \eta c_m \gamma \sigma_L K_L + 8760 F C_p \kappa \sigma_L K_L \tag{A.3}$$

If the multiples κ and γ are assumed to be equivalent between the load and the net load (in other words if the shape of the distribution of the deltas is assumed to be the same for the load and the net load) and constant throughout the year then the unit reserve costs for the 1-min or 10-min deltas simplifies to:

$$URC = \frac{\eta c_m \gamma \frac{1}{8760} \sum_{8760} \left(\sigma_{L-V} - \sigma_L\right) + F C_p \kappa \left(\sigma_{L-V} - \sigma_L\right)}{\alpha C F_v} \tag{A.4}$$

Assuming that the load deltas and the variable generator deltas are uncorrelated[3] implies that the standard deviation of the net load normalized by the peak load (σ_{L-V}) can be calculated as:

$$\sigma_{L-V} = \sqrt{\left(\sigma_L\right)^2 + \left(\sigma_V \alpha\right)^2} \tag{A.5}$$

The unit reserve costs can then be simplified further to:

$$URC = \frac{\eta c_m \gamma \sigma_L \frac{1}{8760} \sum_{8760} \left[\left(1 + \left(\frac{\sigma_V \alpha}{\sigma_L}\right)^2\right)^{\frac{1}{2}} - 1\right] + F C_p \kappa \sigma_L \left[\left(1 + \left(\frac{\sigma_V \alpha}{\sigma_L}\right)^2\right)^{\frac{1}{2}} - 1\right]}{\alpha C F_v} \tag{A.6}$$

Reserve Costs for 60-min Deltas

In the case of the reserves used to manage the 60-min deltas we assume that both spinning and non-spinning resources can be used to meet these 60-min balancing reserve requirements. Furthermore, we again assume that there is there is an opportunity cost of capacity associated with these reserves. The total amount of balancing reserve is the multiple κ times the standard deviation of the load or net load deltas and κ is again assumed to equal three.

The variable cost of non-spinning reserves is assumed to be equal to the product of the difference between the variable cost of energy from the standing plant (c_g) and the variable

[3] The 60-min variable generation and load deltas are likely to be correlated to some degree. The stochastic changes in insolation due to clouds, as captured by the clear sky index, however, are less likely to be correlated with changes in load than the changes in total solar insolation and load. Either way, we do not use time-synchronized load variable generation data to account for correlation between generation and load deltas in our simple estimates. More detailed evaluations of the costs of managing short-term variability for a specific load should account for the potential correlation of generation and load over the 60-min time-scale, but the correlation is not expected to be significant. The equation below can account for correlation by adding $2\rho_{L,V}\sigma_L\sigma_V\alpha$ under the square root, where $\rho_{L,V}$ is the correlation between the deltas of the load and variable generation. The other equations would need to be modified in a similar manner.

cost of the marginal unit (c_m). The amount of energy that is used from the standing plant to provide energy is a multiple ($U(\gamma)$) of the standard deviation of the net load or load deltas. The multiple is called the utilization function, $U(\gamma)$, and it represents the amount of energy that is expected to come from non-spinning reserves in each hour assuming that the amount of spinning reserves is proportional to the multiple γ. The utilization function assumes that the deltas are normally distributed and is given by:

$$U(\gamma) = \int_{\gamma}^{\infty} (x-\gamma) Z(x) dx \tag{A.7}$$

Where $Z(x)$ is the standard normal probability density.

The ratio of the spinning reserves to non-spinning reserves depends on the relative cost of each resource. With the particular numerical assumptions we made in Table 2.2, the least cost way to provide reserves is to manage 0.5 times the standard deviation of the load or net-load deltas with spinning reserves ($\gamma = 0.5$ for 60-min deltas in contrast to $\gamma = 3$ when all of the balancing reserves are met by spinning reserves as assumed for 1-min and 10-min deltas) and to manage the remaining deltas with non-spinning reserves ($U(\gamma = 0.5) = 0.198$). The annual reserve costs for the 60-min load deltas is therefore:

$$ARC_L = \sum_{8760} \sigma_L K_L \left(\eta c_m \gamma + \left(c_g - c_m\right) U(\gamma)\right) + 8760 FC_p \kappa \sigma_L K_L \tag{A.8}$$

Assuming that the portion of the 60-min deltas that is met with spinning reserves (γ) is the same between the load and the net load, and that the 60-min deltas for the load and the variable generator are not correlated, leads to unit reserve costs of:

$$URC = \frac{\sigma_L \left(\eta c_m \gamma + \left(c_g - c_m\right) U(\gamma)\right) \frac{1}{8760} \sum_{8760} \left[\left(1 + \left(\frac{\sigma_V \alpha}{\sigma_L}\right)^2\right)^{\frac{1}{2}} - 1\right]}{\alpha CF_V} + \frac{FC_p \kappa \sigma_L \left[\left(1 + \left(\frac{\sigma_V \alpha}{\sigma_L}\right)^2\right)^{\frac{1}{2}} - 1\right]}{\alpha CF_V} \tag{A.9}$$

Changing Reserves with the Position of the Sun

As operators gain more experience with solar it will be clear that the level of reserves that are needed to accommodate sub-hourly variability in the early morning, late evening, or winter months when insolation is low are not the same as the amount of reserves required to accommodate variability during summer midday hours when solar plants are near capacity. Instead of assuming that reserves are constant throughout the year, in this section we assume that reserve needs are proportional to clear sky insolation. The normalized standard deviation of the deltas of the net-load in Eq. A.6 and Eq. A.9 is assumed to be a time-varying quantity based on the clear sky insolation normalized by the peak clear sky insolation.

$$\sigma_V = \sigma_k \frac{G_c(t)}{G_c^p} \tag{A.10}$$

Where σ_k is a constant parameter throughout the year and is equivalent to the $\sigma_{\Delta k}^{\bar{t}}$ notation used earlier. Unit reserve costs are then calculated by evaluating Eq. A.6 and Eq. A.9 with a time series of one year of clear sky insolation. The clear sky insolation is estimated from a simple "no-sky" set of equations based on the time of year and the location using standard methods available in the "Air-sea" time-series package from the United States Geological Survey.[4] We assume that the reserves during the peak period are planned to accommodate a case where the clear sky insolation is at its maximum during the period of capacity scarcity (i.e. we assume that $\frac{G_c(t)}{G_c^p} = 1$ when estimating the capacity impacts of additional reserves in Eq. A.6 and A.9).

The results of this analysis are summarized in Table 2.4 for deltas on each time scale. The increase in the cost of reserves on each time scale is then summed to estimate the total cost of the increase in balancing reserves across all sub-hourly time scales.

[4]The matlab code for the air-sea package, developed by Bob Beardlsley and Rick Pawlowicz, is available from http://woodshole.er.usgs.gov/operations/sea-mat/.

A.2 Estimated Capacity Factor of Modeled Wind Plants at SGP Sites

The measured 1-min wind speed data at 10-m was scaled to 80-m using a $1/7^{th}$ power law then converted into 1-min wind power data using a wind power curve. The measured wind speed, the scaled wind speed at 80-m, and the estimated capacity factor of the wind power output are summarized in Table A.1. The sites where the capacity factor was less than 20% were excluded from this analysis and are not shown in this table.

Table A.1: Measured wind speed at 10-m, projected wind speed at 80-m, and projected capacity factor for wind sites in SGP network

SGP Cluster	Avg. Annual Wind Speed (m/s)		Capacity Factor^c
	10 m^a	80 m^b	
E1	5.05	6.79	26.4%
E3	4.53	6.10	21.3%
E5	4.59	6.17	22.2%
E6	4.55	6.13	21.2%
E8	5.47	7.36	30.4%
E9	5.29	7.12	28.5%
E11	4.65	6.25	22.8%
E13	5.39	7.25	30.0%
E15	4.71	6.34	23.1%
E24	4.77	6.42	24.7%

a - Measured wind speed
b - Extrapolated wind speed using $1/7^{\text{th}}$ power law
c - Annual average capacity factor based on 80 m wind speed data and multi-turbine power curve from Holttinen, 2005

Appendix B

Valuation

B.1 Overview of the Model

The appendix is structured as follows. Appendix B.1 provides an overview of the model used in the analysis. Appendix B.2 describes the general method used to find a set of conventional generation that leads to a long-run equilibrium. The method chooses different candidate sets of conventional generation that are then tested in the dispatch model, which is described in Appendix B.3. The parameters that are used in the model and additional detail on how the various parameters were estimated are in Appendix B.4. Finally, Appendix B.5 includes the decomposition of the marginal economic value of variable generation with increasing penetration from each of the four sensitivity cases described in Section 3.5. The appendix is not a stand-alone document, rather it provides additional detail that supplements the main text.

The analysis of the long-run economic value of wind and solar in this report is based on an iterative search method that selects a candidate set of conventional generation resources and evaluates how those candidate resources perform over a full year of hourly dispatch and operations in a competitive electric power market with an exogenously set amount of variable generation (VG), namely wind or solar generation. The candidate set of generation can include both new investments in coal, combined-cycle gas turbines (CCGTs), simple cycle combustion turbines (CTs), or nuclear or existing thermal generation of the same type along with existing natural gas steam turbines and geothermal. Pumped hydro storage with 10 hours of storage capacity and an 81% round-trip efficiency can also be part of the candidate set of resources. Existing pumped hydro storage with the same characteristics as the new pumped hydro storage and existing hydro are assumed to not be able to be retired and are therefore always included in the model.

The overall objective is to find a portfolio of non-VG generation that is in long-run equilibrium for the given VG penetration. Long-run equilibrium means that the short-run profit earned by new generation in the portfolio is approximately equal to the fixed investment and fixed O&M cost of the generation and that the short-run profit earned by incumbent generation that remains in the portfolio is equal to or exceeds its fixed O&M cost. Short-run profit is defined as the total revenues earned over the year from the sale of energy and ancillary services less any variable costs (e.g., cost of fossil fuel, variable O&M, start-up costs, and carbon costs in the sensitivity scenario).

The method used to search for a portfolio of generation that is in long-run equilibrium is largely based on an approach that tests if the expected increase in short-run social surplus when generation capacity of a particular vintage is increased in the candidate set of generation exceeds the annualized investment cost of that generation capacity. Short-run social surplus is defined as the difference between the gross consumer surplus (the total economic benefit to consumers of consuming electricity irrespective of the cost of the electricity to consumers, or the area under the demand curve for all consumption) and all of the variable cost associated with producing electricity with a particular set of generation. In general, capacity is added when the expected increase in the social surplus exceeds the fixed cost. Generation capacity is removed if the savings from no longer paying for the fixed cost of that capacity is greater than the expected decrease in the short-run social surplus associated with the lower amount of available generation capacity. The selection of candidate sets of generators and the evaluation of the set in a power market continues until the set of generation cannot be improved upon using this search pattern. The search algorithm is based on insights from the Benders Decomposition method (Conejo et al., 2006).

In some cases this first search pattern fails to yield a solution where the short-run profits of any new generation is about equal to its annualized fixed costs. In this case the candidate set of generation is refined using various techniques, including the bisection method, to ensure that the short-run profit of new generation is approximately equal to its fixed cost. While this approach works for the specific objectives of this research, additional research on methods to identify portfolios of generation that are in long-run equilibrium while accounting for uncertainty between day-ahead and real-time markets is needed for more general studies.

The performance of a candidate set of generators in the power market is evaluated using a simplified, linear commitment and economic dispatch model. The power market is assumed to be composed of a two part day-ahead and real-time settlement process. The day-ahead commitment process determines how much of the thermal generation should be on-line in each hour, within operational constraints, based on the load, a deterministic day-ahead forecast of variable generation, and ancillary service requirements.

The real-time economic dispatch process then locks the day-ahead decision of how much generation is on-line in each hour for all thermal generators that cannot start within the hour (only CTs are modeled as quick start). The on-line capacity and quick start capacity are then dispatched within the operational constraints to meet the load, considering actual variable generation, and assumed ancillary service requirements. Hydro and storage resources are assumed to be able to be dispatched within the real-time market with perfect foresight. Unlike the treatment of variable generation forecast errors, load forecast errors are not explicitly included in this analysis. Instead, load forecast errors and generator outages are assumed to be handled through load-driven operating reserves in the ancillary service requirements.

The model used to evaluate the power market does not make commitment and dispatch decisions for individual generation units. Instead, generation resources with similar characteristics are grouped together as a generation vintage. Each vintage of generation is then dispatched as a single fleet of generation using linear dispatch constraints. Individual unit commitment would require integer variables rather than only linear variables in the dispatch problem which would greatly increase the complexity of the problem and increase the solution time. The linearization of commitment decisions using generation vintages is based on a similar approach used by Müsgens and Neuhoff (2006). The operational constraints for the vintages of thermal generation that are modeled in this way include start-up costs when the amount of on-line generation capacity increases, ramp-rate limits, minimum generation limits for on-line generation, and no-load fuel consumption for on-line generation. New generation resources are treated as separate new vintages with the amount of capacity in the vintage determined by the iterative search method summarized above and described in more detail in the pages that follow.

During challenging periods over the year, the generation resources may not be able to meet the ancillary service targets and load simultaneously either in the day-ahead or real-time process. The model is set up such that ancillary service targets are not met prior to involuntarily shedding load. In extreme cases, however, both ancillary service targets are not met and load is involuntarily shed. In hours when ancillary service targets are not fully met, the power market prices jump to high levels to indicate scarcity conditions. The highest that prices can go is assumed to be $10,000/MWh, which only occurs during times when load is assumed to be involuntarily shed. The power market is assumed to be an "energy-only" market such that high prices during periods of scarcity are used to cover the fixed investment cost of peaking plants (and contribute to covering a portion of the fixed investment cost of other generation) rather than relying on specific capacity obligations (Hogan, 2005; Stoft, 2003). The prices from the power market therefore reflect both the energy and capacity value of generation at any particular point of time throughout the year.

B.2 Detailed Description of Investment Search Procedure

The power system planning and operations objective modeled in this paper is to maximize the gross economic value of consuming electricity while minimizing the investment and operating costs of electricity generation within dispatch constraints. As described later, this ideal situation is complicated by the inefficiency introduced between the day-ahead commitment of generation based on forecasts and the commitment that would have been made if there were no forecast errors. Ignoring forecast errors for now, the problem is summarized as:

$$\max_{\substack{(k_1 \ldots k_m)\\(q_1^t \ldots q_m^t)\\(l^t)}} \quad \text{Social Surplus } (k_1 \ldots k_m, q_1^t \ldots q_m^t, l^t) - \sum_{g=1}^{m} FC_g k_g$$
$$\text{s.t.} \quad \text{dispatch constraints} \tag{B.1}$$

, where k is the capacity of a vintage of generation, q is the dispatch of the generation, and l is the load that is met by generation. The short-run social surplus is the difference between the total economic value of electricity to consumers (the gross consumer surplus, or the area under the demand curve for all consumption) and the variable cost of producing electricity for the generators (the variable production cost).[1] The power plants that generate electricity also have fixed costs (FC_g) including annual fixed maintenance and upkeep costs as well as capital costs for new power plants. These fixed costs are assumed to be proportional to nameplate capacity and are, in the model, annualized.[2]

Simplification of Investment and Operation Problem

This ideal power system planning objective cannot be directly solved due to the lack of perfect forecastability of variable generation between the day-ahead and real-time. Using insight from techniques used in Benders Decomposition (Conejo et al., 2006; Cote and Laughton, 1979, e.g.,), the challenge of determining the best choice of generator investments such that it maximizes the short-run social surplus less the fixed cost can be separated into

[1]Short-run social surplus is an economic term in this context and is not meant to represent all potential costs and benefits to society related to the electric power system. We do not characterize the social costs of pollution, for example. A full societal cost benefit analysis of high penetrations of variable generation should consider these externalities, but is out of the scope of our analysis.

[2]Incumbent plants only have a fixed O&M component of FC_g without any fixed investment cost. In contrast to new investments, the nameplate capacity of incumbent generation chosen by the model, k_g, must be less than or equal to the nameplate capacity of the incumbent generation assumed in the model. As a result, "economic retirements" are implied when the model chooses less than the nameplate capacity of the incumbent generation, while retirements based simply on projected technical life are exogenously determined. The nameplate capacity constraints for incumbent capacity are included in the model but are not explicitly discussed here for clarity.

two problems, the investment and the dispatch problem. All of the constraints related to dispatch of load and generation are contained in the dispatch problem, while decisions related to investment in capacity are contained in the investment problem. The imperfect forecastability of variable generation is included in the dispatch problem, which in turn impacts the selection of candidate generation portfolios in the investment problem. The investment problem becomes:

$$\max_{(k_1 \ldots k_m)} \qquad \beta(k_1 \ldots k_m) - \sum_{g=1}^{m} FC_g k_g \tag{B.2}$$

The function, $\beta(k_1 \ldots k_m)$, is an unknown function that represents the dependence of the short-run social surplus on the choice of installed generation capacity. Specifically, function β is defined as:

$$\begin{aligned} \beta(k_1 \ldots k_m) \equiv \max_{\substack{(q_1^t \ldots q_m^t) \\ (l^t)}} \qquad & \text{Social Surplus } (q_1^t \ldots q_m^t, l^t) \\ \text{s.t.} \qquad & \text{dispatch constraints } (k_1 \ldots k_m) \end{aligned} \tag{B.3}$$

Even though the function β is unknown for all potential sets of generation, the function can be evaluated at specific points (i.e., specific candidate sets of generation capacity) by solving the maximization problem in Eq. B.3 with a defined set of candidate generation capacity (which focuses only on operations or the dispatch of that generation). Solving the problem in Eq. B.3 with a specific candidate set of generation capacity is described in more detail in Appendix B.3. Normal production cost models or unit-commitment and economic dispatch (UC/ED) models are designed to solve the problem in Eq. B.3 with a given set of generators. The dispatch problem is therefore straightforward to evaluate with a specific set of generation using an appropriate dispatch model.

Approximation of the Investment Problem

The investment problem, on the other hand, is not as straightforward to evaluate since the function $\beta(k_1 \ldots k_m)$ is unknown for all possible sets of generation. Since it is possible to evaluate $\beta(k_1 \ldots k_m)$ at specific points using a candidate set of generation capacity in a dispatch model, however, the procedure for solving the investment problem involves approximating $\beta(k_1 \ldots k_m)$ with an increasing number of planes that are tangent to the unknown function $\beta(k_1 \ldots k_m)$ at the evaluated points (or with a candidate set of generation capacity). In more general terms, the unknown relationship between the social surplus and the choice of investment decisions is approximated by evaluating the social surplus in a dispatch model then estimating how the surplus would change with slightly different generator investments. The approximation of the function $\beta(k_1 \ldots k_m)$ within the neighborhood of a particular set of generators, n, is denoted as $\beta^{(n)}(k_1 \ldots k_m)$ and can be estimated as:

$$\beta^{(n)}(k_1 \dots k_m) \approx \text{Social Surplus}^{(n)} + \sum_{g=1}^{m} \frac{\partial \text{Social Surplus}^{(n)}}{\partial k_g} \left(k_g - k_g^{(n)}\right) \tag{B.4}$$

If the unknown function $\beta(k_1 \dots k_m)$ is concave, then the tangent planes that approximate $\beta(k_1 \dots k_m)$ will be greater than or equal to the actual unknown function. The function $\beta(k_1 \dots k_m)$ is approximated as the largest value β that is less than any of the tangent planes, $\beta^{(n)}(k_1 \dots k_m)$. The investment problem, Eq. B.2, is then approximated as:

$$\begin{aligned}
\max_{\substack{(k_1 \dots k_m) \\ (\beta)}} \quad & \beta - \sum_{g=1}^{m} FC_g k_g \\
\text{s.t.} \quad & \beta \leq \text{Social Surplus}^{(1)} + \sum_{g=1}^{m} \frac{\partial \text{Social Surplus}^{(1)}}{\partial k_g} \left(k_g - k_g^{(1)}\right) \\
& \beta \leq \text{Social Surplus}^{(2)} + \sum_{g=1}^{m} \frac{\partial \text{Social Surplus}^{(2)}}{\partial k_g} \left(k_g - k_g^{(2)}\right) \\
\dots \quad & \\
& \beta \leq \text{Social Surplus}^{(n)} + \sum_{g=1}^{m} \frac{\partial \text{Social Surplus}^{(n)}}{\partial k_g} \left(k_g - k_g^{(n)}\right)
\end{aligned} \tag{B.5}$$

, where Social Surplus$^{(n)}$ is the actual social surplus for a particular set of generators as found from a dispatch model. Each additional tangent plane or constraint in the investment problem leads to an evaluation of $\beta(k_1 \dots k_m)$ for a set of generators and a tightening of the estimate of the function that describes $\beta(k_1 \dots k_m)$ for other potential sets of generators. Since the tangent planes are greater than $\beta(k_1 \dots k_m)$, the actual unknown function is estimated "from above" as the estimate is tightened.

Estimating the Change in Social Surplus with Installed Capacity

The next challenge before being able to implement this simplification is to determine how to estimate the change in the social surplus with a change in generation capacity in the neighborhood of a particular set of generators. For a simple power system with perfectly flexible power plants that have constant marginal costs up to their generation capacity, it is straightforward to show (using the Karush-Kuhn-Tucker conditions) that the change in the social surplus with a slight increase in the capacity of a particular generator is based on the difference between the market clearing price (or the intersection of the demand curve and the generator supply function) and the marginal cost of the generator. In a simple system, the generator will be offline when the market clearing price is less than its marginal cost and at its full capacity when the market clearing price is above its marginal cost. It can then be shown that the short-run profit ($SR_{\pi,i}$) earned by a generator that is paid the market clearing price is equivalent to the change in the social surplus with a small change in the amount of installed capacity.

In the more general case, the change in the social surplus with a change in capacity is only approximated by the short-run profit earned by a generator where generators are paid the market clearing price. The short-run profit of the generator is estimated using the dispatch and price results from simulating a particular set of generation in the dispatch model used to calculate the social surplus for a particular set of generation.

The investment problem can therefore be approximated as:

$$\max_{\substack{(k_1 \ldots k_m) \\ (\beta)}} \quad \beta - \sum_{g=1}^{m} FC_g k_g$$

$$\text{s.t.} \quad \beta \leq \text{ Social Surplus}^{(n)} + \sum_{g=1}^{m} SR_{\pi,i}^{(n)} \left(k_g - k_g^{(n)}\right) \quad \forall n \in 1 \ldots \nu - 1 \tag{B.6}$$

Convergence Criteria

With additional estimates of the tangent planes evaluated with a specific set of generators, the simplified maximization problem in Eq. B.6 will be an increasingly accurate representation of the full optimization problem in Eq. B.1. Since each set of generators evaluated in the simplified maximization problem in Eq. B.6 adds tangent planes that are 'above' the true unknown function representing the real-time surplus as a function of generation capacity, $\beta(k_1 \ldots k_m)$, the upper bound to the full optimization problem in Eq. B.1 is given by:

$$\text{UB}^{(n+1)} = \beta^{(n)} - \sum_{g=1}^{m} FC_g k_g^{(n+1)} \tag{B.7}$$

For any candidate set of generators, the true maximum real-time surplus with those generators can be calculated using a dispatch model. Because the candidate set of generators will not necessarily be the optimal generators that would be calculated in the full optimization problem in Eq. B.1, the lower bound is given by:

$$\text{LB}^{(n+1)} = \text{Social Surplus}^{(n+1)} - \sum_{g=1}^{m} FC_g k_g^{(n+1)} \tag{B.8}$$

A sufficient number of candidate sets of generators have been evaluated to create an adequate approximation when the upper and lower bounds converge within some convergence criteria, ϵ.[3]

[3]Typically the convergence criteria used in this report was 2×10^{-8} times the upper bound.

Implementation

In sum, the original problem Eq. B.1 is approximated by the following procedure, starting first with an excess of generation capacity in the candidate set of generator investments:

1. Determine the optimal commitment and dispatch of the chosen set of generation in a dispatch model.

2. Calculate the optimal social surplus for the set of generation (Social Surplus$^{(n)}$) and estimate the change in social surplus with a change in generation capacity as the short-run profits of the generation.

3. Check to see if the current approximation of the social surplus function, $\beta(k_1 \dots k_m)$ is adequate, (i.e. is $\text{UB} - \text{LB} < \epsilon$).

    - If it is adequate, stop: the current set of generation and the dispatch is the best estimate of the solution to Eq. B.1.
    - If it is not adequate: continue.

4. Use the results of the dispatch model with the current set of generation to create an additional tangent plane to the social surplus function, $\beta(k_1 \dots k_m)$. Add the tangent plane as a new constraint in the investment problem, Eq. B.6.

5. Solve the investment problem with the n sets of tangent planes to determine the $n + 1$ set of generators.

6. Return to Step 1 with the new set of generators.

This iterative procedure, which passes a candidate set of generators into the dispatch problem then uses the results of the dispatch problem to generate a new constraint in the investment problem, usually leads to an adequate approximation of the social surplus function, $\beta(k_1 \dots k_m)$. The set of generators and their dispatch in the final run of the dispatch model is the best approximation of the solution to Eq. B.1 and usually leads to a candidate set of generation that is in long-run equilibrium.

In practice, the investment problem did not always converge in the expected manner, likely due to differences between the simplified generators used in the derivation of the search procedure and the complexity of the operational constraints associated with the actual generator vintages modeled for this paper and due to the complexity associated with the uncertainty between the day-ahead and real-time. In these cases, the iterations were stopped when the iteration procedure could no longer improve upon the current set of generators, and alternative techniques were then used to refine the set of generation. The main alternative technique that was used was the bisection method. The objective of the bisection method was to adjust the capacity of the lowest fixed cost generation until the short-run profit of that generator was approximately equal to its fixed costs. Alternatively manual adjustment of the candidate set was made in order to find a candidate set of generation that was in long-run equilibrium. Usually only slight adjustments needed to be made.

B.3 Commitment and Dispatch Model Formulation

The commitment and economic dispatch model maximizes the social surplus over a year with hourly time steps given a particular choice of generation investments, which in simplified form is represented by:

$$\begin{aligned} \text{Social Surplus}^{(n)}(k_1^{(n)} \ldots k_m^{(n)}) \equiv \max_{\substack{(q_1^t \ldots q_m^t) \\ (l^t)}} \quad & \text{Social Surplus } (q_1^t \ldots q_m^t, l^t) \\ \text{s.t.} \quad & \text{dispatch constraints } (k_1^{(n)} \ldots k_m^{(n)}) \end{aligned} \tag{B.9}$$

This section summarizes the formal method for estimating the social surplus and defines the assumed dispatch constraints.

Overall, the day-ahead commitment model is used to generate day-ahead commitment, day-ahead generation schedules, and day-ahead prices for energy and ancillary services. The day-ahead decisions are made using day-ahead forecasts for wind and solar generation and perfectly accurate load forecasts. The commitment formulation largely follows approaches used by Sioshansi and Short (2009) and Müsgens and Neuhoff (2006). In contrast to the simplifications used here, the CAISO uses a much more detailed unit-specific unit-committment model in its DA and RT market. The basic principal of solving a commitment model to determine generation schedules and deriving prices for energy and ancillary services using the shadow value of the load balance and reserve target constraints, respectively, is similar to the way the CAISO market is operated (CAISO, 2009).

The problem nomenclature is as follows:

Problem Parameters

- General:
  - M: number of months in a year
  - T: number of hours, t, in a month
  - I: conventional generation vintage index set
  - V: variable generation vintage index set
- Conventional generation:
  - $VC_i(q)$: generator $i \in I$ convex piecewise-linear variable cost function
  - N_i: generator vintage $i \in I's$ no-load cost
  - SU_i: generator vintage $i \in I's$ startup cost
  - K_i^+: generator vintage $i \in I's$ nameplate capacity

- α_i^{min}: generator vintage $i \in I's$ minimum generation as a fraction of online generation
- α_i^{qs}: generator vintage $i \in I's$ quick start availability for non-spinning reserves (1 for quick-start capacity, 0 for other capacity)
- RR_i: generator vintage $i \in I's$ ramp rate capability per hour

- Variable generation:
  - K_ν^+: nameplate capacity of variable generator vintage $\nu \in V$
  - $CF_{\nu,t}^f, CF_{\nu,t}^a$: forecast and actual hourly variable generation in hour $t \in T$ from variable generator $\nu \in V$ as percentage of nameplate capacity

- Hydropower and pumped hydro storage:
  - $E_{hy,m}$: hydropower energy budget for each month $m \in M$
  - K_{hy}^+: nameplate capacity of hydropower generation vintage
  - $K_{hy,m}^-$: minimum hydropower generation rate in each month $m \in M$
  - K_{pc}^+: nameplate capacity of pumped hydro storage power converter
  - K_{pr}^+: capacity of storage reservoir in number of hours at full converter output
  - ξ^{in}: efficiency of storage while pumping water into storage
  - ξ^{out}: efficiency of storage while converting discharging water into electricity

- Demand, reserves, and virtual load:
  - $p_t(l)$: non-increasing stepped inverse demand function in hour $t \in T$, with an assumed price cap at the value of lost load (VOLL)
  - $\eta^{ns}, \eta^{s,l}, \eta^{r,l}$: nonspinning, spinning, and regulation reserve requirements as a fraction of hourly load
  - $\eta^{ns,\nu}, \eta^{s,\nu}, \eta^{r,\nu}$: non-spinning, spinning and regulation reserve requirements as a fraction of scheduled hourly variable generation
  - $\eta^{vl,\nu}$: Virtual load bid in the day-ahead market as a fraction of the scheduled hourly variable generation
  - $\eta^{vl,l}$: Virtual load bid in the day-ahead market as a fraction of the load
  - $\tau_{ns}, \tau_{sp}, \tau_r$: fraction of an hour by which (1) non-spinning reserve, (2) spinning reserve, and (3) regulation reserves need to be fully available
  - P^r, P^s, P^{ns}: assumed loss of social welfare per unit of regulation, spinning, and nonspinning reserve not procured (loss of social welfare declines with lower quality reserves)

Decision Variables

- Conventional generation:
  - $q_{i,t}$: generation provided by generator $i \in I$ in hour $t \in T$
  - $u_{i,t}$: generation online and spinning by generator $i \in I$ in hour $t \in T$
  - $s_{i,t}, d_{i,t}$: variables indicating if generating unit $i \in I$ started up or shut down in hour $t \in T$, respectively
  - $r^+_{i,t}, r^-_{i,t}$: regulation up reserves and regulation down reserves provided by generator $i \in I$ in hour $t \in T$
  - $sp_{i,t}, nsu_{i,t}, nsd_{i,t}$: spinning and nonspinning (from online (u) or offline (d) generation) reserves provided by generator
- Variable generation:
  - $q_{\nu,t}$: variable generation for $\nu \in V$ scheduled in hour $t \in T$
  - $r^-_{\nu,t}$: regulation down reserve provided by variable generator $\nu \in V$ in hour $t \in T$
- Hydropower and storage:
  - $q_{hy,t}$: hydropower generation scheduled in hour $t \in T$
  - $q_{spill,t}$: hydropower generation spilled in hour $t \in T$
  - $q^{in}_{p,t}$: pumped hydro storage pumping load in hour $t \in T$
  - $q^{out}_{p,t}$: pumped hydro storage generation in hour $t \in T$
  - e_t: energy in pumped hydro storage reservoir in hour $t \in T$
  - $r^+_{hy,t}, r^+_{p,t}$: regulation up reserve provided by hydropower, pumped hydro storage in hour $t \in T$
  - $r^-_{hy,t}, r^-_{p,t}$: regulation down reserve provided by hydropower, pumped hydro storage in hour $t \in T$
  - $sp_{hy,t}, sp_{p,t}$: spinning reserve provided by hydropower, pumped hydro storage in hour $t \in T$
  - $ns_{hy,t}, ns_{p,t}$: non-spinning reserve provided by hydropower, pumped hydro storage in hour $t \in T$
- Demand, reserves:
  - $r^-_{P,t}, r^+_{P,t}$: regulation up and regulation down reserve target not met in hour $t \in T$
  - $sp_{P,t}, ns_{P,t}$: spinning and nonspinning reserve target not met in hour $t \in T$
  - l_t: load served in hour $t \in T$

Dual variables

- λ_t: load balance constraint in hour $t \in T$ (energy price)
- $\lambda_{ns,t}$: nonspinning reserve constraint in hour $t \in T$ (nonspinning reserve price)
- $\lambda_{s,t}$: spinning reserve constraint in hour $t \in T$ (spinning reserve price)
- $\lambda_{r^+,t}$: regulation up reserve constraint in hour $t \in T$ (regulation up reserve price)
- $\lambda_{r^-,t}$: regulation down reserve constraint in hour $t \in T$ (regulation down reserve price)

Day ahead problem formulation:

The objective function for each month is:

$$\max \quad \text{Social Surplus} =$$
$$\sum_t \int_0^{l_t} p_t(x)dx - \sum_t \left(\sum_i \left(VC(q_{i,t}) + N_i u_{i,t} + SU_i s_{i,t}\right) + P^r(r^-_{P,t} + r^+_{P,t}) + P^s sp_{P,t} + P^{ns} ns_{P,t}\right)$$

subject to the following system operational constraints:

- load-balance $(\forall t \in T), \lambda_t$:

$$\sum_i q_{i,t} + \sum_\nu q_{\nu,t}\left(1 - \eta^{vl,\nu}\right) + q_{hy,t} + q^{out}_{p,t} = l_t\left(1 - \eta^{vl,l}\right) + q^{in}_{p,t}$$

- nonspinning reserve target $(\forall t \in T), \lambda_{ns,t}$:

$$\sum_i (nsu_{i,t} + nsd_{i,t}) + ns_{hy,t} + ns_{p,t} + ns_{P,t} \geq \eta^{ns} l_t + \eta^{ns,\nu} CF^f_{\nu,t} K^+_\nu$$

- spinning reserve target $(\forall t \in T), \lambda_{s,t}$:

$$\sum_i sp_{i,t} + sp_{hy,t} + sp_{p,t} + sp_{P,t} \geq \eta^{s,l} l_t + \eta^{s,\nu} CF^f_{\nu,t} K^+_\nu$$

- regulation up reserve target $(\forall t \in T), \lambda_{r^+,t}$:

$$\sum_i r^+_{i,t} + r^+_{hy,t} + r^+_{p,t} + r^+_{P,t} \geq \eta^{r,l} l_t + \eta^{r,\nu} CF^f_{\nu,t} K^+_\nu$$

- regulation down reserve target $(\forall t \in T), \lambda_{r^-,t}$:

$$\sum_i r^-_{i,t} + \sum_\nu r^-_{\nu,t} + r^-_{hy,t} + r^-_{p,t} + r^-_{P,t} \geq \eta^{r,l} l_t + \eta^{r,\nu} CF_{\nu,t} K^+_\nu$$

and the following conventional generator constraints ($\forall i \in I, t \in T$):

- minimum generation constraint

$$\alpha_i^{min} u_{i,t} \leq q_{i,t} - r^-_{i,t}$$

- generation total capacity constraint

$$u_{i,t} + nsd_{i,t} \leq K^+_i$$

- generation from spinning plant

$$q_{i,t} + r^+_{i,t} + sp_{i,t} + nsu_{i,t} \leq u_{i,t}$$

- generation nonspinning reserve from on-line plant capability

$$0 \leq nsu_{i,t} \leq u_{i,t} RR_i \tau_{ns}$$

- generation nonspinning reserve from quick-start plant capability

$$0 \leq nsd_{i,t} \leq K^+_i \alpha^{qs}_{i,t}$$

- generation spinning reserve capability

$$0 \leq sp_{i,t} \leq u_{i,t} RR_i \tau_{sp}$$

- generation regulation up capability

$$0 \leq r^+_{i,t} \leq u_{i,t} RR_i \tau_r$$

- generation regulation down capability

$$0 \leq r^-_{i,t} \leq u_{i,t} RR_i \tau_r$$

- generation ramp down capability

$$q_{i,t-1} - q_{i,t} + r^-_{i,t} \leq u_{i,t-1}RR_i$$

- generation ramp up capability

$$q_{i,t} - q_{i,t-1} + r^+_{i,t} + sp_{i,t} + nsu_{i,t} \leq u_{i,t-1}RR_i$$

- generation start up and shut down transition

$$u_{i,t} = u_{i,t-1} + s_{i,t} - d_{i,t}$$

and subject to variable generation constraints ($\forall \nu \in V, \forall t \in T$)

- variable generation capacity

$$0 \leq q_{\nu,t} + r^-_{\nu,t} \leq K^+_\nu CF^f_{\nu,t}$$

- variable generation regulation down capability

$$0 \leq q_{\nu,t} - r^-_{\nu,t}$$

and subject to hydro generation constraints

- hydropower generation monthly energy budget

$$\sum_t q_{hy,t} + q_{spill,t} \leq E_{hy,m}$$

- minimum hydropower generation rate ($\forall t \in T$)

$$q_{hy,t} - r^-_{hy,t} + q_{spill,t} \geq K^-_{hy,m}$$

- hydropower capacity limit ($\forall t \in T$)

$$q_{hy,t} + r^+_{hy,t} + sp_{hy,t} + ns_{hy,t} \leq K^+_{hy}$$

and subject to pumped hydro storage constraints ($\forall t \in T$):

- storage inventory

$$e_t = e_{t-1} + q_{p,t}^{in}\xi^{in} - \frac{q_{p,t}^{out}}{\xi^{out}}$$

- storage reservoir capacity

$$e_t \leq K_{pc}^{+} K_{pr}^{+}$$

- storage converter capacity limit for generation

$$q_{p,t}^{out} + r_{p,t}^{+} + sp_{p,t} + ns_{p,t} \leq K_{pc}^{+}$$

- storage converter capacity limit for pumping (storing)

$$q_{p,t}^{in} + r_{p,t}^{-} \leq K_{pc}^{+}$$

Once a solution is found for the DA commitment problem, the online generation variable $u_{i,t}$ can be fixed for plants that cannot change their commitment decisions in the real-time market. The day-ahead problem is run for an entire month so that unit-commitment schedules reflect the generation of hydropower (which is constrained to generate only a given amount each month).

For the real-time problem, the same dispatch problem with a few key changes is solved again. The changes include the following: a constraint is added that fixes the commitment of the slow start units based on the day-ahead commitment schedule of those units, virtual load is set to zero ($\eta^{vl,\nu} = 0$ in real-time), and the day-ahead forecast of variable generation (CF_{ν}^{f}) replaced with the actual realized generation (CF_{ν}^{a}) in the variable generation capacity constraint. Note that the anciallary service requirements are maintainted in both the DA and RT as the anciallry service requirements are based on sub-hourly variation and contingencies, both factors that are not explicitly modeled in the real-time problem with hourly intervals. The results from each month are then put together to form the schedules and dispatch over the entire year.

The results of the commitment and economic dispatch over the entire year are then used to calculate the short-run profits of each generator as:

$$SR_{\pi,i} = SR_{\pi,i}^{\mathrm{DA}} + SR_{\pi,i}^{\mathrm{RT}}$$

The day-ahead short-run profit is simply the day-ahead schedule times the day-ahead price premium over the real-rime price. The real-time short-run profit is the difference between the real-time price and the actual real-time generating costs:

$$
\begin{aligned}
SR^{\mathrm{DA}}_{\pi,i} \;=\; & (\sum_t \left(\lambda^{\mathrm{DA}}_t - \lambda^{\mathrm{RT}}_t\right) q^{\mathrm{DA}}_{i,t} \\
& + \left(\lambda^{\mathrm{DA}}_{ns,t} - \lambda^{\mathrm{RT}}_{ns,t}\right) \left(nsu^{\mathrm{DA}}_{i,t} + nsd^{\mathrm{DA}}_{i,t}\right) \\
& + \left(\lambda^{\mathrm{DA}}_{s,t} - \lambda^{\mathrm{RT}}_{s,t}\right) sp^{\mathrm{DA}}_{i,t} \\
& + \left(\lambda^{\mathrm{DA}}_{r^+,t} - \lambda^{\mathrm{RT}}_{r^+,t}\right) r^{+,\mathrm{DA}}_{i,t} \\
& + \left(\lambda^{\mathrm{DA}}_{r^-,t} - \lambda^{\mathrm{RT}}_{r^-,t}\right) r^{-,\mathrm{DA}}_{i,t})/K^+_i
\end{aligned}
$$

$$
\begin{aligned}
SR^{\mathrm{RT}}_{\pi,i} \;=\; & (\sum_t \lambda^{\mathrm{RT}}_t - VC(q^{\mathrm{RT}}_{i,t}) - N_i u^{\mathrm{RT}}_{i,t} - SU^{\mathrm{RT}}_i s_{i,t} \\
& + \lambda^{\mathrm{RT}}_{ns,t}(nsu^{\mathrm{RT}}_{i,t} + nsd^{\mathrm{RT}}_{i,t}) + \lambda^{\mathrm{RT}}_{s,t} sp^{\mathrm{RT}}_{i,t} \\
& + \lambda^{\mathrm{RT}}_{r^+,t} r^{+,\mathrm{RT}}_{i,t} + \lambda^{\mathrm{RT}}_{r^-,t} r^{-,\mathrm{RT}}_{i,t})/K^+_i
\end{aligned}
$$

If the convergence criteria of the investment problem have not been met, the short-run profits for each generation vintage in the candidate set of generation and the social surplus from the real-time market are then used in the investment problem to create an additional tangent line constraint for the problem in Eq. B.6. The investment problem is run again with the new constraint to determine the next set of candidate conventional generators to test in the commitment and dispatch model. This process is repeated in an iterative manner until the investment model chooses the installed capacity that meets the convergence criteria described in Appendix B.2.

B.4 Model Parameters

The parameters for thermal generation, hydropower generation, and pumped hydro storage described in the Data and Assumptions section of the report are summarized in this appendix. The parameters include the definition of 17 thermal generator vintages (Table B.1), the assumed technical life retirement age in the Reference scenario (Table B.2), the incumbent generation in the "No Retirements" scenario and the resulting incumbent generation with the assumed technical life in the Reference scenario (Table B.3), and the assumed thermal plant generation characteristics (Table B.4, Table B.5, and Table B.6). Assumptions for the emissions (Table B.7, Table B.8, and Table B.9) and fixed and variable cost of thermal plants (Table B.10) are also described. Finally, this section summarizes the fuel cost assumptions (Table B.11), the assumed monthly hydropower constraints (Table B.12) and the assumed parameters for pumped hydro storage (Table B.13).

The thermal generation assigned to the California NERC sub-region were grouped into 17 vintages described in Table B.1. The separation of the generation into different vintages was based on an examination of plant heat rate, ramp rate, and pollution generation characteristics. The categories used for separating the plant characteristics were type of prime mover, type of fuel, size of plant, and plant online date.

Table B.1: Thermal generator vintage definitions

Generation Vintage	Prime Mover	Fuel	Capacity Range (MW)	Online Date
Coal_ST_Big	Steam Turbine	Coal	≥ 800	Any
Coal_ST_Small_New	Steam Turbine	Coal	< 200	≥ 1980
Coal_ST_Small_Old	Steam Turbine	Coal	< 200	< 1980
Gas_ST_Big	Steam Turbine	Gas	≥ 400	Any
Gas_ST_Mid_New	Steam Turbine	Gas	200-400	≥ 1965
Gas_ST_Mid_Old	Steam Turbine	Gas	200-400	< 1965
Gas_ST_Small_New	Steam Turbine	Gas	< 200	≥ 1965
Gas_ST_Small_Old	Steam Turbine	Gas	< 200	< 1965
Gas_CC_Big	Combined Cycle	Gas	≥ 800	Any
Gas_CC_Mid_New	Combined Cycle	Gas	200-800	≥ 1995
Gas_CC_Mid_Old	Combined Cycle	Gas	200-800	< 1995
Gas_CC_Small_New	Combined Cycle	Gas	< 200	≥ 1980
Gas_CC_Small_Old	Combined Cycle	Gas	< 200	< 1980
Gas_CT_New	Combustion Turbine	Gas	Any	≥ 1980
Gas_CT_Old	Combustion Turbine	Gas	Any	< 1980
Geothermal	Steam Turbine	-	Any	Any
Nuclear	Steam Turbine	Uranium	Any	Any

A plant technical life was used to estimate the amount of generation that would still be in service in 2030, Table B.2. The technical life of coal and natural gas steam plants is based on an analysis of historic plant retirement ages in North America using the Ventyx Velocity Suite database of plant ages and retirement dates and similar assumptions used in other studies (IEA, 2010; Sims et al., 2007). Fewer retirements of CT and CCGTs were available from the historic Ventyx data, and instead a technical life of 30 years was assumed based on the technical life presented by IEA (2011). The technical life for nuclear plants is based on an original license life of 40 years with a single 20-year license renewal. A similar assumption was used in the 2010 EIA Annual Energy Outlook Alternative Nuclear Retirement Case (EIA, 2010). Hydro plants are assumed to never retire.

Table B.2: Retirement age assumed for different plant types in the Reference scenario

Plant Type	Assumed Retirement Age (years)
Combustion Turbine	30
Combined Cycle	30
Steam	50
Nuclear	60
Hydro	None

The amount of incumbent generation in the California NERC sub-region was estimated using the assumptions of the plant technical life and the online date of the thermal generation, Table B.3. In the “No Retirements” sensitivity scenario, all of the current generation capacity was assumed to still be available in 2030.

Several thermal generator operating characteristics were quantified for each vintage using all of the thermal generation resources in WECC that are characterized in the Ventyx database, Table B.4. These parameters include the following:

- No-load heat rate: hypothetical amount of fuel that would be burned if the thermal plant were online but producing no electricity (in reality thermal generators have a minimum generation constraint that would force the plant to produce some electricity whenever it is online).

- Start-up heat: fuel that is consumed during each start-up of the thermal plant without producing electricity.

- Non-fuel start-up cost: wear & tear and related costs associated with starting a thermal plant. Ventyx does not report this cost. Instead these costs were estimated from non-fuel start-up costs used in WECC transmission modeling (WECC, 2011).

- Minimum generation rate: the percentage of the nameplate capacity that the plant must be above in order to remain online and generate electricity.

Table B.3: Incumbent generator capacity in California NERC sub-region for 2030.

Generation Vintage	Incumbent Generation Capacity (GW)	
	Reference	No Retirement
Coal_ST_Big	1.8	1.8
Coal_ST_Small_New	0.4	0.4
Coal_ST_Small_Old	0	0.1
Gas_ST_Big	0	6.2
Gas_ST_Mid_New	0	1.9
Gas_ST_Mid_Old	0	5.3
Gas_ST_Small_New	0.1	0.2
Gas_ST_Small_Old	0	2.4
Gas_CC_Big	1.8	1.8
Gas_CC_Mid_New	13.1	13.1
Gas_CC_Mid_Old	0	1.0
Gas_CC_Small_New	1.2	2.0
Gas_CC_Small_Old	0	2.0
Gas_CT_New	4.0	7.3
Gas_CT_Old	0	0.4
Geothermal	1.7	2.1
Nuclear	4.6	4.6
Hydropower	13.3	13.3
Pumped Hydro Storage	3.5	3.5
Total Incumbent	45.5	69.4

- Ramp-rate: the maximum rate at which generation can change its output in the up or down direction as a percentage of the online generation.
- Quick-start: only quick start plants can change the amount of generation that is online in each hour. The day-ahead decisions for the amount of generation that will be online in any hour is binding for the remaining non-quick-start generation.

Geothermal and nuclear vintages were assumed to be inflexible and operated at load throughout the year (also these plants are not characterized by the Ventyx database because there are no air emissions from these plants that would be monitored with the EPA CEMS program).

Where Ventyx data were used to estimate the parameters for the other generation, the generating characteristics of each vintage were estimated by averaging detailed unit-specific estimates of individual unit generation operating parameters for existing conventional generation in WECC of the same vintage-type. The individual unit characteristics were reported in the Ventyx EV Market-Ops, Unit Capacity Blocks & Ramprates table. The Ventyx data is largely based on historic plant operations derived from US EPA CEMS data. Since the unit-specific values are averaged across plants and are based on historic plant performance, these generator parameters reflect current plant operation. The plants may technically be able to provide more flexibility than they have historically provided. The parameters used in this study will therefore tend to understate the flexibility of conventional generation.

In addition to the existing generation in WECC, the new investment options were assumed to have operational and emission characteristics similar to recent vintages. The generation vintages that can be built by the model have the prefix "Invest_" before the vintage name in the tables.

Ramp-rates for the CT vintage were found to be very low when using hourly data from the Ventyx dataset. In addition the Ventyx dataset does not include ramp-rates for hydro nor does Ventyx report non-fuel start-up costs. The ramp-rates for the CT vintage and for hydropower[4] along with the non-fuel start-up costs related to wear & tear for all thermal plants are therefore derived from the assumptions used in WECC transmission modeling (WECC, 2011). Ramp-rates and non-fuel start-up costs are listed for individual units in the database listing WECC assumptions used in transmission modeling. The CT ramp-rates are based on a linear fit between individual unit capacity and individual unit ramp-rate in MW/hr. Only those individual units whose ramp-rates fell near a pronounced linear relationship between ramp rate and capacity were used since there was significant scatter between ramp-rate and capacity for a number of units. The non-fuel start-up costs for steam plants (coal and natural gas), CCGTs, and CTs were similarly derived from the database of WECC transmission modeling assumptions by applying a linear fit between non-fuel start-up cost and individual unit capacity. Most of the start-up costs fell along a line and relatively few units clearly did not fall onto the same line as the other units. The linear relationship was used to apply a non-fuel startup cost to the different vintages depending on the capacity range of the vintage. In $/MW-start terms, the non-fuel startup costs for CCGTs and CTs were similar, with CTs having a slightly higher cost. The start-up costs for steam plants were clearly lower than the start-up costs for CTs and CCGTs across all individual unit capacities.

The non-fuel start-up costs for coal plants derived from the WECC assumptions are similar to the warm start costs (i.e., the plant is not down for longer than 120 hours) for coal plants reported by Gray (2001). More recent preliminary research on average "lower-bound" start-up costs for coal, natural gas steam turbines, CCGT, and CT plants by Intertek Aptech shows that the range of start-up costs from actual plants may be somewhat higher for coal plant and lower for CT plants than the assumed average costs used in this analysis (Lefton, 2011). As non-fuel start-up costs are an area of ongoing research, this is an area where assumptions should be revisited as more detailed estimates become available.

[4] The ramp-rates used here are more conservative than the ramp-rates that are reported for CTs and aggregated hydropower plants by Makarov et al. (2008). This lower bound on ramp rate capabilities helps to reduce any bias that would otherwise be introduced by the fact that this study does not include any costs associated with ramping plants.

Table B.4: Thermal generator no-load heat, start-up heat and non-fuel cost, minimum generation, and ramp rate. Source: Derived from Ventyx except where noted otherwise.

Generation Vintage	No-load Heat (MMBtu/ MW-h)	Start-up Heat (MMBtu/ MW-start)	Non-fuel [a] Start-up Cost ($/MW-start)	Minimum Generation (% rated capacity)	Ramp Rate (% per hour)	Quick[b] Start
Coal_ST_Big	2.4	20.6	8	50	25	0
Coal_ST_Small_New	1.8	17.7	14	50	33	0
Coal_ST_Small_Old	0.8	17.8	14	45	33	0
Gas_ST_Big	0.6	11.4	9	25	37	0
Gas_ST_Mid_New	0.5	15.6	10	27	44	0
Gas_ST_Mid_Old	0.6	14.8	10	27	47	0
Gas_ST_Small_New	0.5	11.3	14	30	38	0
Gas_ST_Small_Old	0.7	18.1	14	31	46	0
Gas_CC_Big	1.4	5.0	56	25	24	0
Gas_CC_Mid_New	1.2	7.8	56	29	39	0
Gas_CC_Mid_Old	0.6	11.7	56	27	60	0
Gas_CC_Small_New	1.1	9.0	57	35	40	0
Gas_CC_Small_Old	2.2	20.7	57	41	38	0
Gas_CT_New	1.8	10.0	86	43	197[a]	1
Gas_CT_Old	2.9	16.2	86	52	197[a]	1
Geothermal[c]	2.4	n/a	n/a	100	n/a	0
Nuclear[c]	2.4	n/a	n/a	100	n/a	0
Invest_Nuclear[c]	2.4	n/a	n/a	100	n/a	0
Invest_Gas_CC_Mid_New	1.2	7.8	56	29	39	0
Invest_Coal_ST_Mid_New	0.7	21.9	14	48	22	0
Invest_Gas_CT_New	1.8	10.0	86	43	197	1

a - Derived from WECC assumptions (WECC, 2011)
b - 1 for units that can be committed in real-time, 0 otherwise
c - assumed to operate at full load at all time

Several thermal generation parameters vary depending on the loading of the vintage. These parameters are described for each vintage with constant rates within each of four loading blocks, Table B.5. The first block starts at the minimum generation level and increases up to the second block (Block 0, which occurs between 0% generation and minimum generation is not a feasible state for generation). The fourth block describes the parameters for the thermal generation at full load.

Table B.5: Thermal generator lower limit block definitions. Source: Derived from Ventyx

Generation Vintage	Block 1 (% rated capacity)	Block 2 (% rated)	Block 3 (% rated)	Block 4 (% rated)
Coal_ST_Big	50	67	83	100
Coal_ST_Small_New	50	67	83	100
Coal_ST_Small_Old	45	63	81	100
Gas_ST_Big	25	50	75	100
Gas_ST_Mid_New	27	51	76	100
Gas_ST_Mid_Old	27	51	75	100
Gas_ST_Small_New	30	53	76	100
Gas_ST_Small_Old	31	53	76	100
Gas_CC_Big	25	50	75	100
Gas_CC_Mid_New	29	53	76	100
Gas_CC_Mid_Old	27	51	76	100
Gas_CC_Small_New	35	56	78	100
Gas_CC_Small_Old	41	60	80	100
Gas_CT_New	43	61	80	100
Gas_CT_Old	52	67	84	100
Geothermal	100	100	100	100
Nuclear	100	100	100	100
Invest_Gas_CC_Mid_New	29	53	76	100
Invest_Coal_ST_Mid_New	48	66	83	100
Invest_Gas_CT_New	43	61	80	100
Invest_Nuclear	100	100	100	100

In addition to the fuel consumed in start-up and the no-load fuel consumption, increasing the amount of electricity produced by a thermal plant increases the amount of fuel burned. The incremental increase in fuel consumption for an increase in electricity production is shown for the four blocks in Table B.6 based on Ventyx data. The incremental heat rate is non-decreasing with increases in loading of the online generation. The natural gas fired steam vintages appear to have the greatest increase in heat rate with higher loading. On the other hand, the average heat rate, which includes both the incremental fuel consumption and the no-load heat, decreases with increases in loading.

Table B.6: Thermal generator incremental marginal heat rate.[a] Source: Derived from Ventyx

	Marginal Heat Rate (MMBtu/MWh)			
Generation Vintage	Block 1	Block 2	Block 3	Block 4
Coal_ST_Big	8.0	8.1	8.1	8.1
Coal_ST_Small_New	10.5	10.5	10.5	10.5
Coal_ST_Small_Old	10.9	10.9	10.9	10.9
Gas_ST_Big	9.2	9.3	9.4	9.5
Gas_ST_Mid_New	10.1	10.1	10.1	10.2
Gas_ST_Mid_Old	9.6	9.7	9.8	9.8
Gas_ST_Small_New	10.5	10.5	10.6	10.6
Gas_ST_Small_Old	10.9	10.9	10.9	10.9
Gas_CC_Big	5.6	5.7	5.7	5.7
Gas_CC_Mid_New	5.9	5.9	6.0	6.0
Gas_CC_Mid_Old	8.3	8.3	8.4	8.4
Gas_CC_Small_New	6.9	6.9	6.9	6.9
Gas_CC_Small_Old	7.0	7.0	7.0	7.0
Gas_CT_New	9.0	9.0	9.1	9.1
Gas_CT_Old	12.5	12.5	12.5	12.5
Geothermal	8.0	8.1	8.1	8.1
Nuclear	8.0	8.1	8.1	8.1
Invest_Gas_CC_Mid_New	5.9	5.9	6.0	6.0
Invest_Coal_ST_Mid_New	10.0	10.0	10.1	10.1
Invest_Gas_CT_New	9.0	9.0	9.1	9.1
Invest_Nuclear	8.0	8.1	8.1	8.1

a - The incremental heat rate does not include the no-load heat

The CO_2 emissions from the thermal plants are assumed to be proportional to the fuel consumed (note that this is not equivalent to being proportional to the electricity generated due to part-load inefficiencies and start-up emissions). The emissions of NO_x and SO_2 are not proportional to fuel consumption. In fact, in some cases the emissions due to start-up on a per unit of fuel basis can be much greater than the hourly emissions expected for an on-line plant. The start-up emissions for thermal plants are not included in the Ventyx database. The NO_x and SO_2 emissions during start-up are therefore assumed to be proportional to the hourly full-load emissions of the vintage based on detailed analysis of start-up emissions in Lew et al. (2011), Table B.7. Based on that analysis the ratio of the NO_x emissions due to start-up to the hourly NO_x emissions from a fully-loaded CCGT was 9.5, from a fully loaded CT was 6.7, and from a fully-loaded coal plant was 2.9. Additionally, they found that the ratio of the SO_2 emissions due to start-up to the hourly SO_2 emissions from a fully-loaded coal plant was 2.7. They do not report the ratio of the SO_2 emissions due to start-up to the hourly SO_2 emissions for a fully loaded CCGT or CT plant. In this analysis we therefore assume that the ratio for CCGTs and CTs is the same ratio reported for coal.

Table B.7: Thermal generator start-up emissions for NO_x and SO_2. Source: Estimates from Lew et al. (2011) applied to full-load emissions derived from Ventyx.

Generation Vintage	Start-up NO_x (kg/MW-start)	Start-up SO_2 (kg/MW-start)
Coal_ST_Big	5.109	0.779
Coal_ST_Small_New	2.680	2.103
Coal_ST_Small_Old	7.120	6.655
Gas_ST_Big	0.258	0.007
Gas_ST_Mid_New	0.392	0.007
Gas_ST_Mid_Old	0.537	0.007
Gas_ST_Small_New	4.661	0.008
Gas_ST_Small_Old	3.352	0.014
Gas_CC_Big	0.216	0.005
Gas_CC_Mid_New	0.264	0.005
Gas_CC_Mid_Old	3.070	0.007
Gas_CC_Small_New	0.832	0.006
Gas_CC_Small_Old	4.303	0.010
Gas_CT_New	0.990	0.009
Gas_CT_Old	0.466	0.011
Geothermal	0.000	0.000
Nuclear	0.000	0.000
Invest_Gas_CC_Mid_New	0.264	0.005
Invest_Coal_ST_Mid_New	4.491	3.635
Invest_Gas_CT_New	0.990	0.009
Invest_Nuclear	0.000	0.000

The assumed average NO_x emissions rate for thermal generation depending on the load factor is derived from Ventyx, Table B.8. NO_x emissions from coal plants are much worse per unit of fuel burned relative to natural gas plants. The average NO_x emissions per unit of fuel burned almost always *increases* as the load factor of CCGT and CT plants decreases, as noted by Denny and O'Malley (2006) and Katzenstein and Apt (2009). The same is not found to be true for operating coal plants in the western U.S.

Similar to NO_x, the assumed average SO_2 rate at the four load factor levels were derived from Ventyx, Table B.9. The SO_2 emissions rate for coal plants are three to four orders of magnitude greater than the SO_2 emissions rate for natural gas plants.

The assumed variable O&M costs and the annualized fixed cost for generation vintages are summarized in Table B.10. The variable O&M costs are based on the costs reported by

Table B.8: Thermal generator average NO_x emissions rate. Source: Derived from Ventyx

	Average NO_x Emissions Rate (g/MMBtu)			
Generation Vintage	Block 1	Block 2	Block 3	Block 4
Coal_ST_Big	144.0	134.9	171.7	167.4
Coal_ST_Small_New	81.7	67.8	70.5	74.9
Coal_ST_Small_Old	180.3	191.8	199.0	208.7
Gas_ST_Big	3.1	4.0	6.2	8.8
Gas_ST_Mid_New	3.8	7.7	9.8	12.6
Gas_ST_Mid_Old	4.6	4.8	7.7	17.9
Gas_ST_Small_New	134.8	104.4	117.8	144.6
Gas_ST_Small_Old	52.0	60.5	81.1	99.3
Gas_CC_Big	3.2	3.4	3.2	3.2
Gas_CC_Mid_New	7.6	5.8	3.8	3.8
Gas_CC_Mid_Old	61.6	30.2	46.3	35.9
Gas_CC_Small_New	17.3	11.2	10.9	10.9
Gas_CC_Small_Old	54.3	52.5	49.8	49.3
Gas_CT_New	21.9	16.3	13.1	13.6
Gas_CT_Old	36.2	26.5	4.2	4.5
Geothermal	0.0	0.0	0.0	0.0
Nuclear	0.0	0.0	0.0	0.0
Invest_Gas_CC_Mid_New	7.6	5.8	3.8	3.8
Invest_Coal_ST_Mid_New	115.7	116.7	130.0	143.4
Invest_Gas_CT_New	21.9	16.3	13.1	13.6
Invest_Nuclear	0.0	0.0	0.0	0.0

Ventyx. The fixed costs are based on the capital cost calculator built by E3 for WECC to use in transmission planning studies. The incumbent generation only has fixed O&M costs, while new investments in generation are required to cover both the investment cost and fixed O&M cost (the sum of which is included in the total fixed cost column).

The assumed fuel costs are based on recent projections of natural gas, coal, and uranium prices for 2030 by EIA, 2011, Table B.11. The CO_2 emissions are assumed to be proportional to the fuel use in the thermal plants.

Hydropower is challenging to model accurately due to the many non-economic constraints on river flows downstream of the plant, variable river flows upstream of the plant, and interactions between hydroplants on the same river system. Hydropower modeling is therefore simplified by assuming that the total amount of electrical energy produced by the hydropower vintage in any month must equal the sum of the hydropower generated in a historical year by all hydropower plants within the NERC sub-region, as reported by Ventyx. The hydro generation in the median year between 1990 and 2008 is used to set the monthly hydropower budget, Table B.12.

Table B.9: Thermal generator average SO_2 emissions rate. Source: Derived from Ventyx

	Average SO_2 Emissions Rate (g/MMBtu)			
Generation Vintage	Block 1	Block 2	Block 3	Block 4
Coal_ST_Big	20.6	25.4	22.6	27.4
Coal_ST_Small_New	131.8	92.5	63.9	63.2
Coal_ST_Small_Old	196.5	210.8	221.5	209.5
Gas_ST_Big	0.3	0.3	0.3	0.3
Gas_ST_Mid_New	0.2	0.3	0.3	0.2
Gas_ST_Mid_Old	0.3	0.3	0.3	0.3
Gas_ST_Small_New	0.3	0.3	0.3	0.3
Gas_ST_Small_Old	0.5	0.4	0.4	0.4
Gas_CC_Big	0.3	0.3	0.3	0.3
Gas_CC_Mid_New	0.3	0.3	0.3	0.3
Gas_CC_Mid_Old	0.3	0.3	0.3	0.3
Gas_CC_Small_New	0.3	0.3	0.3	0.3
Gas_CC_Small_Old	0.2	0.4	0.4	0.4
Gas_CT_New	0.7	0.3	0.3	0.3
Gas_CT_Old	0.3	0.3	0.3	0.3
Geothermal	0.0	0.0	0.0	0.0
Nuclear	0.0	0.0	0.0	0.0
Invest_Gas_CC_Mid_New	0.3	0.3	0.3	0.3
Invest_Coal_ST_Mid_New	121.0	119.2	119.8	124.7
Invest_Gas_CT_New	0.7	0.3	0.3	0.3
Invest_Nuclear	0.0	0.0	0.0	0.0

In addition to establishing the monthly generation budget, a minimum and maximum hydropower generation rate are required to model hydropower. The maximum hydropower is assumed to be the sum of the nameplate capacity of all of the hydropower plants in the California NERC sub-region. A minimum hydropower generation rate in each hour was estimated for each month as the average hydropower generation rate that would yield the lowest average monthly generation for that month over the period from 1990 to 2008.

Within these three primary constraints, it was assumed that hydropower plants never shut down or start up. Hydropower is also assumed to be flexible enough to change its generation profile in response to uncertainty and variability in the real-time market. All hydropower is modeled as being co-optimized with the thermal generation (or "hydro-thermal co-optimization") with perfect foresight as opposed to modeling hydro as being dispatched in proportion to the load profile (often called "proportional load-following").

The 3.5 GW of existing pumped hydro storage (PHS) in the California NERC sub-region was assumed to never retire, to have a reservoir capacity of 10 hours, and to have a round trip efficiency of 81%. New investments in PHS could be made with an annualized fixed cost

Table B.10: Variable and fixed operating and maintenance cost and annualized fixed cost of thermal generation in the reference scenario

Generation Vintage	Variable O&M Cost[a] ($/MWh)	Fixed O&M Cost[b] ($/kW-yr)	Total Fixed Cost[b] ($/kW-yr)
Coal_ST_Big	1	66	-
Coal_ST_Mid_New	2	66	-
Coal_ST_Mid_Old	1	66	-
Coal_ST_Small_New	2	66	-
Coal_ST_Small_Old	2	66	-
Gas_ST_Big	1	66	-
Gas_ST_Mid_New	2	66	-
Gas_ST_Mid_Old	3	66	-
Gas_ST_Small_New	2	66	-
Gas_ST_Small_Old	2	66	-
Gas_CC_Big	1	9	-
Gas_CC_Mid_New	1	9	-
Gas_CC_Mid_Old	1	9	-
Gas_CC_Small_New	1	9	-
Gas_CC_Small_Old	1	9	-
Gas_CT_New	1	15	-
Gas_CT_Old	1	15	-
Geothermal	5	204	-
Nuclear	4	92	-
Invest_Gas_CC_Mid_New	1	-	203
Invest_Coal_ST_Mid_New	2	-	494
Invest_Gas_CT_New	1	-	194
Invest_Nuclear	4	-	950

a - Source: Derived from Ventyx
b - Source: WECC, 2010

Table B.11: Cost of fuel in reference scenario and CO_2 emission rate

Fuel	Cost[a] ($/MMBtu)	CO_2 Emission Rate (kg/MMBtu)
Gas	6.39	53.8
Coal	2.35	93.1
Uranium	1.04	0.0
Geothermal	0.00	0.0

a - Source: EIA, 2011

Table B.12: Monthly hydropower energy generation budget and minimum generation rate for the 13.3 GW of hydro capacity in the California NERC sub-region. Source: Derived from Ventyx

Month	Monthly Hydro Generation Budget (GWh)	Minimum Hydro Generation(GW)
1	2,248	1.0
2	1,743	1.0
3	2,240	1.8
4	2,701	2.0
5	3,412	2.9
6	3,344	2.7
7	3,178	3.0
8	2,932	2.4
9	2,265	1.9
10	1,761	1.4
11	1,645	1.0
12	2,000	1.1

based on EIA costs estimates for PHS (EIA, 2010). New PHS was also assumed to have 10 hours of reservoir capacity, Table B.13.

Table B.13: Storage cost and other parameters in the reference case

Characteristic	Parameter
Fixed Cost ($/kW-yr)[a]	706
Reservoir Capacity Ratio (h)	10
Charge Efficiency (%)	90
Discharge Efficiency (%)	90
a - Source: Total storage cost derived from EIA, 2010	

B.5 Decomposition Tables for Sensitivity Scenarios

No Operational Constraints

Carbon Cost

Cost of Capacity

No Retirements

Table B.14: Decomposition of the marginal economic value of variable generation in a sensitivity scenario where operational constraints are ignored.

Component	Penetration of Wind						
($/MWh)	0%	5%	10%	15%	20%	30%	40%
Capacity Value[a]	(79) 20	(31) 10	(29) 10	(29) 9	(27) 9	(24) 8	(20) 6
Energy Value	49	48	48	47	47	46	40
DA Forecast Error	0	0	0	0	0	0	0
Ancillary Services	-0.5	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2
Marginal Economic Value	68	58	57	56	56	53	45

Component	Penetration of PV						
($/MWh)	0%	2.5%	5%	10%	15%	20%	30%
Capacity Value[a]	(128) 41	(107) 34	(80) 26	(25) 8	(12) 4	(8) 3	(6) 2
Energy Value	49	49	49	49	47	47	42
DA Forecast Error	0	0	0	0	0	0	0
Ancillary Services	-0.9	-0.8	-0.7	-0.3	-0.1	-0.1	-0.0
Marginal Economic Value	89	83	74	56	51	50	43

Component	Penetration of CSP_0						
($/MWh)	0%	2.5%	5%	10%	15%	20%	30%
Capacity Value[a]	(119) 50	(85) 36	(51) 22	(4) 2	(1) 0	(0) 0	(-1) -1
Energy Value	50	50	49	48	47	46	32
DA Forecast Error	0	0	0	0	0	0	0
Ancillary Services	-1.1	-1.0	-0.6	0	0	0	0
Marginal Economic Value	99	86	71	50	47	46	31

Component	Penetration of CSP_6						
($/MWh)	0%	2.5%	5%	10%	15%	20%	30%
Capacity Value[a]	(162) 38	(168) 39	(156) 37	(133) 31	(112) 26	(58) 14	(1) 0
Energy Value	49	50	51	53	55	59	59
DA Forecast Error	0	0	0	0	0	0	0
Ancillary Services	1.4	1.3	1.3	2.1	1.6	1.0	0.1
Marginal Economic Value	89	90	90	87	82	74	60

a - Capacity value in parentheses is reported in $/kW-yr terms.

Table B.15: Decomposition of the marginal economic value of variable generation in a sensitivity scenario with a \$32/tonne CO_2 carbon cost.

Component	Penetration of Wind						
(\$/MWh)	0%	5%	10%	15%	20%	30%	40%
Capacity Value[a]	(65) 17	(37) 12	(29) 10	(30) 10	(27) 9	(24) 8	(24) 7
Energy Value	63	62	61	60	60	58	51
DA Forecast Error	-0.3	-4	-4	-2	-2	-4	-7
Ancillary Services	-0.4	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2
Marginal Economic Value	79	70	66	67	66	62	51

Component	Penetration of PV						
(\$/MWh)	0%	2.5%	5%	10%	15%	20%	30%
Capacity Value[a]	(113) 36	(103) 33	(81) 26	(39) 13	(19) 6	(9) 3	(4) 1
Energy Value	68	67	65	61	57	52	36
DA Forecast Error	-0.4	-5	-5	-6	-5	-4	-3
Ancillary Services	-0.9	-0.8	-0.7	-0.5	-0.3	-0.1	-0.0
Marginal Economic Value	102	94	86	67	58	52	34

Component	Penetration of CSP_0						
(\$/MWh)	0%	2.5%	5%	10%	15%	20%	30%
Capacity Value[a]	(108) 46	(81) 35	(52) 23	(22) 10	(11) 5	(6) 3	(5) 2
Energy Value	70	69	66	58	52	44	23
DA Forecast Error	-0.6	-5	-5	-6	-5	-4	-5
Ancillary Services	-1.1	-0.8	-0.5	-0.2	-0.1	-0.1	-0.1
Marginal Economic Value	114	97	83	62	52	43	20

Component	Penetration of CSP_6						
(\$/MWh)	0%	2.5%	5%	10%	15%	20%	30%
Capacity Value[a]	(148) 36	(150) 36	(146) 35	(135) 32	(102) 24	(75) 19	(38) 10
Energy Value	70	70	70	70	71	67	67
DA Forecast Error	-0.2	-1	-1	-1	-1	-2	-2
Ancillary Services	1.4	1.4	1.3	1.2	1.1	0.7	0.1
Marginal Economic Value	107	106	105	101	95	84	75

a - Capacity value in parentheses is reported in \$/kW-yr terms.

Table B.16: Decomposition of the marginal economic value of variable generation in a sensitivity scenario where the annualized fixed cost of a new CT is reduced from $194 to $139/kW-yr.

Component ($/MWh)	Penetration of Wind 0%	5%	10%	15%	20%	30%	40%
Capacity Value[a]	(50) 13	(27) 9	(22) 8	(23) 8	(21) 7	(19) 6	(18) 6
Energy Value	54	53	53	51	52	49	42
DA Forecast Error	-0.1	-3	-3	-2	-2	-3	-6
Ancillary Services	-0.3	-0.2	-0.2	-0.2	-0.2	-0.2	-0.1
Marginal Economic Value	66	59	57	57	57	52	42

Component ($/MWh)	Penetration of PV 0%	2.5%	5%	10%	15%	20%	30%
Capacity Value[a]	(95) 30	(91) 29	(70) 22	(33) 11	(15) 5	(8) 3	(4) 1
Energy Value	59	59	56	52	48	44	27
DA Forecast Error	-0.1	-4	-4	-6	-4	-3	-3
Ancillary Services	-0.7	-0.8	-0.7	-0.4	-0.1	-0.1	-0.0
Marginal Economic Value	88	83	74	57	49	44	26

Component ($/MWh)	Penetration of CSP_0 0%	2.5%	5%	10%	15%	20%	30%
Capacity Value[a]	(91) 39	(67) 29	(44) 19	(16) 7	(8) 4	(5) 2	(1) 1
Energy Value	62	59	55	51	44	34	16
DA Forecast Error	-1.6	-6	-5	-4	-4	-3	-3
Ancillary Services	-0.9	-0.8	-0.4	-0.2	-0.1	-0.2	-0.1
Marginal Economic Value	99	81	70	54	43	33	14

Component ($/MWh)	Penetration of CSP_6 0%	2.5%	5%	10%	15%	20%	30%
Capacity Value[a]	(125) 30	(124) 30	(128) 31	(127) 30	(104) 25	(86) 21	(58) 14
Energy Value	61	59	58	57	60	53	52
DA Forecast Error	-0.1	-1	-1	-1	-1	-2	-3
Ancillary Services	1.3	1.2	1.2	1.1	1.0	0.7	0.1
Marginal Economic Value	93	89	90	88	84	71	63

a - Capacity value in parentheses is reported in $/kW-yr terms.

Table B.17: Decomposition of the marginal economic value of variable generation in case where no retirements occur due to the technical life of thermal generation.

Component	Penetration of Wind						
($/MWh)	0%	5%	10%	15%	20%	30%	40%
Capacity Value[a]	(20) 5	(12) 4	(10) 4	(8) 3	(7) 2	(8) 2	(7) 2
Energy Value	63	61	58	56	53	48	40
DA Forecast Error	-0.2	-2	-2	-2	-2	-3	-5
Ancillary Services	-0.2	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1
Marginal Economic Value	67	63	59	57	53	48	38

Component	Penetration of PV						
($/MWh)	0%	2.5%	5%	10%	15%	20%	30%
Capacity Value[a]	(37) 12	(38) 12	(21) 7	(11) 4	(6) 2	(4) 1	(1) 0.4
Energy Value	68	67	65	59	51	44	26
DA Forecast Error	-0.1	-1	-3	-3	-2	-2	-2
Ancillary Services	-0.5	-0.5	-0.4	-0.3	-0.1	-0.0	-0.0
Marginal Economic Value	79	78	68	59	51	43	24

Component	Penetration of CSP_0						
($/MWh)	0%	2.5%	5%	10%	15%	20%	30%
Capacity Value[a]	(33) 14	(24) 10	(13) 6	(7) 3	(4) 2	(1) 1	(1) 0.3
Energy Value	69	67	65	56	46	34	17
DA Forecast Error	-0.1	-1	-1	-3	-3	-2	-3
Ancillary Services	-0.6	-0.5	-0.2	-0.1	-0.2	-0.3	-0.1
Marginal Economic Value	83	76	69	57	45	32	15

Component	Penetration of CSP_6						
($/MWh)	0%	2.5%	5%	10%	15%	20%	30%
Capacity Value[a]	(54) 13	(48) 12	(47) 11	(41) 10	(16) 4	(14) 3	(0) 0.0
Energy Value	70	69	67	65	62	56	50
DA Forecast Error	0.0	-0.2	-0.4	-0.3	-1	-1	-1
Ancillary Services	1.1	0.9	0.9	0.9	0.6	0.5	0.0
Marginal Economic Value	84	81	79	76	66	59	49

a - Capacity value in parentheses is reported in $/kW-yr terms.

B.6 Scarcity Pricing and Loss of Load Expectation

Overview

Investment decisions in the model used in this analysis are based on the requirement that the short-run profit of any new investments must approximately equal the annualized fixed cost of that generation. If the short-run profit were higher then additional generation would enter the market and depress prices. If it were any lower then the new investments would not be made based on the expectation that the short-run profit would not justify the investment cost. The total amount of non-VG generation built in any case is determined by economic decisions captured by this long-run equilibrium constraint.

In contrast, many power system planning studies use a reliability-based approach to determine the amount of generation capacity that needs to be available in order to meet a reliability planning standard. A common approach sets a target loss of load expecation (LOLE) and determines the amount of generation that needs to be built in order to meet this target LOLE. In contrast to the long-run equilbirium approach, the LOLE-based approach is not explicitly based on economic criteria.

Though these two approaches to determining the amount of generation capacity to build in the future are based on fundamentally different criteria, the objective of this section is to illustrate how the two can be related. Based on an illustrative set of simple market rules, we show how a constant short-run profit for a peaker plant implies a constant LOLE. We then derive a relationship between the value of lost load (VOLL), the fixed cost of the peaker plant, and the LOLE based on arguments similar to the discussion of Reliability, Price Spikes, and Investment in Part 2 of Power System Economics (Stoft, 2002).

Illustration

Consider a simple power market (much more simple than the wholesale power market used in the full model used in this report) where the hourly wholesale price (p^t) can take on only three possible values:

1. $p^t = P_s = VOLL \gg MC$: The wholesale price equals the value of lost load (VOLL) which is much greater than the marginal production cost of the peaker plant (MC)
   - Define the probability of p^t being P_s as ϕ_s^t
2. $p^t = MC$: The wholesale price equals the marginal production cost of the peaker plant
   - Define the probability of p^t being MC as ϕ_m^t
3. $p^t < MC$: The wholesale price is less than the marginal production cost of the peaker plant.
   - Define the probability of p^t being less than MC as ϕ_0^t

Since only three price levels can occur, the sum of the probabilities of each price level is one: $\phi_s^t + \phi_m^t + \phi_0^t = 1$.

The dispatch of the peaker plant is also assumed to be very simple and depend on the wholesale prices:

1. $q^t = K$ when $p^t = P_s$: The peaker plant generates at its full nameplate capacity (K) when the wholesale price is equal to the VOLL

2. $q^t \geq 0$ when $p^t = MC$: The peaker plant is dispatched to any level when the peaker plant is the marginal unit and the wholesale price equals the marginal production cost of the peaker plant.

3. $q^t = 0$ when $p^t < MC$: The peaker plant is off when the price is below the marginal production cost of the peaker plant.

The short-run profit (per unit of capacity) in any hour is based on the revenues earned from selling its output into the wholesale power market and the production costs.

$$SR_\pi^t = (p^t - MC)q^t/K$$

As a result of these three potential prices and the dispatch based on the prices, there are only two resulting values that the hourly short-run profit can be for the peaker plant in each hour.

1. $SR_\pi^t = (P_s - MC) \approx P_s$: When the wholesale price is equal to the VOLL or P_s, the peaker plant is dispatched to its full nameplate capacity. The hourly short-run profit will be the difference between the VOLL and the marginal production cost of the peaker. Since the VOLL is much greater than the marginal cost of the peaker, the short run profit is approximately equal to the VOLL. This hourly short-run profit occurs with a probability of ϕ_s^t.

2. $SR_\pi^t = 0$: When the wholesale price equals the marginal production cost, the short-run profit is zero, no matter how much the peaker plant generates. When the wholesale price is below the marginal production cost of the peaker, the short-run profit is zero because the peaker plant will be offline. Together this hourly short-run profit occurs with a probability of $\phi_m^t + \phi_0^t = (1 - \phi_s^t)$.

Based on the fact that there are only two possible values for the hourly short-run profit of the peaker plant, the expected value of the short-run profit in each hour is:

$$\mathbb{E}(SR_\pi^t) = \phi_s^t P_s + (1 - \phi_s^t)0 = \phi_s^t P_s$$

Over a long period, T, the total expected short-run profit of the peaker plant (SR_π) is:

$$\mathbb{E}\left(SR_\pi = \sum_{t\in T} SR_\pi^t\right) = \sum_{t\in T} \mathbb{E}\left(SR_\pi^t\right) = \sum_{t\in T} \phi_s^t P_s = P_s \sum_{t\in T} \phi_s^t$$

The long-run equilibrium constraint implies that in equilibrium, the expected value of the short-run profit of any new peaker plant that is built will equal the fixed investment cost of the peaker plant (FC_p). Therefore the long-run equilibrium constraint implies:

$$\mathbb{E}\left(SR_\pi\right) = P_s \sum_{t\in T} \phi_s^t = FC_p$$

As long as the system is in long-run equilibrium and some new peaker plants are built, the sum of the hourly probabilities of price spikes across all hours will be kept at a constant level:

$$\frac{FC_p}{P_s} = \sum_{t\in T} \phi_s^t = \text{constant}$$

Even if variable generation were to be added to this simple market or if the shape of the load were to change, as long as the market moves to a new long-run equilibrium and new peaker plants are built in that long-run equilibrium the sum of the hourly probabilities of price spikes across all hours will remain equal to the ratio of the fixed cost of the peaker plant and the value of lost load, FC_p/P_s.

If the only time that the wholesale power price rises to the value of lost load is when the demand (L^t) exceeds the total amount of all generation (G^t) in that hour (including the contribution from the peaker plant and any variable generation), then the probability of the price being equal to the value of lost load is the same as the probability of the demand being than generation:

$$\phi_s^t = \phi(L^t > G^t)$$

The loss of load expectation over a long period T is defined as:

$$LOLE = \sum_{t\in T} \phi(L^t > G^t)$$

Therefore, the loss of load expectation is equivalent to the sum of the hourly probabilities of price spikes across all hours. In long-run equilibrium when new peaker plants are built, the LOLE is constant and is based on the ratio of the fixed cost of the peaker plant and the value of lost load, FC_p/P_s:

$$LOLE = \sum_{t\in T} \phi(L^t > G^t) = \sum_{t\in T} \phi_s^t = \frac{FC_p}{P_s} = \text{constant}$$

An effective load carrying capability (ELCC) analysis of the capacity value of variable generation seeks to determine the change in the amount of load that can be met with and without variable generation while holding the LOLE constant (e.g., Milligan, 2000). This relationship between LOLE and the long-run equilibrium constraint illustrates that the ELCC of variable generation found through an LOLE analysis is based on similar drivers to the implied capacity credit found with a system that is in long-run equilibrium with and without variable generation.

Implications

Since the LOLE is fixed based on the ratio of the fixed cost of a peaker and the value of lost load, FC_p/P_s, the overall reliability of the system modeled in this simple illustration is tied to the estimate of the value of lost load. Assume that the peaker plant has a fixed investment cost of \$200,000/MW-yr. Then if the value of lost load is assumed to be \$10,000/MWh the loss of load expectation will be 20 hours per year (or load shedding will occur during approximately 0.22% of the hours in a year.

If the desire were to have a lower loss of load expectation of 1-day in 10 years (or 2.4 hours per year) then the VOLL would need to be closer to \$83,000/MWh.

The implication for estimating the marginal economic value of variable generation is that the choice of the VOLL determines the number of hours per year when the price spikes to high levels. A higher choice of the VOLL would lead to fewer hours with high prices and therefore relatively more weight on the amount of generation during those high price hours.