The impacts of wind and solar on grid flexibility requirements in the Electric Reliability Council of Texas

Thomas A. Deetjen^{a,*}, Joshua D. Rhodes^{a,b}, Michael E. Webber^{a,b}

^a*Department of Mechanical Engineering, The University of Texas, Austin, Texas 78712, United States*

^b*Energy Institute, The University of Texas, Austin, Texas 78712, United States*

Abstract

The installation of wind and solar capacity in the electric grid can influence net load ramp rates and volatility, affecting grid stability and operating costs. In this study, the statistical analysis of load, wind, and solar data from the Electric Reliability Council of Texas (ERCOT) shows how wind and solar capacity impacts these grid flexibility requirements. Growing wind capacity shows only minor correlation with increasing flexibility requirements, and appears to correlate with decreasing flexibility requirements in some instances. Growing solar capacity might initially improve grid flexibility requirements, particularly volatility. However, beyond a certain penetration level (about 1.0 GW in this study), further solar capacity growth develops a direct correlation with increasing flexibility requirements if load patterns do not change. While adding 15.7 GW of wind power had insignificant effects, adding 14.5 GW of solar to the ERCOT grid increases maximum 1-hr ramp rates by 135%, 3-hr ramp rates by 30%, ramp factors by 140%, 1-hr volatility by 100%, and 1-day volatility by 30%. The geographic location and orientation of solar arrays influences these flexibility requirements, with fixed, southeast-facing panels providing a significant reduction. These results can inform strategies for managing the grid flexibility requirements created by growing renewable capacity.

Keywords:

Flexibility Requirements, Renewable Generation, Solar Location and Orientation, Grid Flexibility

*Corresponding Author

Email address: tdeetjen@utexas.edu (Thomas A. Deetjen)

1. Introduction

Wind and solar generation offer opportunities to provide clean, domestic, and affordable power in the future [1]. Driven by environmentally-minded regulations, such as the United States’ Production Tax Credit and Investment Tax Credit (PTC & ITC) [2] or the European Commission’s 2020 climate and energy package, which sets a goal of 20% renewable energy generation to help reduce greenhouse gases by 20% from 1990 levels [3], the installed capacities of wind and solar are on the rise globally [4]. While increasing penetration of renewable energy on the grid might produce environmental and economic benefits [5], the variability and timing of renewable energy generation can make its output difficult to balance and integrate [6, 7]. While renewable sources with zero marginal cost reduce total dispatch cost, these variability and timing issues exacerbate “flexibility requirements”, such as ramp rates [8, 9], which can increase the maintenance requirements and ancillary costs of operating the electric grid [5, 10, 11]. Increasing flexibility requirements by adding more wind and solar to the grid can also reduce the quality and stability of grid voltage and frequency [12–14].

Thus, the view that wind and solar generation can reduce the total dispatch cost and environmental impacts of the electric grid must be considered in context with the understanding that increasing their capacities will also bring integration costs, grid-balancing challenges, and stability issues. Understanding the severity of these issues begins by exploring the relationship between increased renewable generation capacity and increased flexibility requirements. This study, in response to a lack of consensus in the existing literature [15], suggests a framework for quantifying flexibility requirements. It illustrates this framework by analyzing the correlation of increasing wind and solar generation with grid flexibility requirements in the Electric Reliability Council of Texas (ERCOT, the system operator of the electric grid covering about 85% of Texas’ population). The trends discussed in this study are intended to provide meaningful insight for grid planners as they anticipate the growth of renewable energy resources and the strategies they should implement to maintain reliability and manage integration costs. This insight is especially valuable for grids with rapid penetrations of renewables already underway or looming, such as Germany, China, Australia, Ireland, ERCOT, and many others.

2. Background

Wind and solar energy resources bring an interesting new aspect to the operation of electricity markets. Since wind and solar have low operational costs, they can bid into the day-ahead electricity market at a zero price [16] moving them to the

front of the merit order (the list of dispatchable generators arranged by their energy bid price, see Fig 1). This favorable bid position means that it is desirable (and sometimes required per feed-in regulations [16]) to integrate all available wind and solar generation into the electric grid. In response to this integration, the remaining dispatchable generation must transition from simply meeting the load to balancing the residual load or net load (load minus wind, solar, and other intermittent renewable generation) [17]. This requirement exposes the generation fleet to additional ramping (quick changes in generator power output), cycling (powering down and up in short time periods), and other operational difficulties called “flexibility requirements” [5, 8].

Figure 1: The merit order curve sorts an electricity market’s power plants by their marginal cost, visualizing how the power plants with least expensive marginal cost will be dispatched first. Zero-marginal-cost resources (wind, solar, water) are added to the front of the merit order curve, pushing thermal generators (nuclear, coal, natural gas) later in the order. This shift reduces wholesale prices. This figure shows an example of how 15 GW of renewable generation might reduce wholesale market prices from 50 \$/MWh to 35 \$/MWh.

46 The changes to flexibility requirements caused by wind and solar generation can
 47 be addressed by many different methods. Currently, grid operators respond to flexi-
 48 bility requirements primarily by utilizing the capabilities of the generation fleet [15],
 49 where net load ramping is balanced by quick changes in the generator fleet’s power
 50 output, and large swings between daily or sub-daily minimum and maximum net
 51 loads are balanced by turning power plants on and off. Additionally, using ancil-
 52 lary services to procure reserve capacity is a common market tool for responding to
 53 flexibility requirements [18, 19]. It has been hypothesized that these strategies will
 54 lose their efficacy at higher renewable energy levels and require additional support,
 55 such as energy storage [20] or demand response from interruptible loads. Storage
 56 technologies are capable of providing many services to the grid that would improve
 57 the integration of variable renewable generation, such as bulk energy storage, en-
 58 ergy management, power quality management, and intermittency mitigation, but are
 59 likely to see limited use until they become more economical [21, 22]. Another grow-
 60 ing opportunity for meeting flexibility requirements is the use of demand response,
 61 whereby flexible loads, such as water treatment that can be ramped up and down [23],
 62 adjust their consumption in response to signals from the grid, allowing the grid to
 63 soften demand spikes or large ramping events [24, 25]. Additional grid-supporting
 64 strategies continue to be developed, including the dispatch of grid-connected electric
 65 vehicles [26], transmission restructuring, and market redesign [15].

66 While there are many viable options, choosing the best strategies for increasing
 67 the flexibility of the grid begins with improving our understanding of the flexibility
 68 requirements likely to be imposed on it [8]. Different studies have worked to further
 69 this knowledge. Hirth et al. [11] use economic analysis to dissect how variable re-
 70 newable generation adds costs to the operation of the grid. One major cost category,
 71 “profile costs”, derives from the temporal variability of renewable generation. These
 72 costs are driven by the flexibility effect (the increased ramping and cycling of power
 73 plants) and the utilization effect (the generators’ distribution of fixed annual capital
 74 costs over fewer annual hours of energy production profit). Hirth shows how more
 75 renewable generation leads to larger ramp rates, increased power plant cycling, and
 76 reduced thermal utilization, which all add costs to the system.

77 Hüber et al. [27] give a general look at how flexibility requirements change across
 78 different European countries as their renewable generation and share of solar gener-
 79 ation increase. Using 1-hour resolution, simulated, wind and solar data, the study
 80 uses time series analysis to calculate ramp rates on a 1 to 12 hour time scale. They
 81 show that flexibility requirements will greatly increase at renewable generation pen-
 82 etrations greater than 30%, especially with significant amounts of solar generation.
 83 They conclude that grid size and renewable generation full load hours (FLH) also

84 contribute to changing flexibility requirements.

85 Additionally, a consulting report published by GE Energy in 2008 [19] conducts
86 time series variability analysis of simulated wind data in ERCOT and assesses the
87 ability of ancillary services to accommodate the growing flexibility needs. It is an
88 interesting counterpart to this paper as it was written in 2008 with a future-looking
89 perspective, while this study utilizes historic 2008-2014 data, and both focus on
90 the ERCOT grid. Some key takeaways from the report were that increased wind
91 generation is correlated with increased ramp rates over all 1-minute to 60-minute time
92 spans, and that increasing 15-minute and 60-minute ramp rates are driven by net load
93 variability rather than stochastic variation. It also suggests that the increasing ramp
94 rates created by significant wind penetration will increase the maximum amount of
95 regulation reserves that will need to be provided for maintaining grid stability.

96 This paper improves on the aforementioned flexibility requirement studies in a
97 number of ways. It utilizes 15-minute data to perform calculations on a short time
98 scale. While it does utilize simulated solar data, the majority of its wind flexibility
99 analysis is based on actual historical data from ERCOT. It also discusses the influence
100 of solar array orientation and geographic location on flexibility requirements. It is
101 novel in both its proposal of a framework for calculating flexibility requirements,
102 and its further development of the concept of net load “volatility” as presented in a
103 recent publication by the authors [5].

104 While this work focuses explicitly on the ERCOT electric grid, ERCOT has a
105 number of characteristics that make it a useful example for other networks. It con-
106 tains a large amount of installed wind capacity and has strong potential for solar
107 growth [5]. Since its wind capacity growth might plateau by the time solar instal-
108 lations begin to take off, it is easier to observe the real-world flexibility effects of
109 wind and solar separately as discussed in Subsection 3.1. The ERCOT load is driven
110 by summer cooling demand with approximately half of its peak load coming from
111 residential air conditioning [28], so it experiences the effects of renewable energy
112 penetration during both high-demand (summer and early-autumn) and low-demand
113 (late-winter and spring) seasons. It is anticipated that the correlations between flex-
114 ibility requirements and renewable energy generation in ERCOT will be informative
115 to other grids that can draw some similarities with it. This information is intended
116 to be influential in grid planners’ decisions about the technologies and strategies they
117 will use for addressing changing flexibility requirements in the future.

118 3. Methods

119 The methods for this study are presented in three separate subsections. Subsec-
120 tion 3.1 discusses the calculation of the peak output, a proxy for installed capacity,

121 and illustrates the renewable energy capacity growth used in this analysis. Sub-
122 section 3.2 discusses the data sources used for this study and the methods used to
123 expand them. Subsection 3.3 proposes a series of calculations for defining different
124 flexibility requirements.

125 3.1. Peak Output Calculation

126 Portions of this paper compare the flexibility requirements with the amount of
127 renewable energy installed on the grid. Rather than using the installed capacity, this
128 study compares the flexibility requirements with the greatest demonstrated wind
129 and solar output up to the date being analyzed, referred to now as the “peak out-
130 put”. While installed capacity does not account for capacity factors or solar resource
131 efficacy, these properties are inherent in the peak output, which simplifies its com-
132 parison between grids with different solar resources. Additionally, the peak output,
133 being calculated directly from the data used in this study, is more quantitatively
134 robust than the approximate installed capacity numbers shown herein. Fig 2 shows
135 the growing installed capacity and peak output for wind and solar from 2008-2025.
136 As seen in the figure, the peak output can be roughly divided into the 2008-2015
137 “wind era” where wind output grows steadily and solar output remains negligible
138 and the 2016-2025 “solar era”, which is a simulated forward-looking era during which
139 wind output is held constant and solar output grows steadily. This capacity growth
140 scenario is not meant to suggest that wind capacity will not grow in ERCOT in the
141 future; it simply provides a useful analytical scenario. Thus, this study assumes that
142 changes in flexibility requirements during the wind era are driven by increasing wind
143 output, and changes in flexibility requirements during the solar era are driven by
144 increasing solar output.

145 3.2. Data Generation

146 This study analyzes a set of 15-minute resolution, load, wind, and solar data
147 from 2008 - 2025. This data set was created using different data sets acquired from
148 ERCOT and NREL as described in Table 1. When creating the data, discontinuities
149 between the first interval of any calculated year of load, wind, or solar data and the
150 last interval of the previous year’s data are connected by a linear interpolation with
151 a slight slope (less than 500 (MW/15min)) until the discontinuity has been removed.
152 This adjustment preserves continuity between years without creating artificial peri-
153 ods of significant ramping. See Table 2 for an example of this calculation. By basing
154 all load, wind, and solar projections off of a single year of data (2012), potential
155 weather-related correlations between load, wind, and solar are preserved. ERCOT
156 advised the authors to use 2012 as a base year due to their perception of 2012 as a
157 typical grid operation year without extreme weather, outage, or other outlier events.

Table 1: Different data sets acquired from ERCOT and the National Renewable Energy Laboratory (NREL) [29] were used to create the “Model Data” described in this table.

	Name	Resolution	Description	Source
Source Data	ERCOT 2008-2014	15-minute	Load and wind data from 2008-2014. Solar data from 2012-2014 (solar generation was not tracked until 2012).	ERCOT
	ERCOT 2015	60-minute	Load, wind, and solar data.	ERCOT
	ERCOT Load Projections	60-minute	Projected load data for 2016-2025, based on 2012 weather data.	ERCOT
	NREL NSRDB [29]	30-minute	Historical weather data and calculated solar insolation data, such as global horizontal radiation (GHI), needed to calculate solar panel power output.	NREL
Model Data	2008-2014 Load, Wind, Solar	15-minute	Taken verbatim from “ERCOT 2008-2014” data set.	
	2015 Load	15-minute	The 2012 load data from the “ERCOT 2008-2014” data set was multiplied by a constant scaling factor. The resulting load profile has the same annual peak demand as the “ERCOT 2015” data set.	
	2015 Wind	15-minute	The 2012 wind data from the “ERCOT 2008-2014” data set was multiplied by a linear scaling factor. The resulting wind profile has the same January installed wind capacity as January 2015, and the same December installed wind capacity as December 2015.	
	2016-2025 Wind	15-minute	The 2012 wind data from the “ERCOT 2008-2014” data set was multiplied by a linear scaling factor. The resulting wind profile has the same January installed wind capacity as December 2015, and the same December installed wind capacity as December 2015. This wind profile is repeated annually for 2016-2025, assuming that the installed wind capacity at the end of 2015 (15.7 GW) remains constant through 2025 with no additional wind being installed.	
	2015-2025 Solar	15-minute	Using the “NREL NRSDB” database, 2012 weather profiles for eleven locations across west and central Texas were compiled. These eleven weather profiles are read into the NREL System Advisor Model software [30], which translates the weather profiles and solar array properties into 30-minute resolution, 1-axis tracking, solar generation profiles. By weighting these profiles to accentuate west and central Texas, normalizing the output to the installed capacity, and averaging each pair of adjacent, 30-minute interval data points to create 15-minute interval data points, a 15-minute solar generation profile is created. Each year in the 2015-2025 solar data set is created by multiplying this normalized generation profile by the installed capacities in Table 3.	
	2015-2025 Comparison Solar	15-minute	The method for creating the “2015-2025 Solar” data set is used to create a variety of different solar installation scenarios as shown in Table 3. The flexibility requirements of these scenarios are compared against each other in the analysis.

Figure 2: Growth of the wind and solar peak output can be organized into the 2008-2015 “wind era” and the 2016-2025 “solar era”.

Table 2: Since portions of the data are created by connecting December 31 to January 1 of the same year, discontinuities will arise, as shown here for the load. The discontinuity between the actual load at 12/31 23:45 and 1/1 0:00 leads to an artificial ramp rate of -2,792 MW/15min. Adjusting the load to the indicated values removes the artificial ramp rate and creates continuity between the data.

	12/31 23:15	12/31 23:30	12/31 23:45	1/1 0:00	1/1 0:15	1/1 0:30	1/1 0:45	1/1 1:00	1/1 1:15
Actual Load	29,860	29,570	29,313	26,521	26,441	26,358	26,269	26,058	25,892
Actual Ramp		-290	-257	-2,792	-80	-83	-89	-211	-166
Adjusted Load	29,860	29,392	28,892	28,392	27,892	27,392	26,892	26,392	25,892
Adjusted Ramp		-468	-500	-500	-500	-500	-500	-500	-500

Table 3: The installed solar capacity increases according to the top portion of this table. The bottom portion of this table describes the different solar location and orientation scenarios used for comparison in this study.

Installed Solar Capacity	2015	300 MW total
	2016	1,000 MW total
	2017-2024	+1,500 MW of new capacity added each year'
	2025	14,500 MW total
Solar Scenarios	Location Comparisons (all 1-axis tracking arrays) (see Table 4 for detailed geographic information)	West: emphasis on west and central Texas (best solar resource locations)
		Central: emphasis on central Texas (best proximity to population centers and transmission infrastructure)
		South: emphasis on south and central Texas (another good solar resource location)
	Orientation Comparisons (all West located; 20-deg above-horizontal tilt for all fixed panels)	Fixed West: all solar is fixed, west-facing panels
		Fixed Southwest: all solar is fixed, southwest-facing panels
		Fixed South: all solar is fixed, south-facing panels
		Fixed Southeast: all solar is fixed, southeast-facing panels
		1-axis: all solar is 1-axis tracking (identical to the West scenario)
		2-axis: all solar is 2-axis tracking panels

158 Portions of the 15-minute resolution 2008-2025 load, wind generation, and so-
 159 lar generation data are visualized in Figs 3-5. Fig 3 shows the net load for each
 160 15-minute interval, averaged over all the days in January for each year. It exhibits
 161 the two-peak net load often seen during the winter and shoulder seasons in ERCOT.
 162 From 2016-2025, an increase in projected load drives the load curve upward each
 163 year, but increasing solar generation drives the net load down from 8:00 to 18:00
 164 when solar generation is producing electricity. This reduction of the daytime net
 165 load creates steep ramp rates around 10:00 and 17:00 and moves the minimum net
 166 load to the middle of the day. Fig 4 shows the net load at each 15-minute interval on
 167 February 8th of each year after 2016, when solar capacity begins to trend upward.
 168 In addition to steeper ramp rates, this figure also shows the increasing volatility of
 169 the net load curve as solar penetration increases. Fig 5 shows the net load for each
 170 15-minute interval, averaged over all the days in June for each year. It exhibits the
 171 large mid-day peak driven significantly by air conditioning demand. From 2016-2025,
 172 an increase in projected load drives the net load curve upward each year. As solar
 173 generation turns on around 6:30, it reduces the net load, creating steep downward
 174 ramp rates. As solar generation falls off around 18:30, the net load quickly rises,
 175 creating steep upward ramp rates.

Table 4: Solar data from 19 different cities is used in this study [29]. The solar profile for each “location comparison” scenario is built from the indicated fractions of each city’s solar profile.

Solar Array	Location Comparisons		
Location (City)	West	Central	South
Abilene	0.08	0.08	0
Alpine	0.13	0	0
Amarillo	0.08	0	0
College Station	0	0.08	0.06
Del Rio	0	0	0.14
Fort Worth	0.04	0.2	0
Guthrie	0.08	0	0
Houston	0	0.2	0.06
Laredo	0	0	0.14
Longview	0	0.08	0
Lubbock	0.08	0	0
Lufkin	0	0.04	0
McAllen	0	0	0.14
Midland	0.13	0.08	0.06
Pecos	0.13	0	0
San Antonio	0.04	0.16	0.14
Sheffield	0.13	0	0.06
Sonora	0.08	0.04	0.06
Victoria	0	0.04	0.14

Figure 3: This chart shows the net load for each 15-minute interval, averaged over all the days in January for each year. January exhibits the two-peak net load often seen during the winter and shoulder season months in ERCOT. The years 2008 to 2015 are a period of rapid growth in wind capacity. From 2016-2025, as more solar is added to the grid, it generates power from 8:00 to 18:00, reducing the net load and creating steep ramp rates as the sun rises and sets.

Figure 4: The net load is shown for each 15-minute interval on February 8th of each year after 2016, when solar capacity begins to trend upward. These profiles strongly exhibit the tendency for solar generation to increase the ramping and volatility of the net load as discussed later in this study.

Figure 5: This chart shows the net load for each 15-minute interval, averaged over all the days in June for each year. June exhibits the dramatic single-peak net load seen during the summer months in ERCOT where peak net load is driven significantly by air conditioning demand. The years 2008 to 2015 are a period of rapid growth in wind capacity. From 2016-2025, as more solar is added to the grid, it generates power from 6:30 to 18:30, reducing the net load and creating steep ramp rates as the sun rises and sets.

3.3. Flexibility Requirement Calculations

An important aspect of observing changes in net load flexibility requirements is defining the methods by which they are quantified. Existing literature lacks consensus on how flexibility should be calculated [15], though there is some agreement on the importance of ramp rate calculations with respect to the ramping abilities of generators [19, 27]. As discussed in previous work [5], the authors propose the net load “volatility” as a useful measure of net load flexibility that is being overlooked in the current literature. Volatility is the absolute value of the net load curve’s second derivative, summed over various time frames. It describes the amount of “chatter” of the net load curve as it ramps up and down over short time spans. These quick fluctuations can influence the grid to dispatch faster-ramping resources [10], even though large ramp rates are not necessarily being experienced. To encourage more consensus on the quantification of flexibility requirements, the authors propose the calculations described in subsections 3.3.1-3.3.6, some being adapted from previous work [5].

3.3.1. 1-Hour Ramp Rate

The 1-hr ramp rate is calculated by subtracting the net load 1 hour prior from the current net load as shown in equation 1, where t is time in 15-minute intervals.

For example, the June 19, 2022 net load changes from 36,996 MW at 11:00 to 39,752 MW at 12:00 for a 1-hr ramp rate of 2,756 (39,752 - 36,996). It is measured in units of MW/hr and describes short-term ramping events that might be handled by ancillary services. Thus, an increase in 1-hr ramp rates might indicate the need for improved ancillary services or fast-response ramping resources on the grid.

$$1HrRampRate(t) = NetLoad(t) - NetLoad(t - 4) \quad (1)$$

3.3.2. 3-Hour Ramp Rate

The 3-hr ramp rate is calculated by subtracting the net load 3 hours prior from the current net load as shown in equation 2, where t is time in 15-minute intervals. For example, the June 19, 2022 net load changes from 36,996 MW at 11:00 to 41,900 MW at 14:00 for a 3-hr ramp rate of 4,904 (41,900 - 36,996). It is measured in units of MW/3hr and describes medium-term ramping events that might be handled by dispatching additional capacity rather than relying on ancillary services. Thus, an increase in 3-hr ramp rates might indicate the need to displace slow-ramping base load generators with faster resources.

$$3HrRampRate(t) = NetLoad(t) - NetLoad(t - 12) \quad (2)$$

3.3.3. Ramp Factor

The ramp factor is calculated by dividing the 15-minute ramp rate by the net load of the previous 15-minute interval as shown in equation 3, where t is time in 15-minute intervals. It normalizes the ramp rate in terms of online capacity, where a ramp factor of 0.10 indicates that the dispatchable generation fleet must increase its output by 10% in the next 15 minutes. For example, the June 19, 2022 net load changes from 36,996 MW at 11:00 to 37,637 MW at 11:15 for a ramp factor of 0.017 ((37,637 - 36,996) / 36,996). It is measured in units of (MW/15min)/(MW online). An increase in ramp factors might indicate the need to commit additional generators but dispatch them at partial-capacity to increase the amount of reserve capacity on the grid.

$$RampFactor(t) = (NetLoad(t) - NetLoad(t - 1)) / (NetLoad(t - 1)) \quad (3)$$

3.3.4. Ramp Acceleration

As noted in prior work, the ramp acceleration is calculated by subtracting the previous interval's 15-minute ramp rate from the current interval's 15-minute ramp rate and taking the absolute value of the result [5] as shown in equation 4, where t is time in 15-minute intervals. For example, the June 19, 2022 net load changes from 39,752 MW at 12:00 to 40,422 MW at 12:15 and 40,276 MW at 12:30 for 15-minute

225 ramp rates of 670 MW/15min (40,422 - 39,752) at 11:15 and -146 MW/15min (40,276
 226 - 40,422) at 11:30 and a ramp acceleration of 816 MW/(15min·15min) (abs(-146 -
 227 670)) at 11:30. It's sole use in this study is for calculating volatility.

$$RampAccel.(t) = abs(15MinRampRate(t) - 15MinRampRate(t - 1)) \quad (4)$$

228 3.3.5. 1-Hr Volatility

229 The 1-hr volatility is calculated by summing the ramp accelerations over the
 230 previous hour as shown in equation 5, where t is time in 15-minute intervals. For
 231 example, the June 19, 2022 net loads for each 15 minute period from 12:00 to 13:30 are
 232 39,752, 40,422, 40,276, 40,136, 40,681, and 41,369 MW. These net loads yield ramp
 233 accelerations of 816, 6, 685, and 143 MW/(15min·15min) for each 15 minute period
 234 from 12:30 to 13:30. Adding these ramp accelerations together yields a volatility of
 235 1,650 (816 + 6 + 685 + 143) at 13:30. The 1-hr volatility is measured in units of
 236 MW/(15min·hr) and describes the intensity of short-term “chatter” in the net load
 237 profile that might be handled by faster-ramping resources. Thus, an increase in 1-hr
 238 volatility might indicate a temporary need to commit more fast-response resources
 239 to the grid.

$$1HrVolatility(t) = \sum_{t=1}^{t-4} RampAcceleration(t) \quad (5)$$

240 3.3.6. 1-Day Volatility

241 The 1-day volatility is calculated by summing the ramp accelerations over the
 242 previous 24 hours as shown in equation 6, where t is time in 15-minute intervals.
 243 This calculation is similar to the example calculation for subsection 3.3.5 except that
 244 96 ramp accelerations (24 hours' worth) are summed together instead of 4 (1 hour's
 245 worth). It is measured in units of MW/(15min·day) and describes the intensity of
 246 long-term “chatter” in the net load profile that might be handled by faster-ramping
 247 resources. Thus, an increase in 1-day volatility might indicate a semi-permanent
 248 need to commit more fast-response resources to the grid.

$$1DayVolatility(t) = \sum_{t=1}^{t-96} RampAcceleration(t) \quad (6)$$

249 3.4. Limitations

250 While this study offers some improvements over previous flexibility analyses as
 251 discussed in Section 2, it also experiences some limitations. First, this study fails
 252 to address the contribution of random stochastic noise to the overall flexibility re-
 253 quirements. Random noise contributes to flexibility requirements, especially in the

5-minute or less time scale [19]. Forecast errors due to the weather-related uncertainties of renewable energy power output also contribute to flexibility requirements [11]. Since this study assumes perfect knowledge of 15-minute resolution renewable energy generation, it ignores forecast errors and overlooks much of the random variation that can increase flexibility requirements on shorter timescales.

Additionally, the quality of the solar data might fail to capture extreme flexibility requirements caused by infrequent weather events. While this study uses multiple solar generation locations to simulate the smoothing effect of geographic diversity as recommended by Lettendre et al. [31], data collection over a larger geographic area might better represent this effect. Additionally, while converting the solar data from 30-minute to 15-minute intervals allows this study to be performed on a 15-minute time frame, thus preserving the resolution of the load and wind data, it produces a solar curve that is smoother than actual 15-minute data would be. Higher resolution solar data would improve the model’s ability to observe its variability at this time interval. Historical solar generation data would also be an improvement over the calculated solar data used in this study. Still, a large degree of solar variability results from the path of the sun through the sky, a variable that is easily anticipated [31] and is captured in the data used in this analysis. With these limitations in mind, the results from this study will be used to communicate the general flexibility trends associated with increased renewable energy generation, rather than analyzing specific dates or events.

Finally, though this study quantifies flexibility requirements using five different ramping and volatility metrics, there are numerous other calculations that could be used to discuss changing flexibility requirements [15]. Some of these metrics, such as the range in daily net load, have been excluded either due to their limited correlation with wind and solar peak output or with the brevity of this paper in mind.

4. Results and Discussion

The majority of the results are visualized using three different chart types. Density charts, as shown in Fig 6, plot the density function of the flexibility requirements calculated for each 15-minute interval of each year. The area under each density curve sums to 1. The x-axis is truncated to highlight the changing shape and center of the density curves. The maximum values, being excluded during these truncations, are shown in other chart types.

Contour charts, as shown in Figs 7 and 8, plot the median or maximum value of the flexibility requirements for each week of each year. Moving up the y-axis shows how increasing wind and solar peak output changes the flexibility requirements (since

the wind and/or solar output increases each year per Subsection 3.2). Moving across the x-axis shows how flexibility requirements change throughout the seasons.

Scatter charts, as shown in Figs 9 and 10, plot wind and solar peak output on the x-axis and flexibility units on the y-axis. These charts give a sense of the flexibility requirement quantities being experienced during each week. The solar section of the chart has a constant wind peak output of 13.1 GW while solar increases annually per Subsection 3.2. The regression lines suggest whether increased wind or solar peak output is noticeably correlated with flexibility requirements. Additional statistical analysis of the results can be found in Table A.8 in the Appendix.

4.1. Wind and Solar Peak Output Comparison

The following subsection analyzes the changes to the net load caused by increasing wind and solar peak output. The analysis is performed using the West scenario described in Subsection 3.2. Detailed results are presented in subsections 4.1.1-4.1.5 with a summary of the results shown in Table 5. In each subsection, the results will be discussed in consideration of both the wind era, where wind peak output increases from 2.4 GW to 13.1 GW during 2008-2015, and the solar era, where solar peak output increases from 0.6 to 12.0 GW during 2016-2025.

4.1.1. 1-Hr Ramp Rates

The 1-Hr ramp rate requirements for 2008-2025 are summarized in Figs 6 through 10. As wind peak output increases, the density curves in Fig 6 show no discernible trend and the median stays relatively centered on 0 MW/hr. Fig 8 shows a possible correlation between increasing wind peak output, decreasing December-March ramping, and increasing June-August ramping, but the effect is minor. Fig 10 suggests that early increases in wind peak output might actually reduce the maximum 1-hr ramp rates.

As solar peak output increases, the density curves in Fig 6 tend to widen, showing fewer ramp rates in the -1,000 to 2,000 MW/hr range and more in the <-1,000 and >3,000 MW/hr range with the median staying near 0. Fig 8 shows a noticeable correlation between maximum 1-hr ramp rates and solar peak output, especially from November to May. February 2023-2025 experiences some 1-hr ramp rates in excess of 12,000 MW/hr, the highest in this study. Fig 10 suggests that 1-hr ramp rates will increase with peak solar output.

4.1.2. 3-Hr Ramp Rates

The 3-Hr ramp rate requirements for 2008-2025 are summarized in Figs 11 through 15. As wind peak output increases, the density curves in Fig 11 show no discernible trend,

Figure 6: The 1-hr ramp rate becomes wider as the solar peak output increases while remaining relatively centered on 0 MW/hr.

Figure 7: The small changes in median 1-hr ramp rate do not appear to be correlated with season or year, remaining relatively centered on 0 MW/hr.

Figure 8: The maximum 1-hr ramp rate increases with solar peak output, especially between November and April.

Figure 9: The median 1-hr ramp rate does not appear to be correlated with wind or solar peak output.

Figure 10: The maximum 1-hr ramp rate appears to be positively correlated with peak solar output, while the first additions of wind peak output might have slightly reduced the maximum.

though Fig 12 suggests higher medians during the shoulder seasons in general. Fig 13 shows an increase in summer 3-Hr ramp rates as wind peak output increases, but the effect seems to level off. Fig 15 suggests that greater wind peak output increases maximum 3-Hr ramp rates.

As solar peak output increases, the density curves in Fig 11 tend to widen, showing fewer ramp rates in the -1,500 to 6,000 MW/3hr range and more in the <-1,500 and >6,000 MW/3hr range with the median shifting to the right. In Fig 12, the median summer 3-hr ramp rates change from negative to positive. Fig 13 shows a noticeable correlation between maximum 3-hr ramp rates and solar peak output from November through April. The maximum 3-hr ramp rates in the summer, being dominated by trends in the load, are not significantly altered by adding solar peak output. January and February 2023-2025 experiences some 3-hr ramp rates in excess of 18,000 MW/3hr, the highest in this study. Figures 14 and 15 suggests that 3-hr ramp rate medians and maximums tend to increase with peak solar output.

Figure 11: The 3-hr ramp rate becomes wider as the solar peak increases while shifting slightly towards the right.

4.1.3. Ramp Factors

The ramp rate requirements for 2008-2025 are summarized in Figs 16 through 20. As wind peak output increases, Figs 17 and 19 suggest that median ramp factor increases slightly. Figures 18 and 20 show that maximum ramp factor may tend to slightly decrease as wind peak output increases.

Figure 12: The median 3-hr ramp tends to be greater during the shoulder seasons and less during the summer and winter. Increased solar peak output appears to increase the summer median and reduce the winter and spring median.

Figure 13: Increased wind peak output appears to increase maximum 3-hr ramp rates during the summer. Increased solar peak output appears to increase maximum 3-hr ramp rates from November through April.

Figure 14: The median 3-hr ramp rate does not show a strong correlation with wind peak output, and appears to increase slightly with initial increases in solar peak output.

Figure 15: The maximum 3-hr ramp rate increases slightly with wind peak output and more significantly with solar peak output.

As solar peak output increases, the density curves in Fig 16 tend to widen and shift to the left, showing fewer ramp factors in the -0.005 to 0.025 ((MW/15min)/(MW online)) range and more in the <-0.005 range with the median shifting to the left. Fig 18 shows a noticeable correlation between maximum ramp Factors and solar peak output, especially from November to April. February 2025 experiences some ramp factors near 0.25 when 4.9 GW/15min ramp rates occur after net loads of just over 20 GW, situations where total dispatchable generation would need to increase by almost 25% during a 15-minute interval. Figs 19 and 20 suggest that ramp factor medians tend to decrease and maximums tend to increase with peak solar output.

4.1.4. 1-Hr Volatility

The 1-hr volatility requirements for 2008-2025 are summarized in Figs 21 through 25. As wind peak output increases, Figs 24 and 25 suggest only a small correlation with 1-hr volatility.

As solar peak output increases, the 1-hr volatility density curves in Fig 21 initially narrow and shift to the left, suggesting that the first 1,000 MW of solar in ERCOT might actually reduce median and large 1-hr volatility. Increasing solar peak output beyond this capacity shows a strong correlation with increased 1-hr volatility, as shown in Figs 22 through 25, with the contour charts suggesting a seasonal shift towards higher volatility from February through August and lower volatility from September through January. April-June of 2024-2025 experience some 1-hr volatilities in excess of 9,500 MW/(15min·hr), the highest in this study.

The year 2011, one the hottest and driest years in Texas history, shows uncharacteristically high maximum volatilities in the range of 6,500 MW/(15min·hr). While this year might be considered an outlier, it might provide a historical case study for future work on observing the effects of volatility on prices and dispatch costs.

Figure 16: The ramp factor distribution becomes wider as the solar peak increases while shifting towards the left.

Figure 17: The median ramp factor tends to be greater during April-June and September-November. Increased wind peak output appears to slightly increase the median while increased summer peak output tends to reduce it.

Figure 18: Maximum ramp factors are lowest in the summer when large amounts of online generation can more easily handle ramping from the net load. Increasing solar peak output increases the ramp factor, especially from October-May where ramp factors can reach over 0.20.

Figure 19: The median ramp factor tends to increase with wind peak output and decrease with solar peak output.

Figure 20: The maximum ramp factor tends to decrease slightly with wind peak output and increase with solar peak output.

Figure 21: The first 1,000 MW of solar peak output narrows the 1-hr volatility density curve, shifting it to the left; an improvement over the wind era. Additional solar peak output widens the curve and shifts it to the right.

Figure 22: Wind does not show a strong correlation with the median 1-hr volatility. Initially, increased solar peak output tends to reduce the 1-hr median volatility, especially from May through December, though it eventually increases it, particularly from December through June.

Figure 23: Increased solar peak output strongly correlates with increased maximum 1-hr volatility, especially from February through August. Note 2011, an outlier year, which shows strong maximum 1-hr volatility.

Figure 24: Increased wind peak output reduces 1-hr volatility. In the 9,500+ MW wind peak output range, a small amount of solar peak output (150-1,000 MW) might be responsible for the sharp reduction in median 1-hr volatility. Additional solar peak capacity increases the median 1-hr volatility.

Figure 25: Wind does not appear to be correlated with maximum 1-hr volatility, while peak solar output shows a strong direct relationship.

4.1.5. 1-Day Volatility

The 1-day volatility requirements for 2008-2025 are summarized in Figs 26 through 30. As wind peak output increases, Figs 24 and 25 suggest only a small correlation with 1-day volatility.

As solar peak output increases, the 1-day volatility density curves in Fig 26 initially narrow and shift to the left, suggesting that the first 1,000 MW of solar in ERCOT might actually reduce median and large 1-day volatility. Increasing solar peak output beyond this shows a strong correlation with increased 1-day volatility, as shown in Figs 27 through 30, with the contour charts suggesting a seasonal shift towards higher volatility from January through September and lower volatility from October through December. February and March of 2024-2025 experience some 1-day volatilities in excess of 40,000 MW/(15min·day), the highest in this study.

Figure 26: The first 1,000 MW of solar peak output shifts the 1-day volatility curve to the left without widening it significantly; an improvement over the wind era. Additional solar peak output widens the curve and significantly shifts it to the right.

4.1.6. Section 4.1 Results Summary

A summary of the results presented in subsections 4.1.1-4.1.5 is shown in Table 5. Table A.8, in the appendix (Section Appendix A), shows a more complete picture of the results for each year. The results indicate a number of significant correlations between solar capacity and the flexibility requirements analyzed in this study, while

Figure 27: Initially, increased solar peak output (2015-2017) tends to reduce the median 1-day volatility, especially from May through November, though it eventually increases it, particularly from February through June.

Figure 28: Increased solar peak output strongly correlates with increased maximum 1-day volatility, especially from January through September. Note 2011, an outlier year, which shows strong maximum 1-day volatility.

Figure 29: Increased wind peak output reduces 1-day volatility. In the 9,500+ MW wind peak output range, a small amount of solar peak output (150-1,000 MW) might be responsible for the sharp reduction in median 1-day volatility. Additional solar peak capacity increases the median 1-day volatility.

Figure 30: Wind does not appear to be correlated with maximum 1-day volatility, while peak solar output shows a strong direct relationship.

wind capacity tends to show only a few slight correlations. Based on Table A.8, adding 14.5 GW of solar (from 2016 - 2025) to the ERCOT grid increases maximum 1-hr ramp rates by 135%, 3-hr ramp rates by 30%, ramp factors by 140%, 1-hr volatility by 100%, and 1-day volatility by 30%. Solar tends to influence ramp rates most strongly from November to April and volatility from February through August. Since ERCOT's load is lowest in January, February, and March, it is likely that the most significant ramping and flexibility events will occur when fewer generators are on-line to provide flexibility resources and many generators are traditionally shut down for maintenance. Grid operators will need to anticipate these difficult flexibility situations and procure more flexibility resources on the grid as needed.

The lack of correlation between wind capacity and flexibility requirements contrasts with the results from the GE Energy study [19] discussed in Section 2. The GE Energy study predicts that ramp rates on all time frames from 1 minute to 1 hour will increase as wind capacity increases. The disagreement between these results and those presented in subsections 4.1.1-4.1.5 could be due to the GE Energy study's use of modeled weather data to produce calculated wind generation curves. This method for wind data generation might fail to capture the smoothing effects of geographic dispersion of renewable capacity [31] or other factors that influence wind variability. The GE Energy study does conclude that increasing ramp rates caused by wind generation will drive up the maximum amount of regulation reserves that will need to be provided for maintaining grid stability. If this conclusion holds for solar-induced ramp rate increases, then a more robust ancillary services market might be a necessary market response to increasing flexibility requirements.

Table 5: The results for Section 4.1 are summarized in this table.

		Effect of Increasing Wind Capacity	Effect of Increasing Solar Capacity
1-Hr Ramp Rate	Med.	No correlation	No correlation
	Max.	Slight increase in June-August. Slight decrease in December-March.	Significant increase, especially in November-April.
3-Hr Ramp Rate	Med.	No correlation	Slight increase then slight decrease, overall. Generally, increase in April-October and decrease in November-March.
	Max.	Slight increase, especially in June-September.	Moderate increase, especially in November-April.
Ramp Factor	Med.	Slight increase.	Moderate decrease.
	Max.	Slight decrease.	Significant increase, especially in November-April.
1-Hr Volatility	Med.	Undetermined. Possible synergies with small amounts of solar capacity.	Initial solar capacity might synergize with wind to decrease median. Additional capacity increases median.
	Max.	No correlation.	Significant increase, especially in February-August.
1-Day Volatility	Med.	Undetermined. Possible synergies with small amounts of solar capacity.	Significant increase.
	Max.	No correlation.	Significant increase, especially in January-September.

4.2. Solar Array Orientation and Location Comparisons

The following subsection analyzes the changes to the net load caused by changing the solar array orientation or location. The analysis is performed for the year 2025 using the scenarios described in Subsection 3.2. A table has been created for each scenario comparison listing the maximum, 95th percentile, median, 5th percentile, and minimum values for each flexibility requirement and each scenario. Dark green and dark red cell shading indicates when the absolute value of a cell is 20% less or more than the average value. Light green and light red cell shading indicates when the absolute value of a cell is 10% less or more than the average value. By this convention, green cells represent easier-to-manage flexibility requirements, while red cells represent more-difficult ones, and darker shading represents a stronger sense of that definition.

4.2.1. Orientation Comparison

Table 6 lists the flexibility requirement statistics for the different solar array orientation scenarios in 2025. For example, reading across the “1-Hr Ramp Rate; Max” row, averaging the maximum 1-hr ramp rates of the six scenarios yields 12,401 MW/hr. The “Fixed W” and “Fixed SW” maximum values are within 10% of this

average value and do not warrant special attention. The “Fixed S” maximum of 10,546 MW/hr is more than 10% lower than the average and is shaded light green to indicate this benefit. Additionally, the “Fixed SE” maximum of 7,568 MW/hr is more than 20% lower than the average and is shaded dark green to indicate this benefit. Likewise, the “1-Axis Tr.” and “2-Axis Tr.” maximums of 14,854 and 16,869 MW/hr are more than 10% and 20% greater than the average, respectively, and are shaded light and dark red to indicate this difficulty.

The cell shading indicates a strong tendency for tracking arrays to introduce more difficult-to-manage flexibility requirements to the grid. Among the fixed panel arrays, the south- and southeast-facing arrays show noticeable benefits over the west- and southwest-facing arrays.

There is a give-and-take between energy production, which is maximized by using tracking arrays, and flexibility requirements, which are minimized by using fixed arrays. Grid planners might consider these effects when thinking strategically about future solar capacity, especially as it might pertain to balancing commercial, 1-axis tracking arrays and distributed, roof-top arrays.

Additionally, there is little support here for the theory that west-facing panels might better align with load and reduce flexibility requirements [32]. The other fixed orientations analyzed in this study all produce greater energy with lower flexibility requirements than the west-facing scenario.

4.2.2. Location Comparison

Table 7 lists the flexibility requirement statistics for the different solar array location scenarios in 2025. The cell shading indicates less diversity in flexibility requirements than shown for the orientation scenarios in Table 6. There is a slight tendency for the arrays that generate less energy to require less flexibility from the grid, but this tendency could simply be due to the amount of energy being generated rather something inherent in the geographic location.

5. Conclusions

The primary goal of this study is to quantitatively assess the correlation of growing wind and solar peak output with changing flexibility requirements. When observing the effects of solar generation on the net load flexibility, this study finds a number of strong correlations. In relation to ramp rates, solar significantly increases maximum ramp factors and 1-hr and 3-hr ramp rates, especially during the winter and spring. It flips the median 3-hr summer ramp rates from negative to positive. These trends indicate that grids with growing solar capacity should anticipate their

Table 6: The statistical distribution for each flexibility requirement and orientation scenario is shown below. Dark green and dark red cell shading indicates when a the absolute value of a cell is 20% less or more than the average value of the six scenarios. Light green and light red cell shading indicates when a the absolute value of a cell is 10% less or more than the average value.

		Avg	Fixed W	Fixed SW	Fixed S	Fixed SE	1-Axis Tr.	2-Axis Tr.
Energy Gen.	(TWh)	26.2	20.8	23.5	24.7	23.8	29.9	34.4
1-Hr Ramp Rate	Max	12,401	12,152	12,417	10,546	7,568	14,854	16,869
	95%	3,801	3,538	3,515	3,444	3,535	4,323	4,449
	Med	-7	51	59	55	6	-114	-100
	5%	-3,839	-3,669	-3,722	-3,760	-3,791	-3,936	-4,156
	Min	-8,895	-8,375	-8,375	-8,375	-8,375	-8,873	-10,997
3-Hr Ramp Rate	Max	20,384	19,839	20,838	19,861	17,344	21,096	23,328
	95%	9,412	8,389	8,578	8,960	9,457	10,196	10,892
	Med	294	577	515	413	190	55	15
	5%	-10,320	-10,083	-10,286	-10,365	-10,331	-10,221	-10,634
	Min	-18,866	-18,523	-18,523	-18,523	-18,523	-18,523	-20,581
Ramp Factor	Max	0.18	0.15	0.15	0.10	0.09	0.24	0.32
	95%	0.03	0.03	0.03	0.03	0.03	0.03	0.03
	Med	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	5%	-0.03	-0.02	-0.03	-0.03	-0.03	-0.03	-0.03
	Min	-0.10	-0.07	-0.07	-0.08	-0.09	-0.13	-0.18
1-Hr Volatility	Max	7,943	8,333	7,037	5,184	5,184	10,405	11,518
	95%	2,605	2,216	2,209	1,810	1,601	3,491	4,300
	Med	614	581	589	597	599	651	667
	5%	203	195	201	206	205	206	206
	Min	7	7	7	7	7	7	7
1-Day Volatility	Max	41,319	37,526	37,670	38,011	38,509	44,268	51,933
	95%	28,295	26,410	26,252	25,083	24,236	32,323	35,467
	Med	20,482	18,871	18,652	17,420	16,821	23,852	27,276
	5%	14,451	12,751	12,769	11,923	11,294	17,206	20,765
	Min	9,226	7,557	7,583	7,096	8,251	10,253	14,613

Table 7: The statistical distribution for each flexibility requirement and location scenario is shown below. Dark green and dark red cell shading indicates when a the absolute value of a cell is 20% less or more than the average value of the three scenarios. Light green and light red cell shading indicates when a the absolute value of a cell is 10% less or more than the average value.

		Avg	West	Central	South
Energy Gen.	(TWh)	27.5	29.9	24.8	27.9
1-Hr Ramp Rate	Max	13,259	14,854	12,044	12,879
	95%	4,174	4,323	4,036	4,163
	Med	-91	-114	-58	-100
	5%	-3,847	-3,936	-3,771	-3,834
	Min	-9,676	-8,873	-9,660	-10,496
3-Hr Ramp Rate	Max	19,460	21,096	18,422	18,862
	95%	9,924	10,196	9,742	9,833
	Med	86	55	127	75
	5%	-10,093	-10,221	-10,010	-10,049
	Min	-18,632	-18,523	-18,523	-18,851
Ramp Factor	Max	0.20	0.24	0.15	0.21
	95%	0.03	0.03	0.03	0.03
	Med	0.00	0.00	0.00	0.00
	5%	-0.03	-0.03	-0.03	-0.03
	Min	-0.11	-0.13	-0.09	-0.10
1-Hr Volatility	Max	9,312	10,405	7,951	9,579
	95%	3,077	3,491	2,699	3,040
	Med	671	651	682	681
	5%	208	206	210	210
	Min	7	7	7	7
1-Day Volatility	Max	44,856	44,268	46,034	44,268
	95%	31,975	32,323	31,277	32,323
	Med	23,481	23,852	22,738	23,852
	5%	16,894	17,206	16,268	17,206
	Min	10,364	10,253	10,588	10,253

ability to double or triple their historical peak ramp up rates, especially during low-demand seasons (winter and spring), and to ramp up more regularly during seasons of high demand (summer).

In relation to volatility, solar shows even stronger tendencies to increase flexibility requirements. The median and maximum 1-hr and 1-day volatilities show a significant correlation with increased peak solar output. While this effect is less intense during the fall and winter, increased volatility during the spring and summer can be quite severe. The increasing maximum values require some consideration, though ERCOT experienced a few events with very high volatility in 2011 that it was able to accommodate. But the fact that median volatility also increases means that extreme volatility will be a much more regular occurrence. Based on the results in this study, adding 8+ GW of solar to ERCOT could create a grid where almost every week will be more volatile than the majority of weeks to date.

When observing the effects of wind generation on the net load flexibility, however, this study discovers only minor correlations. Greater wind peak generation might slightly increase ramp rates, particularly in the summer, but in most other metrics its influence is either very small or does not follow a consistent trend. This independence is surprising as it contradicts conventional wisdom in the utility world and the correlations suggested by the GE Energy study discussed in Section 2 [19]. Perhaps the GE Energy study's use of modeled weather data and calculated wind generation profiles might have failed to reproduce the smoothing effects of geographic dispersion of wind farms or other factors that influence the variability of wind. The GE Energy study's conclusion that increasing ramp rates will drive up the need for regulation reserves insinuate that a more robust ancillary services market might be a necessary response to the increasing flexibility requirements discussed in Section 4.1 of this paper.

Perhaps the difference in wind and solar potency can be explained by their generation profiles. Solar generation follows a predictable pattern of daily ramping and cycling punctuated by periods of cloudiness that exacerbate its profile. The timing difference between this daily solar generation pattern and the load profile is the driving factor behind solar's tendency to increase flexibility requirements. Wind does show some daily and seasonal trends [33], but they are not as consistent or as predictable as the daily solar generation profile. Wind generation can be relatively high or low for many days on end. Thus, while wind is capable of creating high flexibility requirements, its tendency to do so appears to be stochastic over a time frame of many years.

There is also noticeable tendency for small amounts of solar generation to actually improve flexibility requirements, particularly in relation to volatility requirements.

499 Perhaps this improvement is related to the tendency of wind generation to slow
500 down during the day [33] when solar generation is peaking. A grid with existing
501 wind capacity and net load volatility concerns might consider the possibility that
502 some solar capacity would improve its situation.

503 This study also draws some important conclusions about the influence of solar ar-
504 ray orientation and geographic location on flexibility requirements. Tracking arrays,
505 while they produce more energy over the year, also create significantly greater flexi-
506 bility requirements than fixed arrays. Facing panels to the west, sometimes suggested
507 as an option for decreasing flexibility requirements [32], actually increases them when
508 compared to other fixed orientations and produces less energy as well. Rather unintu-
509 itively, southeast-facing panels appear to significantly reduce flexibility requirements
510 with minor reductions in energy generation when compared to other fixed panels.
511 Solar array location only shows small correlations with flexibility requirements, and
512 those correlations might depend solely on their different annual energy generation
513 amounts.

514 This study gives a specific look at how flexibility requirements might be changing
515 in the ERCOT marketplace, and a general intuition about how other grids can an-
516 ticipate the influence of renewable generation on their own net loads. Some of these
517 flexibility requirement issues might be reduced with future shifts in the demand curve
518 or increased geographic diversity of renewable generation. For example, widespread
519 implementation of energy storage and demand response schemes would change the
520 demand curve, which would affect the net load and flexibility requirements. Still,
521 planning for increasing ramping and volatility in the grid is an important aspect
522 of solar capacity expansion. Electric grids that have demonstrated their ability to
523 handle large amounts of wind generation should not assume they can handle large
524 amounts of solar. They should consider their future flexibility requirements in light
525 of their existing flexibility capabilities. In this way, shortcomings can be addressed
526 by adjusting the geographic location and orientation of future solar assets, or by em-
527 ploying energy storage, market redesign, or one of the numerous strategies discussed
528 in Section 2, and our electric grids can continue to provide reliable power at the
529 lowest possible cost.

530 6. Future Work

531 This study provides a detailed quantification of the growing flexibility require-
532 ments that will accompany growing solar capacity. The natural progression of this
533 work is to better understand how these changes in ramping and volatility can be
534 addressed. The authors will first employ unit commitment modeling and other tech-
535 niques to assess the costs that each of the different flexibility requirements imposes

536 on the grid. These results will be useful in assessing the economic benefits of reducing
537 different flexibility requirements and providing an opportunity to explore technolo-
538 gies and strategies for doing so.

539 7. Acknowledgments

540 This work was sponsored by funding from the National Science Foundation's
541 Integrative Graduate Education and Research Traineeship Program, the US Depart-
542 ment of Energy, and the Electric Reliability Council of Texas. Data used in this
543 analysis were provided by the Electric Reliability Council of Texas and the National
544 Renewable Energy Laboratory.

8. References

- [1] N. Panwar, S. Kaushik, S. Kothari, Role of renewable energy sources in environmen-
tal protection: a review, *Renewable and Sustainable Energy Reviews* 15 (3) (2011)
1513–1524.
- [2] C. Y. Chen, The geographic disparity of the ptc & itc, *Energy Central* (2016).
- [3] M. da Graça Carvalho, EU energy and climate change strategy, *Energy* 40 (1) (2012)
19–22.
- [4] M. Bilgili, A. Ozbek, B. Sahin, A. Kahraman, An overview of renewable electric power
capacity and progress in new technologies in the world, *Renewable and Sustainable
Energy Reviews* 49 (2015) 323–334.
- [5] T. A. Deetjen, J. B. Garrison, J. D. Rhodes, M. E. Webber, Solar PV integration cost
variation due to array orientation and geographic location in the Electric Reliability
Council of Texas, *Applied Energy* 180 (2016) 607–616.
- [6] H. Lund, Renewable energy strategies for sustainable development, *Energy* 32 (6)
(2007) 912–919.
- [7] California Independent System Operator, What the duck curve tells us about manag-
ing a green grid, (2013).
- [8] H. Holttinen, A. Tuohy, M. Milligan, E. Lannoye, V. Silva, S. Mu, L. Söder, et al.,
The flexibility workout: managing variable resources and assessing the need for power
system modification, *IEEE Power and Energy Magazine* 11 (6) (2013) 53–62.

- [9] H. Holttinen, J. Kiviluoma, A. Estanqueiro, T. Aigner, Y.-H. Wan, M. Milligan, Variability of load and net load in case of large scale distributed wind power, in: 10th International Workshop on Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Power Farms, August 2010., 2010.
- [10] T. A. Deetjen, M. E. Webber, Costs associated with grid-level solar integration, in: 2016 World Energy Engineering Congress Proceedings, Association of Energy Engineers, 2016.
- [11] L. Hirth, F. Ueckerdt, O. Edenhofer, Integration costs revisited—an economic framework for wind and solar variability, *Renewable Energy* 74 (2015) 925–939.
- [12] W. O. Amor, H. B. Amar, M. Ghariani, Grid stability study after the integration of a wind farm, in: 2015 16th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA), IEEE, 2015, pp. 678–683.
- [13] J. C. Boemer, K. Burges, P. Zolotarev, J. Lehner, P. Wajant, M. Fürst, R. Brohm, T. Kumm, Overview of German grid issues and retrofit of photovoltaic power plants in Germany for the prevention of frequency stability problems in abnormal system conditions of the ENTSO-E region continental Europe, in: 1st International Workshop on Integration of Solar Power into Power Systems, Vol. 24, 2011.
- [14] C. W. Potter, A. Archambault, K. Westrick, Building a smarter smart grid through better renewable energy information, in: Power Systems Conference and Exposition, 2009. PSCE'09. IEEE/PES, IEEE, 2009, pp. 1–5.
- [15] P. D. Lund, J. Lindgren, J. Mikkola, J. Salpakari, Review of energy system flexibility measures to enable high levels of variable renewable electricity, *Renewable and Sustainable Energy Reviews* 45 (2015) 785–807.
- [16] S. Clò, A. Cataldi, P. Zoppoli, The merit-order effect in the Italian power market: The impact of solar and wind generation on national wholesale electricity prices, *Energy Policy* 77 (2015) 79–88.
- [17] M. Nicolosi, Wind power integration and power system flexibility—an empirical analysis of extreme events in Germany under the new negative price regime, *Energy Policy* 38 (11) (2010) 7257–7268.
- [18] C. Clastres, T. H. Pham, F. Wurtz, S. Bacha, Ancillary services and optimal household energy management with photovoltaic production, *Energy* 35 (1) (2010) 55–64.

- [19] GE Energy, Analysis of wind generation impact on ERCOT ancillary services requirements, Prepared for the Electricity Reliability Council of Texas. Schenectady, New York: GE Energy (2008).
- [20] P. Denholm, M. Hand, Grid flexibility and storage required to achieve very high penetration of variable renewable electricity, *Energy Policy* 39 (3) (2011) 1817–1830.
- [21] H. L. Ferreira, R. Garde, G. Fulli, W. Kling, J. P. Lopes, Characterisation of electrical energy storage technologies, *Energy* 53 (2013) 288–298.
- [22] C. Harris, J. P. Meyers, M. E. Webber, A unit commitment study of the application of energy storage toward the integration of renewable generation, *Journal of Renewable and Sustainable Energy* 4 (1) (2012) 013120.
- [23] M. E. Clayton, A. S. Stillwell, M. E. Webber, Implementation of brackish groundwater desalination using wind-generated electricity: A case study of the energy-water nexus in Texas, *Sustainability* 6 (2) (2014) 758–778.
- [24] P. Cappers, C. Goldman, D. Kathan, Demand response in us electricity markets: Empirical evidence, *Energy* 35 (4) (2010) 1526–1535.
- [25] A. Pina, C. Silva, P. Ferrão, The impact of demand side management strategies in the penetration of renewable electricity, *Energy* 41 (1) (2012) 128–137.
- [26] W. Kempton, J. Tomić, Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy, *Journal of power sources* 144 (1) (2005) 280–294.
- [27] M. Hüber, D. Dimkova, T. Hamacher, Integration of wind and solar power in Europe: Assessment of flexibility requirements, *Energy* 69 (2014) 236–246.
- [28] R. Searcy, New pilot program offers incentives to reduce electric use during summer peaks, Electric Reliability Council of Texas Press Release (March 25, 2015).
- [29] National Renewable Energy Laboratory, National Solar Radiation Database. Available from <https://nsrdb.nrel.gov/> (Accessed on May, 2016).
- [30] National Renewable Energy Laboratory, System Advisor Model. Available from <https://sam.nrel.gov/>.
- [31] S. Letendre, M. Makhyoun, M. Taylor, Predicting solar power production: irradiance forecasting models, applications and future prospects, Solar Electric Power Association, Tech. Rep. (2014).

- [32] K. Tweed, California’s fowl problem: 10 ways to address the renewable duck curve, Greentech Media (2014).
- [33] Y.-h. Wan, Analysis of wind power ramping behavior in ERCOT, Contract 303 (2011) 275–3000.

Appendix A. Statistical Table of Results

The following table contains some statistical information about the 2008-2025 scenarios as discussed in Subsection 4.1. It shows the maximum, 95th percentile, median, 5th percentile, and minimum values for each of the flexibility requirements over every 15-minute interval per year. It is informative to read across the rows and see how different aspects of the flexibility requirements change with increasing wind and solar peak output.

Table A.8: The following table shows the maximum, 95th percentile, median, 5th percentile, and minimum values for each of the flexibility requirements over every 15-minute interval per year.

		Wind Era									Solar Era								
		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
1-Hr Ramp Rate	Max	6,548	6,023	6,538	6,013	6,426	6,334	6,484	6,223	6,364	7,157	8,125	9,089	10,050	11,010	11,971	12,932	13,893	14,854
	95%	3,049	3,188	3,243	3,471	3,302	3,338	3,327	3,268	3,369	3,397	3,442	3,507	3,613	3,730	3,883	4,035	4,186	4,323
	Med	-14	-25	-48	-37	0	-22	-15	21	25	25	14	-3	-14	-40	-65	-80	-94	-114
	5%	-3,026	-3,034	-3,121	-3,318	-3,253	-3,279	-3,280	-3,340	-3,442	-3,449	-3,468	-3,491	-3,542	-3,596	-3,657	-3,734	-3,819	-3,936
	Min	-5,594	-5,739	-6,024	-6,006	-6,645	-5,739	-6,006	-7,844	-8,241	-8,260	-8,277	-8,293	-8,305	-8,319	-8,333	-8,347	-8,360	-8,873
3-Hr Ramp Rate	Max	12,714	13,300	14,498	15,765	14,975	14,341	14,437	16,380	16,675	16,739	16,796	16,810	16,798	16,809	17,879	18,951	20,023	21,096
	95%	7,859	8,069	8,285	9,079	8,460	8,504	8,356	8,688	8,866	8,805	8,799	8,885	8,999	9,166	9,347	9,571	9,834	10,196
	Med	126	129	16	88	175	72	127	184	222	281	312	315	326	301	261	200	131	55
	5%	-8,182	-8,262	-8,556	-9,258	-8,990	-8,950	-9,006	-9,250	-9,482	-9,509	-9,542	-9,586	-9,645	-9,703	-9,803	-9,937	-10,097	-10,221
	Min	-14,248	-14,078	-15,260	-16,043	-15,565	-15,180	-15,383	-17,337	-17,919	-18,008	-18,089	-18,156	-18,216	-18,277	-18,338	-18,400	-18,462	-18,523
Ramp Factor	Max	0.0770	0.0799	0.0747	0.0840	0.0674	0.0840	0.0904	0.0839	0.1076	0.1049	0.1020	0.1088	0.1216	0.1439	0.1672	0.1916	0.2171	0.2438
	95%	0.0241	0.0251	0.0256	0.0259	0.0258	0.0259	0.0255	0.0254	0.0267	0.0268	0.0272	0.0275	0.0282	0.0289	0.0296	0.0302	0.0308	0.0316
	Med	-0.0002	-0.0003	-0.0004	-0.0004	-0.0002	-0.0003	-0.0003	0.0001	0.0001	0.0001	-0.0001	-0.0003	-0.0005	-0.0007	-0.0009	-0.0010	-0.0012	-0.0014
	5%	-0.0234	-0.0237	-0.0241	-0.0247	-0.0248	-0.0247	-0.0245	-0.0252	-0.0264	-0.0260	-0.0257	-0.0254	-0.0255	-0.0257	-0.0261	-0.0265	-0.0271	-0.0275
	Min	-0.0537	-0.0600	-0.0581	-0.0560	-0.0555	-0.1128	-0.0917	-0.0620	-0.0750	-0.0733	-0.0714	-0.0692	-0.0732	-0.0859	-0.0983	-0.1102	-0.1219	-0.1332
1-Hr Volatility	Max	3,132	3,776	4,280	6,866	3,284	4,608	4,773	4,875	5,188	5,187	5,187	5,186	5,874	6,780	7,686	8,593	9,499	10,405
	95%	1,316	1,299	1,343	1,469	1,281	1,275	1,316	1,136	1,281	1,400	1,589	1,826	2,089	2,349	2,629	2,905	3,196	3,491
	Med	566	528	570	602	566	559	576	450	497	522	542	559	575	592	608	622	637	651
	5%	209	187	207	226	214	216	228	149	163	169	176	183	187	193	196	200	203	206
	Min	23	23	19	22	37	20	17	7	7	7	7	7	7	7	8	7	7	7
1-Day Volatility	Max	24,168	26,740	26,907	43,328	25,067	24,663	25,560	29,585	34,145	34,544	35,269	36,022	36,942	38,066	39,461	40,942	42,570	44,268
	95%	19,080	19,565	20,138	25,288	18,934	18,763	19,798	18,019	20,782	21,556	22,511	23,575	24,781	26,128	27,640	29,145	30,663	32,323
	Med	15,279	14,629	15,328	15,902	15,155	15,052	15,275	12,204	13,525	14,412	15,413	16,482	17,620	18,805	20,034	21,280	22,584	23,852
	5%	11,764	9,981	11,303	11,912	11,499	11,589	12,087	7,724	8,423	9,336	10,421	11,433	12,370	13,365	14,296	15,286	16,266	17,206
	Min	8,176	7,384	7,188	6,975	7,455	7,514	8,421	4,893	5,175	5,701	6,297	7,085	7,917	8,434	8,858	9,278	9,763	10,253