Calculation and Validation of Weather-Informed Renewable Generator Capacities in the Identification of Renewable Resource Droughts

Jessica L. Wert, Thomas Chen, Farnaz Safdarian, Jonathan Snodgrass, Thomas J. Overbye
Department of Electrical and Computer Engineering
Texas A&M University
College Station, TX
{jwert, thomas-chen, fsafdarian, snodgrass, overbye}@tamu.edu

***Abstract*—This paper presents a weather-informed calculation of wind and solar photovoltaic generation capacity, validates the calculated capacity against wind and solar generation totals from the U.S. Energy Information Administration in 2021, and applies the validated technique to determine wind and solar resource droughts in the United States for 1973–2022. As renewable generation sources rely on variable resources such as wind or solar irradiance, the actual availability of the renewable resources may be insufficient if electric grid studies and analyses are performed using its rated capacity. Improved methods for more accurately calculating renewable power outputs given weather data are discussed and resource drought examples are presented for U.S. states with high amounts of renewable generation.**

***Index Terms*—renewable generation, renewable resource drought, weather, power systems planning**

I. Introduction

Renewable generation provides inexpensive power generation that produces no operational emissions and comprises a growing portion of the power generation mix in the United States. Based on U.S. Energy Information Administration (EIA) Form EIA-860 [1] in 2021 around 16% of the overall generation capacity is supplied from renewable energy. This portion is expected to grow in the coming years as more wind and solar capacity is planned [2]. As the percentage of electricity generated using renewable sources is increases, traditional resource adequacy studies must now consider the variablity of renewable resources to ensure electric grid reliability and resiliency [3], [4]. There is a growing concern about outlier weather events that can reduce the total availability of renewable resources over longer periods of time. These events are referred to as wind resource droughts (WRDs), solar resource droughts (SRDs), or more generically as renewable resource droughts (RRDs) [5], [6]. The purpose of this paper is to study the prevalence of RRDs using weather over the previous fifty years.

The concept of a renewable resource drought is inspired by [7] which defines "drought," as "a period of abnormally dry weather sufficiently long enough to cause a serious hydrological imbalance." As illustrated in the literature, both a traditional rain "drought," and RRDs do not have a precisely defined duration or geographic extent but they do need to be sufficiently long and wide-spread to cause an impact. They also needs to be "abnormal," as mentioned in its definition. Just as a rain drought only makes sense in comparison to the average rainfall in a given location or timeframe, a WRD or SRD is only meaningful when compared to typical values of wind or solar generation; thus it would not be meaningful to determine RRDs in areas with little installed renewable generation.

Additionally, there are a variety of definitions in the literature for the criteria of resource droughts. The classification of a drought event involves the resource availability being less than a given threshold for an extended period of time. Similarly to the work in this paper, [8] used historical weather data to calculate possible wind and solar output power, then calculated the occurrence of weather droughts using half of the daily mean value over the 39-year study period as the threshold. In contrast, [9] uses data based on the ERA5 re-analysis [10] and proposes the 10th percentile of the average calculated renewable power as the threshold. However, neither [8] nor [9] validated the calculated wind and solar output power values using actual renewable MW output values.

Much like the thresholds and periods being defined in a variety of ways in the literature, the data considered is different for various studies with respect to geographic regions, years, resolution, and consideration of weather measurements or resulting power availability. Some studies [11]–[14] consider only weather measurements (e.g., wind speed) in their determination of droughts. Others [8], [15], [16] use weather data such as wind speeds as input to wind turbine power curves for hypothetical or approximated generator outputs in the regions of study. In contrast, this paper calculates approximate MW output power for both solar and wind plants using wind speed and cloud cover data. As later demonstrated, these calculations are validated against actual renewable power production data and are shown to be highly accurate in most cases.

Additionally, several references in the literature study the impact of droughts on the electrical grid in different parts of the world. In [17], WRDs were found to be more intense than SRDs in India. Another study evaluated the energy security threat posed by RRDs on the Finnish grid [18]. The role of renewable generation in reducing the risks of droughts in the Brazilian system is presented in [19]. Reference [11] quantified the probability of RRDs in Poland, noting that if the SRDs and WRDs are considered jointly, the result is smaller probability of RRDs and lower intermittency. The

Presented at the IEEE PowerTech 2023, Belgrade, Serbia, June 2023.

costs associated with RRDs in California were shown to be reduced in scenarios in which California shares resources with the remainder of the U.S. Western Interconnection [8]. Finally, a methodology for including the effect of weather (and by extension RRDs) in the power flow is given in [20].

The key point of this paper is to gather the key weather measurements and run simulations to find the outputs of renewable generators based on the availability of these resources. This is accomplished using the power curves of wind and solar plants determined using information in the the EIA-860 data [1]. Next, the calculated weather-informed available power capacity of wind and solar generators are validated against wind and solar generation totals from the 2021 EIA-860 data. The renewable resource droughts are then determined by examining wind and solar outputs that are considerably below normal values for extended periods of time. Methods for improved accuracy and statistics on resource drought severity and duration are discussed with examples presented for U.S. states with high amounts of renewable generation considering that these droughts create problems in the grid relative to the load.

The remainder of this paper includes details on the data and models (Section II), the methodology of calculating weather-informed capacity of wind and solar generators using this data and definitions of RRDs (Section III). Examples and statistics of RRDs from the last fifty years are presented in Section IV. The weather-informed calculation of renewable generator capacity foundational to the RRD identification is validated (Section V), and future directions are presented (Section VI).

II. Data Overview

A. Input Data

The identification of the potential for WRDs and SRDs requires a knowledge of the capacity and location of the wind and solar generators. For this work with its focus on the U.S., this information is publicly available in the yearly U.S. EIA-860 datasets [1]. The actual generation capacity is, of course, continually changing. This work used the more recent dataset, which represents the installed capacity at the end of 2021. This set has a total 1485 wind generators with a combined capacity of 132 GW and a total of 5270 solar generators with a combined capacity of 61 GW. With this data, generators are represented with their main characteristics such as fuel type, capacity, and exact geographic locations.

Since the capacity of wind and solar generators is dependent on the weather conditions, measurements including wind speed and cloud cover are used from several thousands of weather stations. The specific weather data used in this paper includes hourly weather measurements of wind speed, cloud coverage, temperatures, dew point, and humidity over the continental United States from 1973 to 2022. Using the geographic coordinates of the generators and the weather stations, the weather measurements can be mapped to electrical generators based on their geographic proximity [20]. If there is missing data points in the input weather data, either a Delaunay Triangulation-based interpolation or the closest station with valid measurements is used, as explained in [20].

B. Weather Models

Four generic wind models and one generic solar model presented in [20] are used to directly incorporate weather measurements such as wind speed and cloud coverage in the power system model. This enables the calculation of the capacity of renewable generation (i.e., wind and solar photovoltaic) that reflects the weather conditions.

The weather measurements are mapped to renewable generators based on geographic proximity. With the weather stations assigned to generators, the hourly generator capacity can be calculated by using the device power curve. The EIA-860 data contains the model numbers for each of the generators, making it straightforward to represent the performance of the generators [1]. For a wind turbine, this is a speed-power curve. For a solar photovoltaic (PV) generator, the model calculated the power generation capacity based on cloud coverage as well as information on date and time.

III. Methodology

The methodology to find renewable resource droughts (RRDs) begins with the calculation of weather-informed generator capacity as shown in Fig. 1. First, for each hourly timestep from January 1, 1973 to March 1, 2022, the weather measurements including wind speed, wind directon and percent cloud coverage for each region of study are used to calculate the output power of all wind turbines and solar plants in the contiguous United States. Two examples of this approach are illustrated in Fig. 2 and 3, with each showing the spatial distribution of the total wind and solar generation, with the values visualized using the geographic data view (GDV) approach of [21], [22]. In particular, the area of the green ovals (GDVs) is proportional the wind generation whereas the size of the yellow GDVs is proportional to the solar generation. The spatial variation in the wind speed is contoured using the orange color scale. As an example of these GDVs, Fig. 2 presents a visualization of the hour in 2021 with the highest total combined modeled wind and solar generation (a total of 155 GW), whereas Fig. 3 shows the hour in 2021 with the least wind generation in Texas.

The detailed hourly calculated output data of wind turbines and solar farms based on the proposed strategy below is used for the states with the largest wind and solar capacity in the U.S. for each hour of the year to find the historic distribution of wind power availability. The states with the largest capacity of installed wind turbines based on [1] include Texas, Iowa, and Oklahoma and the states with the largest installed solar generation capacity include California, Texas, and North Carolina. Therefore, the historical statistics of these states are studied in more detail. Fig. 4 shows the historic distribution of calculated daily wind energy availability in Texas, Iowa, and Oklahoma, respectively and Fig. 5 shows the historical distribution of calculated daily solar PV energy availability in California, Texas, and North Carolina. Each point in these curves is achieved from the data of calculated hourly MW output of wind and solar plants from 1973 to 2022, aggregated on a daily basis. The various curves in each figure represent the minimum, 10th percentile, 20th percentile, average, 80th percentile, 90th percentile, and maximum values for each day within the year-long historical distribution.

Next, the RRDs are identified using three key aspects of resource droughts: severity, duration, and geographical area impacted. To determine the severity, a daily combined, year-long historical distribution of the calculated renewable data is created for each day of the year across all 50 study years (1973–2022). First, the daily combined MWh values

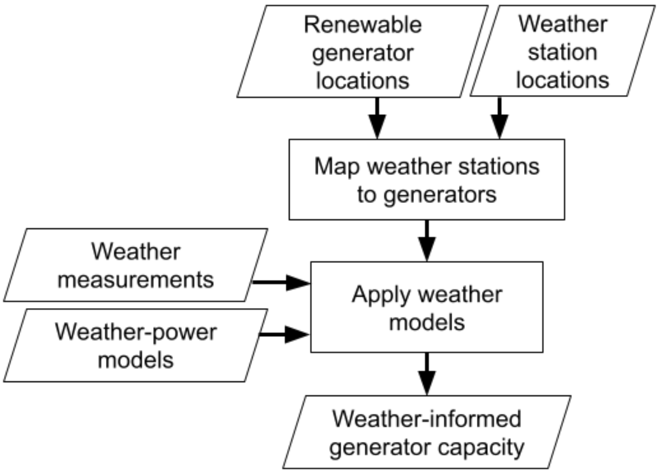


Fig. 1: Approach to calculate wind and solar generator capacity using wind speeds and cloud coverage as weather inputs, respectively.

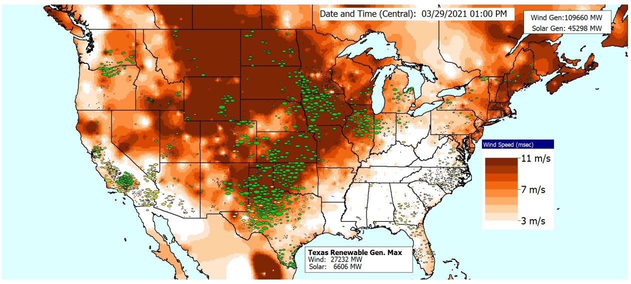


Fig. 2: 2021 Peak combined wind and solar generation

for the wind and solar are computed by adding up the hourly production for each day of the roughly 18,000 day study period (January 1, 1973 to March 1, 2022). Then, a year-long (365-day) historical distribution is created to compare the renewable power output at a given date with ranges of the historical values at that date across the 50 year study period. In other words, starting with January 1, all of the January 1st renewable production data across all 50 years is used to create a historical distribution with 7 quantile values as described above (min, 10th, 20th, 50th, 80th and 90th and max). This process is repeated for all 365 days of the year, across all 50 years. The results shown aggregated on a daily basis in Fig. 4 and 5.

Second, the resource availability threshold for an RRDs is defined as a wind power availability below the 25% of the daily mean of the historic availability curves (Fig. 4 or a solar power availability below 40% of the daily mean 5). For both wind and solar, a time period of 2 days (48 hours) or more is used. However, this definition can be adapted to change based on power system operational conditions such as demand, availability of other conventional generators, and transmission line outages. More importantly, if the resource drought is severe (e.g. below 15% of the mean for wind or 30% of the mean for solar), a shorter period of WRD could also create operational challenges. On the other hand, if the resource drought is not severe but lasts over a long period of time and impacts a very large area, it could also create serious reliability issues for the grid.

Finally, the identification of RRDs requires the specification of the impacted geographic region. The region to

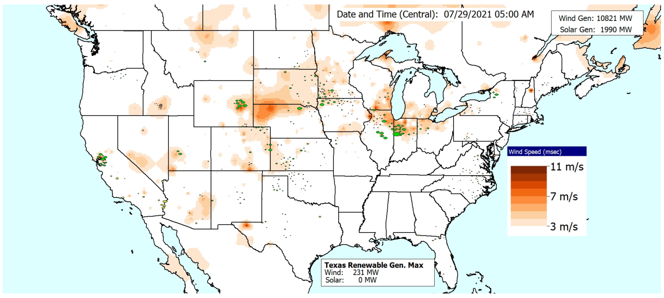


Fig. 3: 2021 Minimum combined wind and solar generation

be considered depends on the magnitude of the RRD and the characteristics of the associated electric grid. Here, for convenience and to aid with validation, the regions are defined as U.S. states, though the approach itself can be generalized for any region.

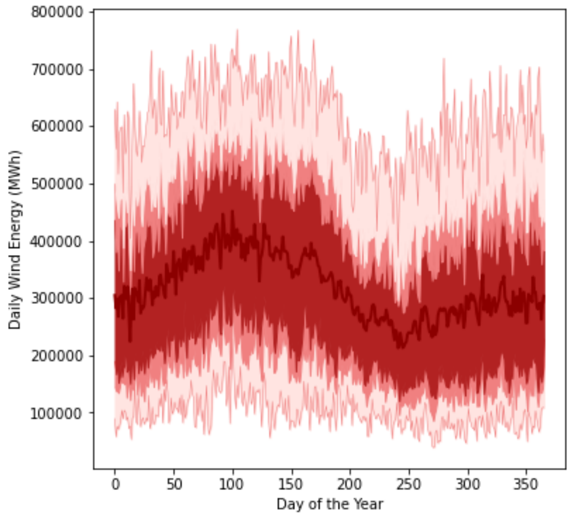
IV. Resource Droughts

The intensity of resource droughts is a function of the severity, duration, and area of the drought. In this work, the severity of a drought is characterized according to power availability for historical weather conditions. SRDs and WRDs are defined to occur when the power availability is below a percentage of the mean of the calculated values based on the historical weather data (25% of the mean for wind, and 40% of the mean for solar). The area of a resource drought is another important consideration with respect to the impact of the drought. This work accounts for this implicitly by aggregating the renewable generation capabilities on a state-by-state basis, but drought intensity is greater if multiple states within the same interconnect are experiencing drought conditions simultaneously.

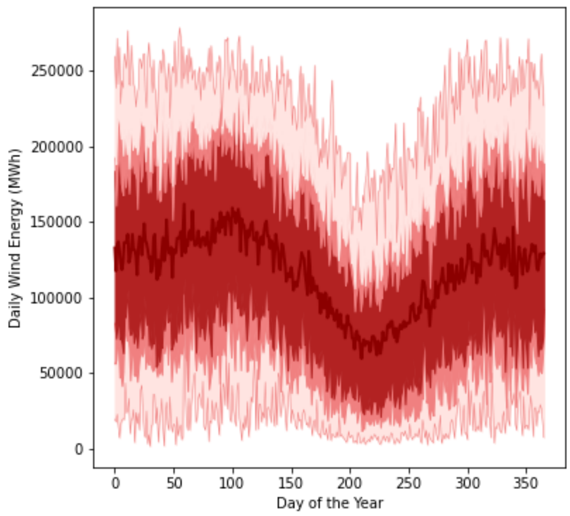
The duration of historical WRDs and SRDs from 1973 to 2022 are calculated as consecutive hours during which the calculated capacity available is at or below 25% of the mean for wind or 40% of the mean for solar of historical capacity availability for the same time of year. For states with high levels of wind and solar generation, WRDs and SRDs lasting at least 48 hours are summarized in Tables I and II. Accounting for a minimum duration of a resource drought occurring for at least 2 consecutive days, the probability ranges between 0.13–2.19% for WRDs for the states with highest levels of wind generation and between 0.65–1.35% for SRDs for the states with the highest levels of solar PV generation. These values were determined using Equation 1, where $P(RRD_g)$ represents the probability of a resource drought for the generation type in question, t is the duration of a resource drought, $d \in D$ is the resource drought within the set of all resource droughts that occurred during the period of study, and n is the total number of timepoints in the duration of study.

$$P(RRD_g) = \frac{\sum^D t_d}{n} \tag{1}$$

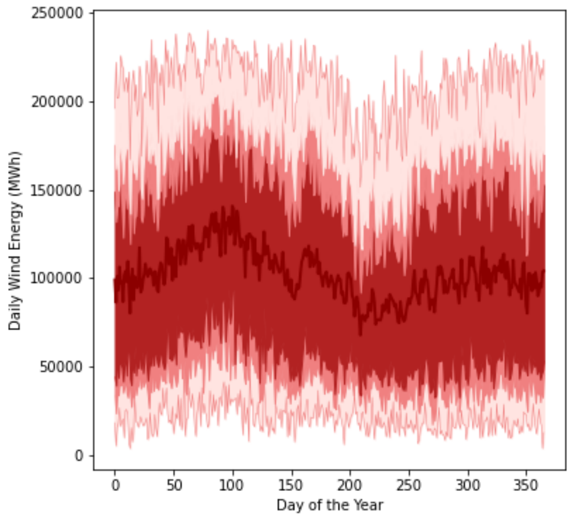
Over the years of weather data studied, 11 WRDs occurred in Texas, the state with the highest penetration of wind generation. The longest of these WRDs in Texas 3 days, occurring in both May 2007 and October 2021. In Iowa, the occurrence of WRDs was higher with 158 WRDs observed between 1973 and 2022. The longest WRD in Iowa during



(a) Texas

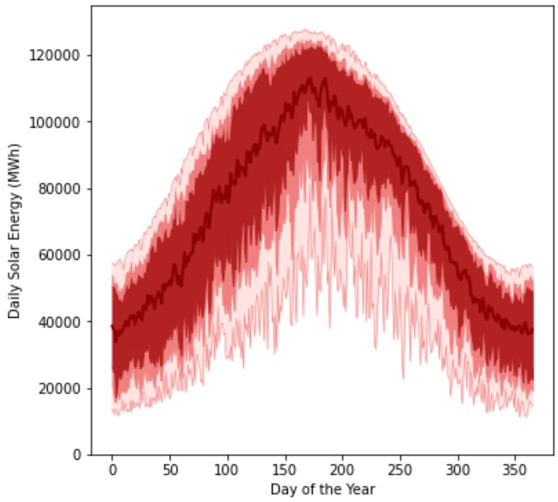


(b) Iowa

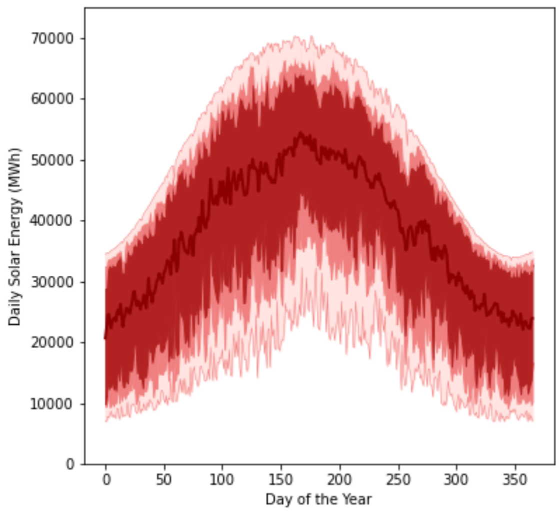


(c) Oklahoma

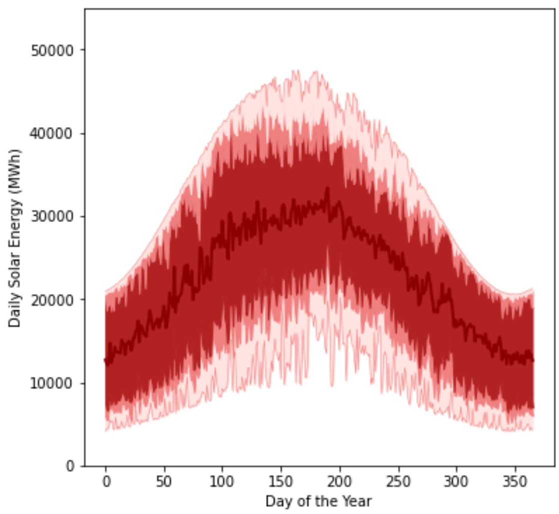
Fig. 4: Historic Distribution of Daily Wind Energy Generation in (a) Texas, (b) Iowa, and (c) Oklahoma



(a) California



(b) Texas



(c) North Carolina

Fig. 5: Historic Distribution of Daily Solar Energy Generation in (a) California, (b) Texas, and (c) North Carolina

TABLE I: WRDs 1973–2022

			Longest Drought	
	Count	Probability	Duration (days)	Date
Texas	11	0.13%	3	5/07, 10/21
Iowa	158	2.19%	7	9/09, 8/14, 7/21
Oklahoma	71	1.27%	5	10/15

TABLE II: SRDs 1973–2022

			Longest Drought	
	Count	Probability	Duration (days)	Date
California	24	0.65%	4	12/77, 1/95
Texas	96	1.35%	5	10/84, 2/89, 1/92, 1/94, 10/18
North Carolina	81	1.10%	5	4/03, 2/21

this period lasted for 7 days in September 2009, August 2014 and July 2021. The occurrence of SRDs lasting at least 2 days is summarized in Table II. During the years studied, California experienced 24 SRDs, with the longest occurring in the winters of 1977 and 1995 and lasting 4 days. These periods of low and extended periods of wind and solar generation availability can pose challenges with respect to resource adequacy, though the impact of such droughts is dependent on system conditions.

The impact of resource droughts is relative to the load experienced on the system. If the load on the system is low, low availability of renewable generation resources has a less severe impact on the grid particularly with diversity in the generation mix. As shown in the historic wind and solar capacity distributions (Fig. 4 and 5), wind generation availability is typically lower on average during the summer, coinciding with higher average solar availability. The complementary trends in these resources indicates that diversity in renewable generation technologies may yield complementary availability of power from renewable generation sources.

V. Validation of Methodology

The U.S. EIA publishes a report on utility-scale net generation by fuel type occurring on a monthly and calendar-year basis [23]. Given that the calculation of renewable generation capacity is performed with the 2021 generators, the validation of the weather-informed renewable generation capacity can be performed by comparing the published values for wind and solar generation at utility-scale facilities from [23] to the renewable generation capacity calculated using weather data incorporated in the power system model.

Table III shows the comparison of these values for the wind generation in the ten states with the most wind generation in 2021. Some discrepancies can be accounted for by recognizing that the calculated generation does not include curtailment or unit commitment and that the generators modeled as reported in the EIA-860 form reflect the generators in-service at the end of the year. Particularly in areas with rapid growth of wind and solar generation in their systems, this would result in the calculated generation being greater than the reported 2021 generation data. For example, the calculated generation in New Mexico was an overestimate by 57%. According to [24], New Mexico installed over 1.3 GW wind generation in 2021 alone, increasing the installed capacity by about 50%. The wind generation calculation is not very representative of the 2021 generation values for California and New Mexico in particular. In addition to the growth of installed wind generation in both states, the mountainous terrain in these regions may mean that the weather experienced at the nearest measurement location is significantly different

TABLE III: Validation of Wind Generation Calculation Methodology with 2021 Data

	Reported Generation (TWh)	Calculated Generation (TWh)	Difference (%)
Texas	100.05	105.64	5.6
Iowa	36.58	36.16	-1.2
Oklahoma	33.39	34.80	4.2
Kansas	25.63	27.92	8.9
Illinois	18.69	16.56	-11.4
California	15.63	21.43	37.1
Colorado	15.03	15.70	4.5
North Dakota	14.54	14.75	1.4
Minnesota	12.94	12.71	-1.8
New Mexico	10.65	16.74	57.2

TABLE IV: Validation of Solar PV Generation Calculation Methodology with 2021 Data

	Reported Generation (TWh)	Calculated Generation (TWh)	Difference (%)
California	32.23	38.30	18.8
Texas	14.14	18.70	32.2
North Carolina	9.92	11.20	12.9
Florida	9.03	8.89	-1.6
Nevada	6.49	7.97	22.8
Arizona	5.99	6.40	6.8
Georgia	4.82	5.60	16.2
Utah	3.47	3.56	2.6
Virginia	3.34	4.20	25.7
South Carolina	2.28	2.13	-6.6

from that experienced at the location of the wind turbine. An approach for mitigating this would be to assign a more representative wind measurement (which may not be closest) to wind turbines located in mountainous regions.

Table IV shows the comparison of the values for solar PV generation in the ten states with the greatest solar PV generation. Again, the calculated generation does not account for curtailment or generator status and the generators used in calculating the capacity are those that were operational by the end of 2021, resulting in mostly overestimated calculations of solar PV generation. The remaining discrepancies could be improved by tuning parameters associated with rated real power such as the azimuth, the tilt angle, the sky diffuse factor, and the inclusion of solar PV tracking capabilities (fixed, single-axis, or dual-axis) for improved accuracy.

VI. Summary and Future Work

This paper presented weather-informed calculations of generation capacity for wind and solar generators, validated these calculations, and identified historic WRDs and SRDs which could present resource adequacy issues in power grid operations if they were to occur again. The calculations presented leverage publicly-available generator information and weather data including wind speed and cloud coverage from nearby weather stations to calculate the generation capacity of wind and solar PV generators according to the modeled weather conditions. For the examples in this paper, generator information from the 2021 EIA-860 form and data from thousands of weather stations in the United States were used, but the methods presented can be applied to any set of generators with local weather data available. The calculated capacity of the generators was validated against published values of actual generation from EIA reports for the ten states with the most utility-scale solar PV generation and those with the most wind generation. For many of the studied states, the generation output values match closely with the published values. However, as discussed, the differences from the simulation are more considerable for some regions. Statistics were presented for historic WRDs and SRDs in states with the highest level of wind and solar generation, respectively, and historically long RRDs were identified.

Future extensions of this work will model and simulate the impacts of RRDs on grid operations and network planning. As part of this analysis, modifications to the severity and duration thresholds will be considered as functions of current system conditions. These weather scenarios should be used to inform network planning to facilitate the anticipated adoption of additional renewable generation and to ensure the robust and resilient operation of the power system.

VII. Acknowledgements

This work was partially supported through funding provided by the Power Systems Engineering Research Center (PSERC) and the U.S. ARPA-E Grant No. DE-AR0001366.

References

[1] (2021) "U.S. Energy Information Administration (EIA)". [Online]. Available: https://www.eia.gov/electricity/data/eia860/

[2] U.S. Energy Information Administration, "EIA projects renewables share of U.S. electricity generation mix will double by 2050," February 2021.

[3] NERC Reliability Issues Steering Committee, "Report on Resilience," November 2018.

[4] National Academies of Sciences, Engineering, and Medicine and others, *Enhancing the resilience of the nation's electricity system*. National Academies Press, 2017.

[5] C. Nayar, F. Thomas, S. Phillips, and W. James, "Design considerations for appropriate wind energy systems in developing countries," *Renewable Energy*, vol. 1, no. 5-6, pp. 713–722, 1991.

[6] D. Raynaud, B. Hingray, B. François, and J. D. Creutin, "Energy droughts from variable renewable energy sources in european climates," *Renewable Energy*, vol. 125, pp. 578–589, 2018.

[7] American Meteorology Society, "Glossary of Meteorology," 2019. [Online]. Available: glossary.ametsoc.org/wiki/Welcome

[8] K. Z. Rinaldi, J. A. Dowling, T. H. Ruggles, K. Caldeira, and N. S. Lewis, "Wind and solar resource droughts in California highlight the benefits of long-term storage and integration with the Western Interconnect," *Environmental Science & Technology*, vol. 55, no. 9, pp. 6214–6226, 2021.

[9] N. Otero, O. Martius, S. Allen, H. Bloomfield, and B. Schaefli, "A copula-based assessment of renewable energy droughts across Europe," *Renewable Energy*, 2022.

[10] H. Hersbach, P. de Rosnay, B. Bell, D. Schepers, A. Simmons, C. Soci, S. Abdalla, M. Alonso-Balmaseda, G. Balsamo, and P. Bechtold, "Operational global reanalysis: progress, future directions and synergies with nwp," 2018.

[11] J. Jurasz, J. Mikulik, P. B. Dabek, M. Guezgouz, and B. Kaźmierczak, "Complementarity and 'Resource Droughts' of Solar and Wind Energy in Poland: An ERA5-Based Analysis," *Energies*, vol. 14, no. 4, 2021. [Online]. Available: https://www.mdpi.com/1996-1073/14/4/1118

[12] D. Raynaud, B. Hingray, B. François, and J. Creutin, "Energy droughts from variable renewable energy sources in European climates," *Renewable Energy*, vol. 125, pp. 578–589, 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148118302829

[13] P. Patlakas, G. Galanis, D. Diamantis, and G. Kallos, "Low wind speed events: persistence and frequency," *Wind Energy*, vol. 20, no. 6, pp. 1033–1047, 2017.

[14] P. G. Leahy and E. J. McKeogh, "Persistence of low wind speed conditions and implications for wind power variability," *Wind Energy*, vol. 16, no. 4, pp. 575–586, 2013.

[15] N. Otero, O. Martius, S. Allen, H. Bloomfield, and B. Schaefli, "A copula-based assessment of renewable energy droughts across Europe," *Renewable Energy*, vol. 201, pp. 667–677, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148122015841

[16] P. T. Brown, D. J. Farnham, and K. Caldeira, "Meteorology and climatology of historical weekly wind and solar power resource droughts over western North America in ERA5," *SN Applied Sciences*, vol. 3, no. 10, Sep. 2021. [Online]. Available: https://doi.org/10.1007/s42452-021-04794-z

[17] A. Gangopadhyay, A. Seshadri, N. Sparks, and R. Toumi, "The role of wind-solar hybrid plants in mitigating renewable energy-droughts," *Renewable Energy*, 2022.

[18] Jääskeläinen, Jaakko and Veijalainen, Noora and Syri, Sanna and Marttunen, Mika and Zakeri, Behnam, "Energy security impacts of a severe drought on the future Finnish energy system," *Journal of Environmental Management*, vol. 217, pp. 542–554, 2018.

[19] J. Schmidt, R. Cancella, and A. O. Pereira Jr, "The role of wind power and solar PV in reducing risks in the Brazilian hydro-thermal power system," *Energy*, vol. 115, pp. 1748–1757, 2016.

[20] T. J. Overbye, F. Safdarian, W. Trinh, Z. Mao, J. Snodgrass, and J. H. Yeo, "An Approach for the Direct Inclusion of Weather Information in the Power Flow," *Proc. 56th Hawaii International Conference on System Sciences (HICSS)*, 2023.

[21] T. J. Overbye, E. M. Rantanen, and S. Judd, "Electric power control center visualization using geographic data views," in *2007 iREP Symposium-Bulk Power System Dynamics and Control-VII. Revitalizing Operational Reliability*. IEEE, 2007, pp. 1–8.

[22] T. J. Overbye, J. L. Wert, K. S. Shetye, F. Safdarian, and A. B. Birchfield, "The use of geographic data views to help with wide-area electric grid situational awareness," in *2021 IEEE Texas Power and Energy Conference (TPEC)*. IEEE, 2021, pp. 1–6.

[23] U.S. Energy Information Administration, "Electric Power Monthly with Data for December 2021," February 2022.

[24] R. Wiser, M. Bolinger, B. Hoen, D. Millstein, J. Rand, G. Barbose, N. Darghouth, W. Gorman, S. Jeong, and B. Paulos, "Land-based wind market report: 2022 edition," Lawrence Berkeley National Lab.(LBNL), Berkeley, CA (United States), Tech. Rep., 2022.