# Wind Resource Drought Identification Methodology for Improved Electric Grid Resiliency

Jessica L. Wert, Farnaz Safdarian, Alex Gonce, Thomas Chen, Dalton Cyr, Thomas J. Overbye
*Department of Electrical and Computer Engineering*
*Texas A&M University*
College Station, TX
{jwert, fsafdarian, alex-gonce, thomas-chen, dwcyr54, overbye}@tamu.edu

***Abstract*—Essential to power systems operation and resilience is having sufficient generation in the system to supply demand plus transmission losses. With increasing penetration of wind power in electric grids, the variable nature of wind as a resource means that extended periods of abnormally low wind power availability (wind resource droughts) could compromise that system's resilience. This paper presents a methodology for identifying wind resource droughts in electric grids. The methodology presented in this paper leverages hourly historic wind speed data from 1973 to 2022 with U.S. generator data from 2021 to determine historic wind power availability. The distribution of historic data is then used to help identify wind resource droughts. Examples are presented for states with high integration of wind generation in the United States such as California and Texas.**

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

## I. Introduction

At its essence, an electric power system must have sufficient generation to meet the total load plus the losses. If there is an overall generation shortage in an interconnected ac system, initially the frequency would drop, and then usually the other generators would make up the shortfall through their governor control and later by automatic generation control. If there is insufficient additional generation available or if in a larger grid there is insufficient transmission capacity then the load would need to be reduced through load shedding. This occurred in the U.S. state of Texas during Winter Storm Uri in February 2021 when cold weather induced generator and fuel supply failures caused the frequency to fall to 59.4 Hz for several minutes and subsequently large amounts of load was involuntarily shed over the next few days [1].

Traditionally, in North America the North American Electric Reliability Corporation (NERC) has divided the reliability of large-scale interconnects into two functional aspects, adequacy and operating reliability, with adequacy focused on ensuring there is adequate electric supply at all times taking into account reasonably expected outages [2]. This was based on the expectation that adequate fuel was almost always available, a quite reasonable assumption when most generation was supplied by coal, natural gas, nuclear or hydro with their larger amounts of on-site or reservoir fuel storage. However, with the rapid growth in wind and solar, in which there is no storage of their fuel inputs, these concepts need to be extended.

Part of this extension is associated with electric grid resilience [2], [3]. While resilience is a term with different shades of meaning, the grid must be resilient even during extremely large events, and a necessary consideration in achieving this is considering the nature of the disruptive event [4]. It also needs to be present for the grid as a whole, including generation, transmission, distribution, markets, and increasingly coupled infrastructures and supply chains. This paper considers an aspect of generation resilience in grids with a large amount of wind generation.

Wind generation is growing rapidly around the world. According to U.S. Energy Information Administration (EIA) data [5], [6] in 2021 around 11% of the overall generation in the U.S. is supplied from wind energy, and within individual state this value is much higher including more than 60% in Iowa, 40% in Oklahoma and about 25% in the Electric Reliability Council of Texas (ERCOT) grid. However a concern about renewable generation is that it relies on the availability of an inherently variable resource. The focus of this paper is on the electric grid resiliency impacts of the more rare, but more severe situations in which wind power generation levels are substantially below normal for extended periods of time, a situation known as a wind drought [7], [8], or wind resource drought (WRD). In particular this paper presents a methodology to relatively easily consider such situations in electric grid planning.

While the WRD term is relatively new in an electric grid context, human knowledge of outlier wind behavior is certainly not new especially with respect to sailing. Also the term "drought" has been used for thousands of years in a precipitation context, and these traditional droughts can impact hydro generation and cooling processes for thermal generation units. A few other references considering WRDs (or more generally resource droughts when solar is also included) are [9], [10], and [11].

Like the general term "drought," defined by [12] as "a period of abnormally dry weather sufficiently long enough to cause a serious hydrological imbalance," a WRD is does not have a precise duration or geographic extent but it does need to be sufficiently long and wide-spread to cause an impact. Like a traditional drought it needs to be "abnormal," so implied in

This work was partially supported through funding provided by the Power Systems Engineering Research Center (PSERC).

Submitted to Texas Power and Energy Conference, College Station, TX February 2023

its definition is an understanding of the expected wind power generation. In addition, a WRD depends on the amount of wind generation actually impacted, so the term would not be appropriate in a region in with no installed wind generation. Finally, whether a WRD is occurring depends not solely on the wind speeds themselves, but on their impact on the wind turbine power outputs. This requires knowledge of the wind turbine power curves. Since wind turbines have both cut-in and cut-out speeds, a WRD could occur when the winds are consistently too high (though this would be more rare). In the U.S. the EIA Form 860 data [5] provides sufficient information to provide estimates of all the wind turbine power curves. A methodology for using this information in the power flow is given in [13].

The remainder of this paper demonstrates a WRD identification methodology using a combination of U.S. hourly wind speed data from the years 1973 to 2022, and the installed U.S. wind turbine portfolio as of the end of 2021 from [5]. The study considers in detail the U.S. states of Texas, which by far has the most installed wind turbine capacity, and California. In the paper Section II provides details on the data and models used in this methodology. Section III details the cases studied, and Section IV highlights and shows the WRDs. A summary and future directions are then provided in Section V.

## II. Data Overview

As has been noted, the data used in the study includes information about the U.S. installed generation capacity from the EIA 860 Form [5] and hourly-locational wind speed information from 1973 to 2021. More specifically, the EIA 860 data provides information on all generators with a nameplate capacity of one MW or greater, allowing the individual wind turbines at a location to be aggregated if they have similar characteristics. The generators at a single location are then grouped into power plants with the geographic location of each provided. For the wind generators this data also contains the turbine manufacturer, model number, design wind speed, wind quality class, and the hub height.

To provide context for the relative amount of wind generation in the U.S. Figure 1 visualizes all the generation using the geographic data view (GDV) approach of [14], [15] in which the size of each oval is proportional to the power plant's MW capacity and its color indicates the primary fuel type (red for nuclear, black for coal, brown for natural gas, blue for hydro, and green for wind). To better show just the wind and solar generation, Figure 2 repeats this visualization except just showing these two fuel types and the GDV oval scaling is increased to better visualize the generation. Figure 3 shows just the wind generation, except aggregated at the state level.

The second portion of the input data is the hourly historical weather information including the wind speed used here. For this work the data was obtained from [16] with values between 1973 and 2021 used. Over this time period the number of weather stations with measurements gradually increased with several thousand in the contiguous U.S. available by 2021 (shown in Figure 4).

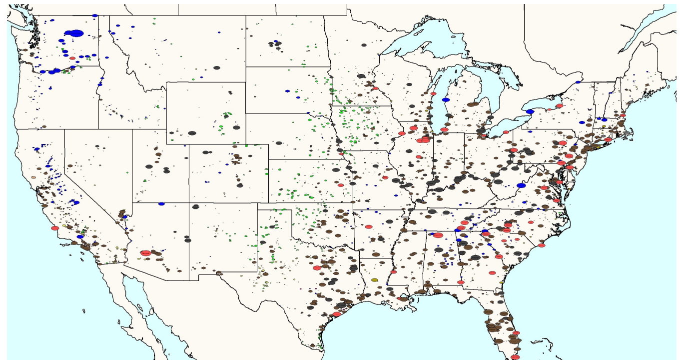


Fig. 1: GDV Visualization of U.S. EIA Form 860 Year 2021 Total Generation Capacity

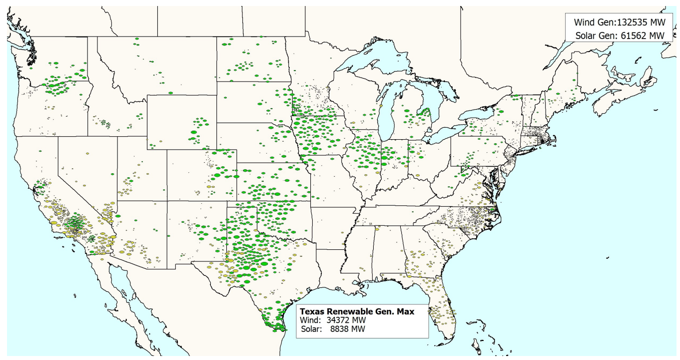



Fig. 2: GDV Visualization of U.S. EIA Form 860 2021 Wind and Solar Generation

To obtain an estimate of the output of each wind generator at each hour the approach of [13] is used. In particular, this requires knowing for each wind generator the wind speed and the power curve relating the wind speed to the power output. While the wind speed measurements are seldom available at the exact location of each generator, usually there are some available nearby. Then 2D scattered data interpolation methods can be used to usually obtain a reasonable estimate. While there is no best interpolation method for all situations,

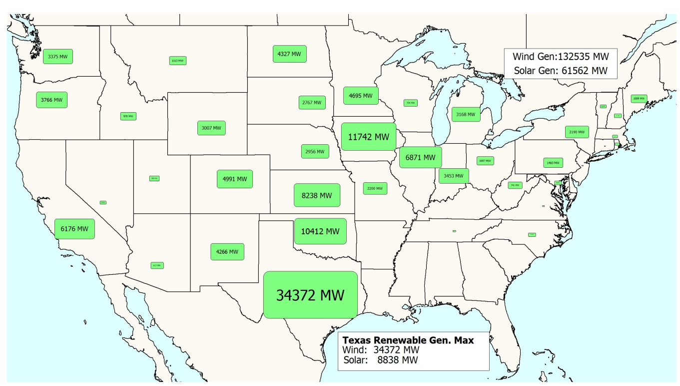



Fig. 3: GDV Visualization of U.S. EIA Form 860 2021 Wind Capacity by State

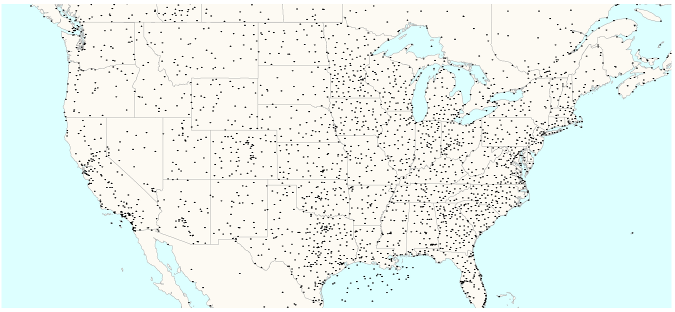


Fig. 4: Weather Station Locations

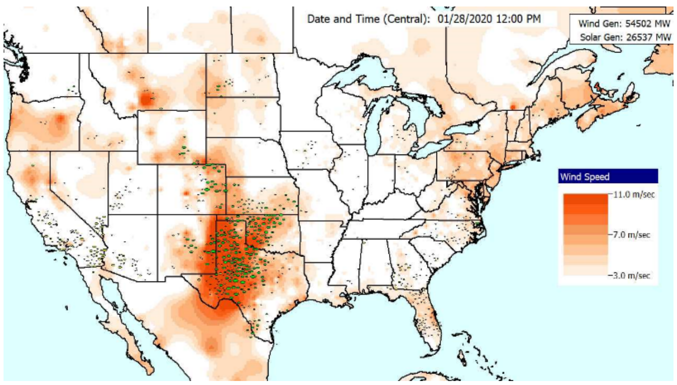



Fig. 5: Wind Speed Contour and Wind Generator Power Outputs

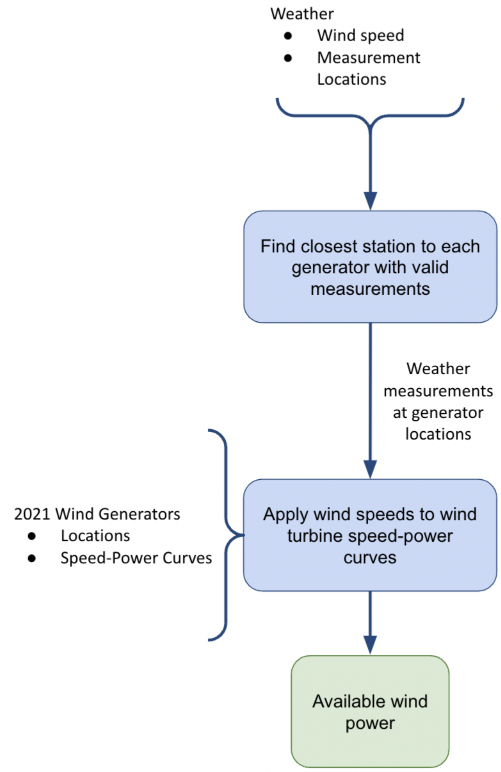



Fig. 6: Approach to calculate wind power availability for each year.

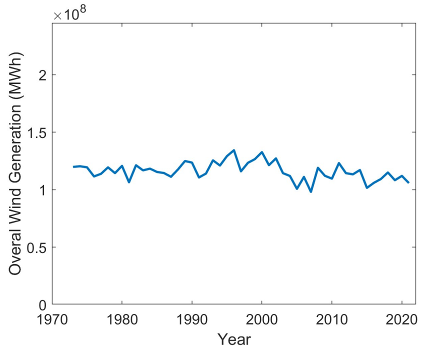
the approach utilized here is to use the closest available measurement station. Since weather measurements are not always available from each station, the closest station with a valid measurement needed to be checked for each wind turbine for each hour, a process that can be computationally quite efficient using a k-dimensional tree algorithm. As noted in [13] there are certainly situations in which the closest weather station does not give the best approximation for the actual wind speed at the generator location, but for the general methodology presentation of this paper it is reasonable approximation. The hub height wind speed is then estimated from this value using a scalar multiplier, noting that hub height information is available in the EIA 860 data.

The estimated hourly power output of each wind generator is then determined using the turbine's power curve. Since the EIA data does contain the model numbers, the actual power curves could be used. However, given this paper's methodology focus, rather four generic curves are utilized based upon the wind quality class obtained from the EIA data. An example of this process, used for each hour, is shown in Figure 5 in which the wind speeds are visualized using the contouring approach of [17] and the wind turbine power outputs for these wind speeds shown using the green GDVs. If desired, animation sequences can be created by showing a series of such images.

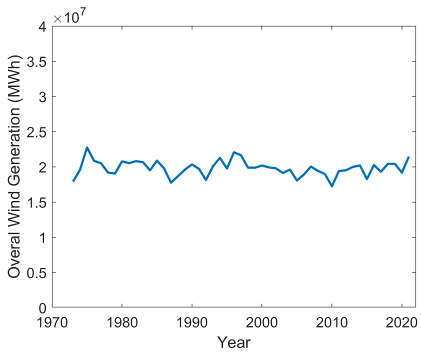
## III. Wind Resource Drought Identification

Based on weather data, the strategy in Figure 6 is used to calculate the available wind turbine generator capacity or wind power output for each time step and for each region of study. Then, for each region of study, the distribution of historical wind power availability is calculated on an hourly basis. Then for each hour of the year, the data over the years of study but for the same hour of the year is considered and the main statistics including minimum, maximum, average, as well as 10th, 20th, 80th, and 90th percentiles of output power generation of wind turbines are calculated. This information, coupled with the drought definition is used in finding WRDs in the dataset. Also, as well as hourly data for the output power of wind turbines the daily and annual output of wind turbines are calculated.

The output data of wind turbines based on this strategy is used for more detailed study in California and Texas in the U.S., which include high capacities of wind generation. Figure 7 shows the results of simulations based on historical wind speed to find annual wind power availability for Texas and California from 1973 to 2022 based on 2021 generator data. The figure shows that the overall trend of wind availability is not significantly changed over these years. Therefore, calculating the percentiles of output power of wind turbines based on the wind availability over the years is a reasonable strategy for determining wind drought. Please note the difference in the scale of Texas power generation through wind turbines based on the availability wind capacity and wind speed during these years by the scale of 10.




(a) Texas




(b) California

Fig. 7: Historical Annual MWh Wind Energy Availability for (a) Texas and (b) California

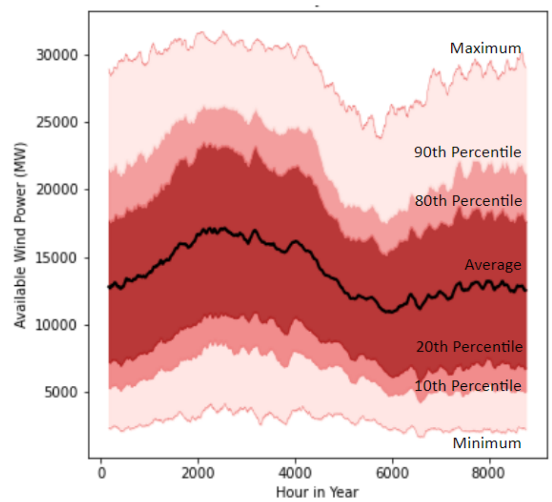



Fig. 8: Historic Distribution of Wind Power Availability in Texas

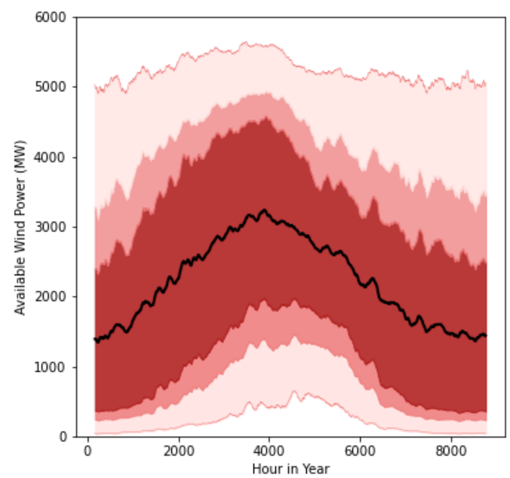



Fig. 9: Historic Distribution of Wind Power Availability in California

Then the more detailed hourly data of these two states is used and for each hour of the year, including 8760 hours in a sample year, the minimum, maximum, average, as well as 10th, 20th, 80th, and 90th percentiles of output power generation of wind turbines over all studies years is calculated to find the historic distribution of wind power availability. These statistics of wind power availability based on 1973 to 2022 wind and using 2021 generator data are presented in Figure 8 for Texas. The same statistics are shown in Figure 9 for California. As wind power data is highly variable, smoothing was applied for the purpose of visualizing trends in historic wind power availability distribution during a year using a rolling window average.

The wind power availability in Texas follows an annual pattern with two peaks. The higher peak typically occurs in March and the lower peak generally occurs in November. Wind power availability in Texas is on average at its lowest from late summer to early fall. California, however, shows a slightly different pattern in its annual wind power availability. The peak wind power availability in California occurs on average in May and the minimum occurs on average in the winter. In both Texas and California, there is a greater range to the higher percentiles of wind power availability than the lower percentiles. Note also that California has a tighter power availability range in its lower 20th percentile than Texas, particularly during winter months.

The definition of WRD should include the severity of the droughts, the period of time that they lasts and the geographical area that is impacted by the droughts mentioning how widespread they are. Also, based on the general definition of the term drought, the abnormally low power output of wind turbines should be long enough to create operation issues such as frequency violations or even cause black-outs. In this work, the wind power threshold for a WRD is considered an event in which wind power availability is below the 20th percentile and the severe WRD threshold is set to wind power availability being below the 10th percentile, while the time threshold for recognizing WRD is considered a day. However, this definition is a caution to look into the WRD more carefully but the operation problem that may occur depend on many other factors such as demand. More importantly, if the WRD is too severe meaning that the output of wind turbines are below say 5th percentile, a shorter period of WRD can create operational challenges. On the other hand, if the WRD is not severe but lasts over a long period of time and impacts a very large area, that can also create serious reliability issues for the grid.

## IV. Severe Wind Resource Drought Examples

For this study, the power grid zones are divided based on the U.S. states and Texas and California as examples of two states with large wind capacity are studied. However, the zones can change based on the goal of study. For each zone, the most severe WRDs are selected as cases of interest by determining historic periods with the lowest wind power availability over a duration of at least longer than a day. Examples of selected severe wind drought cases are visualized in Figures 10 and 11. The color keys used in these Figures are the same as Figure 8 with the difference that the average wind power output over 1973 to 2022 is shown with the dark maroon lines but the actual wind power MW output on that dates are shown with the bolded black lines.

Figure 10 presents the most severe wind drought in Texas from 1973 to 2022 that lasted over 4.5 days. The daily variation of the wind is apparent both in the historic statistics' trends and the wind drought that occurred in 2008 (shown with the black line). Many of the hours from this day are matched with the overall low-wind-availability records of the studied years and this time of year in Texas. It should be noted that for almost all of this period, the wind power output is below 10th percentile of the historical data.

Figure 11 shows the wind power availability for the most severe wind drought from 1973 to 2022 that occurred in late November of 2005 relative to the distribution of historic statistics of wind power availability for this time of year. The drought lasted nearly 1.5 days and not only matches the overall low wind records for the studied years and this time of year, but also presented values very close to 0 MW wind power availability for a long duration of this severe drought. Please note that the wind turbines output power is below 10th percentile of historical data for this period but also the difference between the minimum and 10th percentile is very small. Then year 2021 in Texas is selected to find the duration of WRDs. Figure 12 shows the hourly MW output of wind turbines in 2021 compared to the minimum, maximum, average, 10th, 20th, 80th and 90th percentiles over 1973 to 2022. The WRDs are shown with blue arows. The duration of these WRDs are shown in 13.

Depending on the scale of demand compared to the available generation capacity, these WRDs can create significant operations issues for the electrical grid. Similar extreme weather events should be used for detailed studies of their impact on the operation of power system and then should be considered carefully for the planning for improving power system reliability and resiliency.

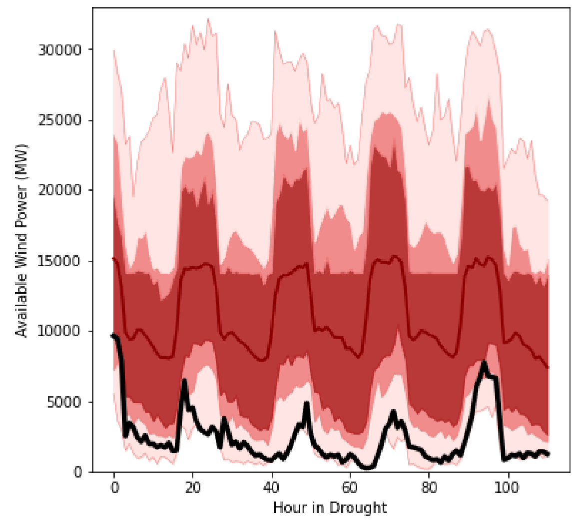



Fig. 10: Late Sept., 2008 Texas Wind Power Availability

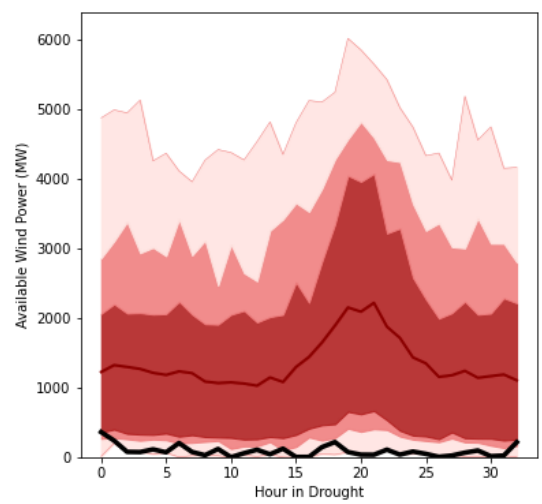



Fig. 11: Late Nov., 2005 California Wind Power Availability

## V. Summary and Future Work

With wind generators representing a rapidly-growing portion of power systems globally, it is important that the availability and variability of wind resources are accounted for when planning reliable and resilient power systems. Historically, adequate fuel supply has been assumed in power systems planning, but with environmental and economic incentives for utilizing renewable resources, the availability of these resources and dependency of the power system on these resources should be studied carefully. Wind power is one of the most important renewable resources that has a variable and intermittent nature. Finding extreme weather scenarios such as severe WRD situations is very encouraging for power system planning.

A methodology has been presented to identify WRDs and

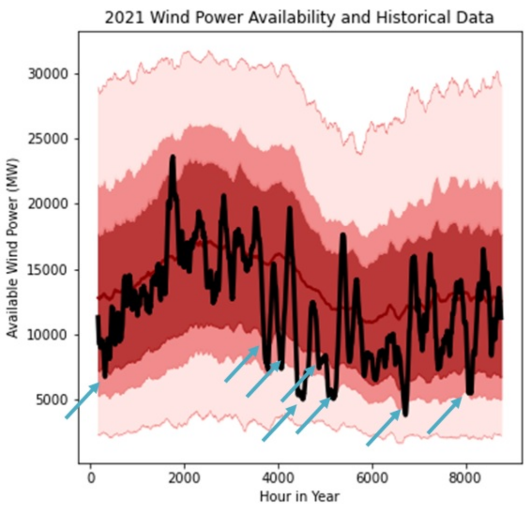



Fig. 12: Wind MW output data in 2021 compared to the minimum, maximum, average, 10th, 20th, 80th and 90th percentiles over 1973 to 2022

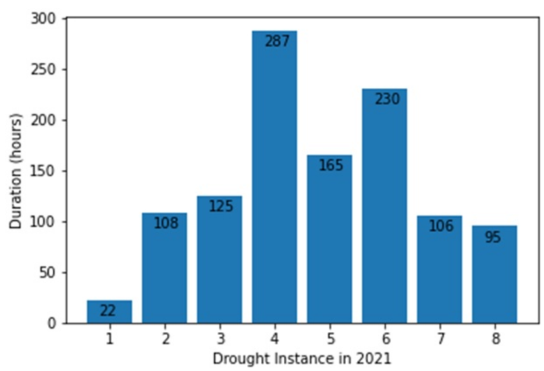



Fig. 13: The duration of WRDs in 2021 in Texas

find examples of severe WRDs are presented from California and Texas. Leveraging publicly-available generator data from 2021, information on the wind turbine manufacturer, model number, design wind speed, wind quality class, and the hub height is used to calculate how much wind power would will be available with historic wind conditions (using wind speed data from 1973 to 2022). The expected available wind power capacities in different hours of a year is determined based on analyzing statistics from historical data in each hour of the studied years. WRDs are found based on comparing the output power from wind turbines in each time with historical statistics on the same time of the year.

Although it is observed that the overall annual availability of wind resources is not changed over these years, different patterns are observed comparing the hourly statistics of historical trends in Texas and California such as two peaks in the average wind generation of Texas in March and November but one peak in California's average wind data in May. These statistics help recognizing extreme WRDs as examples are brought with more details. Since the utilization of wind energy is increasing, the availability of wind resources is having a more significant impact on the operation of power system. Therefore, extreme WRDs can have a significant impact on the reliability and resiliency of the power system. Therefore, similar extreme weather events should be considered carefully in the operation and planning of power systems to improve the reliability and resiliency of the grids. In future, we will also study the solar droughts and the possibility of their coincidence with wind droughts.

## VI. Acknowledgements

This work was partially supported through funding provided by the Power Systems Engineering Research Center (PSERC).

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