Power System Resiliency and Reliability Issues from Renewable Resource Droughts

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***Abstract*—This paper models the outlier but impactful extreme weather scenarios called renewable resource droughts (RRDs) including wind resource droughts (WRDs) and solar resource droughts (SRDs) based on the direct inclusion of weather measurements in the optimal power flow and study their impact on the power systems based on reliability measures such as reactive power available capacities, bus voltage and line congestions. Since the availability of these resources changes the actual capacities of generators and mainly renewable generators, the weather measurements are used to find the generation dispatch in a variety of drought scenarios and show their impact on the power grid. The criteria for drought identification is based on the generation dispatch in each weather scenario rather than just the weather data. The historical weather data is used for drought identification and extreme cases are selected for a more detailed study. The results show the impact of these events on the grid. Preventive and corrective actions are suggested to avoid operation problems in such cases.**

***Index Terms*—AC optimal power flow, extreme weather events, operation and planning of power systems, resiliency, reliability, resource droughts, weather impact**

I. Introduction

Due to economic and environmental concerns, utilizing renewable energy resources is being encouraged and growing quickly all over the world including the United States [1]. This will make the power system operation and planning more dependent on the weather, which has a variable and uncontrollable nature and can cause several reliability and resiliency concerns [2], [3]. The main challenges include extreme, quick, and unpredicted weather changes for which the electrical grid has not been planned. These weather scenarios can specifically create a tragedy when the extreme weather situation remains for longer periods of time and in extended areas. One of the most problematic scenarios is the unavailability of wind or solar energy resources which reduces the available capacities of generators. These events are referred to as renewable resource droughts (RRDs) or more specifically wind resource droughts (WRDs) and solar resource droughts (SRDs) [4], [5].

A. Literature Review

In the literature, there are different definitions for what constitutes a resource drought. Essentially, a drought occurs when a particular resource is unavailable at a level below a certain threshold for an extended period of time. The authors of [6], used historical weather data to estimate the amount of wind and solar power that could be generated, and then set the threshold for a drought event at half of the daily mean value over a 39-year period. Researchers in [7] relied on data from the ERA5 re-analysis [8] and set the threshold at the 10th percentile of the average renewable power output. Similar to the variability in definitions and duration of drought events in the literature, studies also differ in terms of the data that is analyzed, such as geographic regions, years, resolution, and whether raw measurements or resulting power availability is considered. Some studies, including those cited in [9]–[12], only take into account weather measurements such as wind speed to identify drought events. In contrast, other studies [6], [13], [14] use weather data such as wind speeds as inputs to wind turbine power curves to estimate hypothetical or approximate generator outputs in the regions under study.

There are some references in the literature that study the impact of RRDs and suggest solutions to mitigate their impact. Reference [6] suggests long-term energy storage installation to mitigate the impact of RRDs. However, as mentioned in the paper, installing large energy storage devices will be expensive and other preventive measures should be considered. References [9] and [15] show that considering both SRDs and WRDs at the same time has a lower probability and lower intermittency than independent SRDs or WRDs and suggest using local wind-solar hybrid plants to mitigate the impact of RRDs. However, none of the studies suggest preventive and remedial actions to avoid operation issues from RRDs.

B. Contributions

Reference [16] presents a strategy for direct inclusion of weather measurement in the ac optimal power flow (OPF) without changing the algorithms and significantly increasing the computation complexity as the capacities of generators are updated based on the weather measurements. It collects essential weather measurements and determines the renewable generator outputs based on the availability of these resources. Also, the generation dispatch of renewable resources with the same strategy is validated in [17] and criteria for identifying RRDs by analyzing wind and solar outputs that are substantially below typical values for extended durations is defined.

Building on these references, this paper models extreme RRDs including WRDs and SRDs based on the direct inclusion of weather measurements and load changes in ac OPF simulations and studies their impact on the power systems based on reliability measures such as reactive power available capacities, bus voltage, and line congestions. The weather measurements are used to find the generation dispatch in a variety of drought and load scenarios and show their impact on the power grid. The criteria for drought identification is based on the generation dispatch of resources rather than using raw weather measurements such as wind speed and cloud coverage. The historical weather data is used for drought identification and extreme cases are selected for a more detailed study. Then preventive and corrective actions are suggested to avoid operation problems in such cases.

II. Data Preparation

The impact of weather on the electric grid is usually studied based on the outputs of renewable generators. However, if the weather measurements are directly used as an input to the operation studies such as OPF, they can provide a more detailed calculation for each renewable generator and can track quick weather changes. Weather measurements are extracted from International Civil Aviation Organization (ICAO) and the World Meteorological Organization (WMO) [18]. Reference [16] presented a strategy for direct inclusion of weather measurements in the OPF using common strategies such as Newton-Raphson and without increasing the size of the problem significantly.

The information on the location and capacity of generators in the United States and their type is available in publicly available yearly datasets from the U.S. Energy Information Administration (EIA-860) [19]. The dataset includes key characteristics of the generators, such as fuel type, capacity, exact geographic locations, manufacturer, model number, design wind speed, wind quality class, and hub height for wind generators and model classes and details such as tilt angle for solar cells. This data allows for the grouping of individual wind turbines and solar cells at a location with similar characteristics, which are further classified into power plants and their geographical location.

III. Methodology

Since the available capacities of all generators and mainly renewable generators such as wind turbines and solar power plants are directly related to the weather conditions, weather are directly included in the power flow modeling, per the strategy outlined and validated in our previous works [16], [17]. This strategy is applied to the time step simulation to find the output generation of renewable resources based on their available capacity. Since the operation cost of renewable resources are free, usually the available capacities of these resources are used and thermal generators are dispatched based

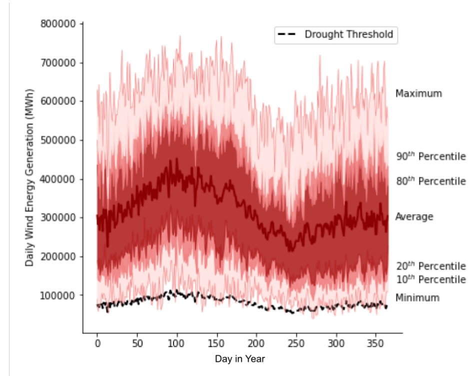


Fig. 1: Historic Distribution of Daily Wind Energy Generation in Texas

on the remaining required demand to be satisfied. In the next step, to find the optimal dispatch of conventional generators, considering reactive power limitations, an ac OPF is solved to minimize cost [20].

A. Identification of Weather Resource Droughts

WRDs and SRDs in this work are identified according to the criteria outlined in [17]. These criteria involve the calculated power of wind turbines being at least less than 25% and solar PV resources being less than 40% of the mean historical capacity for the given time of year for a minimum of two consecutive days.

To visualize the proposed strategy, the weather measurements in state of Texas in the United States are used as an example. According to [17], Texas is one of the top three states with both the highest wind and solar capacity in the US so it is selected for a more detailed study. Figures 1 and 2 show a summary of the overall historical wind and solar generation statistics over a year where each hour in the year shows the average, minimum, maximum, and specific percentiles of the historical data over the studied years from 1973 to 2022 in Texas. Drought thresholds based on the proposed criteria are also shown in these figures with a bolder black line. According to these figures, RRDs are outliers and rare events but can have a significant impact in the power system. The impact of selected RRDs is studied in the following sections.

B. Preventive and Corrective Actions

The proposed data-driven approach identifies extreme operational conditions in power systems and implements preventive and corrective strategies to mitigate resulting issues, utilizing remedial actions like generator set point tuning, line switching, load shedding, and switched shunt tuning. An automated remedial action scheme (RAS) uses a sensitivity-based method for effective decision-making [21]–[23]. This strategy selects controllable elements based on proximity to violation risks, utilizing sensitivity analyses such as line outage distribution factor and transmission loading relief to expedite the selection of corrective actions, thus eliminating the need for continuous simulations. The approach is embedded within an adaptive

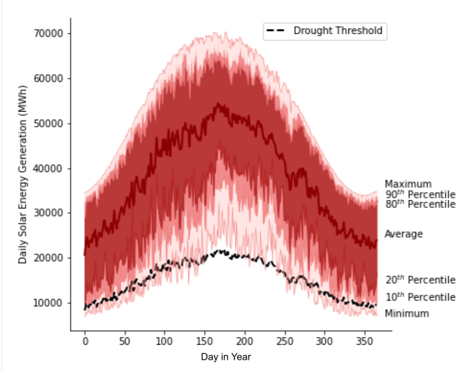


Fig. 2: Historic Distribution of Daily Solar Energy Generation in Texas

Auto-RAS framework, adjusting to different operational situations and systematically determining effective responses to overloads. Further, the design of RAS corrective actions is informed by statistical analysis from real system implementations, considering network connectivity and system properties to refine the selection of controllable elements and ensure the efficiency of the remedial actions.

Additionally, planning actions such as adding switched shunts and upgrading lines are suggested for scenarios where RAS cannot resolve operational problems.

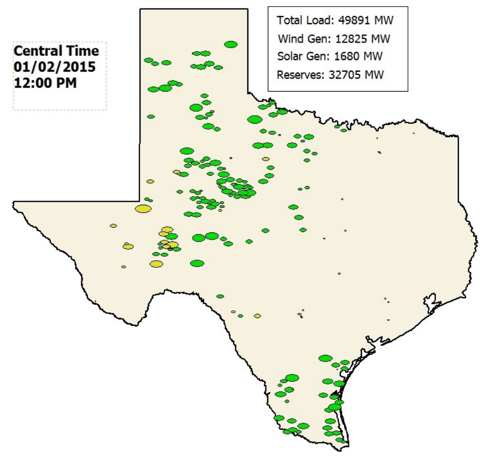
IV. Case Study and Results

A. Electrical Grid

Due to restrictions on access to actual grid data or critical energy infrastructure information (CEII), the authors have used a synthetic but realistic grid that is created over Texas footprint in the United States that is covered by the Electric Reliability Council of Texas (ERCOT) with 6,717 buses created based on publicly available generator data from the U.S. Energy Information Association (EIA) [19] at the end of 2019 as well as 2019 census data to approximate the load. The load time series at each bus is later updated based on the methodology outlined in the next subsection for the same year. The strategy to create the substations, transmission lines, and reactive power control devices is explained in [24]–[26]. This dataset includes information on a total of 1485 wind generators with a combined capacity of 132 GW and a total of 5270 solar generators with a combined capacity of 61 GW. The important characteristics of this synthetic grid is then validated in [27]. The grid is available at [28].

B. Electrical Load Scenarios

The impact of RRDs is directly related to the system demand at the time of such events. Therefore, it is crucial to create and study realistic load time series at each bus. To create hourly time series of bus-level load for a year, the authors follow a method outlined in [29], [30]. This involves using the geographic coordinates of each bus to determine its unique electricity consumption profile. Then, publicly available building-, facility-, and utility-level load



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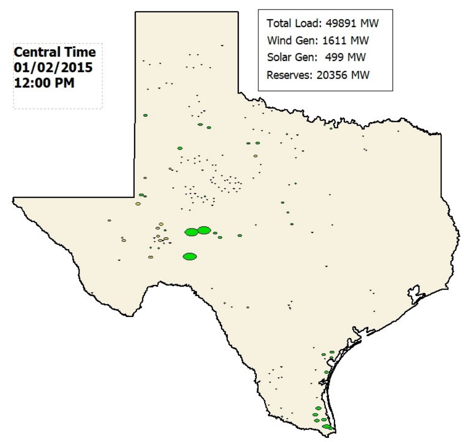


(b)

Fig. 3: Comparison of Wind and Solar Generation in the studied SRDs with (a) nominal capacities (b) available capacities with direct inclusion of weather in OPF in GDV of Wind (green) and solar (yellow) Generation

time series are iteratively aggregated to integrate them at the bus level. The study uses the composition ratio of residential, commercial, and industrial loads at each node in the system, along with location-specific prototypical building-, facility-, and utility-level load time series, to develop the node-level load time series. After load in bus level is created, the overall load in each area is calculated and validated based on the hourly load in each of the ERCOT areas that is publicly available at [31]. Please note that the main benefit from direct inclusion of weather data in OPF is to study the impact of a variety of possible weather and load scenarios in the electrical grid and since the generation data is based on year 2019, the load is also based on the same year to match the generation mix but changes hourly over the year. The load and weather time of

TABLE I: Identified WRDs

Duration (days)	Dates	Average Wind Generation (MW)
3	May 11–13, 2007	78,470.85
3	Oct. 2–4, 2021	49,413.27
2	Sep. 27–28, 2008	40,686.83
2	Dec. 8–9, 2014	63,767.16
2	Aug. 3–4, 2021	58,939.29
2	Nov. 11–12, 1990	63,387.27
2	Oct. 17–18, 1974	60,384.39
2	March 9–10, 2015	75,758.29

the year are then matched.

C. Severe Weather Drought Scenarios

The AC OPF is run over the selected drought scenarios of the studied grid using the PowerWorld simulator [32] and results are visualized using a geographical data view strategy (GDV) [33] and voltage contours [34]. Please note that the grid does not change for studying drought scenarios so although the studied weather scenarios are from 2007 and 2014, the generation mix and load data are from the end of year 2019, when the studied synthetic grid [28] was built. The results for the studied WRD and SRD are analyzed and the proposed corrective and preventive actions are applied to remove the overloaded lines and voltage violations.

1) Severe Wind Resource Drought Scenarios: A range of historic wind generation is calculated for the given sets of wind turbines using the power models of wind turbines as well as historic wind speed and wind directions. In this case, the generators in the studied Texas grid are used and historic hourly wind data are fed in as an input to determine the wind power availability of this set of generators. Table I shows examples of extreme WRD scenarios in the US sorted by duration of droughts. A sample wind drought scenario in May 2007 is selected for simulations and a more detailed study. Figure 4 shows the comparison of the wind generation in the selected dates compared to the historical data from 1973–2022 at the same times of the year.

The voltage contours of each bus from AC OPF results at this time are shown in Figure 6 (a). Congested lines from power flow results are shown with black rectangles.

2) Severe Solar Resource Drought Example: The availability of solar power for the studied grid is also calculated based on historical cloud coverage and radiation data. Table II shows examples of identified SRDs based on the calculated solar generation results in Texas sorted by duration of droughts. From this Table, the identified SRD in Dec 2014-Jan 2015 which has a low average solar generation is selected for a more detailed study. Figure 5 compares the hourly solar generation at this period to the distribution of historical solar energy generated by running historic weather data from 1973–2022 at the same times of the year and on the same set of generators in the Texas grid.

Figure 3 shows the capacities of PVs in yellow and wind turbines in green for the selected SRD scenario at 12 PM of Jan 2, 2015 with (a) nominal wind capacities and (b) calculated available renewable capacities based on direct in-

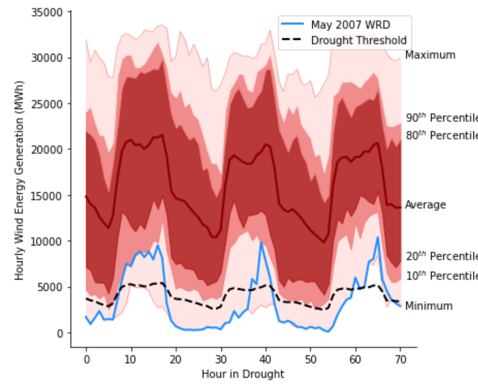


Fig. 4: Wind Generation in May 2007 compared to the Historic Distribution of Daily Wind Energy Generation in Texas

TABLE II: Identified SRDs

Duration (days)	Dates	Average Solar Generation (MW)
6	Jan. 29–Feb. 3, 1975	10,324.47
5	Oct. 22–26, 1984	11,837.86
5	Jan. 20–24, 1994	9,006.49
5	Oct. 31–Nov.4, 2002	9,393.01
5	Oct. 15–19, 2018	7,997.12
4	Dec. 30, 2014–Jan. 2, 2015	6,385.30
4	Nov. 13–16, 2004	7,113.75
4	March 11–14, 2009	10,103.97
4	Feb. 27– March 2, 2015	7,802.83

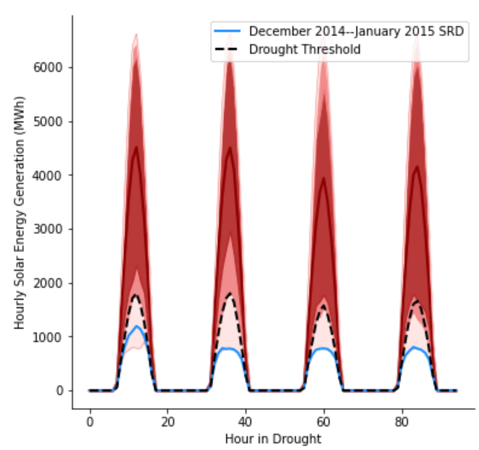
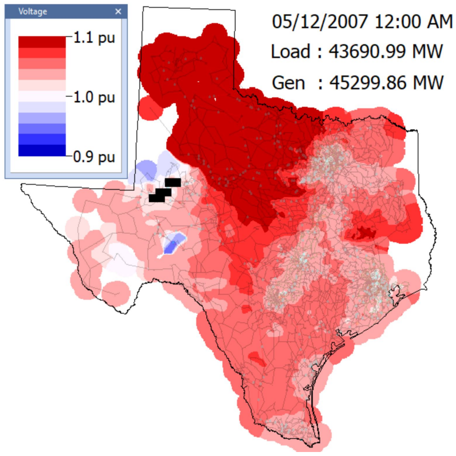


Fig. 5: Solar Generation in December 2014–January 2015 compared to the Historic Distribution of Daily solar Energy Generation in Texas



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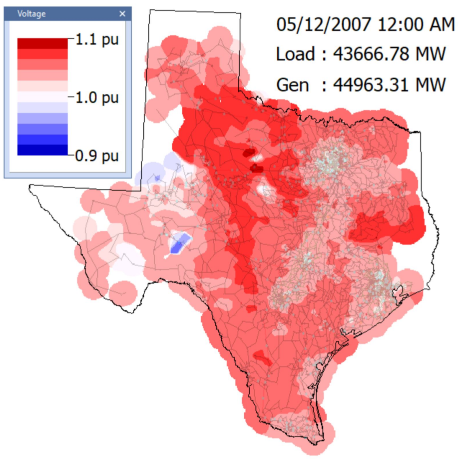

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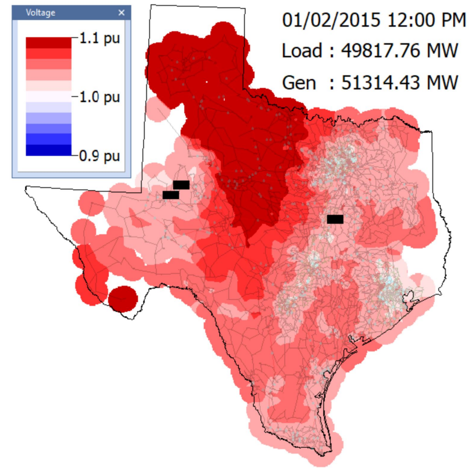
Fig. 6: Voltage contours of the WRD in May 2007 with direct inclusion of weather in OPF before and after remediation



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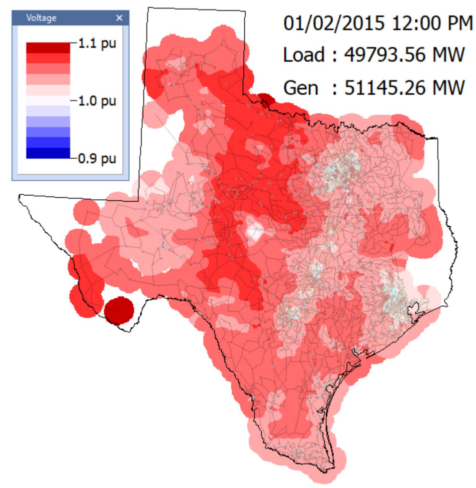

(b)

Fig. 7: Voltage contours of the SRD in Dec 2014-Jan 2015 with direct inclusion of weather in OPF before and after remediation

clusion of weather measurements in OPF. The size of ovals is proportional to the MW capacity and as expected, the wind generation depends on the availability of wind, and without direct inclusion of weather measurements in the AC OPF calculations, the nominal capacities are used which is not a true representation of the scenario situation. This Figure shows the significant impact of the RRD on renewable capacities.

Figure 7 (a) shows the OPF results including voltage of each bus and congested lines at this selected time.

To remove the voltage violations from WRD and SRD based on the proposed strategy, five switched shunts with an overall capacity of 150 MVAR inductive and 465 MVAR capacitive shunts are added. For line overloads in both 2007 and 2015 case, the determined RAS is to reduce the load in bus number 220173 of the case study [28] in the area with the largest overloaded line from 97.8 MW to 73.6 MW. For 2007 case, it is also required to open two generators on buses with numbers 220178 and 220195 to avoid overload in line '220155' to '220021' in the Far West area.

The results show that with the suggested remedial and predictive actions, after solving OPF with direct inclusion of weather measurements that determines the available capacities of renewable generators in times of WRD and/or SRD, the voltage profiles of all buses are maintained between the acceptable range of 0.9 pu to 1.1 pu. Also, no overloaded lines are observed in the AC OPF results after the suggested changes are applied.

V. Conclusion

This paper proposed a comprehensive approach to show the impact of severe WRDs and SRDs, on power systems by directly including weather measurements in OPF and suggested actions to mitigate their destructive impact on the grid. we derive valuable insights into the behavior of renewable generators and their impact in extreme drought scenarios. Weather measurements, coupled with generator power models and types, inform the input parameters for the AC OPF. Employing a synthetic grid based on actual generation data from the end of 2019, our simulations provide a realistic assessment without disclosing and CEII, which can be implemented on real grids. Through the identification of RRDs from historical weather data, we leverage such extreme weather scenarios that can significantly impact power system operation. Our analysis of example scenarios, shows the impact of RRDs on power system reliability and resiliency, often leading to overloaded lines and voltage issues.

Based on the AC OPF results, we propose a range of preventive and corrective actions to mitigate operational challenges arising in the face of extreme weather scenarios. By addressing these issues, we enhance power system resilience and reliability. The methodology developed in this study is not limited to the specific case study and can be extended to assess the impacts of RRDs on power grids worldwide, utilizing the available historical weather data. This research contributes to a deep understanding of the interplay between renewable resources and power systems, with implications for the sustainable and reliable operation of grids on a global scale.

VI. Acknowledgements

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