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PAPER

A resource adequacy assessment of correlated wide-area outages in the power grid

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Abstract

As the power grid is undergoing rapid transformations, numerous questions are emerging about its vulnerability to wide-area extreme events (WAEE), which could influence its operations. Relatively few analyses have been conducted to date regarding the impact of correlated outages during WAEEs on the grid's ability to balance resources with demand. This study addresses this gap by conducting a resource adequacy analysis for a hurricane-inspired WAEE on a 2035 synthetic power grid system for the United States. A sensitivity analysis was also conducted to characterize the relative impact of weather on unserved energy. Our results indicate that although the magnitude and duration of the shortfalls vary depending on weather conditions, persistent shortfalls are observed in some regions. Initial explorations indicate a strong correlation between transmission-constrained regions and regions with persistent shortfalls. Future work could generate empirically-grounded representations for generator outages as well as conduct causal analyses of these shortfalls to improve understanding of drivers as well as possible mitigation strategies. Continued exploration of extreme weather impacts on the grid is important to develop more robust understanding of the reliability and resilience of our power systems, especially as they undergo rapid transformations.

1. Introduction

The power grid, which serves as an important mechanism for providing energy for a variety of end uses, is undergoing rapid transformations. The emergence of different energy generation technologies has further increased awareness of the critical role of the power grid for balancing supply with demand across different regions and time periods. In particular, a combination of low costs, availability across diverse geographies, and its ability to support grid restoration post emergencies has driven a significant increase in solar photovoltaics (PV), accounting for three-quarters of global additions in renewable energy in 2023 [1–4]. Other factors (e.g. renewable energy targets and changing loads) are also drawing attention to the power grid; forecasts indicate loads are expected to increase by 3.4% each year across the globe, with some regions experiencing even greater increases [5]. These changes have identified that more investments are needed for power grid systems to support the evolution of energy systems around the globe [6, 7].

In addition to increasing awareness of its important role, there has also been an increasing awareness of vulnerabilities of power grid systems. News coverages of power outages have highlighted various concerns with maintaining reliable electricity transmission and distribution in many countries around the world, including the United States, Mexico, Kuwait, and Croatia [8]. In particular, outages from wide-area extreme events (WAEEs) such as hurricanes and temperature extremes have been increasing over the last two decades [4, 9, 10]. In fact, over half of the global grid-related blackout events are attributed to hurricanes and winter storms [10]. The specific cause of power outages vary across time and space, with some WAEEs leading to fuel supply disruptions (e.g. Texas outage [11]) and/or coupled with increasing demand in the power grid (e.g. to combat extreme heat [12]). Multiple factors influence resilience (i.e. ability to withstand, operate through, and recover from disruptions) of the power grid, including likelihood of generation availability, proportion of generation to loads, and redundancies in the network to transfer electricity to regions with high demand [4].

In recognition of these issues, various studies have been conducted to assess the power grid, focused on either vulnerability analyses for extreme weather conditions or informing planning activities for evolving systems. For vulnerability analyses, studies have attempted to forecast power outage risks and duration using multiple data science techniques, including machine learning [13–16]. Others have used simulation techniques (e.g. graph theoretic and power flow analyses) to study the impact of extreme events on grid behaviors [17–19]. In contrast, planning-oriented studies have typically focused on optimization build-outs of future systems for different possible scenarios [20]. For example, some used capacity expansion planning models (such as the Regional Energy Deployment System Model (ReEDS)) to assess the impact of cost policies and electrification on achieving decarbonization objectives [21]. Resource Adequacy (RA) techniques, which focus on assessing whether there are sufficient available resources to meet load across multiple scenarios, have also been used to assess uncertainties in different assumptions (e.g. load, battery storage) in these studies [21]. While RA methods have been used to characterize some historical events [22], the impact of WAEE on these synthetic systems has received little attention to date. One study explored short duration WAEEs, noting that the relationship between the distribution of energy generation sources and the geographic extent required further attention [23]. Such insights could help inform emergency management activities in the event of losses in critical utility functions [24].

Historical assessments indicate that a key feature of WAEEs are correlated reductions in generator availabilities [22, 25]. However, many of the assessments to date have not evaluated the impact of these co-occurrences on overall reliability of the planned power grid systems. This study addresses this critical gap by using a RA-based assessment to characterize risk of power grid systems to WAEEs. In particular, this study aims to answer the following questions: How reliable are planned systems to correlated generator outages in WAEEs? How robust are these findings given uncertainties in weather conditions? RA assessments were selected for this analysis because they are especially well-suited for accounting of uncertainties in generation, transmission, and load [26]. Furthermore, they are commonly used to characterize RA by various planning entities at regional and national levels (e.g. [27, 28]) and have been identified as being well-positioned to support exploration of uncertain futures [26]. For this study, we use an open-source model called the Probabilistic Resource Adequacy Suite (PRAS) to evaluate the impacts of a WAEE on the reliability of planned systems. In recognition of the increasing prevalence of solar (both utility-scale and distributed) in most grid systems, we focus on correlated outages of PV generators for a United States-based synthetic grid system developed using ReEDS from a Solar Futures Study [21]. For the WAEE, we use a hurricane-inspired event given the increasing frequency of these hazards [29] as well as their impact on PV generation [30, 31]. In recognition of the uncertainties associated with renewable energy generation, we conduct a sensitivity analysis focused explicitly on incorporation of weather uncertainties (WU) to characterize the robustness of the RA findings. The following sections describe the methods and associated findings in greater detail.

2. Methods

For this study, we analyze the robustness of a synthetic system for the United States (derived from a recent study [21]) to a hurricane-inspired wide area extreme event (HI-WAEE). In particular, this study conducts an RA assessment, which focuses on measuring the duration and severity of potential imbalances between loads and generations [32]. This analysis involved both comparing the HI-WAEE to baseline runs as well as conducting a sensitivity analysis to evaluate the impact of different weather assumptions on model outputs (figure 1). The following sections describe in greater detail the characteristics of this synthetic system as well as how this assessment was conducted using PRAS, an open-source RA model.

2.1. System analyzed: 2035 build-outs

For this analysis, a 2035 synthetic system for the contiguous United States derived from a Solar Futures Study was selected [21]; while the specific year selected was arbitrary, the intent was to focus on a future synthetic system that is being used to inform planning discussions. This synthetic system was developed using the ReEDS capacity expansion planning model, which incorporated information about current operations, costs from the Annual Technology Baseline [33], and policies that could influence how different generation build-outs and associated transmission planning could look into the future [34]. The model also assumed aggressive cost-reduction projections for renewable and energy storage technologies, large-scale electrification, and a policy driver aiming for a 95% reduction in the grid's carbon dioxide emissions by 2035 from 2005 levels [21].

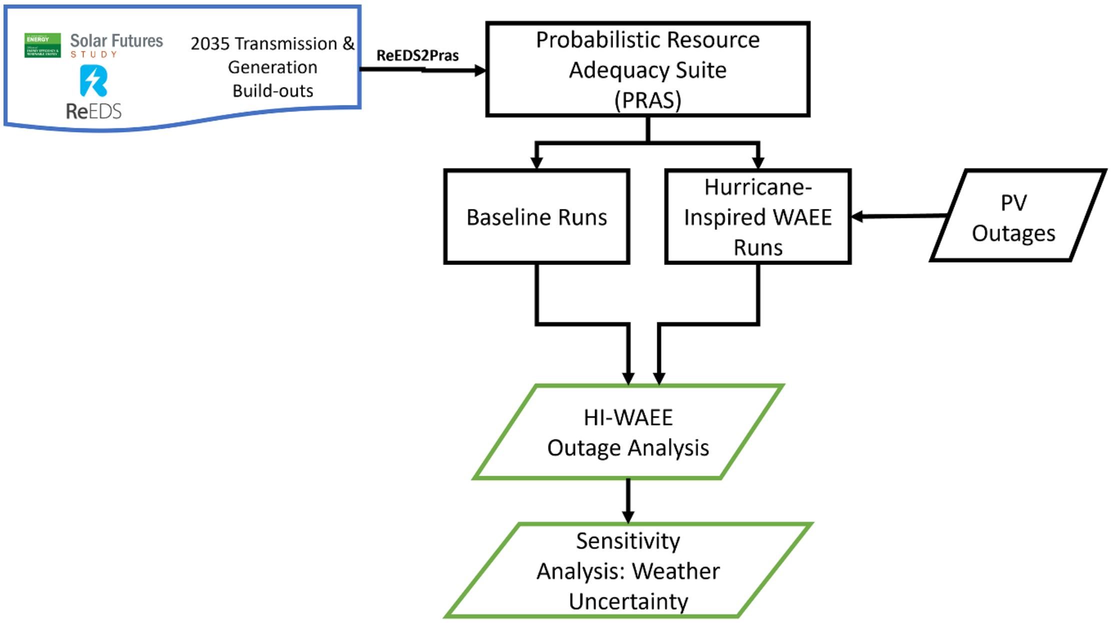

Figure 1. Analysis approach for this study, which focuses on a hurricane-inspired wide-area extreme event (HI-WAEE).

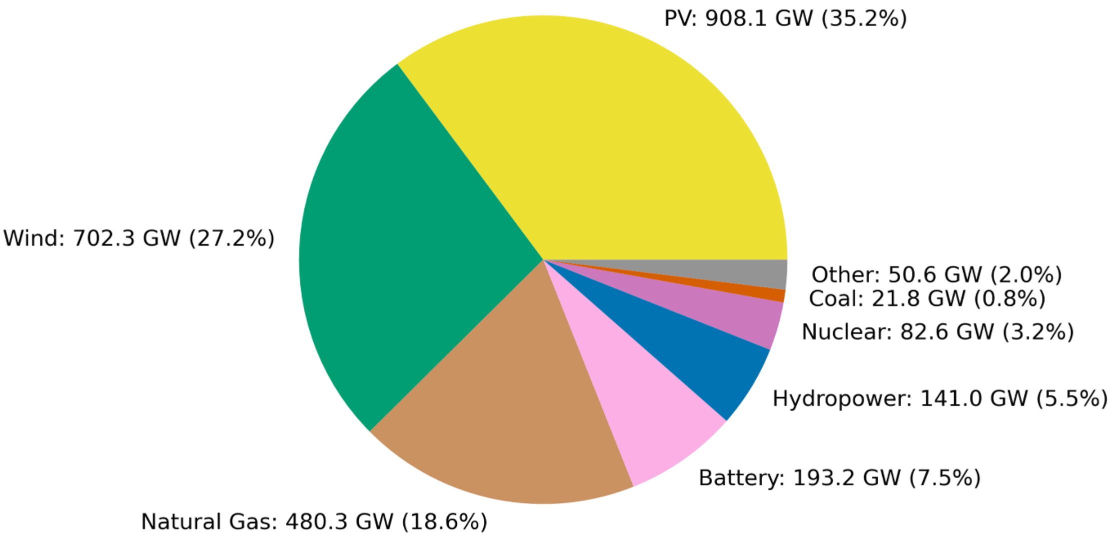

Figure 2. Distribution of generation capacity by category for the entire synthetic 2035 system.

The resulting system for 2035 contained a combination of generation technologies, with PV, wind, and natural gas accounting for nearly three quarters of generation capacity, and other technologies accounting for the rest (figure 2). In particular, the ReEDS 2035 build-out indicated that solar PV accounted for 35.2% (i.e. 908.1 gigawatts (GW)) of the total system capacity; this value reflects an 7x increase from 2023 capacity in the U.S. [35]. Because the ReEDS model is executed at a zonal scale that disaggregates the contiguous United States into 134 zones (hereafter referred to as ReEDS regions) [34], additional information can be also be obtained about the distribution of solar across the country. The 2035 build-out indicates notable differences in both regional capacities of PV and transmission for the US in these 2035 build-outs, with some regions having little to no utility-scale PV to others having over three-quarters of their local installed generation capacity being from PV (figure A2). Transmission capacities also varied across regions, with some having low aggregate transmission capacity between regions while others had significant (> 20 GW in capacity) (figure A2).

2.2. Probabilistic resource adequacy suite (PRAS) model

While the resource portfolios generated by capacity expansion planning models (such as ReEDS) are cost optimal, they do not always ensure that they meet system reliability standards set by regulatory authorities [36, 37]. This is primarily due to the fact that these planning models cannot consider the various uncertainties associated with system operations and weather conditions. Thus, RA models serve as a critical complement to grid build-outs since they can evaluate whether there is enough supply to meet demand within a power system (given a specific reliability target), either under normal operating conditions or during specific conditions, such as failure of equipment and extreme weather events.

For this study, RA was evaluated using PRAS [38]. In addition to being open-source, PRAS was selected for this analysis due to its ability to model hourly availability of power system assets (e.g. generators, storage) as well as its ability to take into account inter-regional transmission and weather dependency of generation, outages, etc [39]. In particular, PRAS enables a probabilistic (sequential Monte Carlo) analysis of a given power system portfolio (e.g. generation and load profiles) and to assess whether there are potential shortfalls and if so, associated characteristics of the shortfalls (e.g. intensity, frequency, and duration). A key distinguishing feature of PRAS is its treatment of generator availabilities from a probabilistic perspective. Specifically, generator availabilities are determined based on outage and recovery probabilities (which can be derived using forced outage rates (FORs); see supplementary information and figure A1), wherein the model performs an hourly draw for each component (for which transition probabilities are available) to determine its availability. These FORs can be used to represent any number of events, including public safety power shutoff, cyber attacks, or extreme weather occurrences.

A similar approach is adopted to determine charge and discharge capacity of storage in a region and flow limits. PRAS uses a greedy dispatch model for storage wherein storage devices charge whenever possible and discharge only to avoid unserved energy. Available generation capacity (G_i), charge capacity (C_i) and discharge capacity (D_i) of storage in each region i and flow limit (F_{ij}, F_{ji}) in each interface with neighbor j is based on random outage state and storage state-of-charge from previous time period. For a given region i, Unserved Energy (UE), UE_i in a region with load, l_i, is defined in equation (1):

$$\mathrm{UE}_i = l_i + c_i + \sum f_{ji} - g_i - d_i + \sum f_{ij} \quad \forall j \in \text{neighbors}_i. \tag{1}$$

In equation (1), neighbors_i is defined as all the regions connected to i via transmission lines. For a given sampled state (G_i, C_i, D_i, F_{ij}, F_{ji}) in a region i, the problem PRAS solves is explained in equation (2):

$$\begin{aligned} &\underset{g_i, c_i, d_i, f_{ij}}{\text{minimize}}\ \mathrm{UE}_i \\ &\text{subject to } 0 \leqslant g_i \leqslant G_i \\ &\qquad 0 \leqslant c_i \leqslant C_i \\ &\qquad 0 \leqslant d_i \leqslant D_i \\ &\qquad F_{ji} < f_{ij} < F_{ij} \quad \forall j \in \text{neighbors}_i \\ &\qquad \mathrm{UE}_i \geqslant 0. \end{aligned} \tag{2}$$

While cost is not considered in this objective function, PRAS does impose a small penalty on transmission to avoid loop flows. Transport between regions is conducted through a simple transport model for interregional powerflow; the transport model does not consider losses, impedance, voltage, etc. For this analysis, we focus on expected unserved energy (EUE) for characterizing RA.

2.3. HI-WAEE representation

As mentioned previously, this analysis focuses on correlated outages for solar associated with a HI-WAEE. The representation of the HI-WAEE in this study involves: (1) identifying which regions are impacted by the WAEE, (2) identifying the time periods impacted by the WAEE, and (3) updating solar availability during the HI-WAEE. Details about each of these assumptions are captured below.

To identify hurricane-prone regions of the country, we leverage the United States Federal Emergency Management Agency's (FEMA) National Risk Index (NRI) [40]. The NRI provides county-level, hazard-specific risk ratings, which categorically describe a community's risk relative to other communities.

These county-level risk ratings were aggregated such that any ReEDS region containing counties with 'very high' or 'relatively high' risk ratings were considered at risk for the WAEE. This involved first assigning each county to the corresponding ReEDS regions and then determining whether any high-risk counties were present with each of the regions. The stringent rating requirement was used to ensure that the subsequent modeling is restricted to regions with significant damage from a given WAEE. The resulting 19 impacted ReEDS regions (see figure 3) set the spatial boundaries during the WAEE-specific PRAS runs.

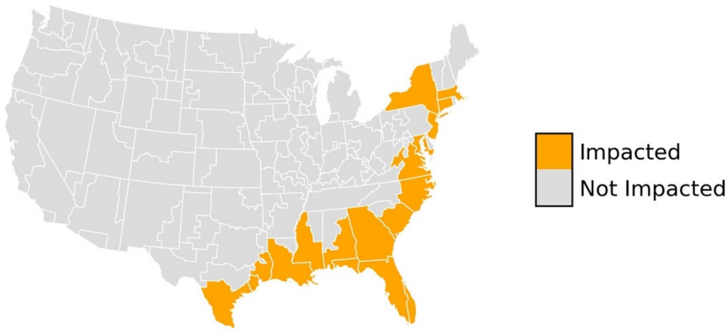

Figure 3. Spatial extent of HI-WAEE (based on FEMA NRI values). There are 19 impacted regions (colored in orange), which reflects those regions where WAEE solar outages were introduced relative to baseline.

In addition to spatial extents, a temporal period also needs to be determined for HI-WAEEs. Hurricanes typically occur between June to November with peak activity occurring between August to October [41]; the peak activity time period is used in this study. Specifically, it was denoted that during the hurricane peak period (i.e. August to October), only solar generation (both utility-scale and distributed PV) would be impacted for this initial study.

Finally, during the HI-WAEE, we need to update the representation of the solar availability. PRAS runs require asset-level details for FORs (see section 2.2). As noted previously, FORs are associated with the removal of a generating unit from service availability [42] and can be interpreted as the likelihood of generator being offline due to any reason other than scheduled maintenance outage (e.g. extreme weather). Assumptions for FORs can result in different patterns in shortfall observed in model outputs (figure A7). FORs in baseline runs were based on the Generator Availability Data System collected by the North American Electric Reliability Corporation (NERC) [43]. While NERC has recently mandated reporting of outages for large PV plants, results from these reports have not been released. Given that hurricane events can vary in space and time, we adopt an extreme scenario wherein all solar generation is offline during peak hurricane season in hurricane-prone areas of the country. For a given location and time period, the PV contributions within the PRAS model were updated from baseline conditions to indicate zero availability during peak hurricane time periods in the hurricane prone regions (table A1).

2.4. Scenario evaluation

The focus of this study is to conduct an assessment of shortfalls from correlated wide-area solar PV outages associated with HI-WAEEs. This is done by executing PRAS for a period of one year (i.e. for the synthetic 2035 build-out) for the HI-WAEE (using the assumptions captured in section 2.3) and comparing those outputs relative to a baseline scenario. Each of the HI-WAEE and baseline scenarios are executed for 10 000 Monte Carlo runs to help capture the probabilistic nature of possible outcomes. Outputs from the resulting runs are then processed and analyzed to identify relevant patterns. Given the focus on generator-impacts for this study, we assume that the transmission infrastructure is fully available (i.e. does not have any forced outages) and a constant mean time to repair of 48 h for all generators. A fixed seed is used for the PRAS runs to enable reproducibility of the analysis. For the initial assessment of HI-WAEE outcomes, we assume an average level of solar and wind resource availabilities (i.e. WU1). However, in recognition of the impact of weather on renewable generation, multiple weather profiles (i.e. WU2-WU7) were also analyzed as part of a sensitivity analysis (table 1). Although the HI-WAEE event was assumed to impact solar only during Aug–Oct months and only in certain regions of the country (figure 3), all months and spatial regions are included in the analyses to capture temporal and spatial dependencies (e.g. influence of storage activities over time and influence of interconnections across space). Below we describe in greater detail the specific metrics of interest, how HI-WAEE outcomes were compared to baseline, execution of the sensitivity analyses, and evaluation of patterns.

2.4.1. Metrics of interest

PRAS outputs can be processed to generate various metrics. For this analysis, we are primarily in interested in characterizing shortfall using a normalized value of expected unserved energy (nEUE) (equation (3)):

$$\mathrm{nEUE}_{r,t} = \frac{U_{r,t}}{D_{r,t}} \times 10^6 \tag{3}$$

Table 1. Summary of scenarios evaluated in this study. Weather Uncertainties (WU) reflect the different weather profiles used for the analysis.

Condition	Scenario: Average Condition: WU1	Scenario: Sensitivity: WU1-WU7	Additional notes
Baseline	×	×	Subtracted from HI-WAEE
HI-WAEE	×	×	Affects sites during peak season (August-October)

where U is the EUE across the Monte Carlo runs, D is the total demand (i.e. load) for a region (r) at time t. The units for EUE and demand are megawatt-hours, so the multiplication of this fraction by one million results in units of parts per million (ppm), a standard approach used in RA analyses. Often, targets vary by region. For this analysis, we consider 10 ppm as an 'acceptable' RA target [44, 45]. To facilitate analysis, the resulting shortfalls are organized into tiers of ppms (similar to [4]), with tier 4 indicating the areas with highest concern (i.e. exceed reliability target of 10 ppm) whereas tier 1 indicate shortfalls of lowest concern.

2.4.2. Comparisons to baseline

The shortfalls from PRAS are subtracted from the baseline conditions to highlight the WAEE-specific impacts across the scenarios. Given the probabilistic nature of PRAS outputs, we expect some natural variability in the results between baseline and scenarios. To ensure that we only capture the differences that are meaningful, we only consider outputs that are outside a certain threshold from the mean baseline EUE:

$$U_{r,t,\mathrm{net}} = \begin{cases} 0 & \text{if } \|U_{r,t,\mathrm{HI-WAEE}} - U_{r,t,\mathrm{base}}\| \leqslant d_{r,t} \\ U_{r,t,\mathrm{HI-WAEE}} - U_{r,t,\mathrm{base}} & \text{otherwise.} \end{cases} \tag{4}$$

U_{base} is the mean EUE in baseline runs, $U_{\mathrm{HI-WAEE}}$ is the mean EUE under HI-WAEE runs, and U_{net} is the net change in mean EUE from baseline after filtering via threshold $d_{r,t}$, which is defined as:

$$d_{r,t} = 1\mathrm{MWh} + 3\sigma_{r,t,\mathrm{base}} \tag{5}$$

where σ_{base} is the standard deviation of EUE over the Monte Carlo samples in baseline. The inclusion of a term proportional to the standard deviation ensures that the mean HI-WAEE EUE falls well outside the probabilistic range observed in baseline. These comparisons to baseline were conducted for both the primary HI-WAEE runs as well as for the sensitivity analysis associated with WU.

2.4.3. Sensitivity analyses

There are multiple inputs involved in the execution of the PRAS runs [38]. Given the importance of weather conditions for influencing renewable resource availability and load behaviors, we conducted a sensitivity analysis to assess the impact of weather assumptions on overall outcomes. The WU sensitivity analysis considered how variations in observed weather could influence the outcomes of the PRAS model. We evaluated 7 possible WUs of wind, solar, and load profiles, which reflect different availabilities of solar and wind in the analysis period for PRAS (see table A2) as well as different loads (figure A3). These different WUs show that capacity factors across the ReEDS regions range from 0% to 68% and 5% to 73% for PV and wind, respectively (table A2). These sensitivity-oriented outputs were analyzed relative to associated baseline WU runs (similar to the overall HI-WAEE scenario) described below.

2.4.4. Pattern evaluation

Shortfalls in HI-WAEE (after being subtracted from baseline) were analyzed in multiple ways. Tallies were conducted to understand the number of regions that experienced shortfalls at different tiers and at what time periods. The differenced nEUEs were analyzed for both aggregate spatial (i.e. summed across the year for a given region) as well as aggregate temporal (i.e. summed across regions for a given time interval) in this analysis. To investigate the impact of weather conditions, we counted the number of WUs out of 7 in which ReEDS regions or time periods experienced annual nEUE of 0.01 ppm or greater, which is equivalent to sum across tiers through 4. To support characterization of shortfalls, additional outputs from PRAS (e.g. transmission utilization and behavior relative to hourly load) were also evaluated. Transmission utilization values were quantified as percentages of flow relative to total capacity. These two outputs were analyzed to determine the relative importance of PV capacity and transmission capacity on shortfall susceptibility and help clarify which aspects of the grid were contributing to shortfalls. For each region, we normalized the PV capacity and the total transmission capacity by the region's mean hourly load; latter in units of megawatt-hours. These normalized capacities allow for simple comparison between regions and an intuitive measure of the magnitude of available PV and transmission contributions toward satisfying local regional loads. Using the implementation in SciPy [46], the Spearman correlation and corresponding p-value were computed between the WU count and each normalized capacity to assess the relationships between each region's solar generation and transmission capacities relative to its shortfall susceptibility of tier 1 or higher.

3. Results

An execution of PRAS for the various baseline and HI-WAEE runs (summarized in table 1) revealed multiple patterns of shortfalls in space and time across the scenarios. As noted previously, baseline conditions are not devoid of shortfalls given the configurations of the capacity expansion planning model that generated the build-outs. In particular, the 2035 build-out had persistent shortfalls in various regions during baseline runs, especially in the southern regions of the country (figure A4) as well as during various times of the year (figure A5). Transmission utilization also varied across regions in the baseline runs (figure A6). The shortfalls in the baseline, which could reflect limitations in the capacity build-outs for 2035 and other model assumptions, are subtracted from the HI-WAEE runs to isolate possible impacts from the extreme event scenario analyses. The following subsections summarize the baseline-differenced findings for the HI-WAEE runs as well as the WU sensitivity analysis.

For the average weather condition, the HI-WAEE runs indicated 10 regions (out of 134) with some level of shortfalls (figure 4(a)). When compared to other WUs, it becomes clear that the specific counts of regions experiencing shortfalls vary depending on weather assumptions (figure 4(b)). In particular, the number of regions experiencing shortfalls ranges from 5–10 (across the tiers) depending on the WU (table A3). However, there are three regions that seem to observe consistent shortfalls greater than 10 ppm (i.e. Tier 4) (table A3). All of the impacted regions are either within the spatial extent of the HI-WAEE or in a neighboring region (figure 3).

From a temporal perspective, the frequency of nEUE across the different hours of the month indicates when these shortfalls are likely to occur. During average weather conditions, shortfalls are observed during 19 of the month-hour periods, all of which occur during the months of August and September (figure 4(c)). Of these periods, the most notable shortfalls occurred between 3pm to 11pm during the month of August (figure 4(c)). While shortfalls are also observed in other months (i.e. July and October) for different WUs, it is clear that majority of these outages are most consistently observed during August to September across the PRAS runs (figure 4(d)). However, the specific breakdown of shortfalls across tiers was a lot more variable across the WUs (table A4).

In addition to shortfalls, transmission utilization for HI-WAEE runs were analyzed. Model outputs indicate that the proportion of flow relative to capacity (i.e. utilization) of the transmission systems was generally higher during the HI-WAEE runs during the average weather condition (figure 5(a)). While most of the regions experienced little to no changes in transmission utilization, some lines between regions experienced up to 8% increases in utilization during WU1 (table A5). When weather conditions are changed, some transmission lines experienced even more utilization (figure 5(b)).

Shortfalls could be generated through various factors, including high demand and low abilities to transfer electricity between regions. For example, the regions in Florida and Texas have a much higher load in the summer months relative to the country as a whole (figure A3). Thus, to understand possible contributors of these factors to shortfalls, we evaluated the relative generation and transmission capacities of each ReEDS region to local loads (figure 6). This visualization highlights that shortfalls are not restricted to regions with high PV installed capacity since regions with persistent shortfalls (i.e. 6–7 WUs) generally had a large variation in PV capacity ranging from 0.15 to 74.4 GW (accounting for 1.2% to 50% of local generation capacity) (figure 6). However, regions with shortfall generally appear to have relatively low transmission capacity relative to mean hourly loads (figure 6). These findings are further supported by a statistical analysis, which indicates that transmission capacity is significantly negatively correlated with the number of regions experiencing shortfalls across WUs whereas PV capacity is not (table 2). In particular, these results indicate that the larger the transmission capacity of a region, the lower the likelihood of a region experiencing shortfalls, with a stronger relationship observed in regions within the spatial extent of the HI-WAEE (table 2). These outputs reflect that although multiple regions could be impacted concurrently (figure A8), the transmission system still play a vital role in reducing the shortfalls observed in the power system during WAEEs.

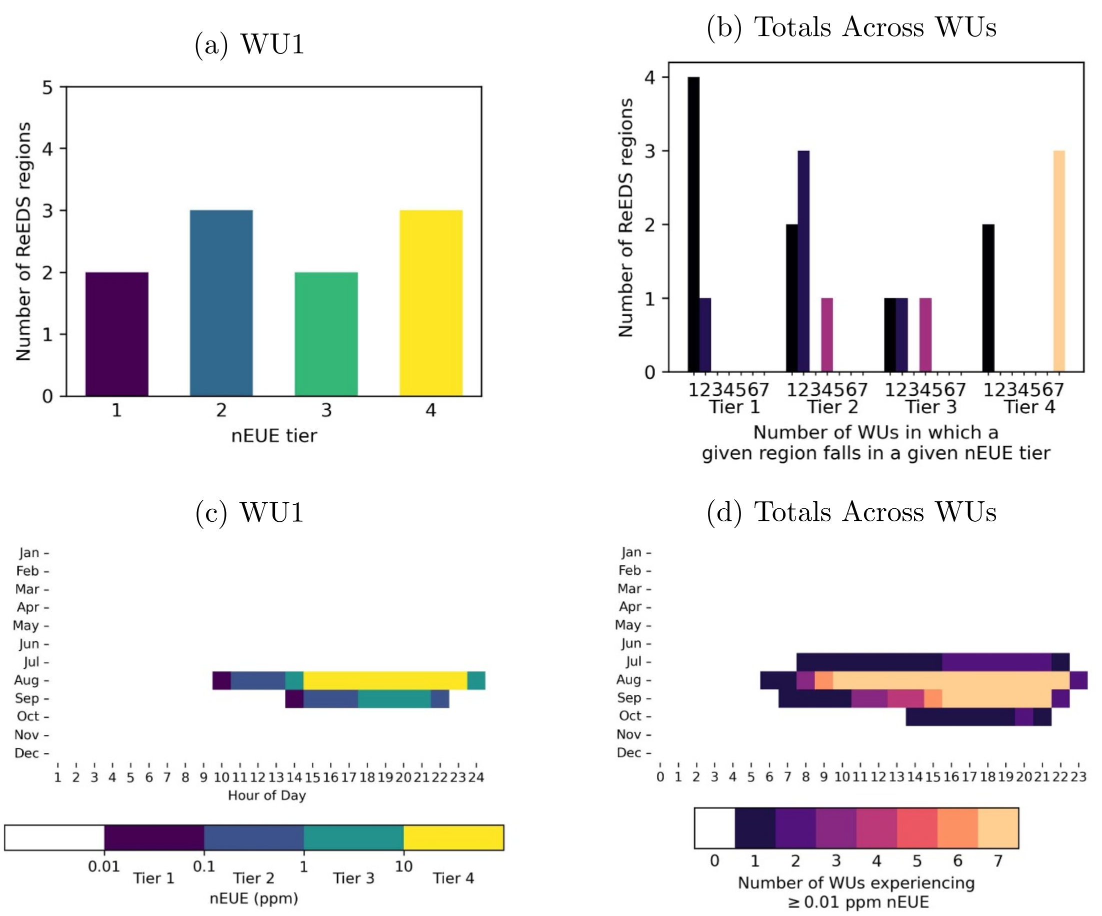

Figure 4. Spatial distribution of yearly and temporal distributions of nEUE for WU1 (a), (c) and aggregated across the 7 WUs (b), (d). These results are measured as the difference from baseline. Color legends are captured at the bottom of the respective columns.

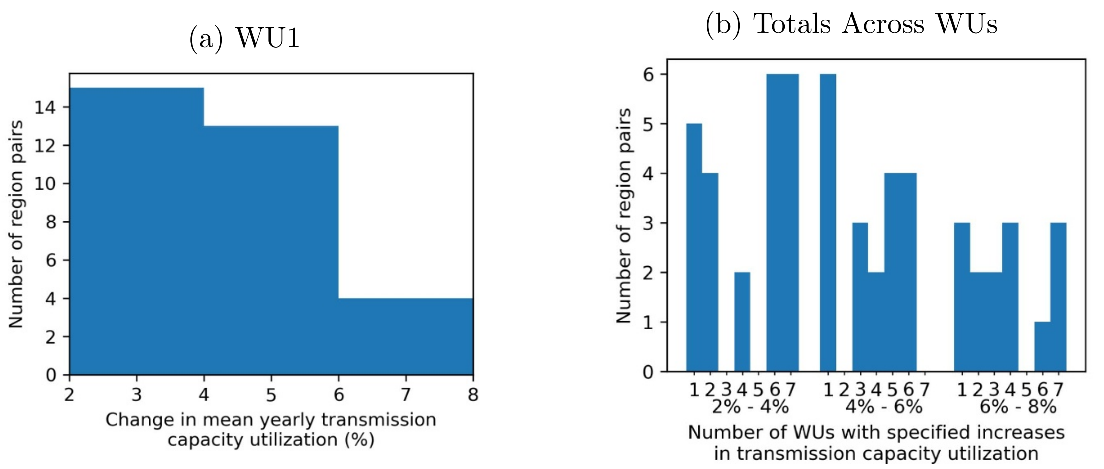

Figure 5. Change in transmission capacity utilization from baseline in WU1 (a) and aggregated across the 7 WUs (b).

4. Discussion and conclusion

4.1. Implications

This study is one of the first to characterize correlated outages in generators arising from WAEE-specific resource inadequacies in possible future theoretical grid systems. Our findings indicate that for a HI-WAEE, there are regions that may experience persistent shortfalls under multiple weather conditions (figure 4(b)). The timing of the shortfalls generally coincided with periods with the highest loads (figures 4(d) and A3).

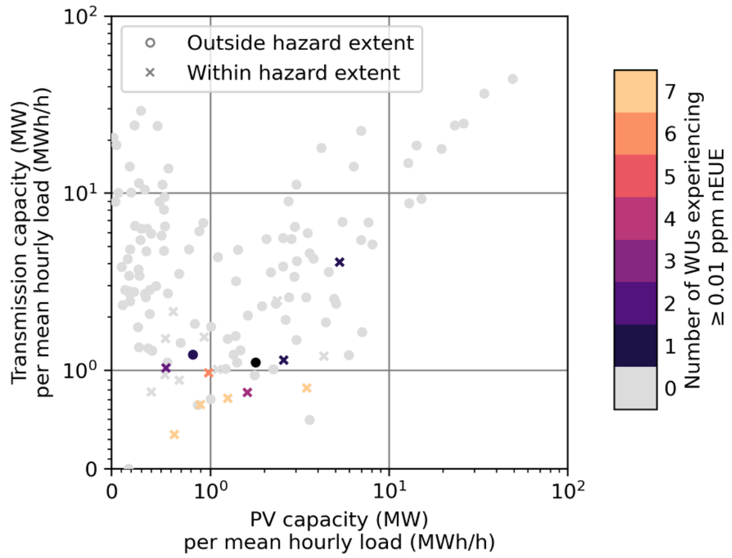

Figure 6. PV capacity and transmission capacity for each region, colored by the number of WUs for which regional nEUE exceeded 0.01 ppm. Both capacities are normalized by the region's mean hourly load for the year to indicate the significance of these energy sources for a given region. Regions with low transmission capacity within the hazard extent seem most likely to experience shortfall.

Table 2. Correlation between the number of WUs experiencing at least tier 1 nEUE and the given capacity type for HI-WAEE runs. For those within the spatial extent of the HI-WAEE run, transmission capacity is significantly negatively correlated with WU count. In contrast, PV installed capacity is not significantly correlated with shortfalls across WUs.

In Spatial Extent?	Installed Capacity type	Spearman's ρ	p-value
Yes	Transmission	-0.616	0.0050
Yes	PV	0.203	0.404
No	Transmission	-0.188	0.044
No	PV	0.020	0.834

Given the complex interactions between varying generation and load as well as the influence of the transmission systems on overall performance of the system, tracing the specific cause of these shortfalls is far from simple. However, initial explorations indicate that the transmission system, whose role is to balance power dynamics across regions, plays a critical role in moderating shortfalls even when multiple neighboring regions experience concurrent reductions in generation (table 2).

System operators often use a planning reserve margin (i.e. having installed capacity exceed peak demand by a certain percentage) to ensure a system is resource adequate. However, this study highlights the value in performing probabilistic RA analysis to consider additional scenarios (e.g. susceptibility to correlated outages) in future builds that could influence a region's ability to rely on local generation or neighboring generation to meet local power demand. While the attributes of the selected system are a key determinant of outcomes, the methods presented in this study can be extended to any current or future system of interest for RA assessments of correlated outages to WAEEs. As grid systems continue to evolve, augmenting current evaluation methods to evaluate risks during WAEEs will be increasingly critical for developing resource adequate systems under rapidly changing environmental and infrastructure conditions.

4.2. Limitations

This work was influenced by multiple limitations, involving a combination of data availability and modeling decisions. A number of assumptions had to be made regarding input and outputs across national boundaries as well as general composition of energy generation and transmission system in 2035 model build-outs that may not reflect true future system states. Also, the representation of the extreme events is across a large spatial extent that is based on historical observations. Thus, they do not capture the path of any single event nor reflect possible increases in severity or frequency of extreme events under future climate conditions. Furthermore, the representation of solar outages assumed an extreme case of full-scale outage during the specified time period and spatial extent, which does not reflect seasonal variabilities (or general underperformance) and acute impacts, such as longer-term damages that may coincide with hurricanes and high winds [30]. Incorporation of these antecedent conditions could greatly influence the actual availability of PV (and other energy) systems during the simulations, including how quickly they are able to recover. Additional explorations of model outputs may also be warranted to understand what features of the PRAS configuration result in higher sensitivities to some parameters (e.g. FOR) but not as much to others. The current analysis also does not incorporate possible impacts to load due to extreme events or influences from operational activities (e.g. wind plants stopping operations when wind is above 25 meters per second), which may impact the robustness of findings.

4.3. Future work

Given the important role of FORs in model outputs (figure A7), future work can start to develop more refined datasets to support model simulations. In the current analysis, PV sites are assumed to perform uniformly for a given hazard or baseline condition. However, we recognize that there are spatial differences in PV performance, which could reflect the age of the sites, different operating behaviors, and specific magnitude of extreme events observed locally [30]. Datasets that reflect that these spatio-temporal differences in PV site performance (both in terms of outage frequency and recover times) as a function of hazard characteristics could help extend the current work to accurately capture hazard impacts. These methods can be extended to develop associated FORs for other generators and transmission lines to develop representation of all energy assets during hurricanes as well as other WAEEs (e.g. high winds, blizzards, and earthquakes). These implementations of FORs could also be extended from the current RA implementations to support how the capacity expansion planning models are executed. Currently, ReEDS build-outs optimize across operating, policy, and cost conditions. Incorporation of feedback from RA analysis into capacity expansion would enable building of a more robust resilience grid system in the future.

Future work could also extend the current analysis to explicitly evaluate possible drivers of shortfalls, include additional metrics, and refine the scale of analyses. For example, machine learning methods could be used to assess if a predictive model could be developed based on regional characteristics across generation, load, and transmission profiles. Assessments could also evaluate the impact of additional capacity at interconnects for mitigating shortfalls [47]. Additional metrics could also be generated to better define effective load carrying capability and capacity values of the regions [48]. Finally, the scale of the analysis could also be revised to conduct RA assessments to focus on specific regions of concern (e.g. Florida or Texas) and understand local nuances further (e.g. seasonal differences in peaking behaviors). Reducing the spatial scale of analysis could also enable more refined representation of critical transmission and energy generation assets within the analyses. For example, inverters have been gaining increasing attention for their impact on PV performance, especially under different environmental conditions [49, 50]. During extreme weather events, the role of these assets becomes even more important given the significant role they play in modulating frequencies [51].

Data availability statement

The model inputs and outputs that support the findings of this study are available online: https://data.nrel.gov/submissions/291 (DOI: https://doi.org/10.7799/2566792).

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The data that support the findings of this study will be openly available following an embargo at the following URL/DOI: TBD post article acceptance. Data will be available from 30 April 2025.

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