Using Utility Outage Statistics to Quantify Improvements in Bulk Power System Resilience

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***Abstract*—CRISP is a new high-level statistical approach driven by utility data to quantify resilience in electric power transmission networks. We extend CRISP to model energy storage, photovoltaics, and generator outages, to account for the spatial spread of cascading outages, and to optimize the restoration process. Illustrative results show how CRISP can measure the resilience impact of combinations of energy storage and photovoltaics on a power system.**

***Index Terms*—Resilience, Transmission system, Statistical modeling, Restoration, Cascading outages, Energy storage.**

I. Introduction

As the bulk electric power system changes in response to climate change, more extreme weather, and new technologies, there is an increasing need to quantify its resilience to extreme events. For example, distributed variable energy resources are increasing and we need to quantify their effect on the resilience of power systems. Similarly, with the rush to add energy storage, it is important to ask if storage can support power system resilience. Recent natural disasters show the importance of resilience of critical infrastructure; hurricane Dorian leaving the Bahamas flooded and in crisis is just one recent example of the devastating effects of natural disasters [1]. Another good example of the effects of extreme weather is the recent record snow falls in Montana causing power outages and road closures.

CRISP stands for Computing Resilience Interactions Simulation Platform, and is a new framework to quantify resilience of transmission networks that was initiated in [2].
CRISP is:

- **a high-level and comprehensive model of all phases of resilience**, encompassing stress, cascading, failure, recovery, and analysis. This allows quantification of the overall risk of different threats and the overall benefits of mitigations.
- **driven by utility data that describe the statistics of the overall outcome of the processes in the resilience phases**. This high-level statistical modeling is different than modeling the details of the process in a particular resilience phase, and avoids many of the difficulties of detailed modeling and its validation. CRISP is driven by data already routinely available to utilities, and each utility would use their own data to apply CRISP.
- **simulated by sampling events** from the statistical modeling of CRISP to obtain probability distributions of resilience outcomes, impacts, metrics, and risk.

In [2], CRISP samples lines out after stress and cascading from utility data, models the response of the network as the recovery proceeds according to utility data, and measures the shape of the resilience trapezoid with the amount of energy not served, the load shed, and event duration. The number of line outages after cascading are sampled from a probability distribution fit to real data and the actual lines outaged are sampled with equal probability. The restoration time for each line is sampled from a probability distribution of repair times obtained from real data. A case study shows the effect of distributed generation on resilience metrics.

In this paper, we extend the previous modeling in CRISP in the following ways:

- **Photovoltaics** are modeled, including their daily variation. Capacity factors and irradiance modeling are driven by utility data in an hourly time frame.
- **Energy storage** is modeled.
- **Distributed generation** now varies over time more realistically.
- **Load variation** over time is modeled.
- **Restoration is optimized** by jointly optimizing the generation, storage and load shed over a receding time horizon to model their deployment.
- **Generator** outages and ramp rates are modeled.
- **Cascading line outage spread** modeling is improved. The spreading now matches the statistics from utility data in [3] of network distance between cascading lines.

These improvements make CRISP more realistic and significantly extend the range of its resilience quantification. In particular, the improvements enable us to assess the impact on overall resilience of storage, distributed generation, PV, and their time variations. Thus, this paper applies the revised CRISP model to the problem of evaluating the impact of PV and storage on grid resilience, with the goals of understanding, validating and improving the model.

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The rest of the paper is organized as follows: Section II reviews the literature on other approaches to quantifying resilience. Section III summarizes the methods for the new formulation and the utility data used, Section IV discusses the case study and the case load and PV data, Section V presents the results of the case study, Section VI discusses the impacts of these results, and section VII concludes the paper.

II. Literature review

There is considerable interest in quantifying resilience, and this section reviews relevant literature. Resilience is the ability of critical infrastructure to maintain, to a limited extent, critical services during disasters [4]. The power systems community has been making progress towards finding metrics to appropriately measure resilience, especially in a risk based approach. Alvehag et al. create a reliability model for distribution grids under severe weather which accounts for weather uncertainties and considers the effect of severe lightening and wind storms across a test case [5]. One way to measure the impact of an extreme event is with a resilience trapezoid, the area of which indicates the size or cost of the event [6]. Panteli et al. [7] use fragility curves of power system components to high winds and simulate wind conditions based on rough regional wind patterns in the UK. Further work in [8] evaluates the severity risk index and the amount of load shed for 4 regions using the RTS24 network over a full year, as well as simulating events to find the load shed and the average error in the severity risk index for the different seasons and regions. In addition to the resilience literature within power systems, there are a number of papers that combine power system modeling with interdependence between other critical infrastructures [9]–[12]. For example, Antenucci et al. [13] propose a model that uses the constraints on the gas network as constraints in the security constrained energy reserves.

There is broad agreement that modeling resilience involves different phases, such as vulnerability, failure, cascading, and recovery. Most of the existing literature focuses narrowly on some subset of these phases. There is significant work on system vulnerability to events [14]–[16]. Fang et al. [17] identify critical components of power systems through vulnerability analysis using attacker-defender interdiction methods, and optimize to pick the best components to harden before wind storms. Cascading failures in power systems has a rich literature, and still has open research challenges [18]–[21]. Some cascading failure work explores cascades across interdependent infrastructures [22]. Power system restoration research has a long history [23] and recent authors have proposed a number of more sophisticated modeling methods for studying restoration [24], [25]. Recent work [26] shows that the distribution of transmission line restoration times has a log-normal heavy tail. Others show that new bottom-up restoration processes are needed given high penetrations of distributed variable energy resources [27].

A few studies measure the effect of distributed generation on power system resilience [4]. Chen et al. [28] use MILP optimization to pick settings of switching devices and distributed generation to form microgrids to serve the critical loads during large disturbances in distribution grids. Farzin et al. [29] optimize a DSO control scheme to exchange power between microgrids in distribution grids to enhance resilience. Recent transmission system work [30] explores islanding the transmission grid into 4 regions to lower the system risk.

III. Modeling

A. Overview

Resilience to a disturbance includes the following five processes: stress leading to initial failures, cascade of failures through the network, finding the post-disturbance degraded system state, restoration, and quantifying the resilience of the network to that event [2]. In order to quantify the resilience of the network it is important to find the resilience to many events from each of the hazards that the network is susceptible to. We measure the resilience of a power system to a particular event by the total energy not served.

A notable improvement to the CRISP modeling is the use of cascading distance statistics in the selection of lines to outage in events with multiple line outages. The modular nature of CRISP makes the framework flexible to easily allow different outage distributions and restoration models. This also makes CRISP easy to implement on different networks with different statistics. We note that the statistics driving CRISP are routinely collected by utilities so that the approach can be easily implemented in industry. In Figure 1, we show the processes that create the events and where data enters the restoration loop. CRISP relies on random sampling of the distributions modeling the outcomes of the resilience processes. The main CRISP outputs are the probability distributions of the energy not served, the initial load shed, and the recovery time.

B. Outage and cascading processes

The line outages that make up the various contingencies and the recovery time of each line outage are chosen based on distributions derived from data from a large US utility [3], [26], [31].

The cascading outages are modeled first by sampling the total number of outages, and then sampling which lines are outaged. As described in [2], the total number of cascading outaged lines is sampled from the Zipf distribution model obtained from the data in [31]. These cascading line outages are then successively located on the grid in order to match a statistic that describes how far cascades spread, as we now explain.

The network distance between lines L_i and L_j is defined as the minimum number of buses in a network path joining L_i to L_j. The network distance can be thought of informally as the minimum number of network "hops" to pass from one line to another along the network. For example, the distance of a line to itself is zero and the distance of a line to a neighboring line with a bus in common is one. Figure 2 shows the distribution of network distance between one line in a cascade and other lines in the same cascade. The distribution of Figure 2 is

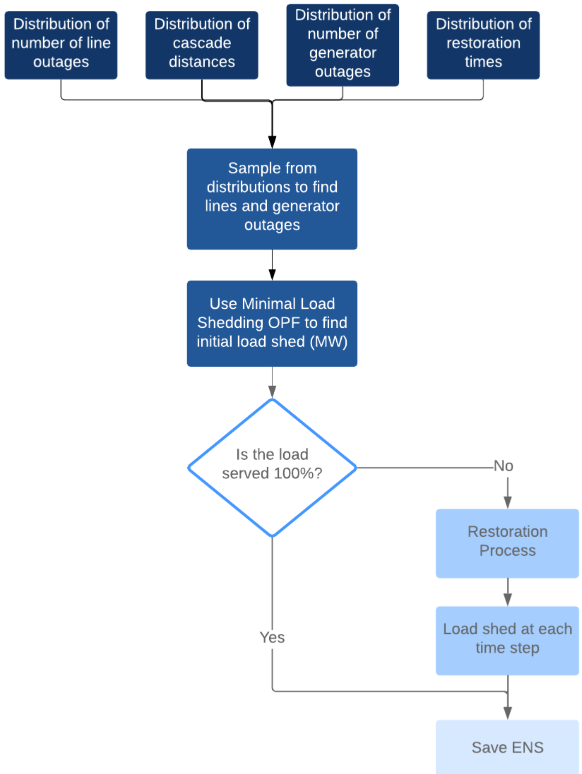

Fig. 1. Diagram of the CRISP model of a single event with cascading failures, generator outages, and the input time dependent data used in the restoration process.

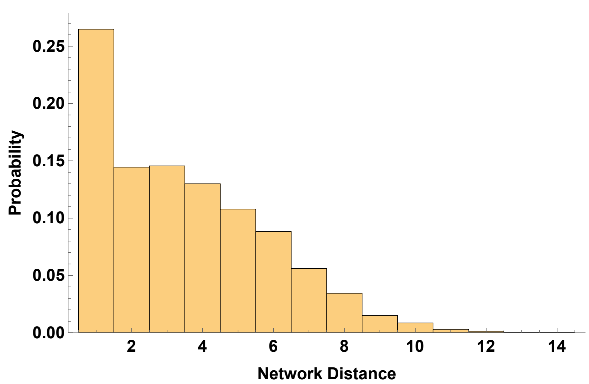

Fig. 2. Distribution of network distances between pairs of lines in the same cascade from historical data.

obtained by computing all the pairwise network distances in each of the cascades in the data of [31], processed into cascades according to [32], and using the network generated from this data according to [3].

The procedure starts by choosing the first outaged line at random on our case study network. If the total number of cascaded lines is one, we are done. If the total number of cascaded lines is more than one, then we apply the distribution of Figure 2 to successively choose the other outaged lines. We choose at random one of the lines L_i that is already outaged, sample a network distance ρ from the distribution of Figure 2, and locate on the network a non-outaged line that is network distance ρ from L_i. If there is no such line available on the network, we resample until such a line is found; if there are several such lines available, we choose one at random. This procedure approximates an aspect of the statistics of a typical spread of cascade on the network. It is a fast, approximated, and data-driven procedure that improves on our previous work sampling the cascaded lines at random [2]. Further improvements in quickly approximating at a high-level samples of the spread of cascades in networks will require more sophisticated statistical data-driven models or a better understanding of how real cascades spread in networks.[1] Although we do not at present have access to data on generator outages, we include the effect of them in the model by using a discrete geometric distribution with the rate parameter set to 1 to determine the number of generator outages in an event. The model samples from a uniform distribution to choose the specific generators to outage. Once the G generators have been selected, the same restoration time distribution used for the lines is applied to the tripped generators. (If there is access to data on generator outages, this should be replaced with the generator restoration time distributions.) Note that we do not include distributed generation, which is added to the case in later experiments in the set of generators that are allowed to fail.

C. Restoration process

The times for the restoration of lines are sampled from a log-normal distribution fit to transmission line restoration times observed in [2], [26]. Note that these statistics describe the outcome of line restoration processes. A receding horizon load shedding optimization determines the initial load shed in the system. The load shed is minimized at each time step as the restoration process continues using the receding horizon load shedding optimization. The formulation of the restoration receding horizon is:

Variables: $Pd_{d,k}$, $Ps_{s,k}$, $E_{s,k}$, $Pg_{g,k}$, θ_k

$$\min \quad \sum_{k=1}^{K} e^{-rk} \sum_{d \in D} C_d(\overline{Pd_{d,k}} - Pd_{d,k}) \tag{1}$$

$$\text{s.t.} \quad 0 \leq Pd_{d,k} \leq \overline{Pd_{d,k}} \quad \forall k \in K, d \in D \tag{2}$$

$$-\overline{Ps_s} \leq Ps_{s,k} \leq \overline{Ps_s} \quad \forall k \in K, s \in S \tag{3}$$

$$E_{s,k} = E_{s,k-1} - Ps_{s,k}\Delta t \quad \forall k \in K, s \in S \tag{4}$$

$$0 \leq E_{s,k} \leq \overline{E_s} \quad \forall k \in K, s \in S \tag{5}$$

$$-R_g\Delta t \leq Pg_{g,k-1} - Pg_{g,k} \leq R_g\Delta t \quad \forall k \neq 1 \in K, g \in G_k \subseteq G \tag{6}$$

$$0 \leq P_{g,k} \leq u_{g,k}\overline{Pg_{g,k}} \quad \forall k \in K, g \in G \tag{7}$$

$$(B_k\theta_k)[b] = Pg_k[b] + Ps_k[b] - Pd_k[b] \quad \forall k \in K, b \in Bus, g \in G_k \subseteq G, s \in S, d \in D \tag{8}$$

$$-\overline{P_{ft}} \leq \frac{1}{X_{ft}}\theta_{ft,k} \leq \overline{P_{ft}} \quad \forall k \in K, ft \in L_k \subseteq L \tag{9}$$

[1]While detailed cascading simulations include some of the mechanisms for cascading, and a few simulations can be tuned to reproduce particular blackout sequences, there is no simulation that is validated to reproduce the typical statistics of the spread of cascading on the network.

where k is the time step, K is the number of timesteps, r is the parameter of the exponential decay, D is the set of demands, C_d is the cost of shedding load, $Pd_{d,k}$ is the load d served at time k, $\overline{Pd_{d,k}}$ is the demand d at time k, $Ps_{s,k}$ is the storage power (note that if discharging $P_{s,k}$ will be positive), $\overline{Ps_s}$ is the maximum power capacity of the storage, S is the set of storage devices, $E_{s,k}$ is the energy of storage asset s stored at time k, $\overline{E_s}$ is the energy capacity of the storage asset s, R_g is the maximum ramp rate of the generator g, $Pg_{g,k}$ is the power produced by generator g at time k, G_k is the set of available generators at time k, G is the set of all generators, u is a matrix of binary values which allows only the generator g to produce power at time k if $u_{g,k} = 1$, $\overline{Pg_{g,k}}$ is the capacity of the generator g at time k, B_k is the B matrix for the line configuration at time k, $\theta[k]$ is the voltage angle of the buses at time k, Bus is the set of buses, $\overline{P_{ft}}$ is the power flow rating of the line from bus f to bus t, ft is the branch from bus f to bus t, L_k is the set of branches that are active at time k, and L is the set of all branches. Note that distributed generation is included in the vector of generators shown above.

The objective function (1) minimizes the amount of hourly load shedding over a 2-day period with higher weights on the most recent times. The weight on the total load shed for time step k in the objective function is e^{-rk}; for our model we set r to 1. Constraint 2 keeps demand served between 0 and the total demand for each time k in the restoration model. Constraint 3 keeps battery charging and discharging within each battery's power limit. Constraint 4 updates the energy level of batteries at time k based on the energy level at the previous time step and the charging or discharging of batteries in the current time step. Constraint 5 ensures battery energy levels remain within the energy rating and 0. Constraint 6 enforces generator ramp rates. Constraint 7 prevents unavailable generators supplying power, and limits available generators to their power capacity. Constraint 8 ensures power balance at each bus. Constraint 9 limits the line power flows to the line capacity.

The restoration times realized from the empirical distribution are used to update the status of the lines and generators in the grid. Formulating ahead of time which generators are shut down during the outage in the restoration process enables the use of a linear program for receding horizon optimization with a binary input to the model in the form of the matrix, u, made up of elements $u_{g,k}$ as shown in (7), which is N_G by N_T, where N_G is the number of generators and N_T is the total number of time steps in the time horizon. The technique ensures that generators only turn on after the full shut down and start up times elapse without drastically increasing the solve time by keeping the optimization a linear program. The input matrix, u also stops damaged generators from turning on until they recover and start up. CRISP updates which lines are operational by rebuilding the B matrix for each time step, in (8), and only adding power flow constraints for operational lines for each time step, in (9). The model uses time dependent upper limits on the variable constraints for the served load and the supplied power from the added PV to implement the varying load and PV capacity, as shown in (7). We solve the linear program optimization in julia's JuMP environment with the Gurobi solver. Note that although we have not studied the scalability of the model to larger test cases, the model is linear and therefore can be expected to scale reasonably well. The output of the receding horizon model is the network state at the first time step within the optimization.

After the restoration period, the load shed is integrated with respect to time to measure the area representing the total energy not served over the outage and restoration processes. Then CRISP is repeated many times over different disturbances of the power system test case to quantify resilience in the form of the probability distributions of the energy not served, the initial load shed, and the recovery time. For the case study described below, over the full event and each of the tested networks the CRISP model runs generally in the 2 to 30 minute range on a home laptop, the average run time over 15 tested events was 9 minutes. Please note this is academic quality code, and was not optimized for speed.

IV. Case Study

To illustrate an application of CRISP modeling, we ask what effect on resilience does the addition of PV and/or storage have on the grid during storms. Our inspiration is winter storms in Vermont, which are in the part of the year with fewer hours of production for PV and are often at night. For comparison, we also look at a sunny day. We chose to use PV and storage as the distributed technologies in this paper, due to their increasing economic feasibility and the availability of data. In future we would like to to explore other technologies for their impacts of added resilience to the grid, such as combined heat and power, flywheels, and small scale wind. The distributed generators and storage are assumed to have microgrid-creating capabilities and are not included in the simulated cascading outages. The distributed energy and storage only affect the restoration process.

A. Demand and solar data

The demand data which we use to produce variable load is from Vermont in 2013 [33]. Each demand is varied hourly based on the aggregate percent of load from the data, and the percent of load is found by normalizing the aggregate load by the yearly peak. To include the effect of PV, we use a subset of the normalized solar PV data from [34] and only use one location within New England from 2013. Although the PV data is hourly, the capacity factors come from the instantaneous value of the normalized solar PV. The maximum power produced by the introduced distributed PV is derived from this normalized solar PV data from the same time period as the Vermont load data. We chose to start the model at the beginning of the year, on a January evening that leads on to an overcast day. As a comparison, we also ran the same set of events where the load and solar data begin during a sunny day, 3824 hours into the year. We do not model the effects of transients within the transmission network on the behavior of inverter connected assets in this work, and we assume islanding/microgrid capabilities for these devices.

B. Case data

The cases examined here are based on the 73 bus RTS-96 case [35]. However, the solar, wind, or storage resources from that case are not included in order to better estimate the effect of only the distributed resources added as described below. Due to the very high reliability of the original case, the load was doubled to allow resilience effects to become more apparent[2]. The case is made $n-1$ secure to line outages by removing a single line and adjusting the line limits if any load is shed to solve the load flow until there is no load shed. This process is repeated until every line in the network has been removed and the line limits adjusted as necessary. Two parallel lines are added for instances when increasing line limits was insufficient to serve the full load. The combination of increasing the case loading and making the case $n-1$ secure is done in an effort to reproduce the effect of operating the grid close to the $n-1$ secure limit.

For the experimental question, several variations on this test case are created with added PV generation and/or storage with a power capacity equal to a chosen percent (5% or 20%) of the demand at each load bus. The storage energy capacity is set to supply 3 hours of power at the power capacity. Cases with each possible combination of these amounts of PV and storage are analyzed. It should be noted that the model exposed each case to the same set of outages and recovery times in order to confidently compare the responses. Since our model is stochastic, and the effect of one event on a network is not a good measure of its resilience, we simulate 10,000 events to find the distribution of outcomes. CRISP measures the energy not served of each blackout in units of MWh. Note that many of the initiating outages lead to 0 MWh of unserved energy.

C. Measuring Resilience Risk

To better understand the resilience of the cases, we examine both size and time dimensions of resilience events. It is helpful to break the events into categories of small and large events in terms of the amount of load shed at the end of the cascade and short and long events in terms of the recovery time from the cascade [2]. Figure 3 [2] provides one way to visualize the contribution to the resilience from these two different dimensions. The event duration is the time between the beginning of the event and the time at which the restoration of the load shed reaches zero with a tolerance of 10^{-4} MW. The cut off between small and large events and short and long events is chosen to make the magnitude of the squares of the base case as equal as possible. For this test case the cutoffs are 1000 MW for event size and 1 hours for event duration.

V. Results

The case study improves the base case by adding PV and/or storage. In order to find the distribution of energy not served, we measure energy not served over 10,000 model runs starting on an overcast night and a sunny day, and then compare the test

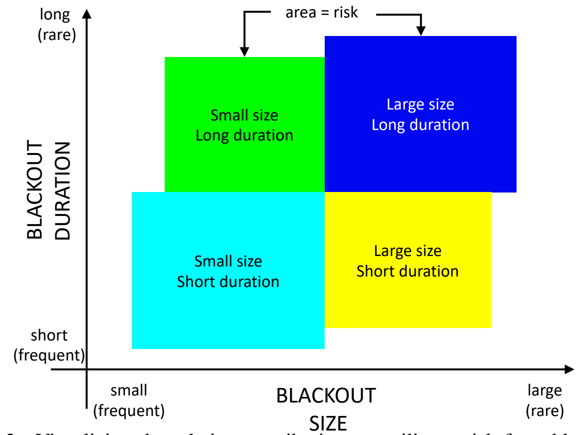

Fig. 3. Visualizing the relative contribution to resilience risk from blackouts of different sizes and durations. The area of each rectangle is proportional to the blackout risk in each category. This figure separates blackouts along two dimensions: blackout size (load lost, customers unserved) and blackout duration. Size and duration inversely correlate with probability: Small (or short) blackout are relatively frequent and large (or long) blackouts are rare. Because risk is the product of probability and impact, the risk from blackouts of different sizes is frequently similar.

cases designed to address the question: What is the impact of distributed energy resources in the form of PV and storage on the resilience of the test case? The distributions of energy not served from the simulated events on seven cases are succinctly displayed in the log space plots shown in Figures 4–6 and 7–9. Note that where the curves intersect the x-axis, e is the fraction of events with nonzero energy not served, so the fraction of events that led to zero energy not served is $1-e$. Figures 4 and 7 show the effect of adding distributed storage to the test case on an overcast evening and a sunny day respectively. Added storage clearly results in a reduction in the number of the events with energy not served at each size. Figures 5 and 8 show the effect of adding PV to the test case on the distribution of energy not served on an overcast night and a sun-filled day respectively. There is minimal to no effect on the resilience to events beginning at night in the winter from the added PV and a smaller but notable increase in resilience for the case with PV added with a capacity of 20% of the load on a sunny day, particularly for large events. Figures 6 and 9 show the effect of added distributed PV with 20% of the load covered by the capacity of distributed storage for all three cases. The effect of the PV is again small, with no effect during the evening events and small increases in resilience during the day-time events. Figures 10 and 11 show the resilience risk for 7 different cases at night and during the day respectively, with each color representing the cumulative risk of a different subset of events. It is clear that storage decreases the risk, and increases the resilience to winter events, and PV has little effect for these events. Adding PV decreases the risk on sunny days, although the effect is smaller than the storage.

VI. Discussion

This work uses probability distributions derived from real utility outage data to quantitatively measure the resilience of an $n-1$ secure test case based on the 73 bus RTS system. The results show the effects of adding PV and/or storage to the test

[2]This load increase was found by maximally increasing load (and some line limits as necessary) while maintaining n-1 security.

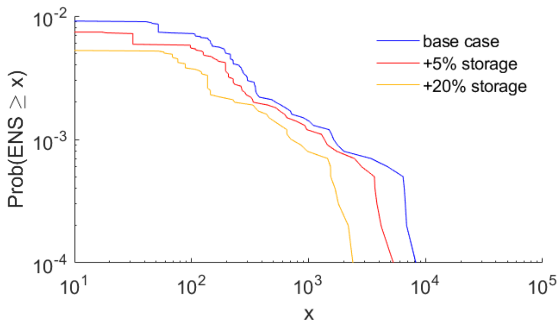

Fig. 4. The CCDF of energy not served of 10,000 events on a winter night for the test case with 0%, 5% and 20% added storage. Storage adds resilience.

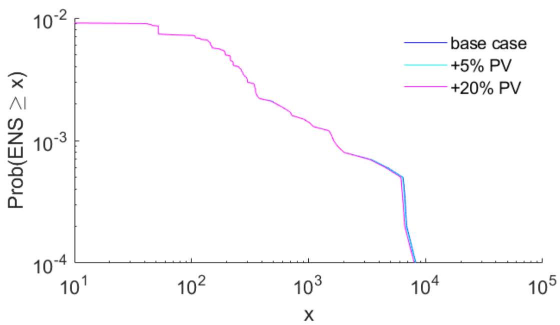

Fig. 5. The CCDF of energy not served of 10,000 events on a winter night for the test case with 0%, 5% and 20% added PV, and does not add resilience.

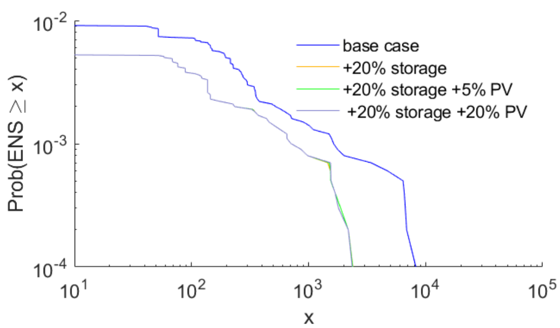

Fig. 6. The CCDF of energy not served of 10,000 events on a winter night for the test case with the base case, 20% added storage, and 0%, 5% and 20% added PV. PV doesn't contribute to the resilience for these events.

case on either an overcast evening or a sunny day. As seen in Figures 4 and 7, even adding a relatively small proportion of the load in storage improves the resilience of the network to both small and large events. When storage is added to the system, many initiating disturbances result in zero energy not served. During extremely long events, storage will no longer have an effect, unless it can be recharged.

As seen in Figures 5, 8, 6, and 9, adding PV to the test case is substantially less beneficial, relative to the results due to additional storage. This is quite different from previous results which show that adding distributed generation can substantially increase the resilience of transmission networks [2]. However, these results should be viewed in the context that, for Figures 5 and 6, the solar (and demand) data is from New England and begins during the night. For disturbances that last only a few hours (which appears to be all of them in this set samples), the cases with added PV will have nearly identical energy not served as the base case. Figures 8 and 9 show that PV does increase resilience on sunny days, although not to

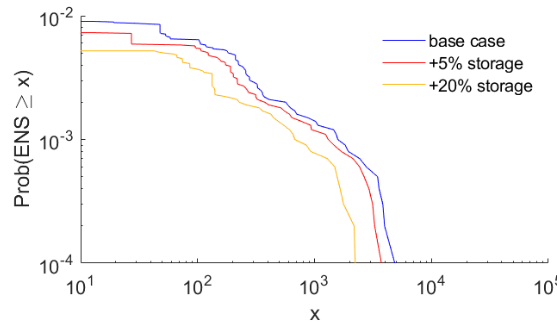

Fig. 7. The CCDF of energy not served of 10,000 events on a summer day for the test case with 0%, 5% and 20% added storage.

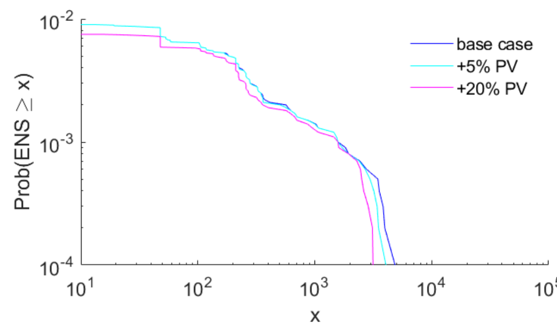

Fig. 8. The CCDF of energy not served of 10,000 events on a sunny day for the test case with 0%, 5% and 20% added PV. While less effective than storage, added PV on a sunny day does contribute to resilience.

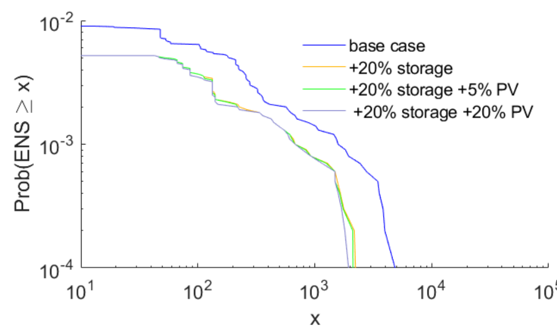

Fig. 9. The CCDF of energy not served of 10,000 events for the test case with 0% and 20% added storage and 0%, 5% and 20% added PV. Note that the PV contributes a small amount to the resilience for these events.

the extent of storage. Since even during the sunny day the peak available power is approximately 80% of the capacity of the PV panel while the storage can operate at it's power limit if it has the energy available these results are reasonable. The fact that there is no improvement to the test case for events occurring at night when the PV is added and that there is improvement for events beginning during the day is reasonable, and suggests that CRISP can capture the resilience impact of variable distributed energy resources.

We expect that the variable availability of PV will cause it to have a larger effect on longer events lasting several days. This leads us to consider the sampling methods used in this study. 10,000 events were sampled, but very few of those events have any energy not served. The Monte Carlo sampling method does not focus on the tail of the distribution of events, and therefore an extremely large number of events must be sampled to find the impact of different solutions on the resilience to these large events.

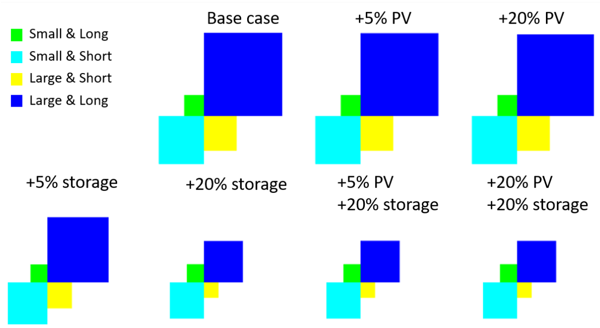

Fig. 10. The categorized risk for small and large, and short and long events for 7 cases as labeled, for events on a winter night.

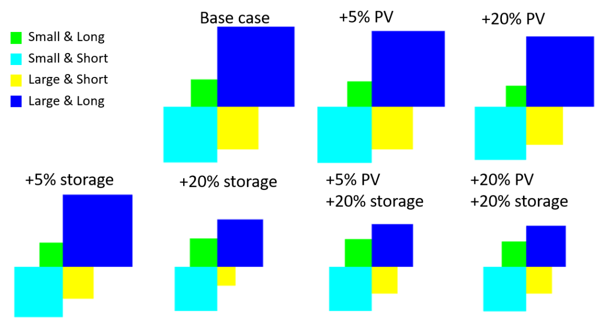

Fig. 11. The categorized risk for small and large, and short and long events for 7 cases as labeled, for events on a sunny day.

VII. Conclusions

This work improves the CRISP data-driven statistical method [2] to quantitatively measure the overall resilience of power systems. This paper reports on improving CRISP to include models of PV, energy storage, load variation, optimized restoration, and more detailed models of generator outages and ramping. We approximate the effect of line outages spreading on the grid by using utility data describing the statistics of distances between lines in cascades.

CRISP samples from probability distributions obtained from utility data to describe outcomes of the stages of resilience and calculate the distributions of energy not served, the initial load shed, and the event duration. Variations from the base case simulation can then be explored to quantify their effect on resilience. In this paper we vary the distributed PVs and storage to study the effects of these assets in increasing resilience.

Our results suggest that CRISP is able to quantify the resilience impact of distributed energy technologies such as PV and storage. The results suggest reasonable conclusions, such that the addition of distributed PV and storage (without retiring conventional generation) can enhance resilience, and that for shorter events, this improvement is only available for distributed solar during sunny time periods. Our results show the importance of flexibility in a distributed grid, and suggest that grid improvements with distributed storage have a much larger impact than improvements with PV when the events take place at night on a cloudy winter day.

Since CRISP is a new approach to high-level simulation and quantification of resilience, there is considerable scope to further improve its data, sampling methods, and the range of models and effects represented. In particular, we would like to improve the sampling methods to efficiently find the rare but high impact large events in the tails of the distributions.

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