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Assessing Transmission Resilience during Extreme Weather with Outage and Restore Processes

Svetlana Ekisheva
North American Electric Reliability Corporation (NERC)
Atlanta, GA USA
Svetlana.Ekisheva@nerc.net

Ian Dobson
Electrical and Computer Engineering
Iowa State University
Ames, IA USA
dobson@iastate.edu

Rachel Rieder
CampusLogic
Mesa, AZ USA
Rachel.jane.rieder@gmail.com

Jack Norris
North American Electric Reliability Corporation (NERC)
Atlanta, GA USA
Jack.Norris@nerc.net

***Abstract*—We automatically extract resilience events and novel outage and restore processes from standard transmission utility detailed outage data. This new processing is applied to the outage data collected in NERC's Transmission Availability Data System to introduce and analyze statistics that quantify resilience of the transmission system against extreme weather events. These metrics (such as outage rate and duration, number of elements outaged, rated capacity outaged, restore duration, maximum simultaneous outages, and element-days lost) are calculated for all large weather-related events on the North American transmission system from 2015 to 2020 and then by extreme weather type that caused them such as hurricanes, tornadoes, and winter storms. Finally, we study how performance of the system changed with respect to the resilience metrics by season and year.**

***Keywords*—Resilience, statistics, reliability, restoration, metrics**

I. Introduction

Extreme weather is a major challenge to transmission system resilience [1, 2], accounting for most of the largest transmission system events in the North American bulk-power system [3-5]. Therefore, extracting these events from recorded automatic outages, computing resilience metrics for each event, and examining the statistics of these metrics is of great interest [5-7], especially since climate change is slowly increasing the severity and frequency of extremes of weather. Our focus is the largest resilience events with 20 or more outages, since these large events, although less frequent than smaller events, have the highest impact on the transmission system, typically causing widespread interruptions of electrical supply in the USA and Canada.

There are many variations of frameworks and definitions of resilience in the literature, all of which include some description of the response of the system to disruptions and unusually stressed conditions [1, 2, 8-11]. For example, according to [11], "Power system resilience is the ability to limit the extent, severity and duration of system degradation following an extreme event." For the practical purpose of assessing transmission system resilience to weather from observed utility data, we focus on the outages and restores of transmission elements during extreme weather events. We need to define these weather-related resilience events so that they can be automatically extracted from the data, and then process the outages and restores during each resilience event so that standard metrics for each event can be calculated.

In particular, we process the automatic outages that are collected in NERC's Transmission Availability Data System (TADS) from 2015 to 2020 in a new way to extract the resilience events with 20 or more outages that are caused by extreme weather. This systematic novel processing uses, instead of stages of resilience, processes of resilience that can overlap in time. Different aspects of each resilience event are studied by its outage process, its restore process, and its performance process, as previously described for distribution systems in [12]. These processes are easily defined: As the event proceeds, the outage process tracks the cumulative number of outages, the restore process tracks the cumulative number of restores of outages, and the performance process tracks the cumulative number of unrestored outages. Each of these processes has useful metrics summarizing aspects of the transmission system response to the extreme weather. By analyzing these metrics, we can describe the typical values and statistical forms of these metrics and their correlations. We also analyze the dependence of the metrics on season, year, and type of weather. Overall, our new processing of 6 years of detailed outage data quantifies aspects of how the transmission system has responded in the larger events caused by extreme weather.

II. Outage Data and Resilience Events

A. TADS Outage Data

NERC has been collecting North American automatic (momentary and sustained) outage data for transmission system elements operating at 200 kV and above since January 1, 2008. Transmission elements reportable in TADS are: 1) AC circuit (overhead and underground); 2) transformer (excluding generator step-up units); 3) DC circuit (one pole of an overhead or underground DC line that is bound by AC/DC terminal on each end); and 4) AC/DC back-to-back converter [13]. In 2015, two additional voltage classes were added – sustained automatic outages of TADS elements operating at less than 100 kV and sustained automatic outages of TADS elements operating at 100 to 199 kV. All automatic outages for all TADS elements reported in TADS from 2015 to 2020 (~62k outages overall) are used in outputs for an outage-grouping algorithm developed to identify resilience events as described next.

B. Algorithm that Defines Resilience Events

For each interconnection, the 2015-2020 automatic outages in TADS are grouped together into resilience events based on the bunching and overlaps of their starting times and durations. The algorithm for defining and automatically extracting events, introduced in [7], is as follows: Every outage in an event has to either start within five minutes of a previous outage in the event or overlap in duration with at least one previous outage in the event that has a difference in starting time not exceeding one hour. In applying this algorithm, repeated momentary outages of the same element are neglected if they occur within 5 minutes of each other. If an outage cannot be grouped together with any other outage, it is placed in an event of size one by itself. However, in this paper we only analyze the large weather-related events with 20 or more outages. We define a weather-related event as any event that contains an automatic outage with a TADS initiating or sustained cause code of Fire, Weather excluding lightning, Lightning or Environmental [13].

C. Overview of 2015-2020 Large Weather-Related Events

The TADS data analyzed has 69 weather-related events involving 20 or more outages of TADS elements. The event size ranges from 20-352 outages and from 4,223-120,064 MVA in the total rated transmission capacity of all the elements outaged. The events last from 3 hours up to 246 days. Events were categorized by the primary driving weather: Thunderstorm, wind (29), Winter Weather, snow (18), Hurricane (12), Tornado (8), and Fire (2). TABLE I. shows a summary of the 10 largest events analyzed.

TABLE I. 2015-2020 TEN LARGEST WEATHER EVENTS

Start Date	Interconnection	Event Name/Exteme Weather Type	Event Size (Number of Outages)	Event Duration Days	Transmission Capacity (MVA)
9/10/17	Eastern	Hurricane Irma/Hurricane	352	19.3	120064
10/8/16	Eastern	Hurricane Matthew/Hurricane	197	58.8	72866
10/28/20	Eastern	Hurricane Zeta/Hurricane	148	40.7	55323
11/17/15	Western	Strong wind storms/Thunderstorm, wind	143	5.9	45578
4/12/20	Eastern	Easter Tornado/Tornado	111	16.0	39373
8/4/20	Eastern	Hurricane Isaias/Hurricane	107	9.4	43191
4/30/17	Eastern	Heavy thunderstorms/Thunderstorm, wind	102	246.0	39040
10/10/18	Eastern	Hurricane Michael/Hurricane	72	28.2	22024
12/16/15	Eastern	Wide-spread snowstorms/Winter weather, snow	62	1.5	23905
8/10/20	Eastern	Windstorms/Thunderstorm, wind	58	13.0	19308

III. OUTAGE, RESTORE, AND PERFORMANCE PROCESSES

The progress of a TADS event can be tracked by the outage, restore and performance processes shown in Fig. 1. The vertical axis either counts the elements outaged or indicates the MVA transmission capacity outaged, which is the total MVA rating of the elements outaged.

First, we consider the processes tracked by the number of elements outaged. Then the outage process is the cumulative number of elements that have been outaged by a given time in the event. Similarly, the restore process is the cumulative number of elements that have been restored by a given time in the event. Both the outage and restore processes start at zero at the start of the event and increase to the total number of elements outaged in the event. The performance process is the cumulative number of elements that remain outaged at a given time in the event, with the sign flipped so that more outages cause the performance curve to decrease. That is, the performance process is the negative of the cumulative number of outages that have not been restored. This form of performance process is standard in resilience studies [2, 8,12,13]. It turns out that the performance process is equal to the restore process minus the outage process [8]. It is also straightforward to start with the performance process for an event and separate it into the outage and restore processes [8].

The corresponding definitions of the processes when the event is tracked by MVA capacity outaged are obtained simply by replacing "number of elements outaged" in the preceding paragraph with "MVA capacity outaged". (If quantities other than number of outages or MVA capacity outaged are available, then similar processes for these other quantities are easily defined.)

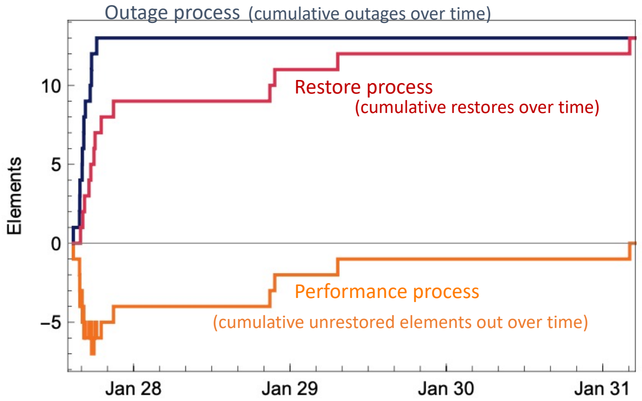

Fig. 1. Outage, restore, and performance processes

For large weather-related transmission system events, the outage process typically increases rapidly at the beginning of the event and maintains a plateau as the weather system passes. The typical restore process generally begins increasing rapidly shortly after the event starts, and then increases more slowly as the number of elements out decreases. After around 95% of the restores are completed, the restore curve often has a long tail where the last few elements require a very long time to restore. The automated extraction of events and finding the outage, restore and performance processes for each event are key to enabling the definition of resilience metrics in the next section.

IV. RESILIENCE METRICS STATISTICS

TABLE II. RESILIENCE METRICS FOR LARGE WEATHER EVENTS

Process	Event Statistics	Mean	Std Dev	Minimum	Maximum	Median	95th Pctl	Fitted distribution
Outage process	Event size (# outages)	44.9	50.0	20	352	27	143	No good fit
	Miles affected	1175	1173	233	6461	850	3638	Lognormal
	MVA affected	17165	18514	4223	120064	10769	55323	Lognormal
	TADS elem affected	38.6	42.5	11	295	25	117	No good fit
	Outage process duration Hrs	6.3	5.3	0.9	35.2	4.7	15.0	No good fit
	Outage rate (elem/Hr)	7.46	3.76	3.4	26.7	6.4	14.5	Lognormal
	Outage rate (MVA/Hr)	3008	2765	997	22260	2220	6343	Lognormal
Restore process	Restore Process Duration Days	14.5	33.1	0.11	246.0	4.6	58.8	Lognormal
	Time to First Restore Minutes	46	51	0	208	31	169	Exponential
	Time to restore 95% outages Days	3.9	5.4	0.05	38.2	2.3	12.4	Lognormal
	Time to restore 95% MVA Days	4.2	6.3	0.05	39.8	2.2	17.1	Lognormal
	% Event Duration to Restore 95%outages	58%	31%	3%	100%	63%	100%	No good fit
	% Event Duration to Restore 95% MVA	58%	33%	1%	100%	61%	100%	No good fit
Performance process	EventDuration Days	14.6	33.1	0.13	246	4.6	58.8	Lognormal
	Max Elemements Out	26.72	28.19	7	181	17	69	Lognormal
	Max MVA Out	9724	10721	1870	60133	6283	32406	Lognormal
	Element-Days Lost	59	104	0.34	558	18.7	336.9	Lognormal
	MVA-Days Lost	21394	39499	73	241730	5535	105772	Lognormal

Next, we calculate and analyze statistics for the 3 processes defined in Section III, with the main results summarized in Table II. These resilience metrics are discussed in detail below.

Table III provides averages by extreme weather type for selected statistics listed in Table II.

TABLE III. AVERAGE METRICS BY WEATHER TYPE

Average Statistics	Hurricane	Fire	Thunderstorm, wind	Tornado	Winter weather
Event Size	92.7	36.5	34.6	38.4	33.6
Outage Process Duration (Hrs)	10.7	7.2	4.8	7.3	5.3
MaxElemOut	57.3	23.0	21.7	25.6	15.9
Timeto95%elemRestored (Hrs)	135.4	472.1	68.4	153.7	47.0
Element-Days Lost	148.4	116.9	45.6	52.8	19.7

A. Outage Process

The metrics for the outage process quantify the impact of extreme weather on the transmission system elements.

The event size is defined as the number of outages in the event. The event size ranges from 20 to 352, with the largest events caused by hurricanes (Tables I, III). The survival function of the distribution of the event size is shown in Fig 2. The straight-line form of the log-log plot in Fig. 2 indicates a heavy-tailed, power law distribution, implying that although the larger events are rarer, they can be expected to occur occasionally; the largest events are not outliers or "perfect storms". Because of multiple outages of the same element that may occur during an event, the number of distinct TADS elements affected by the event is often smaller than the event size.

There are 3095 outages grouped into the 69 large weather events with 20 or more outages. It is noteworthy that these 3095 outages, that cause the largest disruptions in the transmission system, comprise less than 5% of all 2015-2020 automatic outages. Outages of all types of TADS elements are included in the large events, with the vast majority being outages of ac circuits.

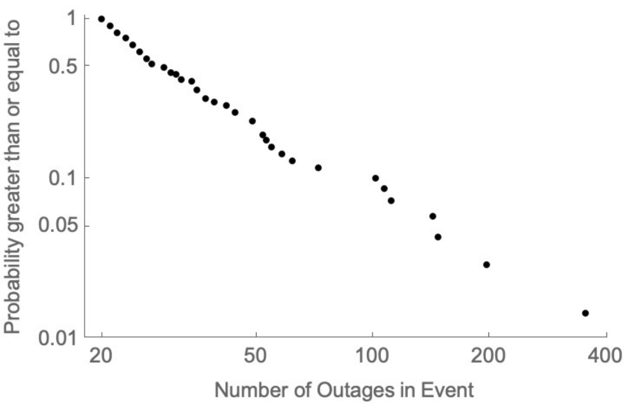

Fig. 2. Distribution of number of outages in laarge weather events shown as a survival function. Note the log-log axes scales.

Some of the metrics may describe similar aspects of events, and this can be quantified by examining the correlations between metrics. The event size is highly positively correlated with the number of elements, MVA capacity, and Miles of transmission line outaged (p-values<0.0001, Pearson's correlation coefficients>0.91). The correlation is particularly strong between the event size and the number of TADS elements, with the linear relationship expressed by (1):

$$\text{TADS Elements}=0.84*\text{Number of Outages}+0.76+\varepsilon, \quad (1)$$

where the random error ε accounts for less than 2% in variability of the number of TADS elements. This means that the event size can effectively predict the number of TADS elements, and (less precisely) both the Miles and MVA capacity outaged.

Further, the event size and the outage process duration are also strongly correlated, with the number of outages roughly proportional to the outage process duration. In addition, the element- and MVA capacity-based outage processes for the large events confirm that during events, outages occur at a nearly constant outage rate (elements per hour and MVA per hour, which are strongly correlated). There is no significant correlation between event size and the outage rates. For example, the greatest outage rate of 26.7 Elem/h reported for a relatively small Thunderstorm/wind event can be explained by the fast-moving weather when the 24 outages occurred in quick succession over 54 minutes. In addition, the MVA capacity-based outage rate depends on the voltage mix of the area hit by the extreme weather.

Analysis of the outage metrics by extreme weather type finds that hurricanes caused statistically significantly larger events (with the average size of 93 outages) than other weather types, while Tornado, Fire, Thunderstorm and wind, Winter weather events had similar mean sizes between 34 and 37 outages. The same holds true for the outage metrics highly correlated with the event size as described above in this section. There were no significant differences in outage process duration and the outage rates (in Elem/h and MVA/h) between the weather types.

B. *Restore Process*

The next group of the resilience metrics is derived from the restore process, and their parameters are listed in Table I. Typically, the restore process starts quickly after the outage process started. Therefore, the restore process duration almost coincides with the event duration. However, there is no strong correlation between restore process duration and event size.

Usually, the first outage is restored within 30-50 minutes, but for several events, the time to first restore was zero. The longest time to the first restore (~3.5 hours) was during Hurricane Laura (August 2020). Time to first restore is uncorrelated with any other resilience metric.

For all events, the outage process is shorter than the restore process. Unlike outages, restores do not occur at a constant rate. The restore process in Fig.1 is typical in that restores start at a fast rate, then slow down until finally a few (sometimes one) elements remain out for days until the event end. This shape of a restore process implies that the system can be "almost" restored or "effectively" restored long before the last outage ends. Generally these few remaining elements are outaged either due to inaccessibility of a portion of the line, damaged structure or equipment or, in some cases, a utility postpones a restoration of a single remaining element (or few elements) after all other outages in the large event are restored because this outaged element is considered not critical for reliability of the grid. To measure the critical partial restoration duration, we introduce Time to Restore 95% of elements and Time to restore 95% of MVA. These metrics do not necessarily coincide but they are strongly correlated. Table 1 informs that both Times are much shorter than the complete restoration (i.e. the restore process duration).

This property can be further quantified by Percent of event duration to restore 95% outages (MVA). The last two metrics are negatively (but not strongly) correlated with the event size and the event duration: all 10 events in which it took longer than 95% of event duration to restore 95% of elements are less than 35 outages large. In contrast, the largest events caused by hurricanes usually have shorter partial restore duration relative to their total duration.

Analysis of the restore process metrics by extreme weather type found no statistically significant differences between their means for events caused by different weather types due to a huge variability in restoration duration and/or small samples. Noteworthy is an observation that recovery does not as strongly depend on the event size as on the weather type. For example, events caused by a tornado are on average significantly smaller than events caused by hurricanes (37 outages versus 93 outages) but the times to first restore and the times to restore 95% of elements and 95% of MVA after tornadoes are greater than for hurricanes (and for other extreme weather types). One of the reasons could be that while a tornado usually affects a smaller area than a hurricane, it may be more destructive and damaging and this slows down restoration.

C. *Performance Process*

The final group of resilience metrics is derived from the performance process, and their parameters are listed in Table I.

As mentioned above, the event duration and the restore process duration virtually coincide (p-value=1, Pearson's correlation coefficient=1.00), since they differ by the time to first restore which is negligibly short compared with both of them. The event duration is weakly correlated with the event size and with each of the resilience metrics that are linearly dependent on the event size as described in Section IVA. Time to Restore 95% of elements and Time to restore 95% of MVA are only weakly correlated with the event duration—this should be expected because a restore process is usually not linear.

The Maximum number of elements out and the Maximum MVA capacity out are the negative of the nadirs (the values at minimum points) of the element- and capacity-based performance curves, respectively. They represent the worst degradation level attained during an event and as such quantify an ability of the system to withstand and absorb an extreme weather event. The nadirs are reached early in an event, while outages are occurring, and they are determined by an interplay between outage and restore rates. The Maxima are strongly correlated with the event size and weakly correlated with the event duration. The correlation is particularly strong between the event size and Maximum number of elements out, with the linear relationship expressed by (2):

$$\text{MaxElemOut}=0.54*\text{Number of Outages}+2.5+\varepsilon_1, \quad (2)$$

where the random error ε_1 accounts for less than 8% in variability of the Maximum number of elements out. This means that the event size can satisfactorily predict the most degraded state of the system during the event as measured by the number of transmission elements out. Similarly, but less precisely, the MVA capacity outaged predicts the Maximum MVA capacity outaged.

The Element-Days lost and the MVA Capacity-Days lost are another pair of metrics calculated from their respective performance processes as the area between the time (x) axis and the performance curve. Each of these metrics is correlated with event size and event duration. The April 2017 Thunderstorm/wind event in the East with the greatest duration of 246 days also has the largest Element-Day loss (558) and the MVA-Day loss (241,730) over the six years, followed by hurricanes Matthew, Irma, and Michael.

Analysis of the performance metrics by extreme weather type found no statistically significant differences between the event duration means, mostly due to a huge variability in event duration for each group. For events caused by hurricanes, the maximum number of elements out and the element-days lost were on average statistically significantly greater than for other groups. This is not surprising because of the strong correlation between each of these metrics and the event size.

D. *Fitted Distributions for Resilience Metrics*

Along with parameters of the empirical distributions of the metrics Table 1 lists the distributions providing a good fit to the empirical distributions. The exponential distribution with the mean and the standard deviation of 46 minutes is a good fit for Time to the first restore.

The remaining metric distributions for which a good fit is found can be approximated by a lognormal distribution. Due to large standard deviations and very heavy tails of the fitted distributions, they are not very useful for practical purposes (e.g. a confidence interval for the mean or a quantile at a standard confidence level is too wide to use for forecasting or modeling [14]).

V. Resilience Metrics by Year

We calculate the resilience metrics by year and track their changes. An event is assigned to a year from 2015 to 2020 as determined by the event start date.

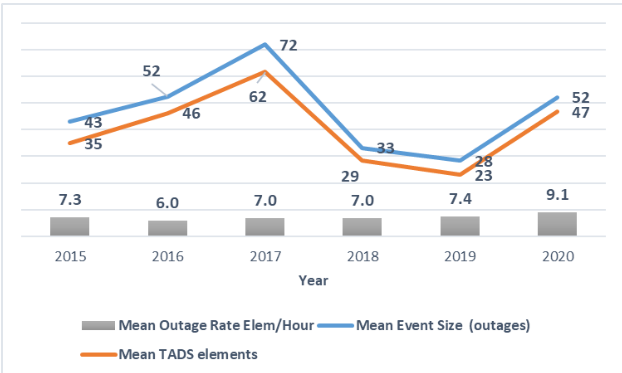

Fig. 3. Changes by year for means of outage process metrics

Fig. 3 shows the means of selected resilience metrics for the outage process. We omit the metrics strongly correlated with the event size as described in Section IV except for the Number of distinct TADS elements outaged in the event. The almost perfect correlation is illustrated in Fig. 3 by blue and orange lines. The year 2017 had the largest transmission event over the 6 years, Hurricane Irma, along with several disruptive winter storms in the East and the West, which together account for the spikes in the 2017 resilience metrics shown in Figs. 3-5. The years 2018 and 2019 had relatively small weather events. In 2020, there occurred several highly impactful events (Hurricanes Zeta, Isaias, Laura, Easter Tornado, Ice storms in Texas and the East) that drove the 2020 averages higher. Note that the 2020 average outage rate was also unusually high due to several events with extremely fast outage process (e.g. the summer 2020 Thunderstorm/wind event in the East when all outages started within one hour).

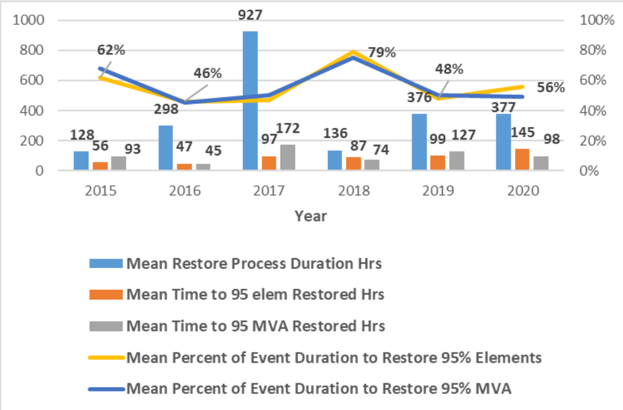

Fig. 4. Changes by year for means of restore process metrics

Fig. 4 shows the mean resilience metrics for restore processes. The sets of bars illustrate differences between durations of the complete restoration and the 95% restoration for each year. In 2017, the partial critical restoration times were similar to those for other years even though the 2017 total restorations were significantly longer. In 2020, the averages of the restoration duration were similar to 2019 despite much larger average event size. However, we caution that the variability of the event duration due to its dependence on the timing of the last restore makes it an unreliable metric.

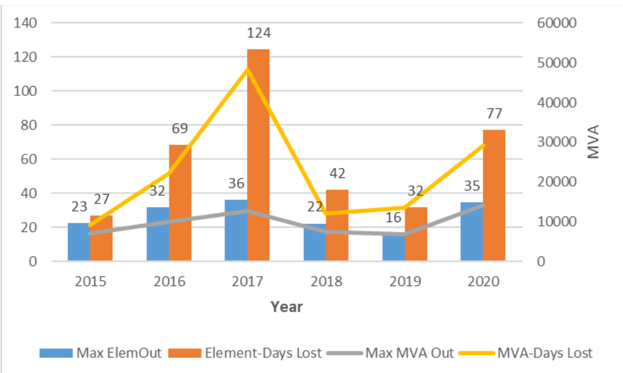

Fig. 5. Changes by year for means of performance process metrics

Next, Fig.5 shows the averages of the resilience metrics for the performance process, except for the event duration, which nearly coincides with the restore process duration shown in Fig.4. One can see two pairs of strongly correlated metrics: the maximum number of elements out and the maximum MVA out (the negative of the nadirs of the performance processes) and the element-days lost and the MVA-days lost. Both pairs are also correlated with the event size and the event duration.

VI. Seasonal Analysis of Metrics

The set of 2015-2020 large weather events is divided in four subsets based on their start date: Winter events (December-February), Spring events (March-May), Summer events (June-September), and Fall events (October-November), and distributions of resilience metrics by season is analyzed and compared. Because of large variability of the resilience metrics, no statistically significant differences among means and medians are detected; the means for selected metrics are shown in Table IV.

TABLE IV. Resilience Metrics by Season

Season	Number of Events	Average by Season					
		Event Size	Restoration Process Duration Hrs	Time to 95% elements Restored Hrs	Time to 95% MVA Restored Hrs	Element-Days Lost	MVA-Days Lost
Winter	11	31	120	85	73	28	9977
Spring	25	36	486	80	125	48	19799
Summer	17	55	335	134	103	73	21768
Fall	16	58	307	81	81	84	31337

Only 11 events occurred in winter; typically, they have smaller size, duration, faster total and partial restorations as shown in Table IV. Summer and fall events are larger, with the greater losses measured in both Element-days and MVA-days lost. Interestingly, summer events are shorter than spring events, but critical partial restoration (95% of elements and 95% of MVA) in summer on average takes longer than in spring.

VII. Conclusion

A. Extracting Events, Processes, and Metrics from Utility Data

In this paper, we study resilience of transmission systems in a new way by analyzing outage, restore, and performance processes defined for large outage events caused by extreme weather. Section II-B gives a new definition of transmission system resilience events based on outage bunching and overlaps that is used to automatically extract the events from North American TADS data. The extraction is generally applicable since the TADS data are essentially the same as the standard detailed outage data that are routinely logged by utilities worldwide. Note that the automatically extracted events are generally useful for further detailed engineering analysis.

We find that transmission line outages and restores overlap in transmission data, particularly at the beginning of the events. Therefore, instead of idealizing outage and restoring as separate phases of resilience [2, 8-9], the outage and restore processes are easily disentangled and separately analyzed. With the exception of the application of this method in the NERC state of reliability report [5], this paper is the first description of these processing methods to transmission systems. These new processing methods easily yield resilience metrics. Indeed, given the automatically extracted resilience events and processes we are able to systematically calculate metrics for weather events with more than 20 outages in North America. This capability to process standard utility outage data to extract resilience events and metrics complements other studies of resilience that rely on models and simulated data [1, 2, 8-10].

It is useful to have distinct metrics for the outage and restore processes, since the outage process metrics summarize the outcome of weather severity and component strengths, while the restore process metrics summarize restoration efforts.

B. Statistics of Large Weather-Related Events

We find that the outage process is relatively short and, on average, takes only 8% of the event duration. A restore process starts soon after an event start and, therefore, its duration almost coincides with the event duration. Typically, a restore rate decreases over the restore duration in contrast with an outage rate that stays almost constant through the shorter outage process. We found that critical partial restoration measured by 95% restoration is relatively short as compared with the event duration. Among the five extreme weather types identified as primary causes of the large events, hurricanes caused larger events with the outage rate similar to and the restore rate greater than for other events.

We find strong correlations between some of the metrics, which can usefully identify a subset of metrics that quantify independent aspects of resilience.

We analyzed changes of the resilience metrics by year. Without linkage of the TADS outage data and the detailed and localized weather data, it is hard to rigorously evaluate transmission system resilience against extreme weather events. However, changes in the resilience metrics paired with information about the extreme weather events that caused large transmission outage events can shed some light on the resilience relative to the weather severity. For example, the National Oceanic and Atmospheric Administration reported in [15] that 2020 was a record year with respect to the number and magnitude of the billion-dollar natural disasters in U.S. Comparison of the resilience metrics by year for the restore process (Fig. 4) shows an improvement in the ability of the transmission system to recover after extreme weather. Future work can better link detailed weather data with outage data, so that the resilience metrics we have extracted will better track how well the transmission system prepares for and withstands extreme weather.

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