Observed Acceleration of Cascading Outages

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***Abstract*—Accounts of extreme power outages of transmission systems suggest the acceleration of cascading outage propagation over time and the splitting of the cascade into a slow phase and a subsequent fast phase. This is significant to network operators, as mitigation actions, such as load shedding, can only be effectively applied during the slow phase. During the fast phase, the network disintegrates too quickly for any manual intervention. To supplement the accounts of extreme outages, we describe the observed acceleration of smaller and more common cascading outages by analyzing transmission outage data published by one North American utility. Our results show that these common cascades accelerate much less than the extreme cascades. This justifies ongoing research in mitigation strategies.**

***Index Terms*—Cascading failures, power systems, power transmission, power system faults, power system reliability.**

I. Introduction

CASCADING outages are widely seen as one of the main mechanisms causing widespread blackouts of power networks [1]–[3]. A cascading outage is the uncontrolled and successive loss of parts of a power network, usually triggered by one or more disturbance events such as extreme weather, equipment failure, or operational errors [4]. Preventing and mitigating cascading outages is crucial for improving power transmission network resilience.

Various approaches to mitigate cascading outages are reported in the literature, including load shedding, defensive islanding, operator intervention, and improved situational awareness [5]–[7]. Literature on large historic blackouts suggests that cascading outages consist of two distinctive phases, a slow and then a fast phase [8]–[10]. The slow phase is mainly governed by overload phenomena while a balance between generation and demand is still maintained. During the fast phase, this balance is broken and various parts of the network trip rapidly due to automatic protection actions that interact with an unusual operation condition outside of the usual design conditions, leading to disintegration and collapse of a wide area of the network. Effective manual mitigation is generally only feasible during the slow phase and no longer possible during the fast phase.

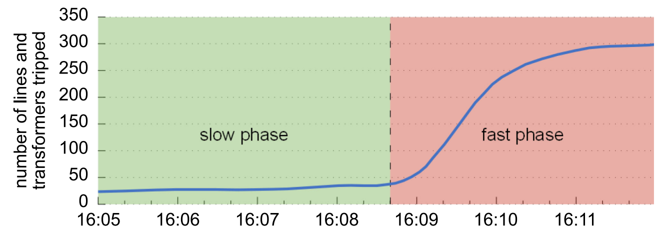

Fig. 1. Cumulative line and transformer trips in August 2003 blackout [14].

From an operator perspective, the existence and amount of such an acceleration of cascading outages determines the viability of mitigation measures. Whilst the largest cascading outages have higher risk [11], they are rare, and cascades of all sizes should be mitigated. This letter uses utility data to investigate, for the first time, whether the observed acceleration of extreme cascading outages can also be observed in the more common, smaller cascading outages that occur more frequently. These more common cascading outages are extracted from line outage data reported by one Northern American transmission utility. To further extend the analysis, cascading outages are differentiated based on their size and whether their cause can be attributed to extreme weather.

The structure of this letter is as follows: The behavior and acceleration of selected extreme cascading outages is presented in Section II. Section III describes how cascade acceleration of common outages is calculated from the line outage data and reports the findings.

II. Acceleration Observed in Extreme Cascades

An acceleration of cascade propagation is reported for several extreme outages, such as: the August 10, 1996 blackout in the USA [12], the September 28, 2003 blackout in Italy [13], the August 14, 2003 blackout in the USA and Canada (Fig. 1) [14], and the July 12, 2004 blackout in Greece [15]. For some other extreme outages, no slow phase is reported, such as: the July 2, 1996 blackout in the US [12], the January 12, 2003 blackout in Croatia, the March 31, 2015 blackout in Turkey [16], and the September 28, 2016 blackout in Australia [17]. However,

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TABLE I
DURATION OF SLOW AND FAST PHASES IN EXTREME OUTAGES. TIMINGS PARTIALLY TAKEN FROM [9]

Extreme outage	Slow phase	Fast phase	Source
Jul 2, 1996, USA	-	1 min	[12]
Aug 10, 1996, USA	1 h 40 min	7 min	[12]
Jan 12, 2003, Croatia	-	30 s	[18]
Aug 14, 2003, USA/Canada	1 h	5 min	[14]
Sep 28, 2003, Italy	24 min	2 min	[13]
Jul 12, 2004, Greece	12 min	2 min	[15]
Mar 31, 2015, Turkey	-	3 s	[16]
Sep 28, 2016, Australia	-	2 min	[17]

this does not necessarily mean that these cascades were not preceded by a slow phase because the slow phase might be unacknowledged or unobserved.

Durations of slow and fast phases for some selected extreme outages are listed in Table I. Durations given are only estimates, because the grouping into slow and fast phase is not standardized and different splitting points are used in the literature. For the extreme cascades with slow phase reported, the data suggests that the duration of the slow phase is at least an order of magnitude longer than the duration of the fast phase.

III. ACCELERATION OBSERVED IN COMMON CASCADES

A. Line Outages Per Generation

Line outage data is taken from one North American transmission utility and includes the name of the outaged line and the time of the outage [19]. Only automatic outages are considered. Within the considered time range from 1999 to 2017, there are 14,259 reported line outages. As all automatic line outages within this time range are recorded, data includes all phases of cascading outages, in contrast to the extreme cascades where outages before the considered time range were sometimes omitted. The line outages are grouped into cascades and then into generations in each cascade based on the outage timings according to the simple method described in [8]. The method assigns successive outages that are separated in time by not more than one hour to the same cascade. Within each cascade, the method assigns outages that occurred within not more than one minute to the same cascade generation. The resulting data contains 8,745 individual cascades, out of which 1,426 cascades (16.3%) exhibit more than one generation.

We first examine in Fig. 2 how the mean number of lines outaged in each generation changes as the generation number increases from 1 to 20. The mean number of lines outaged in each generation shown in Fig. 2 have mean 1.28 with standard deviation 0.12. We conclude that the number of lines out per generation does not change significantly as the cascade progresses. Therefore we proceed to examine the changes in time between generations.

B. Decrease of Time Between Generations

Once line outages are grouped into cascades and cascade generations, time differences between consecutive generations within the same cascade are calculated from the reported outage timings. Cascades with only one generation are neglected. The time differences for the cascades are grouped based on the cascade generation as shown in Fig. 3. The boxplot shows the median, first and third quartile, the interquartile range (IQR), minimum and maximum and any outliers. By convention, outliers are here defined as points that differ by more than 1.5 times the IQR from either end of the IQR. The widths of the boxes are proportional to the square root of the number of outages in the respective generation. The data shows a decreasing median time difference between generations for the first five generations starting from 19.0 s. Time differences then stabilize around 10.5 s. We conclude that the average common cascades accelerate modestly over the first 5 generations, with the outage rate approximately doubling over the entire cascade. To show a smoothed trend of the results we fit an exponential change to the medians in Figs. 3– 5.

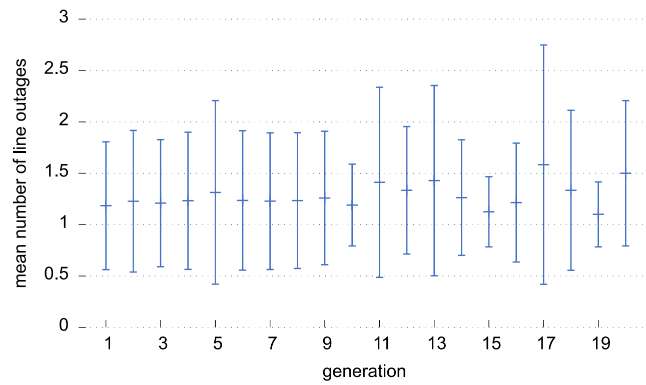

Fig. 2. Mean line outages per common cascade and standard deviation in each generation.

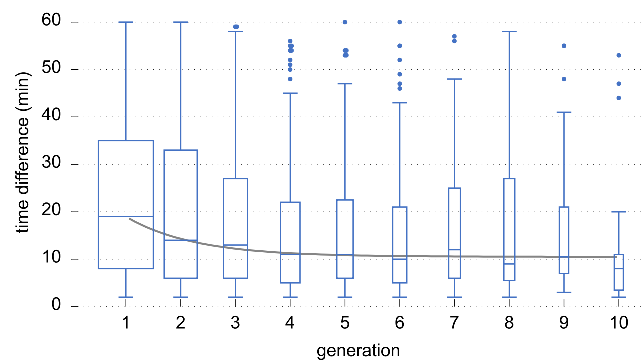

Fig. 3. Boxplot of time differences in common cascades and exponential fit to the median. Box width is proportional to the square root of the number of outages per generation.

C. Cascade Sizes

Differences in the acceleration behavior of common cascades depending on the cascade size are analyzed by splitting the cascades into 1,355 small cascades with less than 10 generations

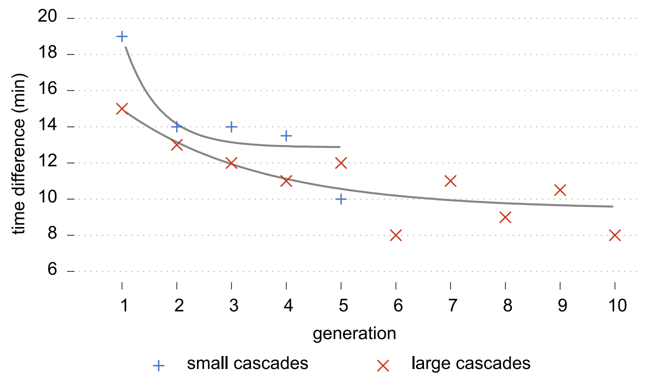

Fig. 4. Median time differences in small and large common cascades. Time differences for small cascades are not displayed for more than five generations due to lack of data.

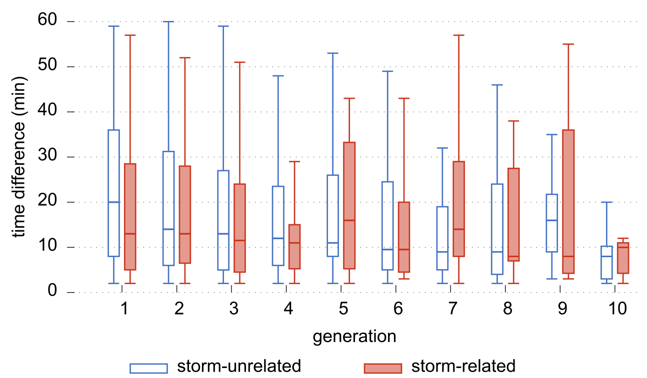

Fig. 5. Boxplot of time differences in common storm-related and storm-unrelated cascades.

and 71 large cascades with more than ten generations (the upper 95% quantile). The resulting time differences show that small cascades are slower but accelerate slightly more than large cascades, which are faster but do not accelerate as much (Fig. 4). Time differences for small cascades cannot be analysed beyond five generations due to lack of data.

D. *Weather-Related Cascades*

Previous research has shown the importance of distinguishing and separately considering cascades during extreme weather [20], [21]. Here, we distinguish stormy weather using the National Oceanic and Atmospheric Administration (NOAA) Storm Events Database for the period from 1999 to 2013 [21]. By doing so, the common cascades are split into 198 storm-related and 954 storm-unrelated cascades. Note that none of the extreme cascades in Table I are weather-related.

Analysis of median time differences between generations show that time differences are shorter for storm-related cascades than for storm-unrelated cascades during the first two generations, meaning that storm-related cascades propagate faster initially (Fig. 5). However, storm-related cascades accelerate less than storm-unrelated cascades over the course of the cascade.

IV. Conclusion

We analyzed the acceleration of cascading outages recorded for some worldwide extreme cascading outages and the more common cascades recorded by one USA utility. Whilst we acknowledge that our analysis may be specific for this utility and remains to be confirmed with data from other utilities, we observed characteristic differences between extreme and common cascades. Some of the extreme outages had a slow phase followed by a fast phase that was at least an order of magnitude faster than the slow phase, whilst common cascades showed a much more modest acceleration of up to a factor of two. Fast phases are critical for network operators, as they render manual outage mitigation impossible once the fast phase has been entered.

The average time between generations of common cascades decreased from 20 to 10 minutes as the cascade proceeded. Grouping outage data based on outage size as well as attribution to extreme weather revealed slight differences in acceleration behavior, but again fast phases similar to extreme blackouts were not observed. The time scale of both the slow phase of the extreme cascades and the common cascades was consistent with prompt operator actions. It is concluded that manual mitigation of common cascading outages is often possible, and further research in mitigation and prevention strategies is suggested.

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