

Heavy-tailed Transmission Line Restoration Times Observed in Utility Data

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Abstract—The empirical probability distribution of transmission line restoration times is obtained from 14 years of field data from a large utility. The distribution of restoration times has a heavy tail that indicates that long restoration times, although less frequent, routinely occur. The heavy tail differs from the convenient assumption of exponentially distributed restoration times, impacts power system resilience, and makes estimates of the mean restoration time highly variable.

Index Terms—Power system reliability, restoration

I. INTRODUCTION

Assessing the impact of blackouts on our society requires adequate modeling of the restoration of transmission lines after they are outaged. Timely restoration of electric power after a blackout depends on the quick restoration of the outaged lines, and even if a line outage does not lead to load shed, the resilience of the power transmission system to other contingencies decreases during the outage. The restoration depends on many factors such as weather, location, type of failure, and crew availability.

When computing mean steady state reliability parameters of a power system, it is customary to assume exponential restoration times for the components. Indeed the repair state steady state probability, frequency and mean repair time are independent of the distribution of restoration times in many useful cases such as independent components. However, the distribution of restoration times affects the mean repair time for some common-mode failures [1], [2] or if there are duration dependent effects [3], and significantly impacts the distribution of reliability indices about their mean values [4].

In distribution systems, log-normal distributions of line restoration times are considered in [4], [5]. In transmission systems, we have not found many published sources of line restoration data. Ref. [6] models field data for restoration times of 345 kV lines using gamma distributions with shape parameter less than one. Ref. [7] fits field data in England and Wales for restoration times of 275 kV and 400 kV lines with a log-normal distribution. With the exception of the log-normal distribution in [7], the distributions assumed for line restoration at the transmission system level are not heavy-tailed. This letter finds a tail somewhat heavier than log-normal in the distribution of restoration times in transmission system field data from a North American utility, and outlines some statistical consequences of the high variability of the restoration times caused by the heavy tail of the distribution.

II. OUTAGE DATA AND THE HEAVY TAIL

We use 14 years of utility data from 1999 to 2012 [8]. Data includes the transmission line restoration time (outage

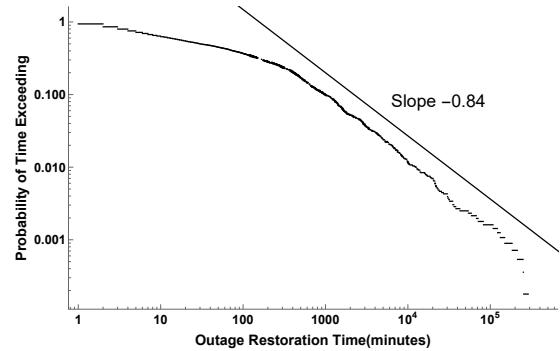


Fig. 1. Survivor function of outage restoration time in utility data

duration), date, time, cause code, and whether the outage is automatic (forced) or planned. 5348 automatic outages with zero minutes restoration time are regarded as momentary. The top 3 causes of automatic outages are foreign trouble, unknown, lightning for the non-momentary outages, and lightning, unknown, foreign trouble for the momentary outages. We now omit the planned and momentary outages and only analyze the 5594 non-momentary automatic outages in the data.

The distribution of the restoration time of non-momentary automatic outages is shown as a survivor function (probability that the restoration exceeds a given time) in Fig. 1. This distribution shows a heavy tail due to the approximately linear behavior of the longer restoration times on the log-log plot. The slope of the heavy-tailed linear region is -0.84 , so that the probability of the restoration time exceeding time t varies as $t^{-0.84}$. (The corresponding tail of the pdf of restoration time varies as $t^{-1.84}$.) The heavy tail implies that long restoration times are rare and highly variable, and, in contrast to distributions with exponentially decaying tails, occur routinely. Another way to see the effect of the power law decay of the tail is that the repair intensity is proportional to $1/t$. This deterioration in the repair intensity over time shows the impact of some very long restoration times. The main definitive conclusion of the analyses of the long restoration times in [9] is that those exceeding 20 000 minutes have cause code “foreign trouble”. The longest outage times may be due to lines in inaccessible locations.

We try fitting several common distributions to the data in Fig. 2. The exponential, Weibull, and gamma distributions do not fit at all. The data is closer to log-normal, but noticeably a bit heavier in the tail. Statistical test shows that the data cannot be confirmed to be log-normal (goodness of fit parameter $p < 0.1$).

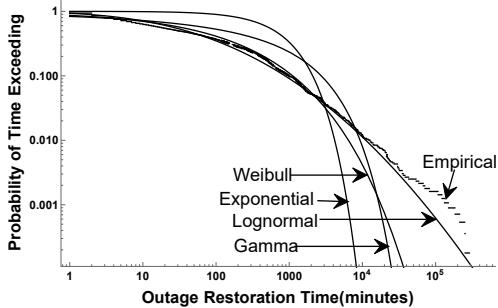


Fig. 2. Survivor function of outage restoration time in utility data and some fitted ideal distributions

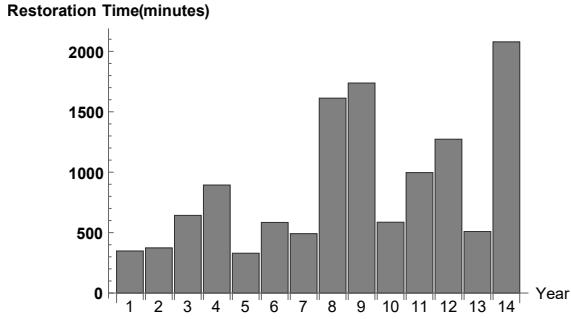


Fig. 3. Annual means of the transmission line restoration times

III. VARYING ESTIMATES OF MEAN RESTORATION TIME

If the linear tail region of slope -0.84 of the outage restoration time distribution in Fig. 2 was extrapolated indefinitely, the variance would be undefined but the mean would be large but finite. In practice, with the bounded distribution in Fig. 2, estimates of the mean can behave erratically. For example, Fig. 3 shows the high variability of 14 annual means.

The data X_1, X_2, \dots, X_n for $n = 5594$ are the restoration times of non-momentary automatic outages over 14 years. There are on average $m = 430$ non-momentary automatic outages per year. The sample mean is $\bar{X}_n = n^{-1} \sum_{j=1}^n X_j = 907$ minutes and the sample standard deviation is $S_n = [(n-1)^{-1} \sum_{j=1}^n (X_j - \bar{X}_n)^2]^{1/2} = 8515$ minutes. We use the m out of n bootstrap resampling method from [10] to estimate a confidence interval for the sample mean: m samples $X_1^*, X_2^*, \dots, X_m^*$ are randomly chosen from the data with replacement and the mean $X_m^* = m^{-1} \sum_{j=1}^m X_j^*$, the bootstrap variance $S_m^{*2} = m^{-1} \sum_{j=1}^m (X_j^* - \bar{X}_m^*)^2$ and the bootstrap Studentized mean $T_m^* = \sqrt{m}(\bar{X}_m^* - \bar{X})/S_m^*$ are computed. This is repeated 100 000 times to obtain an empirical distribution for T_m^* . We estimate $\hat{x}_{95\%} = \sup\{x : P[|T_m^*| \leq x] \leq 0.95\} = 6.30$. Then the 95% confidence interval for \bar{X} is $[\bar{X} - \hat{x}_{95\%} S_n / \sqrt{n}, \bar{X} + \hat{x}_{95\%} S_n / \sqrt{n}] = [191, 1625]$. This shows a substantial variation in the estimates of the mean based on 14 years of data. Estimates of the mean based on annual data will be even more variable.

The variability of the estimates of the mean from 14 years of data causes a corresponding variability in reliability quantities computed from the mean. For example, the transmission line unavailability is 0.0012 with a 95% confidence interval [0.00026, 0.0022].

IV. CONCLUSION

As more automatically processed data sets are becoming available to utilities operating transmission systems, it seems appropriate to re-evaluate observed restoration statistics for the transmission lines. While heavy tails of log-normal form were observed in the data of [7], this letter shows restoration time data distributed with a power law region that is slightly heavier than log-normal. We conclude for the 14 year data set examined that estimates of the mean restoration time are highly variable due to the large fluctuations inherent in the data. It follows that straightforward annual estimates of the mean are too noisy to be representative of the data. Even if the mean can be accurately estimated with longer observation times, the high variability of the mean limits its usefulness for time scales of the order of a decade or less.

The literature shows that a nonexponential form of the distribution of restoration time can affect some results [1], [2], [3], [5]. The results for our dataset suggest that the problems of high variability of estimates of the mean and coping with the implications of the variability of the restoration times about this mean [4] are more important than the inaccuracy of exponential distribution modeling assumptions. Although our dataset is from only one utility, all utilities in NERC collect TADS data that contains the needed outage restoration times (and many utilities worldwide collect similar data) and can easily do similar calculations. Therefore we can generally recommend that the distribution of outage restoration times be checked before placing confidence in annual mean restoration times.

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We gratefully thank BPA for making the outage data publicly available. The analysis and any conclusions are strictly those of the authors and not of BPA. We gratefully acknowledge funding in part from Arend and Verna Sandbulte funds and NSF grant 1609080.