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Distribution Feeder Characteristics and Their Resiliency to Natural Hazards

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Distribution Feeder Characteristics and Their Resiliency to Natural Hazards

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Table of Contents

Acknowledgements	i
List of Figures	iii
List of Tables	iii
Abstract	iv
1. Introduction	1
2. Data and Method	4
2.1 Data Description	4
2.2 Cluster Analysis to Group the Feeders into Like Types.....	6
2.3 Empirical Analysis Specifications.....	8
3. Results	10
4. Discussion	13
5. Summary and Conclusions	15
References	16

List of Figures

Figure 1. Summary of interruption events across all 8 utilities by the interruption causes in 2019 for (a) number of interruptions; (b) total interruption duration (minutes); (c) total interrupted customers; (d) total interrupted customer minutes. Scheduled power outage is not included here. “Natural” cause includes cause code weather, wildlife, and vegetation.....	5
Figure 2. Time series bubble plot of interruption events caused by weather, wildlife, and vegetation for each utility during 2019.....	6
Figure 3. Correlation matrix of feeder characteristics with the sign of correlation coefficient color-coded and magnitude indicated by the size of the dots.....	7
Figure 4. Cluster quality metrics (Davies Bouldin Index and Average Silhouette Width) varying as a function of the number of clusters. The optimal performance is captured at 4 clusters as indicated by both metrics. Note that here inverse of Davies Bouldin Index is plotted so that it shows the greater the value, the better the clustering performance.	8
Figure 5. Spider plots for the three dominant feeder types.....	10
Figure 6. Comparison of feeder types on reliability measures (error bars indicate 90 percent confidence intervals) relative to the reference feeder type “residential overhead”.....	11

List of Tables

Table 1. Utility level summary statistics of feeder characteristics	5
Table 2. Description of a set of reliability and impact measures as outcome variables	9

Abstract

This paper introduces a method and approach for initially screening actions to improve the reliability of distribution systems exposed to three natural hazards (wildlife, weather, and vegetation). The method is well-suited to needs and capabilities of smaller utilities because it relies on readily available information and does not depend on simulations involving detailed engineering models. The method involves first aggregating feeders into like types and then correlating them, separately by hazard, to standard measures of reliability, namely, System Average Interruption Frequency Index (SAIFI) and System Average Interruption Duration Index (SAIDI), and the individual constituents of these measures. The correlations provide both new insights into the efficacy of accepted reliability management practices while and re-confirm long-understood, accepted practices. Importantly, the method does not seek to replace the need for detailed engineering analysis. Instead, in view of the significant costs involved in conducting these more involved analyses, the method is intended to help smaller utilities prioritize their more limited resources to maximize the efficacy of actions they take to improve reliability.

Index Terms— Electric distribution system design, electric distribution system operation, electric distribution system reliability

1. Introduction

The greatest opportunities for improving the reliability of electricity service lie with actions directed toward the distribution system because the distribution system, not the generation nor the transmission system, is the principal source of the causes of power interruptions [1]. Long-standing industry practices group and classify these causes into a handful of cause codes [2]. Of these, natural hazards are the most prevalent causes of power interruptions, including wildlife, weather, and vegetation followed by or in conjunction with equipment failures. Consequently, efforts to reduce the frequency and severity of power interruptions caused by the natural hazards represent important opportunities for efforts to improve reliability.

There is a well-established literature on methods for prioritizing efforts to improve reliability. Reliability-centered maintenance is a general term of art under which many of these approaches have been formalized mathematically [3]. The majority of these methods can be characterized as “model-driven” because they rely on detailed engineering models of the physical linkages among the types of power delivery equipment that comprise a distribution circuit or feeder. They can also be characterized as “simulation-based” because the analysis of reliability generally involves assigning failure probabilities to individual equipment types, assessing the joint likelihood of failures, and then estimating via simulations the resulting loss of electric service delivery to the population of customers served by each distribution feeder.

The literature contains many examples of applications of these methods to address power interruptions caused by natural hazards, including, for example, impacts of storms on momentary power interruptions [4], optimal means for scheduling vegetation management [5], impacts of lightning on distribution system reliability [6], and, more recently, on approaches for improving resilience to severe natural hazards, such as hurricanes [7].

Due to their model-driven and simulation-based formulation, application of these methods depends on having robust records on the historic causes, frequency, scope, and duration of power interruptions, and extensive records on maintenance procedures and costs, and especially on the physical condition of individual distribution assets. This information must then be organized and integrated in order to formulate the relationships represented by the models and also to calibrate and validate simulations employing these models.

While all utilities maintain records on historic power interruptions, equipment inventories, and maintenance activities, not all utilities maintain records that are sufficiently detailed and up-to-date nor have the engineering resources (i.e., staff) available to support application of such formal methods. Creating and maintaining both detailed and accurate records, for example, on the physical condition of individual distribution assets, especially in a manner that they can be readily accessed for application of model-based engineering analyses, is costly and time consuming. These requirements mean that as a practical matter, it is generally not feasible nor realistic for smaller utilities to pursue application of these techniques with the same degree of rigor that they can and are pursued by larger utilities.

This paper introduces a method for analyzing historic data on power interruptions caused by natural hazards that does not depend on these strict information and engineering resource requirements. The goal of the method is to assist smaller utilities in prioritizing their efforts to address power interruptions caused by natural hazards.

The method first involves evaluating the reliability performance of groupings of like distribution feeders, taken as a whole. It then involves unpacking standard measures of reliability performance to provide understanding of how the constituents of these measures are individually affected by natural hazards.

A focus on analysis of individual feeders is, of course, not new; it is common to the majority of published methods for studying distribution system reliability. What is new is that our method does not rely on developing costly and time-consuming, detailed information on the distribution equipment that comprise a feeder (e.g., their physical condition) or on an explicit representation of feeder topology. We can relax these requirements because our method does not involve simulations. Instead, it relies solely on information that can be developed through simple, statistical correlations involving general, overall features of feeders and standard utility records on reliability performance.

The method, in this sense, can be said to be “data-driven.” To an extent, it harkens back to the early days of distribution system reliability analysis when rudimentary applications of this form of analysis were common. For example, one early method created an overall index to classify the reliability performance of feeders on the basis of their physical features (e.g., line length, overhead vs. underground, number and types of customers served, etc.) [8]. Unlike these early methods, which involve relating formal and rigid classifications of physical features to reliability performance, our method involves allowing the data, alone, rather than engineering design principles, to guide the identification of the number and characteristics of like feeders by type.

In this regard, our method also shares similarities with the ideas that underlay prior efforts to estimate the performance of “typical” distribution feeders [9, 10]. In the UK, for example, these methods have been highly codified into detailed descriptions of individual feeder types that in turn drive performance-based incentives [11]. However, rather than defining typical feeders according to fixed sets of detailed, engineering-based classifications (e.g., voltage classes of equipment elements and topological considerations), our method involves classification based on the observed frequencies of only very general features of feeders, rather than on the details of their engineering design. Our means for clustering feeders into like types shares similarities with the use of principal component analysis to relate incidence rates of certain interruption causes to physical feeder characteristics [12]. We extend this earlier approach by focusing only on interruptions caused by natural hazards.

A second feature of our method is to evaluate reliability performance using both standard measures, such as System Average Interruption Frequency Index (SAIFI) and System Average Interruption Duration Index (SAIDI) [13], and, in addition, the constituents of these standard

measures, including power interruption frequency, numbers of customers interrupted, and the duration of individual interruptions.

The potential usefulness of considering these constituents independent of one another can be illustrated as follows: A feeder can have high SAIFI either due to more frequent interruptions or due to more widespread interruptions (i.e., more customers impacted per interruption) or both. Similarly, a feeder can have a high SAIDI either due to more frequent interruptions or due to longer (i.e., more customer minutes of power interruption per interruption). Examining these three constituent measures separately provides for a direct consideration of the contribution of each on overall reliability. Thus, examining how these constituents are individually affected by natural hazards provides deeper insights into the efficacy of the various measures that are considered for improving reliability.

This paper is organized in four sections following this introduction. Section II reviews the feeder and power interruption information we examined from eight small utilities to confirm the predominance of interruptions caused by natural hazards of various types (wildlife, weather, including severe storms, and vegetation). Statistical methods are also described in this section. Section III present the results from the statistical analysis. Section IV offers insights on how application of these methods might improve targeting of efforts to improve distribution feeder reliability, as well as caveats that must be recognized in extending them. Section V summarizes the findings and outlines directions for future research.

2. Data and Method

2.1 Data Description

We analyzed data from 8 small utilities (identified by the letters A through H). The data include the overall physical characteristics of each utility's feeders, and, for each feeder, the cause, duration, and customers impacted by power interruptions recorded over the course of a single year. The data were collected using the American Public Power Association's eReliability Tracker (<https://www.publicpower.org/reliability-tracking>). The eReliability Tracker is a web-based service that allows public power utilities to report, categorize, and summarize power interruption information.

The utilities varied in their physical features, including the number and types of customers served, total line miles, and shares of underground vs overhead lines (Table 1). Two of the utilities are relatively large (E and H), each serving more than 50,000 customers; while two of the utilities are smaller (C and F), each serving less than 10,000 customers. Despite this range in number of customers served, all 8 utilities can be classified as small utilities, in comparison to large investor-owned utilities, which typically serve hundreds of thousands or more customers. Utilities B, F, G and H serve primarily residential customers (>90%), while Utilities A, C, and D also serve a significant number of commercial customers (15~26%). Utilities C and G have primarily underground lines (74~80%), while Utility F is dominated by overhead lines (97%).

The power interruption information consists of more than 4,000 distinct interruptions across the 8 utilities during 2019. For each interruption, the data recorded include the substation name, feeder name, and several characteristics of the interruptions including total customers impacted, interruption start and end date-time, and the cause of the interruption.

A total of 50 distinct cause codes were used originally by the utilities to identify interruption causes. These detailed 50 codes were first mapped into 9 more aggregated cause code categories following guidelines that have been developed by APPA, including natural hazards, electrical equipment faults or failure, and power supply, operations, maintenance, etc. The focus of this study is on the interruptions caused by natural hazards, including weather, wildlife, and vegetation, which together represent the dominant causes of power interruptions (Figure 1).

Table 1. Utility level summary statistics of feeder characteristics

UTILITY ID	NUMBER OF CUSTOMERS ¹	% RESIDENTIAL % COMMERCIAL % INDUSTRIAL	LINE MILES (# OF CIRCUITS, LINE MILES/CIRCUIT)	% UNDERGROUND	CUSTOMER / LINE MILE
A	12000	79% 15% 6%	220 (37, 6)	48%	50
B	22000	94% 6% 0%	530 (18, 33)	53%	40
C	6000	70% 26% 4%	120 (11, 14)	74%	50
D	16000	82% 17% 1%	140 (14, 10)	29%	100
E	86000	79% 21% 0%	1300 (91, 13)	51%	70
F	7000	93% 7% 0%	180 (6, 60)	3%	40
G	23000	91% 9% 0%	780 (19, 43)	80%	30
H	5100	95% 5% 0%	1300 (64, 33)	33%	40

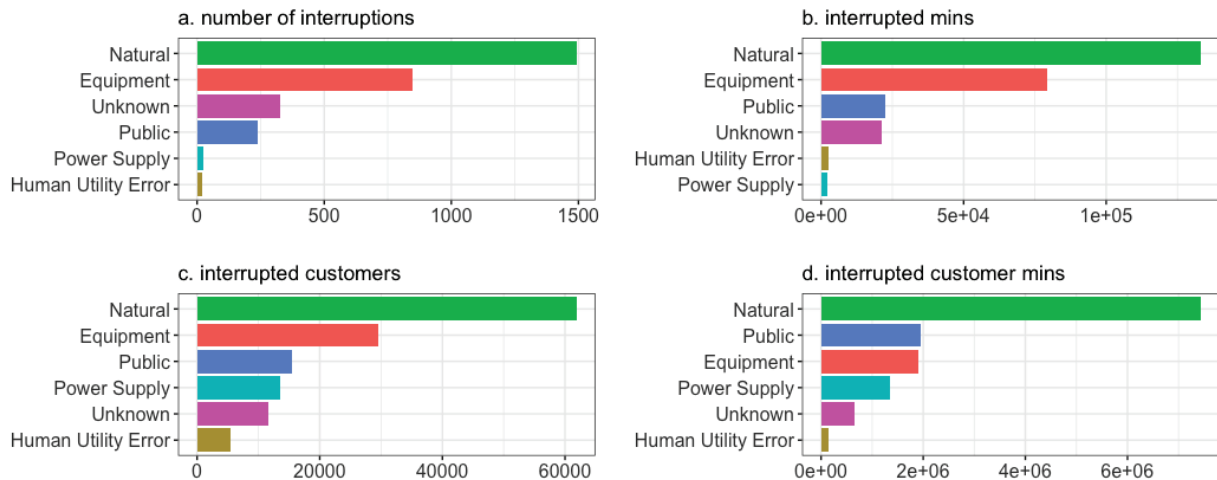


Figure 1. Summary of interruption events across all 8 utilities by the interruption causes in 2019 for (a) number of interruptions; (b) total interruption duration (minutes); (c) total interrupted customers; (d) total interrupted customer minutes. Scheduled power outage is not included here. “Natural” cause includes cause code weather, wildlife, and vegetation.

¹ Numbers of customers, line miles, and customer/line mile have been rounded to mask identity of utilities

Figure 2 further shows the interruptions caused by each of these three natural hazards over time and aggregated to the utility level. Each dot corresponds to a single power interruption event. The size of the dot scales with the total number of customers interrupted. All the dots are transparent, but when the interruptions are close in time, they overlay on top of each other resulting in darker colors. The frequency of the power interruption as well as their impact (i.e. customers impacted) vary widely across the 8 utilities. The Utilities E and H, the two largest utilities, experienced the greatest number of interruptions.

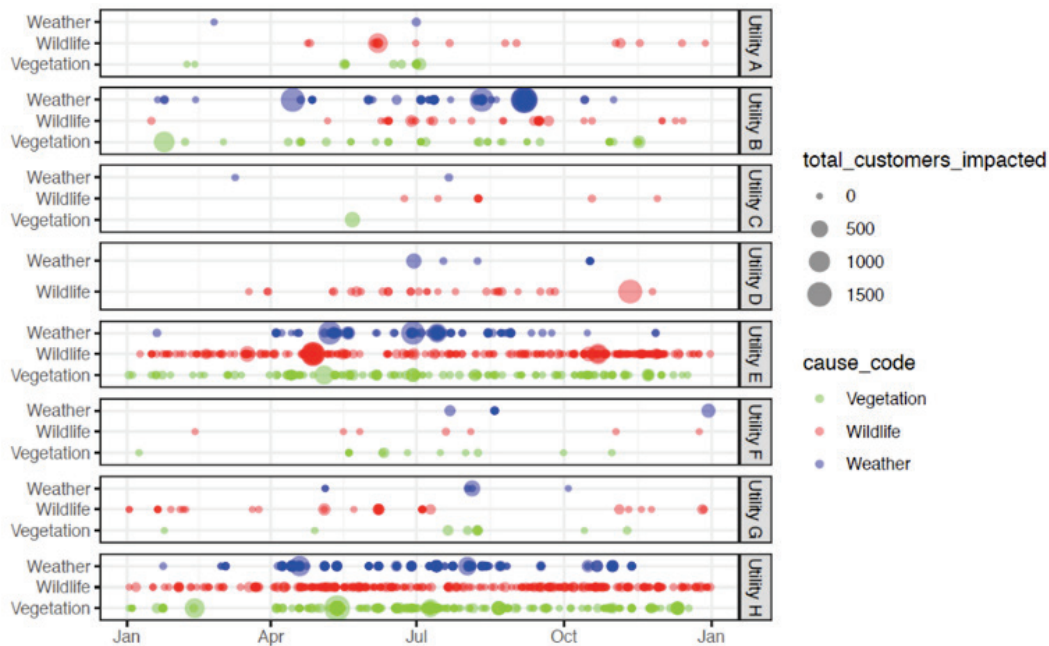


Figure 2. Time series bubble plot of interruption events caused by weather, wildlife, and vegetation for each utility during 2019.

2.2 Cluster Analysis to Group the Feeders into Like Types

The first method we introduce involves identifying and grouping feeders into a small number of like types of feeders through application of statistical clustering procedures. The method is based on the intuition that the reliability performance of a utility's feeders depends on similarities among or groupings of feeder features, not on individual features. The four feeder features we consider jointly are: percentage of customer types (residential, commercial, and industrial), total line length, percentage lines overhead and underground, and customers served per line mile.

The intuition for our method is substantiated by the correlations we observe among these features (Figure 3). For example, we can see that residential feeders also tend to have longer lines, and more customers per line mile, while commercial feeders tend to have shorter lines. Grouping the feeders by their joint characteristics is a straightforward and easy-to-implement means for accounting for such inter-correlations among feeder features.

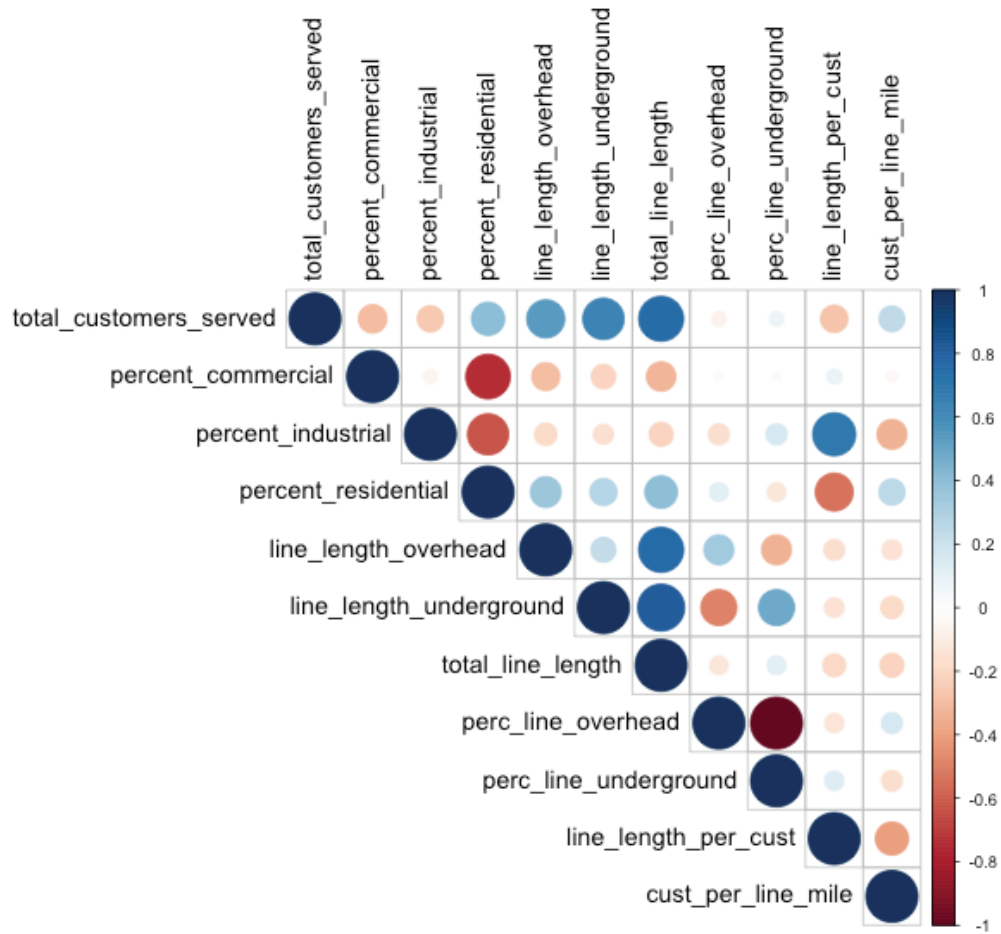


Figure 3. Correlation matrix of feeder characteristics with the sign of correlation coefficient color-coded and magnitude indicated by the size of the dots

The Partition Around Medoids (PAM) clustering algorithm was used to group like-feeders based on combinations of these features. PAM belongs to the k -medoids problem, where a given dataset is broken into groups to minimize the distance between points labeled to be in a cluster and a point designated as the center of that cluster. In contrast to the more commonly known k -means algorithm, PAM clustering is usually more robust in handling outliers [14]. That is, while cluster centers derived from k -means may represent the “average” features of a given type of feeder, a feeder with these exact features may not, in fact, exist in real world. In contrast, the cluster centers derived using PAM are selected from only the actual feeders processed by the algorithm and hence can be used directly as representing a “typical” feeder in subsequent analyses.

The PAM algorithm groups the feeders into k like-types, where the number k is a hyper-parameter in this unsupervised machine learning algorithm. The number k needs to be given before the execution of a k -medoids algorithm. The number selected for k was based on the

Davies-Boulden indicator (DBI) [15] and Average Silhouette Width (ASW) [14], which measure the performance of resulting clusters.

We identified the optimal number for k by reviewing the Davies-Boulden indicator (DBI) and Average Silhouette Width (ASW), which are metrics that assess the performance of our clustering algorithm. Four feeder groupings emerge from the PAM cluster analysis (Figure 4).

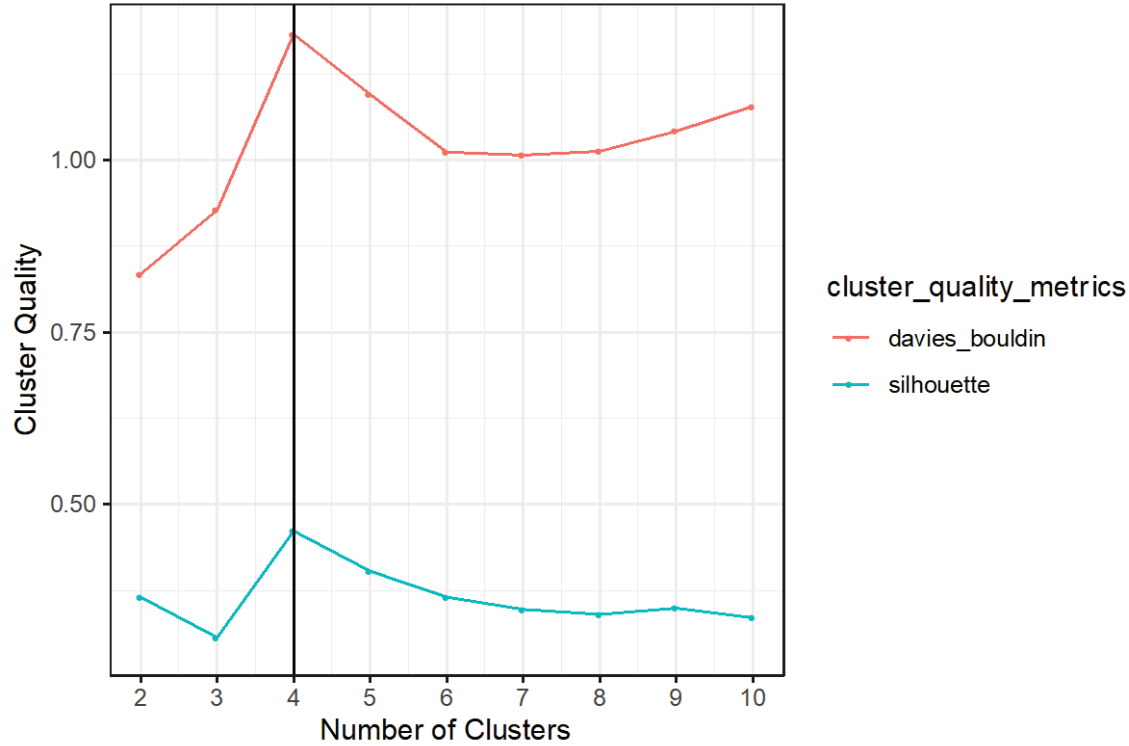


Figure 4. Cluster quality metrics (Davies Bouldin Index and Average Silhouette Width) varying as a function of the number of clusters. The optimal performance is captured at 4 clusters as indicated by both metrics. Note that here inverse of Davies Bouldin Index is plotted so that it shows the greater the value, the better the clustering performance.

2.3 Empirical Analysis Specifications

Correlation analysis is used to understand the relationship between the like-feeder types and power interruptions caused by each of the three natural hazards. The approach is a fixed effect generalized linear model with log link function, inspired by the log transformation used in [16]. The model is specified according to Equation (1) below.

$$\ln(E(Y_{c,h,j})) = u_{j,h} + \beta_{hg}X_g \quad (1)$$

Where, $Y_{c,h,j}$ is the dependent outcome variable of various reliability measures computed for feeder c at utility j , and separately for hazard type $h \in \{\text{Weather, Wildlife, Vegetation}\}$ occurred in 2019. $E(Y_{c,h,j})$ is the expectation of $Y_{c,h,j}$. The independent variables X_g is an indicator variable, with X_g equals 1 if the feeder belongs to group g . The coefficient β_{hg} quantifies the effect of hazard type h on feeder group g relative to a reference group. Utility fixed effects $u_{j,h}$

are used as controls to account for unobservable predictors that vary at the utility level such as overall vegetation cover, climate, design of the distribution system, and so on.

The outcome variables are listed in Table 2, including both traditional reliability metrics, as well as the individual constituents of them.

Table 2. Description of a set of reliability and impact measures as outcome variables

Variable Names	Description and Definition*
C.SAIFI_{c,H}	Circuit Level SAIFI = $\frac{\sum_i Cust_{c,i,h}}{Cust_c}$
C.SAIDI_{c,H}	Circuit Level SAIDI = $\frac{\sum_i Cust_{c,i,h} \times T_{c,i,h}}{Cust_c}$
# Int_{c,H}	Number of interruptions at circuit <i>c</i> caused by hazard type <i>H</i>
Int Cust	Average interrupted customers = $\frac{\sum_i Cust_{c,i,h} / Cust_c}{\#Int_{c,h}}$
Int CustMins	Average interrupted customer minutes = $\frac{\sum_i Cust_{c,i,h} / Cust_c \times T_{c,i,h}}{\#Int_{c,h}}$

*Notations: *c* is the circuit index, *h* is the interruption cause type $\in \{\text{Weather, Wildlife, Vegetation}\}$, *i* is the interruption index, *T* is the interruption duration, and *Cust* is the interrupted customers of a given interruption event.

SAIFI and SAIDI are the most widely used integrated measure of reliability. SAIFI measures how often, on average, customers experience power interruptions, and SAIDI measures how long, on average, their power has been interrupted. Both are normally reported on an annual basis.

In addition, three distinct measures of the constituents of SAIFI and SAIDI were also examined: 1) The total number of power interruptions, 2) The average number of customers interrupted per interruption, and 3) The average number of minutes of power interruptions per interruption. The first and second measures are the constituents of SAIFI, and the first and third are the constituents of SAIDI.

The regression analysis is repeated for each of the five measures of reliability and separately for each of the three interruption causes (a total of 15 regressions).

3. Results

The three dominant feeder groupings are shown in Figure 5 with spider plots.² Each spider plot shows the medoid of derived feeder cluster in terms of the joint feeder features. The center of the spider plots represents the minimum mean value of each feature observed and the outer ring represents the maximum. The range in values between minimum and maximum are scaled so that they are comparable for each factor that is plotted.

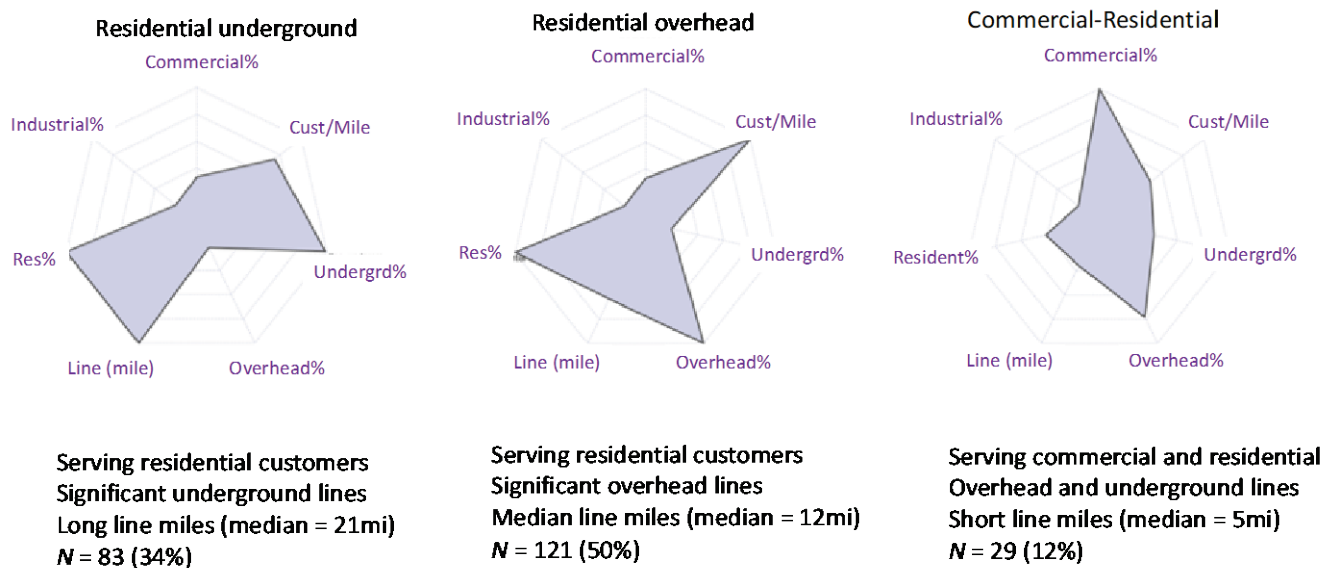


Figure 5. Spider plots for the three dominant feeder types

Moving from left to right in Figure 5, for simplicity, the first grouping is labeled “residential underground.” These feeders serve primarily residential customers have significant percentage of underground lines, and also tend to have long line miles. This grouping accounts for 34% of the feeders in the data set.

The second grouping is labeled “residential overhead” accounting for 50% of the feeders in the dataset. This grouping also serves primarily residential customers, but has a significant percentage of overhead lines, and has median-length line miles.

The third grouping “commercial-residential”. This grouping serves a mixture of residential and commercial customers with a mixture of overhead and underground lines and tends to have shorter total line miles. This grouping accounts for 12% of the feeders in the data set.

In the regression analysis, “residential overhead” group is used as the reference group and the estimation results are plotted in separate panels in Figure 4, one for each of the 5 measures of reliability. Each panel plots the effects of each natural hazard cause on reliability measures of a

² The fourth grouping that emerged from the cluster analysis is an “industrial” set of feeders. This grouping accounted for only 3% of the feeders, all of which were from a single utility. Results from the analysis of this grouping are not presented in this paper.

given feeder type (“commercial-residential” or “residential-underground”) relative to the reference feeder type (“residential overhead” feeders).

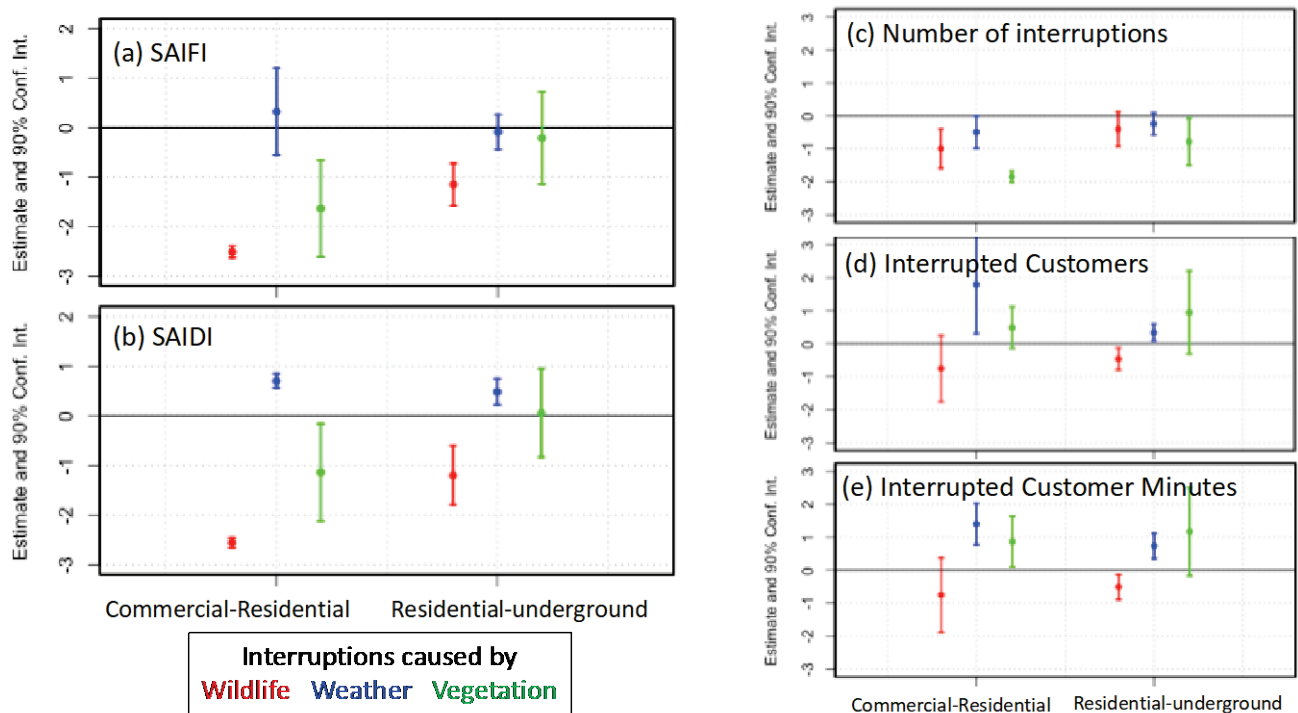


Figure 6. Comparison of feeder types on reliability measures (error bars indicate 90 percent confidence intervals) relative to the reference feeder type “residential overhead”

Relative to the reference “residential overhead” grouping of feeders, a negative sign (i.e., a relative value plotted below the mid-line) indicates a relatively lower value for a given measure of reliability for this feeder grouping. That is, this feeder grouping is more reliable than the residential-overhead feeder grouping is for events caused by this natural hazard.

For example, the coefficient for the “commercial-residential” grouping of feeders is -2.5 for interruptions caused by wildlife as measured by SAIFI in Figure 6a. This means that events caused by wildlife for “commercial-residential” feeders are on average $0.08 (= \exp(-2.5))$ times the SAIFI for this same cause for “residential overhead” feeders. In other words, the wildlife-caused SAIFI for “commercial-residential” feeders is on average 92% ($= 1 - 0.08$) less than that for the “residential-overhead” feeders. In short, “commercial-residential” feeders are more reliable (as measured by SAIFI) than “residential overhead” feeders when they experience interruptions caused by wildlife.

We also examined correlations in which SAIFI was disaggregated to consider, separately, both the total number of interruptions (Figure 6d) and the average number of customers interrupted per interruption (Figure 6c). Compared to “residential overhead” feeders, significantly fewer wildlife related interruptions occurred at “commercial-residential” feeders and when they did occur fewer customers were impacted on average. These two factors, together, explain the

reasons why wildlife-caused SAIFI affect the reliability of “commercial-residential” feeders less than it affects the reliability of “residential-overhead” feeders.

In addition, the wildlife-caused SAIFI and SAIDI of “commercial-residential” and “residential underground” feeders are both significantly lower than they are for “residential overhead” feeders (Figure 5a, b). This is because both fewer interruptions occurred and the impacts of these interruptions (as measured by number of impacted customers for SAIFI or customer minutes for SAIDI) are lower (Figure 5c, d, e).

In contrast, for weather- and vegetation-caused interruptions, the overall reliability measured by SAIFI and SAIDI are more complicated to assess because the underlying constituents of these measures - that is, the interruption frequencies and per-interruption impact (average numbers of customers interrupted, and average duration of individual interruptions) – offset one another. This is indicated by the differences in the signs of the coefficients for the interruption frequencies (Figure 5d) and the per-interruption impact (Figure 5c, e).

Considering weather-caused interruptions, the “commercial-residential” and “residential underground” feeders experience interruptions less frequently but, once interrupted, they may experience more severe and widespread impacts as measured by the number of customers interrupted and the total customer minutes of interruption. Lending credence to our intuition regarding the usefulness of examining the constituents of standard reliability measures individually, note that differences in SAIFI are not distinguishable among the three feeder groupings (Figure 5a). Despite the compensating effects of feeder groupings on frequency and duration, the relative coefficients for overall SAIDI (Figure 5b) show that both “commercial-residential” and “residential underground” feeders are less reliable than “residential overhead” feeder and that this is due to the significantly longer duration of the interruptions caused by weather events they experience.

Similar compensating trends are observed for vegetation-caused interruptions. The “commercial-residential” feeders are overall more reliable than “residential overhead” feeders as indicated by SAIFI and SAIDI (Figure 5a, b) and this is driven primarily by the significantly lower number of interruptions (Figure 5c). As for the “residential underground” feeders, fewer interruptions together with more severe impacts per interruption make the overall SAIFI and SAIDI indistinguishable from those of the “residential overhead” feeders.

4. Discussion

The results presented in the previous section confirm that additional insight into the how different natural hazards affect reliability can be gained by examining the individual contributions of the constituents of SAIFI and SAIDI. Doing so enables a utility to target the constituent directly and thereby maximize the effectiveness actions to improve reliability.

For example, as measured by SAIFI and SAIDI, “residential overhead” feeders are found to be less reliable than the “commercial-residential” feeder for vegetation-caused power interruptions. This is not an unexpected result. Still, it confirms that targeting “residential overhead” feeders for actions to address vegetation-caused power interruptions will be more effective in improving reliability than targeting this cause for “commercial-residential” feeders.

Figure 5 further attributes higher SAIFI and SAIDI for “residential overhead” feeders to the following constituents: greater numbers of interruptions, the comparatively larger number of customers affected by each interruption, and the comparatively larger number of customer-minutes of interruption per interruptions. Each finding points to a distinct type of action by the utility. Vegetation management would reduce the frequency of power interruptions. Distribution system designs that lower the number of customers on a given feeder would lower the number of customers affected. Some system design improvements could involve line segmentation, switching automation, automatic fault indicators to reduce customers on a given feeder. Finally, distribution operational procedures that reduce the time required to restore service would lower the number of customer minutes associated with each interruption.

Further review of Figure 5 suggests that the first of these strategies, increased frequency or targeted vegetation management to reduce the number of vegetation-caused power interruptions, may be the most effective of the three because the distribution of the estimated coefficients for these actions is the furthest from mean than that of the other two actions.

This same logic could also be applied to weather-caused power interruptions for “commercial-residential” and “residential underground” feeders. Figure 5 indicates that they are both less reliable than “residential overhead” feeders, with higher average SAIDI values as suggested by the positive coefficients in SAIDI. Efforts to reduce either the number of customers affected or the total number of customer minutes of interruption during weather events may lead to more effective improvement in SAIDI than efforts to reduce the number of interruptions in the “commercial-residential” and “residential underground” feeders. For these two feeder types, improving customer restoration planning and more frequent fault testing to reduce the duration of power interruptions and number of customers impacted during the weather events would be priorities.

The findings for wildlife-caused power interruptions do not provide as strong an indication of the relative potential effectiveness of efforts to prioritize any one of the three categories of possible actions over one another.

In closing, this discussion is necessarily speculative for two reasons. First, the size of the data set we examined consists only of one year of data from 8 utilities. Second, we did not have information that would enable us to identify whether, when, or what particular actions to improve reliability may have been taken during the year. Still, speculation is warranted both to illustrate the promise that future analysis involving more years of data from more utilities offers and to lay the ground work for the collecting and integrating information on the measured effectiveness of utility actions to improve reliability into future analysis.

5. Summary and Conclusions

This paper has provided empirical evidences on the extent to which differences in feeder characteristics can help to explain differences in the reliability performance of feeders when exposed to each of three different types of natural hazards (wildlife, weather, vegetation). The hypothesis is that understanding these differences can help utilities prioritize their efforts to reduce the impacts of these hazards and thereby improve reliability more efficiently and effectively. Data-driven approaches were employed to quantify the relationships between various measures of feeder reliability and a suite of feeder characteristics, which were considered jointly via a statistically-based clustering method.

Insights into the reliability impacts of natural hazards can be gained by examining entire populations of feeders that have been grouped into like types defined by ensembles of feeder characteristics. Feeders that are “commercial-residential” and “residential underground” are more reliable, as measured by both SAIFI and SAIDI, than the “residential overhead” feeders both because they experience fewer interruptions and because the severity of each interruption (as measured by number of customers interrupted or by total number of customer minutes of interruption) is lower. Hence, here again, it is useful to examine the constituents of SAIFI and SAIDI when reviewing correlations between the natural hazard causes of power interruptions and groupings of feeders. This deeper examination is particularly helpful in understanding differences in the reliability performance of feeders due to power interruptions caused by weather and vegetation.

It is recognized that some of the correlations discussed in this paper simply confirm long-understood accepted practices for improving reliability. At the same time, others provide new insight into the efficacy of accepted practices. Importantly, the methods do not seek to replace the need for detailed engineering analysis required to design and implement specific reliability-enhancing actions. Instead, in view of the significant costs involved in conducting more involved analyses, these methods are intended to help smaller utilities prioritize their more limited resources in order to maximize the efficacy of actions they take to improve reliability.

Going forward, we recommend extension of this form of analysis to data from other small utilities both to confirm the findings presented to date and to explore new correlations to develop additional insights into maximizing the effectiveness of actions to improve reliability.

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