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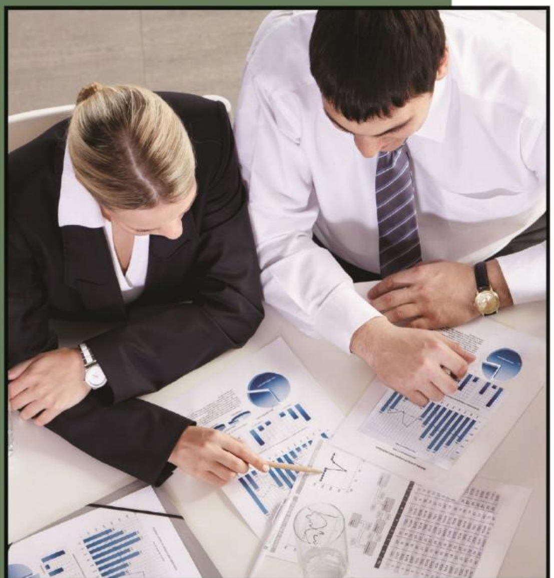

Reliability Targets for Washington's Three Investor-Owned Utilities

Prepared for:

Washington Utilities and Transportation Commission

Prepared by:

Power System Engineering, Inc.

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1 Executive Summary

The Washington Utilities and Transportation Commission ("UTC") engaged Power System Engineering, Inc. ("Power System") to develop customized utility-wide reliability targets and statistical ranges of those targets for the three Washington investor-owned electric utilities. Power System evaluated two reliability metrics: (1) the sustained average interruption duration index ("SAIDI"), and (2) the sustained average interruption frequency index ("SAIFI"). Both of these indexes are important measures of the reliability provided to customers by the utilities.

SAIDI measures the average total outage time experienced by customers in a given year. For example, if an electric utility had a SAIDI of 100 for 2016, it means that the average customer experienced 100 minutes of outages in 2016. Obviously this is just an average; some customers might experience several hours of outages during the year, while some might have had no outages. SAIFI measures the average <u>number</u> of sustained outages experienced by customers within a given year.[1] A SAIFI of 2.0 would indicate that the average customer experienced 2 outages (that met the minimum duration) during the year. Both of these indexes will exclude major event day ("MED") outages.[2]

For this analysis, two econometric models were created: (1) SAIFI with MEDs excluded, and (2) SAIDI with MEDs excluded. The explanatory variables in the models include:

- The forestation levels of each utility,
- Customer density measured by the number of retail customers divided by square miles of service territory,
- The prevalence of thunderstorms in the service territory,
- The standard deviation of elevation in the service territory used only in SAIDI model,
- The percentage of underground plant in total distribution plant, and
- Whether the MED exclusion criteria is based on the IEEE 1366 standard.

The coefficients for the explanatory variables listed above are shown in Table 1. These coefficients are explained in Section 4.3. It should be noted that the model also uses certain variables multiplied by other variables (such as: % Underground * % Forestation); those variables are not presented in this initial table.

[1] Most utilities define a "sustained outage" as an outage lasting five minutes or more. However, definitions vary across the industry. In prior research, we have found that the sustained outage definition does not have the expected influence on reliability metrics. Furthermore, including a sustained definition variable reduces the size of the sample due to unavailability of the definition for a number of utilities. For more information please see page 6 of Power System's expert testimony report filed on behalf of Toronto Hydro entitled, "Econometric Benchmarking of Toronto Hydro's Historical and Projected Total Cost and Reliability Levels".

[2] MEDS are discussed further in Section 4.1. The IEEE standard defines MEDs using the "beta" method. If outages for a certain day exceed 2.5 standard deviations from the normal day, a major event day is declared. A normal day and the standard deviation are determined by the utility's previous five years of normal day data (not including the MEDs).

Table 1 Coefficient Values

Variable	SAIDI Coefficient	SAIFI Coefficient
Forestation %	0.418174	0.261986
Customer Density	-0.184581	-0.117477
Thunderstorms	0.131738	0.191656
Elevation Standard Deviation	0.037079	n/a
% of Underground Plant	-0.163976	-0.158076
MED Exclusion IEEE 1366	0.093083	0.104879

The results of the econometric analysis are shown in Table 2, Table 3, Figure 1 and Figure 2 below. Table 2 and Table 3 give the actual SAIFI/SAIDI and the targets for each individual year.

Table 2 SAIFI Actual and Targets for Individual Years

Year	Avista Corporation		Pacific Power		Puget Sound Energy	
	Actual	Target	Actual	Target	Actual	Target
2011	1.09	1.10	0.55	1.64	1.00	0.93
2012	1.03	1.04	0.66	1.43	0.80	0.89
2013	0.88	1.04	0.79	1.46	0.86	0.90
2014	1.06	1.05	0.79	1.47	0.96	0.89
2015	0.98	1.05	0.85	1.50	1.03	0.91

Table 3 SAIDI Actual and Targets for Individual Years

Year	Avista Corporation		Pacific Power		Puget Sound Energy	
	Actual	Target	Actual	Target	Actual	Target
2011	109	115	80	113	142	129
2012	132	116	100	128	120	114
2013	118	117	113	125	125	105
2014	144	116	122	125	153	113
2015	159	116	100	122	161	103

Figure 1 and Figure 2 show the average targets for the 2011-2015 period. In Figure 1 and Figure 2, the middle data point for each utility (the blue point) indicates the expected value for that utility over 2011-2015. For example, Figure 1 shows that for its Washington service territory Avista had an expected SAIFI of 1.05 for the period 2011-2015.[3] This value indicates the SAIFI we would expect from an average utility with Avista's service territory characteristics for that time period. The red and gray data points represent the upper and lower bounds of the estimate, respectively, using a 90% confidence interval.

[3] Power System requested and received the Washington-only reliability metrics from both Avista and Pacific Power.

Figure 1 Candidate SAIFI Targets (2011-2015)

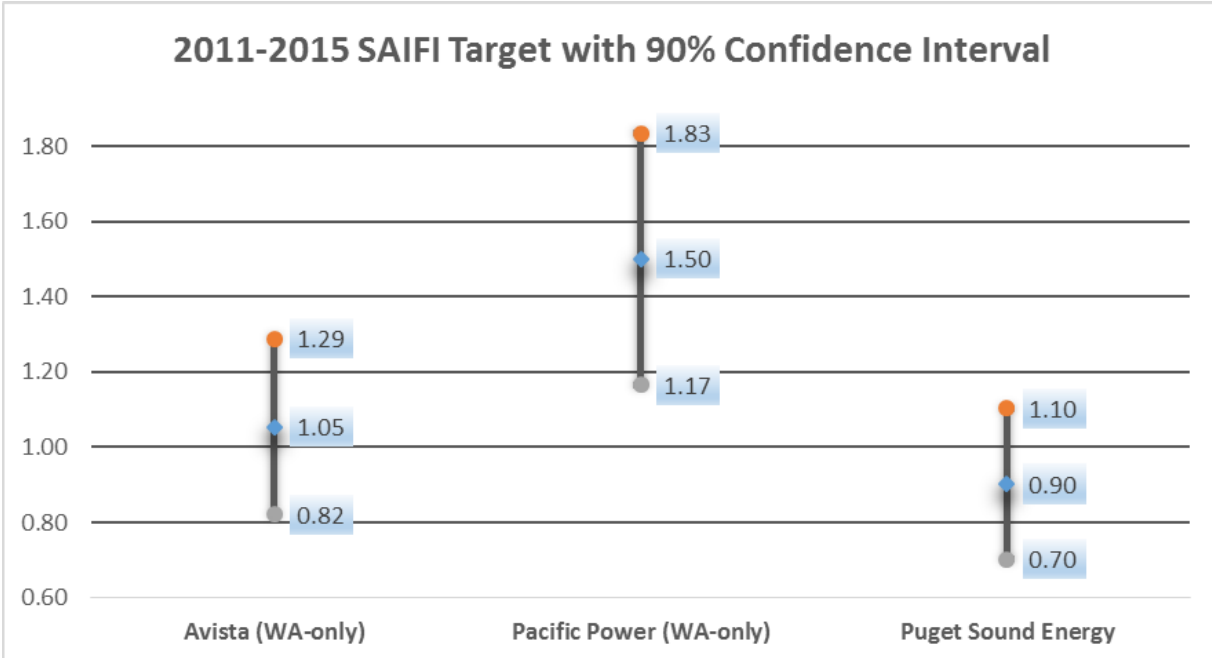
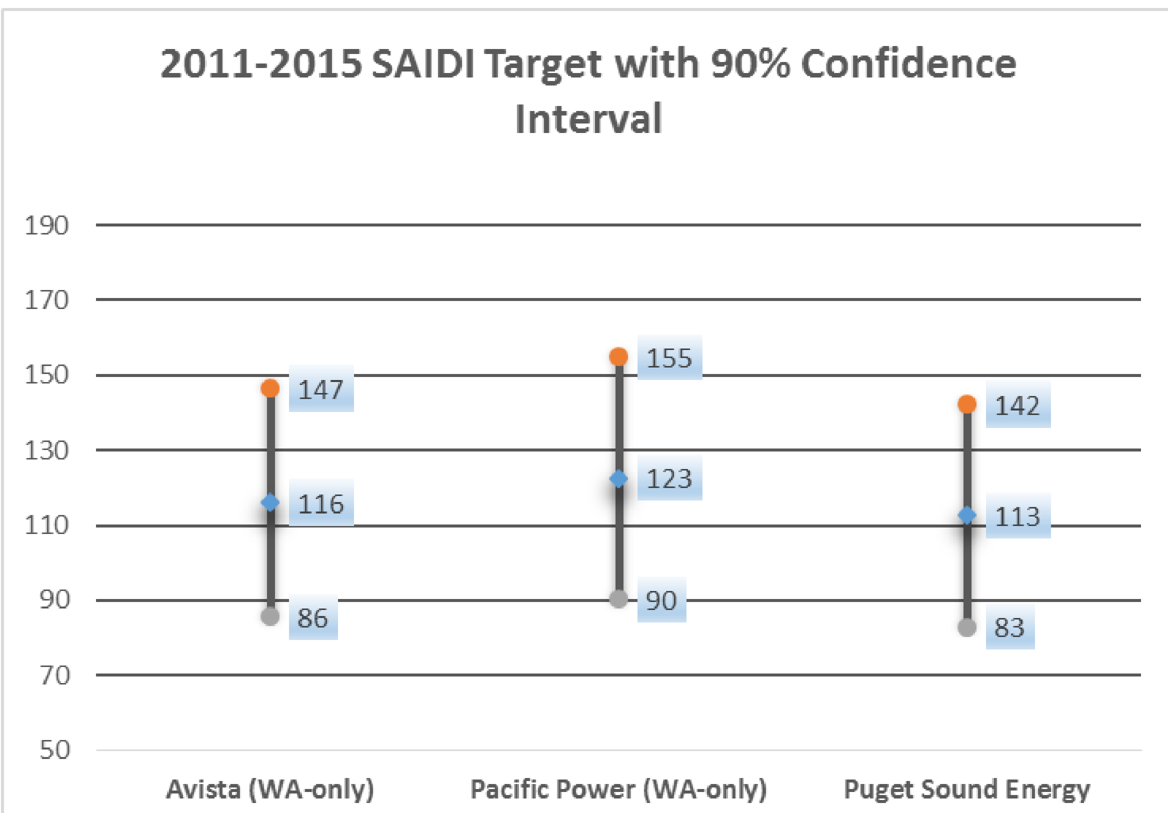


Figure 2 Candidate SAIDI Targets (2011-2015)



2 Introduction

The Washington Utilities and Transportation Commission ("UTC") engaged Power System Engineering, Inc. ("Power System") to provide customized reliability targets and ranges for the three Washington investor-owned electric utilities. These targets are derived from an econometric model, and the targets are based on the service territory conditions of each studied utility. Econometric models use regression techniques to determine how certain independent variables relate to a dependent variable; in this case the dependent variable is reliability, and the independent variables are service territory conditions, such as customer density, percent of service area that is forested, weather, etc.

The three utilities studied are Avista Corporation ("Avista"), Pacific Power & Light Company ("Pacific Power"), and Puget Sound Energy.[4] The examined reliability metrics in this study are the system average interruption frequency index ("SAIFI") and the system average interruption duration index ("SAIDI"). Both of the examined metrics exclude major event days ("MEDs"). The definitions of the metrics and of MEDs are covered in Section 4.1.

In this study, the variables used to benchmark the Washington utilities are specific to each utility's Washington service territory. Although Avista and Pacific Power operate in multiple states, for the purposes of this study only the utilities' Washington service territory characteristics are used to derive expected SAIFI and SAIDI levels.

This study uses an econometric benchmarking approach to formulate reliability targets and develop confidence intervals for those targets. The next section will give a brief overview of benchmarking in general before describing the specific econometric benchmarking method used for this study.

2.1 Overview of Benchmarking

The term "benchmarking" originates with the practice of cobblers, who would draw an outline of a foot on a board or bench, so that they could compare the shoe they were making to the desired foot size. The basic idea behind benchmarking is to compare an actual result with a desired or "expected" result.

For example, a company (the "ABC Company") might want to answer the following question: "Are we paying our employees a competitive salary that is in line with salaries paid by other companies in our industry?" ABC Company might want to set its salaries at the industry average, or alternatively it might want to set its salaries high, at say the top quartile, to attract the best employees.

Benchmarking is a way to determine how the salaries for ABC Company compare to the average across the industry (or the top quartile salary, etc.). One way to do this would be to simply take all

[4] Both Power System Engineering and Puget Sound Energy typically use the same acronym of "PSE". To avoid confusion, we will always refer to Puget Sound Energy by their full name, and Power System Engineering will be "Power System."

the salaries in the industry, and list them from highest to lowest.[5] Then we could calculate an average salary, or a median salary, or a "top 25%" salary, etc.

However, there are problems that arise when we simply compare these "raw" salaries. What if one company on the list is in downtown San Francisco, and ABC Company is in Omaha? This would not make for a meaningful comparison—the company in San Francisco will need to pay higher wages to account for the higher cost of living. Therefore we want some way to adjust for factors that influence a certain metric – in this example, we want to control for the effect cost of living on prevailing salaries in ABC's industry. Two ways of adjusting for these types of factors are the "peer group" method and the econometric method.

2.1.1 Peer Group Benchmarking

In the peer group method, we select a group of peers with whom to compare "raw" data, rather than comparing to a comprehensive list of all peers. The peer group is typically chosen with an eye on including firms that have similar operating characteristics as the target firms.

Continuing the example above regarding salaries, if Company ABC were based in a large city such as Chicago, the peers chosen might be based in other large cities—San Francisco, New York City, Seattle, Toronto, etc. How large the peer group is would be up to the researcher. A cut-off might be used (e.g. cities of two million or more), or the peer group might be simply "eyeballed."

In the case of utility reliability, we would want to pick a peer group that is similar to the utility being studied, and compare their reliability scores. But now the question becomes—similar how? Total number of customers served? Service territory area? Total distribution line miles? Customer density? Vegetation levels? All of the above? If we base the peer group on one metric only (e.g. total number of customers served), the risk is that we ignore a factor that may be very relevant to reliability (e.g. customer density, vegetation levels, etc.). How do we know we are selecting a peer group that is truly "similar" to the target company?

It quickly becomes evident that picking a suitable peer group is not easy—it is difficult to know what factors should be used to determine "similarity." Furthermore, there are questions about how big the peer group should be—too small, and the results may not be very statistically significant. Too large, and too many dissimilar utilities may be included. There is always the chance that we left out a peer that should have been included, or included a peer that was not very similar.

Furthermore, often the utilities with the best reliability scores in a peer group are simply those with the easiest service territory (i.e. fewer vegetation challenges, higher customer density). Additionally, peer groups that contain a small number of utilities can have their results skewed by one or two outlier observations. Or, if the target utility is an outlier within the peer group, that can also skew the findings (because the peer group utilities are not really peers). For these reasons, simple peer group comparison is often not a reliable method in developing meaningful targets. An

[5] For the sake of illustration, here we are assuming that all salaries are public knowledge and that job duties are the same. Obviously in the real world, these assumptions will not be true.

econometric approach that controls for utility-specific service territory characteristics is far more informative.[6]

2.1.2 Econometric Benchmarking

Econometric benchmarking solves many of the issues discussed regarding the simple "list all the utilities" method and the peer group method. Econometric benchmarking discovers the factors (e.g. vegetation, customer density) that affect a certain metric (e.g. reliability), and then adjusts for those factors so that each utility in the sample receives a customized target or benchmark. In econometric benchmarking, typical practice is to make the number of comparison utilities in the dataset as large as feasible; that way we are working with more information with which to test how factors actually affect reliability. Once the econometric model is created, we use it to make comparisons between observed data values for each utility (e.g. actual SAIDI/SAIFI scores) to the predicted values obtained from the model.

For the econometric analysis, we assume that the relationship between a utility's reliability and the conditions that affect it (called independent or explanatory variables) can be quantified and captured by a statistical function (sometimes called a model). This function allows Power System to specify reliability as a dependent variable that can be explained by relevant independent variables, such as customer density, vegetation coverage, etc. Each variable is tested to see if it has a statistical effect on reliability and is signed according to theory. If a variable has a correctly-signed and significant effect, it stays in the function.[7] For the variables that have an effect on reliability, each variable has an associated "parameter," which can be thought of as the magnitude of the effect that variable has on reliability.

The following equation provides an example of a simplified reliability function. For this equation we assume that we ran all the regression calculations, and that the only two factors that influenced SAIDI were (1) customer density (customers per square mile of service territory), and (2) percentage of service territory that is forested.[8]

[6] A 2010 report by the National Regulatory Research Institute ("NRRI") came to the same conclusion: Econometric benchmarking is a more reliable method of performance evaluation than simple peer comparisons. Shumilkina, Evgenia. *Utility Performance: How Can State Commissions Evaluate It Using Indexing, Econometrics, and Data Envelopment Analysis*. National Regulatory Research Institute Research Paper 10-05, 2010.

[7] It should be noted that econometric models generally only test "independent" variables. As implied by the term "independent," the explanatory variables used in the model are factors that are outside the control of utility decision-makers. For instance, the vegetation level in the service territory is largely outside the control of a utility's managers. On the other hand, the number of employees hired are within management's control, and thus cannot serve as an independent variable. One of the variables found to be significant in this report (% undergrounding) is to a certain extent controllable by the utility. However, this variable is controllable more in the long term, rather than the short term.

In general, reliability is assumed to be a function of both dependent and independent variables. While a function specified by econometric means captures a reasonable level of reliability variability, it does not explain all the elements that affect reliability. Therefore, the function includes a random noise term to account for such idiosyncratic factors.

[8] The data used to estimate this relationship can be from a single firm with multiple time observations (time series data), from many firms observed at a single time period (cross-sectional data), or from many firms with multiple time observations (cross-sectional time-series or panel data). The estimation procedure used to estimate model parameters

$$SAIDI = \beta_o + \beta_1 * Y + \beta_2 * P + \varepsilon$$

In this equation, the terms Y, and P denote customer density and percentage of service territory that is forested, respectively. The β terms denote model parameters that capture the magnitude and sign of the effect of the explanatory variables on cost, and the error term captures random noise. The latter is assumed to be independent of the explanatory variables.

Returning to the simplified SAIDI equation above: After this econometric function and its parameters are created, we can plug in a utility's specific service conditions, and the model turns out an "expected" SAIDI value for that utility, also known as a benchmark. This is the value that we would expect an average-performing hypothetical utility (with those particular service conditions) to have. This benchmark is therefore calculated using both: (1) the industry-wide data (this is used to determine which variables influence SAIDI, and the magnitude of the β parameters), and (2) the specific utility's actual service territory characteristics (in the simple case above, this is used to determine *Y* and *P*).

Thus, any utility from the sample can receive a customized benchmark, which represents the performance we would expect from that utility if it were an average performer.

2.2 Simple SAIDI/SAIFI Comparisons Are Not Sufficient

If a utility wants to set a target SAIDI/SAIFI goal, how should this goal be determined? One approach to evaluating a utility's reliability would be to simply look at its "raw" or unadjusted SAIDI/SAIFI scores, and compare these scores to those from other utilities. Many utilities formulate their reliability targets based on raw industry rankings. A "raw" industry ranking is one that simply compared unadjusted metrics, such as unadjusted SAIDI of SAIFI scores. On this method, to set a SAIDI goal, we could just list all the SAIDIs of a group of utilities from high to low, and set the goal at (for example) the top quartile of SAIDIs.

However, we run into the problems mentioned above—the list of utilities may just reflect who has the "easiest" service territory conditions. Another issue—where do we get the list of SAIDI and SAIFI scores? Do we use the list of utilities that have reported reliability scores to the Edison Electric Institute (EEI), which publishes an annual reliability report? There are problems with using EEI data to gauge a utility's reliability. For one thing, submission of data to EEI is voluntary, and so utilities with poor reliability data sometimes do not submit their data, or drop out of the survey, thus skewing the EEI "averages." So it is best to use a list of utilities that is as large as possible—all utilities who publish such data.

But even if the report covered all U.S. utilities, we would have the problem discussed above—the list does not account for how challenging the service territory is. For example, if two utilities each have a SAIDI score of 120, that does not tell us whether achieving that score might be more challenging for one of the utilities—perhaps one of the utilities has a much higher percentage of its territory that is forested, resulting in more tree-related outages on average. Selecting a peer group and comparing "raw" scores does not solve these issues, as discussed above. Econometric

is affected by the type of data used to estimate the model. In our present study, we have a panel dataset with reliability data from multiple firms with observations starting in 2002 and extending to 2015.

modeling can screen out these service territory differences, and provide a more empirical foundation for target-setting.

Similar problems arise when a utility compares its unadjusted SAIDI/SAIFI scores to its own historical values of those metrics. Even within a single service territory, service characteristics can change from year to year. Furthermore, reliability targets based on the historical reliability levels of each utility may also lead to economically inefficient goals. This is because a given utility may historically be providing its customers with an improper level of electric reliability. An old adage applies here: "There ain't no such thing as a free lunch." If the historical reliability levels are too high, the utility will incur added costs as it strives to improve or maintain that challenging reliability level. If historical reliability levels are too low, the utility will not be spending enough to improve its reliability.

2.3 Summary: Why Econometric Benchmarking is Necessary

Above we have discussed three main methods for evaluating utility reliability: (1) Comparisons of "raw" data (from a large list of utilities), (2) Peer group comparisons (comparing raw data from selected utilities), and (3) Econometric benchmarking. We recommend econometric benchmarking for the following reasons:

- If targets are only based on simple reliability rankings (e.g., comparison to a long list of unadjusted SAIDI/SAIFI scores), with no regard for the various challenges inherent within service territories (e.g. vegetation levels, customer densities, undergrounding levels), the targets can end up being far too easy, or too challenging, to achieve. This is because there is no way of adjusting to account for the target utility's characteristics.
- If we try to adjust for a utility's characteristics by using a peer group, other issues arise. If the peer group is too small, the sample size may not be big enough. If the peer group is large, many of the "peers" may not be very similar to the target utility. Furthermore, even if another utility seems like a good peer (e.g. the customer density is similar), there may be other factors that are very different (e.g. vegetation levels). The fact is that even neighboring utilities can have vastly disparate service territories.
- If reliability targets do not account for the diverse external factors faced by specific electric utilities, efforts to achieve these likely inappropriate targets can lead to excessive under-spending or over-spending on reliability-driven projects. These targets promote economic inefficiency and as a result may not be in the best interests of customers. Electricity delivery rates and reliability levels will eventually be either too high or too low, as compared to the optimal rate-reliability balance for the service territory.
- Econometric benchmarking is the method that best takes into account each utility's service territory conditions. Each utility in a dataset receives a benchmark that is specific to its particular service conditions, so that a utility's actual reliability can be compared to its own customized expected reliability.

A detailed description of the particular econometric model used for this report can be found in Section 3.

2.4 Cautions in Interpreting the Targets

While using the econometric approach is a step in the right direction, there are a number of items to be aware of when interpreting the study results.

1. The data collected and reported by the utilities in the sample may contain recording errors, or may have been collected and calculated in a different manner than the Washington utilities. Given the industry move to increasing automation in outage recording, there may be differences from the older to newer data, and differences between utilities. For example, if a utility is in the process of improving its measurement system to better tracks outages, this may result in the appearance of a worsening reliability score, when in reality actual reliability has remained roughly the same. The appearance of a worsening score merely reflects the fact that outages are beginning to be reported automatically, thereby starting the clock for determining outage duration immediately rather than when a customer reports the outage. This concern was raised by one of the Washington utilities.

2. Not all of the uncontrollable service territory variables that impact reliability levels are captured in the models. Responses to the request for information raised the concern that there could be many factors that affect reliability that will not be covered in the econometric model. This concern is valid; some variables are difficult to quantify and include in a model. For example, animals can cause a significant number of outages, but empirically quantifying animal populations across utilities is a difficult endeavor.[9] Although imperfect, an econometric model represents a method that is: (1) superior to "raw" data comparisons or peer group methodology, and (2) a model that can be created with the data that is reasonably widely available.

   Also, certain variables studied in isolation may be correlated with changes in reliability scores, but the econometric analysis may not produce logical signs or statistical significance for that variable, due to the fact that the variable in question is highly correlated with one or more variables already included in the model. This is called multicollinearity in the econometric literature. In these cases, the redundant variables are not included in the model.

3. Reliability-driven investments may result in lags in the realization of reliability outcomes. A utility that is missing its target this year may have just implemented a reliability program, therefore working to improve its reliability, but results from these improvements require time to manifest themselves into improved reliability outcomes for utilities.

4. The model created for this report does not attempt to take into account the technology deployment (e.g., feeder automation) used by each utility, as we do not have a reasonable way to measure the extent of such deployment.

5. The model presents targets (benchmarks) derived from data for past years, namely 2011-2015. Circumstances may change going forward.

[9] Animal populations may indirectly enter the model since they are likely correlated with forestation levels and customer density.

For the above reasons, there may be valid reasons why the estimated targets in this report are too high or too low. The targets, however, do provide a basis for a more-informed discussion on reliability targets and improved context for those discussions. The results help to eliminate a number of known sources of variance and can help focus discussion on other possible sources.

The cautions above illustrate why the confidence intervals provided in this report are important to consider. All empirical studies contain "data noise" and random error. The confidence intervals provide a range of targets that would still be considered "normal" in the presence of the data noise and random error.

3 Description of Econometric Benchmarking Approach

The previous section discussed econometric benchmarking in general. This section describes the specific process for the econometric model created for this report. To recap, the econometric approach estimates the impact of external factors (e.g., vegetation levels, customer density, undergrounding) on reliability indexes. The impacts of these factors on reliability across the industry are estimated and quantified through regression analysis. The resulting econometric model enables a formulation of an expected or benchmark reliability for any utility in the dataset, based on the factors and circumstances of that particular utility. The econometric approach is the most accurate and trustworthy method of formulating reliability targets. Power System recommends this method when setting reliability targets.[10]

Power System's research uses a dataset constructed from publicly available sources, primarily from state commissions and U.S. Energy Information Administration (EIA) Form 861 data. Gathering data from sources that require utility reporting eliminates the bias that is built into voluntary datasets (e.g., EEI reliability survey). Furthermore, the EEI data does not allow us to tie a specific reliability score to a specific utility; this information is required to perform an econometric analysis.

In this report, Power System will provide customized SAIFI and SAIDI targets for each of the three Washington electric investor-owned utilities. The targets are generated using an econometric model; the model is estimated using a dataset which includes 81 U.S. investor-owned utilities. We have gathered both the reliability data from these 81 utilities and the service territory characteristics for each utility, used as explanatory variables.

The dataset is a panel dataset (or cross-section, time series dataset). It contains annual observations for the 81 utilities. The time period was restrained to starting in 2006 and ending in 2015 (ten years); therefore each utility in the dataset has up to ten annual observations each. However, not all utilities will have ten observations due to missing or implausible data in any one given year.[11]

The research process is summarized below:

1. Power System assembled the historical reliability metrics of all utilities in the dataset, along with the variables that affect reliability, such as customer density, vegetation density, percent undergrounding, etc.
2. Using the historical data, Power System estimated two econometric models (one for SAIFI and one for SAIDI) that express the relationship between the explanatory variables and SAIFI or SAIDI.
3. Power System can then produce "benchmark" or "target" value for each utility in a given year. The benchmark values are determined from the model. The benchmark represents the SAIDI or SAIFI value we would expect for an average-performing utility with the same

[10] See Power System's 2012 journal article in *The Electricity Journal*: Fenrick, S. and L. Getachew, 2012, "Formulating Appropriate Electric Reliability Targets and Performance Evaluations," *The Electricity Journal*, 25 (2): 44-53.

[11] This is called an unbalanced panel dataset.

service territory conditions faced by that particular utility.

4. To set the targets for each Washington utility, we took an average of their targets for the most recent five years, 2011-2015.

3.1 Regression Modeling and Confidence Intervals

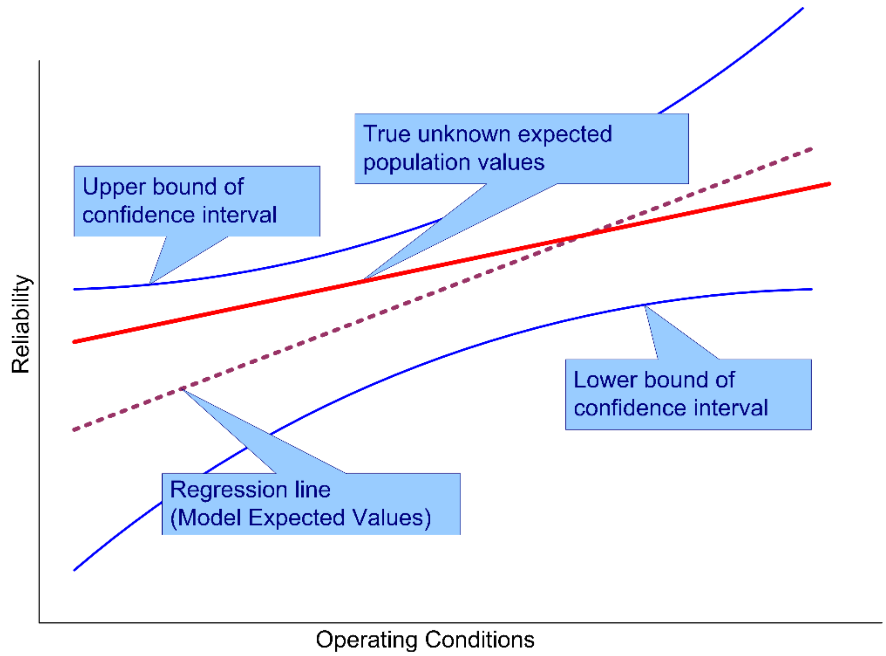
Power System's method of econometric modeling applies regression techniques to a subset of population data to form a mathematical model. The model uses inputs (service territory data, etc.) and produces an expected reliability index for each observation (e.g. each utility in a given year). By using the model, and given a set of explanatory variables, Power System can estimate an expected reliability level for each utility in each year. The model should not be seen as being able to always predict the "true" expected value for each utility with 100% accuracy. This is because the model is formed from a sample of data from which inferences are made concerning the larger population. In addition, the model contains other sources of error from unknown sources. Fortunately, statistical methods provide techniques for handling and quantifying modeling error.

To calculate the CI, the modeling error of the model prediction must be calculated. The error of each annual prediction is calculated directly by EViews (the econometric software used by Power System). The standard error factors in the standard error of the regression and the difference in the explanatory variable values for each observation and the sample mean values. To calculate the standard error of the five-year mean, we averaged the modeling error for the five predictions and divided by the square root of five.

Modelling error is incorporated into the model by using confidence intervals ("CI"). A CI consists of an upper and lower bound placed around the model's expected reliability level. An example of a simple regression model is shown in Figure 3. The regression line provides an estimate for the expected reliability value given specific operating conditions, while the confidence interval attaches a level of precision to the estimate. The width of the CI – the distance from the lower to the upper bound – is determined by the chosen tolerance for risk of the "true" expected value being outside those bounds. Lower risk produces a wider CI and higher risk produces a narrower CI.

CI is specified as a percent, which is 100% (a probability of one) minus the risk level. For example, a 15% level of risk results in an 85% CI. There are two ways to interpret this 85% CI. First, we can say that for an 85% CI, we are 85% confident that the "true" expected value of the population is between the upper and lower bounds of the CI. Stated differently, we can say that we have a 15% risk that the true expected value is *not* between the upper and lower bounds of the CI. Figure 3 shows a hypothetical example, where the population values happen to lie between the upper and lower CI. With a confidence interval of 85%, this will occur approximately 85% of the time.

Figure 3 Example Regression Model



4 Variables, Sample, and Model Details

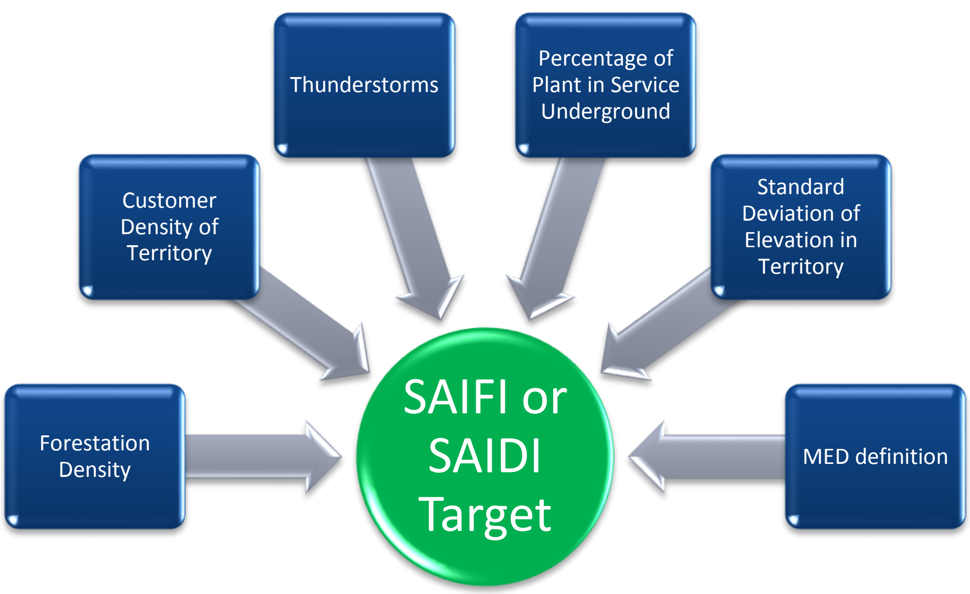
This section provides details on the sample used, the variables use, and the details of the model, and further explains how the targets were calculated. The variables and parameter estimates are provided for both the SAIDI and SAIFI models. The sample used is described in the latter part of this section.

In the electric distribution industry, simple rate or reliability index comparisons do not provide appropriate targets for individual utilities. Uncontrollable factors influence attainable levels of reliability and costs.[12] Such factors include geographical size, consumer density, mix of consumer classes, and vegetation levels. Therefore, more sophisticated tools that normalize for these specific factors must be employed to accurately set targets.

The econometric benchmarking approach relies on comparisons between observed data values to the predicted values obtained from regressions. The researcher determines an appropriate functional form for the relationship between the studied metric and factors that influence it, and uses appropriate econometric methods for obtaining good parameter estimates of the specified model. Point predictions for each firm in each year are obtained by inserting company-specific variable values into the estimated equation. Confidence intervals are measured by examining the standard error of each point prediction.

The variables included in the econometric models for SAIDI and SAIFI are shown in the figure below. Squared and interaction terms for these variables are also included in the models, but not shown below.

Figure 4 Econometric Variables



[12] It should be noted again that one of the variables found to be significant in this report (% undergrounding) is to a certain extent controllable by the utility. However, this variable is controllable more in the long term, rather than the short term.

4.1 Key Reliability Indexes and Major Event Day Exclusions

Nearly all jurisdictions that require reporting of reliability indicators include the metrics of SAIDI, SAIFI, and Customer Average Interruption Duration Index ("CAIDI").[13] SAIDI measures the average duration of sustained interruptions per utility customer. SAIFI is a gauge of the average frequency of sustained interruptions per customer. CAIDI evaluates the average duration time per sustained interruption. SAIDI is thus the product of SAIFI and CAIDI.

Figure 4-5 SAIDI, SAIFI, CAIDI

$$\text{SAIDI} = \frac{\Sigma_i \text{Minutes Customer } \textit{`i'} \text{ is without Service}}{\text{Total Number of Customers on System}}$$

$$\text{SAIFI} = \frac{\Sigma_i \text{Frequency Customer } \textit{`i'} \text{ is without Service}}{\text{Total Number of Customers on System}}$$

$$\text{CAIDI} = \frac{\text{SAIDI}}{\text{SAIFI}}$$

Most utilities report metrics that exclude extraordinary events from reliability statistics, with the goal of increasing historical and peer comparability. The bulk of events stem from major storms. These severe storms vary in number and intensity from year to year. MED definitions are determined by each state regulatory commission. Definitions vary by state and utility; some use the IEEE standard 1366 to determine what constitutes a MED[14] while others have customized definitions. For example, for some states, if 10 percent of a utility's customers experience an outage lasting more than a 24-hour period, a MED has occurred. While considerable differences across utilities remain, the IEEE method is the most widespread among the MED definitions. The three Washington utilities in this study have defined MEDs using the IEEE method.

By identifying and excluding MEDs, a utility's performance during major storms and during normal operations can be analyzed separately. Extreme weather occurrences, which are unpredictable and outside the control of the distributor, will have a significant impact on SAIDI, and to a lesser extent on SAIFI. By segregating these atypical events, a utility can analyze its performance during normal operations free from the effects of major storms or other significant phenomena.[15] Moreover, a utility can analyze its performance during MEDs apart from normal operations. Looking at reliability performance without considering MEDs can distort the data, thus inviting unfair comparisons against other utilities which have experienced more (or fewer) MEDs.

[13] Some states only require reporting of two of these measures. However, the excluded indicator can still be determined by the researcher. SAIDI is equal to the product of SAIFI and CAIDI.

[14] The IEEE standard defines MEDs using the "beta" method. If outages for a certain day exceed 2.5 standard deviations from the normal day, a major event day is declared. A normal day and the standard deviation are determined by the utility's previous five years of normal day data (not including the MEDs).

[15] In practice, identification and separation of major storm events can be difficult and indistinct.

In this study, we have not knowingly excluded loss of service/power (LOS) outages that stem from the transmission or generation system. This is because LOS outages and reliability statistics excluding both LOS and MEDs are not widely reported. Therefore, the study results and targets provided in this report include LOS outages that do not result in a MED. This will have the effect of increasing the targets (i.e., higher SAIFI and SAIDI) relative to the case where non-MED LOS outages were excluded from the dataset.

4.2 Data Sources

The industry reliability data is gathered through reports and rate case filings made public by state commissions and through the EIA-861 data. Power System gathered SAIDI, SAIFI, and CAIDI values for over 100 utilities. However, some utilities only filed reliability data with no MED exclusions made. We eliminated those from our analysis. For those utilities that did report indexes with MEDs excluded, we note whether or not their MED definition was based on the IEEE standard.

Additional variable data is also collected. FERC Form 1 data for the industry is collected via a third-party data service, *SNL Energy*. This data provides us with the total number of retail customers and information on underground gross plant in service. Land types (e.g., forestation, prairie, artificial surfaces) found in the service territory, service territory square miles, and the standard deviation of the elevation in the territory are found using Geographic Information System (GIS) data. A more detailed description of these variables and their data sources is provided below.

The final sample includes 81 utilities across the United States. The data spans the years 2006 to 2015, with 543 total observations points. Some utilities have data available for all ten of those years, while others only have data for some of that ten year period. Both the SAIFI and SAIDI models are estimated using an identical dataset. The following table lists the utilities found in the dataset.

Table 4 Utilities in Data Sample

Alabama Power Company	**New York State Electric & Gas Corporation**
ALLETE (Minnesota Power)	**Niagara Mohawk Power Corporation**
Appalachian Power Company	**Northern Indiana Public Service Company**
Arizona Public Service Company	**Ohio Edison Company**
Atlantic City Electric Company	**Oklahoma Gas and Electric Company**
Avista Corporation	**Orange and Rockland Utilities, Inc.**
Baltimore Gas and Electric Company	**Pacific Gas and Electric Company**
Central Hudson Gas & Electric Corporation	**PacifiCorp**
Central Maine Power Company	**PECO Energy Company**
Cleveland Electric Illuminating Company	**Pennsylvania Electric Company**
Commonwealth Edison Company	**Pennsylvania Power Company**
Connecticut Light and Power Company	**Portland General Electric Company**
Consolidated Edison Company of New York, Inc.	**Potomac Edison Company**
Consumers Energy Company	**Potomac Electric Power Company**
Duke Energy Carolinas, LLC	**PPL Electric Utilities Corporation**
Duke Energy Indiana, LLC	**Public Service Company of Colorado**
Duke Energy Kentucky, Inc.	**Public Service Company of New Hampshire**
Duke Energy Ohio, Inc.	**Public Service Company of New Mexico**
Duquesne Light Company	**Public Service Company of Oklahoma**
El Paso Electric Company	**Public Service Electric and Gas Company**
Empire District Electric Company	**Puget Sound Energy, Inc.**
Entergy Arkansas, Inc.	**Rochester Gas and Electric Corporation**
Entergy Mississippi, Inc.	**San Diego Gas & Electric Co.**
Entergy New Orleans, Inc.	**Sierra Pacific Power Company**
Florida Power & Light Company	**South Carolina Electric & Gas Co.**
Georgia Power Company	**Southern California Edison Company**
Gulf Power Company	**Southern Indiana Gas and Electric Company, Inc.**
Idaho Power Co.	**Superior Water, Light and Power Company**
Indiana Michigan Power Company	**Tampa Electric Company**
Indianapolis Power & Light Company	**Union Electric Company**
Jersey Central Power & Light Company	**United Illuminating Company**
Kentucky Power Company	**Upper Peninsula Power Company**
Kentucky Utilities Company	**Virginia Electric and Power Company**
Kingsport Power Company	**West Penn Power Company**
Louisville Gas and Electric Company	**Westar Energy (KPL)**
Madison Gas and Electric Company	**Western Massachusetts Electric Company**
Massachusetts Electric Company	**Wheeling Power Company**
Metropolitan Edison Company	**Wisconsin Electric Power Company**
Monongahela Power Company	**Wisconsin Power and Light Company**
Mt. Carmel Public Utility Company	**Wisconsin Public Service Corporation**
Nevada Power Company	

4.3 Model Specification, Variables, and Parameter Estimates

Two models are estimated: (1) SAIFI with MEDs excluded, and (2) SAIDI with MEDs excluded. The explanatory variables in the models include:

- The forestation levels of each utility (F),
- Customer density measured by the number of retail customers divided by square miles of service territory (D),
- The prevalence of thunderstorms in the service territory (T),
- The standard deviation of elevation in the service territory used only in SAIDI model (E),
- The percentage of underground plant in total distribution plant (U), and
- Whether the MED exclusion criteria is based on the IEEE 1366-2003 standard (I).

Both the SAIFI and SAIDI models use a translog functional form, where model variables are logged, and explanatory variables include logged first order, square and interaction terms. The translog function form is widely used in research and provides considerable flexibility in estimating variable impacts. This form allows us to adjust for interactions between variables in determining reliability levels. For example, the forestation variable may have differing impacts on reliability at different levels of undergrounding. The interaction terms allow the model to adjust for these different impacts. The equation for the SAIFI model used is given by the following equation:

$$
\begin{aligned}
\ln(SAIFI) = \propto &+ \beta_1 * \ln(U) + \beta_2 * \ln(F) + \beta_3 * \ln(D) + \beta_4 * \ln(T) + \beta_5 * I + \beta_6 * \ln(U) \\
&* \ln(U) + \beta_7 * \ln(F) * \ln(F) + \beta_8 * \ln(D) * \ln(D) + \beta_9 * \ln(T) * \ln(T) \\
&+ \beta_{10} * \ln(U) * \ln(F) + \beta_{11} * \ln(U) * \ln(D) + \beta_{12} * \ln(U) * \ln(T) + \beta_{13} \\
&* \ln(F) * \ln(D) + \beta_{14} * \ln(F) * \ln(T) + \beta_{15} * \ln(D) * \ln(T) + \varepsilon
\end{aligned}
$$

For instance, we note from the equation that customer density (D) enters the model in several ways:

- logged (as $\ln(D)$),
- squared (as $\ln(D)^2$), and
- interacted with other variables such forestation (as $\ln(D) * \ln(F)$).

These inputs allow us to determine the impact of density not just at the mean, but also at various values of the variable. The interaction terms allow us to determine how density affects reliability for given levels of forestation and undergrounding. The last term, ε, represents the random error. The β terms are the coefficients for each variable; they represent the impact each variable has on the studied metric. Since the terms are logged the coefficients are elasticity estimates. That is, they estimate the expected percent change in reliability given a percent change in the explanatory variable value. A β of 0.10 would mean that in general, a 100% increase in that variable would result in a 10% increase in the studied metric.

The equation for the SAIDI model used is given by the following equation:

$$\ln(SAIDI) = \propto + \beta_1 * \ln(U) + \beta_2 * \ln(F) + \beta_3 * \ln(D) + \beta_4 * \ln(T) + \beta_5 * I + \beta_6 * \ln(U) * \ln(U) + \beta_7 * \ln(F) * \ln(F) + \beta_8 * \ln(D) * \ln(D) + \beta_9 * \ln(T) * \ln(T) + \beta_{10} * \ln(U) * \ln(F) + \beta_{11} * \ln(U) * \ln(D) + \beta_{12} * \ln(U) * \ln(T) + \beta_{13} * \ln(F) * \ln(D) + \beta_{14} * \ln(F) * \ln(T) + \beta_{15} * \ln(D) * \ln(T) + \beta_{16} * \ln(E) + \varepsilon$$

The SAIDI equation is the same, except it adds a variable not in the SAIFI equation: the standard deviation of elevation ($\beta_{16} * \ln(E)$). It should be noted that that the coefficients β_1 etc. will have different values in the SAIFI equation and the SAIDI equation.

The SAIFI model includes 81 utilities with varying time-series lengths covering the years 2006 to 2015, which result in 543 total observations. This type of dataset requires an estimation procedure that accounts for the cross-sectional time-series, or panel, nature of the data. We use a feasible generalized least squares ("FGLS") estimator that corrects for cross-sectional heterogeneity as well as addresses the panel form of the data. The estimator accomplishes this by correcting for group-wise (utility-by-utility) heteroskedasticy, and results in parameter estimates that are more accurate, consistent, and precise than other methods.

We note that all first order explanatory variables are statistically significant at a 95 percent confidence level (p-value < 0.05). The p-value column in the table below provides the probability the "true" coefficient is actually zero, that is, the variable has no impact on reliability. The smaller the number the higher the statistical chance is the variable has an impact on reliability. For example, a p-value of 0.0100 means there is a one percent probability that the variable has no influence on the reliability metric.

Table 5 SAIFI Model Variables

Variable	Coefficient Estimate	Coefficient in Model	P-Value
Constant	-0.065957	$\propto$	0.0162
% Underground (U)	-0.158076	β_1	0.0000
% Forestation (F)	0.261986	β_2	0.0000
Customer Density (D)	-0.117477	β_3	0.0000
Thunderstorms (T)	0.191656	β_4	0.0000
IEEE MED Definition	0.104879	β_5	0.0000
U*U	0.132452	β_6	0.0000
F*F	0.005125	β_7	0.6430
D*D	-0.064507	β_8	0.0000
T*T	0.030706	β_9	0.0000
U*F	0.100410	β_{10}	0.0084
U*D	0.001082	β_{11}	0.9633
U*T	0.067185	β_{12}	0.0005
F*D	0.136388	β_{13}	0.0000
F*T	-0.008807	β_{14}	0.5310
D*T	0.070328	β_{15}	0.0000

The SAIDI model is similarly based on a translog specification. The only variable difference is that the standard deviation of elevation variable is included in the SAIDI model. First order explanatory variables are statistically significant at the 95 percent confidence level.

Table 6 SAIDI Model Variables

Variable	Coefficient Estimate	Coefficient Variable	P-Value
Constant	4.629731	$\propto$	0.0000
% Underground (U)	-0.163976	β_1	0.0000
% Forestation (F)	0.418174	β_2	0.0000
Customer Density (D)	-0.184581	β_3	0.0000
Thunderstorms (T)	0.131738	β_4	0.0000
S.D. of Elevation (E)	0.037079	β_{16}	0.0000
IEEE MED Definition	0.093083	β_5	0.0000
U*U	-0.108617	β_6	0.0000
F*F	-0.035252	β_7	0.0000
D*D	-0.104197	β_8	0.0000
T*T	0.007068	β_9	0.4647
U*F	-0.298562	β_{10}	0.0000
U*D	0.279773	β_{11}	0.0000
U*T	-0.157866	β_{12}	0.0000
F*D	0.250083	β_{13}	0.0000
F*T	-0.072504	β_{14}	0.0000
D*T	0.084436	β_{15}	0.0000

The variables used in the equations above are explained in more detail in the next section.

4.4 Variable Definitions and Washington Utility Values

As discussed above, both models use a translog model specification that includes both first order and interaction terms. Power System mean-scaled all the explanatory variables. This entails that the first order terms will indicate the impact of the variables at the sample mean of the data. Below we describe the impacts of each of the variables at the sample mean (i.e. the first order terms).

Some explanatory variables were tested but rejected; the typical reason for rejection was that the statistical significance threshold of 90% was not met. Another reason for rejection could be that the sign of the variable was different than expected. Rejected variables include: percent service area that is artificial (wrong sign), wind speeds in territory (statistically insignificant), percent commercial and industrial sales in total sales (statistically insignificant and wrong sign), and extreme temperatures (wrong sign).[16]

Placing power lines underground lessens the susceptibility of these lines to environmental

[16] Reason for exclusions are in parenthesis and based on the final SAIDI model.

factors.[17] In the SAIDI and SAIFI models, the **percentage of underground plant** tends to reduce both the frequency and total duration of outages. These findings are significant at a 99 percent confidence level. The variable is calculated using the annual FERC Form 1 data for the 81 utilities.[18] The variable is calculated by dividing the distribution gross plant in service accounts of underground conduit and underground conductors and devices by total distribution plant. This calculation is done for every utility and for every year within the sample.

The **percentage of service territory that is forested** is also included in the reliability models. A higher proportion of trees increase the number of incidents of branches or trees falling onto power lines. The forestation parameter estimate is positive in both models, indicating that higher vegetation leads to higher SAIDI and SAIFI values. This finding is significant at a 99 percent confidence level. The percentage of forestation variable is based on GIS (geographic information system) land cover maps. Power System used the GlobCover 2009 product processed and produced by the European Space Agency ("ESA") and the Université catholique de Louvain. These maps are matched with the areas served by each utility to create the forestation variable.

The **customer density of the service territory** and its impact on reliability measures is also tested. Density is measured by the number of retail customers per square mile of service territory. Higher density would be expected to lower SAIDI and SAIFI values, as customers are more concentrated across the service territory, requiring fewer line miles and shorter drive times. In both models, we find that higher density levels tend to lower SAIDI and SAIFI values. This finding is significant at a 99 percent confidence level in both models. The customers per square mile variable is calculated using GIS coordinates of each utility's service area provided to Power System by Platts. The variable equals the total square miles of the area of the distributors service territory divided by the number of retail customers served. The customer variable comes from the FERC Form 1 or EIA-861 data.

The **thunderstorm variable** is included in both models. The thunderstorm variable is defined as the annual sum of hours designated as being hours in which thunderstorms took place. We would expect a higher level of thunderstorm hours to increase SAIFI and SAIDI levels. In both models, we find this to be true with at the 99% confidence level. This data comes from historical weather station data from the counties in each service territory. We gathered weather station data for each county in the country. This data comes from the National Climatic Data Center ("NCDC"). Power System mapped the counties served by each utility in the sample and then population weighted the hours designated as thunderstorm hours based on that mapping.

The **standard deviation of elevation** variable measures the variance in elevation within each utility's service territory. The more "hilly" the service territory, the more difficult restoration of outages is expected to be. This variable is included in the SAIDI model and has the expected positive coefficient sign. It is statistically significant at the 99% confidence level. The variable data is gathered using GIS. More specifically, it uses GTOPO30, which is a global digital elevation model ("DEM") resulting from a collaborative effort led by the staff at the U.S. Geological Survey's EROS Data Center in Sioux Falls, South Dakota. The name GTOPO30 is derived from

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[17] However, underground lines are more susceptible to flooding and damage caused by freezing/thawing soil.

[18] Washington-only plant in service data was provided to Power System directly by Avista and Pacific Power.

the fact that elevations in GTOPO30 are regularly spaced at 30-arc seconds (approximately 1 kilometer).

Also included in the models is a **binary variable denoting whether the MED definition is based on the IEEE standard**. The variable equals "one" if the IEEE definition is used and "zero" otherwise. This allows us to inform our models with data from utilities which report IEEE-based data to their commissions, and at the same time expand our sample by including data from those that do not use IEEE-based exclusion criterion. There is no a priori expectation on the sign of the parameter estimate. The parameter estimate on this variable is positive in both models and statistically significant at the 99% confidence level in both models.

The average 2011-2015 values for the three Washington utilities and the sample mean is provided in the table below.

Table 7 Variable Values

Avista

Variable	2011	2012	2013	2014	2015	2011-2015 Sample Mean
SAIFI	1.09	1.03	0.88	1.06	0.98	1.05
SAIDI	109	132	118	144	159	125
Percent Underground	19.1%	18.8%	18.6%	18.6%	18.6%	20.4%
Percent Forestation	29.0%	29.0%	29.0%	29.0%	29.0%	65.9%
Customer Density	38.9	39.2	39.5	39.9	40.8	312.4
Thunderstorm Hours	6.9	20.8	25.1	17.1	19.0	54.9
S.D. of Elevation	173.5	173.5	173.5	173.5	173.5	147.7
IEEE Binary	1	1	1	1	1	0.73

Pacific Power

Variable	2011	2012	2013	2014	2015	2011-2015 Sample Mean
SAIFI	0.55	0.66	0.79	0.79	0.85	1.05
SAIDI	80	100	113	122	100	125
Percent Underground	9.4%	9.5%	9.4%	9.4%	9.3%	20.4%
Percent Forestation	30.2%	30.2%	30.2%	30.2%	30.2%	65.9%
Customer Density	47.5	47.6	47.6	47.7	48.0	312.4
Thunderstorm Hours	4.1	11.9	9.9	9.9	8.2	54.9
S.D. of Elevation	306.9	306.9	306.9	306.9	306.9	147.7
IEEE Binary	1	1	1	1	1	0.73

Puget Sound

Variable	2011	2012	2013	2014	2015	2011-2015 Sample Mean
SAIFI	1.00	0.80	0.86	0.96	1.03	1.05
SAIDI	142	120	125	153	161	125
Percent Underground	35.7%	42.1%	42.3%	42.2%	42.2%	20.4%
Percent Forestation	85.5%	85.5%	85.5%	85.5%	85.5%	65.9%
Customer Density	117.6	118.2	117.8	118.5	119.8	312.4
Thunderstorm Hours	1.8	4.0	7.7	4.2	9.7	54.9
S.D. of Elevation	576.6	576.6	576.6	576.6	576.6	147.7
IEEE Binary	1	1	1	1	1	0.73

5 Reliability Targets

The models presented in Section 4, combined with the variable values for each Washington utility, are used to calculate the expected SAIFI and SAIDI targets for each utility. These targets represent the model prediction for each utility based on their explanatory variable values. For example, the targets for Avista represent the values we would expect from an average utility with the particular service territory characteristics of Avista. Power System used variable values for each utility that corresponds to only their Washington service territory. Therefore, these targets are applicable only to each utility's Washington service territory.[19]

The targets exclude MED days but include loss of supply ("LOS") outages, due to the lack of industry data that excludes both MED days and LOS. The MED definition for the target is based on the IEEE "2.5 beta" method.[20] We accomplished this by including the IEEE variable in the model, and then setting the Washington utility IEEE variable value equal to "1". For utilities in the sample that did not use the IEEE "2.5 beta" method, we set this variable value to "0".

The actual and expected SAIDI and SAIFI for the individual years 2011-2015 are shown in Table 8 and Table 9.

Table 8 Actual and Expected SAIDI, 2011-2015

Year	Avista Corporation		Pacific Power		Puget Sound Energy	
	Actual	Target	Actual	Target	Actual	Target
2011	109	115	80	113	142	129
2012	132	116	100	128	120	114
2013	118	117	113	125	125	105
2014	144	116	122	125	153	113
2015	159	116	100	122	161	103

Table 9 Actual and Expected SAIFI, 2011-2015

Year	Avista Corporation		Pacific Power		Puget Sound Energy	
	Actual	Target	Actual	Target	Actual	Target
2011	1.09	1.10	0.55	1.64	1.00	0.93
2012	1.03	1.04	0.66	1.43	0.80	0.89
2013	0.88	1.04	0.79	1.46	0.86	0.90
2014	1.06	1.05	0.79	1.47	0.96	0.89
2015	0.98	1.05	0.85	1.50	1.03	0.91

5.1 Reliability Target Results: 2011-2015 Average

The targets in this section are based on a 5-year average of the most recent model predictions (i.e. the above five-year periods are averaged). For this study, those are the years of 2011-2015. Thus

[19] Since Puget Sound Energy operates entirely in Washington, the targets are applicable to its entire service territory.

[20] The IEEE "2.5 beta" method and MEDs in general were discussed in Footnote 2 and Section 4.

these targets represent the average SAIDI and SAIFI that we would expect for these specific utilities over the 2011-2015 period. The targets provide an empirically-driven goal that can be used for future year goal-setting. However, the targets would not necessarily project into the future indefinitely as each utility's circumstances change or the industry reliability expectation changes over time.[21] A 5-year average target should be seen as what the utility's target is for a 5-year rolling average of reliability outcomes. Given that annual reliability metrics will vary based on a host of factors, a longer run target makes sense.

The targets in the tables below are the "Model Expected" targets. These targets are the estimated "average" or "normal" level of reliability derived from the econometric model. One would expect this level of reliability from an "average performer" facing the exact conditions of each of the Washington utilities. While this is our "best estimate" of where each utility's reliability should be to align itself with the industry given its operating characteristics, the model results possess a degree of uncertainty. Accordingly, the expected targets should be considered approximations while the confidence intervals surrounding each target give some sense of the degree of uncertainty for that target.

The model's expected targets for each utility are shown below. These are based on the 2011-2015 average model predictions for each utility. The results for each individual year are shown in the previous section.

Table 10 Expected Targets

Utility	SAIFI Target	SAIDI Target
Avista	1.05	116
Pacific Power	1.50	123
Puget Sound Energy	0.90	113

The next two tables show the upper and lower bounds for SAIFI and SAIDI, respectively. The upper and lower bounds are constructed using a 90% confidence interval. The concept of confidence intervals is discussed in section 3.1 above. The confidence intervals are constructed using the 5-year standard error of each utility's observations.

Table 11 Model Expected Target (SAIFI Upper and Lower Bounds)

Utility	Lower Bound	SAIFI Target	Upper Bound
Avista	0.82	1.05	1.29
Pacific Power	1.17	1.50	1.83
Puget Sound Energy	0.70	0.90	1.10

[21] Power System would suggest updating the reliability benchmarks at least once every five years in order to capture industry expectation changes and service territory variable changes for each utility.

Table 12 Model Expected Target (SAIDI Upper and Lower Bounds)

Utility	Lower Bound	SAIDI Target	Upper Bound
Avista	86	116	147
Pacific Power	90	123	155
Puget Sound Energy	83	113	142

The figures below provide the targets and confidence intervals for each utility.

Figure 6 Candidate SAIFI Targets (2011-2015)

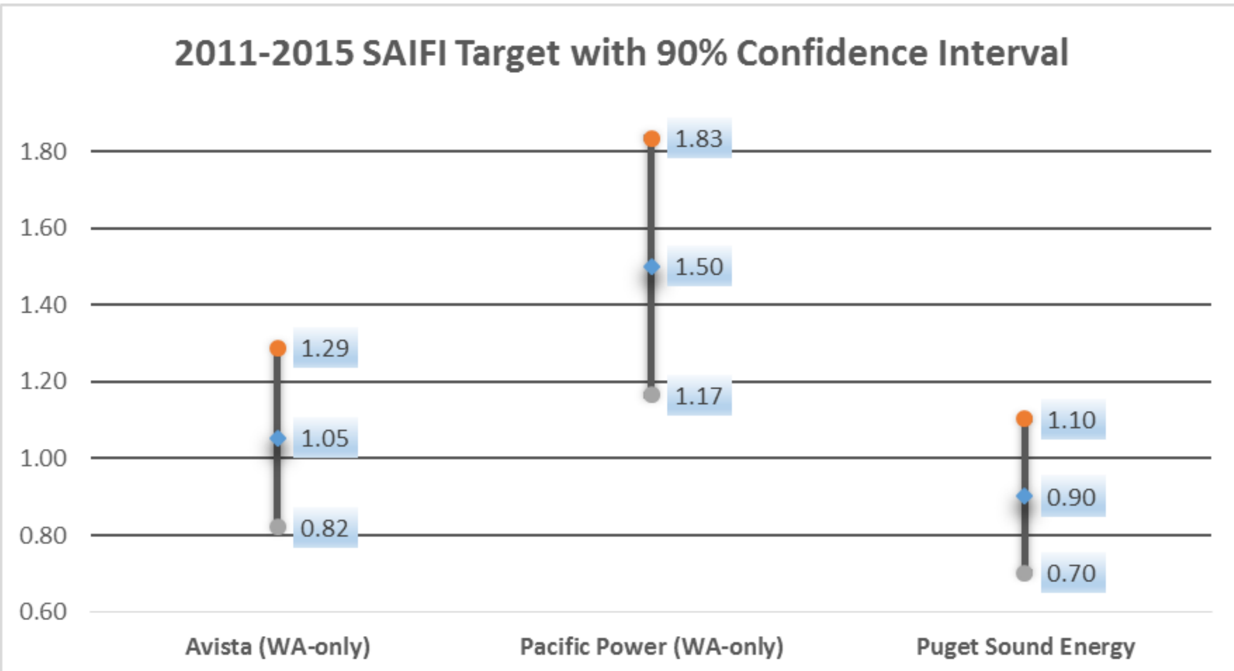
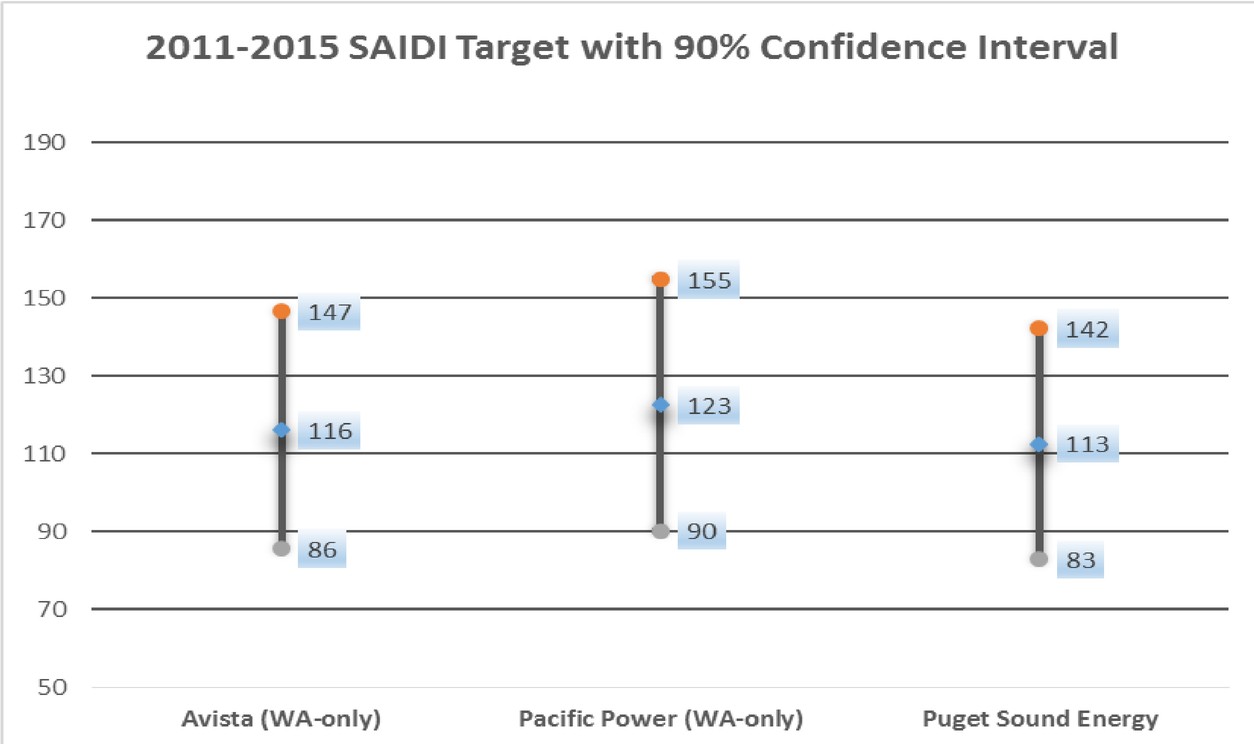


Figure 7 Candidate SAIDI Targets (2011-2015)



6 Concluding Remarks

The targets and ranges found in this report provide the long-run reliability outcomes that our models predict each utiltiy to achieve. Given the annual variability in reliability metrics, a 5-year rolling average target is appropriate, rather than a focus on outcomes in one specific year. In any one given year, fluctuations will be seen primarily due to weather differences. Even though the metrics are normalized and exclude severe weather outages, weather conditions will still have an impact on annual outcomes. Some years will be more or less challenging. Taking a 5-year rolling average enables a smoothing of those fluctuations.

It is important to note that these reliability targets are based on what the industry expectations were for 2011-2015, given the service territory conditions each Washington utility faces. However, there is no guarantee that the industry is in proper balance and is providing the right amount of reliability. The targets are dependent on the "collective wisdom" of the 81 utility sample. If these utilities are not providing the proper cost/reliability balance overall, then the developed targets will also not provide the right balance. The industry may also change the reliability expectations in the future as consumer preferences and available technology transform. Power System recommends updating the reliability benchmarks at least once every five years to account for changing service territory conditions for the Washington utilities and changing industry expectations.

It is also worth stating that being well above or below these targets does not necessarily mean the utility is performing at a "poor" or "good" level. Besides reliability, customers care a great deal about their electric rates. A utility may be missing its reliability targets by a large margin, but saving its customers money on their electric bills through strong cost performance. That is, they may be missing their reliability targets, but have cost levels far lower than what their expected cost targets would be.

About Power System's Economics and Market Research Group

Founded in 1974, Power System is a full-service consulting firm. Power System's benchmarking experience includes research for regulatory purposes and utility management improvement. Our benchmarking team consists of economists, planning and design engineers, rate and financial analysts, communications infrastructure consultants, and smart grid technology experts. Power System's Economics and Market Research group has expertise in the areas of cost and reliability benchmarking, demand response, energy efficiency, value-based reliability planning, merger valuations, load forecasting, load research, survey design, alternative regulation, and cost of service studies. For more information on Power System and a full list of services, visit our website at: www.powersystem.org.

About the Lead Author

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Mr. Fenrick has over 15 years of consulting experience in the evaluation of utility cost and reliability performance. He leads Power System's economics and market research group. He has provided expert witness testimony on performance benchmarking and authored numerous reports on the topic. He has led EUCI's conference on measuring and improving the cost and reliability performance of energy utility distributors on a number of occasions. Mr. Fenrick has evaluated performance relating to electric and gas distribution, power transmission, power plant performance, and water distribution. These evaluations have been conducted for utilities, regulatory agencies, and consumer advocates.