SANDIA REPORT

Impact of Distributed Energy Resources on the Reliability of a Critical Telecommunications Facility

David Robinson
Christopher Atcitty
Jason Zuffranieri
Doug Arent

Sandia National Laboratories

NREL

Impact of Distributed Energy Resources on the Reliability of a Critical Telecommunications Facility

David Robinson, Christopher Atcitty, Jason Zuffranieri
Risk and Reliability Analysis Department
Sandia National Laboratories
Albuquerque, NM 87185-0748
drobin@sandia.gov

Douglas Arent
National Renewable Energy Laboratory
Director, Strategic Analysis
Golden, CO 80401

Abstract

This report documents a probabilistic risk assessment of an existing power supply system at a large telecommunications office. The focus is on characterizing the increase in the reliability of power supply through the use of two alternative power configurations. Telecommunications has been identified by the Department of Homeland Security as a critical infrastructure to the United States. Failures in the power systems supporting major telecommunications service nodes are a main contributor to major telecommunications outages. A logical approach to improve the robustness of telecommunication facilities would be to increase the depth and breadth of technologies available to restore power in the face of power outages. Distributed energy resources such as fuel cells and gas turbines could provide one more onsite electric power source to provide backup power, if batteries and diesel generators fail. The analysis is based on a hierarchical Bayesian approach and focuses on the failure probability associated with each of three possible facility configurations, along with assessment of the uncertainty or confidence level in the probability of failure. A risk-based characterization of final best configuration is presented.

Acknowledgment

Contents

Appendix

Figures

Executive Summary

Telecommunications has been identified by the Department of Homeland Security as a critical infrastructure to the United States. Failures in the power systems supporting major telecommunications service nodes are a main contributor to major telecommunications outages, as documented by analyses of Federal Communications Commission (FCC) outage reports by the National Reliability Steering Committee (under auspices of the Alliance for Telecommunications Industry Solutions). There are two major issues that are having increasing impact on the sensitivity of the power distribution to telecommunication facilities: deregulation of the power industry, and changing weather patterns.

A logical approach to improve the robustness of telecommunication facilities would be to increase the depth and breadth of technologies available to restore power in the face of power outages. Distributed energy resources such as fuel cells and gas turbines could provide one more onsite electric power source to provide backup power, if batteries and diesel generators fail. But does the diversity in power sources actually increase the reliability of offered power to the office equipment, or does the complexity of installing and managing the extended power system induce more potential faults and higher failure rates?

The goal of this effort is to perform Probabilistic Risk Assessments (PRAs) on an existing power configuration for a large telecommunications office (a Sprint Mega-Site with battery backup, and diesel generator backup) and for two alternative power configurations involving gas turbines as a primary power source. The analysis focuses on the failure probability associated with each of the three facility configurations, along with some assessment of the uncertainty or confidence level in the failure probability estimate. Aging effects are not included in the analysis. Failure probability estimates will provide a necessary component to service availability estimates from the alternative configurations, but availability estimates per se will not be part of the study.

Due to the importance of time and the operational dependencies between power system elements, the analysis approach taken involved modeling the supply of power to the facility as a stochastic process. The time to failure for each of the elements necessary to provide power were modeled as a random variable with an associated probability distribution function. Due to the limited availability of data, the parameters of the distributions were further assumed to be random variables. This approach provided a basis for conducting a risk-based comparison of the alternative power configurations.

The system analyzed in the report involved a telecommunications facility consisting of two switch-bays and a satellite reception system. Power is supplied through a 12470 V public utility line. In the event of the loss of power from the utility, there are three diesel generators available and sufficient fuel to operate each of the generators for 72 hours. At least two of the three generators are needed to provide the minimum level of power. In the event that generator power is lost, a backup system of lead-acid batteries can be used to provide a minimum level of power for up to 4 hours.

For this analysis, a worse case scenario was assumed; typical of that encountered in the event of a severe weather event. If utility power was lost, it was assumed that restoration of power could not be achieved before all segments of the backup power were system were exhausted. Similarly, if a diesel generator or gas turbine failed, minor repair was possible, but replacement of the entire generator (or turbine) was not an option. The only available fuel for the generators was that currently stored on-site (assumed to be 72 hours worth for each generator); fuel lost through consumption or contamination could not be replaced within the 4 hours of power assumed to be available from the backup batteries.

Three scenarios were investigated. The first scenario to be investigated was the current configuration, referred to as the Base Case. As discussed above, this consisted of utility power, with backup diesel generators and a bank of batteries. Two alternative power system were also investigated; both of these involved the use of turbines fueled by natural gas. The first configuration consisted of an array of 24 60kW Capstone microturbines. All 24 turbines were under constant load and a minimum combination of 18 turbines were required to provide the minimum level of power for the facility. The second configuration involved the use of a single Kawasaki 1.5 mW turbine as the primary power source. For both turbine configurations, the reliability of the natural gas supply was included in the reliability characterization.

Table 1 summarizes the results of the analyses. Comparing the median time to failure (TTF) for each configuration, it is easy to see that the use of the single Kawasaki turbine was by far the most promising alternative with a 76-fold increase in the expected operation time. The array of Capstone microturbines also showed promise with more than a 6-fold increase in power supply reliability.

Table 1. Analysis Summary

Time to Failure	10.00%	median	90.00%
Capstone TTF T_{F_C}	2698	4960	8706
Kawasaki TTF T_{F_K}	7969	59010	249100
Base Case Total T_{base}	178.8	776.9	2531

A risk-based perspective provided even more support for the conclusions and permitted accounting for the uncertainty in the available failure information. Consider a comparison between the reliability of the current power supply (i.e. Base Case) and the array configuration of Capstone microturbines suggested by Sprint. There is a 90% chance that the utility power will fail before 2531 hours, while there is a 90% chance that the Capstone array will provide power for at least 2698 hours. Finally, consider that there is a 90% probability that the Capstone array will fail to provide power for less than approximately 8706 hours, while there is a 90% probability that the single Kawasaki turbine will provide power for at least 7969 hours.

It should be noted that a significant element in the lower reliability estimate for the Capstone was the configuration and operational plan suggested by Sprint. Other configurations could have quite different reliability characteristics and may warrant further investigation. However, there are installation issues associated with the Capstone, e.g. special enclosure, that could be a factor in the final decision also.

In conclusion, given the operational scenario assumed and given the uncertainties in the three alternatives, the suggested choice is the use of the Kawasaki 1.5 mW turbine as the primary power source for the Sprint telecommunication facility.

Impact of Distributed Energy Resources on the Reliability of a Critical Telecommunications Facility

1   Background

Telecommunications has been identified by the Department of Homeland Security as a critical infrastructure to the United States. Failures in the power systems supporting major telecommunications service nodes are a main contributor to major telecommunications outages, as documented by analyses of Federal Communications Commission (FCC) outage reports by the National Reliability Steering Committee (under auspices of the Alliance for Telecommunications Industry Solutions). There are two major issues that are having increasing impact on the sensitivity of the power distribution to telecommunication facilities: deregulation of the power industry and changing weather patterns.

In 1995-96 Sandia National Laboratories initiated a study of the impact of deregulation on the reliability of the bulk power network [28, 27, 28]. The initial study was based on the ERCOT power grid and was extended to examine the impact of deregulation on the reliability of the Western States Coordinating Council (WSCC) bulk power network. The conclusions of both of these studies highlighted two issues: lack of reserve generation and insufficient/poorly located transmission capacity. The conclusion of the investigation was that, unless a national regulatory body interceded, the result of restructuring would be a national bulk power system that was more sensitive to external disturbance.

A major factor on both the operation of the network and the consumer consumption will be the growing uncertainty in weather events [11, 12, 21, 31]. One of the most widely recognized experts in understanding the impact of weather is Sir John Houghton. In Houghton's book [13], he notes that the recent changes are not part of a short term trend, but are part of a much longer, sustained change. Houghton summarizes weather changes over the 21st century and suggests that, among other significant climate phenomena, it is expected that there will be:

- more intense precipitation events

- increased summer temperatures (leading to higher cooling demands)

- increase in tropical cyclone peak wind intensities, accompanied by increased mean and peak precipitation intensities,

- increased intensity of mid-latitude storms leading to increased infrastructure losses

All of these will have first or second order impacts on the telecommunications and power infrastructures. There is no incentive for the power utilities to make their systems more robust to these disturbances; rather, the industry has moved to change the reliability reporting requirements to avoid financial penalties [30]. As noted by Sandia researchers in 2000, telecommunication companies, emergency services, etc. dependent on a reliability source of power need to be prepared for increased uncertainty in the operation of the national electrical infrastructure [16].

1.1 Robust Telecommunications Infrastructure

One approach toward improving the robustness of the power systems supporting telecommunications offices is to improve the reliability of the necessary supply of power. Current best practices involve a combination of onsite battery backup (for short, intermittent power interruptions) and diesel generators (for longer term interruptions). Occasionally, universal power systems (UPS) technologies are also used for specific data communications equipment backup.

A logical approach to improve reliability would be to increase the depth and breadth of technologies available to restore power in the face of power outages. Distributed energy resources such as fuel cells and gas turbines could provide one more onsite electric power source to provide backup power, if batteries and diesel generators fail. But does the diversity in power sources actually increase the reliability of offered power to the office equipment, or does the complexity of installing and managing the extended power system induce more potential faults and higher failure rates?

The goal of this effort is to perform Probabilistic Risk Assessments (PRAs) on an existing power configuration for a large telecommunications office (a Sprint Mega-Site with battery backup, and diesel generator backup) and for two alternative power configurations adding gas microturbines as a primary power source. The product from the study will be a failure probability associated with each of the three facility configurations, along with some assessment of the uncertainty or confidence level in the failure probability estimate. Aging effects will not be included in the analysis. Failure probability estimates will provide a necessary component to service availability estimates from the alternative configurations, but availability estimates per se will not be part of the study.

2 Introduction

Distributed energy resources technology is a growing focus of research across the energy industry and within the Department of Energy. For example, Sandia National Laboratories has established the Distributed Energy Technologies Laboratory (DETL) to assist in the development and implementation of distributed energy resources. DETL tests microturbine, engine-generator, photovoltaic, fuel cell, and energy-storage technologies both individually

and in a collective microgrid. Collaborators include manufacturers, utilities, the National Renewable Energy Laboratory (NREL), DOE, DoD, the California Energy Commission, universities, standards organizations, and other national and private laboratories. Energy security is one of several important benefits that distributed energy resources will offer to the nations electric power infrastructure.

Natural gas turbines, or microturbines, derivatives of aircraft auxiliary power systems, are one DER technology for cogeneration with particular appeal. Turbines are highly efficient with fuel conversion efficiency on the order of 40% and have a number of fuel options including biofuels, ethanol and natural gas. These turbines are designed for continuous operation, generally operating at 90% of their rated value. Emissions are necessarily low to meet the local environmental pollution requirements (e.g. California NOx limit of 2.5 ppm, 6 ppm of CO corrected to 15% exhaust oxygen).

Two gas turbine alternatives are investigated in the following sections. The first configuration is based on a generation package composed of 4 pallets of 6 Capstone microturbines. The second configuration is based on a single Kawasaki turbine. Both are co-located with a remote telecommunication facility and operate off an external supply of natural gas. In both cases, the primary source of power is co-generation production with the utility subsuming a role as a backup source of power in the event of turbine system failure. The existing diesel generators (in conjunction with the facility battery system) would then be employed if both the turbines and utility power become unavailable.

However, the objective of this effort is to investigate the impact of distributed energy resources (DER) on the reliability of the power supplied to the telecommunications center. The following section outlines the operational scenario assumed with this study and the analysis approach. Following this is a discussion of the fundamental issue driving this analysis: the uncertainty associated with the ability of the local utility to supply power to the telecommunications center. The current facility configuration, referred to as the Base Case, is then characterized.

3   Operational Scenario

Sandia was requested to analyze the impact of distributed energy resources on the *reliability* of a telecommunication center, assuming that the time to repair was not a factor. This analysis constraint, effectively assumes that the facility is isolated from major logistics support, and operation is restricted to the physical equipment currently available for a given configuration. Such a situation might result, for example, from a severe weather incident.

The location of interest is the Sprint Orlando wireline switch facility. This facility is remote - access is via approximately 7 miles of unpaved roads. The utility power at this particular location is particularly unreliable requiring an unusual reliance on standby power at the facility. In the most recent four year period there were 35 utility outages (compared

with a national average of approximately 3 outages per year for 2001 and 2002) [23, 24, 26, 25]

For this analysis, an (almost) worse case scenario is assumed. If utility power is lost, restoration of power will not occur within a time period that will have a significant impact. (The impact of this assumption is investigated early in the report.) Similarly, if a diesel generator or gas turbine fails, minor repair is possible, but replacement of the entire generator (or turbine) is not an option. The only available fuel for the generators is that currently stored on-site (assumed to be 72 hours worth for each generator); fuel lost through consumption or contamination cannot be replaced within 4 hours. The time of 4 hours is used since the batteries are required to provide a minimum level of support for the plants for an additional 4 hours in the event that power is lost from the generators.

4   Analysis Approach

The focus of this effort is to characterize the impact of distributed energy resources (DER) on the reliability of a major telecommunication center. Sandia was initially asked to focus on the application of fault trees for characterizing the reliability impact and a typical fault tree developed to support the analysis is depicted in Figure 1. The remaining fault trees are presented in Appendix A.

The telecommunication center consists of a main facility supported by two switch bays (MSB-1 and MSB-2) and the Earth Station. Power is supplied to the facility primarily through a traditional utility drop. In the event that utility power is lost, at least two of the on-location 1.5MW diesel generators must function. In addition to the two generators, the battery system must be available to provide minimal support for an addditional 4 hours in the event that the generators fail.

However, for the DER configurations to be explored in this effort, the majority of the elements in MSB-1, MSB-2 and the Earth Station would be consistent fixtures. In addition, the fuses, breakers, and other components which lend complexity to the analysis have demonstrated extremely high reliability over many years of field operation and would not have a significant impact on the reliability assessment. For this reason, it was decided to simplify the fault trees and a typical simplified fault tree is presented in Figure 2. However, the need to consider repair was raised as a possible area for investigation. For this reason it was decided not to explore the use of fault trees to support the analysis.

Two alternative analysis approaches were then considered: Markov Chains and stochastic processes. The initial review of the data suggested a great deal of variability in possible parameter estimates. In addition, there was the increasing likelihood of wide variation in the scenarios and equipment configurations to be investigated. For these reasons, it was finally decided to employ a stochastic process approach based in Bayesian statistics (to account for uncertainty in parameter values).
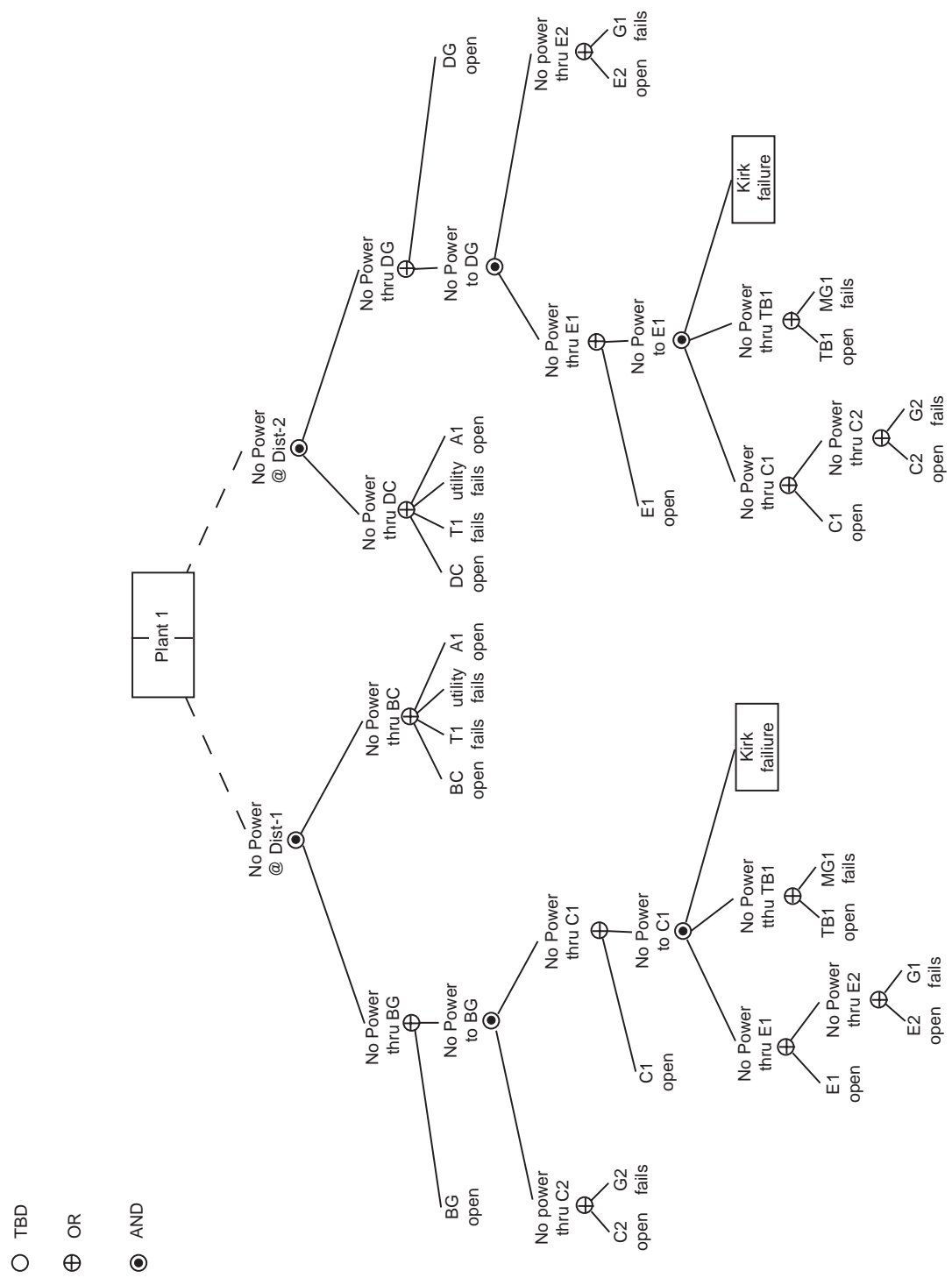
Figure 1. MSB-1 Fault Tree
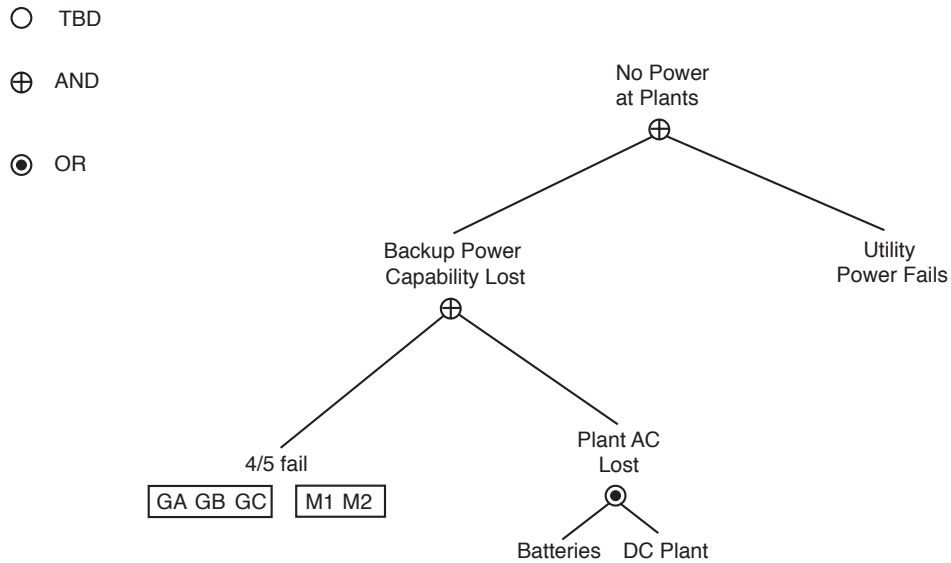
Figure 2. Base Case Fault Tree

The stochastic process approach allows the analysis to be broken down into a series of potentially dependent events. The parameters characterizing the length of each of the events will be assumed to be random variables with uncertainty about the parameters of the probability density functions.

5   Event Characterization

5.1   Basic Approach

The standard methods and data used to estimate the reliability of power systems are documented in the IEEE Std 493-1997 IEEE Recommended Practice for the Design of Reliable Industrial and Commercial Power Systems [2]. A traditional approach is not applied because of the sequential, time-dependent nature of how the system is operated. Analysis methods associated with Markov Chains were investigated and showed promise as an alternative that allowed inclusion of repair. However, Markov Chains rely on a strong historical basis for estimating failure and repair rates.

As noted previously, the lack of an extensive database suggests addressing uncertainty in parameter values, e.g. the failure rate of natural gas pipelines. The approach used in this analysis assumes that the rate at which failure occurs or the time required for repair will be random variables; that is, the time to failure distribution will actually be a family of distributions. As more information and/or experience is gained, then the family of distributions collapses to a single distribution and more traditional methods, such as Markov

16

Chains, can be employed. Specifically, if there was conflict or confusion regarding the final decision, these advanced methods would provide insight into areas where funding spent on additional data would be of greatest return.

For illustration of the approach, consider the supply of utility power. There are two elements to the analyses of power availability: rate at which failures occur and, for the utility power, the time required to restore service. Failure events will be assumed to occur after periods of time T_i has passed. The length of time will be considered a random variable and the choice of the underlying distribution will be a function of the system element being analyzed. For example, since there is not sufficient information to support a more complicated characterization of the utility failure rates, the times will be assumed to be exponentially distributed random variables: $T_i \sim \exp[-\lambda_i t]$, where λ_i represents the rate at which failures occur. Similarly, the length of time to recover from an outage, will be considered a random variable characterized with an exponential distribution: $T_j \sim \exp[-\mu_j t]$, where μ_j represents the rate at which repairs occur. (Note that the assumption of the exponential distribution is also consistent with the reliability approach outlined in IEEE Std 493-197.)

Since there is significant variability in the failure (and repair) rates from year-to-year, the failure rate for the outage time will also be considered a random variable. The probability distribution function describing the uncertainty in the utility failure rate, λ will be assumed to be a gamma distribution:

$$g(\lambda|\alpha,\theta) = \frac{\theta^\alpha}{\Gamma(\alpha)}\lambda^{\alpha-1}\exp[-\theta\lambda], \qquad \lambda,\alpha,\theta > 0.$$

5.2   Stochastic Process

Figure 3 depicts a typical sequence of events. Each event logically follows at the conclusion of the previous event. For example, for the Base Case, the time that the utility is available T_U is randomly selected from $f(T|\lambda_U) = \exp[-\lambda_U t]$. Since the rate at which the utility fails, λ_U, is not known with certainty, a random parameter is chosen from the distribution $\Lambda \sim g(\lambda|\alpha,\theta)$. Because of the conditional structure of the the the distributions for T and λ, Gibbs sampling must be used. The WinBugs computer software was used for all simulations conducted in this report [29] and the computer codes for each system configuration are provided in the Appendices.

Similar to the utility reliability, values for diesel generator operation reliability, T_G, and battery reliability, T_B are simulated. The values are then combined to get the time until system failure, $T_{base} = T_U + T_G + T_B$. Figure 3 depicts the typical time line of events associated with what is referred to in the following discussion as the *Base Case*.

The following sections address each of the elements of the various scenarios. The Base Case is a function of the availability of power from the utility, the backup diesel generators, and the batteries. The additional alternatives explored include the addition of natural gas microturbines from Capstone and Kawasaki.

6 Base Case
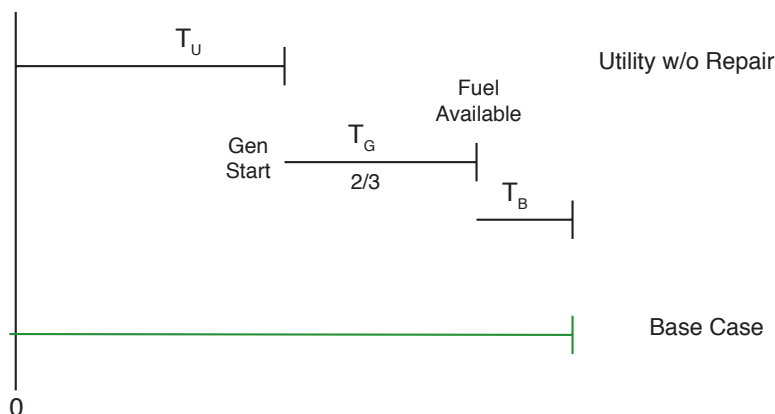
Figure 3. Base Case Time Line of Events

The primary reliability impact of DERs will be related to their use to augment or replace utility power as the primary power source. The utility (or DER) is then coupled with combinations of diesel generators and the battery backup systems within the facility. The current backup power for MSB-1 and MSB-2 is provided through three 1.5 mW stationary diesel generators and the option of two mobile 1.5 mW generators. The Earth Station has a separate backup power source consisting of two 300 kW generators.

The Base Case (depicted in Figure 3) is defined as the configuration of the telecommunication center as it exists today - without support of additional distributed energy resources. The telecommunication center consists of a main facility supported by two switch bays (MSB-1 and MSB-2) and the Earth Station. Power is supplied to the facility primarily through a traditional utility drop. In the event that utility power is lost, at least two of the on-location diesel generators must function. In addition to the two generators, the battery system must be available to provide minimal support for an addditional 4 hours in the event that the generators fail.

The current analysis is based on the *peak* power requirement for MSB-1 and MSB-2 of approximately 1.1mW (total) and 65kW for the Earth Station. These requirements may expand as the demand on the system grows; additional fixed and mobile generators can be added to the Base Case to increase the backup power capacity.

18

The one-line diagrams for the Base Case are presented in Figures 4, 5 and 6. (For reference, the original fault trees for each of the three major elements are provided in Appendix A.)

6.1 Utility Availablility

To be consistent with the literature, the terms utility availability and utility reliability will be used synonomously. The reliability of the utility power source will be defined as the probability that, at any point in time, the telecommunication center is supplied with sufficient power from the local utility. For this study this probability is effectively the fraction of time that utility power is available at the telecommunications center.

Power utility reliability is typically characterized using a number of indices proscribed the IEEE Guide for Electric Power Distribution Reliability Indicies (IEEE Std 1366-2003 [1]); however, not all states have adopted standards as a means of characterizing utility power reliability. For example, the state of Florida has requirements for reporting reliability metrics, but no quality of service incentives or penalties and the state of New Mexico has no power reliability requirements [6]. In addition, weather is recognized by the utilities as a major influence in estimating these indices and, in most cases, power disruptions related to severe weather are discounted in the calculations. For example, *major events* are not necessarily included in reliability indices where a major event might be defined as an outage where more than 10% of the customers within a region are without electricity and power is not restored within a 24 hour period [30].

The following discussion summarizes the major reliability measures used by public power utilies. An interruption is considered countable if the time duration of the interruption exceeds 5 minutes. All indices defined below are for sustained interruptions. Let N_T be the total number of customers served, and N_i be the number of interrupted customers for each sustained interruption.

System average interruption frequency index (SAIFI) The system average interruption frequency index indicates how often the average customer experiences a sustained interruption.

$$SAIFI = \frac{\text{Total Number of Customers Interrupted}}{\text{Number of Customers Served}}$$

$$= \frac{\sum_i N_i}{N_T} = \frac{CI}{N_T}$$

System average interruption duration index (SAIDI) This index indicates the total duration of interruption for the average customer. It is commonly measured in customer
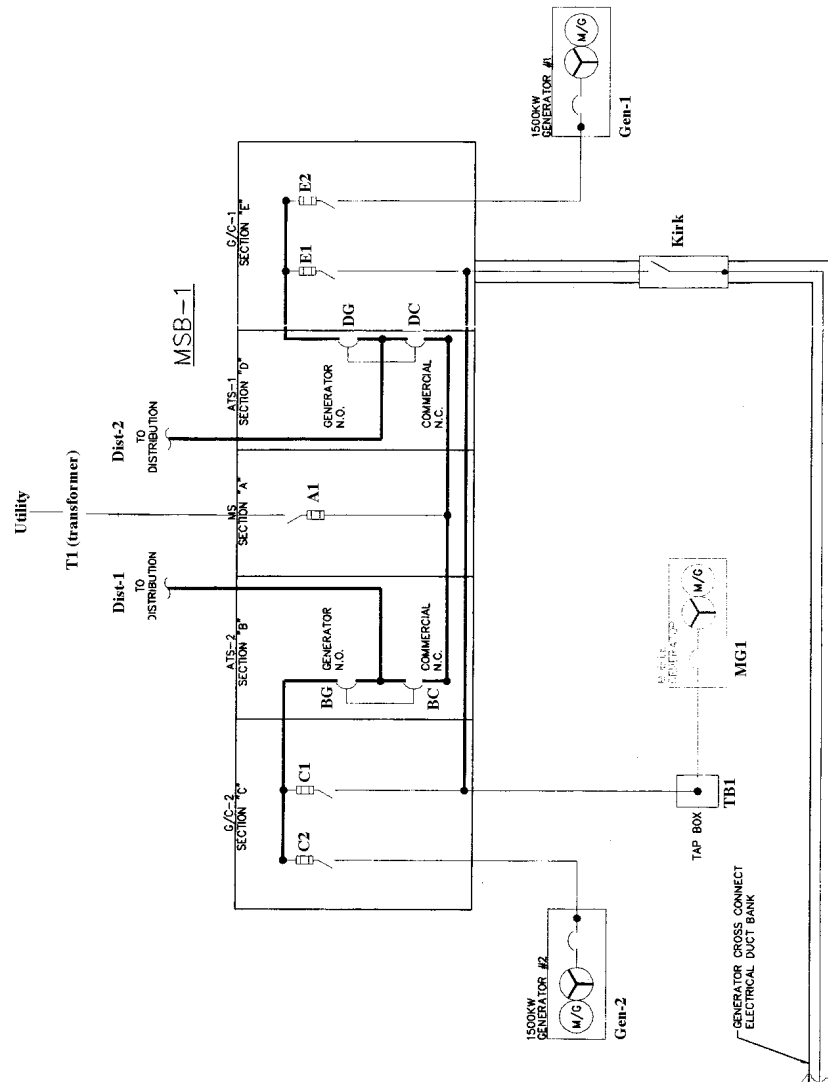
Figure 4. MSB-1 One-line Diagram

20
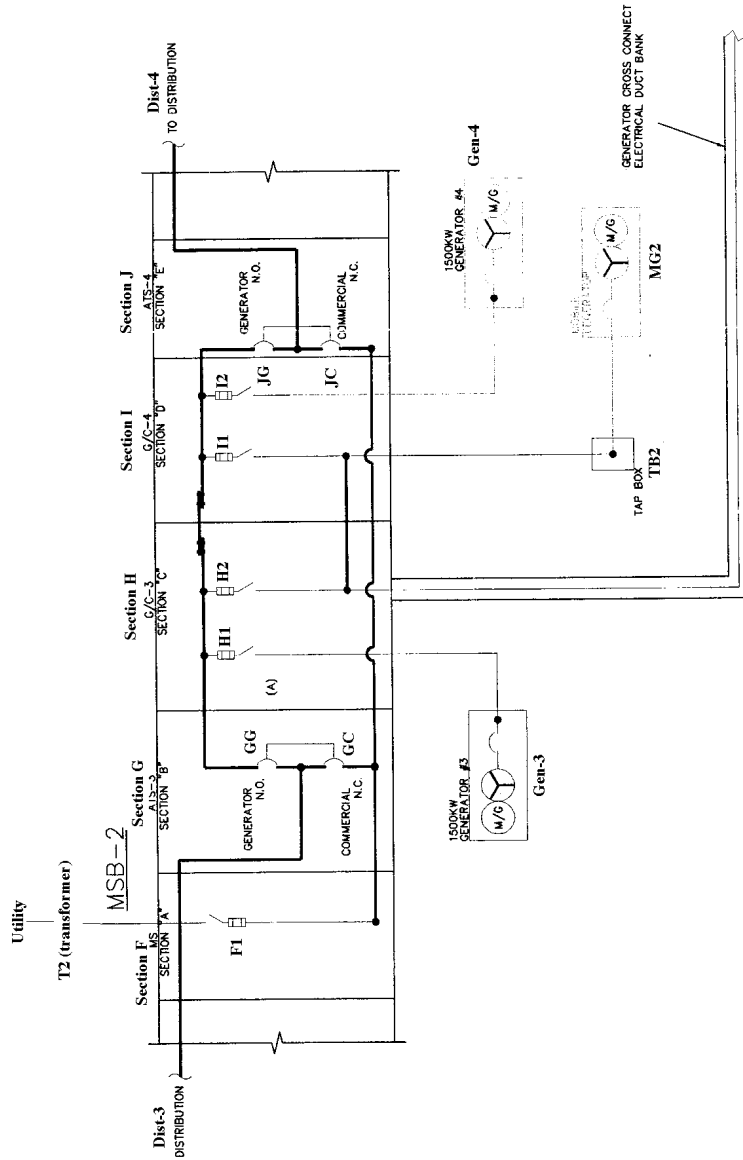
Figure 5. MSB-2 One-line Diagram
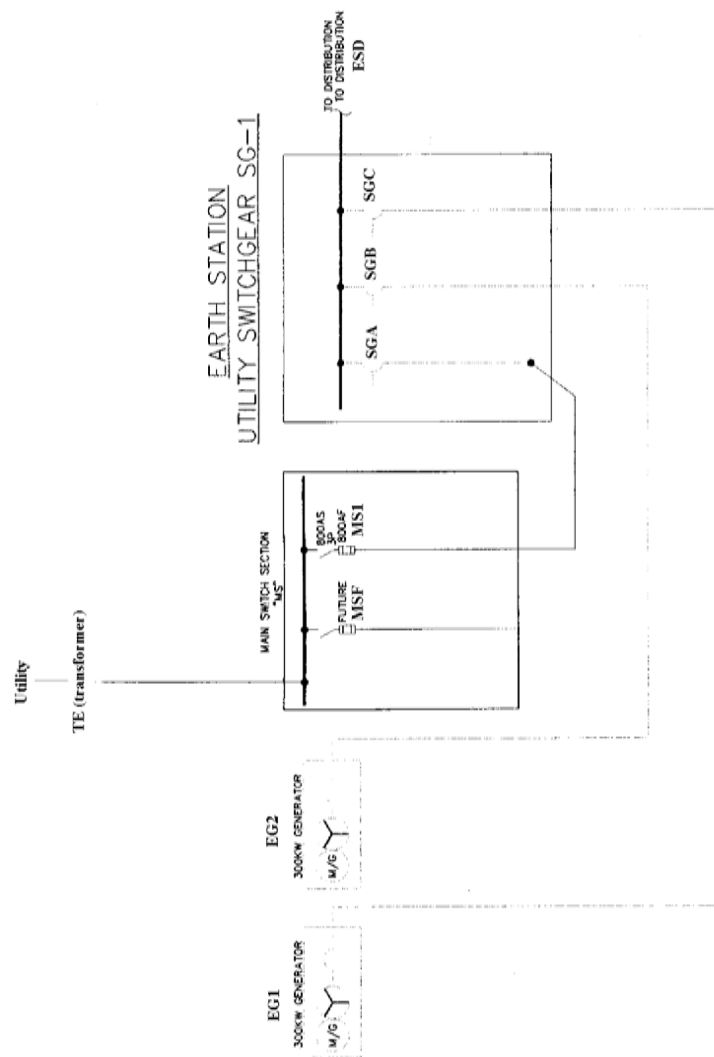
Figure 6. Earth Station One-line Diagram

minutes or customer hours of interruption. Let r_i be the restoration time for each interruption event:

$$SAIDI = \frac{\text{Total Number of Customer Interruptions}}{\text{Number of Customers Served}}$$

$$= \frac{\sum_i r_i N_i}{N_T} = \frac{CMI}{N_T}$$

Customer average interruption duration index (CAIDI) CAIDI represents the average time required to restore service.

$$CAIDI = \frac{\text{Total of Customer Interruption Duration}}{\text{Total Number of Customers Interrupted}}$$

$$= \frac{\sum_i r_i N_i}{\sum_i N_i} = \frac{SAIDI}{SAIFI}$$

Lbar The overall average length of the outages

$$Lbar = \frac{\text{Minutes of Interruption}}{\text{Total Number of Outages}}$$

Note that the CAIDI index can be deceptively low since customers may be counted multiple times; once for each interruption. An alternative measure that is not generally reported by utilities is the Customer total average interruption duration index (CTAIDI), which counts customers with multiple interruptions only once (N_i^*):

$$CTAIDI = \frac{\text{Total of Customer Interruption Duration}}{\text{Total Number of Customers Interrupted (*)}}$$

$$= \frac{\sum_i r_i N_i}{\sum_i N_i^*}$$

Service availability is given by:

$$ASAI = \frac{\text{Total Customer Hours of Service}}{\text{Total Customers Hours Demand}}$$

$$= \frac{(8760)N_T - \sum_i r_i N_i}{(8760)N_T}$$

6.1.1   Florida Public Service Commission Data

The state of Florida, while not having Quality of Service requirements, does require each utility to submit a formal report documenting the reliability metrics for the previous year [8]. Data is adjusted to account for severe storm events; it is believed, but not conclusively clear, that Florida requires the utilities to use the IEEE Std 1366 [1] definitions to adjust the metrics for major events. Table 2 summarizes the 2005 report for the data obtained in 2004 and Figure 7 depicts the data graphically. Note that some of the utilities reported an approximate 20% improvement in 2004 numbers over those from 2003 after one of the most notable hurricane seasons on record (Figure 8).

Table 2. Summary of Utility Recovery Time Related Metrics

Utility	Reliability Metrics			
	SAIDI	CAIDI	LBAR	SAIFI
PEF	77	64.7	111.9	1.19
FPL	73.9	59.4	181	1.24
FPUC	138.06	107.47	77.35	1.26
GULF	93.33	105.93	129.55	0.88
TECO	72.63	75.26	178.07	0.97
Average	90.98	82.55	135.57	1.11
Std Dev	27.60	22.78	44.32	0.17

6.1.2   Sprint Data

In the four years, 2001-2004, Sprint noted 35 incidents where power to the switching station was disrupted [25] for a failure rate estimate of 8.75 events/year. In addition, Sprint collected data on the length of diesel generator operation during these same outages. This may be a consideration since the utility may not demonstrate stability immediately following an outage; the facilities continue to use the already functioning diesel generators during this additional period.

- Data are not available for the specific incidents, but similar Sprint telecommunication facilities have experienced power outages with an average outage time of $\mu_{outage} = 6.45$ hours, and a standard deviation of $\sigma_{outage} = 6.54$ hours [22]. To appreciate the uncertainty in outage length, the shortest duration was an instantaneous outage, while the longest outage lasted approximately 27 hours.

- The generators during these incidents were in-use for lengths of time with the following mean and standard deviation: $\mu_{Genrun} = 9.41$ hours, $\sigma_{Genrun} = 8.14$ hours.

Florida PSC Reliability
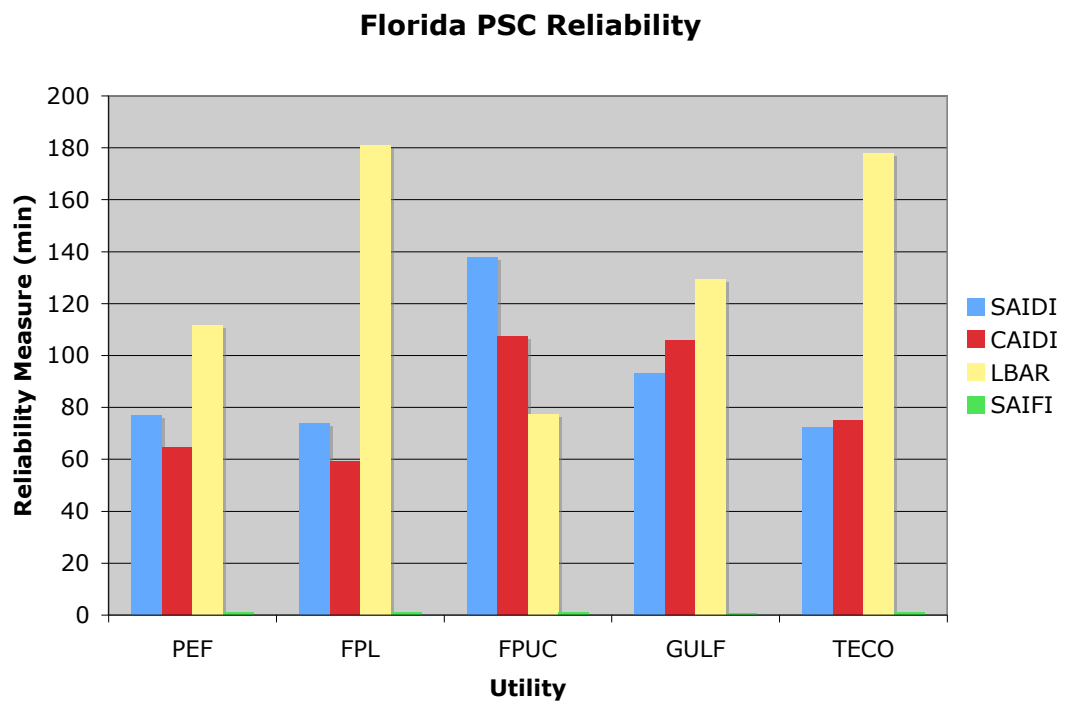
Figure 7. Florida PSC Reliability Metrics (2004)
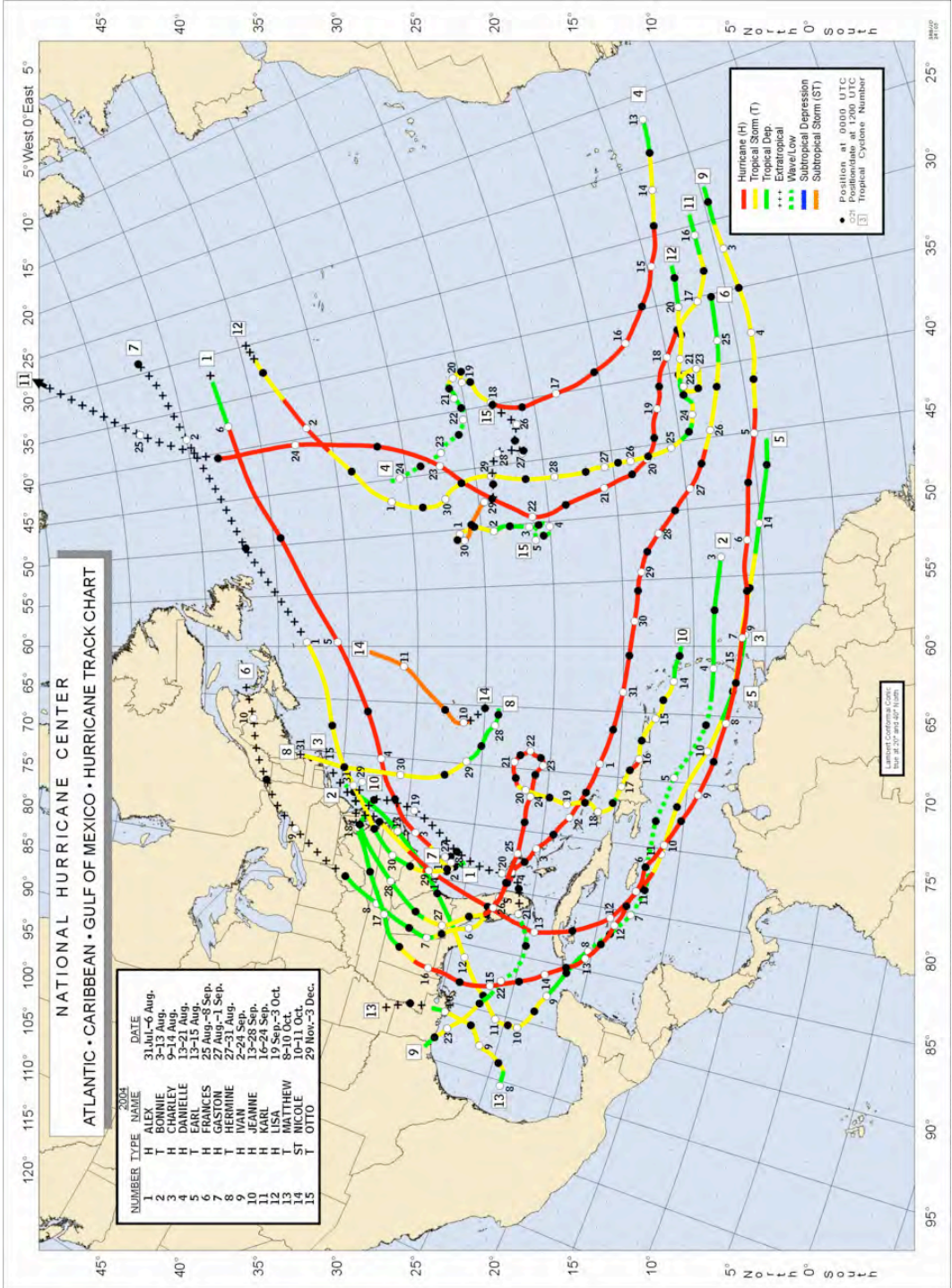
Figure 8. National Hurricane Center 2004 Season

26

6.1.3   IEEE Std 493-1997

As noted previously, the standard methods and data used to estimate the reliability of power systems is documented in the IEEE Std 493-1997 [2]. While an industry standard, the source of much of the data relevant to this effort are from surveys taken prior to 1976. Reference [2], Table 3-33, suggests using an average outage duration of 125 minutes (2.08 hours).

For utility supplies to industrial plants where the voltage line is $\leq 15kV$ the suggested failures per year (again from Table 3-33 [2]) is 3.621. (Note that when verifiable operational/field information is not available, data from this standard will be used in the analysis.)

6.1.4   Loss of Off-site Power (LOSP)

A second, very reliable source of utility data is available from each of the 103 nuclear power plants across the US. It is well recognized that the availability of power to commercial nuclear power plants is essential for safe operations and accident recovery. A loss of offsite power (LOSP) event is therefore considered an important contributor to total risk at nuclear power plants [3].

However, caution must be used when using data from nuclear plants related to utility availability since utilities will do everything possible to assure delivery of power to the nuclear plant; both for safety reasons and since nuclear power plants provide a significant base power load. For example, the two major electrical disturbances on July 2, 1996 and August 10, 1996 that blacked-out most of the western US, did not results in LOSP events. In addition, for similar reasons, restoration times for nuclear plants can be substantially shorter than for industrial loads. Finally, since reactors will often be shutdown in anticipation of a grid or weather related disturbance, the rate at which off-site power is lost is not applicable to the current analysis. Highlights of the published data [3]:

- Recovery time for grid-related events ranged from 125 to 360 minutes with a mean of 190.2 minutes and a standard deviation of 97.4 minutes

- The time to recover from weather related incidents ranged from 37 minutes to 5.5 days, with a mean of 1258 minutes and a 90% probability interval of [23, 5009] using a log-normal probability density function.

6.1.5   Utility Data Input Summary

Figures 9 and 10 summarize the data available for restoration time and failure rate. The data from the utilities reported to the Florida Public Service Commission likely discounts severe events of any type, e.g. weather, and is therefore optimistic. While not clear, the estimates

from the IEEE Std 493 most likely have similar liabilities. The values developed for the Nuclear Regulatory Commission and reported to support LOSP estimates lean toward the optimistic side since reactors are shutdown in *anticipation* of severe events.

For the remainder of the analyses, the mean restoration and failure rate data from Sprint will be used to support the utility availability analyses since this data appears to be the most realistic and applicable to the problem being investigated.

Figure 9. Summary of Restoration Time (min)

6.2   Probability Distribution for Utility Reliability

It is assumed that the length of time that a utility is up and operating, T_U, is an exponentially distributed random variable with parameter λ: $f(t|\lambda) = \exp[-\lambda t]$. The parameter λ represents the number of utility interruptions per year. However, the estimate $\hat{\lambda} = 8.75$ represents a simple average rate at which events occurred over the four years; in reality, there will be a great deal of variation or uncertainty about the rate, λ at which events might occur each year.

Therefore, let λ be a random variable with an average value of 8.75. Without additional information regarding how the rate varies each year, the assumption of a Gamma

28

Figure 10. Summary of Failure Rate (events/yr)

distribution for λ is the simplest assumption that can be made:

$$f(\lambda|\alpha,\beta) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)}\lambda^{\alpha-1}\exp\left(-\frac{\lambda}{\beta}\right), \lambda > 0$$

A distribution for λ and the mean of that distribution are now available. To completely describe the Gamma distribution, one more assumption is necessary to characterize the second parameter of the distribution. Assume that we are confident that the rate at which events occur lies in the range [2, 14] events/year. This range will typically reflect $[\mu - 3\sigma, \mu + 3\sigma]$. Solving, we find that a standard deviation of $\sigma = 2.0$ is a good place to start.

The mean and variance for the Gamma distribution are given by $E[\lambda] = \alpha\beta = 8.75$, and $V[\lambda] = \alpha\beta^2 = 4$, respectively. Simultaneously solving the two equations for the two unknowns yields values of: $\alpha = 19.1406$ failures/year and $\beta = 0.457143$.

The resulting probability density function (PDF) describing the uncertainty in the number of utility outages each year is presented in Figure 11. As noted previously, assume that the length of time that a utility is up and operating, T_U, is an exponentially distributed random variable with parameter λ: $f(t|\lambda) = \exp[-\lambda t]$; since the failure rate, λ is a random variable, the PDF $f(t|\lambda)$ will inherently have an associated probabilistic uncertainty.

Figure 12 depicts this uncertainty as a probability band about the utility time to failure, T_U: there is a 90% probability that the power will be continuously available for more than 1126 hours, a 50% chance that it will be available for less than 106 hours, and a 90% probability that power will be available for less than 2484 hours.

29
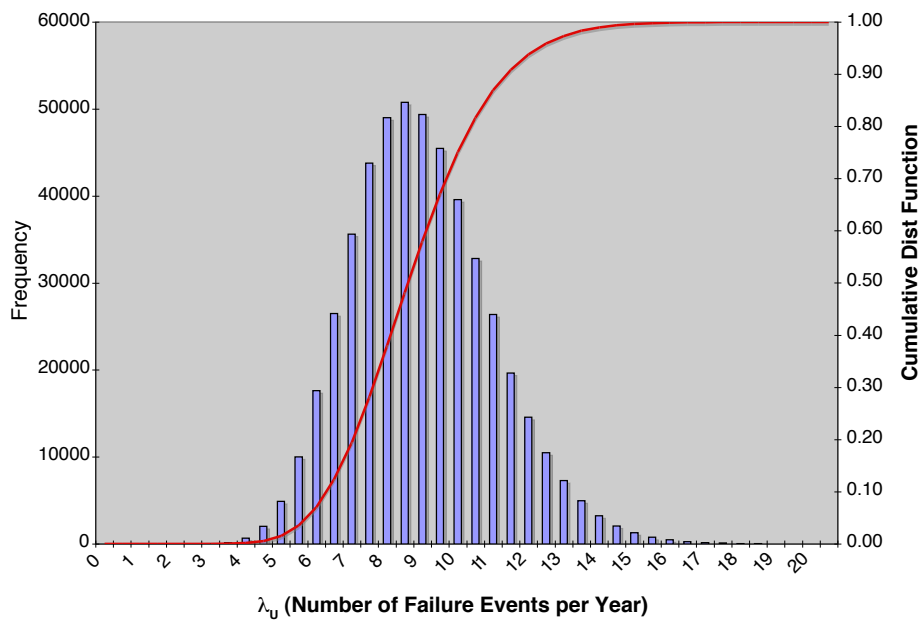
Figure 11. PDF of the Number of Utility Outages per Year
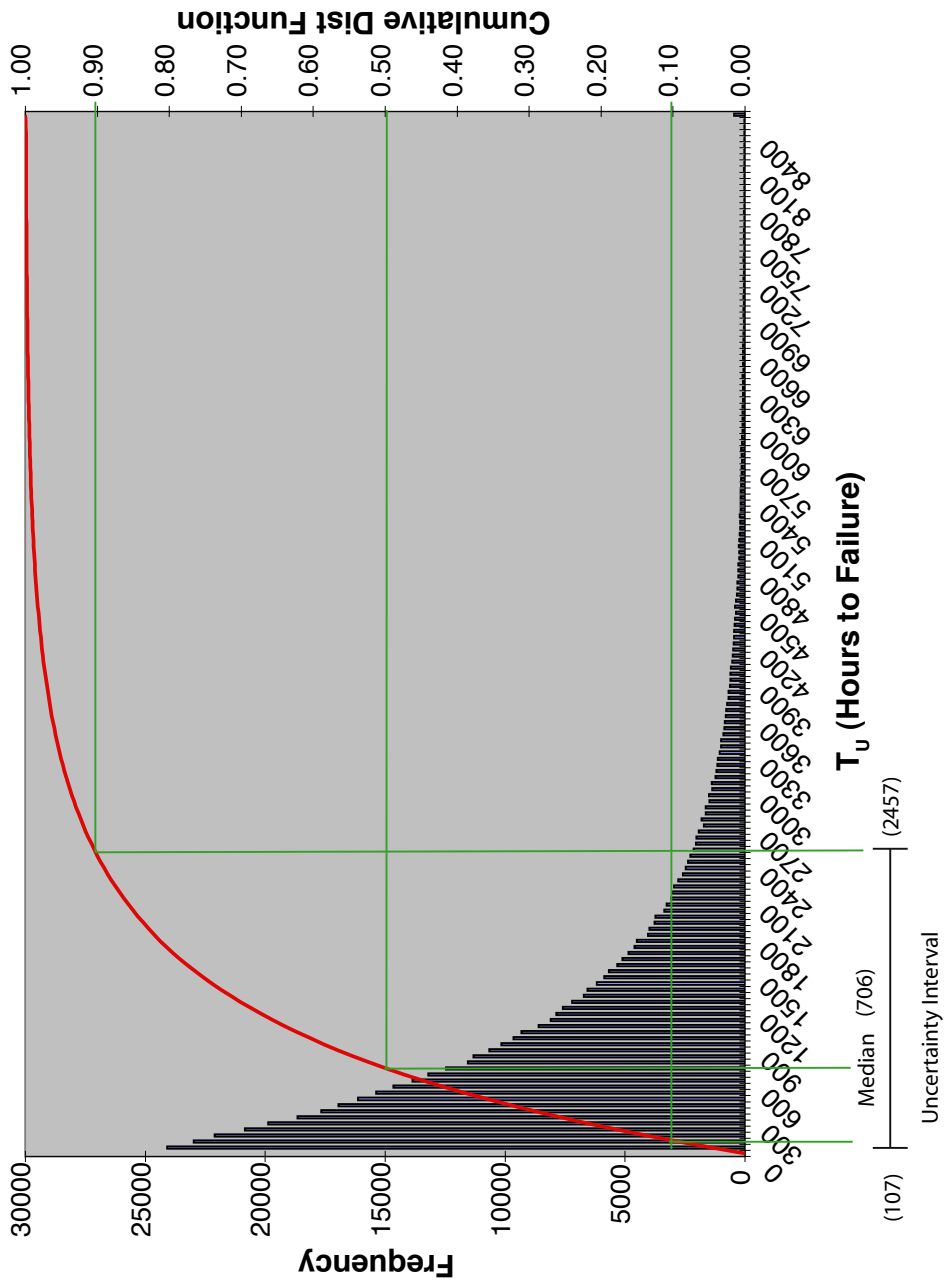
Figure 12. Utility Reliability Summary (T_U)

6.3 Distribution for Generator Reliability

Failure of a diesel generator is defined as a malfunction of the generator or associated support subsystems that prevents the generator from starting and running when a demand has occurred. Failures can occur in two modes:

Failure to start (FTS) A failure of the generator to either manually or automatically start on a bus under-voltage condition, reach rated voltage and speed, close the output breaker, or sequence safety-related electrical loads onto the respective safety-related bus.

Failure to run (FTR) A failure of the generator to continue to supply power to its respective safety-related electrical bus given the generator successfully started.

Using IEEE Std 493 [2], engineers at Sprint estimated a mean time to failure (MTTF) for diesel generators of 9056 hours with a mean time to repair of 3.9 hours [25]. However, the expected failure rate ($\lambda = 1/MTTF$) for diesel generators used in nuclear power plants (NPPs) is approximately 0.0223 failures/hour. In addition, for diesel generators at nuclear power plants the Pr{failure to start} = 0.0241 per demand [9, 10].

As with the utility analysis, the reliability of the generators will be assumed to be a random variable described by the distribution:

$$R(t|\lambda) = \exp(-\lambda t)$$

The required operating period for the generators is $t = 72$ hours at which time the fuel at the facility is expended; refueling is assumed to not be possible.

Given the wide disparity in the reliability data for the diesel generators, assume that the time to failure for the generators is a random variable. The failure rate for the NPP diesel generators: $\lambda = 0.00223$ is based on considerable data for a variety of diesel generators from across the nuclear power plant industry. However, based on operational experience, Sprint has also published an estimate of $\lambda = 0.00011$ failures/hours for the generators.

Given the strong historical basis, $\lambda = 0.00223$ will be used as the expected time to failure and it will be assumed that the $\lambda = 0.00011$ is a lower 5% credibility limit (i.e. 95% probability that the true MTTF is less than 9056 hours). A gamma distribution will be used to describe the variation in the generator failure rate:

$$f(\lambda|\alpha, \beta) = \frac{1}{\beta^\alpha \Gamma(\alpha)} \lambda^{\alpha-1} \exp\left(-\frac{\lambda}{\beta}\right), \lambda > 0$$

The mean and variance are given by $E[\lambda] = \alpha\beta$, $V[\lambda] = \alpha\beta^2$, respectively. Simultaneously solving these two equations:

$$E[\lambda] = \alpha\beta$$

$$F(\lambda < 0.00011|\alpha, \beta) = \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^{0.00011} \lambda^{\alpha-1} \exp\left(-\frac{\lambda}{\beta}\right) \approx 0.05$$

for the two unknowns yields values of: $\alpha = 0.0001115$ failures/hours or $\alpha = 0.976741$ failures per year and $\beta = 20$. (Units of years are used in the remainder of the analysis for consistency.) Given these parameters, the expected number of diesel generator failures per year is approximately 19.54. The resulting probability density function describing the uncertainty in the rate at which failures occur is presented in Figure 13. The results are presented for a single generator; recall that at least two of the three generators must function. Also, the point estimates initially provided by Sprint and the US Nuclear Regulatory Commission are noted.

6.3.1 Failure to Start

Define p to be the probability that a generator will not start on demand. Let p be a beta distributed random variable conditioned on the variables r, s:

$$f(p|r,s) = \frac{1}{B(r,s)} p^{r-1}(1-p)^{s-1}, r,s > 0$$

where $B(r,s)$ is the incomplete Beta function. The mean and variance of p are given, respectively, by:

$$E[p] = \frac{r}{r+s}$$

$$V[p] = \frac{rs}{(r+s)^2(r+s+1)}$$

Given the NRC experience, let the mean be $E[p] = 0.0241$ and the standard deviation be $\sqrt{V[p]} = 2 * E[p]$. This results in a prior distribution that is relatively uniform over the area of interest so that the prior does not overly influence the results. Figure 14 depicts the resulting prior distribution.

Typically, the maximum allowed load on each generator is 60% of the rated value, therefore at least two of the generators are necessary for minimum support of the power required by the two plants. In the event that only two generators are operational, air conditioning (A/C) and other support functions would be cycled on/off to keep the plants fully operational. Figure 15 depicts the time to failure distribution of the diesel generators considering that 2 of 3 must be functioning and that each generator has a certain probability of not starting when called. The sharp rise at 72 hours is due to the limited source of on-site fuel.

6.4 Battery Reliability

Battery backup consists of a bank of valve-regulated lead-acid (VRLA) batteries. VRLA batteries are a well established technology [4] used as a backup power source for short
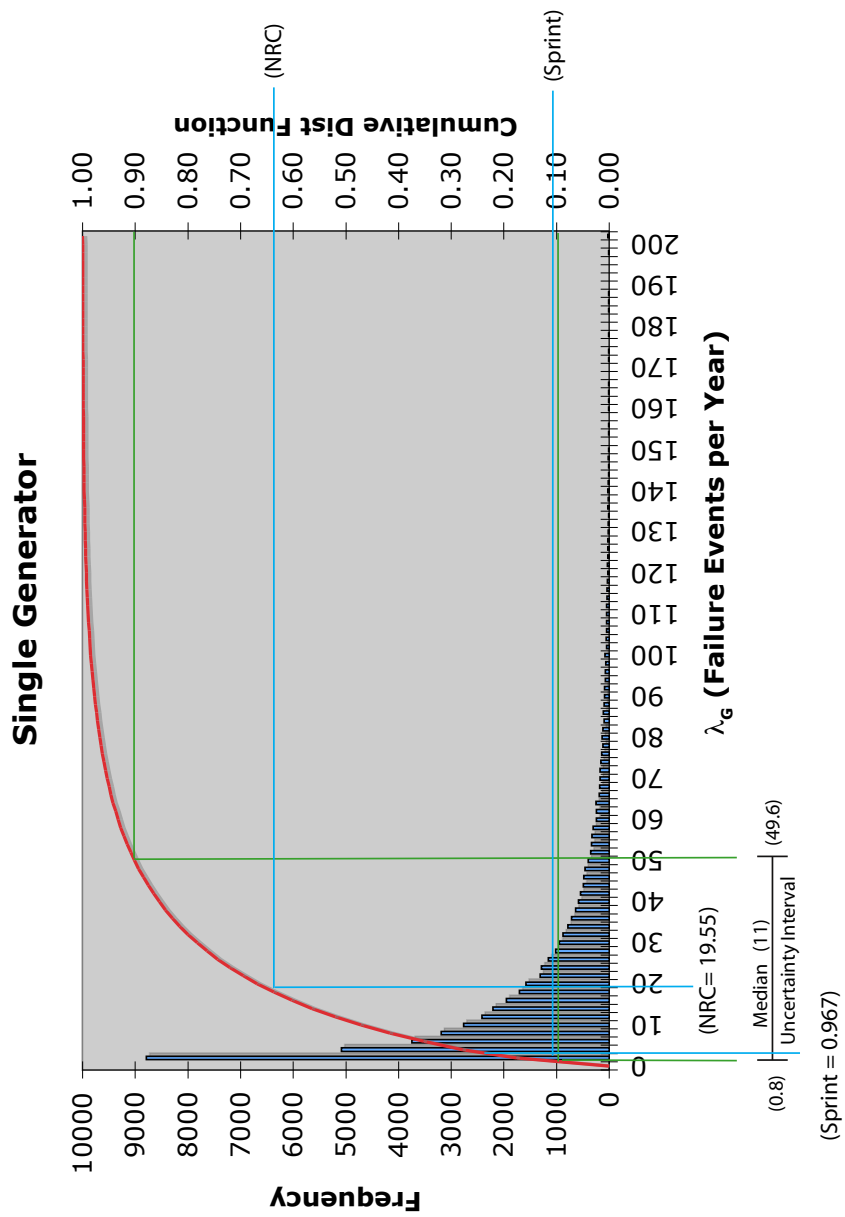
Figure 13. Diesel Generator Failure Rate Distribution
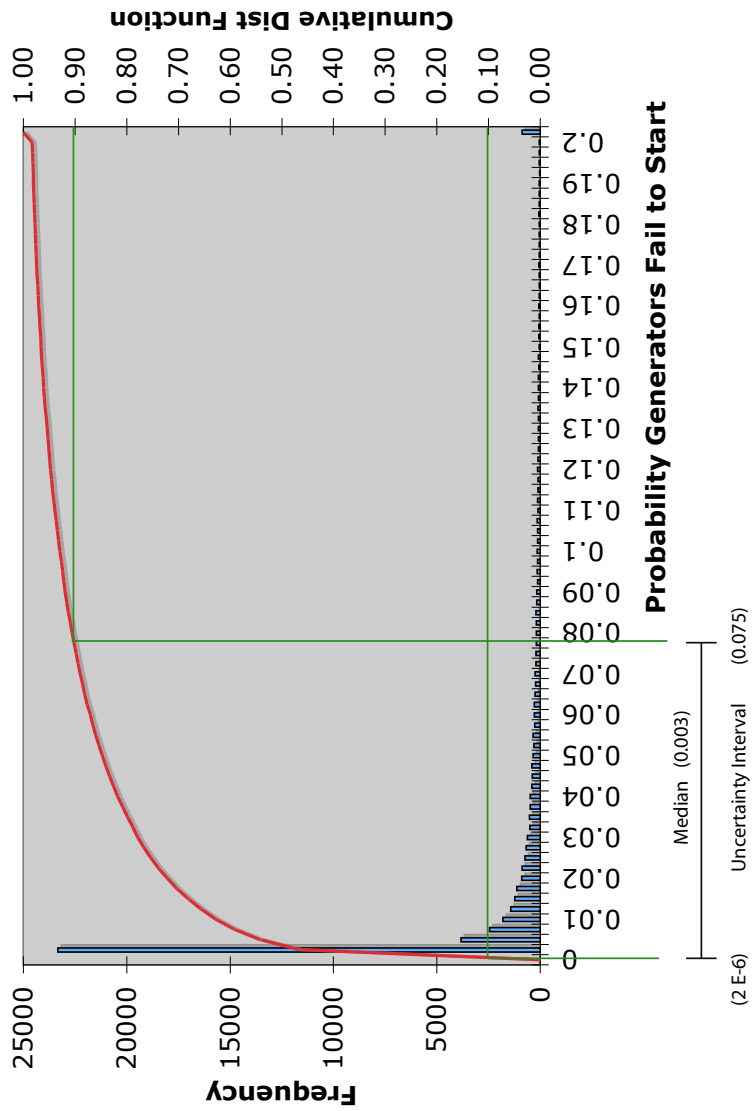
Figure 14. Generator Failure to Start Distribution
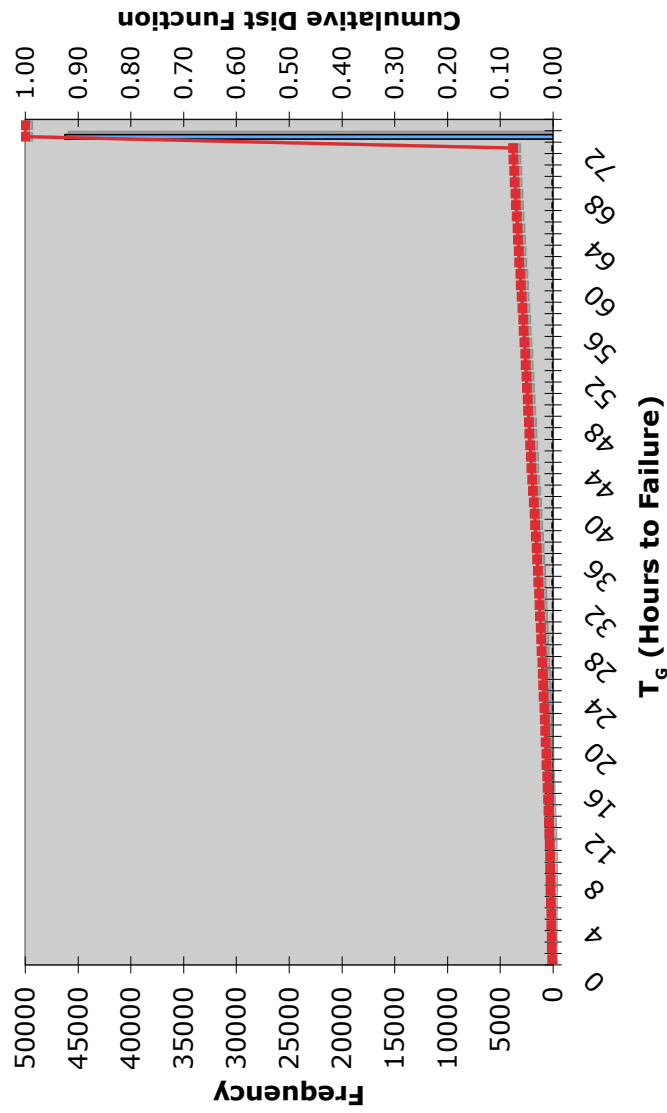
35

Figure 15. Generator Reliability Summary (T_G)

periods of time. Common batteries used in the telecommunications site include C&D [15] and East Penn [7]. The batteries are assumed to be in three groups of strings: Earth Station (16 strings), MSB-1 (28 strings), MSB-2 (16 strings). In particular, Plant 1 has an 8,000 amp shunt and has 16 strings of C&D HD-1300, Plant 2 has a 10,000 amp shunt and has 28 strings of C&D HD-1300, and Plant 3 has a 15,000 amp shunt and has 8 strings of C&D HD-1300 and 8 strings of East Penn AVR95-33.

Cantor et al [5] describes the performance characteristics of VRLA batteries by examining the *capacity* for the cells in its survey of VRLA batteries. Their definition of *failure* as used in their tables is that a cell did not meet a specific battery capacity level (e.g. 80%, 60%, or 50% capacity). Typically, the 80% capacity-level is used by manufacturers to determine a failed battery for the purposes of warranty protection. In communications with Sprint to determine the sizing of the batteries used at their Orlando site, it is assumed that Sprint uses the 80% capacity-level in order to size their batteries to meet a 3-hour backup power protection. If the batteries have not degraded and have closer to 100% capacity, it would be expected that the backup power might last up to 4 hours.

Per IEEE Std 1188 [14], the percent capacity of a VRLA battery at $25°C$ ($77°F$):

$$Pc = \frac{t_a}{t_s} \times 100 \tag{1}$$

where t_a is the actual time of the test to specified voltage level as corrected for temperature and t_s is the rated time to specified terminal voltage.

Per IEEE Standard 1188, it is assumed that although the Cantor paper lists a cell as *failed*, the battery cell is still providing some residual capacity. In particular, in Cantor [5] for VRLA batteries still in their useful life only 2% of the cells (332 out of 13733) failed to maintain a 50% capacity-level, 4% failed to maintain a 60% capacity-level, and 13% failed to maintain an 80% capacity-level. Assuming that this is an appropriate mixture of ages that are seen in the real world and normalizing the results: 5% of the cells would have failed to maintain a 50% capacity-level, 8% would have failed to maintain a 60% capacity-level, and 22% would have failed to maintain an 80% capacity-level.

Since the degradation of capacity is dependent on the use temperature, cycling, charging characteristics, etc., it is assumed that cells in a facility experience the same degradation of capacities over their lifetimes. In particular, consider the East Penn AVR95-33 (a complete 48V string comprised of 2 stacks being 6 modules high where each module has 2 cells and all 24 cells housed in the same cabinet), it is expected that all of the cells in the strings would have the same performance characteristics over their lifetimes.

From a reliability perspective, the multiple string arrangements at the Orlando site are assumed to take on a skewed probability density function curve as depicted in Figure 16. Given IEEE Standard 1188 and that Sprint uses 80% capacity for sizing a 3 hour backup time, the assumed capacities can be translated into the times to failure that would reasonably apply at the Orlando site. For 16-string: 2% chance of not working at all , 5% chance of discharging ≤ 2 hours , 25% chance of discharging ≤ 3 hours , 100% chance of discharging < 4 hours.
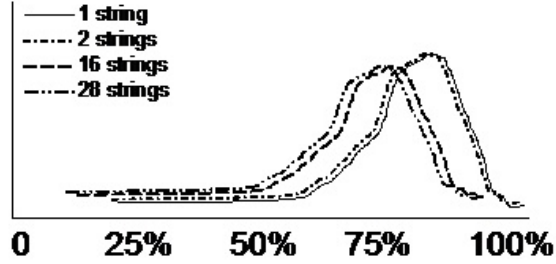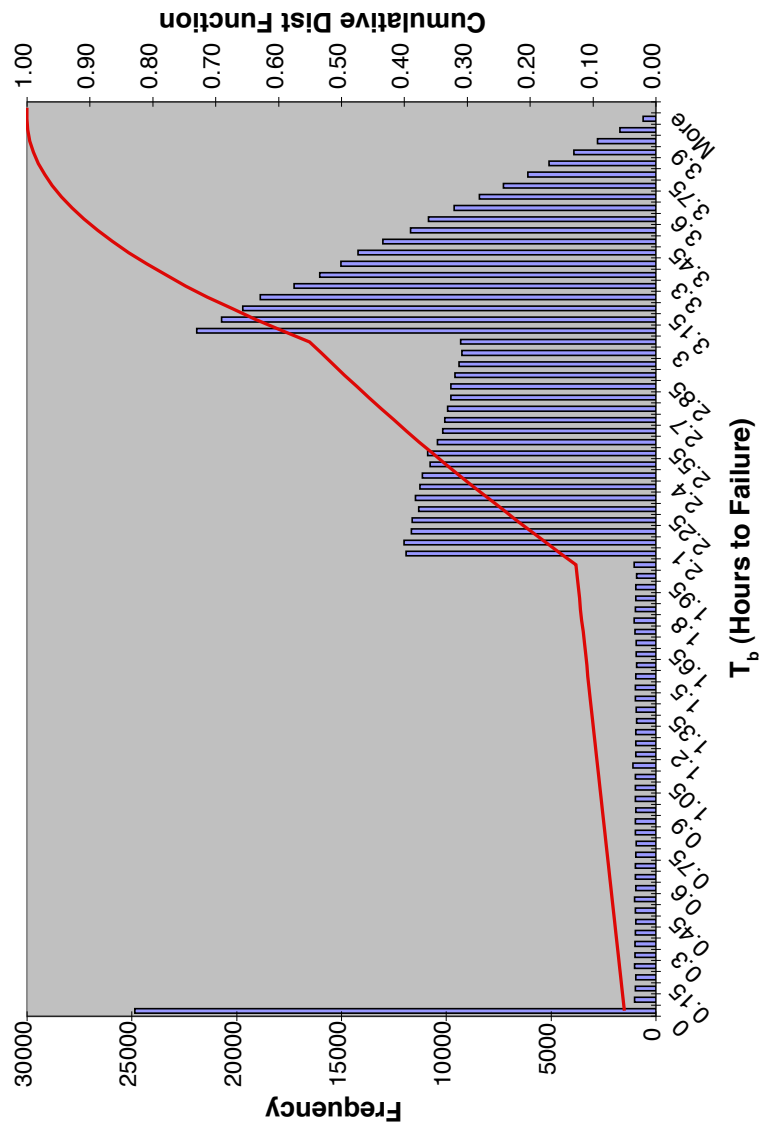
Figure 16. Battery Reliability

For 28-string: 3% chance of not working at all (increased chance over the 16-string), 8% chance of discharging $\leq$ 2 hours, 40% chance of discharging $\leq$ 3 hours, 100% chance of discharging $<$ 4 hours. Considering this distribution of discharge times, the final probability of failure of the supply of battery power to the facility is given in Figure 17.

6.5 Base Case Summary

Table 3 summarizes the results for the Base Case configuration; recall that this represents a summary of the reliability characteristics of the current configuration at the Sprint telecommunications facility under the operational scenario assumed. Figure 18 depicts the results graphically.

Table 3. Base Case Time to Failure Summary

Time to Failure	μ	σ	10.00%	median	90.00%
Base Case Total $T_{base} = T_U + T_G + T_B$	1130	1119	178.8	776.9	2531
Utility Time to Failure - T_U	1058	1120	107	706.2	2457
Generator Failure to Start	0.02414	0.04833	2.03E-06	0.00343	0.07514
Diesel Generator - T_G	69.57	10.04	72	72	72
Battery (time) - T_B	2.625	0.9331	1.294	2.869	3.53

38

Figure 17. Battery Reliability Summary (T_B)
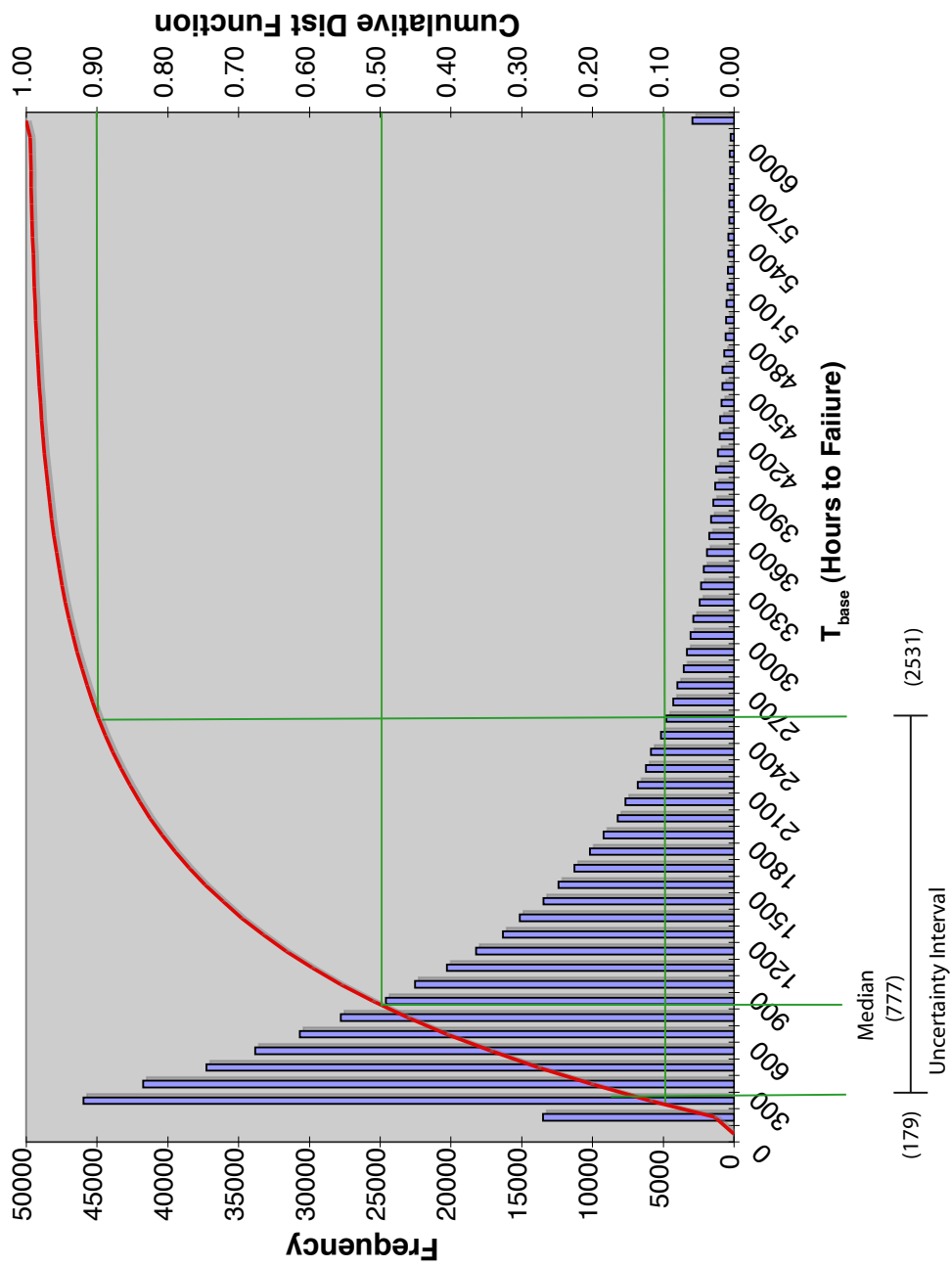
Figure 18. Base Case Reliability Summary (T_{base})

7 Base Case Considering Utility Repair

In this section, the possibility of repair of the utility power is explored. The analysis quantifies the power availability and provides a basis for comparison of the analysis results associated with the Base Case with the experience of Sprint engineers.

Let T_R be the time that it takes for the utility to restore power after an outage. If the time to restore utility power is more than the time that power is available through a combination of diesel generators and batteries, than the facility is without power for a period of time: $P\{facility\ down\}=P\{T_R < T_G + T_B\}$ (see Figure 19). If T_{base} is the time that power is available for the Base Case (no utility repair), then $T_{delta} = T_U + T_R - T_{base}$. The $P\{facility\ down\}= P\{T_{delta} < 0\}$.
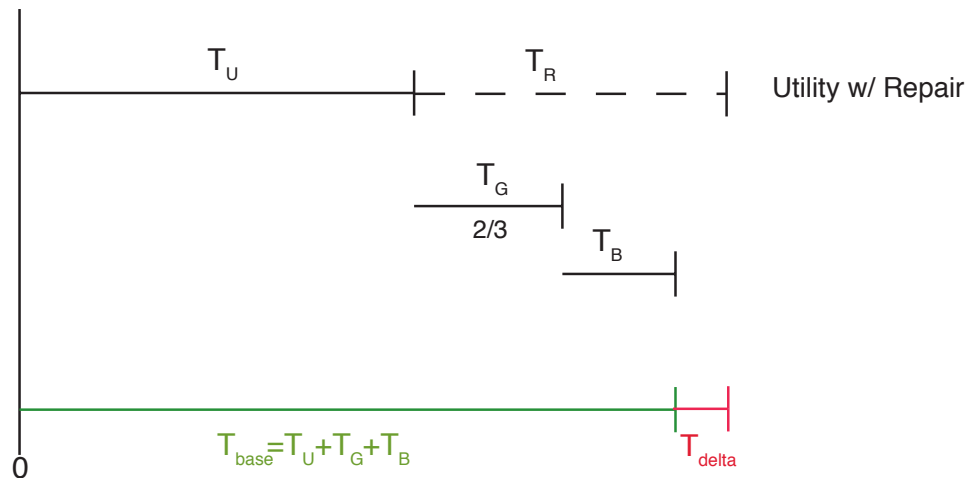
Figure 19. Time Line with Utility Repair (T_{delta})

7.1 Utility Down-time

As with the reliability characterization, it will again be assumed that the length of time that a utility power is not available is also an exponentially distributed random variable. Based on

data from Sprint the average outage time of $\mu_{outage} = 6.45$ hours, and a standard deviation of $\sigma_{outage} = 6.54$ hours [22]. By definition, $\lambda = 1/\mu$ so $E[\lambda] = 0.155$ and $V[\lambda] = 0.0234$.

As before, assume that the rate λ is a random variable characterized by a Gamma distribution with $E[\lambda] = \alpha\beta$, $V[\lambda] = \alpha\beta^2$, respectively. Simultaneously solving the two equations for the two unknowns yields values of: $\alpha = 1.0281$ failures/year and $\beta = 0.150801$. Figure 20 depicts the resulting Gamma distribution. The above analysis implies that there is a 90% probability that the repair rate is in the interval $[0.108634, 0.459933]$ repairs/hour or equivalently, that there is a 90% probability that the time to repair is in the interval $[2.17423, 117.464]$, as depicted in Figure 21.

7.2 Comparison

Figure 22 depicts the probability of the event $T_{delta} = T_R - (T_G + T_B)$ and the results are summarized in Table 4. As noted previously, the $Pr\{T_{delta} > 0\}$ is the probability that, under the assumptions in this analysis, the telecommunications facility is without power; the generators and batteries will either fail or be exhausted before utility power is restored. From the analysis, there is approximately an 8% chance the facility will be without power and a 7% chance that it will be without power for 10 hours or less. Conversations with engineers at Sprint have confirmed that, given the scenario, these results are reasonable. (For convenience, the specific values from Figure 22 are presented in Table 5.)

Table 4. Base Case Time to Failure Summary (w/Utility Repair)

Time to Failure	μ	σ	10.00%	median	90.00%
Base Case Total $T_{base} = T_U + T_G + T_B$	1130	1119	178.8	776.9	2531
Utility Time to Failure - T_U	1058	1120	107	706.2	2457
Generator Failure to Start	0.02414	0.04833	2.03E-06	0.00343	0.07514
Diesel Generator - T_G	69.57	10.04	72	72	72
Battery (time) - T_B	2.625	0.9331	1.294	2.869	3.53
Utility Time to Restore T_R	106.2	15300	0.7199	6.409	56.08
T_{delta}	35.49	12970	-73.99	-67.1	-9.985
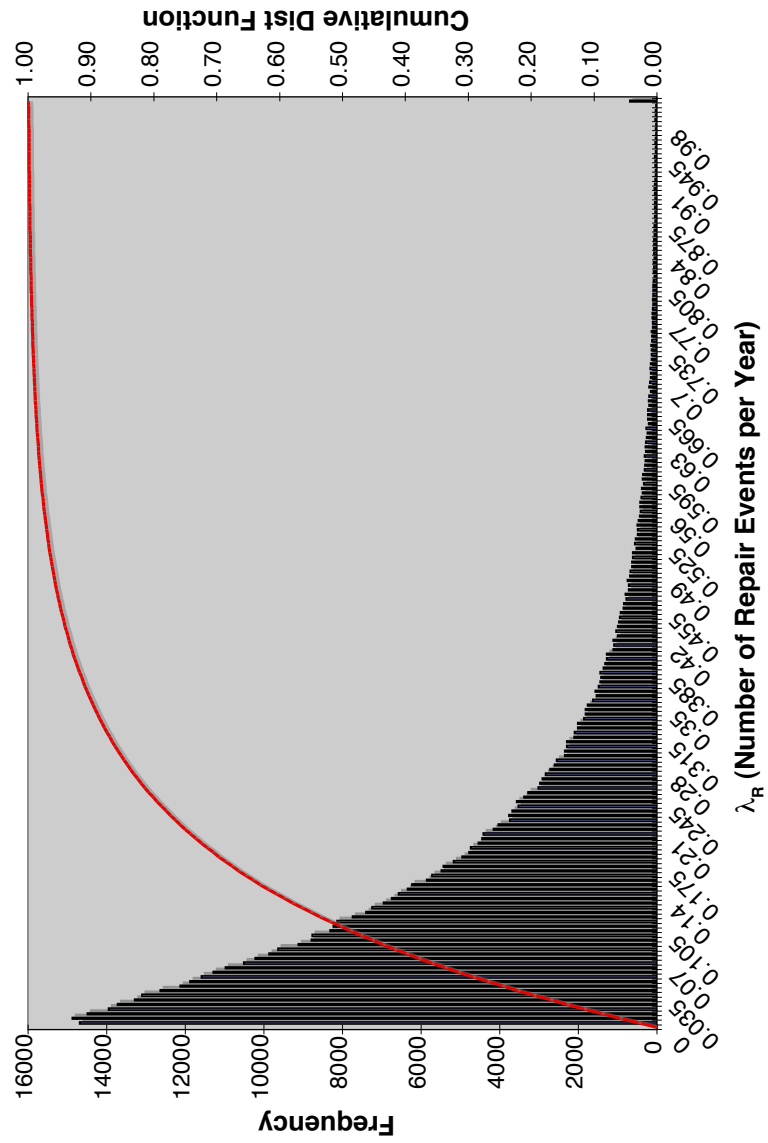
Figure 20. PDF of the Rate of Utility Repairs per Year
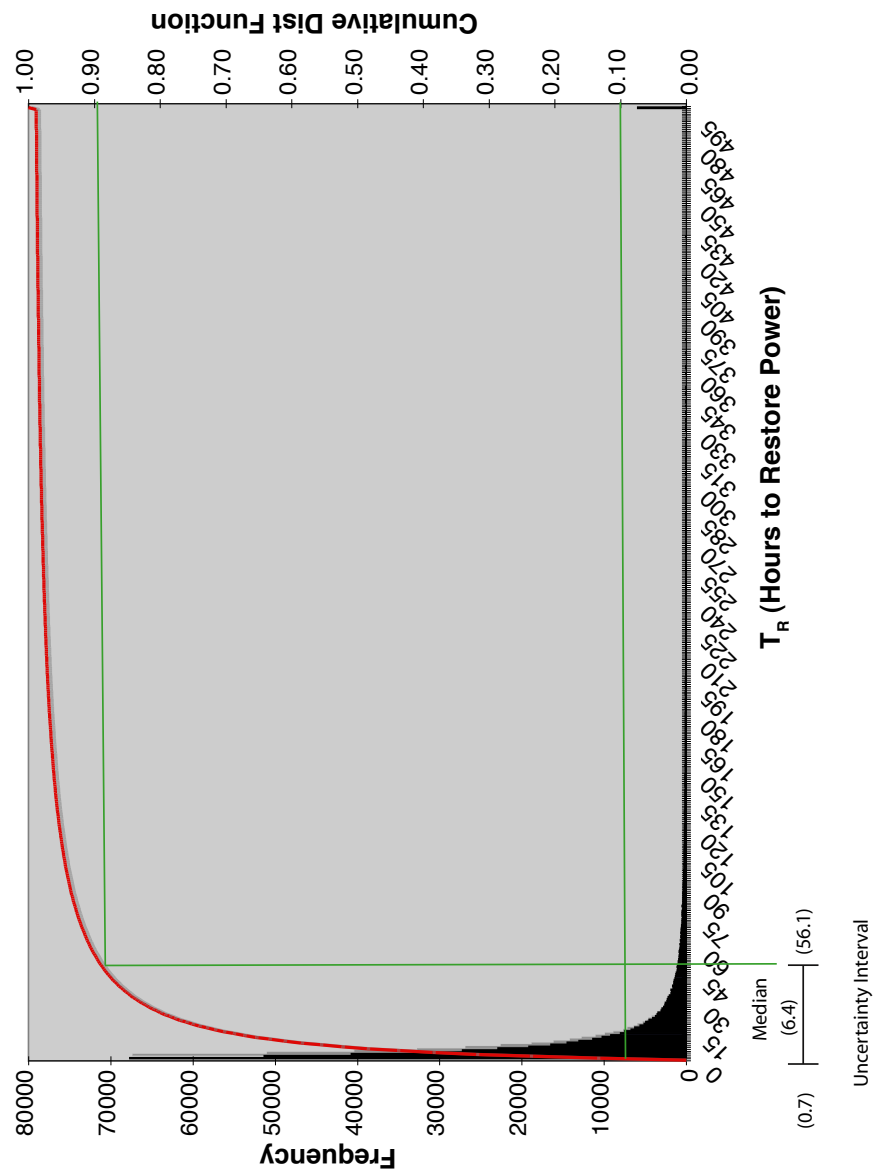
Figure 21. Time to Restore Utility Power (T_R)
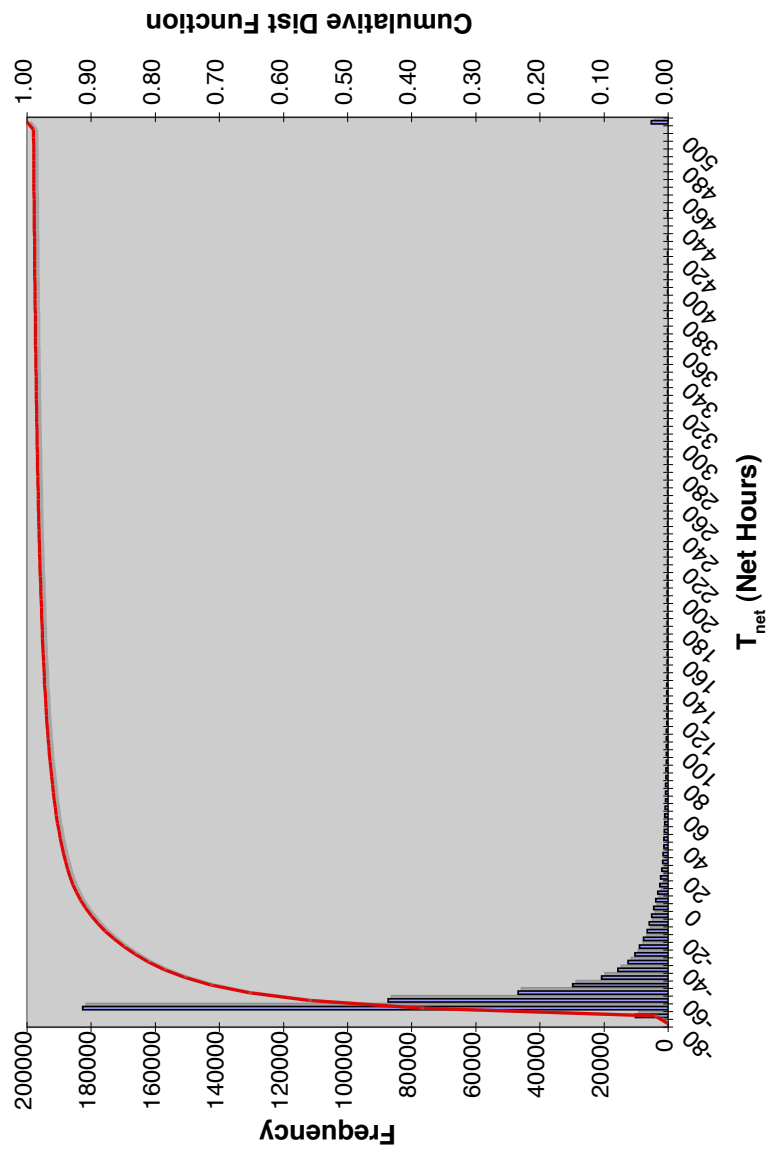
Figure 22. Net Utility Down Time ($T_{delta} = T_R - (T_G + T_B)$)

Table 5. Frequency Table of $T_{delta} = T_R - (T_G + T_B)$

T_{delta}	Frequency	Cumulative %
-80	0	.00%
-75	10137	2.03%
-70	182653	38.56%
-65	87289	56.02%
-60	46811	65.38%
-55	29781	71.33%
-50	20760	75.49%
-45	15691	78.62%
-40	12500	81.12%
-35	10333	83.19%
-30	8900	84.97%
-25	7611	86.49%
-20	6491	87.79%
-15	5831	88.96%
-10	5075	89.97%
-5	4468	90.87%
0	3856	91.64%
5	3207	92.28%
10	2567	92.79%
15	2245	93.24%
20	1917	93.62%
25	1681	93.96%
30	1522	94.27%
35	1333	94.53%
40	1258	94.78%
45	1112	95.01%

8 Distributed Energy Resources

The following sections discuss the analysis of two alternatives to traditional utility power. These alternatives are based on the use of natural gas turbines to provide generation of power immediately at the telecommunications facility. Two configurations of interest to Sprint were a single Kawasaki turbine and an arrangement of four pallets, each with six Capstone natural gas microturbines. Both of these configurations depend on a supply of natural gas; therefore, the reliable supply of the natural gas is critical. The immediate section addresses the supply of natural gas and the following sections document research into the two turbine configurations.

Effectively analysis of the operational scenario proposed by Sprint involves relying on the turbine as the primary facility power source and the use of the Base Case configuration as the backup power supply. This is depicted in Figure 23.
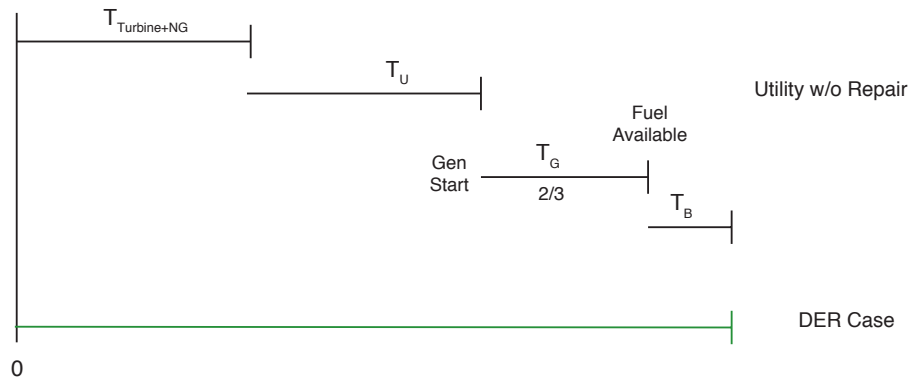
Figure 23. Time Line for DER Analyses

8.1 Natural Gas Pipeline Reliability

The Office of Pipeline Safety (OPS), within the U. S. Department of Transportation, Pipeline and Hazardous Materials Safety Administration (PHMSA), has overall regulatory responsibility for hazardous liquid and gas pipelines under its jurisdiction in the United States. Federal safety standards are described in U.S. Code of Federal Regulations (CFR), Title 49 *Transportation*, Parts 190 - 199 [19]. There are over 2 million miles of pipelines that support the movement of hazardous liquids, natural gas and propane. The two types of natural gas pipelines are transmission and distribution. Transmission lines typically involve the transportation of natural gas between a storage facility or between a distribution center and a large volume customer. There are approximately 305,000 miles of transmission pipeline in the US. In general, pipelines that are not transmission related are distribution pipelines. Distribution lines branch from transmission lines and supply natural gas to consumers. The

focus of this effort involves the 1,860,000 miles of pipeline involved with distribution of natural gas.

There are a number of failure modes for pipelines, most of which are unique to the area where the pipeline is located and include corrosion, external forces (such as excavation or natural forces), and material failure among many other factors. To characterize the probability of failure of a particular distribution line can be extremely complicated. For example, failure due to corrosion is dependent on such factors as the type and condition of the pipes coating, the effectiveness of corrosion control equipment, and the soil conditions surrounding the pipe. Alternatively, the probability of pipeline damage as the result of third party damage depends on, for example, the extent and type of excavation or agricultural activity along the pipeline right-of-way and the depth of cover over the pipeline.

The natural gas provider in Orlando has indicated that they will furnish and install the pipeline some 4 miles (6.437 km) away. A typical feeder line for a natural gas turbine (e.g. a 1.5 mW Kawasaki turbine site in San Luis Obispo, CA) has a 4" (101.6 mm) feeder with cutoff connected into an on-site turbine compressor station. A 4" (101.6 mm) pipe is connected into the turbine from the pump station.

Historically, the dominant failure mode for natural gas distribution pipe line is a result of external factors involving third-parties, e.g. excavation. The rate at which these failures occur are a function of the buried depth, how well the pipeline is marked, the density of the population and the land use of the area of interest. The factors can be used to augment the basic failure rate established for pipes of a particular diameter [17].

Contribution of external factors to the failure rate of the pipeline:

$$\lambda_{Ext} = \lambda_d K_{dc} K_{wt} K_{pd} K_{pm}$$

where λ_d is the basic failure rate for pipes of diameter d, and the correction factors K_{dc}, K_{wt}, K_{pd}, and K_{pm} account for failure due to third-party activities: buried depth, wall thickness, population density and prevention method. Assuming a distribution pipe diameter of 102 mm, an estimate of the basic failure rate is $\lambda_d = 0.218$ failures/ 1000 km-year (Table 2, [17]) .

It is assumed that for the facility in question that the area is rural $K_{pd} = 0.81$ and best protection method is employed and the length of pipe is 6.44 km. Estimates of the failure rates are from [20], and [17]. Specifically, the following assumptions are made in the analysis:

K_{dc} - worst case is to assume depth of cover is less than 0.91 m: $K_{dc} = 2.54$, best case is to assume that depth of cover is greater than 1.22 m: $K_{dc} = 0.54$.

K_{wt} - worst case is to presume that the wall thickness of pipe will be no more than the minimum of 4.8 mm: $K_{wt} = 1.0$ and best case assumes that the thickness is greater than 4.8 mm: $K_{wt} = 0.2$.

K_{pd} - the location of the telecommunication center appears to be rather remote (7 miles of dirt road). Assume that the area is rural (best case): $K_{pd} = 0.81$ and the worst case assumption is that the distribution pipe is laid through a densely populated area: $K_{pd} = 18.77$.

K_{pm} - worst case situation implies that there are only marker posts to delineate the location of the distribution line: $K_{pm} = 1.03$ while for best case additional methods are used: $K_{pm} = 0.91$.

Best Case (failures/year):

$$
\begin{aligned}
\lambda_b &= \lambda_d K_{dc} K_{wt} K_{pd} K_{pm} * d \\
&= (0.000218)(0.54)(0.2)(0.81)(0.91)(6.44) \\
&= 0.000112
\end{aligned}
$$

Worst Case (failures/year):

$$
\begin{aligned}
\lambda_b &= \lambda_d K_{dc} K_{wt} K_{pd} K_{pm} * d \\
&= (0.000218)(2.54)(1.0)(18.77)(1.03)(6.44) \\
&= 0.06894
\end{aligned}
$$

The probability of failure in one year is then assumed to be in the range: $F_{ng} = \{1 - \exp[-0.000112] = 0.000012, 1 - \exp[-0.06894] = 0.06662\}$. The failure rate of pipeline is assumed to be a random variable characterized by a lognormal distribution with a 5% lower limit of 0.000112 and an upper 95% limit of 0.06894.

$$
f(\lambda|\mu, \tau) = \sqrt{\frac{\tau}{2\pi\lambda^2}} \exp\left[-\frac{\tau}{2}(\log\lambda - \mu)^2\right], \qquad \lambda > 0 \tag{2}
$$

Solving for μ and τ given the upper and lower bounds yields values of $\mu = -5.88577$ and $\tau = 0.262366$. Figure 24 depicts the final distribution for the time to failure of the natural gas pipeline. As with other elements in the system, the time to failure for the pipeline is assumed to be an exponentially distributed random variable: $T_{NG} \sim \exp[-\lambda_{NG}t]$, where λ_{NG} represents the rate at which pipeline failures occur.

8.2   Capstone Microturbine Analysis

The Capstone microturbines were suggested by Sprint as one possible alternative power generation source. Emissions are low: approximately 2.3 ppmvd NOx per generator for 75% loading and about 2.0 ppmvd NOx for 100% loading (parts per million on dry volume basis).

Figure 25 shows six C60 microturbines being used to provide prime power and heat at the Guisborough Hall luxury hotel in the UK (photo courtesy of Capstone).
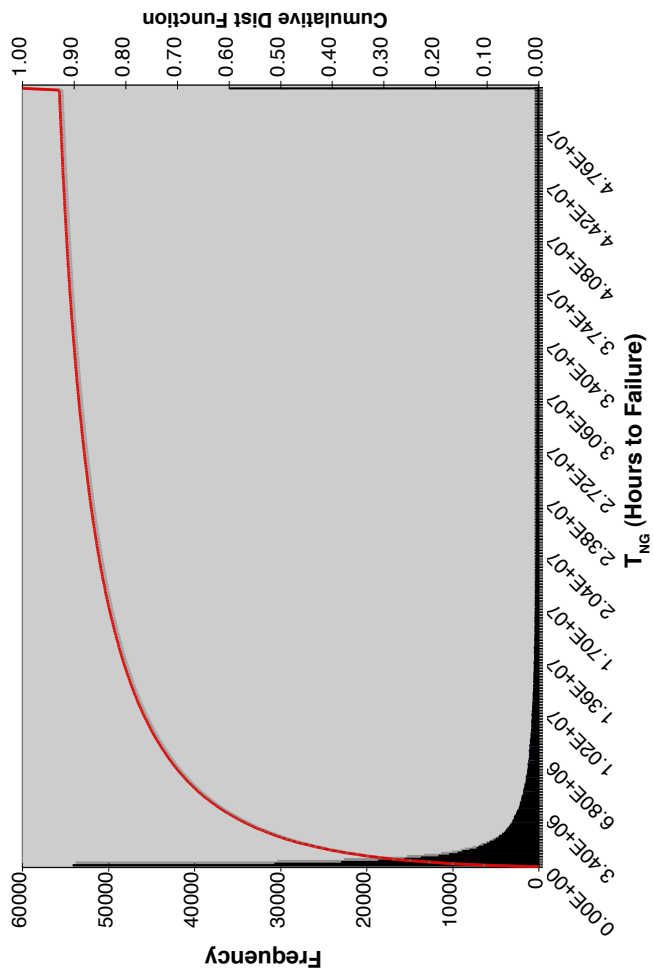
Figure 24. Natural Gas Time to Failure (T_{NG})

50

Figure 25. Six Capstone C60 Turbines at Guisborough Hall, UK

The current planned configuration of Capstone turbines consists of four pallets of six turbines for a total of 24 turbines. Each turbine is capable of 60 kW of output and for efficiency purposes the turbines are exercised at 90% of their capacity. The total available power is then 1.296 mW. The current maximum demand is approximately 1.1 mW, leaving an excess capacity of 196 kW. At the peak level of loading, only 21 of the 24 Capstone turbines are needed to supply power for MSB-1, MSB-2 and the Earth Station combined. Sprint suggested that the facility could be supported at a minimum level if even seven of the microturbines were unavailable.

According to Capstone engineers, these turbines are currently in-place at a variety of locations and have attained 95% availability. The overall design life is 40,000 hours and Capstone engineers have estimated the mean time to failure to be 8000 hours and noted that they expect this to double over the next few years. There are scheduled maintenance activities at 8,000 and 20,000 hours. The 8,000 maintenance is to change air and some other filters and replacing the igniter. The downtime for this service is 3 hours. The 20,000 hour service includes the 8,000 hour actions plus changing of fuel injectors. The downtime for this service is 12 hours.

To characterize the uncertainty in the failure rate for a single Capstone microturbine, it was assumed that there was a 20% chance that the failure rate would be greater than $\lambda = 1/8000$. Further, it was assumed that there was an 90% probability that the failure rate

would be less than $\lambda = 1/16000$. (The relatively large value of 20% was due to the lack of field data to support the $1/8000$ estimate.)

Finally, assuming an underlying lognormal distribution for the turbine failure rate and solving for μ and τ yields values of $\mu = -9.40558$ and $\tau = 9.38253$. The time to failure for a single Capstone turbine is assumed to be an exponentially distributed random variable: $T_{C_1} \sim \exp[-\lambda_{C_1}t]$, where λ_{C_1} represents the rate at which turbine failures occur. Figure 26 depicts the resulting distribution for the time to failure for a single Capstone turbine.

Since there is excess capacity with the Capstone package of turbines, the system can be operated in two modes: cold standby or hot standby. In cold standby, the excess turbines are not operated and are started only in the event of a failure of one of the primary generators. In hot standby, all 24 turbines are operated continuously, but each at a lower load level. In either case, the minimum number of turbines operating at full capacity defines the point at which the DER system can successfully provide power to the facility.

One configuration suggested by Sandia consisted of running the 21 turbines with the full available load and the cycling through the remaining three turbines during peak load. In this case the three turbines are available in 'cold standby'. In this configuration, the turbines are running at approximately 87% of their capacity for a net efficiency of about 28%. While this configuration was not fully investigated, the overall reliability of the Capstone system would increase (relative to the following discussion). However, issues associated with failure at turbine start-up from cold-standby would need to be considered and may offset the gain in reliability.

An alternative configuration suggested by Sprint involved running the full bank of twenty-four turbines to support the available load. The drawback of this approach is a small drop in turbine efficiency. In this configuration, the turbines are running at approximately 76% of their capacity for a net efficiency of approximately 27.5%. The final configuration proposed by Sprint and addressed in the following discussion, involves running all 24 turbines until seven turbines fail. It was felt by Sprint engineers that this was a more likely scenario and that the seven failures would reflect a worst case operational configuration.

Figure 27 depicts the results for the analysis assuming the failure of seven turbines or the loss of the supply of natural gas. The median time to failure for the seventh turbine is perhaps a bit surprising at 3800 hours, considerably less than the 8300 hour median time to failure for an individual Capstone turbine. This is an artifact of running all 24 Capstones simultaneously with no repair. As depicted in Figure 23, assume that the Capstone microturbines as the primary power source for the facility and the current system, (i.e. Base Case) is used as a backup power source. Figure 28 summarizes the probability distribution of the time to failure for the Capstone configuration. Finally, another reliability issue relates to the physical configuration of four pallets of six turbines. Depending on how the the power system was configured, it is possible that a single failure of the power distribution system might result in an entire pallet of six (operational) turbines being off-line. The outcome would be configuration that was a single point of failure for the entire facility. The likelihood of these events is very low, but requires attention during design.
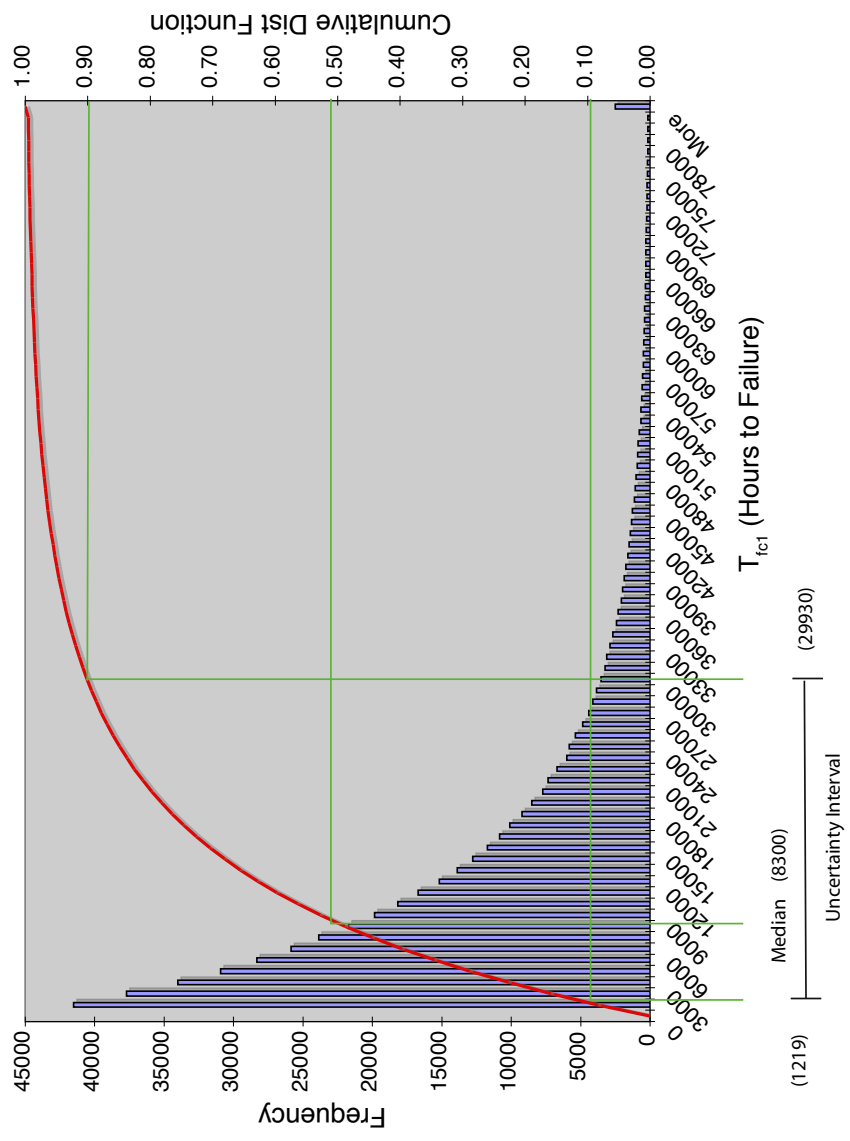
**Figure 26.** Capstone Single Turbine Hours to Failure (T_{C_1})
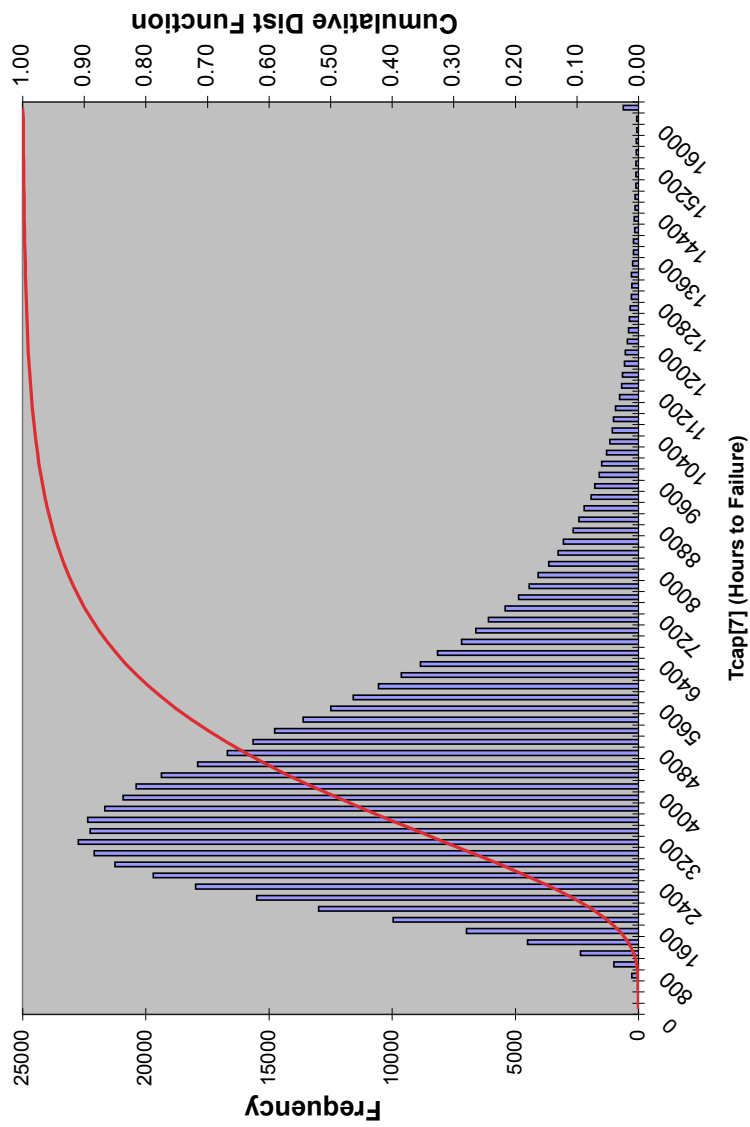
Figure 27. Capstone Configuration w/7 Failures (T_{cap7})
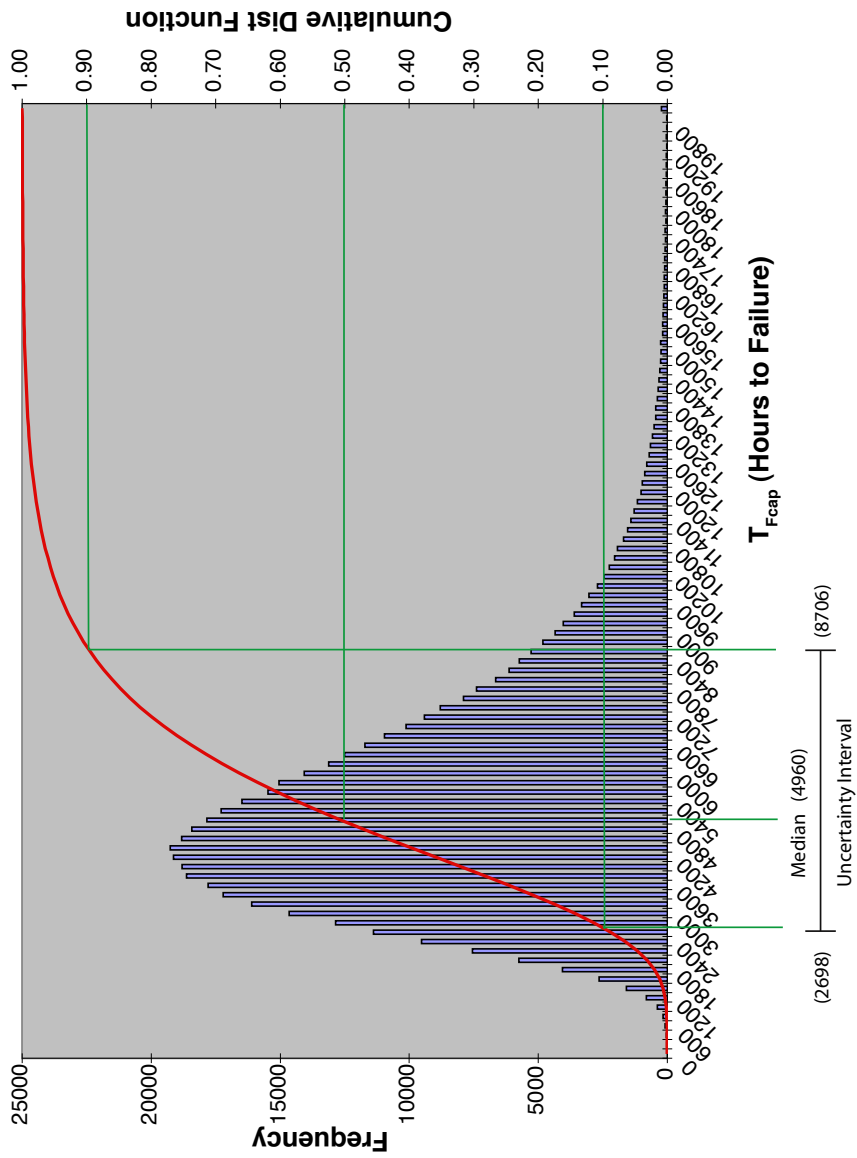
Figure 28. Facility Time to Failure w/Capstone Configuration (T_{FC})

8.3 Kawasaki Turbine

A second power system configuration involves the use of a single Kawasaki natural gas turbine. A typical turbine for this application is the GPB 15X 1.5 mW turbine (Figure 29). With the addition of an combustion/catalyst system the emissions of the Kawasaki turbine are low: approximately 3 ppmvd (parts per million on dry volume basis) NOx (15% O^2) over a broad range of power. Kawasaki has provided an MTTF = 200,974 hours and an
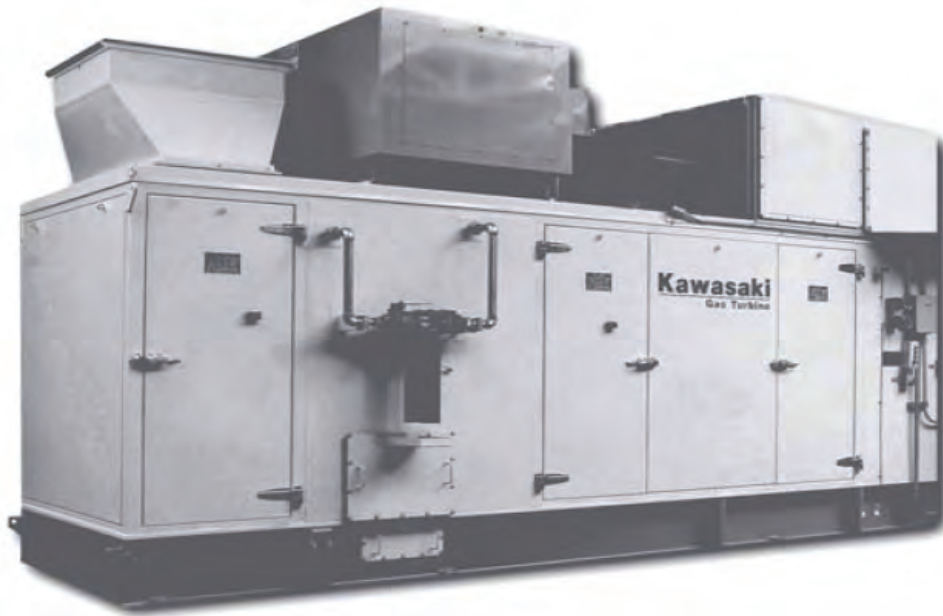

Figure 29. Kawasaki Turbine

MTTR = 3.1 hours, based on a sample of 150 installed units. The pictures in Figure 30 are from the Kawasaki GPB brouchure [18]. To characterize the uncertainty in the failure rate for a Kawasaki turbine, it is assumed that there was a 10% chance that the failure rate would be greater than $\lambda_K = 1/200974$. Since this number is exceptionally high, to be conservative, it is assumed that the median failure rate was twice as bad as that reported by Kawasaki. This implies that there is a 50% chance that the failure rate might be as high as $2 \times \lambda_K$.

As with the Capstone mircroturbine, the failure rate is assumed to be a random variable characterized with a lognormal distribution. Solving for μ and τ yields values of $\mu = -11.5.178$ and $\tau = 3.41839$. The time to failure for a single Kawasaki turbine is assumed to be an exponentially distributed random variable: $T_K \sim \exp[-\lambda_K t]$, where λ_K represents the rate at which turbine failures occur. Given the estimated values for μ and τ, Figure 31 depicts the resulting distribution for the time to failure for a Kawasaki turbine. Note that, while the lower bound on the uncertainty interval is very high, there is substantial uncertainty in the time to failure. This is an artifact of the assumption that there may be
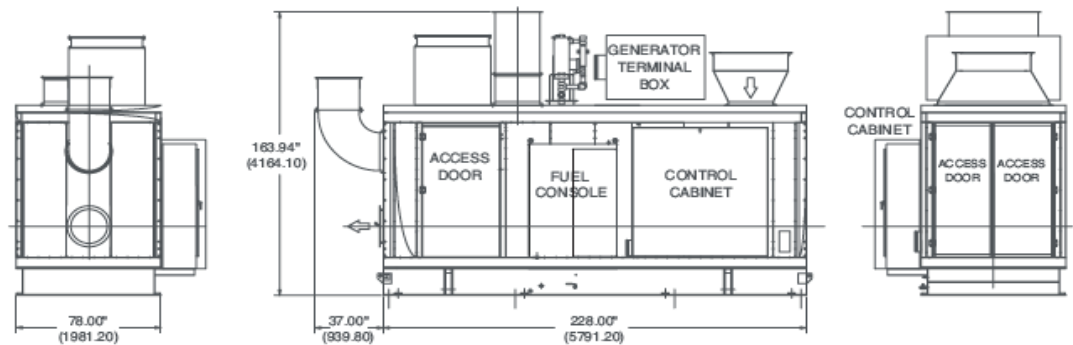
Figure 30. Kawasaki Footprint

considerable uncertainty assumed in the failure rate estimate provided by Kawasaki. The assumptions used in characterizing the failure rate 'pulled' the time to failure distribution in Figure 32 to the left while allowing for the possibility that the estimates of the failure rate provided by Kawasaki may be reasonable. One perspective on this result is that there is a high probability that the Kawasaki turbine will result in a much higher reliability.

As depicted in Figure 23, assume that the Kawasaki turbine acts as the primary power source for the facility and the current system, (i.e. Base Case) is used as a backup power source. The time to failure for a facility depending on a single Kawasaki natural gas turbine as the power source is summarized in Figure 32.
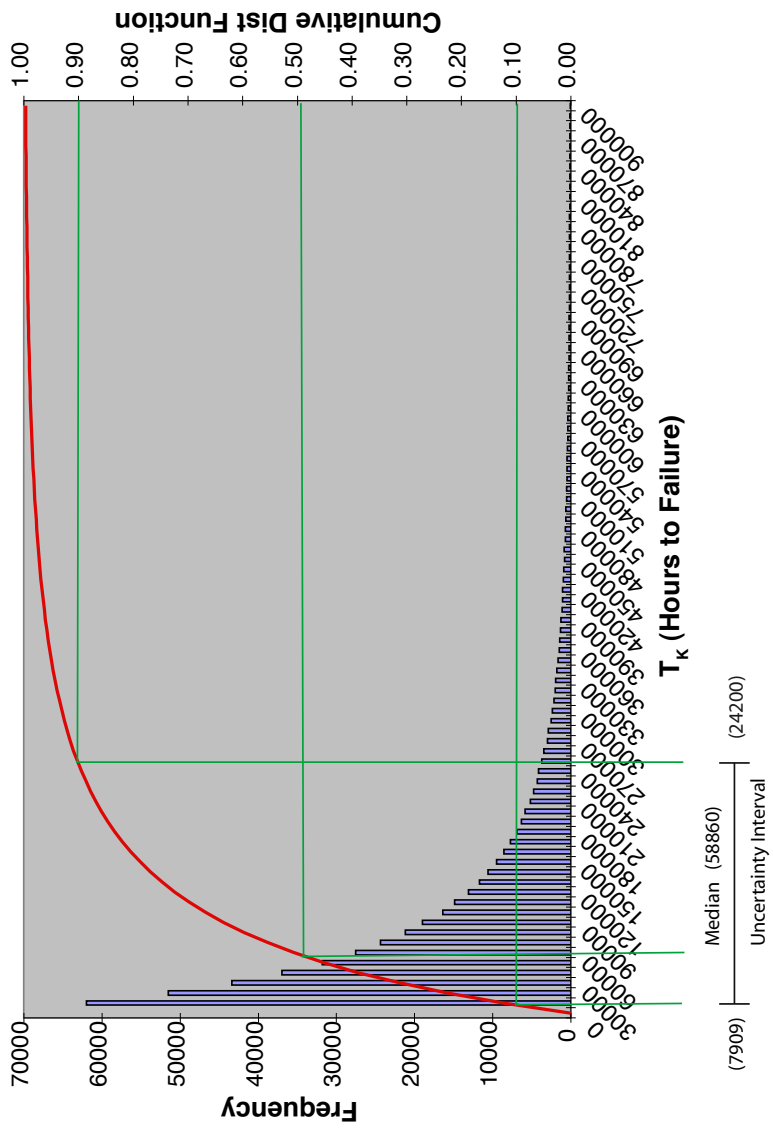
Figure 31. Kawasaki Turbine Hours to Failure (T_K)

58
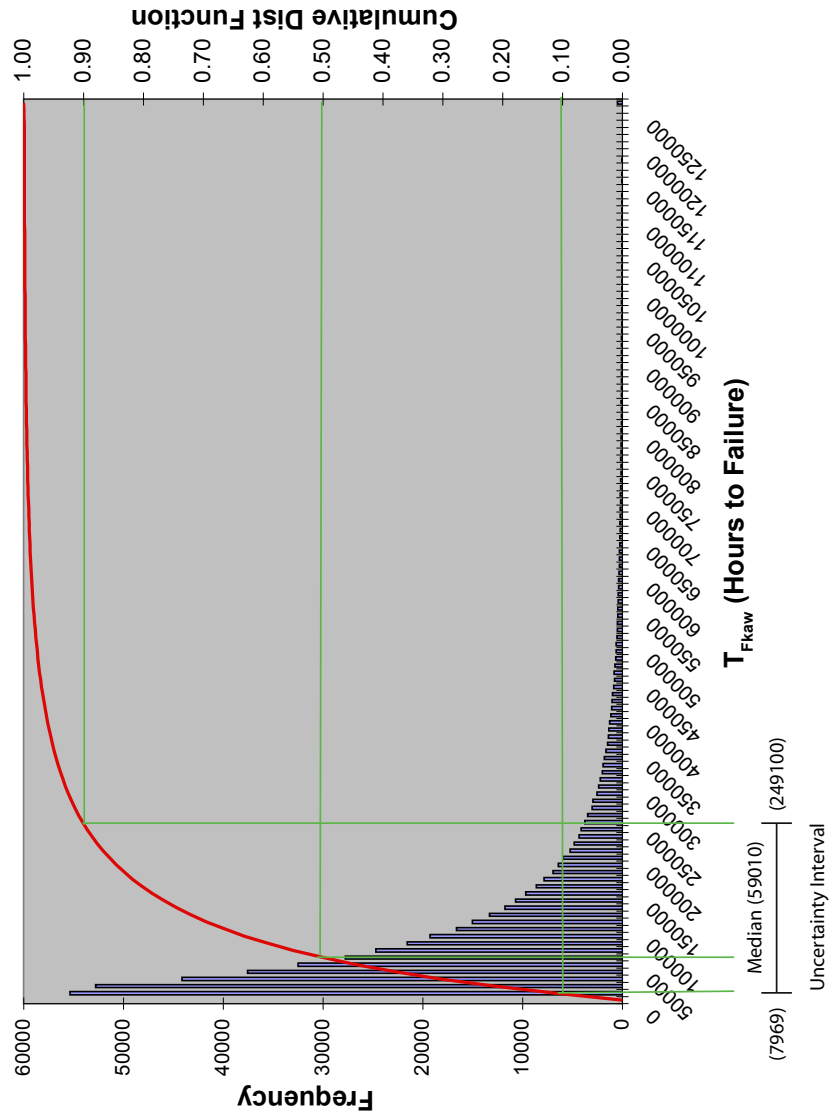
Figure 32. Facility Time to Failure for Kawasaki Configuration (T_{F_K})

9 Conclusion

Figure 33 summarizes the results of the three analyses: Base Case, Capstone microturbine array, and the single Kawasaki turbine. The overlay provides the capability to make a risk-based decision of the relative reliability benefits of the the three alternatives through a comparison of the credibility limits for each alternative. Table 6 provides a summary of all previous related analysis.

Table 6. Analysis Summary

Time to Failure	μ	σ	10.00%	median	90.00%
Capstone TTF T_{F_C}	5419	2514	2698	4960	8706
Kawasaki TTF T_{F_K}	1.04E+05	137200	7969	59010	249100
Base Case Total T_{base}	1130	1119	178.8	776.9	2531
Utility Time to Failure - T_U	1058	1120	107	706.2	2457
Generator Failure to Start	0.02414	0.04833	2.03E-06	0.00343	0.07514
Diesel Generator - T_G	69.57	10.04	72	72	72
Battery (time) - T_B	2.625	0.9331	1.294	2.869	3.53

Since there is no overlap between the credibility limits a comparison is relatively straightforward. Consider a comparison between the reliability of the current power supply (i.e. Base Case) and the array configuration of Capstone microturbines suggested by Sprint. There is a 90% chance that the utility power will fail before 2457 hours, while there is a 90% chance that the Capstone array will provide power for at least 2698 hours.

Finally, consider that there is a 90% probability that the Capstone array will fail to provide power for less than approximately 8706 hours, while there is a 90% probability that the single Kawasaki turbine will provide power for at least 7969 hours.

A significant, but not decisive element in the lower reliability estimate for the Capstone was the configuration and operational plan suggested by Sprint. Other configurations could have quite different reliability characteristics and may warrant further investigation. However, there are installation issues associated with the Capstone, e.g. special enclosure, that could be a factor in the final decision.

Not considered in the analysis for either the Kawasaki or Capstone configurations is the probability that the turbines will fail to start when called. Just as with the diesel generators, there is a likelihood that if the Capstone turbines are left in cold-standby, they will fail to start. Clearly, this is less of a consideration of the Kawasaki turbine since this turbine is on 24/7. Also, not considered in the analyses is consideration for the differences in the control systems for the two turbines.

In conclusion, even given the uncertainties in the three alternatives, the clear choice

is the use of the Kawasaki 1.5 mW turbine as the primary power source for the Sprint telecommunication facility.
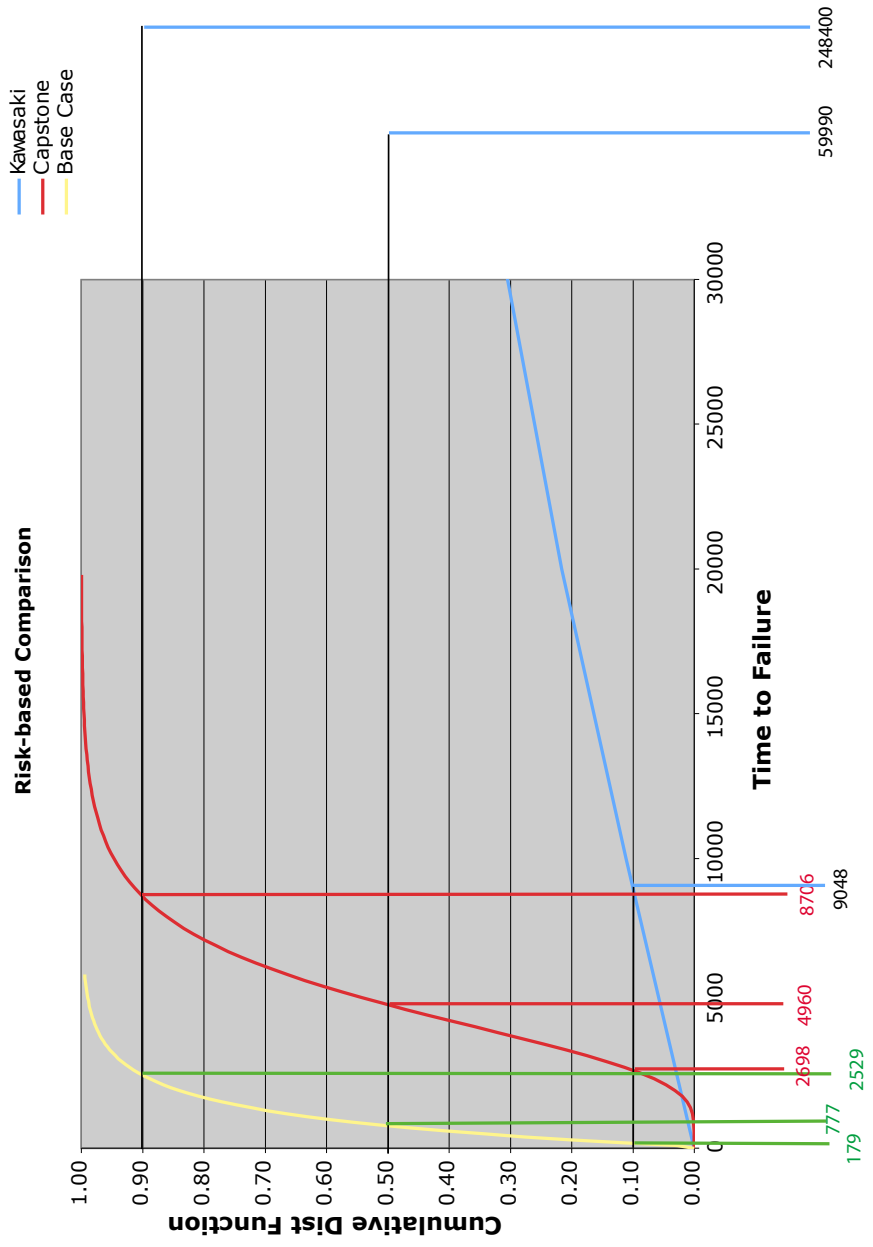
Figure 33. Summary of Results

References

[1] IEEE Std 1366-2003. *Guide for electric power distribution reliabilty indices,*. IEEE, 2004.

[2] IEEE Std 493-1997. *Recommended Practice for the Design of Reliable Industrial and Commercial Power Systems*. IEEE, December 1997.

[3] C. Atwood, D. Kelly, F. Marshall, D. Prawdzik, and J Stetkar. Evaluation of loss of offsite power events at nuclear power plants: 1980 - 1996. Technical Report EXT-97-00887, Idaho National Engineering and Environmental Laboratory, Nuclear Operations Support Programs Lockheed Martin Idaho Technologies Company Idaho Falls Idaho 83415, November 1997.

[4] P. Butler, J. Dunleavey, M. Farber-DeAnda, and P. Mosely. Performance of valve-regulated lead-acid batteries in real-world stationary applications - utility installations. *J. of Power Sources*, (96):94–101, 2001.

[5] W. Cantor, E. Davis, D. Feder, and M. Hlavac. Performance measurement and reliability of vrla batteries. II. the second generation. *Telecommunications Energy Conference, 1998. INTELEC. Twentieth International*, pages 269–380, October 1998.

[6] Davies Consulting. State of reliability related regulation in the United States. Presentation, EEI, April 2005.

[7] Deka. Telecommunications batteries, 2006. http://www.eastpenn-deka.com/index.html.

[8] T. Devlin. Annual distribution service reliability reports. Technical report, Florida Public Service Commision, Capital Circle Office Center, 2540 Shumard Oak Blvd., Tallahassee, FL 32399, March 2005.

[9] G. Grant, J. Poloski, A. Luptak, C. Gentillon, and W Galyean. *Emergency Diesel Generator Power System (1987-1993)*, volume Vol. 5. U.S. Nuclear Regulatory Commission, 1996.

[10] G. Grant, J. Poloski, A. Luptak, C. Gentillon, and W Galyean. *Emergency Diesel Generator Power System (1997-2003)*. U.S. Nuclear Regulatory Commission, 2005.

[11] P. Hoeppe and G. Berz. Risks of climate change - the perspective of the (re-)insurance industry. In *2005 IEEE POWER ENGINEERING SOCIETY GENERAL MEETING, VOLS, 1-3*, pages 2023–2026, 2005. Article English.

[12] C. Hor. Analyzing the impact of weather variables on monthly electricity demand. *IEEE transactions on power systems*, 20(4):2078–2085, 2005. 0885-8950.

[13] J. Houghton. *Global Warming*. Cambridge University Press, Cambridge, 4 edition, 2005.

[14] IEEE-STD-1188-1996. *IEEE recommended practice for maintenance, testing, and replacement of valve-regulated lead-acid (VRLA) batteries for stationary applications.* IEEE Std ; 1188-1996. IEEE, New York, 1996.

[15] C & D Technologies Inc. Standby Power Division, 2005. http://www.cdstandbypower.com/.

[16] M. Ivey, A. Ahkil, D. Robinson, K. Stamber, J. Stamp, and K. Chu. Accomadating uncertainty in the planning and operations of electric power systems. Technical Report SAND2000-1681, Sandia National Laboratories, July 2000.

[17] Bum Jong Ahn Jo, Young-Do. A method of quantitative risk assessment for transmission pipeline carrying natural gas. *Journal of Hazardous Materials*, (A123):1–12, 2005.

[18] Kawasaki. Kawasaki gas turbines - america.

[19] Office of Pipeline Safety. Department of Transportation. http://primis.phmsa.dot.gov/comm/Index.htm.

[20] G. A. Papadakis. Major hazard pipelines: a comparative study of onshore transmission accidents major hazard pipelines: a comparative study of onshore: transmission accidents. *Journal of Loss Prevention in the Process Industries*, 12:91–107, 1999.

[21] S. S. Parkpoom. Climate change impacts on electricity demand. In *UPEC 2004: 39TH INTERNATIONAL UNIVERSITITIES POWER ENGINEERING CONFERENCE, VOLS 1-3*, volume 1, pages 1342–1346, 2005.

[22] M. Pitts. Ne outage summary.xls, 2003.

[23] M. Pitts. Epripower outage2.xls, 9 September 2005.

[24] M. Pitts. Orlando generator and power history1.xls, 9 September 2005.

[25] M. Pitts. Orlando wireline switch: Standby power system study, 22 March 2005.

[26] M. Pitts. Power outages 2003-04.xls, 9 September 2005.

[27] D. Robinson. Impact of deregulation on power grid reliability: A case study. In *American Nuclear Society Workshop*, Washington, DC, 1998. American Nuclear Society.

[28] D. Robinson, A.D. Patton, and C. Sing. The impact of restructuring policy changes on power grid reliability. Technical Report SAND98-2178, Sandia National Laboratories, 1998.

[29] D. Spiegelhalter, A. Thomas, and N. Best. WinBUGS version 1.4.1 user manual, September 2004. http://www.mrc-bsu.cam.ac.uk/bugs/.

[30] C. Warren and J. Bouford. Classification of major event days. In IEEE, editor, *Transactions IEEE T&D Conference*. IEEE Working Group on System Design, July 14 2003.

[31] A. F. Zobaa. Climate change risks and financial sector. In *IEEE Power Engineering Society General Meeting*, pages 2945–2949, 2005.

A Original Fault Trees
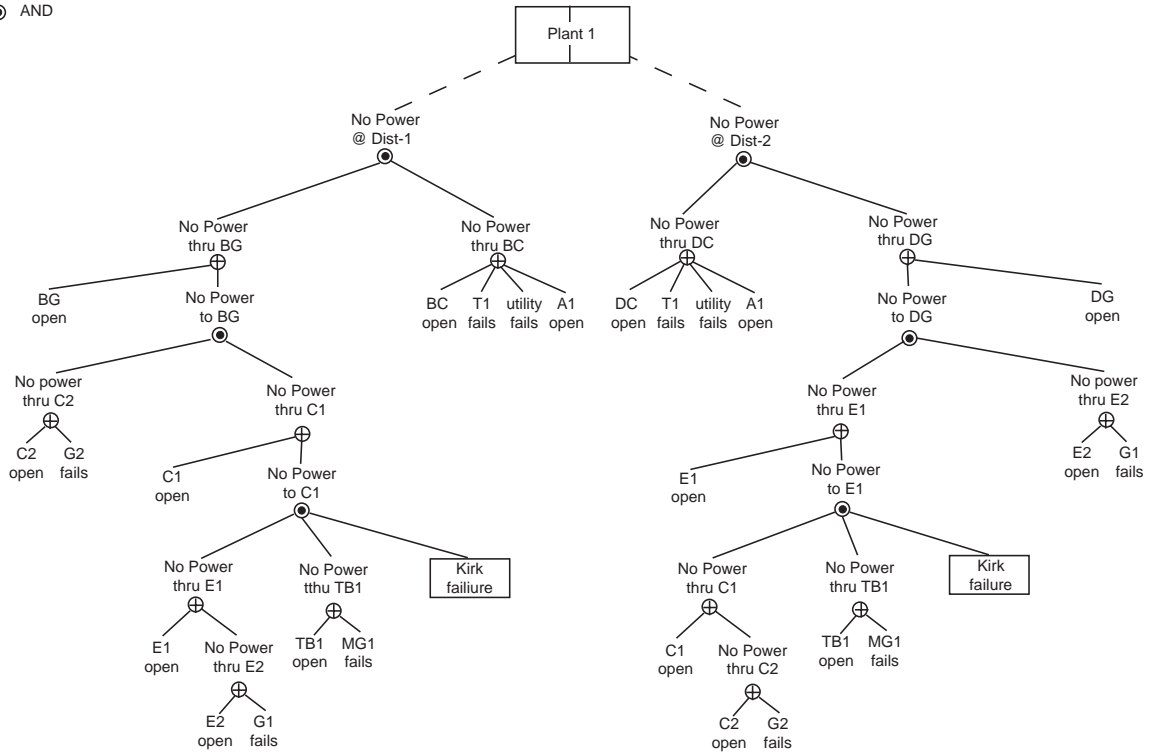
Figure A.1
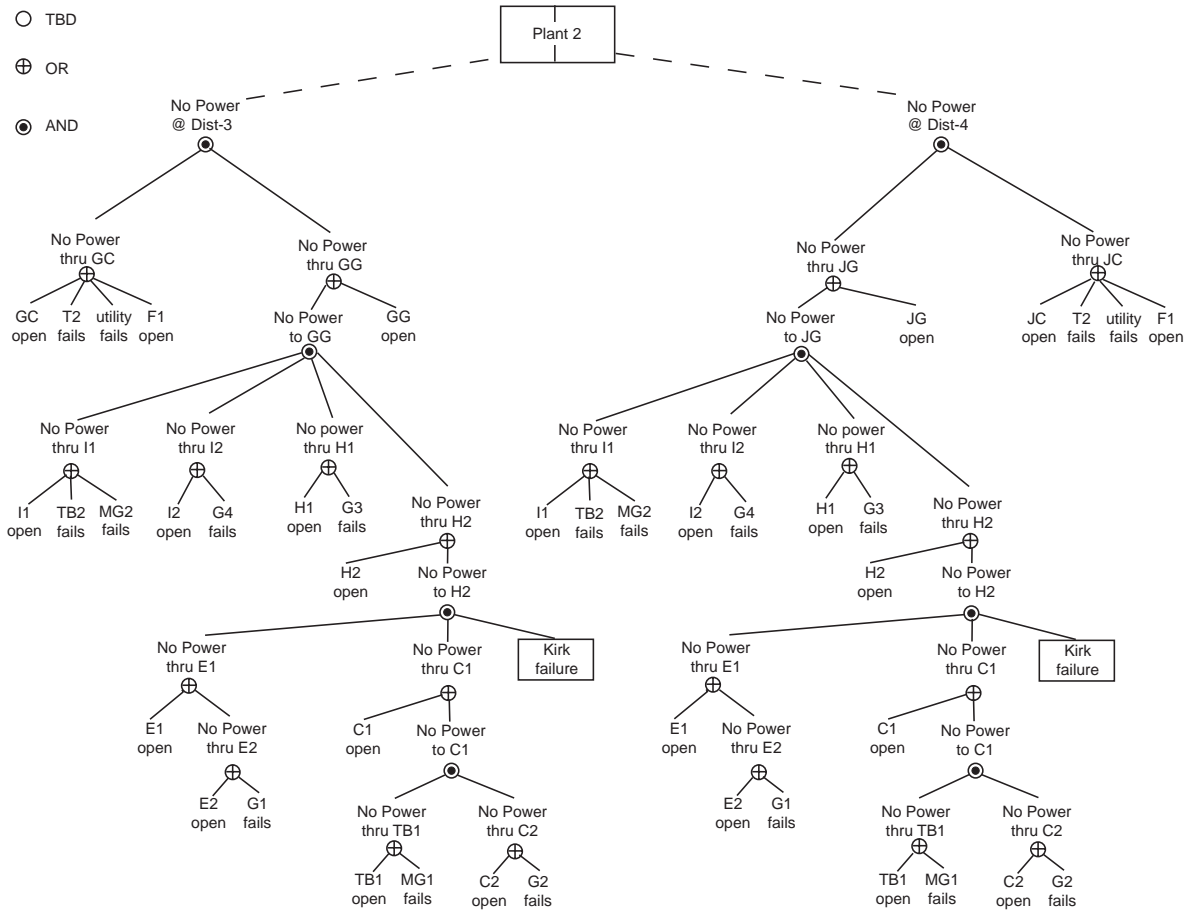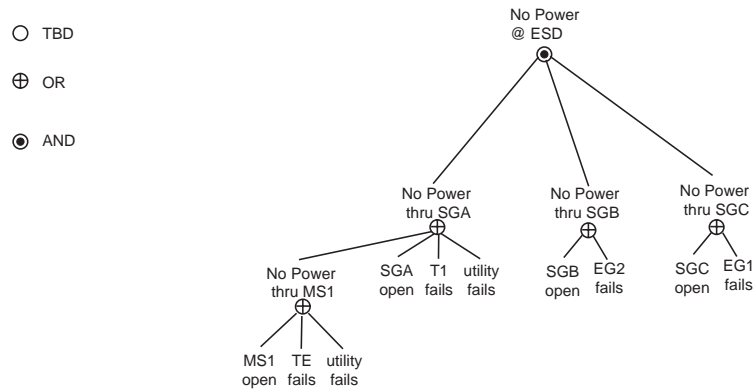
○ TBD

⊕ OR

◉ AND

Figure A.1. MSB-1 Fault Tree

Figure A.2. MSB-2 Fault Tree

Figure A.3. Earth Station Fault Tree

B   Base Case.v7 - WinBugs Code

Analysis based on using WinBugs 1.4, 100000 burn-in followed by an additional 500000 samples.

```
model{
fstart1~dbeta(af,bf)
fstart2~dbeta(af,bf)
fstart3~dbeta(af,bf)

e1~ dbern(fstart1)
e2~ dbern(fstart2)
e3~ dbern(fstart3)
# ei=1 (if generator fails to start) with probability fstarti
# we need to be careful to keep the time units the same
# LambdaG is in units of years
tfG1~dexp(LambdaG)I(0,fueltime)
tfG2~dexp(LambdaG)I(0,fueltime)
tfG3~dexp(LambdaG)I(0,fueltime)

tg1<-(1-e1)*tfG1*hours
tg2<-(1-e2)*tfG2*hours
tg3<-(1-e3)*tfG3*hours

LambdaG~dgamma(aG,bG)
tfG<- min(min(tg1,  tg2)+tg3, max(tg1,tg2) )

LambdaUu~dgamma(aUu, bUu)
tyUu~dexp(LambdaUu)
tfUu<- hours*tyUu

#LambdaUd is already in hours
LambdaUd~dgamma(aUd, bUd)
tfUd~dexp(LambdaUd)

fbat~dbeta(aB,bB)
eb~ dbern(fbat)
# we will assume that if the battery works, we will get timebat hours of use from t
# eb=1-> success eb=0 (failure)
tfB<- eb*timebat

TFdelta<- tfUu + tfUd
TF<- tfUu + tfG + tfB
Tdelta <- TFdelta - TF
```

```
}
list(af=0.22, bf=8.9, fueltime=0.008219, hours=8760, timebat=3,
     aG=0.6667, bG=0.03412,
 aUu=19.14, bUu=2.19,
aUd=1.0281, bUd=6.63126,
  aB=3.70868, bB=2.78512)
list(fstart1=1, fstart2=1, fstart3=1,LambdaG=1)
```

C Capstone.v2- WinBugs Code

Analysis based on using WinBugs 1.4, 100000 burn-in followed by an additional 500000 samples.

```
model{ # Capstone 7/24 v2.2 lognormal turbine failure rate PDF)
fstart1~dbeta(af,bf)
fstart2~dbeta(af,bf)
fstart3~dbeta(af,bf)

e1~ dbern(fstart1)
e2~ dbern(fstart2)
e3~ dbern(fstart3)
# ei=1 (if generator fails to start) with probability fstarti
# we need to be careful to keep the time units the same
# LambdaG is in units of years
LambdaG~dgamma(aG,bG)

ttfG1~dexp(LambdaG)
ttfG2~dexp(LambdaG)
ttfG3~dexp(LambdaG)

tfG1<- min(ttfG1, fueltime)
tfG2<- min(ttfG2, fueltime)
tfG3<- min(ttfG3, fueltime)

tg1<-(1-e1)*tfG1*hours
tg2<-(1-e2)*tfG2*hours
tg3<-(1-e3)*tfG3*hours

tfG<- min(min(tg1,  tg2)+tg3, max(tg1,tg2) )

# utility up-time
LambdaUu~dgamma(aUu, bUu)
tyUu~dexp(LambdaUu)
tfUu<- hours*tyUu
#LambdaUd is already in hours
LambdaUd~dgamma(aUd, bUd)
tfUd~dexp(LambdaUd)

#Battery Code

j ~ dunif(0, 1)
tfb16 <- alpha16[J] + beta16[J]*(j - x.change16[J])
```

```
J <- 1 + step(j - x1.change16) + step(j - x2.change16) + step(j - x3.change16)

k ~ dunif(0, 1)
tfb28 <- alpha28[K] + beta28[K]*(k - x.change28[K])
K <- 1 + step(k - x1.change28) + step(k - x2.change28) + step(k - x3.change28)

tfB <- min(tfb16, tfb28)



# natural gas
# for the Turbine, two failure modes are possible
# either the natural gas line is cut or the turbine fails
ttfNG~dexp(LambdaNG)
LambdaNG~dlnorm(aNG,bNG)
tfNG<-ttfNG*hours

LambdaC~dlnorm(aC,bC)
#generate failure times for operational turbine
for (i in 1:24) {
tfc[i] ~dexp(LambdaC)
}
# Capstones are lost when 7th turbine fails
tfCh <- ranked(tfc[],7)
tfC1 <- ranked(tfc[],1)

# power can only last as long as either
#   the NG is available or Capstones are operating
tfCap<-min(tfNG, tfCh)

#Tdelta = time without backup (including restoration)
TFdelta<- tfUu + tfUd

Tbase <- tfUu+tfG+tfB
TF<- tfCap + tfUu + tfG + tfB
Tdelta <- TFdelta - (tfUu+tfG+tfB)
}

list(af=0.22, bf=8.9, fueltime=0.008219, hours=8760,
aG=0.6667, bG=0.03412,
 aUu=19.14, bUu=2.19,
 aUd=1.0281, bUd=6.63126,
aNG=-5.89, bNG=0.26236,
aC= -9.40558, bC=9.38253,

beta16 = c(0, 66.67, 5, 1.333),
```

```
alpha16 = c(0, 0, 2, 3),
x.change16 = c(0, 0.02, 0.05, 0.25),
x1.change16 = 0.02,
x2.change16 = 0.05,
x3.change16 = 0.25,

beta28 = c(0, 40, 3.125, 1.667),
alpha28 = c(0, 0, 2, 3),
x.change28 = c(0, 0.03, 0.08, 0.40),
x1.change28 = 0.03,
x2.change28 = 0.08,
x3.change28 = 0.40)
list(fstart1=1, fstart2=1, fstart3=1,LambdaG=19, LambdaC=1)
```

D   Kawasaki.v5- WinBugs Code

Analysis based on using WinBugs 1.4, 100000 burn-in followed by an additional 500000 samples.

```
    model{   #Kawasaki v8 (lognormal Kawasaki failure rate PDF)
fstart1~dbeta(af,bf)
fstart2~dbeta(af,bf)
fstart3~dbeta(af,bf)

e1~ dbern(fstart1)
e2~ dbern(fstart2)
e3~ dbern(fstart3)
# ei=1 (if generator fails to start) with probability fstarti
# we need to be careful to keep the time units the same
# LambdaG is in units of years
LambdaG~dgamma(aG,bG)

ttfG1~dexp(LambdaG)
ttfG2~dexp(LambdaG)
ttfG3~dexp(LambdaG)

tfG1<- min(ttfG1, fueltime)
tfG2<- min(ttfG2, fueltime)
tfG3<- min(ttfG3, fueltime)

tg1<-(1-e1)*tfG1*hours
tg2<-(1-e2)*tfG2*hours
tg3<-(1-e3)*tfG3*hours

tfG<- min(min(tg1,  tg2)+tg3, max(tg1,tg2) )

# utility up-time
LambdaUu~dgamma(aUu, bUu)
tyUu~dexp(LambdaUu)
tfUu<- hours*tyUu
#LambdaUd is already in hours
LambdaUd~dgamma(aUd, bUd)
tfUd~dexp(LambdaUd)

#Battery Code

j ~ dunif(0, 1)
tfb16 <- alpha16[J] + beta16[J]*(j - x.change16[J])
```

```
J <- 1 + step(j - x1.change16) + step(j - x2.change16) + step(j - x3.change16)

k ~ dunif(0, 1)
tfb28 <- alpha28[K] + beta28[K]*(k - x.change28[K])
K <- 1 + step(k - x1.change28) + step(k - x2.change28) + step(k - x3.change28)

tfB <- min(tfb16, tfb28)
# natural gas
# for the Turbine, two failure modes are possible
# either the natural gas line is cut or the turbine fails
ttfNG~dexp(LambdaNG)
LambdaNG~dlnorm(aNG,bNG)
tfNG<-ttfNG*hours

LambdaK~dlnorm(aK,bK)
ttfK~dexp(LambdaK)
tfKh<-ttfK

tfK<-min(tfNG, tfKh)

#Tdelta = time without backup (including restoration)
TFdelta<- tfUu + tfUd

Tbase <- tfUu+tfG+tfB
TF<- tfK +  tfUu + tfG + tfB
Tdelta <- TFdelta - Tbase
}
list(af=0.22, bf=8.9, fueltime=0.008219, hours=8760,
aG=0.6667, bG=0.03412,
 aUu=19.14, bUu=2.19,
 aUd=1.0281, bUd=6.63126,
 aNG=-5.89, bNG=0.26236,
aK=-11.5178, bK=3.14839,

beta16 = c(0, 66.67, 5, 1.333),
alpha16 = c(0, 0, 2, 3),
x.change16 = c(0, 0.02, 0.05, 0.25),
x1.change16 = 0.02,
x2.change16 = 0.05,
x3.change16 = 0.25,

beta28 = c(0, 40, 3.125, 1.667),
alpha28 = c(0, 0, 2, 3),
x.change28 = c(0, 0.03, 0.08, 0.40),
x1.change28 = 0.03,
```

```
x2.change28 = 0.08,
x3.change28 = 0.40)

list(fstart1=1, fstart2=1, fstart3=1,LambdaG=19, LambdaK=0.01)
```

DISTRIBUTION: