Development of a Sustainable Transmission Structure Replacement and Maintenance Strategy

By

Max Tuttman

Sc.B. Mechanical Engineering, Brown University, 2009

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Signature of Author: Signature redacted
Department of Mechanical Engineering, MIT Sloan School of Management
May 11, 2018

Certified by: Signature redacted
Georgia Perakis, Thesis Supervisor
William F. Pounds Professor of Management

Certified by: Signature redacted
Konstantin Turitsyn, Thesis Supervisor
Professor of Mechanical Engineering

Accepted by: Signature redacted
Rohan Abeyaratne
Chair, Mechanical Engineering Graduate Program Committee

Accepted by: Signature redacted
Maura Herson
Director, MBA Program
MIT Sloan School of Management

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and Master of Science in Mechanical Engineering.

ABSTRACT

This thesis proposes methods to both estimate optimal aggregate investment levels for a system of transmission towers by means of an integrated corrosion and failure simulation as well as a method to identify specific assets in need of investment through a statistical model of structural health.

Limited tower replacements over the past decade have resulted in an overall aging of PG&E's transmission system, leading to managerial concerns about potential increased maintenance and replacement costs going forward. The utility is seeking to be able to forecast its future needs despite a minimal history of asset failure.

This work establishes long-term investment scenarios by simulating asset aging due to atmospheric corrosion and integrating those simulations with maintenance, replacement, and failure cost estimates. In addition, the aggregate investment forecasts are supplemented with an asset health ranking methodology that enables more targeted resource deployment.

Implementation of the simulation based forecasting provides long-term spend estimates – on the order of many decades – and enables the production of sensitivity analyses based on underlying parameters grounded in physical system properties. This advances current industry spend forecasting which relies on qualitative risk assessments and past cost trends. Asset health indices generated from structural properties and environmental data are also shown to correctly rank a structure with a historic reported structural issue as at higher risk than a structure without a reported issue at a rate of 70%.

Thesis Supervisor: Georgia Perakis
Title: William F. Pounds Professor of Management

Thesis Supervisor: Konstantin Turitsyn
Title Professor of Mechanical Engineering

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1 Introduction and Background

1.1 Company Overview

Pacific Gas and Electric Company (PG&E) is an investor owned utility incorporated in 1905 that operates in a 70,000 square mile service area in northern and central California. The 20,000 person company provides natural gas and electric service to approximately 16 million people through 5.4 million electric and 4.3 million natural gas customer accounts.

PG&E's electric system comprises both company owned and independent generators, as well as PG&E owned and operated transmission and distribution networks. The transmission network consists of 18,466 circuit miles of lines operating at voltages from 60 to 500 KV. A mix of wood and steel structures support this system, with over 45,000 steel structures currently in use [1].

1.2 Industry Background and Motivation

1.2.1 State of Electric Grid Infrastructure

Much of the energy system in the United States, including more than 640,000 miles of high-voltage transmission lines, was constructed in the 1950s and 1960s, with an original life expectancy of approximately 50 years. The American Society of Civil Engineers estimates that the cumulative investment gap for all electricity infrastructure in the United States, including generation and T&D, will be $177 billion between 2016 and 2025. ASCE has subsequently given the energy sector as a whole a D+ grade on their infrastructure report card, indicating that the system is in poor to fair condition with many elements approaching the end of their service life and exhibiting significant deterioration [2].

A similar conclusion was reached in 2003 by the Department of Energy (DOE), who pronounced the U.S. electricity grid "aging, inefficient, congested, and incapable of meeting the future energy needs of the information economy without significant operational changes and substantial public-private capital investment over the next several decades"[3].While the DOE notes in a 2015 report that significant improvements have been made to the grid since that time, they reiterate this same conclusion [4].

1.2.2 Regulatory Environment

Electric power utilities operate in a heavily regulated environment, and these regulations greatly influence investment decisions within the companies, including investments into the transmission network.

California contains three large investor-owned public utilities (IOUs) that own and operate most of the state's transmission facilities. In addition to PG&E, Southern California Edison and San Diego Gas and Electric operate in the south of the state. In their capacity as transmission owners (TOs), these IOUs are required to provide transmission service at rates that are deemed "just and reasonable." These rates are designed to enable the TOs to meet their revenue requirements which cover the costs of providing transmission services as well as a return on capital invested [5].

Revenue requirements for TOs are set by the Federal Energy Regulatory Commission (FERC) – an independent agency that regulates the interstate transmission of electricity, natural gas, and oil – through proceedings known as rate cases [6]. When an IOU files a rate case, stakeholders including the California Public Utilities Commission will submit filings on behalf of ratepayers.

These rate proceedings are critical to meeting the business objectives of any IOU, and as such, analysis that supports anticipated investment need is critical for achieving the appropriate remuneration these investments.

1.3 Problem Statement and Objectives

Currently, PG&E replaces tens of steel transmission towers per year in a system containing over 45,000 such structures and conducts maintenance on an as needed basis per their inspection procedures. Given this rate, towers are either not being replaced at steady state, or they must remain in services for thousands of years. This work aims to identify the maintenance and replacement levels that minimize total costs over the ongoing life of the system.

In pursuit of this objective, two primary analyses were performed: (1) an engineering simulation of general atmospheric corrosion and (2) a statistical model of transmission tower health as a function of intrinsic characteristics and environmental factors. These models enable the development of appropriate asset investment rate and identification the appropriate assets in which to invest.

1.4 Thesis Contribution

This thesis advances the state of steel structure asset management by applying asset aging simulations, maintenance scheduling optimization, and statistically driven inspection prioritization. Specifically, the following contributions will be described:

- An integrated model that combines a simulation of corrosion and maintenance decisions to forecast future investment needs

- The optimization of a maintenance schedule that accounts for cost of repairs, replacements, and failures
- A quantitative assessment of optimal repair and replacement point for an individual asset as a function of its cost of failure
- The application of machine learning methods to identify at risk structures

1.5 Thesis Outline

The literature review in chapter 2 contains a summary of relevant prior art. In particular, work associated with the study of corrosion in the utility industry and the application of machine learning to asset risk assessments in the utility industry is explored. Furthermore, a review of asset management strategies from across the industry is conducted.

Chapter 3 describes the integrated simulation used to forecast spending for steel transmission structures. Several sub-sections of the simulation are discussed, including the corrosion rate calculations, maintenance frequency optimization, and total spend aggregation. The derivation of model inputs including costs, asset age, corrosion zone identification, and failure distributions are also explored.

In chapter 4 an explicit asset investment breakeven analysis is performed using the corrosion simulation and failure distributions calculated in chapter 3. These two elements, used in tandem, allow for the derivation of an expected time to failure distribution, which in turn can be used for an explicit net present value optimization of maintenance decisions.

Chapter 5 discusses the derivation and application of a logistic regression model constructed to provide insight into asset health. The input data, modeling methodology, and results are described.

Chapter 6 summarizes the findings of this work and provides guidance on areas for future development. Inspection methods, maintenance scheduling, cost of failure determination, and additional asset health factors are discussed.

2 Literature Review

2.1 Corrosion in the Utility Industry

The impacts of corrosion have long been a topic of interest for utilities, and historically has been a focus of their gas operations. In this field several works have sought to predict leaks through the application of corrosion simulations and statistical analysis. In two recent MIT master theses, graduate students, along with teams from PG&E, studied the possibility of predicting corrosion in the natural gas distribution system, addressing both buried pipelines [7] and above grade atmospheric corrosion in the gas distribution system [8].

Corrosion is also increasingly becoming an area of interest in the electricity sector as transmission networks begin to age. Australia's Integral Energy company, for example, recently undertook the drastic step of performing full tower pull over tests to assess the impact of aging and corrosion on the strength of their transmission towers [9].

Utilities around the world are becoming increasingly aware of the corrosion driven investment need in their aging steel structures, and this work provides a methodology for quantitatively deriving investment need through the application of corrosion simulations.

2.2 Machine Learning for Asset Inspections

A recent MIT masters' thesis, also in partnership with PG&E, explored the use of machine learning methods to analyze utility wood pole asset and inspection data. This work presented a method for estimating inspection rejection rates for subpopulations of wood poles, and also proposed a simulation method, to provide a rough estimation of the rejection rates the company can expect in the next several decades [10].

The work presented in chapter 5 of this thesis extends similar machine learning methodologies to the area of steel structures – which have different aging modes than wood structures – in order to develop a health index for this asset class.

2.3 Asset Management of Transmission Towers

Historically utilities have taken a qualitative approach to strategic asset management of the transmission network. For example the Bonneville Power Administration (BPA) in a 2013 asset management strategy overview, lays out a qualitative risk matrix for its assets with the dimensions of Consequence and Likelihood [11]. Figure 1 shows one such set matrix, where assets are plotted under different scenarios, with the size of the bubble representing the number of assets.

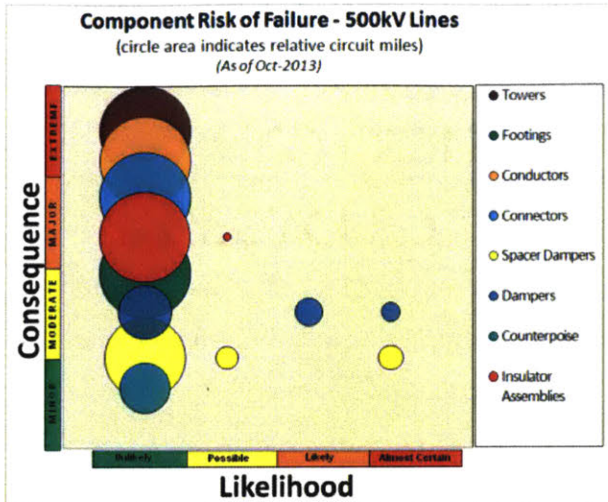

Figure 1: BPA Risk Matrix

BPA identifies age as the primary indicator of the likelihood of failure, and for towers, they have assumed a life of 100 years, and their classifications are based upon the assumptions shown in Table 1. This table appears to have an error in that the age ranges for the classifications overlap, however what is shown here has been reproduced as it appears in the BPA document.

Table 1: BPA Tower Likelihood of Failure Classification

Likelihood of Failure	Age Range
Unlikely	<= 81
Possible	80-111
Likely	110-131
Almost Certain	>130

BPA notes that a future goal is to develop standard metrics for collecting and retaining asset data granular enough to identify condition trends, target replacement efforts, manage components over time, and better predict remaining service life. The work presented in this thesis aims to answer directly several of these questions through the use publicly available information and PG&E's data.

The New Zealand based company, Transpower, has taken a more quantitative approach to asset management [12]. Two key indices underpin their streel transmission structure asset strategy, a condition assessment (CA) score and an asset health index. The CA is a qualitative score determined from inspections, which occur every 8 years for towers and every 6 years for poles. Each asset is scored on a scale of 100 (new), to 20 (replacement or decommissioning required), to 0 (where failure is likely under everyday conditions). If a CA drops below 50, than the frequency of inspection is doubled. Furthermore, an asset health index is calculated using:

- The current condition of the asset (CA)
- The age of the asset
- The typical degradation path of that type of asset
- Any external factors that affect the rate of degradation, such as proximity to the coast affecting the rate of corrosion of steel towers

As Transpower notes, the greatest asset management challenge for an aging fleet of towers is from corrosion of the steel. To combat corrosion Transpower has undertaken a tower painting program, in which the structures are coated at a regular frequency in order to prevent degradation of the underlying steel. This is because the coating adds an additional layer of protection, much like the galvanizing layer, which creates a window of time in which the underlying steel is not corroding, but instead the coating layer is being eroded.

Transpower determines the appropriate coating frequency through a life cycle cost model that factors in tower steel degradation rates, as estimated by the series of corrosion zone specific curves shown in Figure 2, as well as the tower coating cost, which increases as CA score is decreased. This increasing cost results from the observation that as towers deteriorate, the amount preparation for coating, such as abrasive blasting, increases. Furthermore, as the CA score decrease, bolts and members will also require replacement, in addition to the required coating. While maintenance costs change with CA score, the tower is assumed to always be restored to the same condition, a CA score of 60. An example of a tower lifecycle, as a function of CA is illustrated in Figure 3.

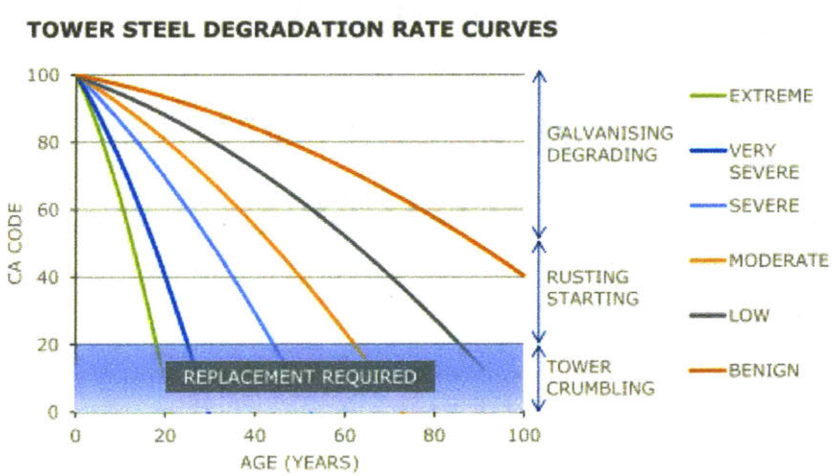

Figure 2: Transpower Condition Assessment Degradation Rate Curves

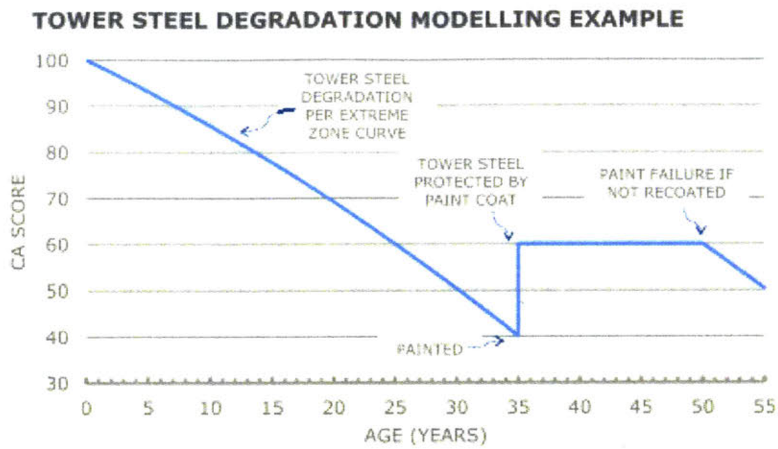

Figure 3: Transpower Degradation Modeling Example

Transpower optimizes for the tradeoff between the increased cost of coating at a lower CA score and the cost associated with treating a tower earlier, due to the time value of money. Their analysis holds constant the maintenance frequency for each corrosion zone and also assumes that towers are always treated before failure. From this analysis under these conditions they conclude that:

- Tower painting has a lower lifecycle cost than replacement
- By managing the impact of corrosion through painting, the life of towers can be extended indefinitely
- Newer, better condition towers should be left to age, allowing them to reach the optimum condition for painting
- Towers should be painted before the condition goes significantly beyond the economically optimum point, to avoid excessive future costs for maintaining overall asset health

The work presented in this thesis extends much of the methodology employed by Transpower, with key distinctions including:

- Replacing the qualitative CA and AHI with a quantitative calculation of section loss due to atmospheric corrosion
- Including the expected cost of failure in the overall cost optimization
- Optimizing for both the initial coating time as well as the ongoing coating frequency

3 Steel Structure Budget Forecasting

3.1 Forecasting Approach and Model Structure

A steel transmission structure can reach the end of its life through one of several mechanisms: a planned line upgrade or replacement, an acute failure due to an external factor, such as a vehicle collision, or an aging related failure. This work aims to estimate systemic investment needs, and as a result focuses on system aging.

In order to forecast spending several factors must be considered including:

- The rate at which assets in the system age
- The current condition of assets in the system
- The cost of asset replacement, maintenance, and failure
- The optimal frequency of asset replacement and maintenance

Due to the interactions between these factors, the forecast is built up from a number of building blocks. The primary aging mechanism for steel structures in outdoor environments is atmospheric corrosion, and as a result established corrosion models are used to estimate the material loss of the structure over time. Both restoration costs and failure probabilities are calculated as a function of this material loss parameter.

The elements of corrosion rate, failure cost, failure probability, and maintenance cost, together with a maintenance schedule enable the simulation of life cycle costs for a single tower. A Monte Carlo optimization is performed for each corrosion environment by varying the maintenance schedule and environmental conditions in this simulation to find the maintenance parameters that minimize total cost.

A system-wide simulation can then be constructed by assigning these maintenance parameters to each structure in the system by environment, and simulating the lifecycles of each of the 40,000 structures under these conditions. The lifecycle events, including maintenance, replacement, and failure, are then converted into costs and presented as the aggregated spend forecast.

Figure 4 illustrates the forecasting flow. Shaded boxes in the figure represent simulation steps, while unshaded boxes are simulation inputs. Boxes with a dashed outline are inputs that were determined through optimization or were varied for scenario planning.

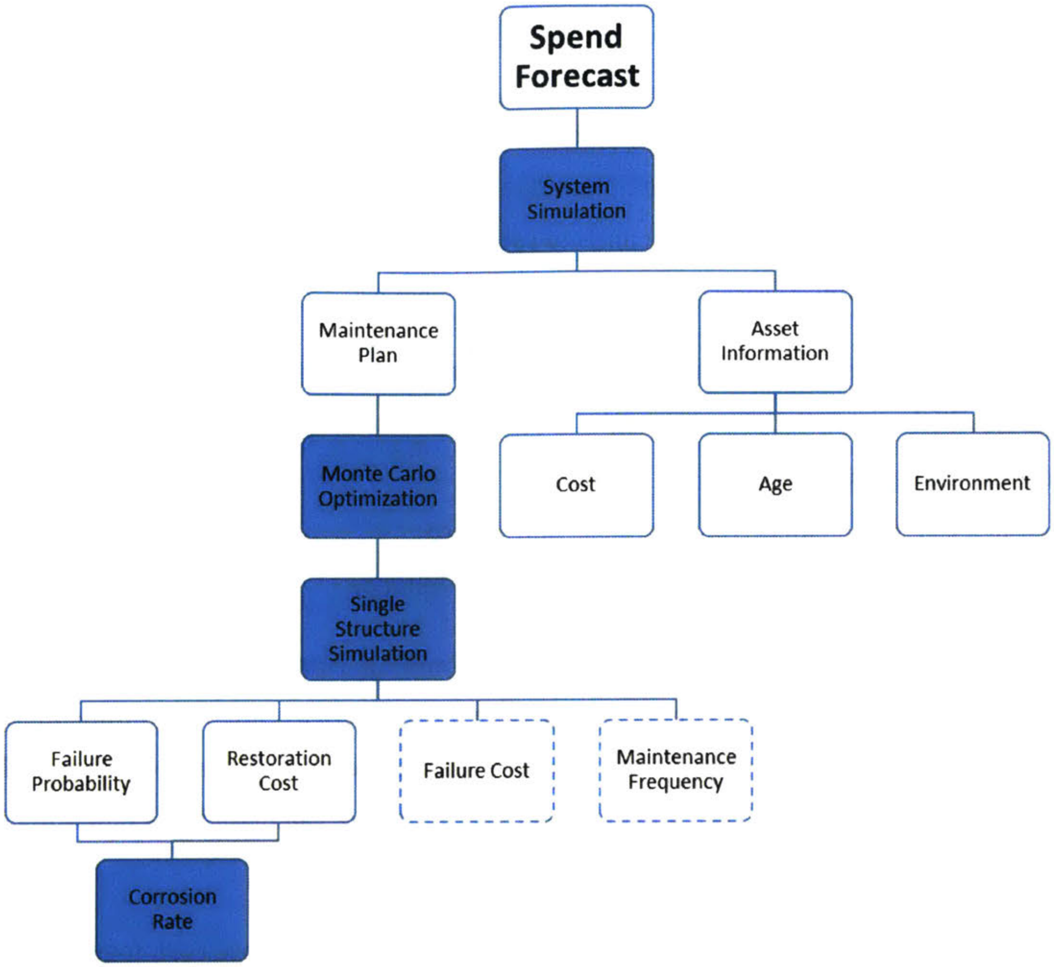

Figure 4: Forecast Flow

3.2 Corrosion Modeling

3.2.1 General Corrosion Background

Corrosion can be defined as the destructive attack of a metal by its reaction with the environment [13]. This process is an electrochemical process by which anodic and cathodic reactions occur in a coupled manner at different places on a metal's surface. This chemical reaction is therefore the sum of the two half-cell reactions, which for steel can be written as follows:

At the local anodes: $$Fe \rightarrow Fe^{2+} + 2e^{-} \quad (1)$$

At the local cathodes: $$2H^{+} + 2e^{-} \rightarrow H_2 \quad (2)$$

Overall reaction: $$Fe + 2H^{+} \rightarrow Fe^{2+} + H_2 \quad (3)$$

The focus of this work is on atmospheric corrosion, which occurs in outdoor atmospheres due to the presence of thin film electrolytes formed on the metal surface. The rate of the metal dissolution process is strongly influenced by both endogenous factors, related to the metal itself, as well as exogenous factor related to the atmospheric composition, including humidity and the concentration of contaminants such as sulfur dioxide and chlorides [14].

3.2.2 Corrosion Calculation Methodologies

3.2.2.1 Overview of Methodologies

A number of efforts have been undertaken to develop methods for calculating the material loss of metals due to corrosion as a function of age and environment. These models can be classified as first level and second level models. First level models are based on physical laws, whereby the dissolution of metal and the formation of corrosion products are evaluated at a microscopic level. Second level models are based on fitting parameters to corrosion rate data collected through observation or experimentation [14]. Second level are generally used for structural engineering applications as they allow for macro-level predictions about the impact of corrosion over longer time periods.

Most corrosion models describe the corrosion depth as a function of time in a power model, as the formation of corrosion products on a metal's surface causes a decrease in corrosion rate over time. A general formulation of this model is shown in equation 4.

$$d(t) = A * t^B \tag{4}$$

Where:

d(t)	is the corrosion depth
t	is the exposure time
A	is the corrosion rate in period 1
B	is the corrosion rate long term decrease

Examples of second level corrosion models include those created by the International Standard Organization [15], the European Committee for Standardization [16], Albrect and Hall [17], the International Cooperative Programme [18], and Klinesmith [19]. Landolfo compares these models, and illustrates the range of predicted section loss over time for the various models considered [14]. These plots are reproduced in Figure 5.

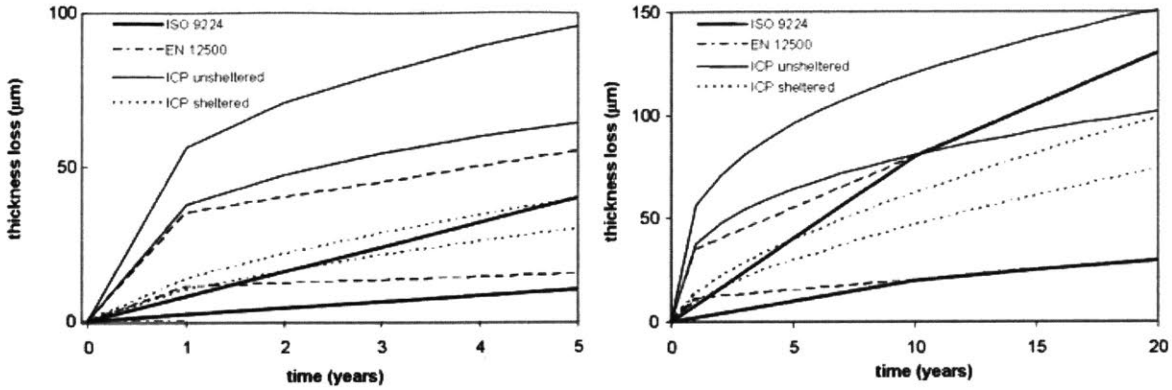

Figure 5: Landolfo's Comparison of Corrosion Model Predictions for Five and Twenty Years

3.2.2.2 ISO Corrosion Model

The simulation constructed for this analysis is based upon the methodology presented in ISO standards 9223-9226.

The ISO framework was chosen for its transparency, simplicity, and the industry credibility of the underlying organization. These standards also provide both qualitative and quantitative means for corrosion environment classification, which allows them to be combined with PG&E's internal corrosion zone classifications.

The general form of the atmospheric corrosion attack, and subsequently corrosion rate, is given in ISO 9224 as [15]:

$$D = r_{corr} t^b \tag{5}$$

$$\frac{dD}{dt} = b r_{corr} (t)^{b-1} \tag{6}$$

$$D(t > 20) = r_{corr}[20^b + b(20^{b-1})(t - 20)] \tag{7}$$

where:

t is the exposure time, expressed in years;
r_{corr} is the corrosion rate experienced in the first year expressed in micrometers per year;
b is the metal-environment-specific time exponent

In the ISO standards, like other second level models, atmospheric corrosion rates are estimated to progress with exponential decay, as the corrosion layer inhibits further corrosion. The impact of this effect however is found to no longer provide additional protection after a sufficient coating of corroded material is built up, after which point the material loss proceeds linearly. The ISO standards estimate this time to linearity as 20 years, reflected in equation 7.

3.2.3 ISO Model Implementation

3.2.3.1 Initial Corrosion Rate Determination

ISO 9223 provides multiple methodologies for determining the initial rate of corrosion, expressed in ISO 9224 as r_{corr}. The two primary methods are via a dose response function that takes as inputs environmental parameters, and a method that uses qualitative environmental characteristics to estimate an initial rate of corrosion. The direct dose-response calculation incorporates environmental measurements of sulfur dioxide dry deposition rate, chloride dry deposition rate, temperature, and relative humidity into material specific equations for initial corrosion rate [20]. The equations are calculated by fitting coefficients of the dose-response function based on worldwide corrosion field exposure tests in addition to location specific pollutant and climactic data. For steel the resulting initial rate is expressed as follows:

$$r_{corr} = 1.77 * P_d^{0.52} * \exp(0.020 * RH + f_{St}) + 0.102 * S_d^{0.62} * \exp(0.033 * RH + 0.040 * T) \quad (8)$$

$$f_{St} = 0.150 * (T - 10)\ when\ T \leq 10°\text{C};\ otherwise - 0.054 * (T - 10) \quad (9)$$

where:

r_{corr} is first-year corrosion rate of metal, expressed in micrometers per year
T is the annual average temperatures, expressed in degrees Celsius
RH is the annual average relative humidity, expressed as a percentage
P_d is the annual average SO_2 deposition, expressed in milligrams per square meter per day
S_d is the annual average Cl^- deposition, expressed in milligrams per square meter per day

Because specific pollutant measurements were not available for PG&E's service territory, the dose-response equation estimation of initial corrosion rate was not utilized for this work; however ISO 9223 also provides numerical values for the first-year corrosion rates for standard metals based on qualitative corrosion categories. These categories range from C1 (very low) to CX (extreme). The description of these environments is shown in Table 2 [20].

Table 2: ISO 9223 Corrosion Categories

Corrosivity Category	Corrosivity	Typical Environments - Examples
C1	Very Low	Dry or cold zone, atmospheric environment with very low pollution and time of wetness, e.g. certain deserts, Central Arctic/Antarctica
C2	Low	Temperate zone, atmospheric environment with low pollution (SO2 < 5 µg/m3), e.g. rural areas, small towns Dry or cold zone, atmospheric environment with short time of wetness, e.g. deserts, subarctic areas
C3	Medium	Temperate zone, atmospheric environment with low pollution (SO2: 5 µg/m3 to 30 µg/m3)or some effect of chlorides, e.g. urban areas, coastal areas with low deposition of chlorides Subtropical and tropical zone, atmosphere with low pollution
C4	High	Temperate zone, atmospheric environment with high pollution (SO2: 30 µg/m3 to 90 µg/m3) or substantial effect of chlorides, e.g. polluted urban areas, industrial areas, coastal areas without spray of salt water or, exposure to strong effect of de-icing salts Subtropical and tropical zone, atmosphere with medium pollution
C5	Very High	Temperate and subtropical zone, atmospheric environment with very high pollution (SO2: 90 µg/m3 to 250 µg/m3) and/or significant effect of chlorides, e.g. industrial areas, coastal areas, sheltered positions on coastline
CX	Extreme	Subtropical and tropical zone (very high time of wetness), atmospheric environment with very high SO2 pollution (higher than 250 µg/m3) including accompanying and production factors and/or strong effect of chlorides, e.g. extreme industrial areas, coastal and offshore areas, occasional contact with salt spray

The ISO standards additionally provide the following initial corrosion rate guidelines, in micrometers per year, as a function of corrosion zone [20].

Table 3: ISO Corrosion Rates in µm/yr

Corrosivity Category	Carbon Steel	Zinc
C1	$r_{corr} \leq 1.3$	$r_{corr} \leq 0.1$
C2	$1.3 < r_{corr} \leq 25$	$0.1 < r_{corr} \leq 0.6$
C3	$25 < r_{corr} \leq 50$	$0.6 < r_{corr} \leq 1.3$
C4	$50 < r_{corr} \leq 80$	$1.3 < r_{corr} \leq 2.8$
C5	$80 < r_{corr} \leq 200$	$2.8 < r_{corr} \leq 5.6$
CX	$200 < r_{corr} \leq 700$	$5.6 < r_{corr} \leq 10$

For this work, the ranges provided for each corrosion zone were translated into a normal distribution with the high and low bound of the range each assumed to be two standard deviations from the mean rate.

3.2.3.2 Corrosion Rate Temporal Correlation

The model is structured in such a manner that the corrosion rate from one time period to another is correlated, therefore a structure that has an initial rate at the high end of its given corrosion level distribution will continue to age at this accelerated pace throughout its lifetime. Additionally, the corrosion rates for zinc and steel are taken from the same point in their relative distributions. If the rate between time periods were each selected independently, than the average rate of corrosion after a period of many years would revert to the mean for each structure evaluated, thereby reducing the variation in section loss from structure to structure.

3.2.4 Structure Properties

PGE&E design specifications for a standard lattice tower call for a structural steel member thickness of 5000 um, or approximately 3/16" in accordance with PG&E design specifications [21]. Furthermore, these specifications call for steel to be galvanized in accordance with ASTM A123, which results in a zinc coating layer of 75 um [22]. While some towers and tower components may vary from these parameters, this standard was used across all steel structures in this analysis. This allows for a baseline aggregate forecast, however when considering any single structure, the specific properties of that asset should be considered.

3.2.5 Corrosion Model Output

By applying the ISO corrosion methodology to steel structures, a range of section loss over time can be calculated for each corrosion zone. The section loss is defined as a percent of the total member thickness, including the galvanized layer. The range in section losses within a corrosion zone is due to the range of possible starting corrosion rates as defined in the section above.

The resulting section loss over time for each zone is shown in Figure 6 with the lightly shaded area indicating the full range of outcomes and the darker shaded region highlighting cases within one standard deviation of the average, shown by the solid line.

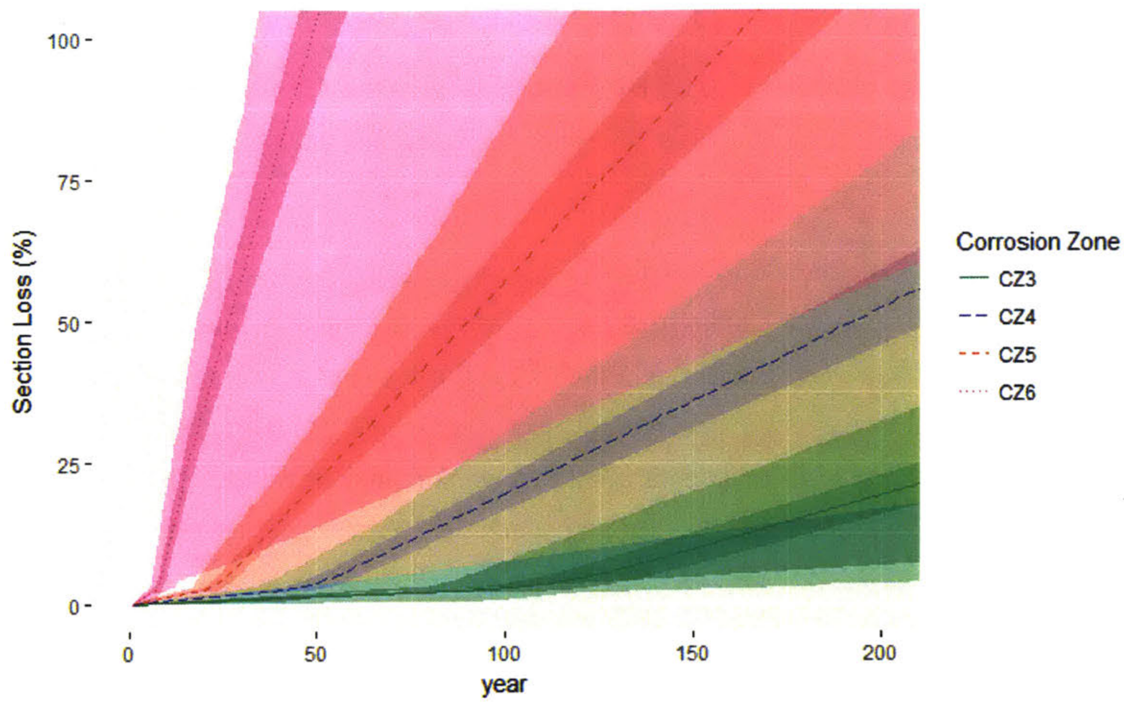

Figure 6: Section Loss over Time

The shape of these curves is due to two primary factors. There is a small, and barely visible, range of accelerated section loss due to the exponential initial corrosion rate prior to the corrosion layer inhibiting additional deterioration of the structure and entering the linear range of decay. The more visible elbow that occurs in each range is due to transition from the zinc galvanized layer to the steel layer which corrodes at a faster rate. Here the efficacy of a galvanized coating in slowing overall corrosion can clearly be seen.

3.3 Single Structure Simulation

3.3.1 Failure Likelihood Estimation

In order to simulate the life cycle of a steel structure, the failure point of these structures must be estimated. Because towers have not failed regularly in the field, no observed mean time to failure statistics exist; however the design standards for towers can be used in order to estimate when the structures would be at risk for such failures. In this work, a distribution of the failure probability of a tower was created as a function of material section loss.

The IEEE National Electric Safety Code establishes a load factor requirement of 1.5 for vertical loads in addition to transverse-wind and dead-end loads require safety factors of 2.5 and 1.65 respectively[23].

Table 4: IEEE Transmission Structure Load Factors for Construction Grade B

	Load Factor
Vertical Loads	1.50
Transverse Loads - Wind	2.50
Transverse Loads - Wire Tension	1.65
Longitudinal Loads - In general	1.10
Longitudinal Loads - At deadends	1.65

Given these load factors, the average failure was estimated to occur at a section loss of 33%, the point at which the vertical load factor would be exceeded. A normal distribution with respect to section loss was used to model failures, and a standard deviation of 10%. This results in an estimate that only 2% of towers fail before the reach a section loss of 13% and only 2% of towers can last beyond a 53% section loss before failure. A plot of the cumulative distribution function for tower failures as a function of section loss is shown in Figure 7.

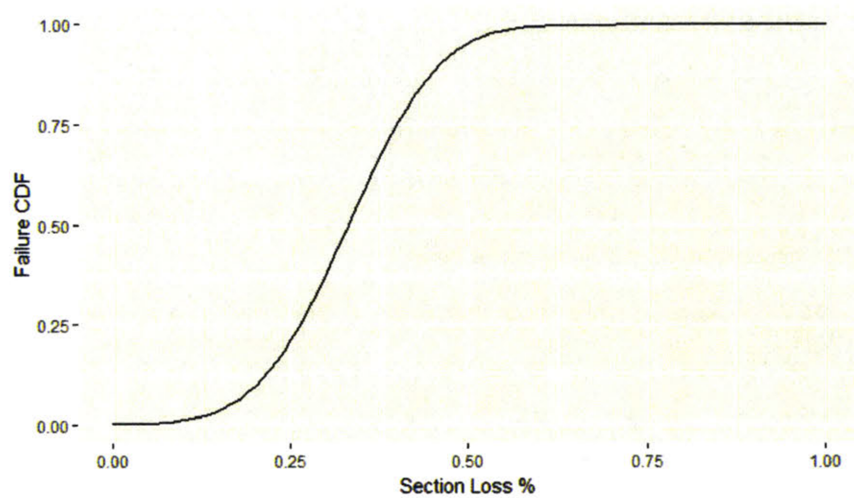

Figure 7: Tower Failure Distribution

3.3.2 Modeling Life Cycle Events

Similar to the work performed by Transpower, maintenance events are assumed to be able to restore the life of the tower through the replacement or treating of the most heavily corroded elements of the tower, thereby reducing the average section loss of the tower, as well as temporarily prevent future section loss through the application of a coating.

A maintenance event is assumed to restore the asset to a maximum average section loss of 5%, and as specified by the National Association of Corrosion Engineers, the application of a coating is assumed to prevent additional section loss for 5 to 12 years, depending on the corrosion zone of the asset [24].

3.3.3 Cost Estimates

The benchmark cost estimates used for this analysis were derived by previous work performed by PG&E. In that work, replacement costs for a variety of steel structure types was assembled, and an estimate of $35,000 per structure for coating was developed.

This analysis maintains the replacement costs used in that analysis, and uses the $35,000 coating cost as an upper bound, with the lower bound being set at 10% of the tower replacement cost. An adjustment factor of 10x was also included for structures located on a body of water, given the increased costs associated with these jobs.

The cost of failure is also considered in this analysis. This cost is intended to include not only the structure replacement, but any associated externalities including customer outages, emergency response, damaged property, loss of reputation, and any other additional costs. The average cost of failure was assumed to be 10x the replacement cost. In future work this cost can be refined on a structure by structure basis as a function of several factors including customers served by the line, system stability parameters, population safety risk, fire risk, and any additional safety hazards.

Table 5: Tower Cost Index – Normalized to 115 KV Suspension Tower

KV	Conductor	DE / Susp	Lattice Pole	Tubular Pole	Tower	200+ foot tall Special Susp and the Short Stout DE
60	Single	DE	0.56	0.61	0.83	N/A
60	Single	Susp	0.53	0.58	0.78	N/A
70	Single	DE	0.56	0.61	0.83	N/A
70	Single	Susp	0.53	0.58	0.78	N/A
115	Single	DE	0.83	0.89	1.06	1.67
115	Single	Susp	0.78	0.83	1.00	9.72
115	Bundled	DE	0.89	0.94	1.17	N/A
115	Bundled	Susp	0.83	0.89	1.11	N/A
230	Single	DE	1.06	1.17	1.67	2.50
230	Single	Susp	1.00	1.11	1.53	12.50
230	Bundled	DE	1.17	1.28	1.81	2.78
230	Bundled	Susp	1.11	1.22	1.67	16.67
500	Bundled	DE	1.94	1.67	4.17	5.56
500	Bundled	Susp	1.53	1.39	3.33	19.44

Consistent with methodology established by Transpower, the cost of maintenance was assumed to be a function of the degradation of the asset. Because the simulation assumes that any maintenance activity restores the tower to the same condition, the cost becomes the dependent variable in the relationship between maintenance timing, asset condition, and cost.

The cost was modeled with a floor of the coating cost – defined as the smaller of 10% of the replacement cost and $35,000 – and a ceiling of the replacement cost. A logarithmic function was created to return this range of values over the range of section losses consistent with the expected section losses that could be seen in the field prior to failure. An example of this curve for a structure with a $100,000 replacement cost is illustrated in Figure 8.

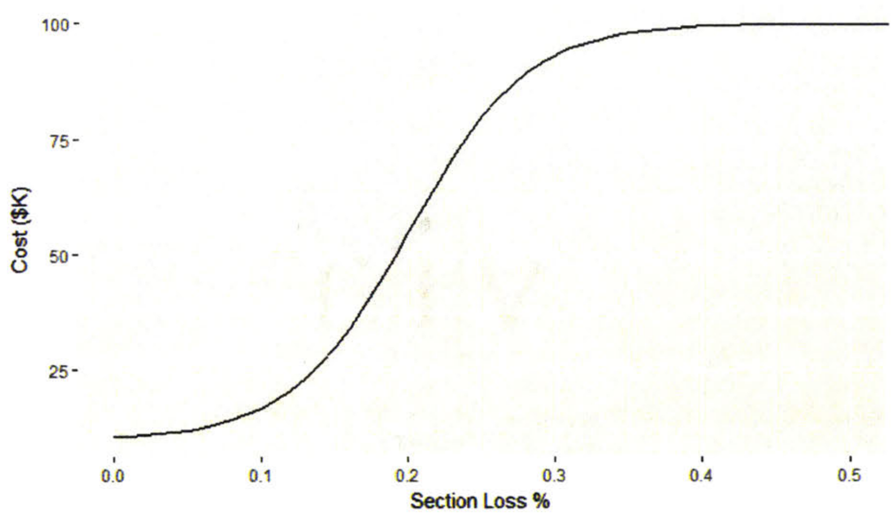

Figure 8: Tower Maintenance Cost Curve

3.3.4 Tower Life Cycle Simulation

The life cycle of a single tower can be simulated by applying the corrosion aging equations together with the failure probabilities and an assumed maintenance schedule. As the simulation iterates over each year, some amount of section loss occurs as a function of the corrosion rate distribution and the material being exposed – steel, zinc, or coating. Each iteration through the simulation the structure also experiences some probability of failure as a function of its state of section loss. Maintenance and coating occurs on a predetermined cadence, resetting the section loss of the tower to the 5% threshold, and preventing the corrosion of the underlying structure for the life of the coating. A diagram of this simulation is shown in Figure 9.

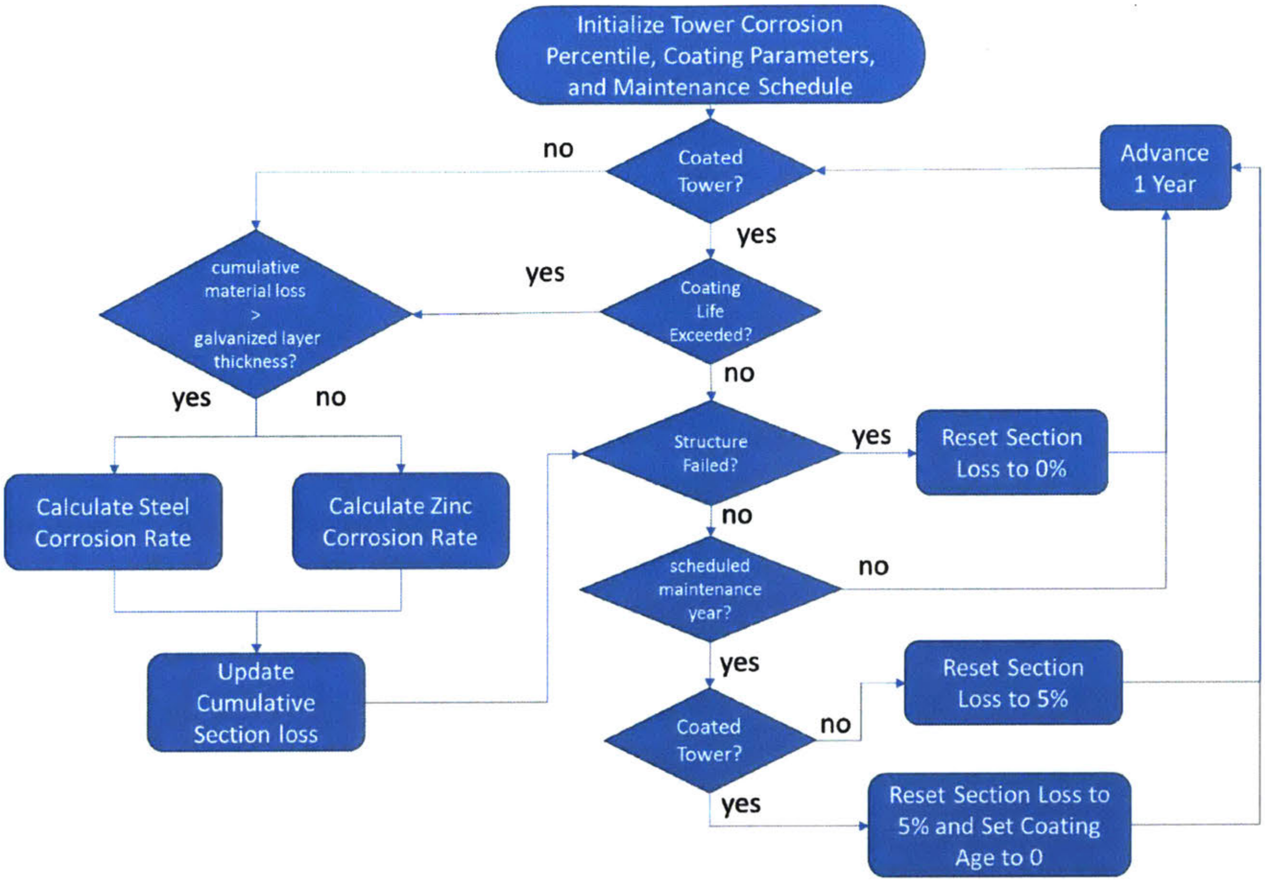

Figure 9: Tower Aging Simulation Flow Diagram

As example of the results of this simulation for a tower in a severe corrosion zone with coating and maintenance occurring every 30 years is shown in Figure 10. As can be seen the simulation applies the corrosion rate associate with zinc until approximately 3% section loss occurs. Beyond this point, the simulation uses the corrosion rate of the underlying steel, and an acceleration in the corrosion rate occurs. 30 years after the galvanized layer has been corroded away, the tower goes through a maintenance cycle, which restores the structure to a 5% material loss. The simulation also applies a coating at this point, which lasts for approximately 6 years, after which point the steel again begins to corrode. At just after year 90, a failure and subsequent replacement occur in the simulation, after which point the aging cycle begins again.

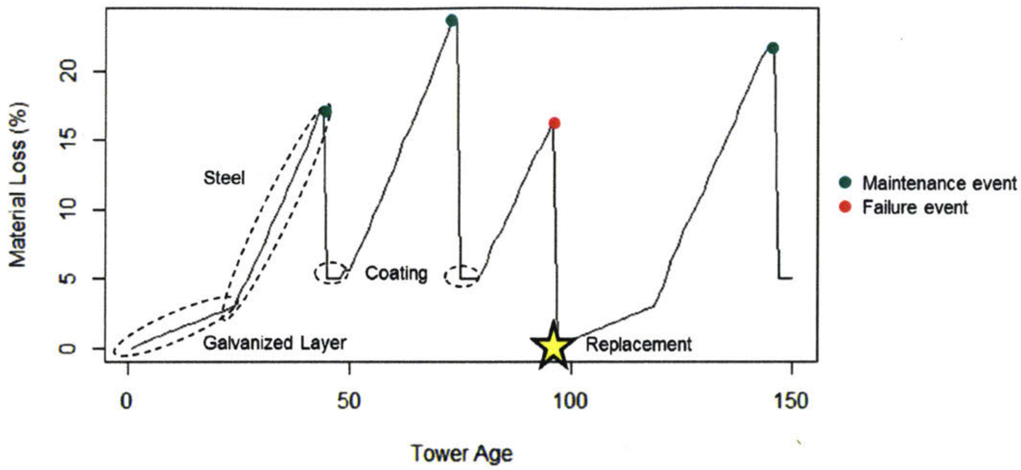

Figure 10: Example Tower Simulation

3.4 Maintenance and Replacement Optimization

In order to determine an appropriate maintenance schedule for calculating total system spend, an optimal maintenance and replacement cadence for transmission structures was calculated.

The optimization is formulated in equations 10 and 11, where the goal is to minimize the present value of all cash flows associated with failures or repairs, where in this case replacements qualify as a subset of repairs.

Objective Function:

$$min \sum_{t=0}^{\infty} PV_t \tag{10}$$

Present Value Calculation:

$$PV_t = \frac{F_t C_f + R_t C_R}{(1+r)^t} \tag{11}$$

Where:
R_t: Binary decision variable with value 1 if repairs occurring at time t, 0 if not
PV_t: Present Value of costs at time t
F_t: Probability of failure at time t given section loss at time t
C_f: Cost of failure
C_R: Cost of repairs at time t given section loss at time t
r: Discount Rate

No closed form solution exists for this system, and as a result the optimal maintenance and replacement cadence could not be calculated directly. Instead, the lowest cost maintenance schedule was identified through a Monte Carlo simulation. In this analysis, 10,000 trials were performed under each set of maintenance parameters – including the timing of initial maintenance and the frequency of maintenance thereafter – and at each corrosion zone.

In each of these simulations the cost of each maintenance event, as well as any failures that may occur were tracked, and summed in accordance with a discounted cash follow equation using a 7% discount rate applied. The average was then calculated for the 10,000 runs under each set of conditions. Figure 11 shows the result of each of these calculations over the ranges of parameters considered.

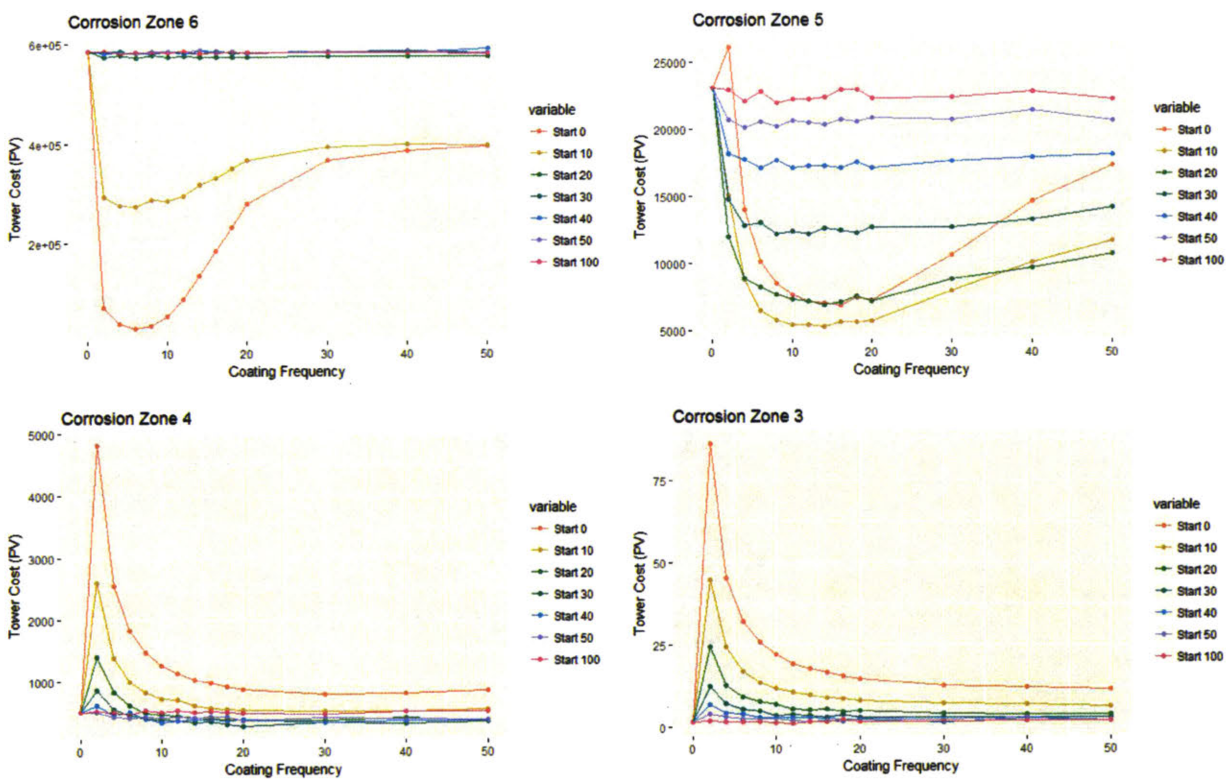

Figure 11: Maintenance Plan Discounted Costs

The analysis demonstrates that in more aggressive corrosion environments, a more frequent coating schedule leads to a lower total cost. This is because in these faster aging environments, the probability of failure, and the associated cost, increases more rapidly than in less corrosive environments, and as such investing in preventative measures becomes worthwhile. For assets in lower corrosion zones the optimal maintenance strategy is to wait several decades before beginning maintenance, and then only to perform occasional preventative maintenance. This further illustrates that the optimal maintenance schedule balances the tradeoff between cost due to structure failures and costs associated with preventative maintenance.

The lowest cost scenario for each corrosion zone is shown Figure 12. In low corrosion environments, an optimal maintenance strategy does not require maintenance until 40 years after the structure first loses its galvanized layer, and only every 30 years after that point. In a highly corrosive environment, however, maintenance may be required in the first year after the galvanized layer is lost and as frequently as every 6 years after that point. To illustrate the necessity for more frequent maintenance for structures in a more aggressive corrosion zone, an image of a tower structure located in the San Francisco Bay, taken 5 years after maintenance activity is shown in Figure 13.

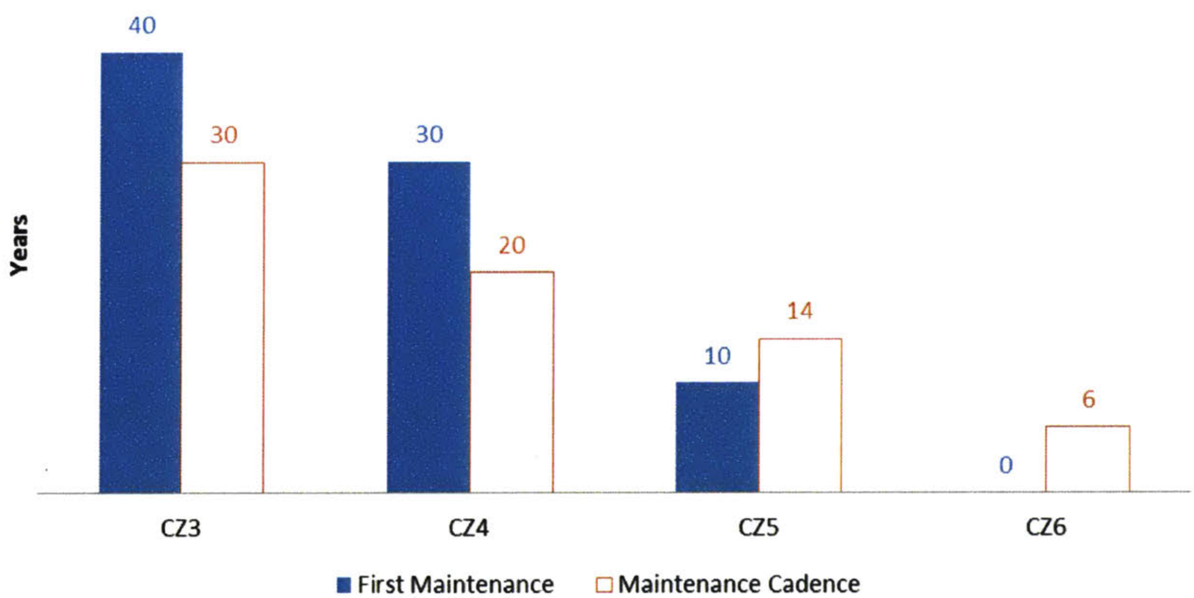

Figure 12: Optimal Maintenance Schedule Parameters

Figure 13: Tower in Corrosion Zone 6 after 5 years

3.5 System Simulation

3.5.1 System Simulation Inputs

In order to perform an aging simulation across the system simulation, each structure must be given initial conditions based upon its location and age, and a maintenance schedule must be applied. Maintenance schedules in accordance with the asset's corrosion zone and the analysis performed in the previous section were used.

3.5.1.1 Corrosion Zone Assignment

Based on the location of the structure, the structure is classified into one of four corrosion zones defined by ISO 9223. These metrics were simplified in order to maximize model transparency by taking advantage of the internal PG&E corrosion zone maps which had been produced the company's Electric T&D engineering department [25].

In order to classify each asset into one of these six categories, the following heuristic was employed. All structures were placed into a category of C3 at a minimum to help ensure a conservative estimation of degradation.

Table 6: Corrosion Level Classification Heuristic

Corrosion Level	Parameter
CX	In San Francisco Bay
C5	On water OR in PG&E severe corrosion zone OR near coast
C4	In moderate PG&E corrosion zone
C3	All others

Results of this classification are displayed in Figure 15.

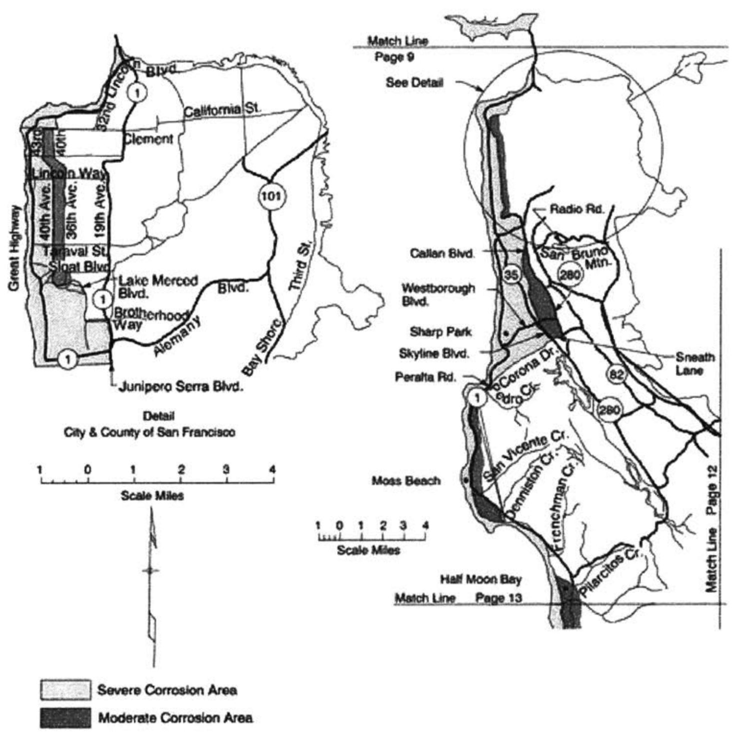

Figure 14: PG&E Corrosion Map - San Francisco County

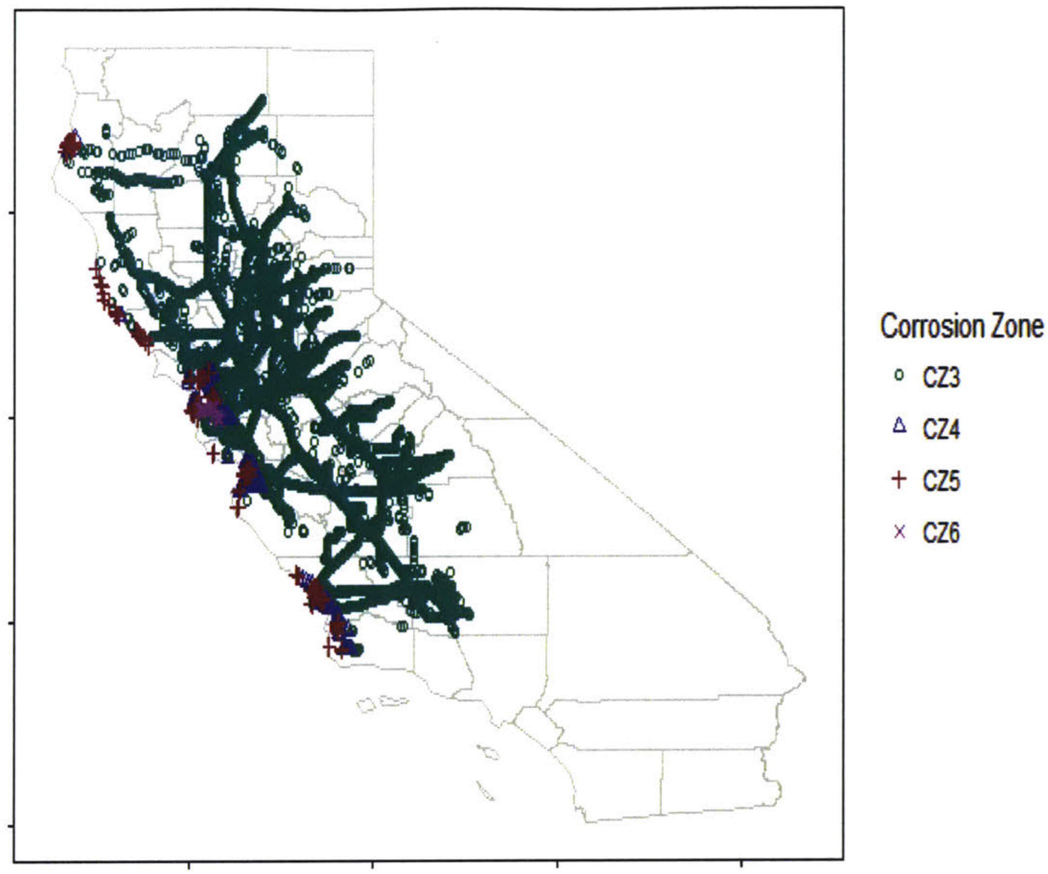

Figure 15: Assets by Corrosion Zone

3.5.1.2 Asset Age

Asset age was determined from internal PG&E records that indicate the installation year for each transmission line. Assets with no given installation date were removed from the dataset for the aging simulation, resulting in the inclusion of 38,997 of the 48,061 total records.

A histogram of the installation history of PG&E's steel transmission structures is shown in Figure 16, where the dominance of post-war construction, particularly of the high voltage system is evident.

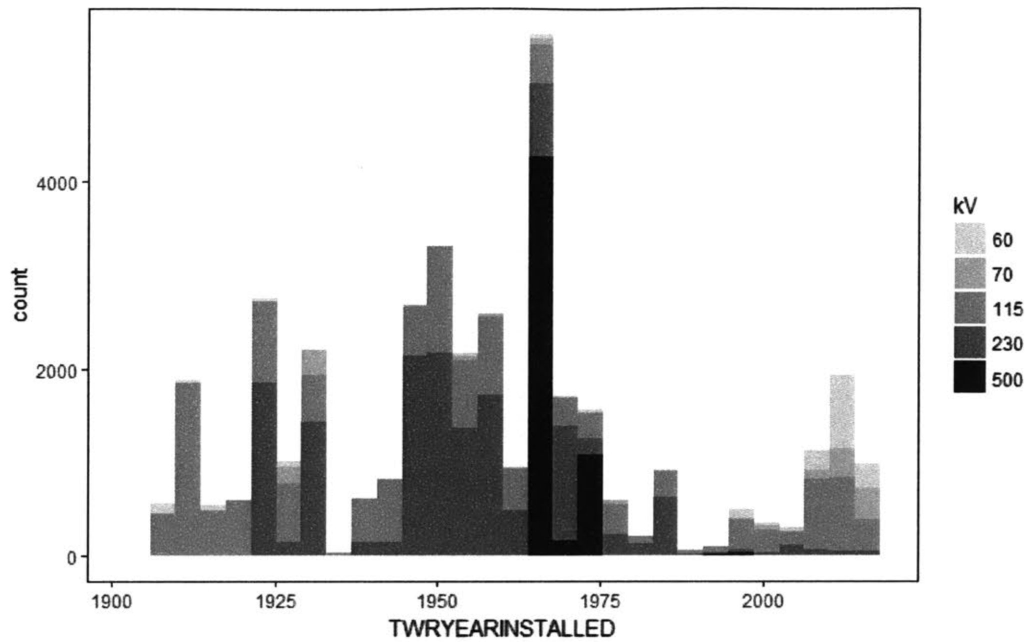

Figure 16: Structure Installation Year

3.5.2 Simulation Execution

The maintenance cadence for each asset, along with its corrosion zone, age, and costs, comprise the necessary initial conditions for a system-wide simulation. The simulation is executed beginning at a time prior to any towers being installed, in this case 1900 was used, and as each structure's installation year arrives, that structure begins to age in accordance with the ISO guidelines. As the simulation iterates forward in time, the cost of each maintenance and failure event is tracked. If a maintenance event occurs and over 95% of the structure's replacement cost is necessary, this event is classified as a replacement.

Given that no systemic preventative maintenance plan has been put into place to date, no maintenance activities are assumed to begin until the current year, 2018.

3.5.3 Spend Forecast

3.5.3.1 Cost Events

The cost events resulting from the system simulation, including the application of the optimized maintenance schedules, by corrosion zone, are shows in Figure 17. These results have been smoothed over a 10 year period in accordance with the assumption that maintenance schedules can be smoothed to some degree over this period. The insert to the left zooms in on the estimated number of failures and replacements, which are significantly fewer than the estimated number of repairs.

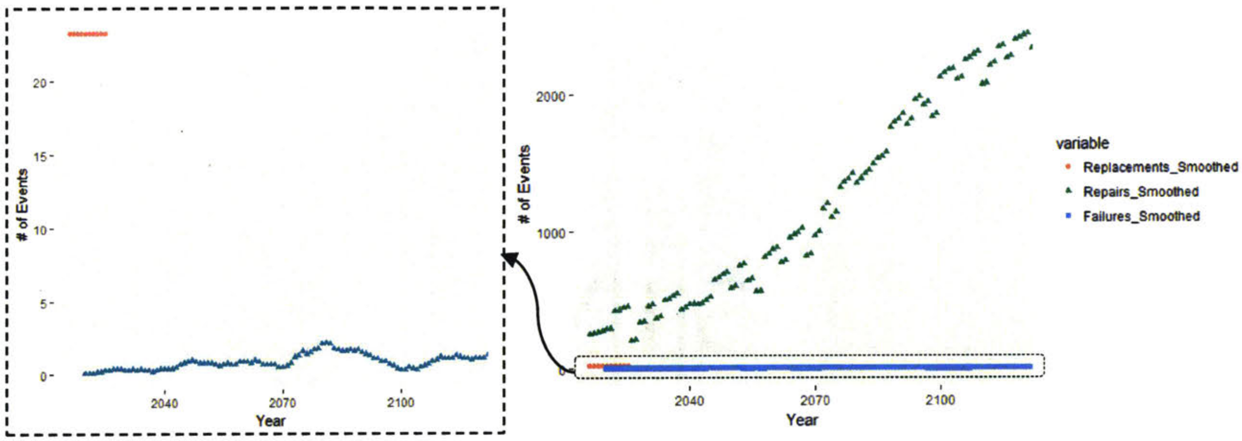

Figure 17: Asset Cost Events

In this optimized plan all replacements occur in the early years, and are a result of replacing a backlog of high risk towers. In future years, the plan is dominated by preventative maintenance. While this plan calls for no replacements, other than those towers which have already endured excessive aging prior to the implementation of the optimized maintenance schedule, some conditions may arise which would call for additional replacements. For instance, the implementation of a just-in-time replacement strategy that occurs later in the life of a structure may be possible if the variance in the distribution of expected tower lifetime is narrowed due to:

- More precise estimation of failure point as a function of section loss
- More precise predictions of corrosion rates
- Or the implementation of inspection procedures that able to provide more complete information regarding asset likelihood of failure.

Additionally, if preventative maintenance is unable to restore tower health as much as assumed in this work and the work of Transpower, than the trade-off of replacement versus repair may advantage replacing structures under some conditions.

3.5.3.2 Total Cost Projection

The associated cost projection associated with the events from Figure 17 is shown in Figure 18.

While working through the backlog of accumulated maintenance resulting from prior underinvestment, and conducting the necessary replacements, spend levels are estimated to be at an elevated level. After this point, beginning around 2030, repair spend becomes dominant with levels dropping to approximately one third of the starting levels, after which point spend slowly escalates as the system continues to age, and preventative maintenance needs increase.

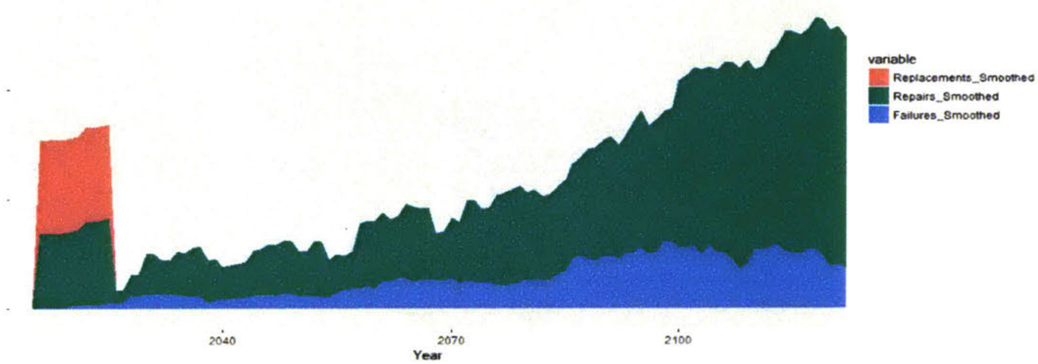

Figure 18: Cost Projection by Event Type

3.5.3.3 Cost Projection by Corrosion Zone

The system spend estimation can also be viewed by corrosion zone, as shown in Figure 19. Assets in corrosion zone 6, largely composed of the towers located in San Francisco Bay, have an outsized effect on the spend forecast as they undergo accelerated corrosion and are significantly more costly to repair or replace as they are built on water. These structures are anticipated to need significant maintenance and replacement work over the coming decade, and in then they will require ongoing preventative maintenance in perpetuity to prevent an increasing likelihood of failure.

A ramp up in spend for the lower corrosion towers that make up the majority of the system occurs after 2050.

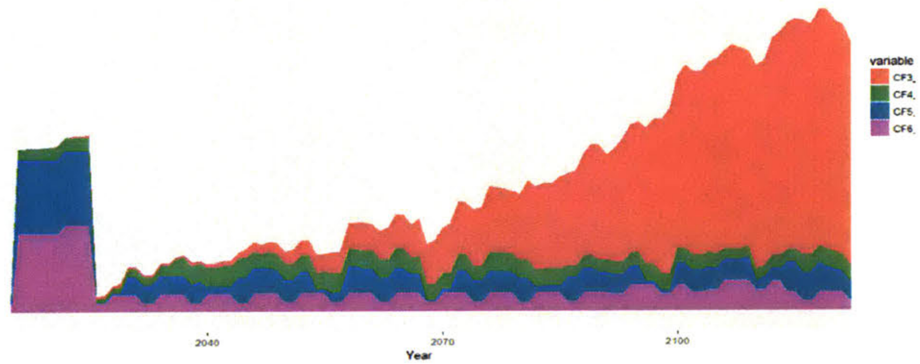

Figure 19: Cost Projection by Corrosion Zone

3.5.3.4 *Cost of Failure Sensitivity*

Figure 17 shows that in this cost optimized plan, some number of structure failures are still estimated, reaching a level of approximately 5 per year in year 2100 and beyond. Adjusting the maintenance schedule to reduce spend associated with failures is possible; however doing so would implicitly increase the cost of failure, as this would result in a higher spend to avoid these failures.

To illustrate this a sensitivity analysis was performed by adjusting the cost of failure from a multiple of 2x the replacement cost, to 100x the replacement cost, and optimizing the maintenance cadence in each zone accordingly. This maintenance reoptimization lead to more frequent maintenance events as a higher cost of failure leads to a greater sensitivity to failure and therefore increases the optimal level of prevention. Section 4 of this thesis will more rigorously demonstrate this balance.

As can be seen in Figure 20 and Figure 21 higher failure costs lead to a schedule with more maintenance and fewer failures, while lower failure costs lead to an optimal strategy of running to failure. This eliminates maintenance for lower corrosion zone towers, but resulting in increasing failures as these assets age.

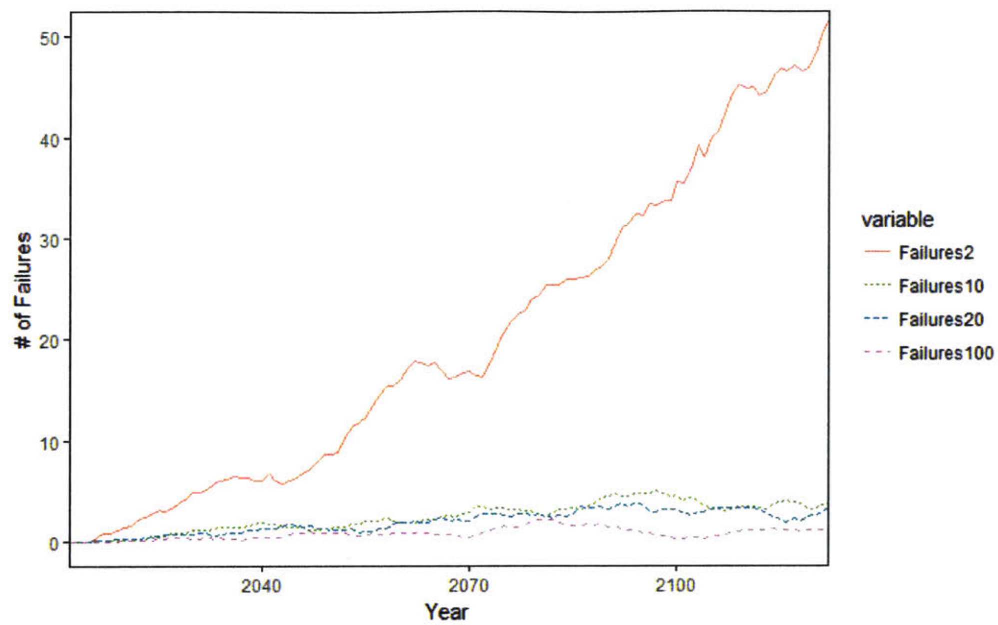

Figure 20: Asset Failures over Time by Failure Cost Factor

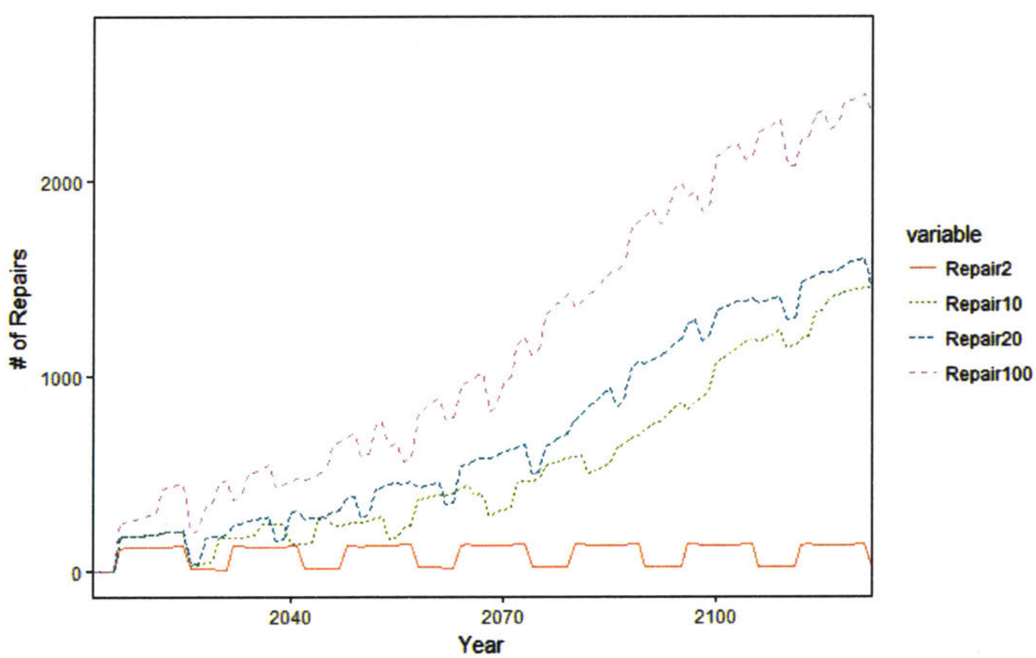

Figure 21: Repairs over Time by Failure Cost Factor

The impact on net present value for each of these plans as a function of the baseline assumption of a 10x failure cost multiple are shown in Figure 22. As expected, plans burdened by a higher failure cost result in a higher NPV, but by reoptimizing the maintenance plan under each condition, the impact of these additional costs are mitigated.

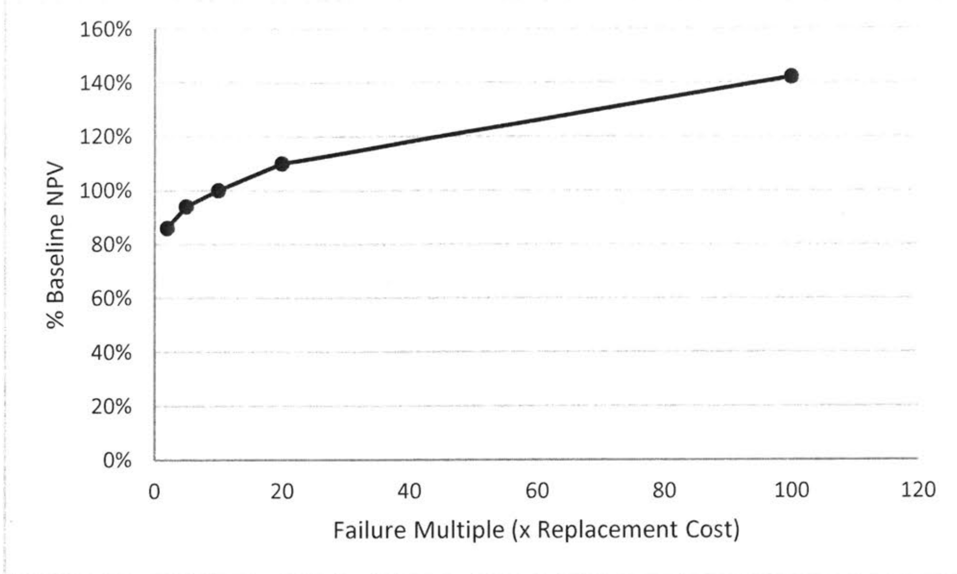

Figure 22: Optimized System NPV Costs as a Function of Failure Multiple

3.6 Conclusions

A spend forecast for the ongoing operation of the steel transmission structure fleet, optimized for cost, was developed by combining estimates of atmospheric corrosion rate, structural properties, repair costs, failure costs, and maintenance scheduling. This integrated approach allows for the development of an aggregate forecast, and enables sensitivity analysis on the underlying factors.

Through this forecasting the following conclusions were reached:

- An NPV optimized maintenance strategy includes more frequent maintenance activities for structures in more aggressive corrosion zones, while structures in less aggressive environments require maintenance at a significantly lower cadence.
- For aging systems with no history of regular preventative maintenance, replacement of older structures in high corrosion zones may be necessary in the near term, after which point the optimized maintenance schedule should be applied.
- Given the level of uncertainty regarding tower life expectancy, due to the underlying uncertainty in the distributions of both corrosion rate and failure point, a strategy of preventative maintenance has lower overall costs than a replacement strategy. If data collected in the future allows for a true just-in-time replacement option, then this may no longer be the case; however under current conditions the elevated expected cost of failure

for an aging tower due to uncertainty around failure estimates does not warrant this approach.

- The lowest NPV strategy of preventative maintenance will likely rely heavily on an increase of expense dollars as opposed to capital dollars. While like any business, utilities should be seeking to lower their overall costs, this accounting tradeoff may require additional discussions with regulators in order to align the interests of all stakeholders, given that currently utilities are generally remunerated through a return on assets mechanism.

4 Investment Breakeven Analysis

A novel method for determining the appropriate investment level into an asset was developed using the tower life distribution estimates. This method is generalizable to any asset with a calculated or measured failure distribution, and is a practical way to determine whether a particular maintenance or replacement activity is worthwhile.

This calculation takes into account the total cost of failure of an asset – including both the replacement cost, as well as any costs associated with the consequence of failure – as well as the failure distribution as a function of time, or a property that changes with time, such as section loss, and a discount rate.

4.1 Formulation

The costs are normalized to current day costs by use of the net present value calculation, which sums all cash flows, discounted to present day dollars using a determined discount rate.

$$NPV = \sum_{i=0}^{\infty} \frac{CF_i}{(1+r)^i} \tag{12}$$

From these variables the expected cost of failure for a new asset can be calculated as follows:

$$ENPV_f = C_f \sum_{i=0}^{\infty} P(t_i) \frac{1}{(1+r)^i} \tag{13}$$

where:

C_f: Cost of failure
r: Discount rate
$P(t_i)$: Probability of failure at time t_i
$ENPV_f$: Expected net present value of failure over the sum of all years, i

As an asset ages, the probabilities of failure for each year must be updated to reflect the current state of the asset. The can be done by use of Bayes' theorem which states:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{14}$$

In this case, P(A|B) is the probability of a asset failing in an interval, P(A), given that the tower has reached the current interval, P(B).

Given this, P(A) is equal to the result of the probability mass function for asset failure in a given year and P(B) is equal to the inverse of the cumulative distribution function of asset failure up to the given year. P(B|A), the probability of a tower reaching the current interval given that it fails in the current interval or later is always equal to 1. Therefore, Bayes' theorem applied to asset failure over a given time period can be reduced to the following:

$$P(t_i) = \frac{pmf_i}{(1 - cdf_i)} \tag{15}$$

The expected value of failure calculation, shown above for an asset starting at time zero (i.e. a new asset), can be generalized to an asset of any age.

$$ENPV_{f,s} = C_f \sum_{i=s}^{\infty} P(t_i) \frac{(1+r)^s}{(1+r)^i} \tag{16}$$

Where s is the age of the asset at the starting year of the calculation.

Substituting in the calculation for $P(t_i)$ results in the following:

$$ENPV_{f,s} = C_f \sum_{i=s}^{\infty} \frac{pmf_i}{(1 - cdf_i)} \frac{(1+r)^s}{(1+r)^i} \tag{17}$$

Given this equation for the expected net present value of the failure costs of an asset at time s, the value of restoring a calculation can be calculated as the following:

$$Restoration\ Value = ENPV_{f,s} - ENPV_{f,0} \tag{18}$$

The value of restoring an asset to a new condition, or replacing that asset, is equal to the difference in expected cost of failure of the old asset less the expected cost of failure of a new asset. If the cost of this repair or replacement is less than that value, than the action is NPV positive, and should be performed. Conversely, if the repair or replacement cost is greater than this value, than the action is NPV negative, and not a prudent investment.

A similar calculation can be performed for repairs that do not restore the asset to a new condition if an effective age or condition can be calculated for the asset in its post-repair state. In this case, the restoration value would be the difference in expected net present costs of the asset in state 1 less the net present costs of the asset in state 2.

4.2 Calculating Failure Probability

In order to produce this analysis for steel transmission tower, a distribution of tower failure as a function of time was needed. In order to generate this distribution, the single tower life simulation described in section 3.3 was run under the conditions of no maintenance for10,000 trials in each corrosion zone. In each trial, a random starting corrosion rate is assigned and the asset is run to failure. In each time iteration of each simulation a random number is generated from a 0 to 1 uniform distribution and that number is compared to the probability of failure from the failure distribution as a function of the current section loss of the asset. If the random number is smaller than the probability of failure then the tower fails. The time to failure is recorded for each of the 10,000 trials and comprises the estimated life distributions.

In Figure 23 the expected tower life in each corrosion zone is shown along with a fit of distributions. Normal, lognormal, and Weibull distributions are all shown. Lognormal curves are seen to be the best fit for the data, which is consistent with the exponential nature of the underlying corrosion equations.

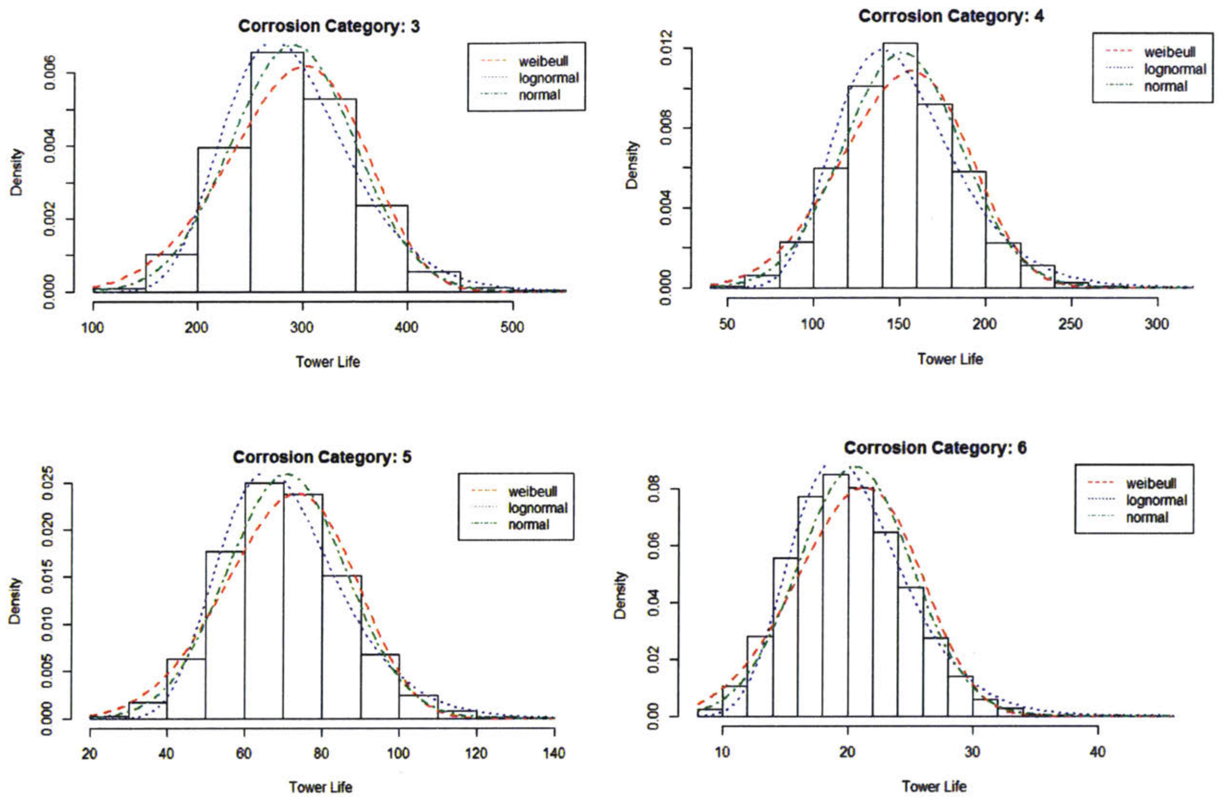

Figure 23: Tower Life Estimates

4.3 Maintenance Breakeven Analysis of Steel Transmission Structures

The repair breakeven cost calculation was performed using the derived lognormal failure distribution estimate of a transmission structure and a 7% discount rate. This analysis was normalized to failure cost because this cost can span multiple orders of magnitude for transmission towers. A failure on a redundant line in a rural environment with no fire-risk for example, is likely to have minimal cost beyond the cost of replacement, while the cost of failure for a radial line or line in a high-consequence environment can have a cost of failure significantly larger than the replacement cost.

Results of this analysis are shown in Figure 24 as a function of asset age, separated by structure corrosion zone.

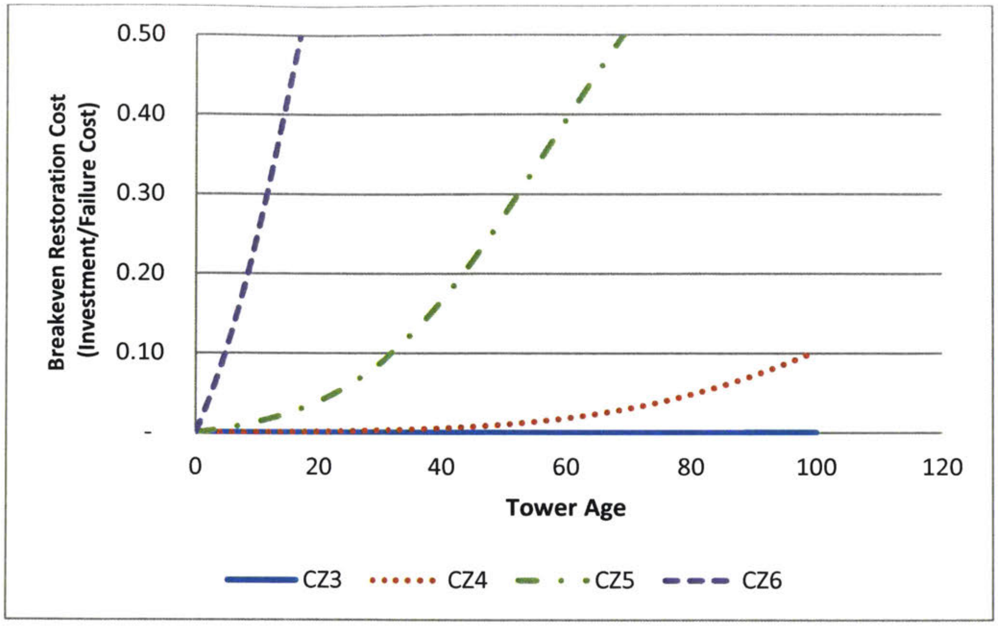

Figure 24: Breakeven Restoration Cost by Age

These plots illustrate the investment amount that would be justified to replace or restore a tower as a function of that tower's age or corrosion state. For example, the breakeven restoration cost of a 100 year old tower in corrosion zone 4 with a cost of failure of $1M, would be $100k, given that the investment to failure cost breakeven ration at that point is 0.1.

4.4 Conclusions

In explicitly formulating the total future cost of an asset as a function of both maintenance costs and the expected cost of failure, the breakeven point for maintenance investments was explored. Through this work, the following insights were derived:

- Determining the appropriate level of investment for asset replacement or preventative maintenance requires balancing the cost of these actions with the expected cost of failure. The expected cost of failure is a function of both the probability of failure at any given time in addition to the cost incurred if a failure occurs.
- Maintenance or replacement activities can be thought of as buying time. When an asset is restored the time to expected failure is extended, thereby discounting the cost of failure more significantly.
- Breakeven restoration or replacement costs scale linearly with the cost of failure. If the cost of failure for one asset is twice as high as another, the breakeven restoration cost for the first asset is twice as high as the second.

5 Asset Health Modeling

5.1 Model Motivation

Atmospheric corrosion engineering simulations enable the evaluation of different replacement scenarios given the bulk behavior of the system of transmission structures. In order to implement any given replacement plan created with the assistance of those models, however, appropriate candidates for replacement must be identified. By performing a statistical analysis on the health of existing towers, risk factors can be identified and each individual asset can be scored for potential decay susceptibility. This analysis can be used to reduce the system of over 45,000 towers down to a smaller target population of several hundred which can then be inspected in the field in order to determine an appropriate course of action.

5.2 Data Overview

The data used for modeling consisted of intrinsic asset data, such as age and structure type, environmental data, such as chloride deposition rate and mean annual frost free days, and inspection records.

5.2.1 Asset Data – PG&E GIS System and Asset Inventory

Asset data was collected from PG&E's internal Electric Transmission Geographic Information System (ET-GIS) in addition to an asset inventory database. These internal records systems were joined using the unique ID of each asset. These systems contains information about both the tower structures themselves, as well as the surrounding environment.

Several of the fields required additional cleaning. For example foundation type, which likely originated as a manually input field, contained records for not only CONCRETE foundations but also C0NCRETE (with a zero), CONCRETE***, CONC. PILE FOOTING, SPEC. CONCRETE, and several others. While these distinctions – aside from typos – may be useful in a line by line evaluation of specific towers for modeling purposes, all similar types are mapped into a single factor.

The resulting key fields, after cleaning, included those shown in Table 7.

Table 7: Key Asset Information Data Fields

Variable	Units	Type
Position	Latitude and Longitude	Continuous
Installation Year	Date	Continuous
Line Voltage	5 Categories	Categorical
Structure Type	4 Categories	Categorical
Peak Wind Speed	MPH	Continuous
Corrosion Zone	3 Categories	Categorical
Flood Zone	3 Categories	Categorical
Soil Group	7 Categories	Categorical
Landslide Hazard	6 Categories	Categorical
Peak Ground Acceleration	g	Continuous
Property Description	26 Categories	Categorical
Pole_Tower	2 Categories	Categorical
Division	20 Categories	Categorical
Fire Hazard	4 Categories	Categorical
Foundation Type	6 Categories	Categorical

5.2.2 Environmental Data

The internal PG&E data was further enriched through the use of public databases. This enrichment was performed using GIS tools that enabled the spatial joining of the asset data with environmental data.

5.2.2.1 USDA SSURGO database

The SSURGO database contains information about soil as collected by the National Cooperative Soil Survey over the course of a century. The information was gathered by walking over the land and observing the soil. Many soil samples were analyzed in laboratories. The mapping is intended for natural resource planning and management by landowners, townships, and counties [26].

The maps are linked to information about the component soils and their properties for each map unit. Examples of information available from the database include soil corrosivity, mean annual precipitation, mean annual air temperature, elevation, and mean annual frost days.

5.2.2.2 *National Atmospheric Deposition Program Data*

The National Atmospheric Deposition Program (NADP) is a cooperative effort between many different groups, including federal, state, tribal and local governmental agencies, educational institutions, private companies, and non-governmental agencies [27].

Sites in the NADP precipitation chemistry network began operations in 1978 with the goal of providing data on the amounts, trends, and geographic distributions of acids, nutrients, and base cations in precipitation. The network now known as the National Trends Network (NTN) currently has 250 sites, including 17 in California.

Data on chloride and sulfur dioxide deposition was used from this dataset. The methodology for this data collection was not suitable for use in the direct calculation of corrosion rates in the ISO methodology used in the engineering simulation, however this data was still tested for use as part of a statistical health index.

5.2.2.3 *Geography Data*

The structure dataset was further enriched with data regarding the location of hydrological bodies and the state of California's coastal zone boundaries [28],[29]. These enabled the creation of binary features for both of these variables.

5.2.3 Inspection Records

The asset information and environmental data is useful for characterizing the system of towers; however it lacks any target variables that can be used to analyze tower health. In this context, a target, or response, variable is a variable that a model would attempt to make a prediction about.

While ultimately, the objective is to predict tower failures, not enough tower failures have occurred historically to generate a large enough dataset for such a prediction. As a result, a proxy variable must be used, and the proxy selected is field notifications.

5.2.3.1 *Inspection and Notification Generation*

Notifications result from inspections which occur on an established frequency, as a function of line voltage. The guidelines for inspection frequencies are as follows.

Table 8: PG&E Inspection Schedule

Voltage (kV)	Inspection Type	Structure Type	Inspection Frequency (years)
500	Detailed inspection (ground)	Steel	3
230	Detailed inspection (ground or aerial)	Steel	5
230	Bay Waters Foundation Inspection	Steel	5
115	Detailed inspection (ground or aerial)	Steel	5
115	Bay Waters Foundation Inspection	Steel	5
60/70	Detailed inspection (ground or aerial)	Steel	5
60/70	Bay Waters Foundation Inspection	Steel	5

During inspections a record, known as a notification or a tag, is made if a structural issue is identified. These records are categorized based on priority, with different priority codes allowing for a different amount of time in which corrective action must be taken.

5.2.3.2 Notification Structure

Data associated with a notification includes several dates – including the date of discovery in the field, date recorded, as well as dates associated with any status updates – the company ID of the inspector, a unique notification number, the unique equipment number associated with the asset, the notification priority code, as well as a short description. An example of how the notification number, equipment number, and notification description may appear is shown in Table 9.

Table 9: Example Notifications

NOTIFICATION_NBR	SAP_EQ_NBR	NOTIFICATION_DESCRIPTION
123456789	50510101	LINENAME SW STA CC 25/161 RPL TWR
123456790	50510102	LNNM:2/17 INST ACG
123456791	50510103	LINE-NAME #1 6/47 NON-ROUTINE GROUND
123456792	50510104	LINE NAME, 01/12, RUSTED STUV=

5.2.3.3 *Target Data Enrichment*

The raw inspection notifications are a flawed proxy for predicting structural decay on their own. An asset can be tagged for a variety of reasons, most of which do not indicate that the asset is in a state of decay. For example, a tower can receive a tag if it is missing a danger sign, or if it needs a light installed due to FAA regulations. This challenge was resolved by running a simple keyword algorithm that identified if each tag contained any of a list of words indicating a health issue within the description. These keywords included "RUST", "FOOT", "SPLICE", "CONCRETE", "STEEL", "BOLT", "STUB", "LEG", "BROKE", "PLUMB", "TOWER DOWN", and "LEAN ".

After sub-setting the notifications to only those with a keyword in the description, the notifications were then aggregated to the tower level, as defined by a unique SAP equipment id number. Any tower with at least one of these notifications associated with it was then marked as a "tagged" tower.

NOTIFICATION_NBR	SAP_EQ_NBR	NOTIFICATION_DESCRIPTION	KEY_WORD_FLAG
112633335	40591332	BIRDS LNDG SW STA CC 25/161 RPL TWR	FALSE
112418816	40804568	LAKEWD-MEADOWLANE-CLAYTN :2/17 INST ACG	FALSE
112421728	40910988	COTTONWOOD #1 6/47 NON-ROUTINE GROUND	FALSE
112407347	40684308	METCALF-MORGAN HILL, 01/12, RUSTED STUV=	TRUE

SAP_EQ _NBR	KV	FUNCTIONAL _LOCATION	FOUNDATION _TYPE	STRUCTURE _TYPE	TOWER_ INSTALL_YEAR	TAG _COUNT	TAGGED _TOWER
40587409	230	ETL.5320	CONCRETE	LST	1972	5	TRUE
40603619	230	ETL.4580	CONCRETE	LST	1924	5	TRUE
40663712	230	ETL.5320	CONCRETE	LST	1972	5	TRUE
40757689	230	ETL.5540	CONCRETE	LST	1950	5	TRUE
40590818	230	ETL.5540	CONCRETE	LST	1950	4	TRUE

Figure 25: Notification Cleansing

5.2.3.4 *Target Data Limitations*

One challenge with using notifications as a response variable is that the data only contains notifications for towers that have received inspections. This means that without additional knowledge of which towers have been thoroughly inspected and which have not, a tower that has not received a tag may have not received a tag because it is in good condition or because it has not been thoroughly inspected. Due to this issue, the number of false negatives in the data is likely to be large.

This issue of imperfect response data will limit the ability of any statistical model to make clear distinctions between the healthy and unhealthy groups of assets, and particularly inhibit the model's ability to have high specificity – the ability to correctly identify a high percentage of healthy assets as such.

5.3 Model Construction

5.3.1 Modeling Methodology

Several approaches were explored in attempting to develop a statistical model for predicting asset health. These included regression as well as tree based machine learning methods. Ultimately, logistic regression was determined to be an appropriate modeling approach as this method provides more interpretable results than other methods, such as random forest, which is often considered by industry to be a "black box" in terms of the intermediate steps.

The logistic regression model attempts to separate the data into two groups, "tagged" and "not tagged", by applying coefficients to each of the characterizing variables. These coefficients determine the shape of a boundary that best separates the variables.

In constructing the model, the objective is to maximize the model's predictive power, while minimizing its complexity, and also ensuring that the model is not overfit, so that it can be applied to data beyond that which was used to train the model.

5.3.2 Training Data

The data used for modeling consisted of 38,699 records, the subset of the 41,648 records in the GIS database that contained an installation year. Of these records, 1,678 (4.3%), were identified as "tagged." This 4.3% is a useful reference point, as a tower with a predicted probability of having a tag as 0.043 is an "average" tower.

A 75/25% split was performed, maintaining an equal ratio tagged towers in both sets. The resulting training set consisted of 29,024 records, and the test set, used for validating the model, contained the remaining 9,675 records.

5.3.3 Variable Selection

A method known as forward variable selection was implemented to select variables. This is an iterative method in which the model begins with no variables, and a variable is added to the model with each iteration until the optimal complexity/performance trade-off has been reached.

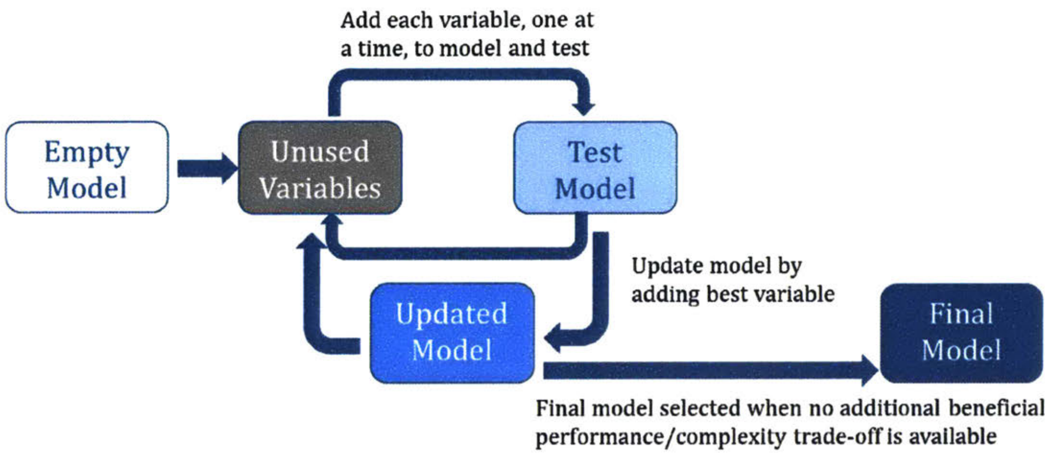

Figure 26: Forward Variable Selection Schematic

After performing forward variable selection, the equation for predicting the probability of a tower having a tag took the following form:

Tagged Tower Probability = f(# of Frost Days, Date Installed, Chloride Deposition Rate, Foundation Type, Soil Type, SO_2 *Deposition Rate, Landslide Risk)*

5.3.4 Model Coefficients

The model structure resulting from the forward variable selection is shown below, along with the associated coefficients. The low P values for each of these coefficients indicate the strong likelihood of a relationship between the independent model variables and dependent response variable.

```
glm(formula = CuratedTag ~ mean_annual_frost_free_days_r + INSTALLED_DATE +
    cl_tw + FOUNDATION + SOILGROUP + LANDSLIDE_HAZARD + so2_dw,
    family = binomial, data = trainSet)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.3828  -0.3292  -0.2648  -0.1816   3.2405

Coefficients:
                                          Estimate Std. Error z value Pr(>|z|)
(Intercept)                              39.012074   2.823603  13.816  < 2e-16 ***
mean_annual_frost_free_days_r             0.007519   0.001176   6.392 1.64e-10 ***
INSTALLED_DATE                           -0.022063   0.001444 -15.280  < 2e-16 ***
cl_tw                                     0.032562   0.016653   1.955 0.050545 .
FOUNDATIONCONCRETE                        1.344296   0.288367   4.662 3.14e-06 ***
FOUNDATIONEARTH                           0.966550   0.306180   3.157 0.001595 **
FOUNDATIONOTHER                         -11.274747 194.532700  -0.058 0.953782
FOUNDATIONPILE                            1.927804   0.320032   6.024 1.70e-09 ***
FOUNDATIONUNKNOWN                        -0.001106   0.327149  -0.003 0.997303
SOILGROUPbedrock/bedrock-like materials  -1.949751   0.562214  -3.468 0.000524 ***
SOILGROUPclays                           -1.381153   0.478508  -2.886 0.003897 **
SOILGROUPgravels/cobbles/boulders        -1.826586   0.486636  -3.753 0.000174 ***
SOILGROUPloams                           -1.023503   0.485805  -2.107 0.035133 *
SOILGROUPpeats and mucks                 -2.046580   0.550442  -3.718 0.000201 ***
SOILGROUPsands                           -1.750569   0.530341  -3.301 0.000964 ***
SOILGROUPvariable                        -1.334292   0.547255  -2.438 0.014763 *
LANDSLIDE_HAZARDLow                      -0.905249   0.239938  -3.773 0.000161 ***
LANDSLIDE_HAZARDLow to moderate          -0.808983   0.254362  -3.180 0.001470 **
LANDSLIDE_HAZARDModerate                 -1.119547   0.256407  -4.366 1.26e-05 ***
LANDSLIDE_HAZARDModerate to high         -0.743532   0.262782  -2.829 0.004663 **
LANDSLIDE_HAZARDNone                     -0.963758   0.228300  -4.221 2.43e-05 ***
so2_dw                                    0.149663   0.045709   3.274 0.001060 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 27: Model Summary

Several of the significant model coefficients were corrosion related parameters, including number of frost free days, installation date, chloride deposition rate, and sulfur dioxide deposition rate. This result is encouraging as it helps to validate the choice to drive the engineering simulation with atmospheric corrosion equations. A plot showing the impact of installation year on the probability of a tower having a tag is shown in Figure 28. The shaded range represents 95% confidence interval of the model's tower installation year coefficient estimate.

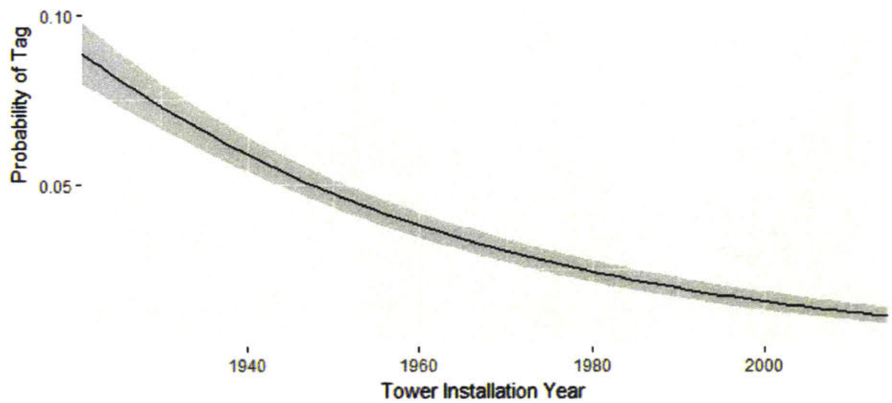

Figure 28: Impact of Installation Year on Tag Probability

The strong model dependence on atmospheric corrosion factors is expected, as the model would not be expected to pick up on underground corrosion factors. This is because inspections do not capture these effects, thereby leaving then absent from the notification data being used to generate the model.

5.4 Model Performance

The performance of a model can be measured by the AOC, area under the receiver operator characteristic (ROC) curve. The ROC is a plot of the true positive rate of the model (how often it correctly identifies a tagged tower as tagged) versus the false positive rate (how often it identifies a tower as tagged when it is not) with each point on the ROC plot representing a threshold probability that could be chosen as the classification cutoff of tagged versus not tagged.

The area under this curve shows the proportion of the time that if given one tagged and one untagged tower, you would correctly rank them correctly. Pure guessing gives an AOC of 0.5 and perfect classification gives an AOC of 1.0. The ROC for the structure classifier is shown in Figure 29, and achieves an AOC of 0.71, indicating good predictive power.

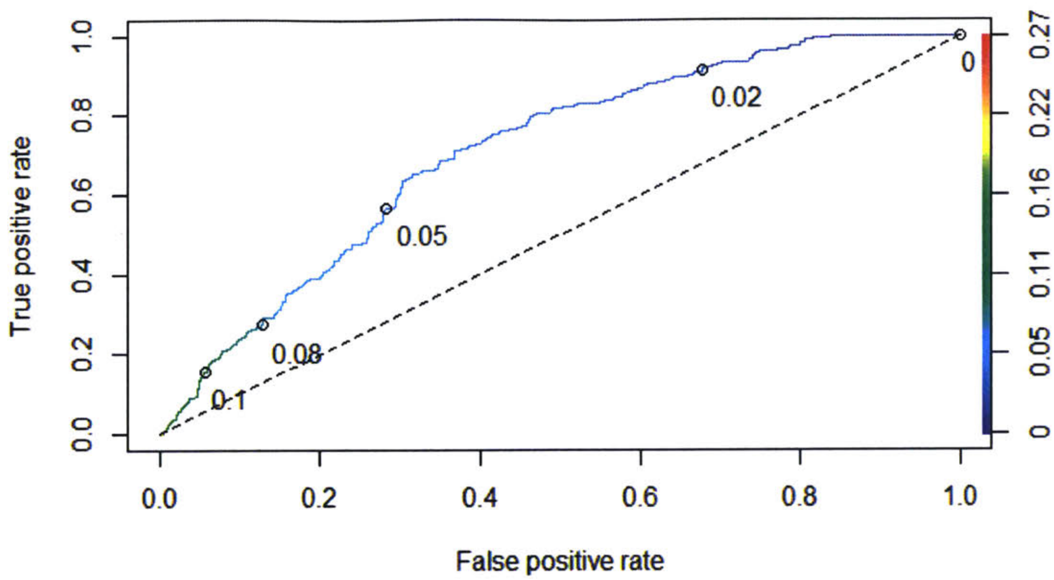

Figure 29: Receiver Operator Characteristic Curve for Structure Classifier

Another way of visualizing the performance is through a density plot of towers separated by tag status as a function of the prediction value, as shown in Figure 30. A perfect classifier would separate these two curves completely, while pure guessing would have them entirely overlapped

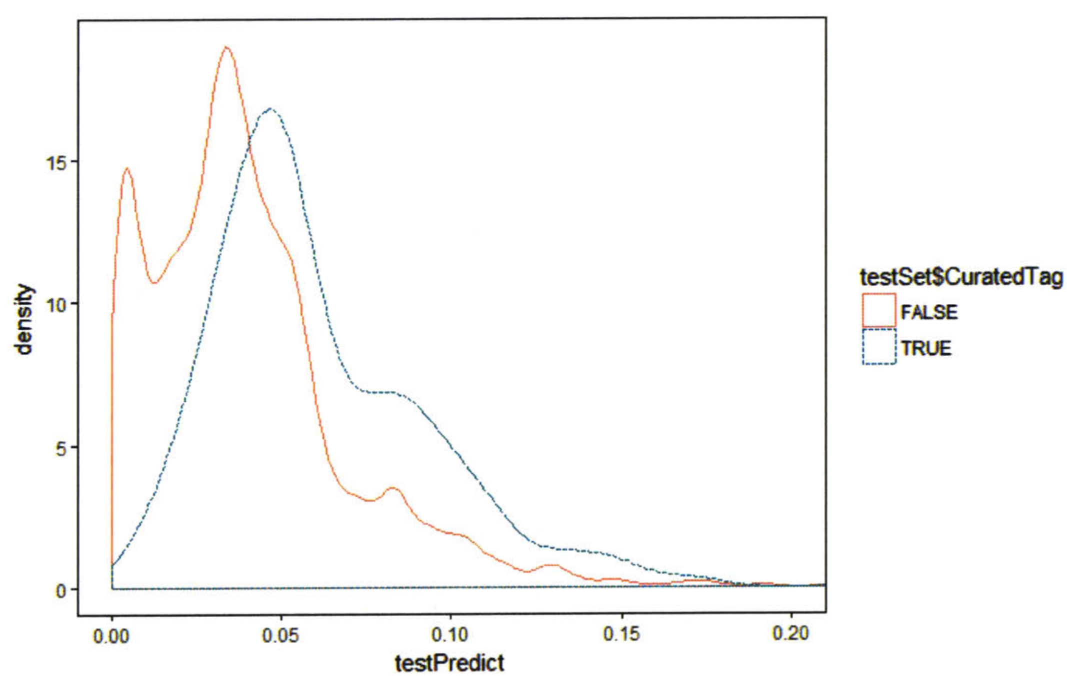

Figure 30: Classifier Density Plot by Prediction

5.5 Visualizing Results

Because 4.3% of all towers in both the test and training sets have been tagged, the low baseline predicted probability is expected. Figure 31 illustrates that few tagged towers are captured at the low end of the predictions, below 0.025, indicating that the 25% of assets receiving predictions below this threshold can be predicted to be untagged with high confidence.

Several untagged towers are still captured at the higher predicted probabilities due to the high false negative rate expected from the inspection data.

For visualization purposes towers have been classified into 4 categories*:

Good health: 9,831
Uncertain health: 16,558
Elevated health risk: 9,049
High health risk: 2,236

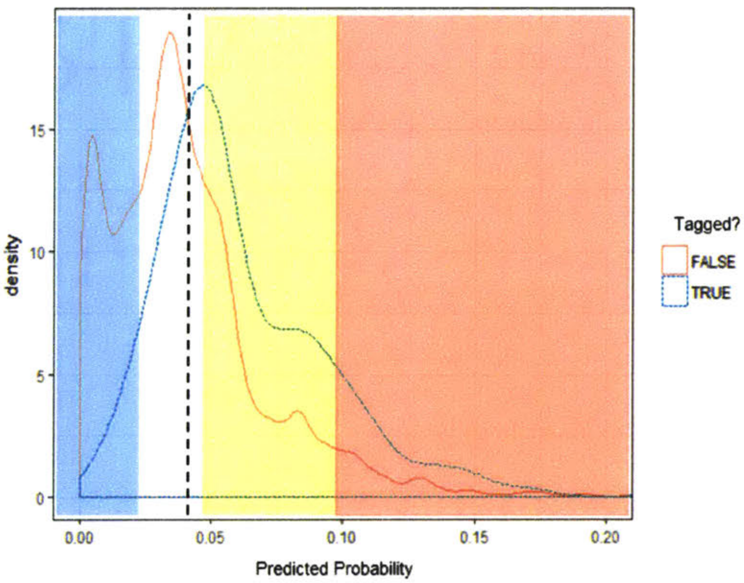

Figure 31: Classification by Predicted Probability

After classifying the assets into one of the four risk categories defined by the predicted probability thresholds shown in Figure 31, these results can be mapped. Figure 32 shows all steel transmission structures in PG&E's territory mapped by health risk. The San Francisco Bay region has been highlighted, as the highest density of elevated risk towers are located in this area.

From these visual results, the clustering of at-risk assets by line can be seen. This is to be expected given the dominance of structure age in the model, and that all assets in a given line were generally constructed during the same period. The model results are shown on a line by line basis in Figure 33, where the average health score for the line is plotted, along with the minimum and maximum scores for any given asset on that line.

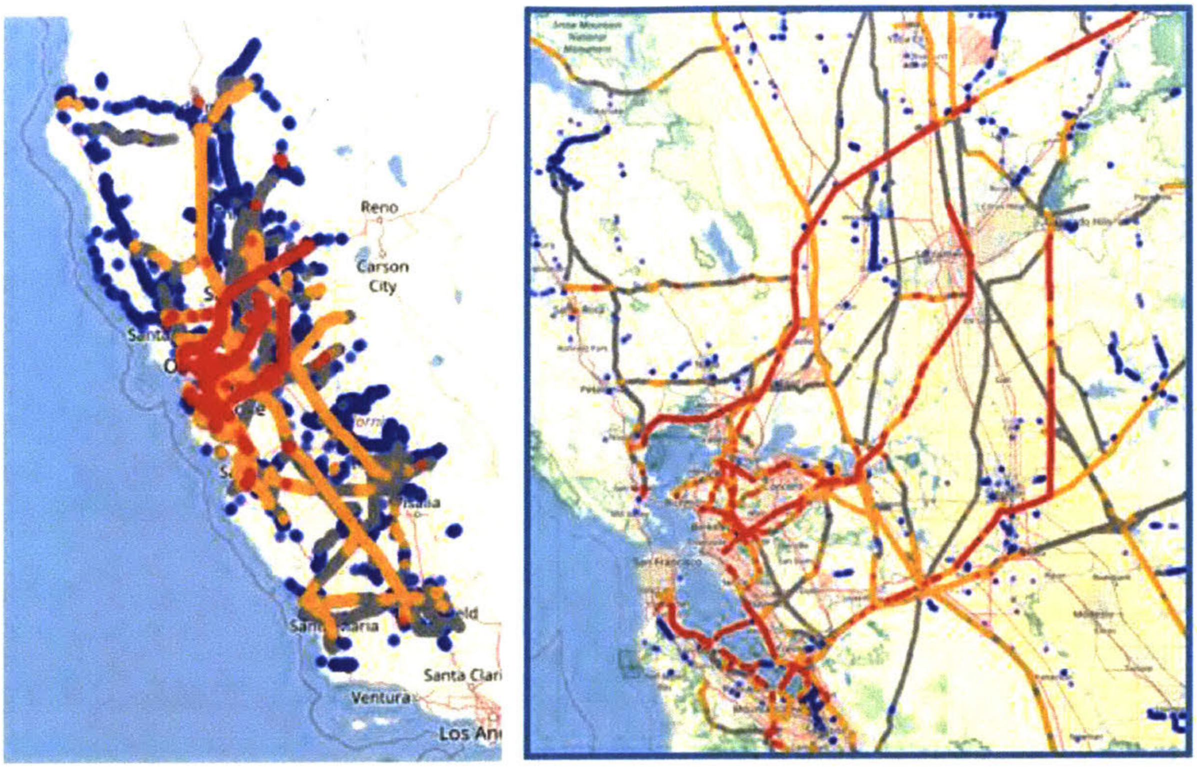

Figure 32: Mapped Results

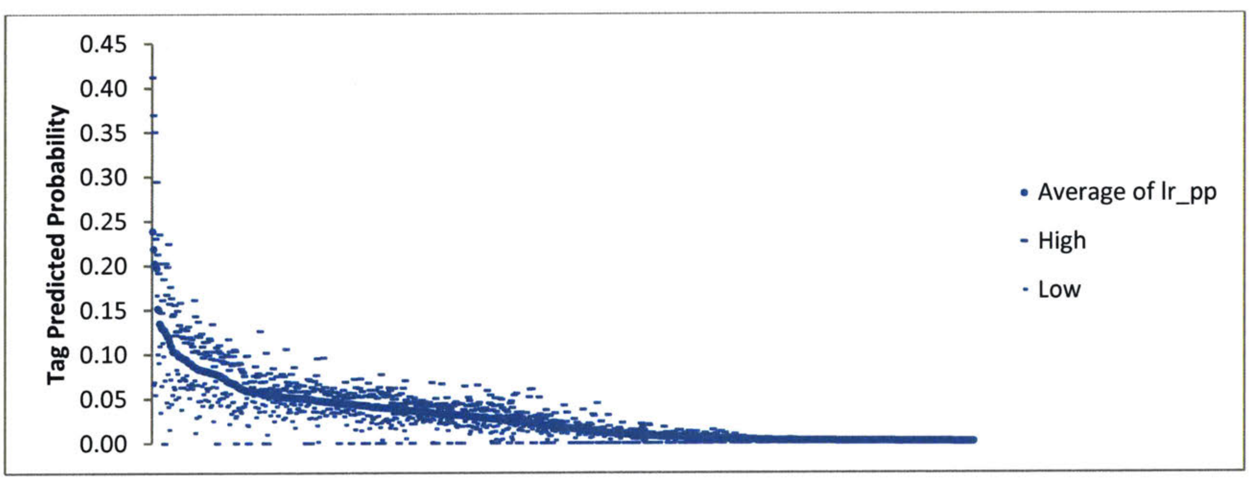

Figure 33: Health Index by Line

5.6 Conclusions

This work enabled the construction of a health index that is useful for prioritizing assets for further inspection. This in turn, assists in translating the general investment forecast developed in section 3 into a specific asset management plan.

Through this statistical modeling work, the following insights were uncovered:

- Existing inspection notification data can be mined for key words that allow for the prediction of structure decay
- Environmental factors and asset characteristics can be used to train a simple logistic regression model that has moderate predictive power for asset health
- Several factors known to drive atmospheric corrosion also contribute to the statistical model of asset health, despite variable selection for this model not necessitating this outcome

6 Areas for Future Development

6.1 Inspection and Data Collection

Currently, inspection data provides no way to distinguish between a false negative and true negative. This can be corrected by establishing a centralized database that captures inspection records, including towers that have been inspected and deemed to be in good condition. With these records of true negatives, a more selective model can be constructed by using only those assets which are known to have been inspected.

In addition to the inability to identify true negatives in the current data, tower inspections are currently performed in a qualitative manner, and with varying methodologies. For example, some towers are assessed through walking inspections, while others are only observed by means of a helicopter flyover. One way to correct for this may be to institute a quantitative assessment of steel member thickness. This measurement can provide quantitative data that enables the creation of section loss prediction models, and not only classification models on tags. These physical measurements will also require inspectors to be in close contact with the structures, ensuring that a more consistent qualitative assessment is performed in addition to the new quantitative measure.

6.2 Targeted Inspection and Maintenance Scheduling

By proactively determining an inspection and maintenance cadence for assets based upon their corrosion zone, total asset ownership costs can be reduced, from current levels which rely upon just in time maintenance. As the pool of assets continues to age, the risk of failure increases, and this increased risk of failure leads to an overall increase in expected cost over the expenses incurred through preventative maintenance.

In addition to instituting a proactive inspection and maintenance regime, the inspection data should feed back into the atmospheric corrosion estimates. If the distributions used around corrosion rates can be narrowed, this will enable even more targeted maintenance, and lower the overall cost of ownership.

6.3 Cost of Failure Estimation

Separating out asset characteristics that lead to additional failure costs from those characteristics that increase the probability of failure is important for optimizing the maintenance cadence or replacement point of an asset. The analyses presented in this work focuses primarily on factors contributing to the probability of failure, but not on the cost of failure. Factors that may contribute to the cost of failure, and that warrant additional exploration include reliability costs such as outages for meshed or redundant lines, as well as the impact of failure in high-risk areas, such as fire zones, residential areas, and proximity to critical infrastructure.

Performing this analysis will enable the further refinement of maintenance priorities, while also increasing the precision of the overall spend forecast.

6.4 Failure Mode Analysis

An engineering analysis of potential failure modes, and the impact of corrosion on these modes can help to inform a more precise estimation of tower failure probability as a function of section loss. Narrowing this distribution in turn helps to further refine maintenance scheduling and allows for more efficient allocation of resources.

6.5 Foundation Health Analysis

This work focuses primarily on atmospheric corrosion and the above-grade structures, however below grade corrosion also degrades asset health. Internal PG&E data is currently limited on below grade structure health, and partnering with a national contractor that has data on these issues may be helpful in developing metrics for measuring foundation and below-grade asset health.

6.6 Conclusions

The goal of this work was to develop a sustainable maintenance and replacement strategy for steel transmission structures based on analytic tools. Two primary methods were implemented: a corrosion simulation of aging, and a statistical model using inspection results. The corrosion simulation enabled for the development of an aggregated spend forecast based on an optimized maintenance schedule. This high level forecast was complimented by the statistical model which is able to provide an asset prioritization that assists in targeting where that forecasted investment will be most effective.

Chapter 3, Steel Structure Budget Forecasting, demonstrated the following through the creation and application of a corrosion simulation enabled spend analysis:

- An NPV optimized maintenance strategy includes more frequent maintenance activities for structures in more aggressive corrosion zones, while structures in less aggressive environments require maintenance at a significantly lower cadence.
- For aging systems with no history of regular preventative maintenance, replacement of older structures in high corrosion zones may be necessary in the near term, after which point the optimized maintenance schedule should be applied.

Chapter 4, Investment Breakeven Analysis, explicitly formulates the tradeoff between maintenance and failure costs. This work demonstrated the following:

- Determining the appropriate level of investment for asset replacement or preventative maintenance requires balancing the cost of these actions with the expected cost of failure. The expected cost of failure is a function of both the probability of failure at any given time in addition to the cost incurred if a failure occurs.
- Maintenance or replacement activities can be thought of as buying time. When an asset is restored the time to expected failure is extended, thereby discounting the cost of failure more significantly.
- Breakeven restoration or replacement costs scale linearly with the cost of failure. If the cost of failure for one asset is twice as high as another, the breakeven restoration cost for the first asset is twice as high as the second

Chapter 5, Asset Health Modeling, uses statistical methods to develop an asset health index for steel transmission structures. Through this analysis the following was illustrated:

- Existing inspection notification data can be mined for key words that allow for the prediction of structure decay
- Environmental factors and asset characteristics can be used to train a simple logistic regression model that has moderate predictive power for asset health
- Several factors known to drive atmospheric corrosion also contribute to the statistical model of asset health, despite variable selection for this model not necessitating this outcome

The methods applied in this thesis, including the application of a corrosion simulation at an aggregate level coupled with a statistically based health index, demonstrate an effective strategy that can be applied to the field of asset management for steel power transmission structures.

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