Quantitative Risk Assessment Probabilistic Modeling (RAMP – D)

November 30, 2016

TABLE OF CONTENTS

1. Introduction

Southern California Gas Company (SoCalGas) and San Diego Gas & Electric Company (SDG&E) ("the utilities") are expanding their usage of quantitative approaches for risk modeling. Several efforts are currently in place, and modeling of more risks will soon be undertaken. This chapter contains an overview of quantitative risk modeling as well as some examples of how the utilities are implementing those models. Also included is a table of the status of how quantitative risk modeling is being used for the top risks at both companies.

In short, quantitative risk modeling attempts to use numerical data, including calibrated subject matter expert opinion, as inputs to determine the likelihood of outcomes. There are different levels of sophistication and complexity for each model, and those levels should be correlated to the risk themselves; that is, smaller risks do not require as much sophistication. Quantitative modeling relies on logic that describes how events occur and what their consequences might be, while attributing likelihoods to each of the steps. For less complicated risks, a likelihood can be a simple mathematical term like "1 in 10 years", but in other situations with uncertainties, the likelihoods may be taken from an appropriate probability distribution. The sophisticated models might utilize a Monte Carlo approach that samples randomly chosen data from probability distributions, and does so many times until the types and likelihoods of outcomes is well understood. In the end, the quantitative approach is a flexible method that uses numerical data and logic to find the most realistic model of real-world risks.

2. Definitions

Quantitative

Typically used as a contrast to "qualitative." Involves using numerical values and attributes rather than descriptive attributes. Quantitative information can be obtained from empirical measureable data; as opposed to qualitative information that are subjective and difficult to measure. The distinction between quantitative and qualitative is important because the quantitative nature of the analysis uses numbers that can have arithmetic performed. A model can have varying degrees of quantitative characteristics; some models being completely quantitative and other models have quantitative elements.

Probabilistic

A method is considered probabilistic if it incorporates information that uses probabilities or likelihoods in a quantitative sense. These methods can range from simple uses of likelihoods or failure rates to sophisticated Monte Carlo modeling.

Probability Distribution

A probability distribution is a mathematical function that describes the likelihood of different outcomes occurring. Below is a simple example using standard dice. There is a 1 in 6 chance of any specific value being rolled, so the probability distribution would simply be 1/6 for each value of 1, 2, 3, 4, 5 and 6 (shown in Figure 1 below).

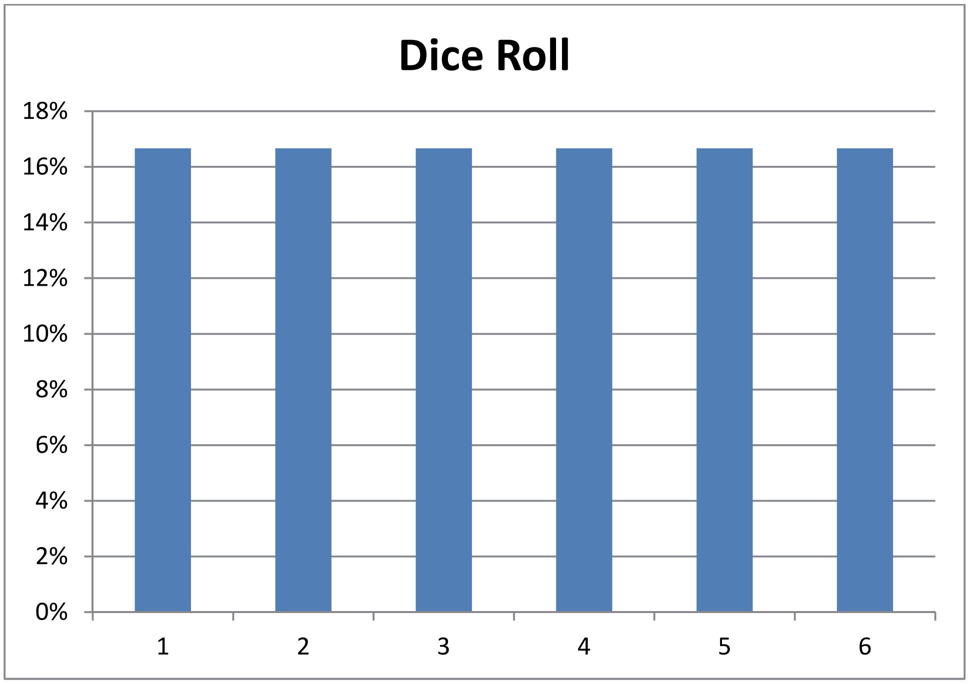


Figure 1. Probability Distribution for the outcome of a single die

A more complicated example of a probability distribution uses the "normal" distribution or bell curve, as seen below. In this example, the average is 100 and the standard deviation is 15. Once the probability distribution is described mathematically, it is possible to perform calculations using that distribution, such as determining the likelihood that the result will be between two values or the likelihood that the result is above a certain value.

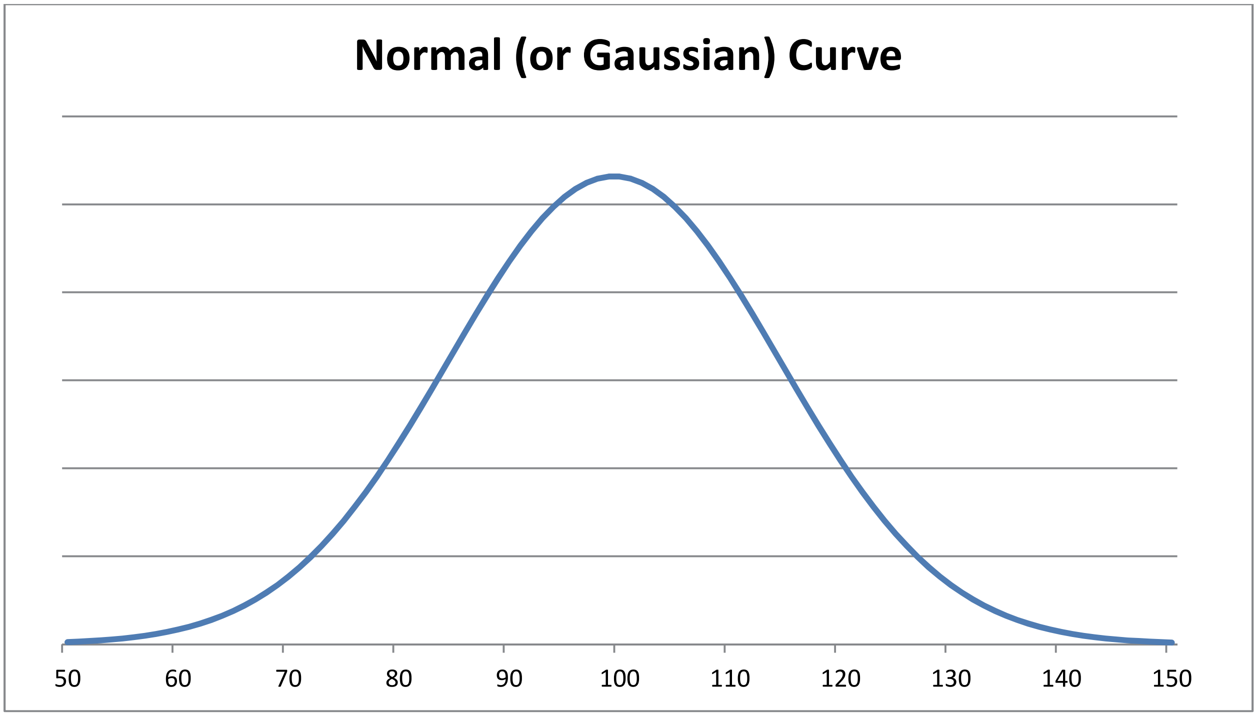


Figure 2. Probability Distribution of the "normal" curve when mean = 100 and standard deviation = 15.

Using the above probability distribution as reference, the likelihood that a result is above 100 is 50%. The likelihood that a value is between 70 and 80 is 6.8%. Another common use of probability distributions is to determine the most likely 90%; frequently used in the expression "90% confidence." With the above probability distribution, 90% of all values are between 75 and 125.

Stochastic

A stochastic method or process is one that incorporates uncertainty of the inputs, which usually leads to uncertainty of outcomes. Stochastic methods frequently use inputs from probability distributions which mimic or simulate the real world. If, for example, a casino were modeling the roll of a single die, it could use a probability distribution like the one shown in Figure 1 as part of a stochastic model. Stochastic models are most suited for use in a situation when multiple independent variables have uncertainty.

Stochastic methods are a contrast to deterministic methods. A deterministic method uses approaches which give the same outcome each time. Imagine that a bag of your favorite candy-coated chocolate was, on average, ½ red and ½ blue. Using a deterministic approach, a bag of 40 candies would always yield 20 red and 20 blue candies. But using a stochastic approach, the likelihood of each candy is considered. In fact, as can be seen in Figure 3 below, the chance of exactly 20 red candies occurring is about 12%. There is actually a 1% chance that 13 red candies will show up. In other words, if the process of distributing red and blue candies was truly random, out of 100 bags of candy, it would expected that one of those 100 bags would have only 13 red candies (and another bag would have only 13 blue candies).

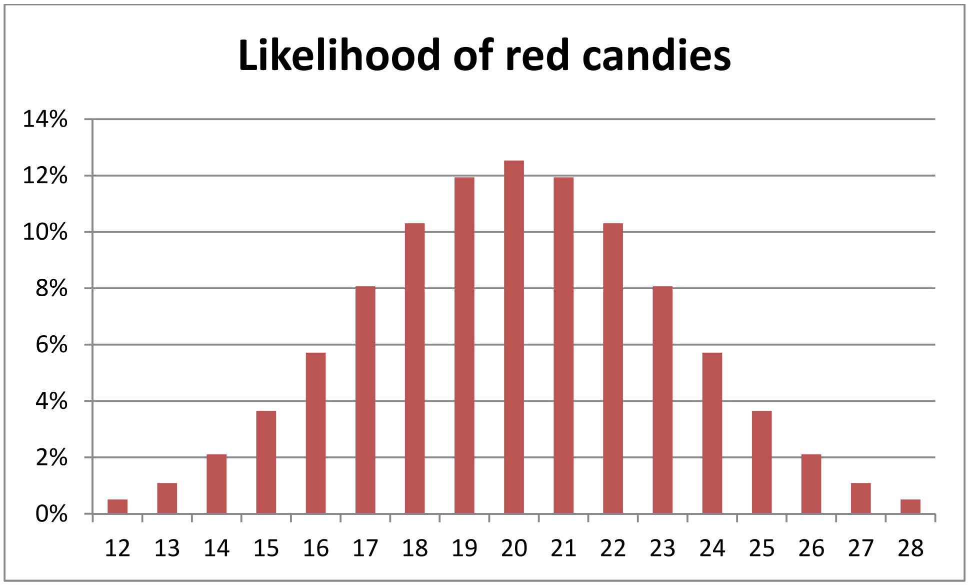


Figure 3. Likelihood of red candies in a 40-candy bag

Stochastic modeling is extremely powerful because it allows the analysis to demonstrate the actual variety of outcomes, rather than single, deterministic outcomes. Note in the candy example above, the deterministic approach would only have been correct 12% of the time, and therefore incorrect 88% of the time.

Model

A model is a set of tools that simulate something else; usually "the real world." Models can range in sophistication from simple to very complex. The sophistication of the model should be commensurate with the circumstance; meaning, complex models are better suited for complex problems. During a model's simulation process the analysis can test hypotheses, quantify results, determine the sensitivity of inputs, understand the likely ranges of outcomes, etc.

Models can be physical models like a miniature version of an airplane tested in a wind tunnel to analyze wind flow characteristics. Models can also be virtual models which are based in computer software. Most of the models that Risk Management groups work with are computerized logical models which process information in a certain fashion with if/then statements and likelihoods given by probability distributions. Computerized models can be simulated many times in a short amount of time which allows the analysis to easily adjust the model. Each model is purpose-built and, although many models appear similar, each element in the model is chosen for the specific reason.

Expected Value

The expected value (EV) of an event is the average outcome given the weighted likelihood of all possible outcomes. When rolling a single die, the EV is 3.5, because there is a 1/6 chance of each of 1, 2, 3, 4, 5, and 6 occurring.

The math behind EVs is: The sum of (all possible outcomes multiplied by the likelihood of that outcome). So for dice the EV is the sum of (1/6)*1 + (1/6)*2 + (1/6)*3 + (1/6)*4 + (1/6)*5 + (1/6)*6 = 3.5.

Expected values are very appropriate to use in some settings but can be misleading in others. The most appropriate situations to use expected values are when the variety of outcomes is not too disparate, or when the likelihoods of outcomes are also fairly similar. In the case of dice, the outcomes range from 1 to 6, and the likelihood of each is exactly 1/6. However, in an extreme case such as a nuclear disaster, EV might not be an appropriate technique to utilize. Because the computation of EV multiplies the outcome by probability, those events with small probabilities get diluted even though they have tragic outcomes. Suppose a nuclear plant has a probability of 1 in a billion of a catastrophic failure, and 999,999,999 out of a billion that everything is fine. And further assume that if there were a catastrophic failure it would cause 1,000 deaths. In this case, the EV would be: (1/1,000,000,000)*(1,000) + (999,999,999)/(1,000,000,000)*0 = 0.000001. But when the value of 0.000001 is observed it might be easy to forget the devastating possibilities. An EV of 0.000001 is likely much lower than many other risks that utilities confront, but few would suggest that nuclear catastrophes should be ranked low.

For this reason, it is not suggested to use a "one size fits all" approach to either modeling or how the model output is analyzed. Different situations require different statistics and tools, and different communication strategies.

3. Direction Forward

SoCalGas and SDG&E have a plan to address all non-trivial risks. The ultimate goal is to identify, assess, find mitigation for, determine mitigation effectiveness, create a portfolio of mitigation efforts, seek funding levels for mitigations, and carry out the mitigation efforts.

There are quantitative aspects in many of the steps mentioned above. The direction that the utilities are striving toward is to utilize quantitative approaches where appropriate throughout the risk management process. There is subjectivity to what is appropriate, but certainly risks that have numerical data and are significant to the company should eventually have some level of quantification. Risks that have almost no safety impacts may not require quantification. Additionally, it is important to understand the level of sophistication of models is also relative to the importance of the risk; where top risks will have thorough models, and lower risks will not. Not all risks will require Monte Carlo simulations with multiple stochastic inputs.

Model Sophistication

The utilities have already used quantitative risk models to affect business decisions. As the risk management process matures, more and more risks will have quantitative models. The evolution of models can be described loosely as:

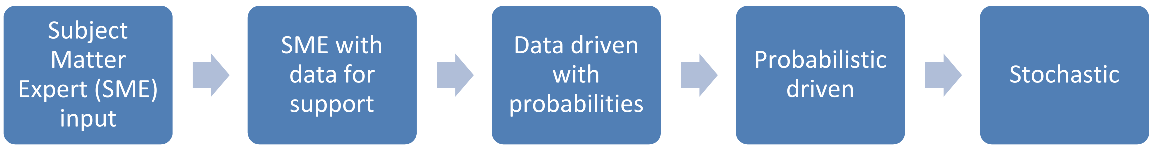


Figure 4. Evolution of Models

In reality, not all models will be able to be categorized exactly as shown above, as the complicated models will have elements from many of them.

Frequently during the evolution of a risk model, it becomes apparent that more data is needed to progress. Obtaining data can sometimes be done quickly or it may take years. In some cases, data specific to the need is not available but data that is similar can be used. In some situations, national organizations collect data that can be used to estimate local data – with the need to understand how the data is related. For example, when SDG&E was analyzing aviation risk, it was determined that National Transportation Safety Board (NTSB) data could be useful. However, the NTSB data contains all sorts of aviation risks, and some amount of filtering was necessary to get the data that was desirable. For example, the aviation data contains helicopter uses such as personal use, which are very different than external load. Luckily, the NTSB data was coded in such a way that filtering could get the data closer to what is appropriate for SDG&E's aviation risk. The same is true for PHMSA[1] data for pipeline risks.

Fault Tree

Most models will utilize a fault tree / decision tree type of logic flow. Fault trees help logically analyze the types of "triggers" that lead to a risk event. For example, note that an electrical outage can occur from many triggers such as vehicle contact, equipment failure, shutoff for safety, etc. A fault tree might list all of the triggers with probabilities. The tree might include several requirements. For example, a transmission outage typically occurs only after at least 2 transmission lines or substations have issues, but can also occur during ISO[2] curtailments. The fault tree shows the necessary steps before the outage occurs.

[1] US Department of Transportation Pipeline and Hazardous Materials Safety Administration (PHMSA).
[2] California Independent System Operator (Cal-ISO or ISO).

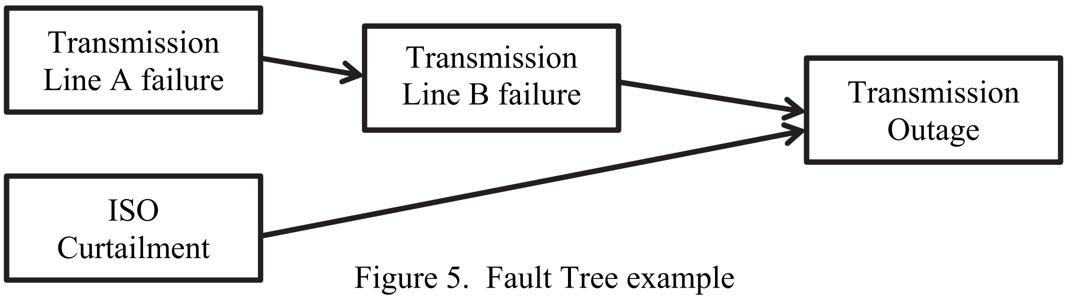


Figure 5. Fault Tree example

Each step on the Fault tree can have a probability associated to it. In stochastic models, the probability of failure may not be a single point, but rather a value drawn from a probability distribution.

Event Tree

Similarly, Event Trees are used to analyze the consequences of a risk event occurring. Using an electrical outage as an example, many negative consequences can occur:

- impact to public safety (*e.g.* traffic lights, hospitals, life support systems, communication);
- loss of valuable asset (*e.g.* food spoilage, industrial processes); or
- loss of productivity.

An Event Tree logically describes consequences in a manner that is conducive to probabilistic analysis. Using "food spoilage" listed in the above consequences for electrical outages, analysis indicates that food spoilage is not either $0 or $250 per customer (for example), but a continuous range of dollar values (possibilities). Historical data helps the analysis determine the characteristics of the probability distribution. One can quickly understand the levels of sophistication that can be applied to just the food spoilage portion of electrical outages. Knowing the number and type of customers is important. Business/commercial customers have different needs than residential. Also, estimating the length of outage affects the consequences. Food may not spoil for at least an hour. To truly understand the likely consequences of food spoilage, several inputs can be estimated/simulated.

Stochastic Analysis

For risks that require sophisticated analysis, probability distributions are commonly used to describe the likelihood of triggers and consequences. Using the food spoilage example from above, a simple probabilistic analysis can be illustrated. Say that a particular distribution circuit is configured in such a way that, due to the location of fuses, if an outage were to occur the following likelihood table would be true:

Customers Affected	Likelihood
5	50%
10	30%
15	20%

Furthermore, to simplify, assume that all customers are residential customers and that the outage will last exactly 6 hours. Assuming that data was available to create an estimate, a fictitious probability distribution of the value of their food spoilage given a 6 hour outage is given as:

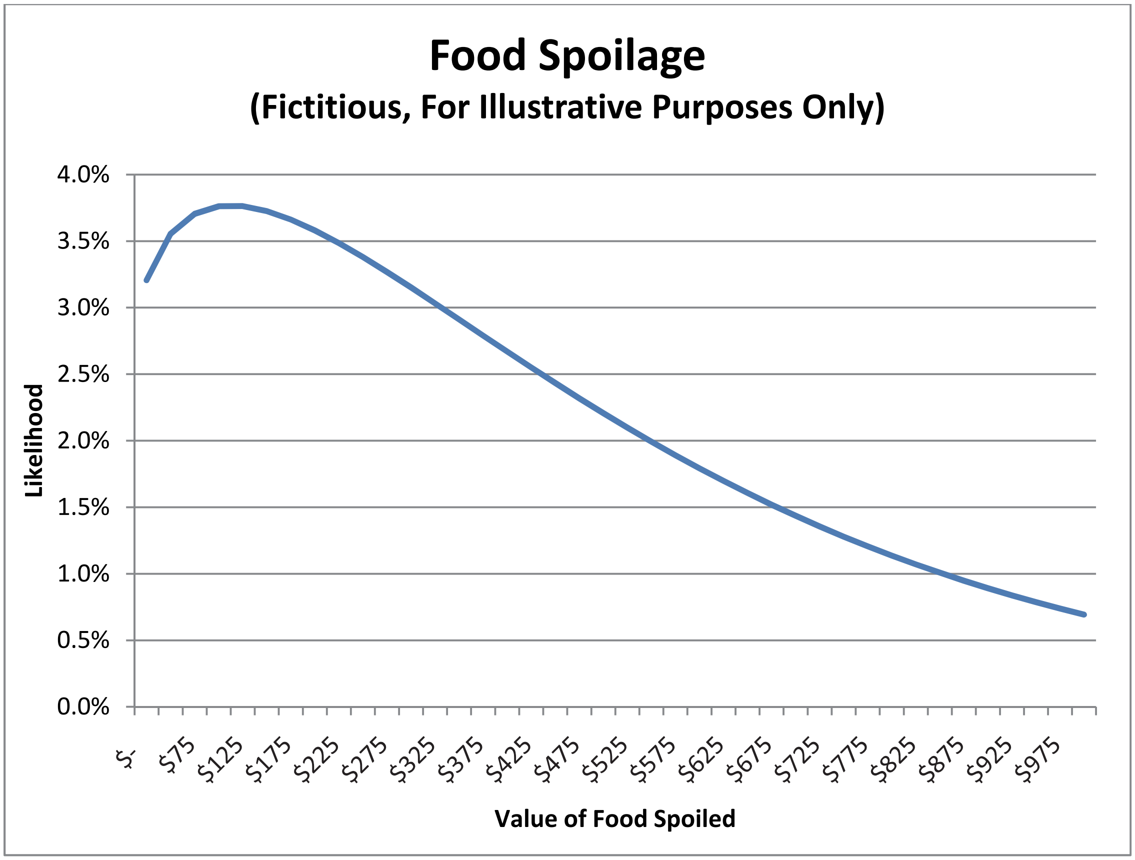


Figure 6. Food Spoilage

So, the first step is to randomly determine the number of customers affected. The second is to randomly determine the amount of food spoilage that each customer experienced. The output from both of these probabilistic inputs, with 2,000 randomized trials, is shown in Figure 7, below:

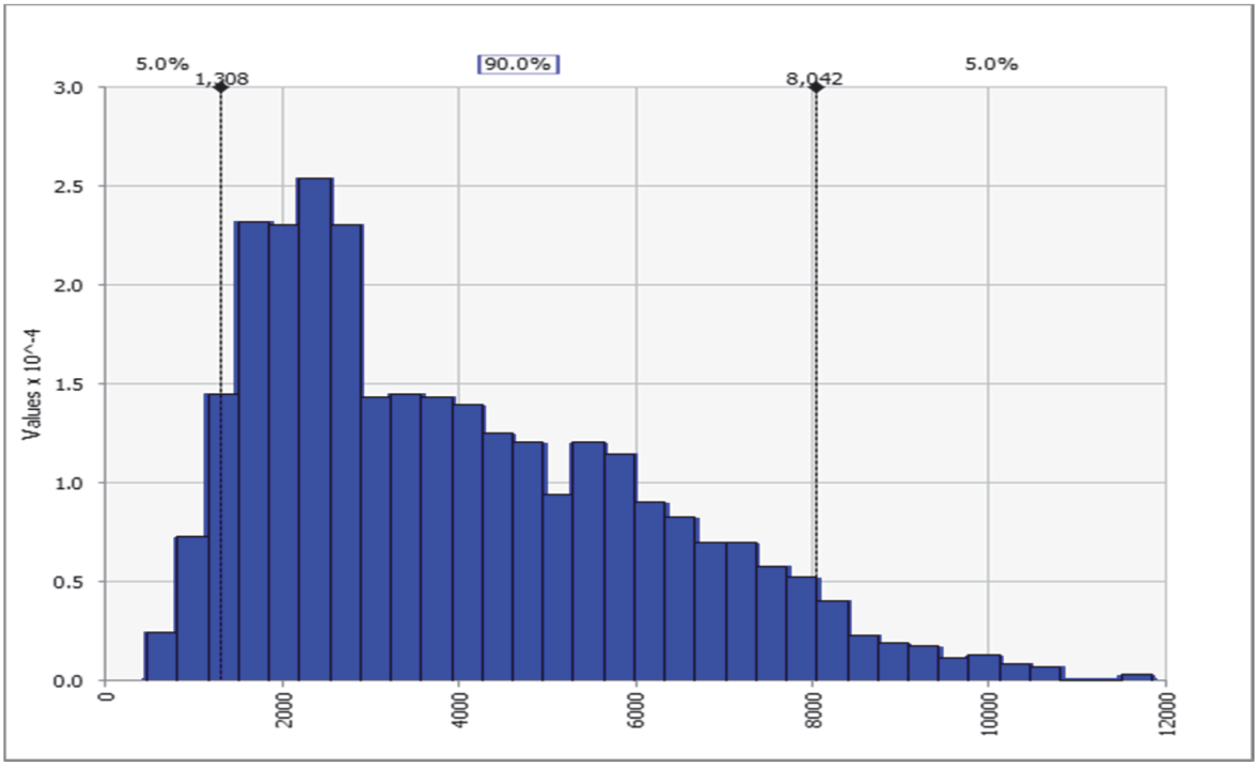


Figure 7. Impact (2,000 trials)

The average amount of the 2,000 trials is $3,985. The P95 (*i.e.* the 95th percentile – or 5th percentile from the worst[3]) is $8,042.

The utilities believe that it is important to consider both the average (expected value) and the extreme data points. In the example above, without the richness of data that is portrayed in the Total Impact, a single value of $3,985 could be misleading.

Interpretation of Model Output

The basics of determining mitigation effectiveness is analyzing the difference in risks before and after the mitigation, then considering the cost and other constraints of the mitigation. For risks that require quantitative modeling, the before and after risk assessments will likely be a distribution of outcomes and not a single point value.

Consider another illustrative example of vehicle collisions, using fictitious data. Suppose analysis can create probability distributions for "Before Mitigation" and "After Mitigation". Here are the two outcomes:

[3] The Company currently uses the" credible worst case" scenario as comparable to the P 95th scenario.

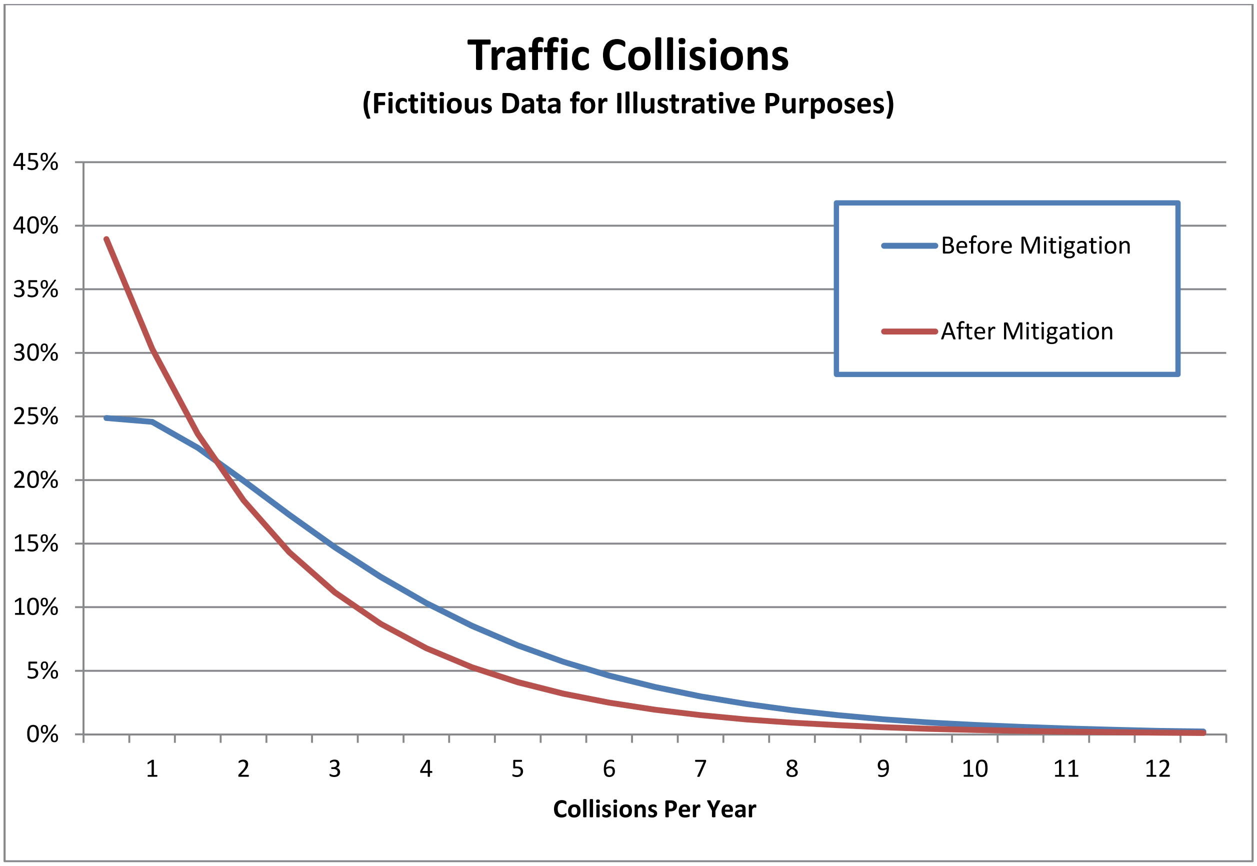


Figure 8. Traffic Collision Example, pre- and post-mitigation

If one were to consider the "average" case, there would be 2.2 instances a year before mitigation, and 1.4 instances per year after mitigation, for a reduction of 0.8, or 36%. But if the P95 case is considered, the values are 7.5 instances per year, to 6 instances per year, for a reduction of 1.5 instances or 20%.

The data is summarized in the following table:

	Before Mitigation	After Mitigation	Change in Collisions	Change in Collisions (%)
50% (Median)	2.2	1.4	0.8	36%
95% (P95)[4]	7.5	6	1.5	20%
Average (Mean)	3.2	2.3	0.9	27%

[4] The current risk reduction is equivalent to the credible worst case which will evolve to the mitigation curves reflected above.

One can see that there is a different result depending on which part of the information that is specified. The effectiveness of the mitigation effort can come down to subjective decisions, or acceptability of risk. If the utility was focusing on ensuring there were no more than 6 collisions per year, the mitigation effort might be considered successful. If the intent of the mitigation was to reduce the "average" amount of collisions, it only reduced the average by 0.9 which, depending on the cost of the mitigation effort, may not be deemed effective.

In short, the full view of the probabilities of outcomes helps the analysis determine different aspects of the issue. If everything is "boiled down" to a single number, it isn't clear if the mitigation is affecting the likely case or the dangerous case.

The path forward for the utilities is to view risks with their entire probability distributions and make appropriate decisions as they arise; as opposed to using a recipe style approach that mandates that only the P95 or the average case is viewed.

Summary of status of quantitative assessments

Using the 2015 Risk Registries, the following table includes asset-associated risks on either the SoCalGas or SDG&E Registries that have high consequence[5] and high frequencies[6] for their safety scores.

Risk Name	Description	Quantitative Assessment Status
Wildfire	The risk of an uncontrolled fire associated to utility equipment	Stochastic models in use
Electric Infrastructure Safety and Reliability	The risk of safety, environmental or reliability events due to degraded or overloaded equipment (i.e. transformers, breakers, relays, pole loading, overhead conductor, underground cable, PCB issues).	Electric reliability probabilistic studies involving underground cable and other equipment. Substation transformer CBM project is in-flight.
Aviation Incident	An aviation incident by our contractor, subcontractors or other third parties who may enter SDG&E's service territory that damages electric transmission, distribution and/or gas transmission facilities and may also result in an employee and/or customer injury or death.	Probabilistic study in use for our contractor and subcontractor flights. Non-utility aviation issues being addressed through studies of marker balls placement.
Cyber Security	A major cyber security incident that causes disruptions to electric or gas operations (e.g. SCADA system) or results in damage or disruption to company operations, reputation, or disclosure of sensitive data.	Risk assessments involving likelihoods and consequences have been undertaken and will continue to expand.

[5] Score of 4 or higher

[6] Score of 4 or higher

Catastrophic Damage involving Gas Infrastructure (Dig-Ins)	Risk of catastrophic damage involving gas infrastructure due to third party activity (dig ins).	Numerical data for likelihoods and consequences is used to create relative risk scores. Future work hopes to integrate probabilistic methods and a more robust quantitative approach.
Distributed Energy Resources (DERs) Safety and Operational Concerns	Risks related to both the intermittency of energy delivery due to PV, and the risk of PV causing safety issues during certain situations.	Quantitative risk assessments involved likelihoods and consequences have been undertaken and continue to expand.

Summary of Direction Forward:

- Identify risks using previously discussed methods.
- Assess risks with varying degrees of quantitative aspects depending on available data and appropriateness of outstanding risk.
- Assess mitigation efforts with varying degrees of quantitative aspects depending on available data and appropriateness of outstanding risk.
- Consider effectiveness of mitigations using a fully probabilistic approach, and choosing the emphasis of the mitigation improvements on a case by case basis.
- View all mitigation efforts in a single portfolio, and rank the items in order of effectiveness; determine the most appropriate level of spending given the real-world constraints that are present.

4. Completed Models

Below are some examples of models that are "complete" in the sense that they are being used by the company for decision making. However, no model is truly complete. Models can always be improved; due to the two reasons that better logic may be implemented, and that new data may become available.

Fire

Background: Wildfire risk is one of the most important risks to SDG&E. The complex nature of the risk is suitable for computerized modeling techniques. The Wildfire Risk Reduction Model (WRRM) was created to focus on equipment failures that lead to ignitions, and how those ignitions spread due to vegetation and weather.

Method: Fault tree and event tree analysis was performed on overhead equipment. This endeavor utilized many different sources of data including Geographic Information System (GIS), electric reliability, ignition, vegetation management. Each distribution pole in SDG&E service territory was considered.

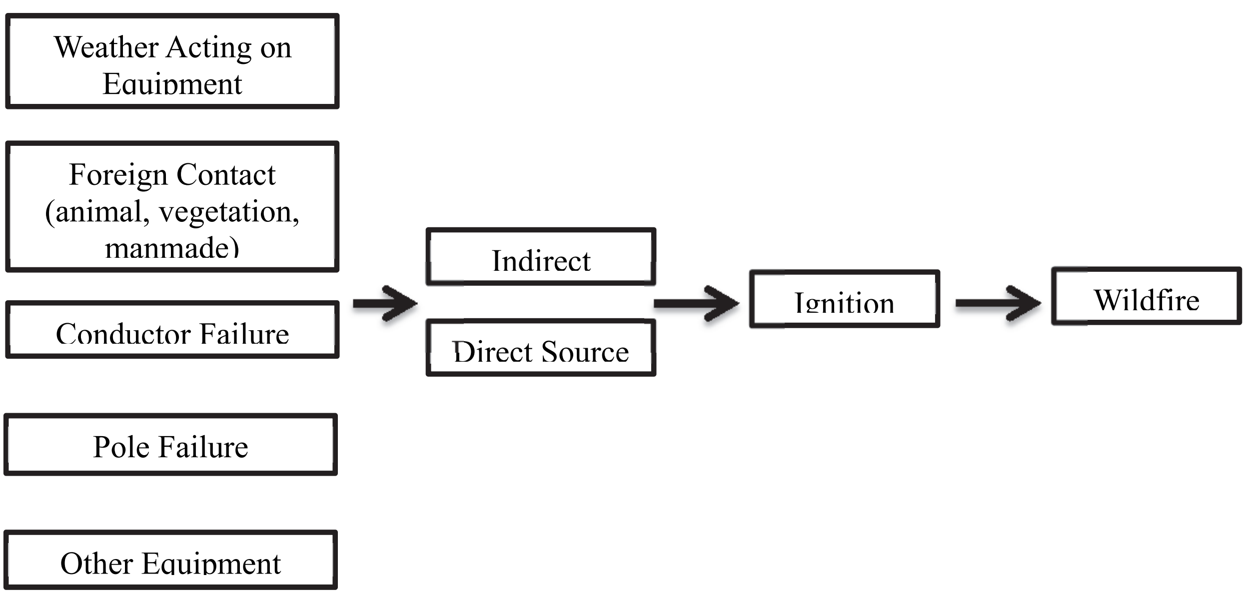
A brief overview of the steps undertaken is as follows:

a) The likelihood of failure at each pole was estimated based on equipment and equipment characteristics.
b) The likelihood of ignition from a failure was estimated based on vegetation and weather conditions.
c) The fire spread was simulated given initial conditions of fuel and weather.
d) The damage to property was estimated using land parcel data.
e) The above steps were used to calculate outstanding (or inherent) risk.
f) The improvements to each individual distribution pole were then assumed, and the data was rerun to understand the risk reduction due to those specific improvements.
g) Calculations were made to determine which poles, and which improvements, lead to the largest reduction of risk per $ spent.

Study: As mentioned elsewhere, each model is different than the others. For the case of fire, due to its importance, SDG&E used a sophisticated approach and sought the assistance from outside contracting. The concepts, data, and framework were developed internally, and the contractors implemented the ideas while adding their own expertise.

The product of the work is called the Wildfire Risk Reduction Model (WRRM, pronounced like the invertebrate). However, WRRM is not just a model, it is a group of endeavors. Firstly, it is a group of data that is stored in a database. The data is geographically/logically related using GIS data. It also utilizes a fire behavior model that the contractors developed. Finally, the data and analysis is summarized in a standalone software package that allows project managers to determine which pieces of equipment to change out.

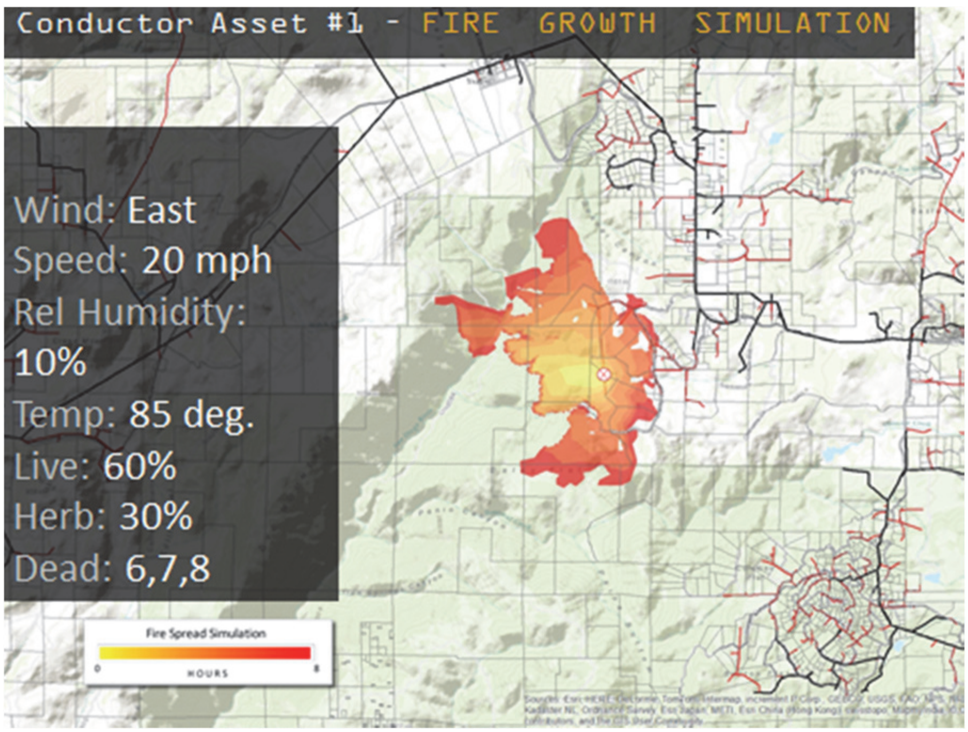
The heart of the model is the fault tree / event tree methodology such as the following:

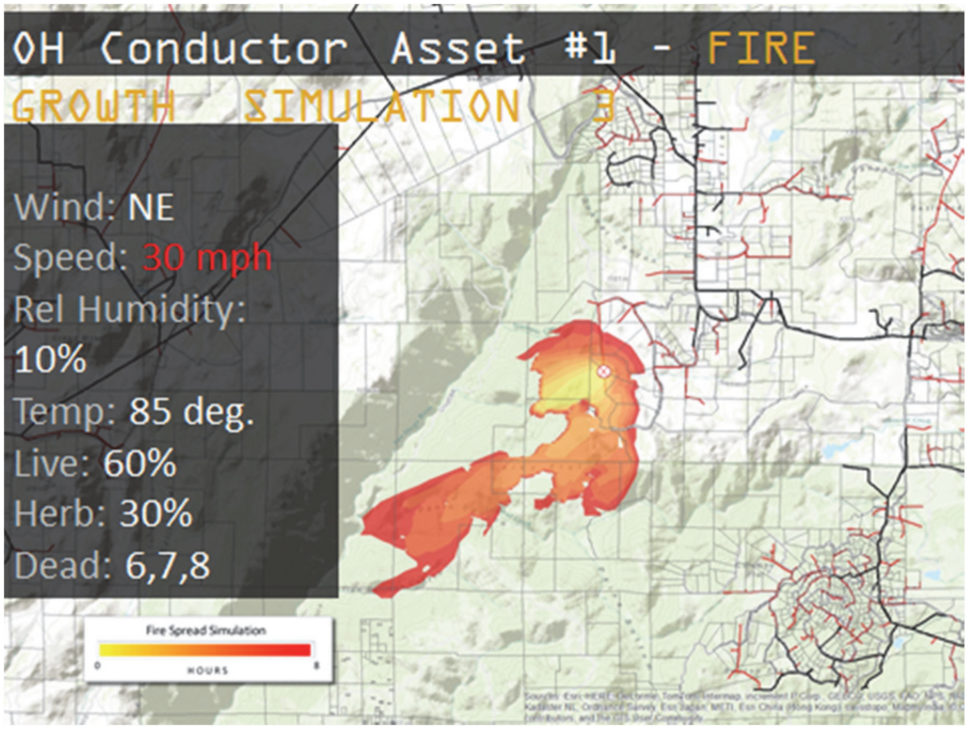


Post-event, the contractor's fire behavior model determines the event tree. There are two very important pieces of data that are used for the fire behavior: weather and fuel. SDG&E has extensive weather data and has simulated weather across its service territory to understand the distribution patterns of wind speed, wind direction, relative humidity, etc. Fuel data, or vegetation, is also well known in SDG&E service territory.

Virtual fires are ignited at each pole, and given initial conditions of weather, the fire model simulates fire growth. Different weather patterns are grouped together and run as a simulation. Over 100 simulations are run at each pole given the different conditions. Then, because the likelihood of the grouped weather pattern is known, weightings are applied to the results of each model that match the likelihoods of each grouping.

Below are two slides that demonstrate the model. Noting the weather conditions in each figure, observe the difference in predicted fire behavior when stronger winds are present.





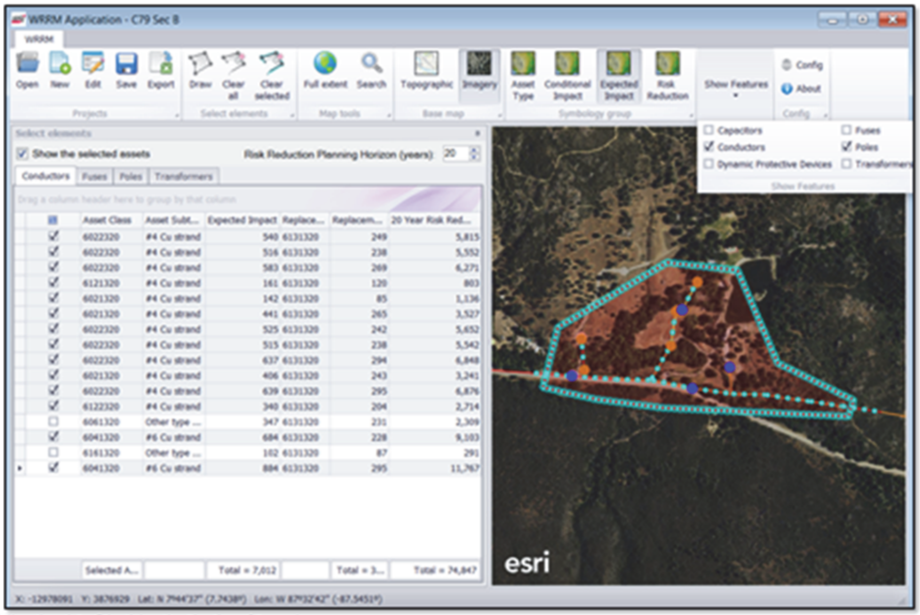
SDG&E chose to use property damage as a proxy for risk, because data supports that when more structures are burned the likelihood of safety and social impacts increases. Publicly available parcel data was used to identify where properties were located. The resulting data of each fire simulation is acres burned, and number of properties damaged. In the end, over 90 million fire simulations were run across SDG&E service territory.

Without overstating it, this analysis is a major breakthrough in risk management, as it fundamentally helps the company understand fire risk. The fire simulations indicate what level of risk currently exists, which locations have the highest risk, and the priority of repair work.

Although the plan for the WRRM is to utilize it in many ways, its first usage is to demonstrate which equipment to replace, in order to lower the likelihood of ignitions. To accomplish this task, the requirement is to estimate the post-renovation likelihoods of failures. Existing equipment has a wide range of types and ages. New construction in fire prone areas will be a standardized set of equipment. Therefore, the incremental improvement to the new construction depends upon the current equipment. Equipment that is known to have higher failure rates will have a larger incremental improvement upon renovation. This information, coupled with the risk at the location, help determine which locations to perform work.

SDGE A Sempra Energy utility® SoCalGas A Sempra Energy utility®

WRRM SOFTWARE



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Screenshot of WRRM software that Project Managers use to determine scope of renovation projects.

Future uses of WRRM will include other risk reduction considerations. It may be possible to understand how fire suppression activities lower risk, or how vegetation clearances around structures lower risk. The model could be used to determine the impacts from climate change. There is a myriad of uses for WRRM that will be available to the utility and society in the future.

An exciting new usage for WRRM is already being piloted to assist with real-time fire risk assessments. A version of WRRM called WRRM OPS is being developed that utilizes forecast data and current fuels information to estimate threats. Recall that WRRM utilizes historical weather data to determine areas of interest. WRRM OPS uses specific weather forecasts that predict upcoming wind patterns, temperatures, humidity etc. Because SDG&E has a robust fire preparedness plan during fire weather, the output from WRRM OPS will allow the operations groups to focus on particular geographical areas and alert the community of specific hazards. To elaborate, certain fire weather may be broad in geographic scope, affecting much of SDG&E service territory, but it is also common to have weather that targets only the eastern sections or the northwestern sections. There is also a timing component gleaned from WRRM OPS which gives insight where the risk is as the weather event crosses the service territory.

Both WRRM and the piloted WRRM OPS are world class quantitative tools that dramatically assist in risk management. SDG&E is enthusiastic about these products and is willing to share details with any interested parties.

Aviation

Background: SDG&E utilizes aviation assets for several business purposes. The main reasons are inspecting equipment, assisting in construction, and assisting in fire suppression activities. One of the aviation assets used was a single engine helicopter. The Aviation Services Department (ASD), in an effort to assist with strategic goals of the company, considered whether the additional costs of owning a twin-engine helicopter would be beneficial.

Method: The entire model was created using Microsoft Excel, R, and @Risk. The work was done completely in-house and consumed approximately 80 to 120 man-hours (though the time was not measured precisely due to multiple projects being undertaken simultaneously). The results were presented to ASD who then processed the findings through its management and the appropriate budget committees.

Study: The Quantitative group of Enterprise Risk Management (ERM) met with ASD to discuss the situation. As with many risk issues, the first task was to quantify existing risk associated to the current helicopter. Because the dataset of helicopter related usage and risk events is small, the situation was appropriate to seek outside information.

As mentioned above, the National Transportation Safety Board (NTSB) has data on helicopter related safety (in addition to vast amounts of data regarding many forms of transportation safety). The data at the NTSB was filtered to create a relevant source of data that was suitable for comparative purposes. Fortunately, the NTSB has data that identifies both single and twin helicopter safety records. NTSB data also indicates the severity of the incident, in terms of fatalities, injuries, and damage to the aircraft.

To fit the NTSB data to SDG&E's purposes, various data for flight conditions were removed. SDG&E flights are typical "low and slow" as well as close to obstructions. These conditions are considered very risky due to the increased likelihood of contacting structures, as well as the reduced ability to recover from various mechanical or external issues. At higher altitudes than commonly flown at SDG&E, or when flying at higher speeds, helicopters have more ability to land using a maneuver known as "autorotation." For these reasons, ASD and ERM applied an increased incident rating to the NTSB data.

For business purposes, it was suitable to analyze the risk from a 10-year perspective, rather than year-by-year. ERM computed risk annually but grouped the years into 10 year segments.

There were 3 inputs that were used stochastically:

- Failure rates/hour;
- Hours flown per year; and
- Consequence of Failure.

Failure rates/hour

Risk events at the NTSB are measured by events per flight hour. Importantly, the events per flight hour statistics vary quite dramatically from year to year. NTSB data goes back approximately 10 years, and each year has a wide distribution of failure rates. For example, a particular accident rate per flight hour changed from 2.98 to 2.30 to 3.10 to 3.96 within 4 consecutive years. There is a near 70% difference from the minimum to the maximum. The variation of the data is yet another reminder that there exist natural distributions of information that are not completely known beforehand. Because of this variation, SDG&E used a distribution of events/flight hour based upon the observed variance in the historical data.

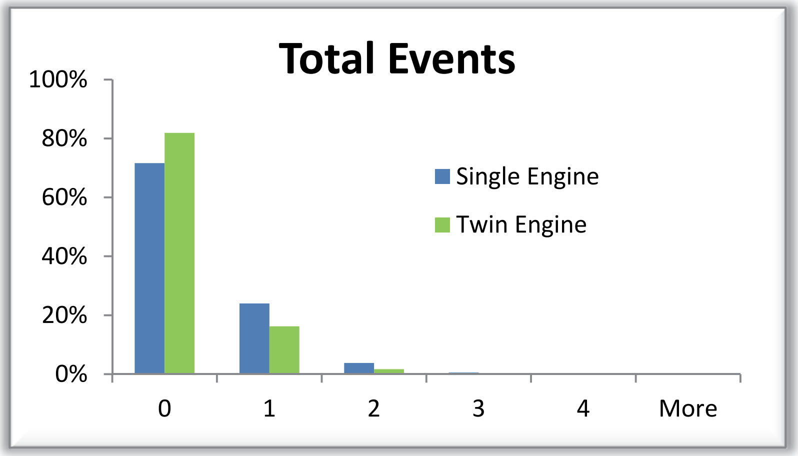
Hours flown per year

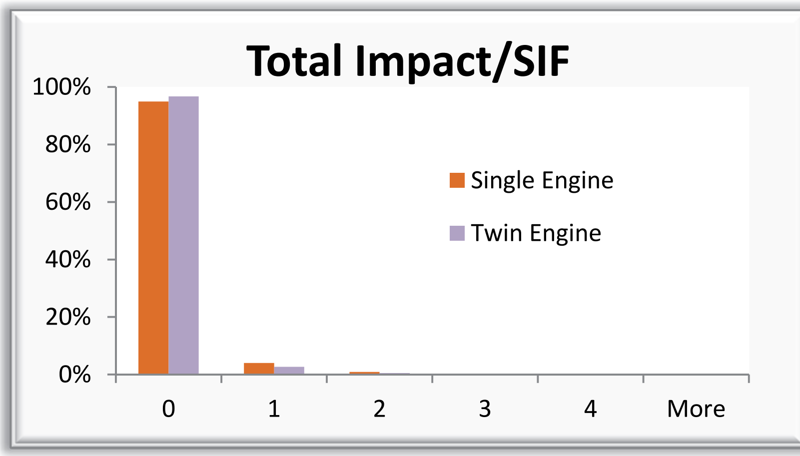
The number of flight hours expected to be flown each year were drawn from a probability distribution that was based on historical information and audited by ASD for reasonableness. The variance of the hours flown per year is not as large as the failure rate/hour, but it nonetheless is an important concept to model. The probability distribution that was chosen provided that 95% of the years that were modeled would have flight hours between 700-1100 hours per year.

Consequence of Failure

The NTSB houses large amounts of information regarding the consequences of helicopter crashes. Some assumptions were made, and a probability distribution was chosen that fit the data the most appropriately. The probability distribution of consequences was monetized and ranged across the range of $0 to $90 million. This distribution had the widest variance of the three inputs and therefore the analysis was most sensitive to this input.

Below is some sample output from the work. The data shows the reduced likelihood and impact from twin-engine helicopters in the conditions under which SDG&E operates:





Medium Pressure Pipeline

Background: SoCalGas and SDG&E have multiple pipeline integrity programs. They are divided into categories based on pipeline pressure, and also the location/purpose of the equipment. For example, there are programs for the meter, service, and pipeline of the system. Each asset has different risk assessment inputs. The Distribution Risk Evaluation and Management System (DREAMS) analyzes medium pressure pipe segments using relative assessments of probabilities and consequences of pipeline risk events.

Method: Assessments are performed at a pipe segment level and are used to determine which segments should be mitigated. Mitigation is usually performed through repair or replacement. Analysis reviews critical inputs to both probability of an event and the consequent of an event. The work is performed in-house, and requires several professionals to collect, receive, and analyze relevant data.

Study: The analysis is broken into two sections; probability and consequence. Steel pipe and plastic pipe are evaluated separately. For steel pipe analysis, the probability calculation is comprised of four weighted factors: age of pipe, wrap of pipe, cathodic protection, and historical leaks. For plastic pipe analysis, the probability calculation comprises three weighted factors: material, construction method, and historical leaks. For both steel and plastic pipe analysis, the coefficients are used to weight the inputs and create a probability score. The maximum potential score is a value of 100.

Next, a consequence score is calculated by using five factors: pressure of line, proximity to structures, population density, pipe diameter, and leak codes. These factors also have coefficients that provide weightings for the consequence score. The maximum consequence score is a value of 50.

The risk score and the consequence score are multiplied together then divided by 10for a max score of 500. Data is updated annually to ensure the most recent leak data, to account for work performed during the year, and other information gleaned from inspections.

The coefficients used for weightings are based on a combination of numerical input and subject matter expertise. Different coefficients are used for plastic pipe versus steel pipe. Internal leak data is used to calibrate the values.

With a given budget allocated specifically to medium pressure pipeline mitigation, projects are risk-prioritized. With the prioritized list, project managers and engineers identify the appropriate mitigation approach, and review other constraints of performing the mitigation. The amount of work is then performed to match the budget.

Although the current methods are not stochastic, the DREAMS program is an example of relative assessments, and has done an excellent job in prioritizing mitigation efforts. There is a plan to review the program and determine if a stochastic approach is warranted. A desired end result for all pipeline integrity programs is to be able to compare across programs to allow for the best portfolio approach of risk mitigation.

Electric Reliability

Background: For many years, SDG&E has utilized quantitative approaches to understand electric reliability issues. As early as the mid-1990s, the CPUC instituted Performance Based Ratemaking (PBR) with SDG&E. During that time, PBRs were used for more than Electric Reliability (such as Customer Satisfaction). In short, the Electric Reliability PBRs are a way to incentivize SDG&E to maintain good reliability, at the cost or reward to its shareholders. The PBRs have very clear definitions and benchmarks. In the electric reliability industry there are calculations that are annually undertaken that are used to state that reliability. One of those calculations is called SAIFI (which stands for System Average Interruption Frequency Index). SAIFI is calculated by determining how many customers experienced an outage during a year then dividing by the number of customers in the electric system. A SAIFI value of 1 means that, on average, each customer experienced one outage that year. One of the PBR incentives might associate .01 SAIFI to a certain amount of money. Currently, in 2016, the PBR states that .01 SAIFI is equal to $375,000. Note that SAIFI is not the only index that is in the current PBR.

To maximize reward – and therefore electric reliability - SDG&E studied reliability using PBR as its measuring stick. SDG&E determined the most effective methods of reliability improvement for the fewest $ spent. The issue of spending fewer $ not only keeps rates down, but it allows more work to be performed each year.

Method: SDG&E performed (and continues to perform) various analysis that seeks to minimize SAIFI per $ spent. These approaches include knowing the likelihood of incidents occurring and the impact of each incident. Failure rates of equipment, likelihood of vehicle contact, aviation contacts, etc. were all studied to determine the best path.

Study: A suite of possible projects is considered by working teams and taken to management for funding.

An example of a particular issue involves the failure of underground cable. Prior to 1983, much of the underground cable installed in SDG&E's service territory had a characteristic that made it fail earlier than expected. Because large amounts of that cable type were installed, there was the potential for severe impacts to electric reliability. Studies were undertaken to identify failure rates of the different kinds of that cable type; looking at size, year installed, manufacturer, etc.

Additionally, SDG&E GIS system allows the analysis to estimate the number of customers affected if a particular piece of cable were to fail. Note that a cable failure will cause a large ground fault that will cause a circuit breaker or fuse (or some other protective device) to operate.

Armed with the likelihood of failure, and with the consequence if a failure occurred, it was possible to estimate the SAIFI impact using the typical before and after mitigation approach. Management then determines the appropriate amount of funding to seek.

Stochastic approaches have been used to validate the above analysis. Monte Carlo simulations were performed that randomly place outages on the electric distribution system, to determine the impacts from the outages. The simulations show that the number of customers experiencing outages match with historical numbers, further indicating the randomness of events; in this case the randomness of the outage. If, for example, SDG&E believed that a particular type of cable will fail 1 out of 10 years per mile, it isn't known which piece of cable will fail. There is nothing deterministic about the failure - the location is not known. The analysis does indicate, however, that given everything else equal, the location of an outage which will affect the most customers is the best place to reduce SAIFI impacts – and therefore improving the customer experience.

Other probabilistic studies involving electric reliability have looked at the sizing of transformers and fuses, the addition of switches and so on.

This forward-thinking view of reliability has won SDG&E the Best in West Region award for electric reliability for 11 years in a row, and during that time has received the National Best reliability award twice.

Additional probabilistic analysis is looking into the relationship between weather and the need for electric line personnel. With a strong understanding of the relationship between weather and electric outages, and accurate weather predictions, personnel decisions can be made to optimize the best electric restoration responsiveness without asking too many crews to standby.

5. In Flight

Transmission pipeline

Discussion: Over the past year, SoCalGas initiated a pilot study with an outside consultant. The study is looking into a fully probabilistic, stochastic analysis of the high pressure gas transmission system. Although much analytical work has been performed, early results are still being considered and adapted to meet the business needs of the utility.

In short, the study focuses on assessing the reliability of pipelines. Probability of failure is estimated for each segment of pipe using various distributions and Monte Carlo simulation. The probability distributions are used in the same manner as described above.

The end result will be the ability to determine existing risk to seek appropriate funding of mitigation and prevention efforts, as well as to be able to rank-prioritize those mitigation efforts to bring the risk down to the desired levels in the most efficient manner.

Electric Infrastructure (Substation Transformers)

Discussion: SDG&E undertook an industry-leading approach when it began a Condition Based Maintenance (CBM) program on its fleet of substation transformers. To this date, many transformers have been updated to allow for real-time monitoring and sophisticated sensing. In general, CBM allows the utility to better understand the actual condition of the equipment, and saves time and resources compared to the traditional Time Based Maintenance – which calls for routine inspection and maintenance with less consideration for the actual condition of the equipment. CBM measures several chemical and physical aspects of the transformer, such as temperature and the presence of undesirable chemicals inside the structure.

CBM will lead to better reliability because some issues will be sensed before they eventually lead to failure. Reliability at the substation transformer level is important due to the large amount of customers potentially affected by a failure. In some cases, the transformers supply power to up to 20,000 customers each. A failed transformer can take very long to replace and causes significant operational concerns during the outage.

CBM should also save money and resources for its maintenance programs. The analogy is similar to a motor vehicle where many people change their oil once every three to five thousand miles. The new technologies can sense when the oil needs to be changed and can dramatically prolong the time between necessary oil changes.

SDG&E is currently collecting data, and has built IT systems to monitor the data. In the next few years, the data will be able to be analyzed in a probabilistic sense to determine when maintenance and potential repair/replacement operations should be undertaken. Working together with national and international consortiums, relationships between failures and CBM data is being considered.

6. Starting Soon

Fleet

While still early, the utilities are considering applying quantitative risks specific to vehicle fleet safety issues. The utilities have a large fleet of vehicles that drive many miles each year. Each time a trip is undertaken there is a chance that something undesirable may occur. The future analysis will likely include safety implications to the public in general, as well as employee safety.

The initial work will analyze current risk, determined by likelihood and consequence, based on available data. Then the utilities will explore mitigation strategies and determine the effectiveness of those strategies.