**BEFORE THE PUBLIC UTILITIES COMMISSION
OF THE STATE OF CALIFORNIA**

Order Instituting Rulemaking to Further Develop A Risk-Based Decision-Making Framework for Electric and Gas Utilities.	Rulemaking R.20-07-013 (Filed July 16, 2020)

DRAFT

TAIL RISK AND EVENT STATISTICS FOR UTILITY PLANNING

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1. INTRODUCTION

This whitepaper has been prepared by Mussey Grade Road Alliance (MGRA) expert Joseph Mitchell, Ph.D. at the request of the Safety Policy Division (SPD) to provide a technical analysis for the proper use of power laws and the proper incorporation of tail risk to be considered in the Risk-Based Decision-Making Framework (RDF) proceeding R.20-07-013.

For the sake of this discussion, the Scoping Memo[1] defines "tail risks" or "tail values events" as low probability, high consequence risk events. In Phase 1 the Commission analyzed the use of power law distributions to represent wildfire consequences, and while supporting their use did not make them a requirement or define them as a "best practice", but rather deferred tail risk as a high priority for future work.[2]

This paper will summarize the current state of "tail risk" analysis by the three largest utilities, including the use of power law distributions. The current white paper will provide an assessment of the strengths and weaknesses of these approaches along with recommendations for current practice and future research and development.

2. HISTORY

During Phase 1 of the current proceeding, MGRA submitted a white paper on the use of power laws to describe the size distribution of wildfires.[3] In this paper, MGRA described how "fat-tailed" power law distributions have been shown by many studies to provide a good fit to wildfire size distributions over many orders of magnitude. This type of distribution arises from a process known as "self-organized criticality", which applies to various build-up/breakdown phenomena such as sandpiles, landslides, and earthquakes, as well as wildfires.[4] In the case of wildfires, the

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[1] R.20-07-013; ASSIGNED COMMISSIONER'S PHASE 3 SCOPING MEMO AND RULING EXTENDING STATUTORY DEADLINE; May 31, 2023.
[2] Phase 3 Roadmap Proposal; p. 4.
[3] R.20-07-013; WILDFIRE STATISTICS AND THE USE OF POWER LAWS FOR POWER LINE FIRE PREVENTION; FINAL: FEBRUARY 11, 2021
https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M368/K055/368055506.PDF
Appendix A.
[4] Bak, P., 1999. How Nature Works: the science of self-organized criticality, First Softcover edition. ed. Copernicus, New York.

exponent associated with the power law is such that the cumulative distribution does not converge – in other words that the more data that is collected over time the larger the average size will become, and also implies that the majority of losses will come from the very largest fires. The MGRA whitepaper suggested that we apply the model from Moritz,[5] which assumes a cut-off in the maximum wildfire size based on the physical limitations of burnable areas.

In response to MGRA's white paper, Safety Policy Division (SPD) Staff's preliminary recommendations were to "*apply power law functions to model wildfire risks, as a best practice, and in the event they choose an alternative approach, to provide thorough justifications*…"[6] The later revision of Staff's recommendations removed the reference to best practice in response to party comments and Decision 21-11-009 determined that: "*We adopt Staff's proposal and defer requiring or recommending use of the power law probability distribution as an MAVF best practice at this time. We direct Staff to continue to monitor this issue in their reviews of IOU RAMP filings and, if and when appropriate, to work with the TWG to provide a follow up recommendation on this topic as early as Phase II of this proceeding, if feasible*."[7]

Meanwhile, Pacific Gas and Electric (PG&E) offered to do its own analysis of the power law distribution and provided its own whitepaper published in September 2021.[8] PG&E's analysis provided a skillful review of the available literature and data, and performed fits to the data using both Generalized Pareto distributions (equivalent to power law distributions) and a lognormal distribution, which it had previously been using to model extreme losses. In their conclusion PG&E stated that it:

"*currently lacks the analytical tools to confirm or reject the hypothesis that truncated PD1 (truncated power law) and truncated PD2 distributions describe extreme-value wildfire consequences significantly better than do other distributions - in particular, the truncated lognormal distribution. PG&E ultimately decided to use the power law distribution to describe*

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[5] Moritz, M.A., Morais, M.E., Summerell, L.A., Carlson, J.M., Doyle, J., 2005. Wildfires, complexity, and highly optimized tolerance. Proceedings of the National Academy of Sciences 102, 17912–17917. https://doi.org/10.1073/pnas.0508985102

[6] R.20-07-013; Safety Policy Division Risk Assessment and Safety Analytics Section; Staff Memo; Rulemaking 20-07-013 Phase I Track 1 Scoping Issues; April 30, 2021; p. 16.

[7] p. 33.

[8] Pacific Gas and Electric Company; "Power Law Distribution"; September 3, 2021. Available at: https://data.mendeley.com/public-files/datasets/8nds4cx88k/files/c0178e67-92fc-4ab3-9ea7-7fdcdf3b4556/file_downloaded

some of its data based on a combination goodness-of-fit test results and because it assigns, consistent with historical frequencies, more weight to extremely high consequence events. However, the use of truncated PD1 and PD2 distributions currently introduces many complexities and trade-offs that are dependent on the data being studied and the limitations of the analytical methods. Hence, PG&E cannot currently recommend the adoption of the power law for generalized settings. PG&E will continue to investigate the appropriateness of the power law's use and better methods for calibrating the upper truncation and shape values."[9]

While other distributions could not be definitively excluded due to the small number of catastrophic wildfire events available to fit, PG&E chose to move forward with Generalized Pareto distributions because they are consistent with historical data and because they adequately weight high consequence events. PG&E incorporated the distribution into the enterprise risk model, which uses a "Monte Carlo" program to simulate potential losses to calculate the risk value used in its Risk Assessment Mitigation Phase (RAMP) and General Rate Case (GRC) proceedings.[10]

In 2021, MGRA provided comment on SDG&E's RAMP showing that SDG&E's use of a gamma function to model tail risk was likely to underestimate catastrophic losses.[11] Based on this input, Safety Policy Division recommended that SDG&E re-evaluate its use of a gamma distribution for its enterprise risk calculations in its comments on SDG&E's RAMP filing.[12] SDG&E then adopted PG&E's model of a Generalized Pareto Distribution in its GRC.[13]

Only SCE has not adopted a power law distribution for its enterprise risk model, instead claiming that:

"*While power law analyses may be beneficial in understanding system-wide tail-end risk in instances where more granular circuit or circuit segment level analysis is unavailable, the generalized power-law types of analyses should not supplant more detailed and granular analyses,*

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[9] Id.; pp. 9-10.
[10] A.21-06-021; MUSSEY GRADE ROAD ALLIANCE OPENING BRIEF ON PACIFIC GAS AND ELECTRIC COMPANY'S 2023 GENERAL RATE CASE; November 4, 2022; pp. 17-18.
[11] A.21-05-011, A.21-05-014; Safety Policy Division Staff Evaluation Report on SDG&E's and SoCalGas' Risk Assessment and Mitigation Phase (RAMP) Application Reports; November 5, 2021; pp. 2-5. (SPD SDG&E RAMP Report)
[12] SPD SDG&E RAMP Report; p. 11.
[13] A.22-05-015/016; Exh. SDG&E-03-2R; SECOND REVISED PREPARED DIRECT TESTIMONY OF GREGORY S. FLORES AND R. SCOTT PEARSON (CHAPTER 2: RAMP TO GRC INTEGRATION); November 2022; pp. RSP/GSF-9, RSP/GSF-B-2,5,10,11,16.

which SCE has already included. In SCE's RAMP Report, tail-end wildfire risk is characterized by using the maximum simulated consequence over an eight-hour simulated burn period for each individual circuit segment. The benefit of this approach is that it allows SCE to expand the analysis beyond historical catastrophic wildfire information, which, as power law implies, are relatively rare events and for which data may not be available at a granular level."[14] MGRA's informal comments on SCE's 2022 RAMP claimed that the eight hour wildfire spread modeling was inadequate to capture the most extreme events that dominate overall loss statistics.[15]

In its SCE 2022 RAMP evaluation report, SPD concludes:

"*SPD agrees with MGRA that SCE needs to develop an enterprise risk model (ERM) that accurately describes catastrophic wildfire risk. As MGRA referenced, the Commission required in D.21-11-009 that 'Any best practice for wildfire modeling must produce a set of consequences for wildfires that sufficiently incorporate high-end losses.'*

Hence, SPD recommends that SCE demonstrate the extent to which its risk model correctly characterizes extreme catastrophic fires by showing its predicted loss distribution fits a power law distribution and is consistent with the size distribution of historical catastrophic fires. SPD also recommends that if SCE's current risk model does not adequately represent catastrophic losses, then SCE should develop and implement an enterprise risk model (ERM) similar to that of PG&E and SDG&E, using a power law distribution to represent catastrophic losses, prior to the submission of its Test Year 2025 GRC filing."[16]

SCE has served its 2025 GRC filing, and upon initial review it does not appear that SCE has adopted SPD's recommendation to adopt a power law model in its enterprise risk analysis, though discovery has not commenced in that proceeding. Instead, SCE has developed a novel approach to potentially catastrophic fires that dispenses entirely with probability estimation. Instead, it creates specific categories of potentially catastrophic fire, and recommends the maximum mitigation of undergrounding.   SCE calls this methodology its Integrated Wildfire Mitigation Strategy

[14] A.22-05-013; SOUTHERN CALIFORNIA EDISON COMPANY'S (U 338-E) REPLY TO PROTESTS TO RAMP REPORT; June 30, 2022; p. 5.

[15] MGRA Informal Comments to SPD re SCE's RAMP Filing, 10/10/22, pages 4-11.
Included in
A.22-05-013; Safety Policy Division Staff Evaluation Report on the Southern California Edison Company's 2022 Risk Assessment and Mitigation Phase (RAMP) Application; p. 66/142. (SPD SCE RAMP Report)

[16] SPD SCE RAMP Report; p. 31.
Cites: MGRA Informal Comments to SPD re SCE's RAMP Filing, 10/10/22, pages 4-11.

(IWMS).[17] While SCE's approach will be tested in the ratemaking proceeding, its technical foundations will also be briefly discussed in this White Paper.

Additionally, SCE and SDG&E use Technosylva Wildfire Analyst to determine consequence for modeling their operational and planning risk models, with an eight hour fire spread limitation.[18] PG&E has developed a complex consequence model that takes into account fire intensity and flame length values from Technosylva Wildfire Analyst, CAL FIRE wildfire history, and VIIRS satellite data.[19] To date, power law distributions have only been used for the Monte Carlo simulation of wildfire consequences that go into enterprise planning models. However it is important that all risk models, including planning and operational models, correctly "incorporate high-end losses", as D.21-11-009 states. This White Paper will open the discussion of how this may be best accomplished, which may require additional work in a future phase of the proceeding.

3. QUESTIONS REGARDING TAIL RISK

3.1. Definition of Tail Risk

How is "tail risk" defined for the purpose of utility wildfire mitigation?

The R.20-07-013 Phase 3 Scoping Memo defines "tail risks" or "tail values events" as "low probability, high consequence risk events". [20]

The Scoping Memo further explains that "*Work on this issue in Phase 3 will center on understanding the IOUs' use to date of the power law probability distribution function to model wildfire tail risk, the results, strengths and any weaknesses of this approach, and what further*

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[17] MUSSEY GRADE ROAD ALLIANCE PROTEST TO SOUTHERN CALIFORNIA EDISON COMPANY 2025 GENERAL RATE CASE APPLICATION; p. 5-6.
[18] OEIS Docket 2023-2025 WMPs;
Southern California Edison Company; 2023-2025 WILDFIRE MITIGATION PLAN;
March 27, 2023; TN11952-2_20230327T125844_20230327_SCE_2023_WMP_R0.pdf; p. 95. (SCE WMP)
San Diego Gas & Electric Company; 2023-2025 Wildfire Mitigation Plan; March 27, 2023; TN11948_20230327T160734_20232025_SDGE_WMP_with_Attachments-1.pdf; p. 54. (SDG&E WMP).
[19] OEIS Docket 2023-2025 WMPs; Pacific Gas and Electric Company; Wildfire Mitigation Plan; March 27, 2023; TN11965-1_20230327T160416_PGE's_20232025_Wildfire_Mitigation_Plan.pdf; pp. 146-147. (PG&E WMP).
[20] p. 5.

guidance by the Commission may be needed. Specifically, work will address whether the Commission should require use of the power law probability distribution function to model wildfire risk, whether the Commission should recommend use of this approach as a best practice, or whether the Commission should take some other course of action to ensure appropriate modeling of wildfire tail risk and communication of associated uncertainties in IOU RAMP filings?

Additionally, discussions will consider how the IOUs have represented other low probability, high consequence risk events in their RAMP filings to date, including risks related to hydro dam safety and seismic events. Work in this area will explore whether additional guidance is needed regarding modeling of low probability, high risk events more generally in the RDF and RAMP filings."[21]

The purpose of this White Paper is to specifically discuss power law probability distributions with respect to wildfire sizes, and the impact of high-end wildfire loss events in general. As hydroelectric and seismic risks are not my field of expertise I will defer to subject matter experts in these areas, and will note that the power law size dependency is specific to certain domains and based upon the physics of the underlying system.

3.1.1. Standard definition of "Tail Risk"

The traditional use of "tail risk" comes from finance and concerns the management of financial risk and asset portfolios. Tail risk is generally defined with respect to a normal distribution (bell curve) and describes deviations from the mean of three standard deviations or more.[22] Its usage in Commission proceedings is more closely related to a specific category of tail risk events characteristically known as "Black Swan" events,[23] which describe the out-sized impact of rare events that cannot be explained by the standard normal distribution. From the Commission's standpoint, the "tail-risk" describes the fact that the vast majority of damage and harm done by utility fires comes from a few rare catastrophic events. Part of this observation arises from the nature of the power law distribution, and the remainder may be attributed to what are known as

[21] Id.; pp. 6-7.
[22] https://en.wikipedia.org/wiki/Tail_risk
[23] From: Taleb, N.N., 2010. The Black Swan - The Impact of the Highly Improbable, Second. ed. Random House, New York.

"common cause failures". Both of these factors contribute to the utility wildfire problem and both will be addressed in this whitepaper.

3.1.2. Power Laws and wildfire

A full description of power laws was provided in the Phase 1 Whitepaper submitted by MGRA.[24] Highlights from that paper will be repeated here for the reader's convenience.

Power laws are a class of statistical distributions that follow "scaling" or "self-similar" distributions over many orders of magnitude. If two variables are related by a power law, then the increase or decrease of the magnitude of one variable will be proportional to the increase or decrease in the magnitude of the other variable. Mathematically this is shown as:

$$y = Cx^{-\alpha}$$

These are often plotted on log-log plots, since this demonstrates the linear relationship between the scales:

$$\log y = -\alpha \log x + \log C$$

Power laws are observed in numerous disciplines: physics, economics, information technology, sociology, biology, ecology, urban planning, to name some. While some power laws are direct manifestations of physical laws (for instance Kepler's Law in astronomy), some power law relationships arise spontaneously from interrelationships between system components, or are "self-organized". This has led to an entire discipline of "complexity science" that attempts to explain phenomena as a result of universal scaling laws. The literature on this topic is extensive, including not only academic articles but numerous books, as well as popular treatments.[25] Per Bak, one of the founders of complexity science explained that "complex behavior in nature reflects the tendency of large systems with many components to evolve into a poised, 'critical' state, way out of

[24] R.20-07-013; WILDFIRE STATISTICS AND THE USE OF POWER LAWS FOR POWER LINE FIRE PREVENTION; FINAL: FEBRUARY 11, 2021 https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M368/K055/368055506.PDF

[25] For example, "Scale: The Universal Laws of Growth, Innovation, Sustainability, and the Pace of Life in Organisms, Cities, Economies, and Companies", by Geoffrey West; 2017; Penguin Press.

balance, where minor disturbances may lead to events, called avalanches, of all sizes. Most of the changes take place through catastrophic events rather than by following a smooth gradual path."[26]

Wildfire sizes were among the first natural hazard phenomena to be characterized as power law distributions. Malamud, Morein and Turcotte's pioneering work in 1998[27] found scaling behavior when looking at a variety of wildfire size data sets. This work and others[28] also demonstrate that the power law behavior can be generated by simple toy models of wildfire ignition, such as cellular automata.

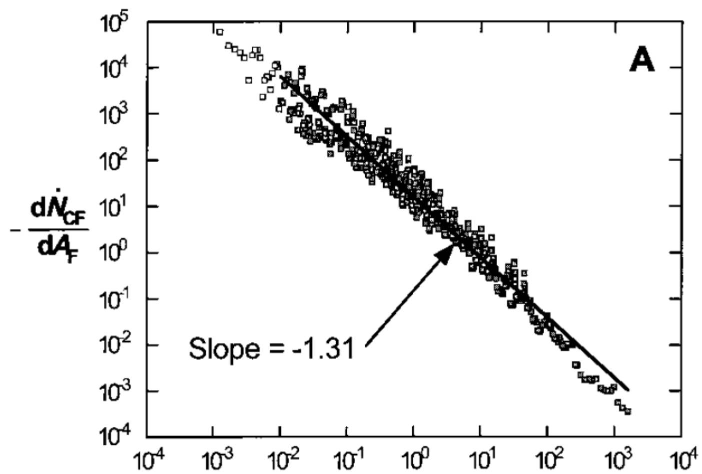

Figure 1 - Example wildfire size distribution from Malamud, et. al. (Reference 27). This distribution shows wildfire sizes in km^2 (horizontal axis) from US Fish and Wildlife Service lands from 1986 to 1995. The data are plotted as a non-cumulative distribution, in which the y axis value represents the total number of fires within a particular size bin. Power laws show a linear distribution when plotted on a log-log plot.

This relationship was studied by other authors as well. Some authors such as Beguini and Marinov[29] confirmed the direct power law relationship for wildfire sizes. Others, using wildfire sized distributions from different areas, such as Newman, which uses a larger data set, shows an apparent truncation in the data, which he asserts "could follow a power law but with an exponential

[26] Bak, P., 1999. How Nature Works: the science of self-organized criticality, First Softcover edition. ed. Copernicus, New York.
[27] Malamud, B.D., Morein, G., Turcotte, D.L., 1998. Forest Fires: An Example of Self-Organized Critical Behavior. Science 281, 1840–1842. https://doi.org/10.1126/science.281.5384.1840
[28] Turcotte, D.L., Malamud, B.D., Guzzetti, F., Reichenbach, P., 2002. Self-organization, the cascade model, and natural hazards. PNAS 99, 2530–2537. https://doi.org/10.1073/pnas.012582199 https://www.pnas.org/content/99/suppl_1/2530
Drossel, B., Schwabl, F., 1992. Self-organized critical forest-fire model. Phys. Rev. Lett. 69, 1629–1632. https://doi.org/10.1103/PhysRevLett.69.1629
[29] Benguini and Marinov, 2015; Reference 4.

cutoff'.[30] Li and Banerjee have shown that California wildfire size distributions since 2000 are best described by a truncated Pareto distribution (a power law).[31]

The consensus of the literature is that utility wildfire size distributions follow a power law over a wide span of sizes. Therefore, the modeling of utility fires should be able to either directly utilize or alternatively reproduce the "naturally" occurring distribution.

Recommendation:

Wildfire risk models should either 1) directly use an appropriate power law distribution, such as the base distribution for a Monte Carlo simulation or 2) be able to show that their model produces results that are consistent with a power law when appropriately weighted by probability and consequence.

3.2. Fat-Tailed Distributions and Extreme Consequences

What might be the consequences of failing to adequately model tail risk in enterprise, planning, and operational models? How significant are these consequences?

Power laws are an example of "fat-tailed" distributions, in which the overall weight of the distribution is dominated by rare or even extreme events. In fact, for certain values of the exponent ($|\alpha| < 1$ for the cumulative distribution) the integral of the power law (used for weighting probabilities) does not converge, which means that the contributions from extreme events will always dominate the results.[32] The mean, if calculated, becomes larger as more events are included in the distribution, so it is impossible to predict the mean accurately based on any amount of past data. Contributions from future events will always be larger (in the long run) than those from past events.

[30] Newman, M.E.J., 2005. Power laws, Pareto distributions and Zipf's law. Contemporary Physics 46, 323–351. https://doi.org/10.1080/00107510500052444

[31] Li, S., Banerjee, T., 2021. Spatial and temporal pattern of wildfires in California from 2000 to 2019. Sci Rep 11, 8779. https://doi.org/10.1038/s41598-021-88131-9

[32] Id.

The absolute value of the power law exponent for power line wildfires is small, less than 0.5. This throws a monkey wrench into standard statistical treatments, which are based on projections from historical data. An exponent this small implies that one cannot derive an accurate mean using past history. Future events will always be larger, and throw off any mean based on backwards-looking data. This is true for any exponent with an absolute value less than 1.0. As Taleb writes about this class of power law, *"…there is no mean. We call it the Fuhgetaboudit. If you see something in that category, you go home and you don't talk about it*."[33] Those of us who have homes or operate businesses in the wildland urban interface (WUI) and regulators who oversee companies in the WUI do not have the luxury of "fuhgettingaboudit". We have to determine how best to determine and bound this risk.

One key consideration with fat-tailed distributions is uncertainty. Out on the tail of the distribution the statistical uncertainty is larger, as well as the potential for systematic uncertainties, such as effects driven by rare and as yet unmeasured phenomena. Because of the overweighted contribution of the extreme tail to the overall result, these uncertainties can have a significant or even dominant effect.

3.2.1. Effect of underestimation of tail risk

In wildfire, one can easily observe that the cumulative losses are dominated by the very largest fires. This is evinced in the following graph:

[33] Taleb, N.N., 2020. Statistical Consequences of Fat Tails: Real World Preasymptotics, Epistemology, and Applications. STEM Academic Press. https://arxiv.org/abs/2001.10488; pp. 27-28.

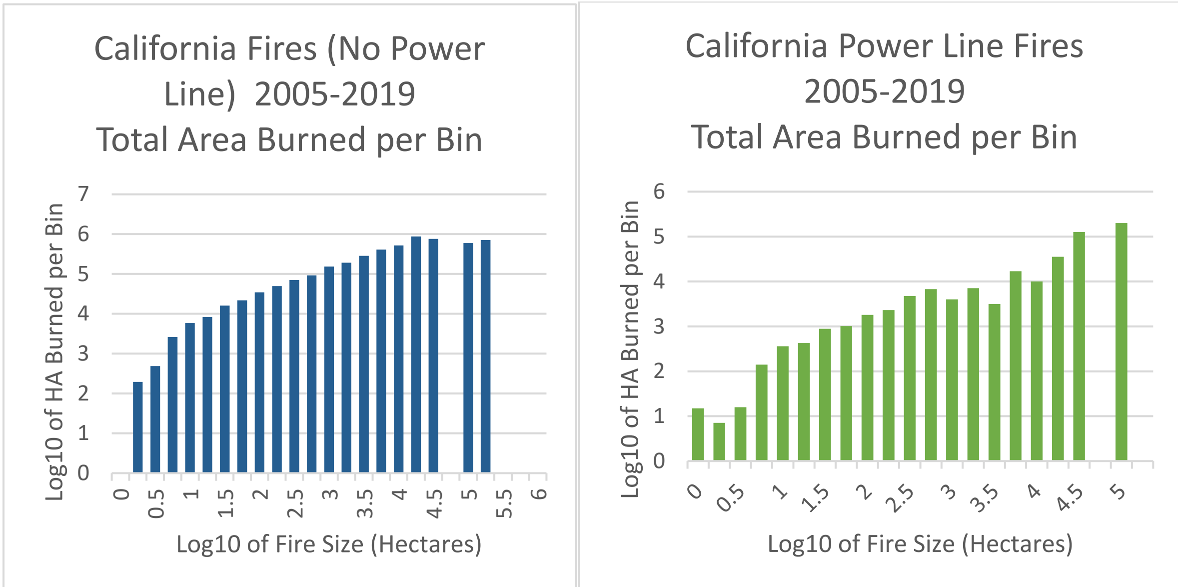

Figure 2 - Total area burned per logarithmic bin for California wildfires 2005 to 2019, calculated by multiplying logarithmic mean of bin by number of wildfires in the bin. Power line related wildfires are compared against full sample with wildfires removed. It is important to note that these are not cumulative plots.

These data show that the total losses for both power line and non power line caused fires are dominated by the very largest fires. Underestimating wildfire size has a number of direct consequences:

- Risk models will show overall financial and safety consequences that are too small, and therefore underestimate the value of mitigation. This may lead to underinvestment in mitigation, and consequently the loss of life and property.
- When applied to fire spread models, such as are used by SCE and SDG&E for planning and operation and by SCE for its enterprise risk models, underestimating fire size will "urbanize" predicted risk, since the model will not adequately represent risk from ignition points at a great distance from the area where losses occur.

3.2.2. Wildfire simulations and the 8 hour limitation

As pointed out in numerous previous MGRA filings and as acknowledged by the Commission and OEIS, the 8 hour limitations place upon fire spread simulations by the utilities places an inherent cap on the size of possible wildfires.[34] This is evidenced by the figure below,

[34] MGRA 2023 WMP Comments; pp. 33-36.

which shows raw Technosylva fire size data provided by SCE and PG&E in data requests in other proceedings:

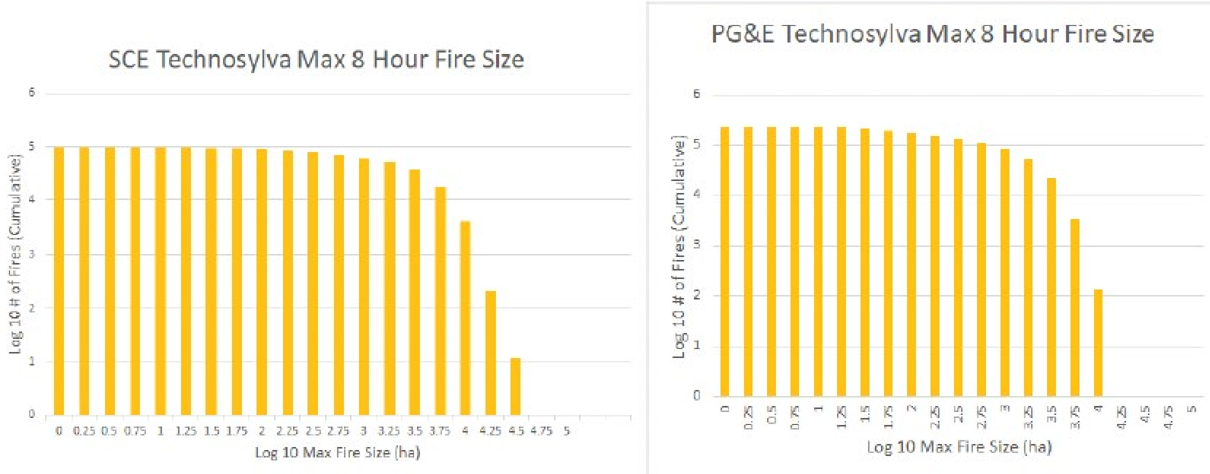

Figure 3 - Raw Technosylva simulation data was provided by SCE and PG&E in response to MGRA data requests, and the logarithm of maximum wildfire size for each set of 8-hour runs was accumulated into histograms.[35]

As can be seen from these figures, the size of the distribution is flat, then falls off rapidly to a cutoff. For SCE, this cutoff is approximately 50,000 acres and for PG&E it is approximately 25,000 acres. The flat mesa-like distribution is an artifact of the fact that Technosylva simulations are only run on "worst-case" wildfire days.[36] Hence the fire sizes are heavily biased to be larger. However, the 8 hour cutoff prevents wildfires from growing to the full extent typically seen under worst case conditions, sometimes exceeding 200,000 acres.

Recommendation:

Technosylva should be requested to provide a probability-weighted wildfire size distribution that will remove bias introduced by use of the "worst case" weather days. This distribution can then be validated on a log-log plot to validate whether the Technosylva simulations follow the power law dependency seen in natural wildfires.

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[35] MGRA 2023 WMP Comment workpapers: https://github.com/jwmitchell/Workpapers/blob/main/WMP23/perimeters_19_1.xlsx

[36] Op. Cite.

3.2.3. Effect of the 8 hour limitation on operational and planning risk models

In its 2022 Wildfire Mitigation Plan, PG&E's WDRM v2 consequence model used only Technosylva wildfire spread modeling with an 8 hour cutoff to estimate consequences. The results of this are shown in the wildfire risk map for PG&E's service area in the vicinity of Sacramento and Lake Tahoe:

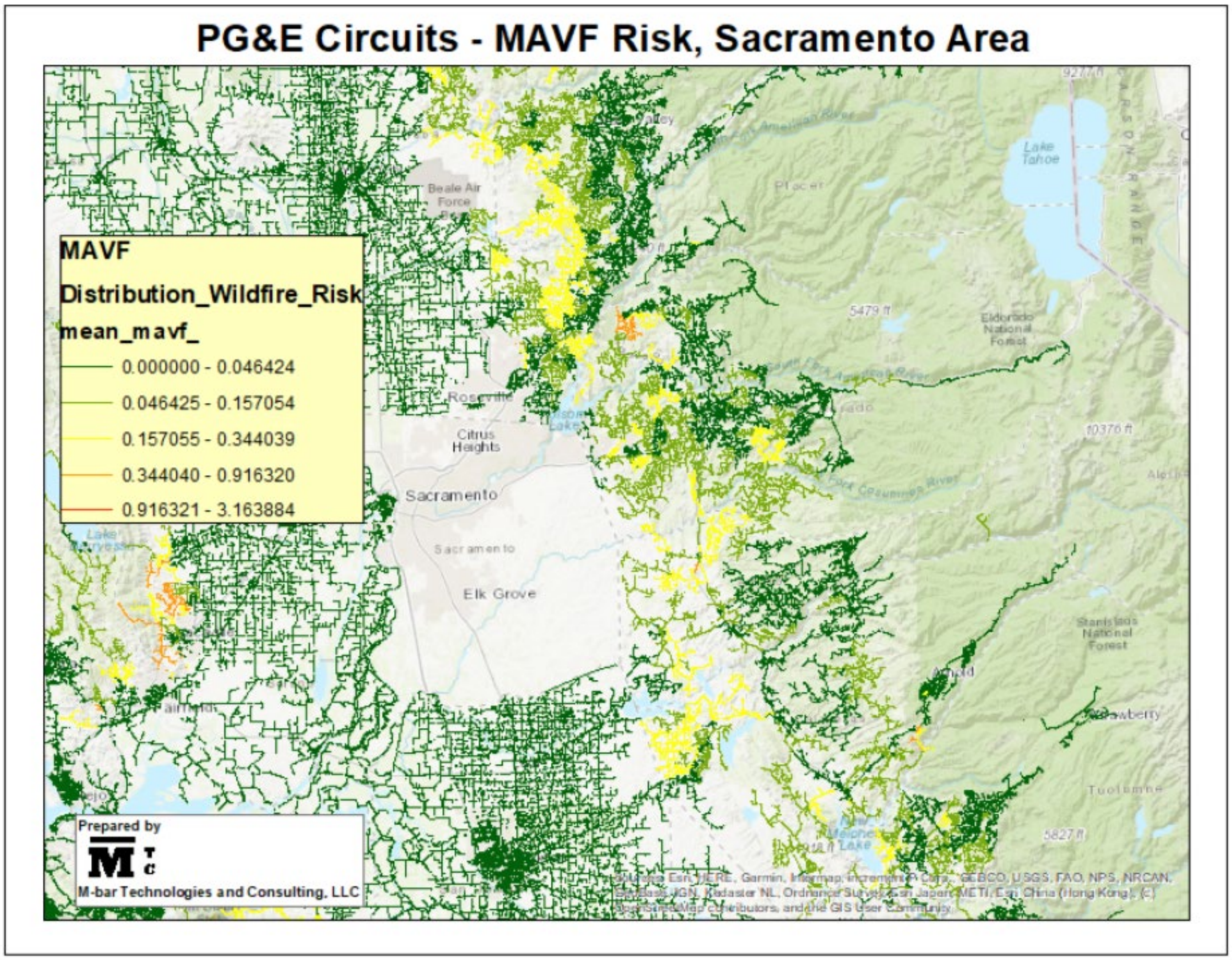

Figure 4 - PG&E's calculated risk scores using its WDRM v2 in the Sacramento / Lake Tahoe area.[37]

The noteworthy feature of Figure 4 is that the higher risk circuit segments (shown in orange and yellow) are closer to the urban areas. More remote areas generally show lower risk. This dependence is driven by the consequence values, which are higher near the point of ignition if the size of the fires is limited.

[37] OEIS Docket 2022-WMPs; MUSSEY GRADE ROAD ALLIANCE COMMENTS ON 2022 WILDFIRE MITIGATION PLANS OF PG&E, SCE, AND SDG&E; April 11, 2022; p. 46.

In 2023, PG&E adopted WDRM v3, its more complex and elaborate consequence model that no longer depends directly on fire sizes calculated by Technosylva fire modeling. As noted earlier, it uses flame length and fire intensity calculations by Technosylva, but also uses historical fire sizes and VIIRS satellite data. Consequence values calculated in this manner result in a very different risk distribution, as seen below:

FIGURE PG&E-6.2.2-9:
WILDFIRE CONSEQUENCE PIXEL MAP

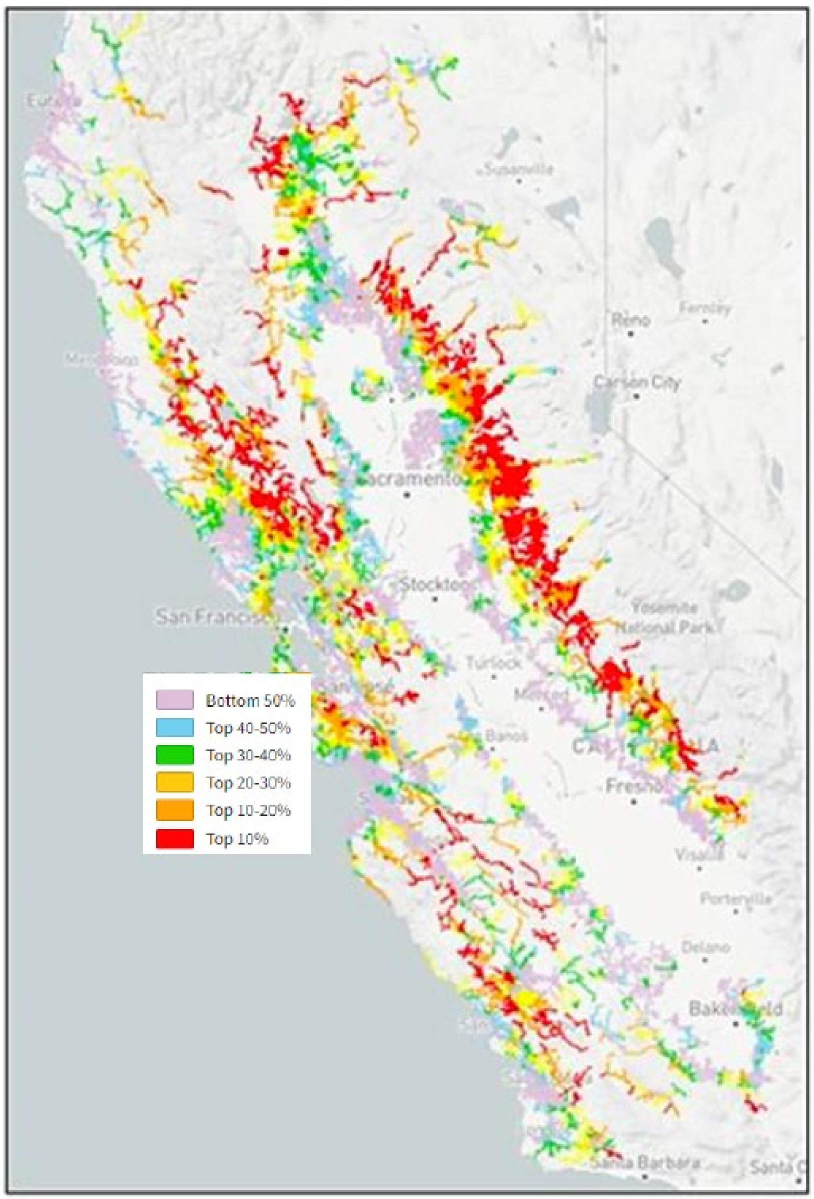

Figure 5 – Figure PG&E-6.2.2-9 of PG&E's WMP showing WDRM v3 consequence scores for the PG&E service area.[38]

[38] 2023 PG&E WMP; p. 169.

It is clearly evident that the modelled consequence in WDRM v3 is radically different from that seen in WDRM v2. Primarily, it shows that the greatest consequence scores are more generally found in more remote regions where large fires are more likely to start. In this way, WDRM v3 appears to more accurately model large fires. However, MGRA's 2023 WMP comments noted a number of issues with it that suggest that WDRM v3 too may underrepresent the tail risk posed by large fires.[39]

A final example of how consequence models with limitation on fire sizes affect planning risk calculations is shown below in SDG&E's 2023 wildfire consequence modeling.

[39] MGRA 2023 WMP Comments; pp. 62-63.

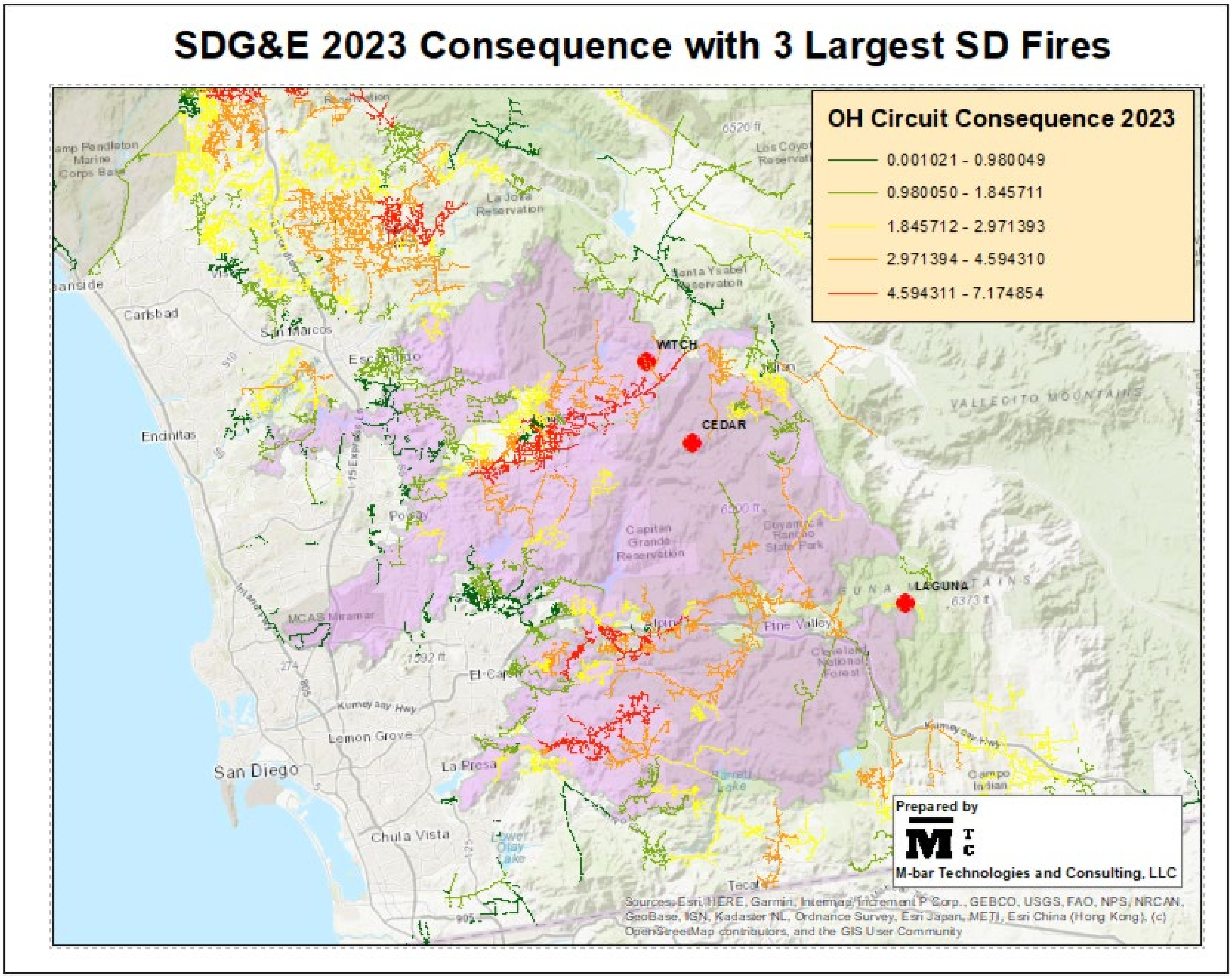

Figure 6 – SDG&E WiNGS v3 consequence scores for overhead circuits, on a scale of green for lower risk to red for higher risk. Superimposed are the ignition points and final perimeters for the Witch/Guejito, Cedar, and Laguna fires.[40]

SDG&E's WiNGS v3 consequence model, also using Technosylva Wildfire Analyst with an 8 hour fire spread limitation, finds the greatest consequences in the immediate vicinity of populated areas – specifically within and directly east of the population centers of Ramona, Alpine, and Valley Center. More remote and mountainous areas (eastward in San Diego County) have lower predicted consequences.

For comparison, the ignition points of the three largest historical wildfires in San Diego County are plotted: The Witch/Guejito fire (2007, 198,000 acres), the Cedar fire (2003, 273,000 acres), and the Laguna fire (1970, 170,000 acres). The superimposed perimeters of these three fires are indicated by the violet area. These three fires caused more loss of life and property than all the

[40] Id; pp. 40-41. Ignition and perimeter data from Cal Fire. SDG&E circuit risk data from 2023 WMP Data Request Response CalAdvocates-5-Q4.

other San Diego fires combined, demonstrating how the risk of wind-driven Southern California fire is dominated by "tail risk" events.

3.3. Risk Drivers

<u>Are there specific drivers of "tail risk" (catastrophic) events or are "tail risk" events simply the limit of a continuous distribution?</u>

This is an important question because it asks whether use of a power law distribution is *sufficient* to characterize the risk of utility power line fires. Looking at California fires divided by origin into "power line" fires and others, we can see that both of these are well-represented by a power law distribution over several orders of magnitude:

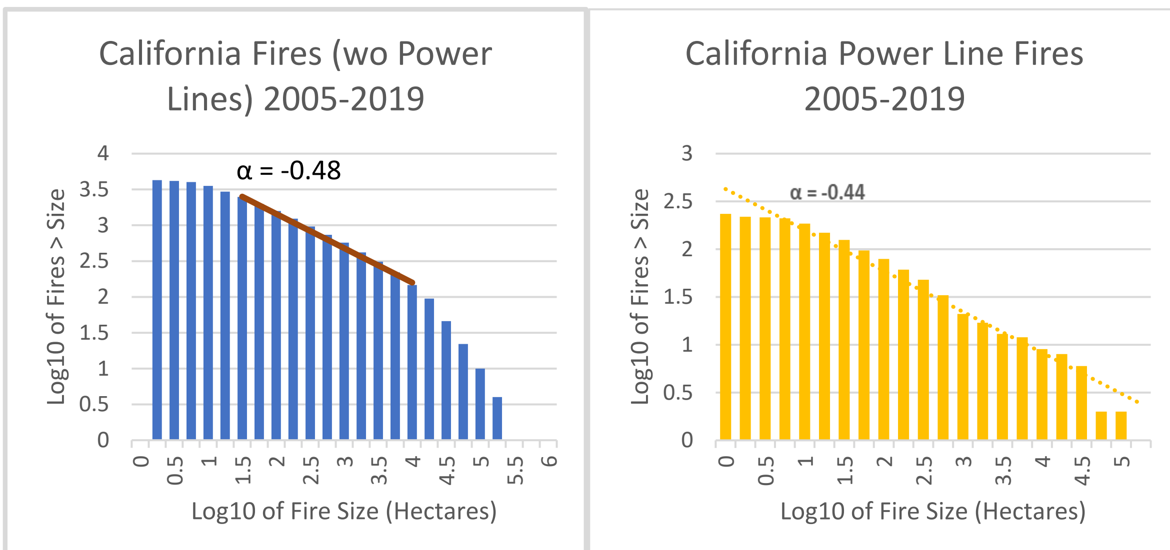

Figure 7 – CAL FIRE perimeter data for wildfires attributed to power line ignitions, shown as cumulative distributions plotted on log-log axes. 2007 and 2017 fire attributions are corrected with CAL FIRE and CPUC assessments. The trendlines are a guide to the eye, rather than a best fit and shows how power line exponents would appear. These are extreme fat-tailed distributions. Deviations from power law behavior appear above 30,000 acres (without power lines) and 80,000 acres for power line fires. Maximum scale may be 500,000 acres, with large uncertainty.

Trendlines are plotted and serves as a guide to the eye.[41] For wildfires, with power line fires excluded, a power law with exponent of -0.48 would describe the data over 3 orders of magnitude.

[41] As per Clausset 2009 (Footnote 11), least squares methods are prone to bias by tail statistics and a maximum likelihood method should be employed to obtain accurate power law exponents.

For power line fires, a power law with exponent of -0.44 would fit the data over 3.5 orders of magnitude. Both distributions show a drop off, with non-power line fires deviating from power law above 30,000 acres and power line fires deviating over 80,000 acres. Statistics are poor and uncertainties large for the largest fires, but the data is at least apparently consistent with a maximum size scale on the order of 500,000 acres for California fires, which is the cap chosen by PG&E and SDG&E for their modeling (Section 3.4).

So superficially, power line fires follow a similar size distribution to other fires in California. However, non-power line fires seem to truncate much more steeply for the largest fires. In practical terms, this means that fires from electrical sources tend to have larger impacts than fires from other sources. This can be seen in the CAL FIRE "Top 20" fire listings:

Wildfires	Number of Electrically Caused(out of 20)	Fraction of Losses Due to Electrically Caused Wildfires
Deadliest	4	39%
Most Destructive	8	66%
Largest	3	21%

Table 1 - CAL FIRE "Top 20" deadliest (by fatalities), most destructive (by structures), and largest (by acres burned) as of November 2022 showing relative contribution of electrically ignited wildfires to total numbers and total losses.

3.3.1. Tail risk from wind - a "common cause" risk driver

As electrically caused wildfires typically make up less than 10% of overall wildfires, there is something about them that makes them especially pernicious. As MGRA filings have noted since 2009, this is because of the coincidence of weather conditions that *cause* the outage that ignites the fire and weather conditions conducive to the rapid spread of wildfire.

The answer to the questions posed for this section is that severe utility wildfires are natural outcomes of a power law distribution that can be amplified by external driver events.

The extreme dependence of outage rates on local wind speeds was shown by Mitchell.[42] This work studied SDG&E outage data and measured the relative probability of outages on circuits

[42] Mitchell, J.W., 2013. Power line failures and catastrophic wildfires under extreme weather conditions. Engineering Failure Analysis, Special issue on ICEFA V- Part 1 35, 726–735. https://doi.org/10.1016/j.engfailanal.2013.07.006

based on the peak wind gust speed at the nearest weather station.

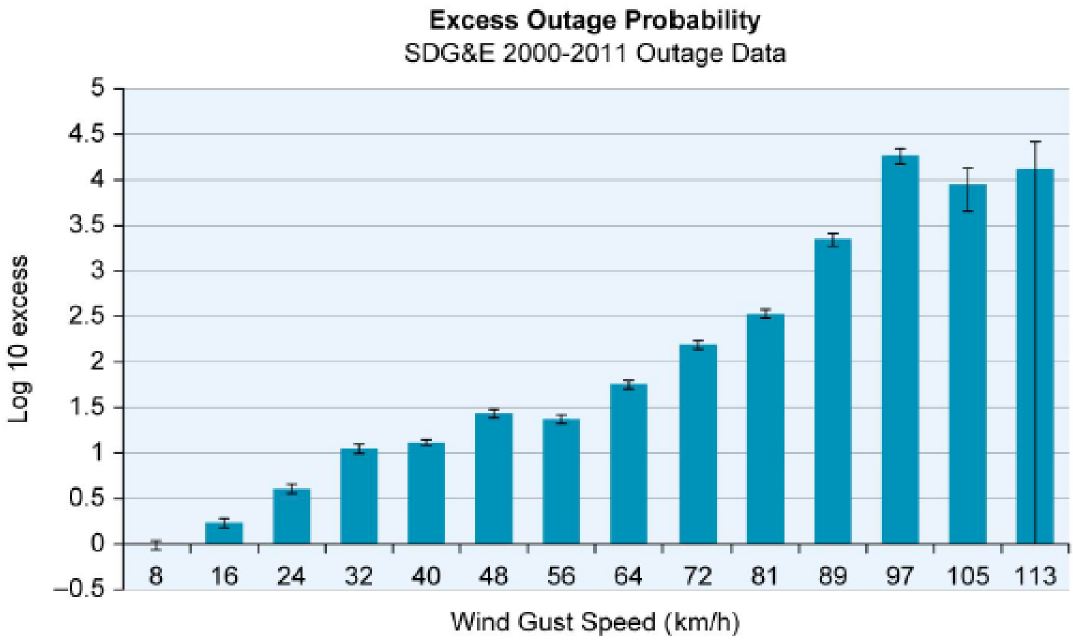

Figure 8 - Excess outage probability as a function of wind speed obtained by normalizing SDG&E outage data with historical Mesowest weather station data. For each outage, a wind speed was determined at the nearest appropriate weather station for the circuit having the outage. Historical data for each of these weather stations was analyzed to determine what fraction of time the wind speed exceeded the speed at which the outage occurred. Data were then normalized against a baseline wind speed of 8 km/hr, giving the number of outages per unit time at a particular wind speed at that location compared to number of outages that would be expected during calm weather. The vertical scale is logarithmic. Data show a ten-fold increase in outage rate for every 15-20 mph increase in wind gust speed. Reproduced from Mitchell 2012, Footnote 42.

Mitchell also demonstrates that catastrophic utility wildfires are usually caused by a "common cause" failure. The external cause – wind – creates the conditions for 1) damage to utility equipment that causes sparks, 2) increased probability that arcing utility equipment will ignite vegetation, 3) situations where fire agencies will have a smaller chance of controlling the ignition,[43] and 4) situations where the wildfire will spread rapidly, potentially becoming catastrophic.

[43] Mitchell, J.W., 2009. Power lines and catastrophic wildland fire in southern California, in: Proceedings of the 11th International Conference on Fire and Materials. Citeseer, pp. 225–238.

3.3.2. Tail risk from external drivers

In the context of "tail risk" we should introduce the concept that the external drivers (wind, temperature, and drought) are also subject to statistical fluctuations, and that their extrema will have an outsized effect on wildfires:

- Extreme drought. California has recently suffered two severe droughts (2012-2016 and 2020-2022). Lower fuel moisture leads to greater potential for more easily ignited and larger fires. It was during the latest drought that the Dixie fire became the largest recorded California wildfire from a single ignition.
- Extreme fire winds. It is not known what the most intense foehn event (Santa Ana, Sundowner, Diablo) wind event can possibly be, but planning and mitigation must be robust against the potential that future events will exceed historical events in intensity. However, the most recent climate models show a weak prediction that the intensity of Santa Ana winds will decrease over time, though this has not yet been observed in data.[44,45]

Recommendation:
Use of a power law distribution to model utility risk should tune parameters to fit the curve shown for power line fires, which tends to have a higher cutoff due to the influence of external risk drivers.
Recommendation:
Risk models using simulation must be able to incorporate consequence events from the largest and most destructive wildfires.

3.4. Cap of the Truncated Power Law Distribution

What should be the appropriate cap, or method for determining the appropriate cap, in the case of a truncated power law probability distribution?

[44] Hughes, M., Hall, A., 2010. Local and synoptic mechanisms causing Southern California's Santa Ana winds. Clim Dyn 34, 847–857. https://doi.org/10.1007/s00382-009-0650-4
[45] Guzman-Morales, J., Gershunov, A., 2019. Climate Change Suppresses Santa Ana Winds of Southern California and Sharpens Their Seasonality. Geophysical Research Letters 46, 2772–2780. https://doi.org/10.1029/2018GL080261

3.4.1. Justification for and importance of a cap on the power law distribution

The first item that should be considered with regard to selecting an appropriate cap for the power law distribution is whether such a cap actually exists. The statistics in this region, corresponding to the very largest wildfires, are extremely limited. It is possible that larger fires are possible and that we simply haven't seen them yet. Such a hypothesis would be supported by the fact that the record for the largest wildfire in California has been broken every few years over the past two decades. So, the possibility of larger future fires cannot be discounted.

However, there is theoretical support justifying a maximum fire size. A physical limit will be reached as the wildfire size approaches that of the largest contiguous burnable spaces which are bounded by the sea and non-vegetated areas, and fire-resistant developed areas. This effect is captured in Moritz et. al. which examined data from the Los Padres National Forest and found that scaling of wildfire sizes followed a power law with exponent of $\alpha = 0.5$. [46] Moritz et. al. use a "highly optimized tolerance" (HOT) probability loss resource (PLR) model to fit the data, which incorporates deviation from power law behavior at both low and high size limits:

$$y = C[(a + x)^{-\alpha} - (a + L)^{-\alpha}]$$

where a is the small size cutoff and L is the large size cutoff.

Newman (2005), who used a larger data set size than other researchers, suggested that the wildfire size distribution can be described as a power law with an exponential cutoff. Li and Banerjee (fn 31) also have determined that a truncated Pareto distribution provides a better fit to recent California fire data than other "fat tail" distributions.

The tractability of a utility wildfire risk calculation depends on the truncation of the power law dependency at a maximum size. Otherwise, the overall risk goes to infinity as time increases.

[46] Moritz, M.A., Morais, M.E., Summerell, L.A., Carlson, J.M., Doyle, J., 2005. Wildfires, complexity, and highly optimized tolerance. Proceedings of the National Academy of Sciences 102, 17912–17917. https://doi.org/10.1073/pnas.0508985102

However, there are physical limitations on physical systems. Trees do not grow to the sky. The question is how one estimates the size of the largest fire that has not occurred yet.

3.4.2. PG&E approach – Sensitivity analysis

In its 2021 White Paper, PG&E posits a maximum consequence size that is roughly equal to five times the losses faced in the Camp fire.[47] PG&E tested a number of truncation values from 1.5 to 100 times the losses of the Camp fire for goodness of fit to existing data. This is shown in the figure below:

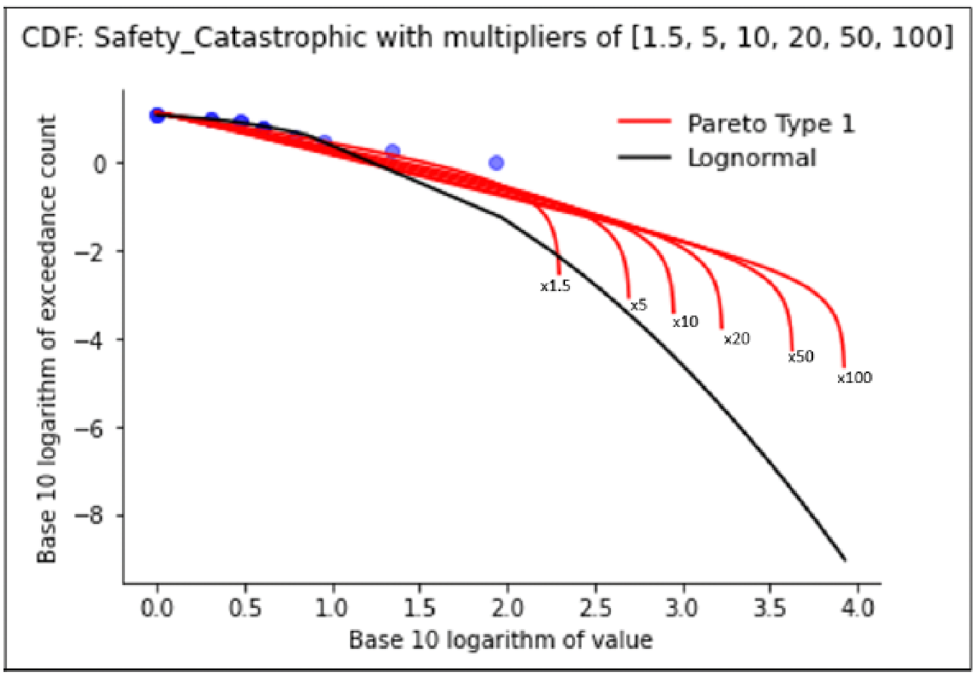

Figure 9 - Truncated PD1 (Type 1 Pareto Distribution) and untruncated lognormal distribution fits to wildfire safety consequence dat**a.**[48]

PG&E performed a test of out likely the exceedance of a catastrophic safety consequence value was for different cutoffs and for comparison the lognormal distribution.

[47] PG&E Power Law White Paper; p. 6.
[48] Id; p. 15; Figure C1.

Safety Catastrophic	lognormal	P1D Multiplier 1.5	P1D Multiplier 5	P1D Multiplier 10	P1D Multiplier 20	P1D Multiplier 50	P1D Multiplier 100
>= 1	88%	100%	100%	100%	100%	100%	100%
>= 5	42%	33%	28%	26%	24%	22%	21%
>= 10	22%	20%	16%	14%	13%	12%	11%
>= 50	1.7%	4.9%	4.0%	3.5%	3.0%	2.6%	2.3%
>= 100	0.3%	1.9%	2.0%	1.8%	1.6%	1.3%	1.2%
>= 200	0.05%	0.00%	0.83%	0.86%	0.79%	0.68%	0.60%

Table 2 - PG&E's calculated survival probability (probability to exceed a specified safety consequence) when using each distribution with right truncation points set at various multipliers of the maximums observed from the datasets.[49]

Using this method, PG&E decided to use a multiplier of 5 "*to strike the balance of not flattening the curve too much but also preserve the tail risk of extreme events*."[50]

PG&E's tail risk analysis methodology was rigorous and should be considered a best practice. However, as can be clearly seen in Figure 9, the fits that are being conducted are *extrapolations* from areas where data exists into areas where data does not exist, leaving room for considerable uncertainty. Future work in this area should include an exploration of what the physical limitations are that would limit wildfire sizes.

Recommendation:

PG&E's estimation of safety and financial caps is rigorous and should be adopted as a best practice.

3.4.3. Determining maximum wildfire sizes

While PG&E's method is statistically rigorous, it is still a statistical extrapolation and therefore prone to uncertainties once the size of historical fires is exceeded. It may be of value in future work in this proceeding or others to determine the maximum "worst case" fire size that can be generated from ignition at a specific geographic point. The distribution of these "worst case" wildfire sizes would set an upper limit on the cutoff parameter for enterprise risk models, and the geography-specific worst cases could be used in determining tail risk for operational and planning models.

[49] Id; p. 16; Table C2.
[50] Id.

One way of determining "worst case" wildfire risk scenarios would be to run simulations such as Technosylva's Wildfire Analyst for a considerably longer period than the 8 hours typically used for utility consequence modeling. Twenty-four hour simulations were run, for example, when Technosylva provided simulations of potential fires that might have been prevented from PSPS damage.[51]

There are two issues with longer wildfire simulations. First, the computing time, and therefore cost, increases exponentially with the length of the run. This is not particularly relevant because a simulated test of the wildfire maximum size would be a single run per location, whereas utility planning and operational simulations typically do large numbers of weather scenarios (planning) or periodic runs based on new weather information (operational). More important is that the reliability of the simulation decreases as time progresses. Wildfire simulations do not take into account fire suppression, and it is not likely they will do so in the foreseeable future because fire suppression is based on individual human decisions in a dynamic and evolving landscape. One particular area where suppression plays a significant role is encroachment of wildfire into developed areas, which would drive losses for long wildfire runs. It might be that a combination of extended wildfire modeling and input from subject matter experts with experience in wildland firefighting could be used to construct reasonable "worst case" scenarios. These scenarios can then be compared against the caps derived from purely statistical means and used to adjust maximum losses.

Recommendation:

"Worst case" simulations should be considered for utility service areas consisting of extended wildfire simulations in combination with input from SMEs with strategic firefighting knowledge.

3.4.4. Plume-driven wildfires and climate change

Technosylva claims to be able to adequately model wind-driven wildfires but is challenged by "plume-driven" (vegetation driven) wildfires. Examples of vegetation driven wildfires include the Butte and Dixie fires. Wildfire models using more detailed atmospheric physics perform better

[51] California Public Utilities Commission; Safety Enforcement Division; 2019 PSPS Event –Wildfire Analysis Report IOU: Southern California Edison (SCE); and other utilities. Located at: https://www.cpuc.ca.gov/consumer-support/psps/technosylva-2019-psps-event-wildfire-risk-analysis-reports

in this domain,[52] but consume considerable computing time and cannot yet be scaled to mass-production in the way that the Technosylva models have been.

Specific characteristics of plume/vegetation driven wildfires are relevant to the CPUC:

- Because surface winds play a secondary role in wildfire spread, PSPS is not an effective mitigation against this kind of wildfire.
- For wind-driven wildfires, the typical outage causes leading to ignition are equipment damage and vegetation contact. For vegetation-driven wildfires any ignition is equally likely to contribute to ignition. The probability of ignition (POI) machine learning models used by SCE and PG&E are therefore currently adequate to accommodate this scenario.
- "Worst case" plume-driven wildfires can be expected under drought scenarios and under conditions of high temperature and low vegetation water content. Climate change scenarios should therefore consider these scenarios.

Recommendation:
It may be beneficial to model "worst case" plume wildfire events in selected areas using models capable of incorporating wildfire and atmospheric dynamics to determine the tail risk from this class of event.

3.4.5. Extreme wind events

Most of California's wildfire losses, particular loss of life and property, have occurred due to extreme wind events. Hence we have some experience of "tail-risk" wind events, and in fact some mitigations in place – specifically PSPS. The impact of a PSPS event is not evenly distributed, with some areas experiencing high winds and other areas quiescent. Different PSPS events also have different lengths. In the table below, weather station data is shown from SDG&E, who has the densest weather station mesh in California. It shows a tally of data collected between 2015 and 2022, showing the number of weather stations above a certain threshold, as well as the

[52] Coen, J.L., Schroeder, W., Conway, S., Tarnay, L., 2020. Computational modeling of extreme wildland fire events: A synthesis of scientific understanding with applications to forecasting, land management, and firefighter safety. Journal of Computational Science 45, 101152. https://doi.org/10.1016/j.jocs.2020.101152

number of measurements taken above that threshold (each measurement corresponding to a time increment, mostly 10 minutes).

Wind gust speed greater than (mph)	Stations	Measurements	M – Sill Hill
48	146	54030	46488
55	104	17499	13285
70	26	1391	482
85	6	133	5
111	0	0	0

Table 3 - Wind speed exceedance at SDG&E weather stations, 2015-2022. 'Stations' is the count of the stations exceeding threshold at least once during this period. 'Measurements' are the total number of measurements (usually 10 minute intervals), and is a measure of how much time is spent over threshold. 'M-Sill Hill' removes data from the anomalously high Sill Hill weather station, whose corresponding circuit has since been undergrounded.[53]

The "M-Sill Hill" column has the data from the "Sill Hill" weather station removed, which regularly experiences gusts over 85 mph. Otherwise, gusts over 85 mph have historically been rare, although that does not preclude them from occurring in the future.

Even though maximum fire wind speeds are not expected to increase in climate change scenarios, it is prudent to project what would happen if projections change or if we simply see a "tail-risk" wind event. We would likely have adequate warning of such an event from both governmental and utility meteorologists. Historically, a severe or extreme fire wind event, compared to a milder one, is characterized by three things: 1) peak winds are at high or record-breaking levels at many weather stations, 2) the geographical area over which the event occurs is larger, possibly extending beyond areas that typically see this type of event, and 3) the event tends to last much longer than milder events.

From the utility standpoint, even if the public is adequately protected from utility-ignited wildfire by PSPS, they would still not be protected from the protracted negative impacts of power

[53] MGRA 2023 Comments; p. 109, cites:
Workpaper TURN-SEU-015_ATTACH_Q7_Q8_8584_Weather_jwm.xlsx
https://github.com/jwmitchell/Workpapers/blob/main/WMP23/TURN-SEU-015_ATTACH_Q7_Q8_8584_Weather_jwm.xlsx

loss. It is possible that in a conceivable "tail risk" even utility supplies of portable generators, etc. would be exhausted early in the event, and its personnel may not be sufficient to cope with issues experienced by vulnerable and special needs customers. Utilities should have the capability to withstand an "off-scale" wind event without imposing an undue burden on customers.

Recommendation:

Utilities should have contingency plans in place to manage an extreme intensity and duration fire wind event. Utilities should coordinate with partner stakeholders, agencies, and CES. Utilities should construct mutual aid agreements with other regions if possible. The contingency plan should be periodically tested by table-top exercises.

Recommendation:

Hardening or undergrounding should be prioritized for areas with frequent or extended PSPS outages.

3.5. Power law distributions as a best practice

Should the power law probability distribution be required as the baseline distribution function for modeling the consequences of wildfire risk? Should it be recommended as a best practice?

Does the power law probability distribution appropriately incorporate tail risk events in the wildfire risk, as compared to the use of other distribution functions?

The power law function was shown in Section 3.1.2 to be widely accepted as describing wildfire size dependencies over many orders of magnitude. PG&E's analysis stops short of recommending the power law distribution as a best practice,[54] because the technical complexities involved and limited data do not permit it to reject other distributions with reasonable statistical certainty.

PG&E investigated various loss parameters (area, buildings, fatalities) in its own service area and found a visually good match to power law dependencies:

[54] PG&E Power Law Whitepaper; p. 9.

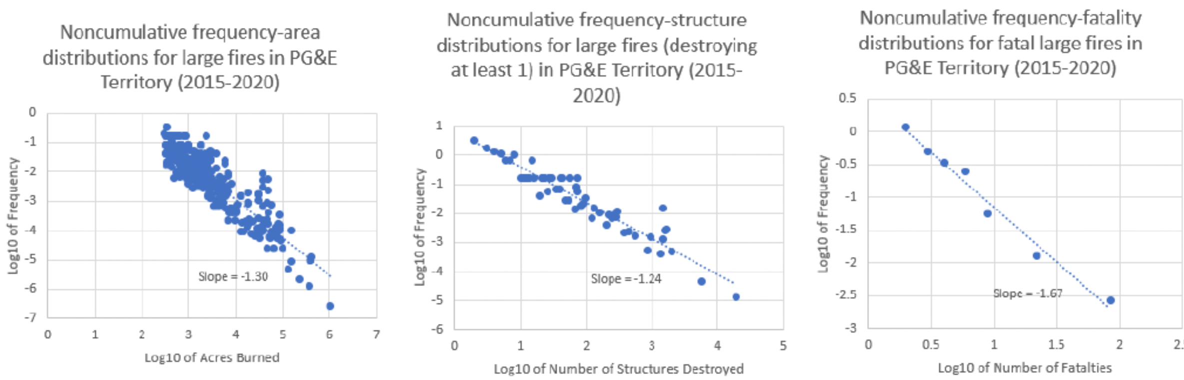

Figure 10 – PG&E White Paper: Noncumulative frequency-area, frequency-structure, and frequency-fatality graphs using large fire (greater than 300 acres) data in PG&E Territory (2015-2020).[55]

PG&E provides both visual and statistical analysis comparing potential power law distributions against the lognormal distribution it had been using. Their analysis shows that the lognormal tends to provide a best fit in the low to moderate loss region but significantly underestimates tail risk, as shown in the example below:

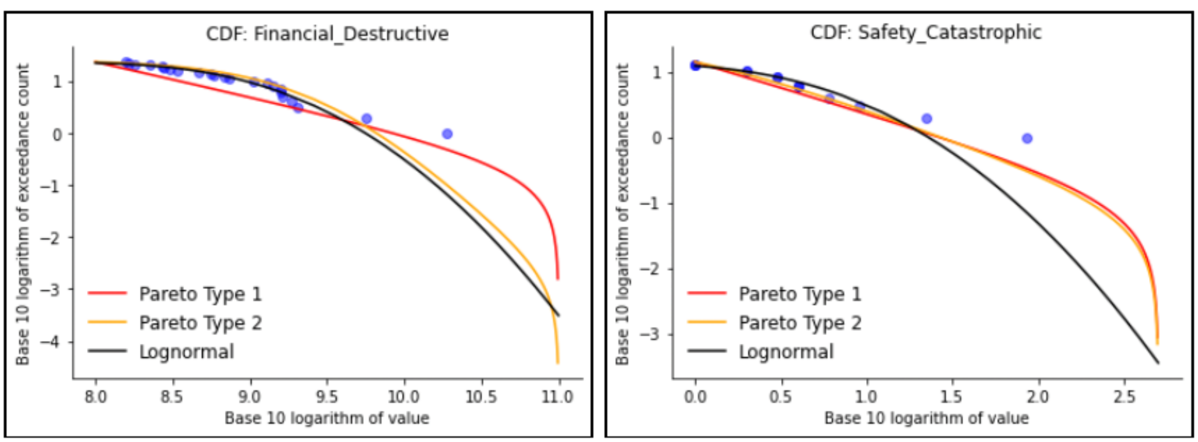

Figure 11 - PG&E Whitepaper Figure 3 - Wildfire data and truncated PD1, truncated PD2, and untruncated lognormal distribution fits. In both graphs, the logs of the ranks of the data are plotted against logs of their x values (dollars and fatalities).

PG&E also performs goodness-of-fit testing using the Kologorov-Smirnov (KS) test, which performs fitting across the entire data set. Generally, the lognormal fares somewhat better than the power law distribution in most attribute tranches, as might be expected from the curves shown in Figure 11, since most of the low and moderate values lie closer to the lognormal curve. However,

[55] Id.; p. 4. Figure 1.

the figure also makes clear that the lognormal distribution will tend to underestimate ***tail risk*** by orders of magnitude.

Li and Banerjee (fn 31) reached a similar conclusion to PG&E, which when it examined wildfires in California from 2000 to 2019 also found that the truncated Pareto distribution provided a fit superior to other "fat tail" distributions, as shown in the table below:

	Wildfires in 1920–1999			Wildfires in 2000–2019		
Distribution	**AIC**	**K-S**	**CvM**	**AIC**	**K-S**	**CvM**
Gamma	186,942.2	0.2967	277.72	75,814.81	0.4713	240.94
Lognormal	178,499.6	0.0234	1.37	69,481.42	0.0869	13.24
Pareto	178,987.2	0.0333	2.38	69,470.16	0.1033	5.69
Truncated pareto	177,643.5	0.0317	3.40	67,562.65	0.0129	0.15
Weibull	180,347.5	0.0764	19.02	71,096.81	0.1637	31.55

Table 4 - Li and Banerjee, 2021 Table 2 showing goodness of fit results for California wildfires between 1920 and 1999 and 2000-2019. Goodness of fit test results are Akaike Information Criterion (AIC), Kolmogorov–Smirnov (K–S) test, and Cramer-Von Mises (CvM) test for heavy-tailed distribution fitting. Best fit is shown by the smallest value of the test metric.

The important question with respect to how a particular function fits the wildfire size distribution is whether these functions are *predictive* in the ranges responsible for most losses and also outside the range of existing data. The advantage of the power law distribution is not so much that it provides an adequate fit to existing data (which it does), but rather that it is based on physical and dynamical models that are known to apply to the physical, dynamic wildfire system.

This is exemplified in the comparison performed by MGRA between a power law distribution function and a gamma function, which SDG&E had been using for its enterprise risk models.

Wildfire Losses, $ Billions	Gamma (3,0.8)	Power Law (-0.5)	Power Law, $40 B Max
2.1	46.3814%	49.8813%	51.0296%
2.64	61.6927%	55.3316%	57.8912%

3.33	76.3285%	60.1893%	64.0067%
4.19	87.9305%	64.5187%	69.4570%
5.27	95.2107%	68.3772%	74.3147%
6.64	98.6246%	71.8162%	78.6440%
8.36	99.7388%	74.8811%	82.5026%
10.52	99.9707%	77.6128%	85.9415%
13.25	99.9983%	80.0474%	89.0065%
16.68	100.0000%	82.2172%	91.7382%
21.00	100.0000%	84.1511%	94.1728%
26.44	100.0000%	85.8746%	96.3426%
33.28	100.0000%	87.4107%	98.2764%
41.90	100.0000%	88.7798%	100.0000%

Table 5 - Comparison of power law to gamma function from MGRA informal comments on SDG&E RAMP. The table shows Probability of wildfire losses less than specified amount using gamma distribution (SDG&E), power law, and power law truncated at $40 billion (MGRA). The gamma function values were calculated using Microsoft Office Excel's GAMMA.DIST function, and match the P95 and P98 values reported by SDG&E in its data request responses.[56]

It was this in part, and partially because the fit was adequate, that PG&E and SDG&E chose to use Pareto Distributions to model their enterprise wildfire risk.

As to the question of whether this should be a best practice, the answer is that:

Wildfire size distributions follow a power law up to a large truncation point, and this should be represented in utility risk models. Utilities may use this relationship itself, for instance in a Monte Carlo distribution. If a utility uses another method to calculate risk, such as fire spread simulation, it must show that its method is equivalent to a power law distribution with a cutoff adequate to incorporate tail risk.

3.6. Use of Power Law for Operational and Planning Risk Models

[56] Safety Policy Division Staff Evaluation Report on SDG&E's and SoCalGas' Risk Assessment and Mitigation Phase (RAMP) Application Reports (A.) 21-05-011, (A.) 21-05-014; November 5, 2021, (pp. 209-213/295) Appendix: MUSSEY GRADE ROAD ALLIANCE INFORMAL COMMENTS TO THE SAFETY POLICY DIVISION REGARDING SAN DIEGO GAS AND ELECTRIC COMPANY'S RAMP FILING; October 22, 2021; pp. 2-5.

Currently, power law distributions are applied only to enterprise risk calculations. How can we represent tail risk in 1) planning and 2) operational risk models?

The original scoping of tail risk and power laws within this proceeding does not include operational and planning risk models. However, the considerations applied to enterprise risk models apply equally to operational and risk models, so it is important to raise this issue now so as to show that the treatment of tail risk will be incomplete until these issues are addressed. This section therefore lays out potential areas for future discussion regarding tail risk and power laws for potential future phases or proceedings.

Current utility planning and operational models have not been shown to reflect the power law size dependency for losses. Figure 3 shows clearly that the wildfire simulations used for modeling utility risk do not show a power law dependency. Technosylva representatives have said that such a dependency might become evident if the fire simulation results were weighted by the probability of the weather event leading to each result. This should be verified.

However the most important issue is whether operational and planning models properly capture tail risk. This is an involved question that extends beyond the scope of Phase 3, but the Commission should at the least lay out a roadmap for how the utilities and stakeholders (who have been carrying on technical discussions on these issues in Energy Safety's Risk Mitigation Working Group)[57], should finally begin to ensure that their risk estimations capture tail risk.

One of the primary issues is that an eight hour simulation by Technosylva's Wildfire Analyst, used by both SCE and SDG&E, does not capture the largest wildfires. SCE for its part has decided to live with the 8 hour limitation, but has in compensation defined classifiers based upon consequences alone under which SCE classifies circuits as high risk and assigns them to be undergrounded.

3.6.1. Determining tail risk from a wildfire simulation

[57] https://efiling.energysafety.ca.gov/eFiling/Getfile.aspx?fileid=54072&shareable=true

Since it is known that 8 hour fire spread simulations are inadequate to model worst-case tail events, what are the difficulties with allowing for longer wildfire spread simulations? As noted in Section 3.4.3, Technosylva ran 24 hour simulations to determine the potential losses from wildfires that might have been ignited during PSPS events. These calculations have never been validated. Perhaps it is time to see whether longer duration Technosylva runs could be useful to at least determine statistical distributions of potential wildfire sizes.

A "toy" example of such a study was presented by SCE in its 2023 WMP. In the following figure, SCE studied 174 historical wildfires and compared their final sizes to the size at 8 hours based on a simulation program:

Figure 12 - SCE study of 174 wildfires comparing the final size of the fire based on a simulation (Sim Table) estimate of its size at 8 hours.[58]

As can be seen in this figure, much of the wildfire growth is occurring after 8 hours has passed. It is important to note that these simulations are *not* Technosylva's but rather a product called "SimTable".[59] This product apparently produces simulations that always end up matching the actual wildfire perimeter as the final result, as shown in the figure below:

[58] SCE 2023 WMP; p. 217; Figure SCE 7-19.
[59] http://www.simtable.com/
Example fire result:
https://www.simtable.com/apps/fireProgression/output2019/CAINF_000903_JORDAN.html

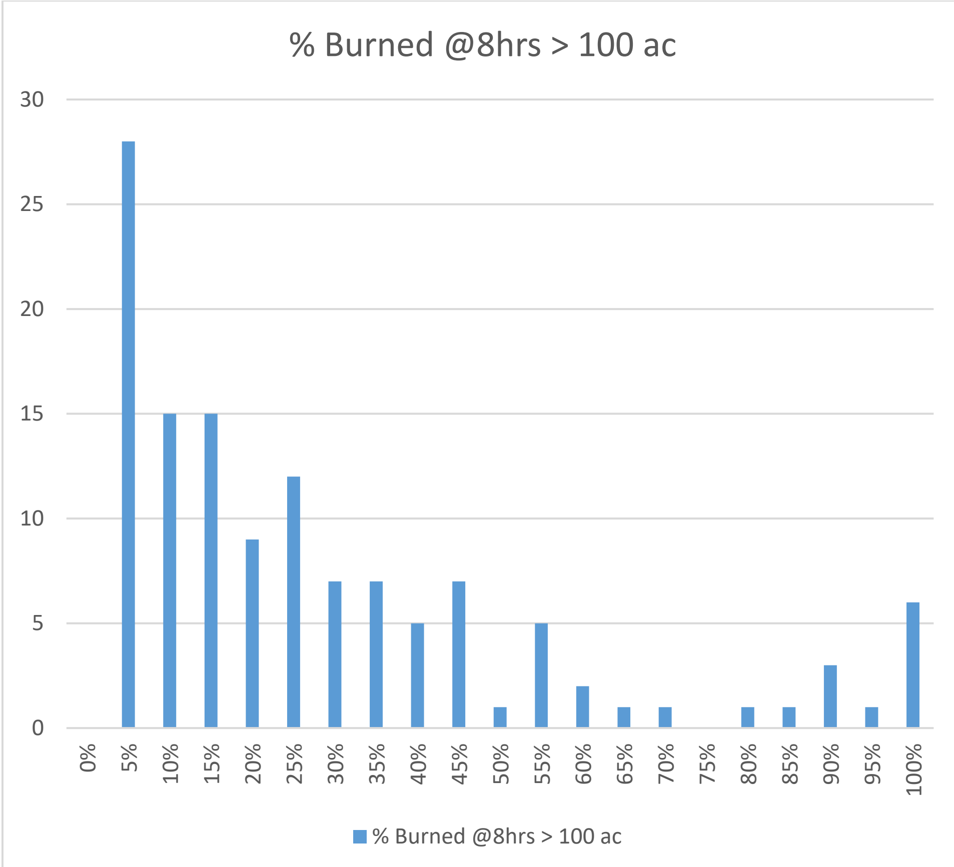

Figure 13 - Plot of raw SimTable data provided by SCE.[60] As can be seen, no fire is ever larger than the actual measured value, which means this is a post-hoc simulation.

Figure 13 shows all wildfires larger than 100 acres, and calculates percentage burned after 8 hours, with the actual wildfire size as an upper bound. A simulation such as Technosylva, in contrast, can produce a final result that either exceeds or is smaller than the actual wildfire perimeter.

The basic principle – that we can compare simulations to historical real fires and obtain statistical relationships that might provide additional predictive value – should be tested with the simulation model being used by utilities.

There are two approaches, not exclusive, that might be used to approach this problem:

[60] 2023-WMPs; SCE reply to MGRA DR-6.
Data at https://github.com/jwmitchell/Workpapers/blob/main/R2007013/02_MGRA%2006%20Q2%20-%20jwm.xlsx

1. Run Technosylva 8 hour simulations for historical wildfires. These should be "raw" simulations and not adjusted in any way for the specifics of the wildfire. Compare the 8 hour wildfire size value to the final measured wildfire size and obtain a ratio. This ratio will form a distribution. It may be possible to use this distribution as a weighting function or a source distribution for a Monte Carlo that could be applied to the 8 hour consequence values. The same approach can be applied to structure losses.
2. Run longer Technosylva simulations for historical fires to determine how long the simulation needs to run to reproduce observed acreage burned and structure loss. This value may depend upon weather conditions. This could be used to adjust the Technosylva run time according to weather conditions.

On July 11, 2023, SCE presented at an OEIS workshop on large wildfires at which it displayed comparisons of 8 and 24 hour simulation spreads, and claimed they were not effectively different. It presented data for its service territory as a consequence chart, shown below.

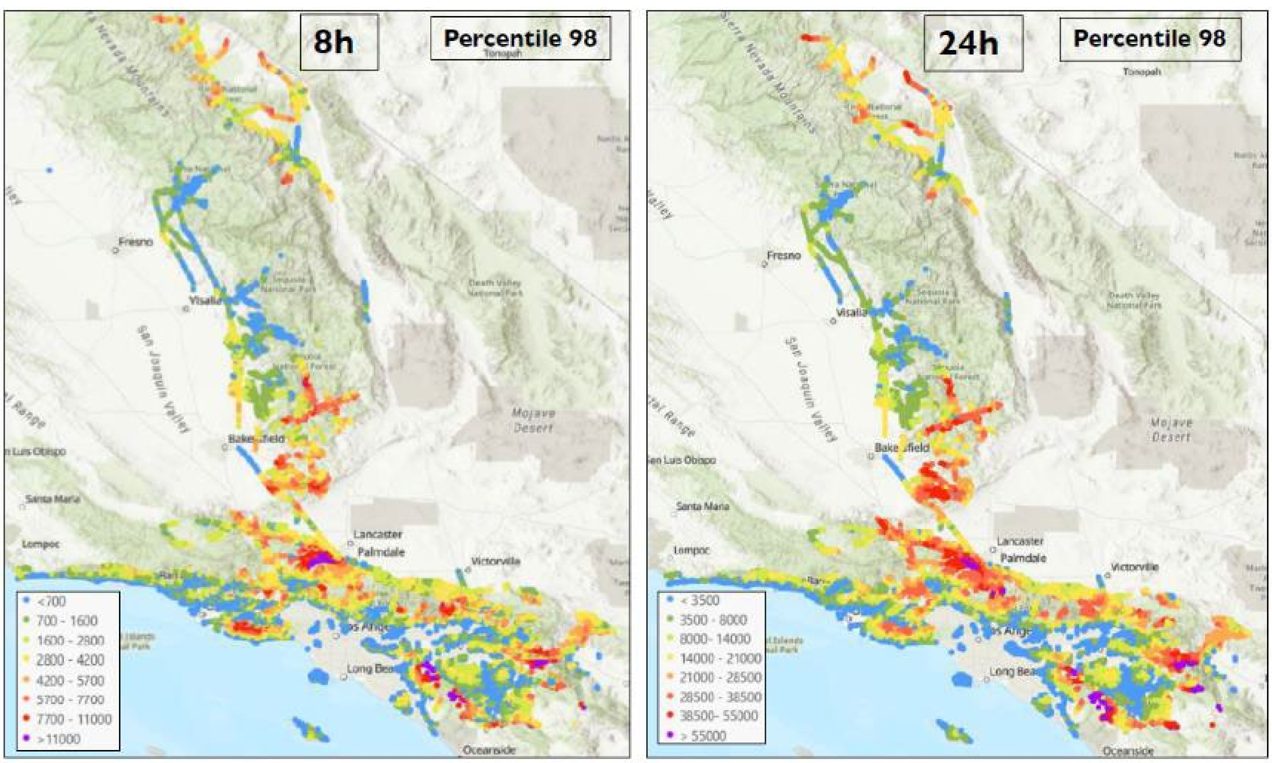

Figure 14 - Simulated consequence map generated by SCE in its service area, showing runs for 8 and 24 hours. Spatial characteristics are generally similar, though magnitudes of losses are higher. Edison claims to see a slight shift to more rural areas in the 24 hour run, which is as expected.[61]

[61] OEIS; Risk Mitigation Working Group; July 11, 2023 meeting slide deck; p. 78.

SCE claims that this figure shows that the effective losses after an 8 hour and 24 hour simulation appear to be in the same areas, as evidenced by the similarity of the two plots. SCE's explanation is that most fires reach a maximum size as they encounter physical boundaries such as built areas. However, it is the *difference* in these two plots that would identify the areas that might be underserved by an 8 hour simulation. SCE provided another example that can be used to demonstrate this point.

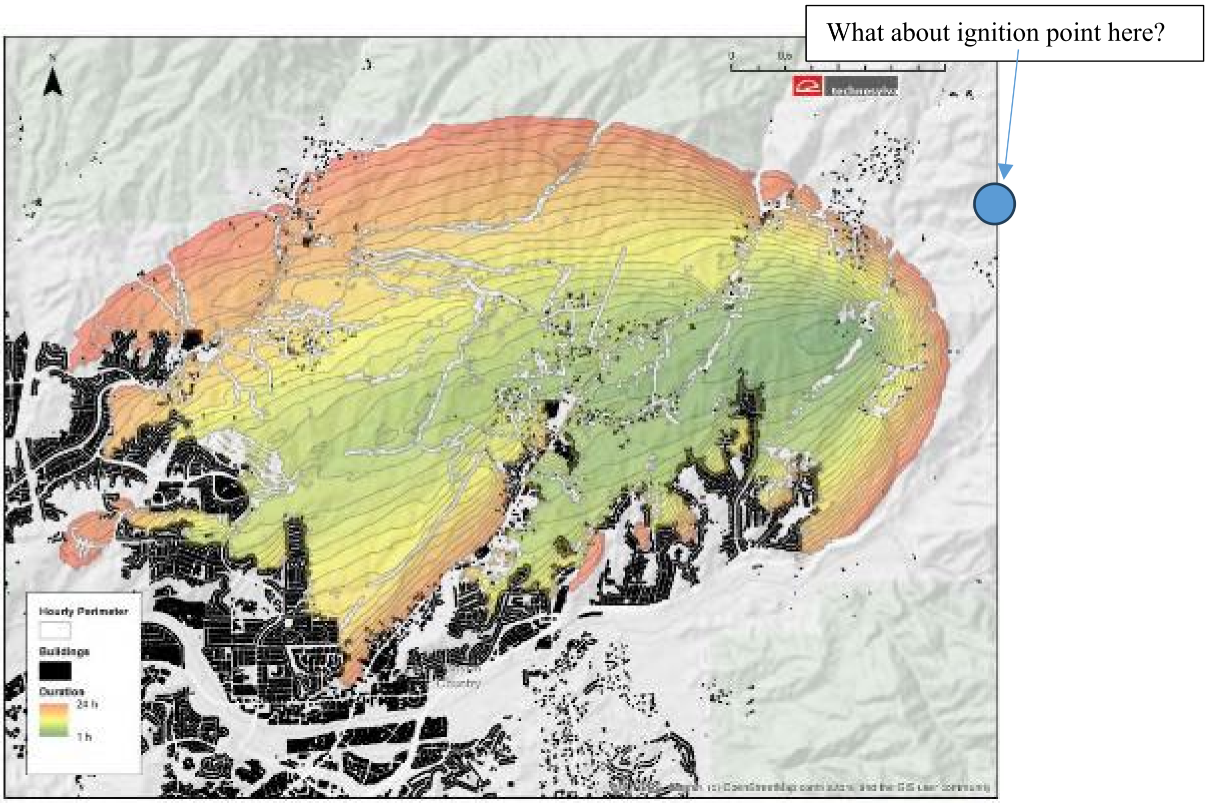

Figure 15 - Technosylva 24 simulation performed as part of its "PSPS damage" exercise shows 24 hours of wildfire growth. Colors and ticks show hourly spread from ignition to the 24 hour point.[62] A potential ignition point to the northeast was added by the author.

The figure above demonstrates that fire size growth is limited by the physical boundaries, but losses may increase as wildfire encroaches into neighborhoods. In the particular example, only a quantitative difference between the 8 hour and 24 hour simulations would be seen. However, if the point of ignition is shifted slightly to the east, then the fire front would not reach the developed area in 8 hours, and there would be both a quantitative and qualitative difference between the 8 hour and 24 hour runs. The erstwhile ignition point, indicated by the blue circle, would be ranked as having a

[62] [62] OEIS; Risk Mitigation Working Group; July 11, 2023 meeting slide deck; p. 78.

much lower consequence value, even though a 24 hour simulation would bring it into full contact with the Wildland Urban Interface.

It is not important for the purposes of computing tail risk that every risk value be accurate, but rather that as an aggregate the distribution takes into account the potential for large losses. Technosylva experts understand that their model results become harder to trust as simulations become longer due to the myriad non-linear effects of weather and fire suppression. The goal is not to be able to represent each wildfire accurately, but to determine the distribution of the *inaccuracies* to see whether this can be used as a correction to the existing methods to incorporate tail risk and to ensure areas that may reasonably be expected to be at risk from major fires are included in utility consequence calculations.

Recommendation:
The hypothesis that Technosylva's wildfire size distribution will follow a power law distribution when properly weighted by probability should be tested.

Recommendation:
Technosylva's Wildfire Analyst fire spread model should undergo further vetting to see if it can be leveraged to accurately predict the magnitude of tail risk events. Possibilities include:
- Simulations of historical wildfires and comparison with the Technosylva 8 hour consequence values
- Longer simulations using Technosylva to obtain an appropriate run time that would allow it to produce losses equivalent to those of historic wildfires.

3.6.2. PG&E's WDRM v3 risk model

PG&E describes its WDRM v3 risk model thusly:

"*In v3 of the model, PG&E has moved from exclusively using consequence outputs from Technosylva and CalFire to using Technosylva, PG&E's FPI R-score (which is used to call PSPS events), and public satellite data from the Visible Infrared Imaging Radiometer Suite (VIIRS). This updated approach leverages real and observed fire behavior and consequence outcomes, which is an improvement over v2. However, while these outcomes are actually ranges, PG&E is using the mean consequence from each range in their risk modeling. The current structure of the consequence* *model uses VIIRS observed fires and Technosylva simulations to classify fires or simulations as either destructive, or potential conditions, or not destructive potential conditions by ignition point. The probability of a destructive or non-destructive fire for each ignition point is then determined to be the number of days within the sample window, 2014-2020, where conditions matched those defined for a destructive or non-destructive fire, over the total number of days in the timeframe. PG&E then manually calculated the cost of each historical VIIRS fire by assessing the number of acres and facilities burned, assigning $1M/structure and $1,175/acre. The cost of a destructive fire was defined as the mean value for each category, destructive or non-destructive. The actual consequence value at each ignition point is then calculated to be:* $Consequence\ of$ Risk Event ($CoRE$)= ($Probability\ of\ destructive\ fire \times Mean\ cost\ of\ historical\ destructive\ fires$)+($Probability\ of\ nondestructive\ fire \times Mean\ cost\ of\ historical\ nondestructive\ fires$)

The use of the mean for prioritization may poorly characterize risks in areas with large ranges of consequence. The use of the mean cost to calculate total risk could overlook areas with potentially very high risk or prioritize them lower. Using the mean to calculate risk-spend-efficiency could also improperly overlook areas with high mitigation efficiency and promote smaller scale mitigations in areas that actually require more fundamental changes. The reverse is true if the mean is obviating a very low range. We recognize the clarity a point estimate brings to the prioritization process but recommend exploring other more robust measures than the average expected value to replace the single point estimate which might improve the quality of information communicated to decision-makers and SMEs. These new metrics, which could be supplementary, could capture more of the long-tail effects that may impact decision-making. Specifically, if SMEs are made aware of the probability of destructive fires for a given location and the range of cost consequences, that may serve as an additional point in their decision-making process. In that case, they could identify mitigations that may better serve that location.

Additionally, while the use of consequence data on historical fires is a decent place to start and this valuable information should not be discarded, E3 recommends PG&E attempt to supplement this data with more specific cost estimates. These estimates should be developed alongside the regulator, but could be based on characteristics of the geography such as number of people in a given area, density of buildings, value of land (e.g. cropland). It is also important to consider equity in these calculations as well to ensure that the consequence model does not inappropriately overweight affluent neighborhoods only.

Finally, particularly over the timeframes that mitigation can be implemented, a look-back approach to consequence, using fire weather data from the 2014-2020 period, may create inaccuracies and bias in consequence estimates because climate, weather, and drought conditions are non-stationary. Best available science indicates an acceleration in fire weather conditions. We recommend that PG&E at least evaluate the possibility of using estimates of intensification of key fire weather variables that may increase consequences for the longer-term use cases of the model."[63] (Emphasis added)

PG&E acknowledges that its approach of binning is problematic for capturing tail risks. Due to the power law distribution, an "average" bin will always underestimate wildfire risk because losses are driven by the largest wildfires. PG&E's model was reviewed by E3, who concluded that "*The use of the mean for prioritization may poorly characterize risks in areas with large ranges of consequence. The use of the mean cost to calculate total risk could overlook areas with potentially very high risk or prioritize them lower. Using the mean to calculate risk-spend-efficiency could also improperly overlook areas with high mitigation efficiency and promote smaller scale mitigations in areas that actually require more fundamental changes. The reverse is true if the mean is obviating a very low range*."[64]

PG&E's consequence WDRM v3 model therefore likely does not fully incorporate tail risk. Instead of using mean values, PG&E may benefit from using a statistical model, in which large fires in its categories are fit to a distribution incorporating the known power law size dependencies of wildfire. PG&E does this in its enterprise risk model, which uses a Generalized Pareto Distribution. PG&E could then use this distribution to generate Monte Carlo data from the distribution to estimate consequences, thus capturing tail risk using a physically supported model.

Recommendation:

The Commission should ensure that all utility risk models: enterprise, operational, and planning, properly incorporate tail risk. This should be noted as a subject for future phases or proceedings.

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[63] 2023-2025 WMPs; E3 Review of PG&E's Wildfire Risk Model Version 3; 3 WMP; pp. 22-23.
[64] Id; p. 22.

Recommendation:

PG&E should consider modifying its risk model so that tail risk is captured in a such a way that it is not limited to historical events. Fitting its "extreme" distribution bin to a power law with cut-off model should allow it to statistically include extreme tail events in its calculation.

3.6.3. SCE's IWMS Framework

SCE's IWMS Framework is currently being litigated and reviewed both in the OEIS 2023-2025 cycle and in its General Rate Case. Nevertheless it is mentioned here because at its foundation it is a radically different way to calculate risk and tail risk since it is related to the concept of "risk tolerance" that will be discussed during a later phase of this proceeding. MGRA discussed SCE's framework in some detail in its 2023-2025 WMP Comments, portions of which are reproduced below.[65]

What SCE calls its IWMS (Integrated Wildfire Mitigation Strategy) Risk Framework, is an alternative planning framework to MARS (Multi-Attribute Risk Score),[66] which is based on the methodology of the Settlement Agreement.[67] As SCE describes it in its 2023-2025 WMP:
"*The IWMS Risk Framework defines three risk tranches within SCE's HFRA based on potential consequences should an ignition occur at a specific utility asset location. This analysis includes elements such as potential egress constraints and Communities of Elevated Fire Concern (CEFC). The IWMS Risk Framework is anchored on wildfire consequence should an ignition occur and does not adjust consequences based on the probability of ignition. SCE takes this approach because probability of ignition changes over time due to many variables such as age, loading, etc. Furthermore, in some locations the consequences of an ignition that leads to a wildfire may be so extreme that it is prudent to mitigate ignition risk regardless of probability*."[68]

The classical definition of risk, particularly in terms of the CPUC S-MAP Settlement Agreement is

Risk = Probability of Risk Event X Consequences of Risk Event

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[65] MGRA 2023-2025 WMP Comments; pp. 69-76.
[66] SCE 2023-2025 WMP; p. 89.
[67] D.18-12-014; Appendix A; p. A-3. (Settlement Agreement)
[68] Id; p. 90.

Under this definition, IWMS is not a risk framework, because it has no probability component. IWMS implicitly rejects the risk framework agreed to by the Stakeholders.

As justification, SCE cites a number of potential overriding concerns that merit specific SCE infrastructure in certain locations, which it terms an "SCE High Fire Risk Area (HFRA)" as being subject to IWMS and not the standard MARS framework. Specifically:

- Egress issues, specifically constrained evacuation, high fire frequency, or the potential for burn-in of an egress route,
- Areas for which an ignition can result in a fire significantly larger than 10,000 acres,
- High wind areas,
- Areas where smaller fast-moving fires have a potential to impact communities under "benign" weather conditions (CEFCs or Communities of Elevated Fire Concern).[69]

HFRAs are divided into three risk tranches: Severe Risk Areas, High Consequence Areas, and Other HFRA depending on the potential for large fires.[70] This process of classification is a manual process that SCE admits is "time consuming and labor intensive".[71] These tranches define SCE's preferred mitigation. For Severe Risk Areas, SCE proposes undergrounding when feasible, and covered conductor plus REFCL when not. For High Consequence Areas, it proposes covered conductor plus REFCL. For other HFRA it proposes enhanced inspections and vegetation management.[72]

Noteworthy is that probability does not come into these calculations at all, so they deviate from the Settlement Agreement. However, it is important to understand the statistical and ethical foundations of these arguments in order to properly analyze what place if any they have in the Risk-based Decision-Making Framework.

[69] SCE 2023-2025 WMP; pp. 101-103.
[70] Id.
[71] Id.; p. 113.
[72] Id.; p. 206, and
DR Response 08_CalAdvocates-SCE-2023WMP-08 Q.08.

3.6.4. What is acceptable risk?

SCE is appealing to the philosophy that risk, particularly extreme risk, should be mitigated to the full extent possible. There is some philosophical and technical backing for such an approach with regard to tail risks. The ALARP (As Low As Reasonably Practicable) proposal from CPUC staff was a proposed framework for such an analysis.[73] The ALARP premise is that there is a societally acceptable level of risk, and conversely that there are certain risks which are unacceptable and should be mitigated – not necessarily to zero but to the level where the risk is again within the acceptable range.

This is particularly applicable with respect to tail risk, because as demonstrated in the previous sections, most of the risk comes from large events. PG&E and SDG&E have adopted a Pareto Distribution (power law) with a cutoff of 500,000 acres for their enterprise risk calculations, but as noted in Section 3.4, the uncertainties of that calculation are considerable and need to be improved. In fact, for this type of distribution the uncertainty is large with respect to the value itself. This has implications. As Taleb describes it in his book The Black Swan:

"… we do not realize the consequences of the rare event.

What is the implication here? Even if you agree with a given forecast you have to worry about the real possibility of significant divergence from it… I would go even further and, …state that it is the lower bound of estimates (i.e. the worst case) that matters when engaging in a policy — the worst case is far more consequential than the forecast itself. This is particularly true if the bad scenario is not acceptable."[74]

As MGRA contends in its Comments in the 2023-2025 WMPs, this framing of the problem may be reasonable under certain circumstances. In the specific case of utility wildfire risk there are issues that must be resolved before a consequence-only model should be considered:

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[73] A.15-05-002-5; COMMENTS OF THE MUSSEY GRADE ROAD ALLIANCE (MGRA) ON THE INTERVENOR SMAP WHITE PAPER; February 12, 2016.

[74] Taleb, Nassim Nicholas. The Black Swan - The Impact of the Highly Improbable. Second edition. New York: Random House, 2010; pp. 161-162.

- The decision of what constitutes acceptable risk is a societal decision, and not one that should be left to an interested party. This determination must be made by regulators, as proxies for the public, and not a utility acting in its own interest.
- Criteria used in SCE's particular case are non-transparent and appear somewhat arbitrary.
- It may be possible to quantify probabilities for SCE's IWMS classification and thereby integrate them properly into its risk model.
- The risk of truly catastrophic fire is not solely from utility lines. In fact, as utilities argued for many years at the initiation of CPUC wildfire proceedings, utility ignitions represent a small fraction of ignitions, though a significant fraction of losses. If the goal is to protect the public from catastrophic wildfire loss then other more holistic mitigation needs to occur outside of the utility sphere.
- The burden of rate increases on the poorest and most vulnerable populations may offset risk improvements for Wildland Urban Interface residents.

Specific decisions made by SCE for its classification of risk tranches worthy of this special treatment will be discussed and reviewed in the records of the 2023-2025 WMPs and in the SCE GRC. However, the idea of addressing tail risk solely by using consequence and not probability is related to the idea of risk tolerance, and needs further review by the Commission.

Recommendation:
The Commission should address the question of what tail-risks are acceptable and whether it is possible to ignore probability based on specific criteria when determining mitigations. This should be raised in a future phase or proceeding.

Recommendation:
Other companies should be discouraged from taking a similar approach to mitigation planning until SCE's IWMS has been adequately reviewed.

3.7. Additional Reporting Requirements

Should there be any additional reporting requirements or guidelines to accompany the application of the power law distribution to make the results accessible to the layperson?

If a group is using the power law in the standard manner, additional reporting requirements are not necessary. It is helpful if the utility is able to analyze the degree to which the power law function affects the outcome, i.e. how much of the risk is tail risk. For example, SDG&E reports that using the power law distribution function increased its estimate enterprise wildfire risk by 15%.[75]

In the event that a utility uses a method that doesn't directly use a power law, it should demonstrate that function's performance with respect to a power law. Two examples are the data submitted by MGRA to support the use of power law against SDG&E's use of the gamma function,[76] and the extensive comparisons performed by PG&E in its "Power Law Distribution" white paper.

Recommendation:

Utilities should report the effect of using a power law distribution function in order to gauge the amount of risk coming from tail events.

Recommendation:

When a utility opts to use a method other than a power law, it should justify its use by direct comparison with the power law distribution.

3.8. Other Tail Risk Events

Should the use of the power law distribution be required (or other Commission guidance provided) to address other non-wildfire risk events that similarly have low probability, high consequence risk events (e.g., hydro dam failure, seismic events, etc.)?

[75] A.22-05-016; MGRA-01-2E; DIRECT TESTIMONY OF THE MUSSEY GRADE ROAD ALLIANCE SAN DIEGO GAS AND ELECTRIC COMPANY 2024 GENERAL RATE CASE; ERRATA 2; June 8, 2023; p. 12.

[76] Safety Policy Division Staff Evaluation Report on SDG&E's and SoCalGas' Risk Assessment and Mitigation Phase (RAMP) Application Reports
(A.) 21-05-011, (A.) 21-05-014; November 5, 2021, (pp. 209-213/295) Appendix:
MUSSEY GRADE ROAD ALLIANCE INFORMAL COMMENTS TO THE SAFETY POLICY DIVISION REGARDING SAN DIEGO GAS AND ELECTRIC COMPANY'S RAMP FILING; October 22, 2021; pp. 2-5.

The concept of tail risk is applicable to many other domains in which there is potential for extreme risks with outsized consequences. However, the power law distribution emerges naturally in physical systems with build up / cascade dynamics, otherwise known as “self-organized” systems. Other physical domains will have different underlying dynamics and therefore may have different statistical distributions describing their extreme events. I am not an expert in these domains and therefore this whitepaper doesn’t offer specific recommendations on them. Many of these utility risks, however, have well-developed standards, engineering practices, and bodies that can provide additional guidance on how to deal with worst-case scenarios.

Some lessons from the wildland fire domain still apply. For example, a long-term utility outage can arise from a number of risks – not only extended fire wind events but also cyberattack and coronal mass ejections. In any of these cases the utility must have a contingency plan in place, have completed a scenario analysis, should have run simulations with tabletop exercises, and should be coordinating with partners and emergency agencies on strategies in case such a foreseeable but low probability event occur.

It is also important that external drivers that can lead to multiple failure modes be understood. For example, a tail-risk atmospheric river event[77]might not only cause flooding and landslides, but could potentially lead to simultaneous dam failures.[78] The Commission should ensure that utilities have plans in place and can recognize the warning signs of an impending tail risk event and have responses prepared.

Recommendations:
The Commission should require that utilities conduct scenario analysis and have contingency plans in place for reasonably conceivable tail risk events, such as seismic, dam failure, cyberattack, solar coronal mass ejections, and extreme PSPS. These should be accompanied by periodic tabletop exercises including essential partners such as Emergency Services.

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[77] Huang, X., Swain, D.L., 2022. Climate change is increasing the risk of a California megaflood. Science Advances 8, eabq0995. https://doi.org/10.1126/sciadv.abq0995
[78] Cox, C., Lowell, S., 2023. The Trillion-Gallon Question: What if California’s Dams Fail? The New York Times. https://www.nytimes.com/2023/06/22/magazine/california-dams.html Downloaded 7/12/2023.

4. CONCLUSION

Wildfire size distributions have been shown to be well-represented by power law distributions over many orders of magnitude, so there is sufficient justification for using them either directly for wildfire simulations or indirectly as a check on other methods such as wildfire spread simulations. PG&E and SDG&E have adopted power law distributions for their enterprise risk models, and SCE should be encouraged to do so or to validate the method it chooses against a power law distribution to show that its model produces equivalent results. The same arguments apply to operational and planning risk models. While these may be outside the scope of the current phase of this proceeding, the Commission should examine how tail risk estimation can be improved in these models in the future.

Currently, PSPS provides significant protection against tail-risk wind-driven fires but will be less effective against plume-driven fires. Utilities, even if not directly mitigating against low-likelihood tail-risk events, should have contingency plans in place, consult with essential partners, and periodically conduct simulation exercises to ensure that the effect of future tail risk events can be minimized.

5. SUMMARY OF RECOMMENDATIONS

- Wildfire risk models should either 1) directly use an appropriate power law distribution, such as the base distribution for a Monte Carlo simulation or 2) be able to show that their model produces results that are consistent with a power law when appropriately weighted or probability and consequence.
- Technosylva should be requested to provide a probability-weighted wildfire size distribution that will remove bias introduced by use the "worst case" weather days. This distribution can then be validated on a log-log plot to validate whether the Technosylva simulations follow the power law dependency seen in natural wildfires.
- Use of a power law distribution to model utility risk should tune parameters to fit the curve shown for power line fires, which tends to be somewhat shallower and have a higher cutoff due to the influence of external risk drivers.

- Risk models using simulation must be able to incorporate consequence events from the largest and most destructive wildfires.
- Utility climate change analysis in utility risk models must be able to incorporate potential increase in size of wildfire events and their correspondent consequences.
- PG&E's estimation of safety and financial caps is rigorous and should be adopted as a best practice.
- "Worst case" simulations should be considered for utility service areas consisting of extended wildfire simulations in combination from input by SMEs with strategic firefighting knowledge.
- It may be beneficial to model "worst case" plume wildfire events in selected areas using models capable of incorporating wildfire and atmospheric dynamics to determine the tail risk from this class of event.
- Utilities should have contingency plans in place to manage an extreme intensity and duration fire wind event. Utilities should coordinate with partner stakeholders, agencies, and CES. Utilities should construct mutual aid agreements with other regions if possible. The contingency plan should be periodically tested by table-top exercises.
- Hardening or undergrounding should be prioritized for areas with frequent or extended PSPS outages.
- Technosylva's Wildfire Analyst fire spread model should undergo further vetting to see if it can be leveraged to accurately predict the magnitude of tail risk events. Possibilities include:
  - Simulations of historical wildfires and comparison with the Technosylva 8 hour consequence values
  - Longer simulations using Technosylva to obtain an appropriate run time that would allow it to produce losses equivalent to those of historic wildfires.
- The Commission should ensure that all utility risk models: engineering, operational, and planning, properly incorporate tail risk. This should be noted as a subject for future phases or proceedings.
- PG&E should consider modifying its risk model in such a way that tail risk is captured in a such a way that it is not limited to historical events. Fitting its

"extreme" distribution bin to a power law with cut-off model should allow it to statistically include extreme tail events in its calculation.

- The Commission should address the question of what tail-risks are acceptable and whether it is possible to ignore probability based on specific criteria when determining mitigations. This should be raised in a future phase or proceeding.
- Other companies should be discouraged from taking a similar approach to mitigation planning until SCE's IWMS has been adequately reviewed.
- Utilities should report the effect of using a power law distribution function in order to gauge the amount of risk coming from tail events.
- The Commission should require that utilities have contingency plans in place for reasonably conceivable tail risk events, such as seismic, dam failure, cyberattack,solar coronal mass ejections, and extreme PSPS. These should be accompanied by periodic tabletop exercises including essential partners such as Emergency Services.

To be:

Respectfully submitted this 26th day of July, 2023,

By: __/S/____***Joseph W. Mitchell***______________________

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