PG&E HEARING ROOM EXHIBIT PG&E Ex-27

A.25-05-009

GRC-2027-PhI_DR_CalAdvocates_Oral004-Q001

(Witness: Shawn Holder)

PACIFIC GAS AND ELECTRIC COMPANY
2027 General Rate Case Phase I
Application 25-05-009
Data Response

PG&E Data Request No.:	CalAdvocates_Oral004-Q001
PG&E File Name:	GRC-2027-PhI_DR_CalAdvocates_Oral004-Q001
Request Date:	September 11, 2025
Requester DR No.:	004
Requesting Party:	Public Advocates Office
Requester:	Ry Andersen
Date Sent:	September 23, 2025
PG&E Witness(es):	Scott Strenfel – Electric Operations

QUESTION 001

Provide the Audit Final Report from UCLA that examines the PG&E WFOII Local Conditions Assessment tools as defined in the PG&E Wildfire Safety Plan, the 2021 and 2022 Wildfire Mitigation Plans, and the CPUC PG&E Local Conditions Audit #134777.

ANSWER 001

See attachment "*GRC-2027-PhI_DR_CalAdvocates_Oral004-Q001Atch01.pdf.*"

In addition to the attached report, in the meeting with Cal Advocates on September 11, 2025, CalAdvocates requested during the meeting the reference to the testimony or workpapers where PG&E describes the model that supports PG&E's Public Safety Power Shutoff (PSPS) decisions. PG&E responded at the meeting that the description on the model can be found in Exhibit (PG&E-4), WP 5-54 through WP 5-152.

GIRS-2025-03L

The B. John Garrick Institute for the Risk Sciences
UCLA ENGINEERING

PG&E WFOII

Local Conditions Audit

California Public Utilities Commission

FINAL REPORT

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Prepared For

California Public Utilities Commission

Pacific Gas and Electric Company

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Executive Summary

This is the **Final Report** of the PG&E Local Conditions Audit performed by the University of California Los Angeles (UCLA) and University of California Santa Barbara (UCSB) Review Team (RT), under the shared umbrella of the B. John Garrick Institute for the Risk Sciences at UCLA (GIRS-RT). The audit examines the PG&E WFOII Local Conditions Assessment tools as defined in the PG&E Wildfire Safety Plan, the 2021 and 2022 Wildfire Mitigation Plans, and the CPUC PG&E Local Conditions Audit #134777. The GIRS-RT has reviewed the methodology, implementation, and effectiveness of the tools utilized in this time frame and has provided recommendations for future improvements with support for the recommendations. The Local Conditions Audit covers tools divided into three categories: Identify, Design & Construct, and Operate.

The *Identify Category* includes 1) *Wildfire Distribution Risk Model (WDRM v2)*, 2) *Vegetation Risk Model (VRM)*, 3) *Conductor Risk Model (CRM)*, 4) *Consequence Model (CoRE)*, 5) *Service Territory Fire-Threat Evaluation and Ignition Risk Trends (STFT&IRT)*, and 6) *Transmission Operability Assessment (TOA)*. The tools in the *Identify Category* have been developed for planning purposes to support PG&E's wildfire mitigation strategies by recognizing, categorizing, and ranking the risk in PG&E territories. The GIRS-RT finds that these tools 1) show stronger prediction power than earlier versions, 2) undergo robust validation and external expert review, 3) align with industry-standard tools used by other major utilities, 4) provide a clear, data-driven view of changing wildfire risk, 5) use reliable engineering principles, and 6) are fit for use.

The *Design & Construct Category* includes 1) *System Hardening Decision Making*, 2) *Fire Rebuild Design Guidance for System Hardening*, and 3) *Mitigation Checklist Decision Framework*. Tools in the Design and Construct Category have been developed to provide a framework for decision making, design, and construction for system hardening and equipment upgrades and replacement in the context of PG&E's Wildfire Mitigation Plans. The GIRS-RT finds that these tools 1) comply with the relevant General Orders (GOs) and other design protocols, 2) incorporate PG&E's wildfire risk-models where appropriate, 3) meet or exceed industry standards, and 4) are fit for use.

The *Operate Category* includes the 1) *Fire Potential Index (FPI) model*, 2) *Catastrophic Fire Probability model for Distribution (CFP_D),* 3) *Catastrophic Fire Probability model for Transmission (CFP_T)*, and 4) *Enhanced Powerline Safety Settings (EPSS) program.* The tools in the *Operate Category* have been developed to enhance operational decision-making and mitigation during periods of extreme wildfire hazard in PG&E High Fire Threat District (HFTD) Tier 2, Tier 3 territories and select adjacent buffer zones. The GIRS-RT finds that these tools 1) are correctly designed and implemented from a data perspective, 2) are built with a solid foundation on probability theory, and therefore are suitable for risk quantification and mitigation purposes, 3) meet or exceed industry standards, and 4) are fit for use.

The Local Conditions Audit covers a period (2021-2022) of increasing risk of Catastrophic Wildfires in California. During this period, PG&Es development and applications of risk-based methodologies grew substantially. This period also coincides with a time of expansive growth in machine learning, data science, and computational modeling. PG&E faces significant challenges given the size and diversity of their territory, and has been a leader in the industry, employing

modeling at a level that meets or exceeds industry standards. The GIRS-RT recommends thorough data-driven validation and sensitivity analysis be conducted and documented as integral steps of tool development. The GIRS-RT also notes that certain components of the models are siloed, leading to less efficient use of model outputs and creating opportunities for more cohesive model integration.

During this period new field-tested methods have been developed and expanded. The GIRS-RT finds that PG&E Design & Construct protocols are compliant with the relevant GO's and utility standards. Additional methods for addressing wildfire risk have been developed and implemented to lower risk. These methods (PSPS, EPSS, and increased implementation of undergrounding) are found to be effective. The GIRS-RT notes that as new methods evolve, it is important that guidelines for implementation are updated, and that risk, reliability, and cost are balanced effectively.

Overall, the GIRS-RT finds that the 2021-2022 Local Conditions tools meet, or exceed industry standards, and are determined to be fit for use.

Acknowledgements

This project required the collaboration of many professionals at CPUC, PG&E, and The B. John Garrick Institute for the Risk Sciences (GIRS) at UCLA and UCSB. We acknowledge the GIRS staff who manage computing facilities, contracts and grants, and administration and scheduling. We acknowledge the contributions of CPUC members of the California Public Utilities Electric and Reliability Branch, Safety and Enforcement Division who oversaw this audit. We also recognize the contributions from over 30 individuals from the following PG&E organizations: Wildfire Mitigation, Data, Analytics, and Insights, Vegetation Management, Wildfire Emergency and Operations, Electric Asset Management, Electric System Planning, Emergency Preparedness and Response, Local Customer Engagement, and especially Electric Compliance, which managed the schedule of interviews, data collection, and other aspects of the program.

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I. Administrative Overview

This section includes a summary of the context for the Local Conditions Audit and the scope of work. For each of the categories—Identify, Design & Construct, and Operate— this section also includes a high-level summary of the objectives, tools, and primary GIRS-RT assessments. More detailed reviews and assessments are provided in the sections that follow.

I.A Background

The California Public Utility Commission (CPUC) General Order (GO) 95 Rule 31.1 states that electric systems must be designed, constructed, and maintained in accordance with accepted good practice for the intended use and known local conditions. Regarding ignition reduction, this includes CPUC Decision 12-12-024, which incorporated High Fire Threat District Tier 2 and 3 into asset construction and maintenance. In addition, California Senate Bill 901[1] amended California Public Utility Codes 8386 & 8387 to continually review and evolve the HFTD maps based on local knowledge.

The programs that Pacific Gas & Electric (PG&E) has developed to identify fire ignition can be divided into three categories: Identify, Design & Construct, and Operate. PG&E has tools within each of these categories that use local fire condition understanding to reduce ignition risk. These tools are operationalized and support numerous programs and processes to enhance safety at PG&E.

- *Identify*: Recognizing, categorizing, and risk ranking local conditions that warrant modifications to design, construction, and maintenance practices.
- *Design & Construct*: Incorporate identification into design standards and construction procedures.
- *Operate*: Risk ranking and operations utilized during events to mitigation wildfire hazards.

The Wildfire Mitigation Plan (WMP) identifies key projects that PG&E has developed and utilized to gain a better understanding of local conditions as they pertain to ignition risk reduction. This audit covers the tools in these categories as described in the 2021 & 2022 WMPs and related documents provided by PG&E.

[1] *CA SB-901, Section 38.14 - Identification of any geographic area in the electrical corporation's service territory that is a higher wildfire threat than is currently identified in a commission fire threat map, and where the commission should consider expanding the high fire threat district based on new information or changes in the environment.*

I.B Scope of Work

The following tools constitute the total scope of the audit:

Identify	• **Wildfire Distribution Risk Model (WDRM)** • **Vegetation Risk Model (VRM)** • **Conductor Risk Model (CRM)** • **Consequence of Risk Event Model (CoRE)** • **Service Territory Fire-Threat Evaluation and Ignition Risk Trends** • **Transmission Operability Assessment Model (TOA)**
Design & Construct	• **System hardening decision making for design and the resulting construction standards and procedures.** • **Utility Bulletin TD-9001B-009 - Fire Rebuild Design Guidance for System Hardening** • **This document covers a variety of PG&E design standards which are detailed within the bulletin.** • **Utility Bulletin TD-9001B-009 Attachment 3 – Mitigation Checklist/Decision Framework**
Operate	• **Fire Potential Index Model (FPI)** • **Catastrophic Fire Probability Model for Distribution (CFP_D)** • **Catastrophic Fire Probability Model for Transmission (CFP_T)** • **Enhanced Powerline Safety Settings Program (EPSS)**

The GIRS-RT has worked with the PG&E wildfire mitigation program to understand the relationship between these tools and how they are used to ensure that local conditions are considered for ignition risk reduction. The GIRS-RT conducted the audit for the period 2021-2022 and practices described in the 2021-2022 WMPs only. The scope of the audit includes the following:

- Understand the full scope, inputs, principles, and methodology of each model.
    - Assess if the model uses the correct data and methodology to properly assess local conditions within the given scope of the model.
    - Evaluate implementation of the model to understand risk of local conditions and wildfire mitigation.
    - Critique and provide feedback on model and implementation.
        - Assess and identify deficiencies and adequacies.
        - Verify that models properly identify local area risk associated to fire ignition.
- Review the decision-making criteria within the identified standards and procedures.
    - Assess the application of known local conditions within the decision making for deficiencies and adequacies.
    - Review the decision framework to identify any gaps where local conditions knowledge could be used to further reduce wildfire risk.

- Evaluate the Enhanced Powerline Safety Settings program.
  - Assess the use and efficacy of fast trip settings for ignition reduction.
  - Verify the proper local condition criteria are used to initiate fast trip settings.

This final report documents the GIRS-RT findings for the full set of PG&E Local Conditions tools covered in the audit. Previous tool and category reports were submitted for the Identify, Design & Construct, and Operate Categories and each individual tool therein. At each stage, draft versions were submitted to PG&E and the CPUC for their feedback which has been incorporated upon revision prior to the official final report submission.

I.C Summary of the Identify Category Tools

The *Identify Category* of the PG&E Local Conditions tools in the 2021–2022 Wildfire Mitigation Plans (WMPs) includes 1) *Wildfire Distribution Risk Model (WDRM v2)*, 2) *Vegetation Risk Model (VRM)*, 3) *Conductor Risk Model (CRM)*, 4) *Consequence Model (CoRE)*, 5) *Service Territory Fire-Threat Evaluation and Ignition Risk Trends (STFT&IRT)*, and 6) *Transmission Operability Assessment (TOA)*. The tools in the *Identify Category* have been developed for planning purposes to set priorities in PG&E territories on a time scale of one or more years in Tier 2 and Tier 3 High Fire Threat Districts (HFTD). They support PG&E's wildfire mitigation strategies by recognizing, categorizing, and ranking the risk associated with local environmental and infrastructure conditions. They provide spatially resolved risk scores that can prioritize vegetation management (VM) and system hardening (SH) workflows. Through the integration of machine learning, fire simulation, and engineering frameworks, these tools tackle the challenging problem of predicting wildfire ignition risk on PG&E's distribution and transmission networks across its broad and diverse service territories.

The *Wildfire Distribution Risk Model (WDRM v2)* quantifies wildfire risk on the PG&E distribution network by combining Ignition Probability (LoRE) and Wildfire Consequence (CoRE). The LoRE is estimated by the *Vegetation Risk Model (VRM)* and *Conductor Risk Model (CRM)* using a machine learning method (MaxEnt). CoRE is estimated by the *Consequence Model*, which combines Technosylva fire simulations with various risk attributes. *Service Territory Fire-Threat Evaluation and Ignition Risk Trends (STFT&IRT)* identifies macro-trends impacting ignition probability and wildfire consequences and discusses PG&E's updates of the High Fire Threat Area (HFRA) map. The *Transmission Operability Assessment (TOA)* estimates the probability of transmission asset failure under extreme wind events.

The GIRS-RT finds that these tools meet or exceed industry standards, supported by several notable strengths: 1) WDRM v2 shows significant improvements over previous versions, incorporating diverse covariates and delivering enhanced predictive capabilities; 2) model validation for the VRM and CRM was conducted and supplemented by external expert reviews; 3) adoption of Technosylva for wildfire simulations aligns PG&E with industry practices used by other large California investor-owned utilities, enhancing consistency and comparability of results across agencies; 4) the STFT&IRT demonstrates a thoughtful and well-referenced approach to understanding evolving wildfire risks; 5) the TOA framework is based on well-established engineering principles and greatly benefiting the operating and planning of the PG&E transmission network; and 6) these tools are fit for use.

The GIRS-RT also identifies several areas where future upgrades to the modeling framework are recommended: 1) future WDRM model versions should address the exclusion of non-negligible ignition drivers such as third-party contacts and animal-caused ignitions; 2) efforts should be made to align the conditions used in the ignition and consequence models to ensure internal consistency in risk calculations; 3) the consequence model could be enhanced by expanding the use of up-to-date localized data, as some components currently rely on a look-up table derived from historic data for all areas; 4) PG&E has made good use of machine learning methods, but given the rapid pace of advancement in this field, future models should take the advantage of newer techniques to improve prediction accuracy and precision; 5) the current modeling framework would benefit from incorporating more comprehensive uncertainty analysis, especially in the consequence model, where only average risk values are currently reported.

I.D Summary of the Design & Construct Category Tools

The *Design & Construct Category* of the PG&E Local Conditions tools in the 2021-2022 WMPs includes 1) *System Hardening Decision Making*, 2) *Fire Rebuild Design Guidance for System Hardening, and* 3) *Mitigation Checklist Decision Framework*. Tools in the *Design & Construct Category* have been developed to provide a framework for decision making, design, and construction for system hardening of the distribution and transmission systems and equipment upgrades and replacement related to safety and reliability within the PG&E service territory in context with PG&E's Wildfire Mitigation Plans. This problem of work prioritization is challenging due to the size of PG&E's service territory and the proportion of assets in HFTDs.

System Hardening Decision Making includes procedures to increase the resilience of the grid to ignition risk, asset failure, and the associated management and response to equipment failures. Approaches include updates to grid topology to minimize ignition risk in HFTD areas, strategically coordinated maintenance of distribution and transmission systems for both electrical and mounting equipment, and upgrades related to PSPS in HFTD Tier 2 and Tier 3 areas. *Fire Rebuild Design Guidance for System Hardening* includes comprehensive instructions for standard overhead design guidance for all new construction and reconstruction work in Tier 2, Tier 3, and Zone 1 (tree mortality) areas for service planning. Guidance is leveraged for estimating capacity and reliability for planning and engineering purposes, for use by electrical and monitoring-and-control personnel and contractors associated with fire rebuild areas. *Mitigation Checklist Decision Framework* provides updates to the Decision Framework from which a preliminary design decision is made by the PG&E System Hardening team. The checklist, dated 2019, was largely replaced by development of the Wildfire Risk Governance Steering Committee (WRGSC) in October 2020 and the associated protocols for work reporting and approval.

The GIRS-RT finds that these tools 1) comply with the relevant general orders and other design protocols, 2) account for PG&E's wildfire risk models where appropriate, 3) meet or exceed industry standards, and 4) are fit for use. Overall, the *Design and Construct Category* tools are formulated to provide robust guidance for system hardening decision making and construction that mitigates wildfire risk across PG&E's broad and diverse service territories. During the audit period, PG&E made substantial infrastructure updates to reduce ignition likelihood, increase customer reliability and community safety. Work prioritization was based on relevant parameters including wildfire risk and community impact.

Future improvements and refinements can be made to the *Design & Construct Category* of PG&E Local Conditions tools to increase procedural efficiency and reduce wildfire risks. New protocols that increased the number of tags and the logistical challenges associated with work orders have resulted in a significant backlog. While it is challenging to balance the workload across the territory, PG&E may be able to update prioritization and scheduling for work orders to increase efficiency by eliminating redundancies. For example, the decision-making process for hardening in the transmission system is subdivided among different teams and initiatives in PG&E. To prevent redundancy and inefficiencies in risk mitigation, PG&E would benefit from unified processes for hardening decision making and work prioritization.

I.E Summary of the Operate Category Tools

The *Operate Category* of the PG&E Local Conditions tools in the 2021-2022 WMPs includes 1) *Fire Potential Index (FPI) model*, 2) *Catastrophic Fire Probability model for Distribution (CFP_D)* 3) *Catastrophic Fire Probability model for Transmission (CFP_T)*, and 4) *Enhanced Powerline Safety Settings (EPSS) program.* The tools in the *Operate Category* have been developed to provide a framework for real time operational decision-making and mitigation during periods of extreme wildfire hazard in PG&E High Fire Threat District (HFTD) Tier 2 and Tier 3 territories and select adjacent buffer zones. Operating the system, while considering both wildfire safety and efficiency, is a challenging task due to the dynamic environmental and weather conditions that exist in PG&E's service territory.

The Fire Potential Index (FPI) model is a machine learning-based classification model that aims to predict how likely it is that an initial ignition results in a wildfire with a small, large, or catastrophic severity. For this, the FPI model divides the service territory into cells, defining weather, fuel, and topography variables for each one of them. The Catastrophic Fire Probability models for distribution and transmission are data-driven models that aim to predict the likelihood of a catastrophic fire initiated by the distribution and transmission networks, respectively. For this, the models are constructed by joining several models, including the FPI model, the Ignition Probability Weather (IPW) model, and the Outage Producing Wind (OPW) models. The last tool within this category is the Enhanced Powerline Safety Settings program, which aims to reduce wildfire risk by increasing the sensitivity of PG&E equipment to fault currents during periods of elevated wildfire risk and shutting down the power faster than under normal operating conditions, preventing these faults from developing into ignition events.

The GIRS-RT finds that these tools 1) are correctly designed and implemented from a data perspective, 2) are built on a foundation of probability theory, and therefore are suitable for risk quantification and mitigation purposes, 3) meet or exceed industry standards, and 4) are fit for use. Overall, the *Operate Category* tools provide a strong suite of operational models to enhance local and temporal awareness regarding wildfire conditions.

Future improvements and refinements can be made to the *Operate Category* of PG&E Local Conditions tools to increase performance and continue addressing existing wildfire risk. These improvements are focused on the evaluation procedures used to validate the models within this category, particularly for the CFP_T model. While the GIRS-RT recognizes that this is a challenging task, as the transmission system presents lower levels of failures data, as new data becomes available, the validation process should be adapted to make use of this new information.

I.F Organization of the Report

This remainder of this report presents a detailed technical review of each of the tools and is organized as follows:

- Section II presents the GIRS-RT's description and assessments of the tools included in the *Identify* category.
- Section III presents the GIRS-RT's description and assessments of the tools included in the *Design & Construct* category.
- Section IV presents the GIRS-RT's description and assessments of the tools included in the *Operate* category.

For convenience, a summary of features and assessments contained in the section follows the review of each tool.

II. Technical Findings: Identify Tools

II.A Overview

Section II covers the GIRS-RT findings for the Identify Category of the PG&E Local Conditions tools in the 2021-2022 WMPs. This includes The Wildfire Distribution Risk Model (WDRM v2), the Vegetation Risk Model (VRM), the Conductor Risk Model, the Consequence Model (CoRE) for VRM and CRM, the Service Territory Fire-Threat Evaluation and Ignition Risk Trends (STFT&IRT), and the Transmission Operability Assessment (TOA).

Tools in the Identify Category have been developed for planning purposes to set priorities in PG&E territories on a time scale of one or more years in Tier 2 and Tier 3 High Fire Threat Districts (HFTDs). The WDRM estimates the risk associated with electric grid infrastructure-caused ignitions on the PG&E distribution networks. The VRM focuses on vegetation caused ignitions, the CRM focuses on conductor caused ignitions, and the CoRE model is the Consequence model for both VRM and CRM. The TOA model focuses on risk for PG&E transmission networks, while STFT&IRT describes PG&E's development of the High Fire Threat Area (HFRA) map, which is a modification of the CPUC HFTD map used in considering Public Safety Power Shutoffs (PSPS) and identifies macro-trends impacting ignition probability and estimated wildfire consequence within the utility service territory.

Overall, the GIRS-RT finds that these tools meet or exceed industry standards and are fit for use. More detailed assessments and suggestions for future upgrades are provided within the individual tool review sections. Overall, the Identify Category tools have been designed to address the challenging problem of identifying and prioritizing actions to lessen wildfire risk across PG&E's broad and diverse service territories. The suite of tools in this category provides PG&E with frameworks that allow for an integrated approach involving model scoping (planning), data intake, risk identification, risk assessment, risk management, and risk mitigation. During the period covered by this audit (2021 and 2022 WMP), geospatial, risk-based, methodologies for planning were a new and rapidly developing approach for public utilities. PG&E tools have continued to move forward since the period covered by the audit. The recommendations made in this review are intended to guide the ongoing development of these modeling tools.

II.B WDRM: Wildfire Distribution Risk Model

II.B.1 WDRM Overview

The Pacific Gas and Electric Company (PG&E) Wildfire Distribution Risk Model (WDRM) is a planning tool developed to set priorities in PG&E territories on a time scale of one or more years. The WDRM estimates the risk associated with electric grid infrastructure-caused ignitions. In principle, this framework allows for an integrated approach involving model scoping (planning), data intake, risk identification, risk assessment, risk management, and risk mitigation.

The WDRM consists of three main components: the ignition probability model, the wildfire consequence model, and the risk model; the risk model fuses the first two components to compute a risk score for each geographical location within the vicinity of PG&E's distribution network located within Tier 2 and Tier 3 High Fire Threat Districts (HFTDs).[2]

The Local Conditions Audit focuses on the 2021 WDRM (referred to as WDRM v2). During the period covered by this audit (2021 and 2022 PG&E WMPs), the GIRS-RT finds that, overall, WDRM v2 exceeds industry standards and is fit for use. WDRM v2 is a significant improvement over the previous PG&E WDRM v1 model in both the ignition and consequence models and allows risk scores to be compared across territories. However, non-negligible ignition risk drivers were left out of WDRM v2, such as third-party contact or animal caused ignitions,[3] and many data sourcing and modeling choices are made within the WDRM framework which warrant additional consideration in future versions of the model.

II.B.2 Ignition Models: Maximum Entropy (MaxEnt) Formulation

WDRM v2 calculates risk by multiplying the consequence of a risk event (CoRE, discussed in Section II.E) with the likelihood of a risk event (LoRE). The likelihood is determined as the probability of an infrastructure-caused ignition. In accordance with PG&E's 2020 Risk Assessment Mitigation Phase (RAMP) report,[4] the primary causes of ignitions are vegetation and equipment failures, accounting for 38% and 26% of all ignitions systemwide, respectively.

Building on this insight, for WDRM v2 PG&E chose to focus its modeling efforts exclusively on these two ignition drivers,[5] arguing that they capture a significant portion of the total ignitions. Consequently, PG&E has created two separate ignition probability models. Both models utilize the same fundamental mathematical techniques but diverge in the input data utilized for the training and the test data used for validation.

The foundation of both ignition probability models lies in the Maximum Entropy (MaxEnt) model. This data-driven, machine learning formulation is widely used in ecology for species distribution modeling (SDM) (Phillips, Anderson, and Schapire 2006; Elith et al. 2011). In that case, the objective is to leverage a collection of affirmative observations of a specific species and the

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[2] As determined by the California Public Utilities Commission (CPUC), Available at https://www.cpuc.ca.gov/industries-and-topics/wildfires/fire-threat-maps-and-fire-safety-rulemaking.
[3] PG&E's Wildfire Mitigation Plan 2021, p. 95.
[4] Application of Pacific Gas And Electric Company (U39m) To Submit Its 2020 Risk Assessment And Mitigation Phase Report, available at: https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M341/K517/341517004.PDF
[5] The equipment failure models only include failures reported in conductors for the 2021 version of the WDRM.

environmental attributes at the observation locations to forecast the likelihood of the species being present across a given area. The MaxEnt model is classified as a presence-only model as it solely relies on data pertaining to positive observations. This differs from presence-absence models, where knowledge of both the species' presence and absence are required.

PG&E employs the MaxEnt model for risk assessment, substituting species distribution modeling with modeling of the distribution of ignitions. In this setting, areas near the PG&E distribution network in Tier 2 and Tier 3 HFTD territories are segmented into 100x100m cells, each characterized by a vector of covariates encompassing environmental, weather, and asset characteristics. Examples of covariates used are the maximum tree heights, the local humidity and the conductor's material and age. Additionally, areas where ignition events have occurred during the training period are labeled as presence data for the MaxEnt algorithm.

MaxEnt enables PG&E to estimate the spatial probability distribution of ignitions during the fire season in Tier 2 and Tier 3 HFTDs. The model performs best if it is trained on data which is representative of the conditions in which the ignitions are predicted. In PG&E's application of the MaxEnt methodology, two models were independently trained using vegetation-caused ignitions and conductor-caused ignitions data from the 2015-2018 fire seasons, with 75% of the data used for training the model and 25% used for statistical validation. The output and predictive capability of the model was also illustrated by training on 2015-2018 data and running an annual post hoc prediction test for the 2019 fire season. The outputs of both the vegetation- and conductor-caused ignitions may be used to compute risk scores for vegetation management and system hardening purposes, respectively.

II.B.3 Ignition Data

Ignitions data used to calibrate the ignition models include only CPUC-reportable ignitions. These are defined as ignitions that 1) the utility has knowledge of; 2) produce self-propagating fires which travel a distance greater than one linear meter from the ignition point; 3) burn any material other than electrical or communication facilities managed by PG&E.[6] CPUC reportable ignitions can be attributed to many factors including vegetation contact, conductor failures, splice failures, animals, and 3rd party contact (e.g., car crash). While the conductor and vegetation ignition models were calibrated using only conductor- and vegetation-associated ignitions respectively, the conductor- and vegetation-associated ignition data exhibit substantial overlap (ignitions that are both conductor- and vegetation-caused).[7]

Ignition data used to train the ignition models was filtered to only include CPUC-reportable ignitions that occurred between 2015 and 2018 in HFTDs Tier 2 or Tier 3 during wildfire season (June-November). This filtering limited the vegetation-caused ignition data to just over 220 ignitions and the conductor associated ignitions to just over 240 ignitions.[8] While the number of ignitions is small compared to that of outages (which number in the thousands), fitting a model to predict the ignition likelihood directly was found to be superior to fitting a model that predicts

[6] PG&E 2021 WDRM Overview, p. 14, 43, 72.
[7] PG&E 2021 WDRM Overview, p. 14.
[8] PG&E 2021 WDRM Overview, p. 14.

outages and then subsequently models the probability that an ignition would occur given an outage. The difference in the area under the curve (AUC) values of these models differed only by 0.026 with the model trained on ignitions performing slightly better.[9] This is arguably due to contrasting spatiotemporal distributions of ignitions and outages, which complicates the straightforward relationship needed to predict the probability of an ignition occurring given an outage.[10] Since the precise origin of ignitions may be next to impossible to establish, in addition to ignitions, outage locations that are suspected to coincide with ignitions may be considered as ignition locations.[11] This is satisfactory for the MaxEnt algorithm where knowledge of the exact locations of ignitions is not required.[12]

The spatial resolution of ignition and covariate data was set to 100x100m, requiring up-sampling of some covariates.[13] Tree height data was obtained from Salo Sciences which generated the dataset using computer vision algorithms to process satellite imagery collected in November 2019 (the end of the fire season).[14] Covariate datasets were generated from the tree height data expressing maximum tree height and average tree height in each pixel.[15] Topography data is defined as the Topographic Position Index (TPI) as extracted from USGS National Elevation Dataset (NED), which is a relative difference in the elevation of a pixel to the mean elevation of neighboring regions.[16] HFTD zones (Tier 2 and Tier 3) provided by CPUC are used as an additional covariate.[17] Data used to distinguish unburnable zones were extracted from the 2016 LANDFIRE surface fuel model (USGS, 2016).[18] Land use types within the 2016 LANDFIRE surface fuel model that are considered unburnable (as a covariate) include those designated as urban, perennial snow/ice, agriculture, water, or barren regions.[19] The imperviousness product from the National Land Cover Database (NLCD), which was used as a covariate to train ignition models, reports the percentage of the land surface that has been developed.[20]

Covariates that capture the influences of environmental and meteorological data spanning 2014-2016 were extrapolated from the Gridded Surface Meteorological Dataset (gridMET) from UC Merced.[21] Regarding environmental data, gridMET provides 100-hour fuels (percentage of 1-3-inch diameter fuels) and 1000-hour fuels (percentage of 3-8-inch diameter fuels) as well as the USNFDRS Burn Index (BI) and Energy Release Component (ERC).[22] The ERC is a number related to the available energy per unit area within the flaming front at the head of a fire, which changes in

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[9] E3 Review of PG&E's 2021 Wildfire Distribution Risk Model, p. 33 (Table 3).
[10] E3 Review of PG&E's 2021 Wildfire Distribution Risk Model, p. 31-33 (Section 3.3).
[11] PG&E WDRM SME Interview (September 28, 2023).
[12] PG&E 2021 WDRM Overview, p. 13 (2).
[13] PG&E 2021 WDRM Overview, p. 74.
[14] PG&E 2021 WDRM Overview, p. 73.
[15] PG&E 2021 WDRM Overview, p. 105 (in table).
[16] PG&E 2021 WDRM Overview, p. 74.
[17] PG&E 2021 WDRM Overview, p. 105.
[18] PG&E 2021 WDRM Overview, p. 73 - (Cited on p. 68 as: USGS. (2016). LANDFIRE dataset. Retrieved from https://landfire.cr.usgs.gov/distmeta/servlet/gov.usgs.edc.MetaBuilder?TYPE=HTML&DATASET=FBK).
[19] PG&E 2021 WDRM Overview, p. 73.
[20] PG&E 2021 WDRM Overview, p. 73.
[21] PG&E 2021 WDRM Overview, p. 74 (Cited on page 111 as: University of California, Merced. (n.d.). GRIDMET: University of Idaho Gridded Surface Meteorological Dataset. Retrieved from Earth Engine Data Catalog: https://developers.google.com/earth- engine/datasets/catalog/IDAHO_EPSCOR_GRIDMET#description).
[22] PG&E 2021 WDRM Overview, p. 103-104.

response to the moisture content of the fuels present.[23] The BI, derived from ERC and the theoretical forward rate of spread at the head of a fire in the region, is closely related to 10 times the flame length in feet.[24] In terms of meteorological data, gridMET provides precipitation, specific humidity, vapor pressure deficit, and temperature data. Meteorological covariates derived from the gridMET dataset included average precipitation, average specific humidity, average vapor pressure deficit, and average daily maximum temperature.[25] Wind velocity data spanning 2016-2018 that were sourced from RTMA (Real-Time Mesoscale Analysis - a NOAA hourly weather raster data product) were used to derive four covariates including 1) average and 2) maximum wind velocities in m/s, and the percentages of summer days where wind velocities exceed 3) 15mph and 4) 20mph all at a height of 10 meters.[26]

Asset data obtained from EDGIS includes the conductor material, estimated age, splice record, conductor diameter and whether the conductor is in a coastal zone (resulting in an increased rate of corrosion).[27] The three conductor material covariates include 1) copper conductors, 2) aluminum conductors, and 3) aluminum conductors that are steel reinforced.[28] Covariates that correspond to conductor diameter are conductor size 2, conductor size 4, and conductor size 6 (largest to smallest).[29] The estimated conductor ages, spice records, and coastal proximity were used as asset-associated covariates too.[30]

II.B.4 Ignition Model Validation

PG&E's model validation process used quantitative performance metrics in addition to more qualitative measures: internal quality assurance practices like code review and external review and validation of the WDRM by consulting firms.[31]

To analyze the performance of the ignition model, PG&E introduced two quantitative performance metrics: a recall score and the area-under-curve (AUC) of the receiver-operating characteristic (ROC) curve. The recall score is the ratio of true positives to all true occurrences (true positives and false negatives). PG&E required a recall score of 95%; with this choice, less than 5% of ignitions should go unpredicted. However, this metric neglects the role of false positives in analyzing the predictive power of the model. The tradeoff between a high recall score and the rate of false positives of the prediction model is characterized by the ROC curve.

From the ROC curve, one can compute the area under the curve (AUC), resulting in a number, the AUC-ROC metric, which is understood to characterize the predictive performance of the model. The AUC-ROC metric measures the performance of a binary predictive model by looking at the joint rates of true positives and false positives: random guesses will have an equal number

[23] *Energy Release Component (ERC), National Wildfire Coordinating Group, https://www.nwcg.gov/publications/pms437/fire-danger/nfdrs-system-inputs-and-outputs#ERC.*
[24] *Burning Index (BI), National Wildfire Coordinating Group, https://www.nwcg.gov/publications/pms437/fire-danger/nfdrs-system-inputs-and-outputs#BI.*
[25] *PG&E 2021 WDRM Overview, p. 104.*
[26] *PG&E 2021 WDRM Overview, p. 104.*
[27] *PG&E 2021 WDRM Overview, p. 105-106.*
[28] *PG&E 2021 WDRM Overview, p. 29 (Table 3).*
[29] *PG&E 2021 WDRM Overview, p. 29 (Table 3), p. 79.*
[30] *PG&E 2021 WDRM Overview, p. 29 (Table 3).*
[31] *PG&E 2021 WDRM Overview, p. 30-34.*

of true and false positives (AUC of 0.5) while a perfect predictor will have no false positives (AUC of 1). The AUC metric was used to validate both the vegetation and conductor-based ignition models in the 2021 WDRM. Both had 0.7 < AUC < 0.75, indicating above random but not outstanding performance. In contrast, when the 2021 model was compared to the 2019 model in its predictive power for ignitions in the year 2019, the 2019 model barely exceeded the random threshold with an AUC of 0.51 (though no performance metric was originally reported for the 2019 model). The 2021 model therefore represents a large step forward in modeling capability according to this metric.

A choice of a recall score defines a point along the ROC curve at which the model operates. PG&E aims for a recall score of around 95%, a conservative choice so that very few (<5%) of ignitions go unpredicted. With this choice of recall score, the vegetation ignition model operates with a false positive rate 0.7-0.8 and the conductor model with a false positive rate >0.8. Given the ROC curves of both models, when the recall rate is set as conservatively as 95%, the models will have a high rate of false positives.

Fundamentally, the choice of a high recall score reflects the high cost of false negatives in the present context. For ignition prediction and asset management, false positives risk a misallocation of resources but do not present a direct danger to life and property. However, false negatives (unpredicted ignitions) risk a catastrophic outcome and should be avoided even if it is coupled with high costs. While the false positive rate can be lowered by improving the model performance, the choice of a conservative recall score and hence an over-sensitive ignition prediction model is appropriate given the goal of the WDRM to prioritize the minimization of fire risk over all other concerns.

II.B.5 Assessment of Ignition Models and MaxEnt Formulation

The GIRS-RT concludes that MaxEnt is suitable for estimation of the spatial probability of ignitions, given the available data and the intended purpose for planning on a timescale of a year or more. Furthermore, the 2021 model marks a significant advancement over its predecessor, WDRM v1.

The GIRS-RT has identified the following areas where future work by PG&E subject matter experts may increase the performance of the ignition models and their validation:

II.B.5.A1 <u>Exclusion of other drivers of ignitions aside from vegetation and conductors</u>

While the vegetation and conductor models developed by PG&E capture 64 percent of the drivers for ignitions,[32] the percentage not captured by the current version of the model is still significant. The PG&E WMP 2022 indicated that WDRM v3 will include more comprehensive coverage of the ignition drivers, and account more accurately for overlapping sources (e.g., vegetation induced conductor ignitions).

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[32] *PG&E 2021 WDRM Overview, p. 7*.

II.B.6 Consequence Score

The Wildfire Consequence Model provides a consequence score for fire events which is multiplied by the ignition probability to give the overall risk. These consequence scores are unique to specific locations (100m intervals along the distribution network in Tier 2 and Tier 3 territories) and set the scale for magnitude variations of final risk scores in the WDRM v2 due to the relatively large scale of consequence values compared to ignition probabilities. The Wildfire Consequence Model has three components: the Technosylva fire simulation model, the Multi-Attribute Value Function (MAVF) wildfire score, and the consequence model.

To estimate the spatial impact of an ignition, Technosylva fire simulations are carried out, beginning with ignitions located at 200m intervals along the distribution network and run for the equivalent of 8 hours under extreme weather conditions. For these ignition points on the distribution network, the simulation is repeated for 452 separate extreme weather days, creating a catalog of 452 model fires initiated at each location. Technosylva implements the Rothermel equation[33] and supplementary fire spread mechanisms to calculate the fire burn area, structures impacted, and Fire Behavior Index (FBI) based on available fuels, local topography, and meteorological conditions for each initial ignition.

The Consequence model maps MAVF scores to the fire burn area based on fire severity information from the Technosylva model, the HFTD data, and the red flag warning probability associated with the location. The consequence score undergoes a further calibration step as the Technosylva model is expected to overestimate wildfire size and other consequences. This overestimation is attributed to the use of worst-case fire weather conditions in Technosylva.[34] Lack of suppression in Technosylva may also contribute to overestimates of fire spread.[35] A more complete assessment of the overestimation is conducted in the GIRS-RT Consequence (CoRE) model review in Section II.E.

Technosylva simulations were compared to the REAX fire simulator used in the 2019 WDRM (v1). Both simulators were run using ignition locations for historically destructive fires. With only a few exceptions, Technosylva was more consistent with recorded severity metrics for these fires, computing higher consequence scores than REAX. Both are Rothermel-based simulations, so the improvement is attributed primarily to utilization of more densely sampled data (e.g. fine grain structure density information, better ladder fuels, and burnable vegetation information) and additional sub-models used in Technosylva. As of 2020, all large California investor-owned utilities use Technosylva as a fire simulation tool, which allows for comparison of results across agencies. The validation method used to compare Technosylva and REAX has not been verified in detail by the GIRS-RT; documentation of the motivation to choose Technosylva over other comparable fire simulation software consists of the stated increased fidelity of fuel data and simulation results which indicate improved modeling by Technosylva (versus REAX) of a small set of historically destructive fires.

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[33] *PG&E 2021 WDRM Overview, p. 120.*
[34] *PG&E 2021 WDRM Overview, p. 131.*
[35] *PG&E 2021 Calculating Meteorological and PG&E Fire Risk, p. 41,* *https://efiling.energysafety.ca.gov/eFiling/Getfile.aspx?fileid=53842&shareable=true*

The development of the MAVF risk score system is beyond the scope of this review as those scores are determined as a part of the CPUC Risk Assessment Mitigation Phase (RAMP) proceeding. However, the assignment of MAVF scores to fire simulations is another important aspect of the overall assessment of risk. The translation of a fire simulation into a consequence score uses fire severity, categorized as small, large, or destructive based on the fire burn area, structure damage, and fire behavior index from the Technosylva fire simulation. Since the fire simulation model does not explicitly include fatalities or serious injuries, catastrophic fire information is estimated from the CAL FIRE database of historical fires. A corresponding MAVF score is assigned to each fire category, and the procedure is followed for all the 452 historical weather days considered in the Technosylva model. The average over all the 452 MAVF scores gives the pre-calibrated consequence score.

The pre-calibrated consequence score obtained from the consequence model undergoes a calibration step to ensure that the total risk in WDRM v2 aligns with the distribution wildfire risk reported in the WMP. The calibration is carried out using the standard wildfire bow tie model. Calibration is important as the pre-calibrated values overestimate the consequence score.

II.B.7 Assessment of the Consequence Model

II.B.7.A1 <u>Dependence on choices of fire simulation parameters</u>

The Technosylva wildfire simulations used to compute the consequence score involve numerous parameters, such as the length of the run (8 hours), meteorological conditions (extreme weather days), and number of simulations (452). The choices regarding simulation length and meteorological conditions are primarily based on Technosylva fire model performance: the model is expected to be most accurate in aggressive fire conditions and over a less extended timeframe. The number of simulations conducted is based on historical extreme weather day scenarios derived from PG&E's 30-year historical data. Consequence scores may change as these parameter choices are modulated.

II.B.7.A2 <u>Validation of Technosylva fire behavior sub-models</u>

Technosylva includes sub-models to capture a variety of fire behaviors but may not fully capture certain mechanisms which play important roles in fire severity, such as fire ember transport (Fernandez-Pello 2017) and suppression. Given the complexity and uncertainties associated with variables and mechanisms involved in the fire simulation process, a comprehensive validation of Technosylva fire simulation is necessary.

II.B.7.A3 <u>Mismatch between simulation resolution and consequence score resolution</u>

The MAVF method of computing the consequence score combines high resolution fire simulations with low resolution consequence estimation. These two components are spatially inconsistent. In addition, the consequence model does not include population and demographic information in the MAVF calculation.

II.B.7.A4 <u>No uncertainty in averaged consequence scores</u>

The Technosylva model considers only the worst weather scenarios, resulting in an overestimation of CoRE values in the consequence model. The final consequence score is estimated by calculating the average of CoRE values from all 452 simulations at each location. A range that reflects the uncertainty arising from these 452 scenarios at each location would be more informative than providing only the average value.

II.B.7.A5 Understanding weather forecast uncertainty in fire simulation results

The Technosylva model uses wind data from the dynamical weather forecast model for fire spread predictions.[36] The PG&E team has indicated that they trained and validated the model to ensure that the wind data performs satisfactorily across its service territories. However, the wind forecast in the dynamical weather forecast model has considerable uncertainties (Pan et al. 2021) and assessment of such uncertainty and its consequence on fire simulation is necessary.

II.B.7.A6 Event identification between CoRE and LoRE estimates

The WDRM v2 model computes risk as the product of the ignition probability $P(E)$ and the consequence $C(E)$: $Risk(E) = P(E) \times C(E)$, where E is an event of interest. The underlying assumption behind this definition of risk is that the events, and therefore the conditions used to compute ignition probability and consequence, are the same. However, PG&E documentation[37] indicates that:

- The local conditions used to train the probability model (MaxEnt) are often time integrated averages and maximums of weather and environmental features during the fire-season months, or datasets that represent a snapshot in time.
- The conditions used in the computation of the consequences represent the worst historical weather conditions for fires.

While using worst-case conditions can have the effect of overestimating consequence and therefore may be interpreted as a conservative modeling choice, the sets of conditions used for likelihood and consequence models are different. As a result, the events E in the probability model and the consequence model are expected to be different as well. In other words, the ignitions that the probability model is predicting could occur under different conditions than the ones used to simulate wildfire spread and compute consequence. To standardize the calculation of risk, aligning it with the conventional definition, in future versions of WDRM, the GIRS-RT suggests use of the same conditions when modeling LoRE and CoRE.

II.B.8 Comparison to Industry Norms

The two other large California investor-owned utilities (IOUs) are Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E). As a point of comparison, the GIRS-RT reviewed the public wildfire mitigation plans filed by SCE[38] and SDG&E[39] for the operational year 2021.

PG&E's ignition probability model is as or more advanced in approach than the models of both other large IOUs. SCE also uses machine learning techniques to regress an ignition probability

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[36] *2021 Calculating Meteorological and PG&E Fire Risk - Page 40. https://efiling.energysafety.ca.gov/eFiling/Getfile.aspx?fileid=53842&shareable=true*
[37] *PG&E 2021 WDRM Overview, p. 14, p. 19.*
[38] *Southern California Edison, "Southern California Edison 2020-2022 Wildfire Mitigation Plan"(SCE 2020-2022 WMP) March 2020, https://www.sce.com/safety/wild-fire-mitigation.*
[39] *San Diego Gas & Electric, "San Diego Gas & Electric Company 2020-2022 Wildfire Mitigation Plan Update" (SDG&E 2020-2022 WMP) February 2021, https://www.sdge.com/2022-wildfire-mitigation-plan.*

distribution from an array of drivers: historical asset data, environmental data, and location data.[40] SDG&E has so few ignitions that statistical inference is infeasible.[41] The SDG&E ignition probability model was an estimate based on the asset class, defined by local condition and asset history and prorated by the length of the circuit.[42] They employed a Monte Carlo approach to stochastically sample the estimated ignition probability distribution. [43]

All IOUs define wildfire risk as the product of an ignition likelihood distribution and an impact distribution, the latter of which is defined in all cases by an ensemble of fire simulations. As of 2021, all three large CA IOUs use Technosylva to simulate fire events, with different choices of fuel, weather, and structure data being used for each. While all IOUs now use an approximately equivalent fire simulation tool, the calculation of the impact score varies between them. SCE, after estimating structure impact from US Census data, adds estimated risk flags for egress availability and social vulnerability.[44] SDG&E uses a financial consequence score with impact on homes being equivalent to safety.[45]

In the 2021 wildfire mitigation plans, PG&E's ignition probability approach and their consequence calculation are up to or above the standards of SCE and SDG&E. However, SCE integrates extra risk flags in computing consequences that PG&E does not, at least in WDRM v2. While SDG&E's ignition probability module is much more rudimentary than PG&E's, SDG&E involves extra models in its estimation of asset failure rates and local weather: a pole failure model, a local circuit risk index, and a Santa Ana wildfire threat index.[46] They also incorporate into all their analysis the impact of PSPS events, both on ignition and impact. PG&E's 2021 WDRM does not incorporate these extra effects.

PG&E's approach to wildfire risk modeling equals or exceeds industry norms for large CA IOUs. In certain key aspects, the PG&E model is an improvement: an advanced ignition prediction system, multiple attempts at model validation, and state-of-the-art fire simulation software.

II.B.9 Applications of WDRM v2 for Vegetation Management and System Hardening, and Roadmap for Future Applications and Improvements

WDRM v2 provides a risk ranking for prioritization of vegetation management and system hardening. The Enhanced Vegetation Management program (EVM) has been retired and was removed from the scope of this audit. However, during its application it utilized WDRM v2 risk scores from the vegetation risk model as a factor in prioritizing the workflow. EVM used a list of worked tree data in the Oracle EVMGIS database. Tree data was filtered such that 1) the tree work date was in 2019, 2) the tree work was completed, 3) the tree diameter at breast height was at least 4 inches, and 4) tree data was not from LiDAR but rather inspections. There were 133,666 tree records satisfying these criteria, all of which had latitude-longitude coordinates. Calculated WDRM v2 risks in grid pixels within HFTDs were applied to EVM 2019 trees and summarized per

[40] SCE 2020-2022 WMP, p. 43.
[41] SDG&E 2020-2022 WMP, p. 28.
[42] SDG&E 2020-2022 WMP, p. 76-81.
[43] SDG&E 2020-2022 WMP, p. 34-35.
[44] SCE 2020-2022 WMP, p. 44-45.
[45] SDG&E 2020-2022 WMP, p. 27.
[46] SDG&E 2020-2022 WMP, p. 75-98.

Circuit Protection Zone (CPZ) quantifying work per CPZ for prioritizing and planning. Following inspection, some trees were tagged as candidate trees requiring work in the vegetation management database SQL-SERVER database (VMD).[47] As a result of this prioritization, in 2021 PG&E performed near 98% of their EVM work on segments which were in the top 20% WDRM risk category. [48]

Upgrades to WDRM v2 are scheduled for WDRM v3 and are charted in the PG&E 2022 WMP.[49] WDRM v3 is beyond the scope of this audit but is expected to include additional risk drivers and ignition categories, additional equipment types and failure models for, e.g., poles and transformers to improve the predictive power of the model and better inform mitigation programs, and to provide risk-reduction estimates for wildfire risk mitigation initiatives.

II.B.10 Summary of GIRS-RT Findings for WDRM v2

WDRM v2 represents a significant improvement in modeling techniques, inclusion of diverse covariates, and predictive power over WDRM v1, and captures most of the drivers of ignitions on the PG&E distribution network. The GIRS-RT finds WDRM v2 to be a strong step forward in modeling capability and that, at deployment, it defined the state of the art in CA IOU wildfire ignition prediction.

Features:

- WDRM v2 provides spatially resolved risk scores across PG&E Tier 2 and Tier 3 HFTD regions for vegetation and conductor ignition driven wildfires.
- It combines data-driven ignition likelihood with Technosylva wildfire simulations and MAVF consequence values into a risk score.
- WDRM v2 can in principle be used to set workflow priorities for vegetation management, system hardening, and other projects involving maintenance and upgrades.

Summary of Assessments:

II.B.5.A1 <u>Exclusion of other drivers of ignitions aside from vegetation and conductors</u>

The GIRS-RT recommends including additional ignition drivers into the WDRM model, since the percentage of ignitions not categorized as caused by vegetation or conductor failures is still significant.

II.B.7.A1 <u>Dependence on choices of fire simulation parameters</u>

The outcome of the fire simulations, and accordingly the consequence score, is informed by simulation parameter choices made by the modeling team; if other reasonable choices were made, the spatial distribution of consequence may be significantly altered.

II.B.7.A2 <u>Validation of Technosylva fire behavior sub-models</u>

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[47] *PG&E 2021 WDRM Overview, p. 45.*
[48] *2022 PG&E Wildfire Mitigation Plan Update Revised, p. 53.*
[49] *2022 PG&E Wildfire Mitigation Plan Update Revised, p. 150.*

The fire simulation tools developed by Technosylva include proprietary sub-models addressing more complex fire behavior, the performance of which is not validated against field data in contrast to the more traditional models which make up the backbone of the fire simulation system.

II.B.7.A3 Mismatch between simulation resolution and consequence score resolution

The combination of high-resolution fire simulations with low resolution consequence estimation is spatially inconsistent and the consequence model does not include population and demographic information in the MAVF calculation.

II.B.7.A4 No uncertainty in averaged consequence scores

A distribution that reflects the variability that arises from the 452 Technosylva wildfire simulations at each location would be more informative than reducing the simulation information to only the average value which is all that is currently utilized.

II.B.7.A5 Understanding weather forecast uncertainty in fire simulation results

There are significant uncertainties in the wind forecast data used for fire spread prediction in the Technosylva fire model; it is necessary to assess these uncertainties and their impact on fire simulations.

II.B.7.A6 Event identification between CoRE and LoRE estimates

The event conditions considered in the LoRE and CoRE components of the WDRM model are not equal. To maintain fidelity to the traditional definition of risk, the GIRS-RT suggests use of the same conditions when modeling LoRE and CoRE.

II.C VRM: Vegetation Risk Model

II.C.1 VRM Overview

PG&E's Vegetation Risk Model (VRM) is a planning tool developed to set priorities for (enhanced) vegetation management in PG&E territories on a time scale of one or more years. The VRM estimates the risk associated with vegetation triggered electric grid infrastructure-caused ignitions. The VRM consists of three main components: the vegetation ignition probability model, the wildfire consequence model, and the risk model, which fuses the first two components to compute a risk score for each geographical location within the vicinity of PG&E's distribution network under Tier 2 and Tier 3 High Fire Threat Districts (HFTD).[50]

The Local Conditions Audit focused on the 2021 version of the VRM which is the vegetation component of the 2021 Wildfire Distribution Risk Model (referred to as WDRM v2). For the duration covered by this audit (2021 and 2022 PG&E WMPs), the GIRS-RT finds that overall VRM exceeds industry standards and is fit for use. VRM and WDRM v2 incorporate significant

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[50] As determined by the California Public Utilities Commission (CPUC), Available at https://www.cpuc.ca.gov/industries-and-topics/wildfires/fire-threat-maps-and-fire-safety-rulemaking.

improvements over the previous PG&E WDRM v1 model in both the ignitions and consequence models, allowing risk scores to be compared across territories.

This section focuses on the vegetation ignition probability model. The wildfire consequence model, which is the fourth tool in the audit scope, is reviewed in Section II.E. The review of the vegetation ignition probability model has three primary components: the covariate data set, the MaxEnt model for ignition probabilities, and the tools used to validate the ignition probability model. Additional data analysis and correlations of model predictions with observed fire sizes are also included in the assessment.

II.C.2 VRM Model Covariates

Table II.C-1: Covariate data used to train the VRM.[51]

Covariate	Category	Source	Brief description
100-hour fuel moisture	Meteorological data	gridMET	Daily, 4 km. All gridMET data averaged over fire seasons (Jun 1 to Nov 30) from 2014 to 2016
1000-hour fuel moisture			
Burning Index			
Energy Release Component			
Precipitation			
Specific humidity			
Vapor pressure deficit			
Maximum temperature			
Wind average		RTMA	Hourly, 2.5 km. All RTMA data averaged/assessed over fire seasons from 2016-2018
Wind maximum			
Windy summer day percent			
Gusty summer day percent			
Maximum tree height	Tree data	Salo Sciences	100 m.
Average tree height			
Impervious surface	Surface condition data	NLCD NED	30 m, scaled to 100 m.
Local topography			100 m. TPI was extracted from NED
High Fire Threat Districts	HFTD data	CPUC	100 m. High Fire Threat Districts

The VRM uses the MaxEnt machine learning algorithm to predict ignition probabilities at 100mx100m spatial resolution along the PG&E distribution network in Tier 2 and Tier 3 HFTD territories. Covariate vectors characterize local conditions throughout the distribution grid including pixels that host the vegetation-caused CPUC-reportable ignitions used to train the

[51] *PG&E 2021 WDRM Overview, p. 103-105.*

model. The following table summarizes the pool of covariates used in the VRM ignition probability model.

II.C.2.1 Meteorological data

The meteorological data used for covariates are from the Gridded Surface Meteorological dataset (gridMET) produced by the University of Idaho and the Real-Time Mesoscale Analysis (RTMA) produced by NCEP.

gridMET

The gridMET data product combines the spatial attributes of climate data from Parameter elevation Regression on Independent Slopes Model (PRISM) with desirable temporal attributes from regional reanalysis, North American Land Data Assimilation System phase 2 (NLDAS-2), using climatically aided interpolation (Abatzoglou 2013). NLDAS-2 data are downscaled to 1/24th degree (~ 4 km) resolution and are upscaled to daily timestep, with the bias corrected by using monthly humidity, air temperature, and precipitation data from 1981 to 2010 in PRISM (Abatzoglou 2013).

The gridMET datasets provide both primary climate data (e.g., precipitation) and secondary values derived from the primary data (e.g., Burning Index).[52] Covariates derived directly from primary climate variables are the maximum temperature, precipitation, and specific humidity. Covariates produced from secondary values derived from the primary climate data are the 100-hour (fm-100) and 1000-hour dead fuel moisture (fm-1000), Energy Release Component (ERC), Burning Index (BI), and vapor pressure deficit (VPD).

- The fm-100/fm-1000 can be computed from 24-hour/7-day average boundary condition composed of day length (daytime), hours of rain, and daily temperature/humidity ranges.[53] The 100-hour/1000-hour is the time lag corresponding to the duration required for two thirds of the dead fuel to respond to atmospheric moisture (fuel moisture decreases with low atmospheric moisture and vice versa). These responses account for large fuels that are 3-8 inches in diameter, such as dead fallen trees and brush piles, up to 1000 hours, and smaller fuels that are 1-3 inches in diameter, including small branches and twigs, up to 100 hours.
- The ERC and BI are computed using a common fuel model (fuel model G), which is applied to dense conifer stands.[54] The ERC is considered a composite fuel moisture index as it reflects the variations in moisture content of both dead and live fuels.[55] The fm-1000 (a primary input for ERC calculation), daily max/min temperature, relative humidity, and precipitation duration all affect ERC. The BI combines the ERC and the spread component (SC - another fuel model output). BI variations are primarily driven by changes in wind speed and moisture content of live and dead fuels.[56]

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[52] *GRIDMET, Climatology Lab, https://www.climatologylab.org/gridmet*
[53] *Dead Fuel Moisture, NOAA National Centers for Environmental Information, https://www.ncei.noaa.gov/access/monitoring/dyk/deadfuelmoisture*
[54] *GRIDMET, Climatology Lab, https://www.climatologylab.org/gridmet*
[55] *Energy Release Component (ERC), Wildfire.gov, https://www.wildfire.gov/page/energy-release-component-erc*
[56] *Burning Index (BI), Wildfire.gov, https://www.wildfire.gov/page/burning-index*

- The VPD is calculated from air temperature and relative humidity to represent the difference between the moisture amount in the air and the moisture content the air holds at saturation.[57]

Average values derived from gridMET during the fire seasons (June to November) from 2014 to 2016 served as covariates. This includes averages of daily minimum and maximum values (e.g., maximum temperature – See Table II.C-1).

RTMA

RTMA has a spatial resolution of 2.5 km and a temporal resolution of 1 hour. It assimilates data from ground-based weather stations and occasionally incorporates new data sources (Blankenau, Kilic, and Allen 2020). Covariates derived from the RTMA dataset include the 1) wind avg (hourly wind speed average), 2) wind max (annual 99th percentile hourly wind speed), 3) windy summer day percent (percentage of days with sustained hourly wind speed over 15 mph), and 4) gusty summer day percent (percentage of days with sustained hourly wind speed over 20 mph) at 10 m height (above topography) from 2016 to 2018 during fire season (June-November).

II.C.2.2 Tree data

The covariates derived from tree data include tree height max and tree height average. Tree data was acquired from Salo Science Forest Observatory, which is a satellite-based forest monitoring system. The satellite imagery was collected in November 2019.

II.C.2.3 Surface condition data

The two covariates reflecting surface conditions include impervious surfaces from National Land Cover Database (NLCD) and the Topographic Position Index (TPI) from National Elevation Dataset (NED). The NLCD imperviousness areas represents urban impervious surfaces as a percentage of developed surfaces and are asserted to be regions that would not burn if subjected to an open flame. The TPI is the difference between elevation at the central point and the average elevation around it within a predetermined radius. Positive TPI values indicate that the central point is located higher than its surroundings, while negative values indicate that the central point is topographically lower.

II.C.2.4 High Fire Threat Districts

The High Fire Threat District (HFTD) covariate is based on the CPUC defined HFTD zones, with the value of 1 representing non-HFTD locations, 2 representing Tier 2, and 3 representing Tier 3.

II.C.3 Assessment of the Covariate Datasets

The model inputs include variables derived from meteorological, surface condition, tree, and HFTD data, which collectively capture the many crucial factors affecting fire ignition.

The gridMET data was used for temperature-, humidity-, and precipitation-related covariates and the RTMA was used for wind-related covariates for the vegetation risk model. The gridMET is downscaled from NLDAS-2 with bias correction based on PRISM. RTMA assimilates weather station data. The gridMET dataset was validated against weather stations across the western

[57] Vapor Pressure Deficit (VPD), Wikipedia, https://en.wikipedia.org/wiki/Vapour-pressure-deficit

United States (Abatzoglou 2013) and a recent publication demonstrated that the gridMET and RTMA performed best among various gridded weather datasets over the US in the comparisons with weather station data (Blankenau, Kilic, and Allen 2020). The gridMET and RTMA include variables that are critical in predicting and managing wildfires at relatively high spatiotemporal resolution. The GIRS-RT asserts that the usage of gridMET and RTMA for the vegetation risk model is a reasonable choice.

The GIRS-RT has identified the following issues related to the covariates for further investigation by PG&E SMEs for potential future improvements of model performance.

II.C.3.A1 <u>Vegetation data addresses fuel moisture but not species-level traits associated with flammability</u>

The 100-hour and 1000-hour fuel moisture (fm-100 and fm-1000) are purely based on the meteorological data. The flammability of vegetation does not solely depend on its moisture content, as chemical composition and physical structure can significantly influence combustion. The relationship between plant traits and flammability at the species level is important for the understanding of the vegetation-fire dynamic (Popović et al. 2021). The GIRS-RT recommends 1) deriving covariates that capture vegetation species, and 2) testing the extent to which these covariates improve the efficacy of the model.

II.C.3.A2 <u>Wind-related covariates may not capture gust speeds</u>

WDRM v2 uses a diverse range of geospatial data to calibrate the vegetation risk model, including aggregated meteorological data (means, maxima, and exceedance frequency). Upon evaluation, the influences of wind-related covariates yield low predictive value for ignition. It is argued in the 2021 WDRM Overview on Page 66 that “the majority of ignitions are not caused by wind at all, and 95% of outages do not occur during NE wind event days.” However, most catastrophic fires did happen under high wind conditions during NE wind event days (Mitchell 2013). Wind-related variables are defined hourly, which fail to capture gusty wind speeds, and typical durations of the highest wind speed events (gusts) are seconds to minutes. The GIRS-RT recommends including wind gust speeds to better capture these infrequent but crucial events.

II.C.3.A3 <u>Strong correlations exist between humidity-related covariates</u>

Strong correlations exist between the following meteorological variables: specific humidity, fm-100, and VPD.[58] The vegetation risk model identifies maximum tree height, fm-100, and VPD as the three covariates with the highest permutation importance.[59] However, the fm-100 and VPD are highly correlated. The number of covariates that are identified as significant based on permutation testing is extremely small (only three, two of which are highly correlated based on meteorological conditions). It may be useful to consider additional covariates, especially factors that are important inputs for predicting fire behavior in the consequence model (covariates that capture tree density or land use).

[58] *PG&E 2021 WDRM Overview, p. 82.*
[59] *PG&E 2021 WDRM Overview, p. 47.*

II.C.4 Maximum Entropy (MaxEnt) Model for VRM Ignition Probabilities

The VRM utilized by PG&E in WDRM v2 assesses the risk of an ignition event as the product of its likelihood (LoRE)[60] and its consequence (CoRE).[61] The LoRE for VRM is calibrated using a form of machine learning known as MaxEnt to model the spatial distribution of ignition likelihoods resulting from a vegetation-caused failure in PG&E's distribution network. The model is restricted to distribution lines that fall within HFTDs Tier 2 and Tier 3.[62] Distribution lines are discretized by location in a grid comprised of 100m x 100m pixels in which ignition probabilities, consequence scores, and risk scores are calculated.

The ignition probability model is trained using CPUC-reportable ignitions that occurred from 2015-2018 from June-November in HFTDs and the covariate data related to environmental and meteorological conditions described above (Table II.C-1). To validate the application of MaxEnt, a preliminary model was trained using 75% of the ignition data and evaluated using the remaining ignitions (25%) to test performance (see Figure II.C.1). Following the trial run, an official model was calibrated using all the training ignitions (100%). This model was used by PG&E VM for planning and mitigation.

VRM uses only CPUC-reportable ignitions resulting from vegetation failures. MaxEnt is categorized as a presence-only model since it only requires knowledge of positive observations (detected ignitions). For calibration, each pixel (potential ignition location) is linked to a corresponding vector that contains elements that consist of covariate values directly extracted from datasets (e.g., Imperviousness, HFTDs, TPI), and linear and non-linear transformations of data (e.g., averages/maxima/minima of tree and meteorological data). These transformations were necessary because, for the application of MaxEnt, each pixel must correspond to a single value for each covariate used to calibrate the model (see Table II.C-1). This constraint mandated the collapse of time series datasets to single values representative of regional conditions over the calibration period.

Using the ignition data and the covariate stacks, PG&E trained a machine learning model based on the Maximum Entropy principle to estimate ignition likelihood in each pixel. This model is inspired by works from (Elith et al. 2011) and (Phillips, Anderson, and Schapire 2006) and is often used by ecologists to estimate geospatial distributions of fauna in habitats that can be remote or inaccessible due to treacherous terrain. PG&E has adapted the MaxEnt framework to model the ignition probability as a function of the environmental covariates along the distribution lines. When calibrating a model using MaxEnt, the training data imposes constraints on the maximization of statistical entropy such that, for each feature used to train the model, its empirical mean computed from the sample data must be equal to its estimated mean computed from the maximum entropy distribution. Since an equality criterion may be overly restrictive and could result in overfitting (jeopardizing the model's generalization capabilities), the formulation

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[60] LoRE stands for "Likelihood of a Risk Event".
[61] CoRE stands for "Consequence of a Risk Event".
[62] As determined by the California Public Utilities Commission (CPUC), Available at https://www.cpuc.ca.gov/industries-and-topics/wildfires/fire-threat-maps-and-fire-safety-rulemaking.

used by PG&E relaxes these constraints by changing equality to closeness within a distance β_j, for each feature z_j.

This entropy maximization formulation was shown to be equivalent to minimizing the negative log-likelihood of a Gibbs distribution by (Della Pietra, Della Pietra, and Lafferty 1997). This minimization problem results in a distribution of ranking scores over the locations of interest, ordered with respect to the ignition probability. However, these scores do not represent a valid probability distribution and therefore cannot be used directly to assess risk. PG&E transforms the scores into ignition probabilities using the methodology described by (Elith et al. 2011) in a process PG&E refers to as τ-calibration in documents provided.[63] This procedure uses the average annual number of training ignitions to convert the MaxEnt outputs into a valid probability distribution suitable for risk calculation.

II.C.5 Assessment of the VRM Ignition Model

The GIRS-RT finds that MaxEnt is an appropriate model choice for estimating the ignition probability from vegetation-caused failures. PG&E has tested the statistical significance of each covariate through both permutation importance and jackknifing.

The GIRS-RT highlights two areas for future improvements in the implementation of MaxEnt in WDRM v2.

II.C.5.A1 Ignition dataset size and modeling ignitions instead of outages

The model was trained exclusively using CPUC-reportable ignitions. This decision was made to prevent biasing the model towards low-consequence ignitions. Still, ignitions that exert negligible consequences in one instance could be catastrophic in another given the complex nature of fire propagation. For example, a pole ignition, which may not meet the requirements to be considered CPUC-reportable, clearly exhibits characteristics of an event that could trigger a wildfire (an open flame). In future versions of WDRM, GIRS-RT recommends expanding the set of ignitions in the training data, by considering both CPUC-reportable and non-reportable ignitions.

In WDRM v2, PG&E justifies the use of CPUC-reportable ignitions rather than the much larger set of outages which are automatically recorded by PG&E. This decision was motivated by the observations that peak outage rates occur during winter storms rather than during the fire season and that the regions that are most prone to outages differ from those most prone to ignitions during the fire season.[64] In future versions of WDRM, GIRS-RT recommends further consideration of the outage data combined with a model to predict the conditional probability of an ignition given an outage. These conditional models are already under consideration at PG&E.[65] While calibrating a model using the larger training data set associated with outages may remove potential sources of bias associated with data collection or the inherent nature of small datasets, such a model may fail to capture rare ignitions that occur without an outage.

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[63] *PG&E 2021 WDRM Overview, p. 102.*
[64] *PG&E 2021 WDRM Overview, p. 7.*
[65] *SME interview, November 7, 2023.*

II.C.5.A2 Model regularization parameters and their optimization

Models based on the Maximum Entropy principle are prone to overfitting, jeopardizing their out-of-sample generalization capabilities. To overcome this shortcoming, the MaxEnt model includes regularization terms in its training process controlled by the parameter set $\{\beta_j\}_{j=1}^{N}$, where *N* is the total number of features included in the model. In PG&E's implementation, these parameters were adjusted by executing multiple trials using different parameter values and retaining those that produce the best performant model over a validation set.[66] Alternative approaches to determining the optimal regularization parameter values have been outlined in the MaxEnt literature, including Bayesian or evolutionary (Alibrahim and Ludwig 2021), and could aid in enhancing the performance of future models designed for risk assessment.

II.C.6 MaxEnt Validation and Evaluation

The primary methods PG&E employs to evaluate the MaxEnt models are the recall and the ROC curve (Figure II.C.1).[67] The recall is defined by the ratio of successful ignition predictions, i.e., True Positives (*TP*), to the sum of *TP* and missed ignitions, i.e., False Negatives (*FN*):

$$recall = \frac{TP}{TP + FN}$$

The recall score characterizes the fraction of positive occurrences (ignitions) correctly identified by the model. Since the outputs of MaxEnt are continuous, to obtain a binary prediction the user defines an operational threshold for the recall or, equivalently, the omission rate, defined as (1 – recall). As discussed in Section II.B.4, PG&E sets a threshold of <5% for the omission rate. As the cost of a false negative prediction (an unpredicted ignition) is high, the GIRS-RT confirms that PG&E's high recall threshold is consistent with a conservative risk tolerance and is therefore appropriate for the present application.

However, a model that always predicts positives will have perfect recall but clearly little predictive value. Accordingly, PG&E considers metrics which account for the false positive rate: the ROC curve and associated area under the ROC curve (AUC-ROC). The ROC curve tracks the true positive rate versus the false positive rate and is parametrized by the recall/omission threshold; it is shown in Figure II.C.1 for the vegetation risk model. The AUC-ROC values obtained for the vegetation and conductor models indicate the presence of non-trivial predictive power of the model (i.e., above random prediction), but may still have room for improvement. A mock-validation test using ignitions from 2019 (in HFTDs from June-November) was also performed and demonstrated that the 2019 ignitions occurred in regions of high ignition probability more often than by random chance (with a weaker ROC-AUC=0.64 than the results in Figure II.C.1).

[66] *SME interview, November 2, 2023.*
[67] *PG&E 2021 WDRM Overview, p. 30-33.*

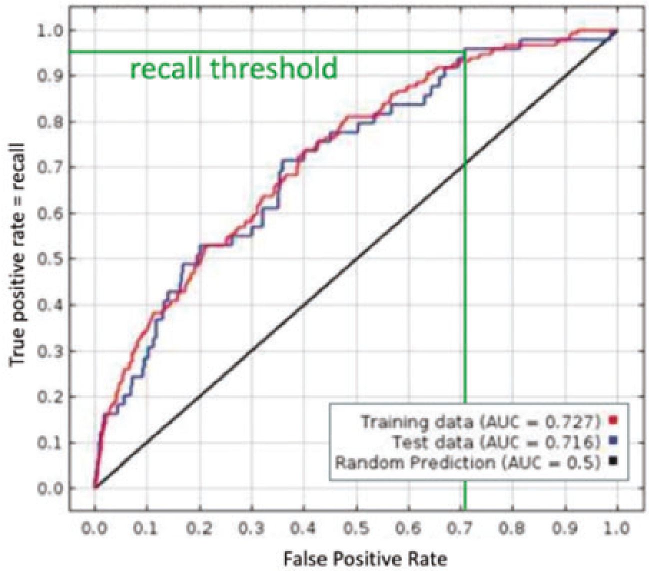

Figure II.C.1: ROC curve for the vegetation ignition probability model for both training and test data; the operational recall threshold is denoted in green. Model hyperparameters are chosen when test and training curves are similar, indicating ability to predict well out of sample. The black diagonal line corresponds to random prediction.[68]

II.C.7 Assessment of MaxEnt Validation and Evaluation

PG&E uses the recall score and the ROC curve to validate, optimize, and evaluate model performance. While the GIRS-RT deems both these metrics appropriate for the modeling task, in the GIRS-RT's assessment, there are additional metrics which should be reported to better characterize these models' performance.

The ROC is recall-threshold independent, which makes it very general as an evaluation metric. However, this metric does not capture the high false positive rate exhibited by the model. For the test data (blue) in Figure II.C.1, the model has a false positive rate of >70% at the chosen threshold. This high false positive rate is reflected by the low operational precision of the vegetation model. The precision is a technical metric defined in statistics as

$$precision = \frac{TP}{TP + FP}$$

In Section 11.5 of the *WDRM Overview,*[69] PG&E reports the precision of the vegetation ignition model as 0.00038. This implies that a large fraction of positive predictions are false positives (i.e., one correct positive prediction would be associated with ~2600 false positive predictions). Between precision and recall, which metric to emphasize depends strongly on the cost imbalance of prediction outcomes. In the present context, the cost of unpredicted ignitions (false negatives) vastly outweighs the cost of false positives. A false negative could mean completely missing a potential ignition, while a false positive would mean an overly conservative risk expectation. To

[68] *Figure adapted from PG&E 2021 WDRM Overview, p. 64.*
[69] *PG&E 2021 WDRM Overview, p. 46.*

quantitatively analyze the precision-recall tradeoff, the GIRS-RT recommends using a precision-sensitive performance metric in addition to the recall score and ROC curve: for instance, the precision-recall curve and the associated area under the precision-recall-gain curve (Flach and Kull 2015). The precision-recall curve is analogous to the ROC curve except that it tracks precision versus recall. The area under the precision-recall-gain curve is the analog of the AUC-ROC, with the technical details discussed in the cited reference. The rationale for such a metric to evaluate the WDRM ignition sub-models is summarized below.

II.C.7.A1 <u>A low value of the precision metric can confound predictive power</u>

At low precision values the number of false positives is much greater than the number of true positives. A low risk tolerance requires a high recall, which necessitates a high false positive rate. However, for instances in which the outputs of the model are used to prioritize mitigation work with a limited scope, numerous false positives dilute the effectiveness of the mitigation prioritization. A metric which tracks the decrease of precision as the recall threshold is modulated would quantitatively display the extent to which false positives begin to overwhelm the true positives.

II.C.7.A2 <u>For data with a low underlying prevalence, the ROC curve may be artificially inflated due to the presence of true negatives</u>

In Sofaer, Hoeting, and Jarnevich (2019), the authors study the effect of prevalence (the unconditional probability of observation) on performance metrics for MaxEnt-like binary classification models. They find that for low prevalence data the ROC curves are inflated for otherwise identical models. The reason for this is that low prevalence (rare) occurrences are less likely to be observed in general. Therefore, the models typically produce many true negatives. CPUC reportable ignitions are rare and occur with a very low prevalence throughout the distribution network. At a fixed recall threshold, including many true negatives results in a lower false positive rate (since FPR ~ 1/TN) and therefore an ROC curve which appears further from the diagonal. While this leads to a higher AUC-ROC, it does so because of the class imbalance in the underlying data. The precision-recall curve does not depend on the number of true negatives and is therefore unaffected by this issue; its introduction in addition to the ROC curve would provide a more holistic view of model performance.

The GIRS-RT notes that PG&E is aware of the effect of true negatives on model performance (zero inflation) and addresses the issue briefly in Section 28.1 of the WDRM Overview. PG&E reduces this effect by constraining their datasets regions along the distribution network, in HFTDs, and periods during the fire season, which are locations and times that are most prone to fires. A corollary of the assessment above is that if PG&E had not chosen to restrict their data, the model would appear to be performing better in terms of AUC-ROC. However, this apparent increase in performance would not be caused by improved prediction capability. The GIRS-RT cautions that an absolute interpretation of AUC-ROC scores (versus a relative interpretation) would ignore these types of inflation effects. In the GIRS-RT assessment, PG&E's restriction to regions along the distribution network, in HFTDs, and during the fire season, while likely reducing the AUC-ROC metric of the ignition prediction model, constitutes best-practices modeling and its effect should not be misinterpreted as a reduction in model quality.

In summary, the GIRS-RT finds the recall score and ROC curve are appropriate evaluation metrics for the ignition probability modules, and the choice of a high operational recall threshold is consistent with PG&E's goal of minimizing wildfire risk. However, these metrics do not completely characterize the performance of a binary classification model like MaxEnt. The GIRS-RT therefore recommends introducing precision-recall curves and reporting the area under the precision-recall-gain curve as additional quantitative performance metrics. These metrics incorporate the low prevalence of CPUC reportable ignitions without bias, and they are already employed in the literature in which MaxEnt was developed. As they depend only on MaxEnt model outputs, they are readily calculated and can be used to validate models and more completely characterize performance as illustrated in section II.C.8.

II.C.8 Spatial Analysis of Covariates: Metrics for Validation and Correlations with Fire Size

PG&E provided spatial data for VRM including ignition data, MaxEnt vegetation training ignitions/covariates/output ignition probabilities, and MAVF CoRE consequence scores.

Using the training ignitions and MaxEnt model outputs, the GIRS-RT verified the ROC curve for the official VRM calibration (Figure II.C.2.A), which agrees with the ROC-curve provided by PG&E (Figure II.C.1). This demonstrates successful reproduction of PG&E's statistics and validates that ignitions are being predicted at rates exceeding random prediction (AUC > 0.5). Figure II.C.2.B illustrates the corresponding precision-recall curve (described above), which illustrates high recall is associated with low precision in the ignitions data. As the recall threshold is increased, for each true positive predicted hundreds to thousands (2600 on average) of false positives are recorded.

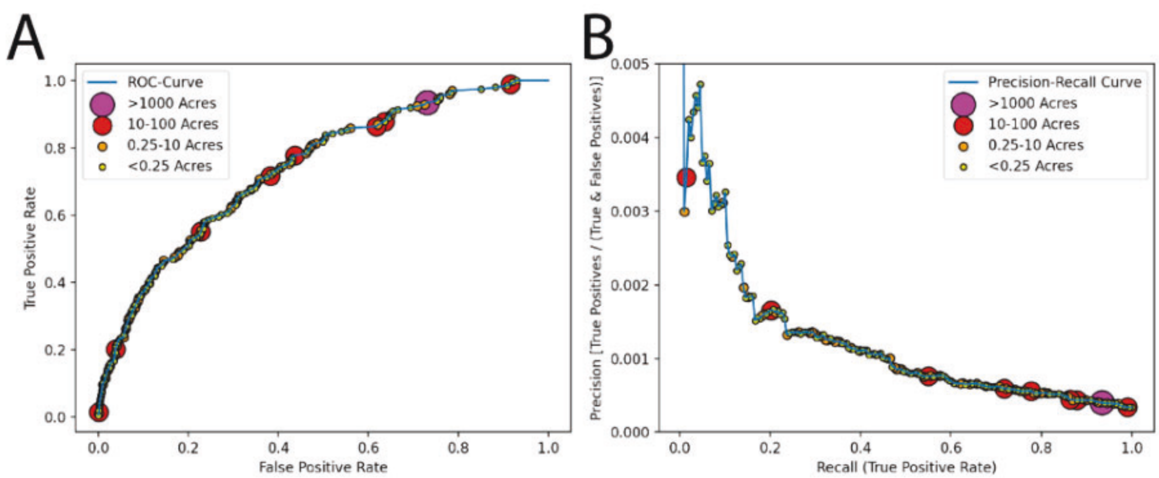

Figure II.C.2: ROC (Panel A) and precision-recall (Panel B) curves for the official MaxEnt run of the VRM ignition model.[70] The ROC-curve calculated from the data and model outputs provided by PG&E is visually indistinguishable from the ROC curve provided by PG&E (Figure II.C.1). Note that the ignitions that correspond to larger fires plot at high true positive rates and that for every positive predicted ignition corresponds to 100's-1000's of false positives.

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[70] *DRU12565.001, PGE Fire Incident Data Collection; DRU12640, (veg_ignition_summer_logistic.tif; veg._ignition_summer_samplePredictions.csv).*

Additionally, by cross-matching the PG&E ignition data with the training ignitions, the ROC and precision-recall curves are augmented with the observed fire size associated with each ignition in the training set. Fire size is indicated by color and size of the dots on the ROC and precision-recall curves in Figure II.C.2. Note that most of the training ignitions lead to small fires that burn <10 acres. Larger fires (> 10 acres) primarily lie on the right side of the precision-recall curve (recall>0.5), and the largest fire (>1000 acres) has recall >0.90. This signifies that larger fires occur at relatively low ignition probabilities. That is not surprising, as extreme conditions are associated with relatively rare red flag events. It also provides additional justification for setting a high recall threshold for planning and mitigation to encompass these abnormal events.

II.C.9 Applications of VRM for (Enhanced) Vegetation Management

VRM provides a risk ranking for prioritization of vegetation management. The Enhanced Vegetation Management program (EVM) has been retired and removed from this audit. However, during its application it utilized VRM risk scores as a factor in prioritizing the workflow. EVM used a list of worked tree data in the Oracle EVMGIS database.[71] Tree data was filtered such that 1) the tree work date was in 2019, 2) the tree work was completed, 3) the tree diameter at breast height was at least 4 inches, and 4) tree data was not from LiDAR but rather from inspections. There were 133,666 tree records satisfying these criteria, all of which had latitude-longitude coordinates. Calculated VRM risk scores were summarized per Circuit Protection Zone (CPZ) for planning purposes. Following inspection, some trees were tagged as candidates trees requiring work in the Vegetation Management Database (VMD).[72] As a result of this prioritization, in 2021 PG&E performed nearly 98% of their EVM work on segments which were in the top 20% WDRM risk category.[73]

The EVM program was retired by PG&E in 2022, and regular Vegetation Management (VM) is applied across the entire HFTD distribution network annually. Since the risk areas are fully inspected and maintained annually, there is no longer a need to use VRM for VM prioritization. EVM has been replaced by actions such as undergrounding and the Enhanced Powerline Safety Settings (EPSS) Program which provides additional safeguards against ignitions by rapidly and automatically shutting off power when objects such as a tree or a branch fall into a power line. The EPSS Program will be reviewed as part of the Operate category of the Local Conditions Audit. While the VRM is not used to set priorities for VM, the GIRS-RT recommends continued assessment of the risk of vegetation caused ignitions as part of PG&E's overall WDRM Program.

II.C.10 Summary of GIRS-RT Findings for VRM

The GIRS-RT finds that the VRM model was fit for use and exceeded industry standards at the time of deployment. The VRM model is a significant improvement over the previous analogous used in WDRM v1, allowing probability scores to be compared across PG&E territories.

[71] PG&E 2021 WDRM Overview, p. 45.
[72] PG&E 2021 WDRM Overview, p. 45.
[73] 2022 PG&E Wildfire Mitigation Plan Update Revised, p. 53.

Features:

- VRM provides spatially resolved risk scores across PG&E Tier 2 and Tier 3 HFTD regions for vegetation driven wildfires.
- It combines data-driven ignition likelihood with Technosylva wildfire simulations and MAVF consequence values into a risk score.
- VRM was used to set priorities for Enhanced Vegetation Management (EVM) when the EVM Program was active.

Summary of Assessments:

II.C.3.A1 <u>Vegetation data addresses fuel moisture but not species-level traits associated with flammability</u>

The GIRS-RT recommends incorporating covariates that capture vegetation species since the vegetation flammability is influenced by species-level traits in addition to fuel moisture.

II.C.3.A2 <u>Wind-related covariates may not capture gust speeds</u>

Including wind gust speeds, which can last from seconds to minutes, is recommended to capture crucial features of high wind events that are not effectively represented by current wind-related covariates.

II.C.3.A3 <u>Strong correlations exist between humidity-related covariates</u>

Two of the three covariates with the highest permutation importance in VRM are highly correlated humidity covariates, suggesting the need for additional covariates, such as tree density or land use.

II.C.5.A1 <u>Ignition dataset size and modeling ignitions instead of outages</u>

The GIRS-RT recommends expanding the set of ignitions in the training data by considering both CPUC-reportable and non-reportable ignitions, and the consideration of the outage data coupled with a model to predict the conditional probability of an ignition given an outage.

II.C.5.A2 <u>Model regularization parameters and their optimization</u>

While PG&E's strategy to define hyperparameters used in the MaxEnt model is suitable, the GIRS-RT recommends the exploration of more advanced methodologies for parameter definition.

II.C.7.A1 <u>A low value of the precision metric can confound predictive power</u>

At its operational classification threshold, the VRM operates with a high rate of false positives (over 2000 false positives: 1 true positive), potentially causing spurious rankings of low ignition risk areas.

II.C.7.A2 <u>For data with a low underlying prevalence, the ROC curve may be artificially inflated due to the presence of true negatives</u>

Large number of true negatives in predictions over an imbalanced dataset can decrease the apparent false positive rate of a model while the rate of correctly identifying true positives remains fixed; PG&E combats this effect by modeling ignitions only in HFTDs and during fire season, but alternative evaluation metrics unaffected by the true negative rate could be used to characterize model performance independently of this effect.

II.D CRM: Conductor Risk Model

II.D.1 CRM Overview

The Pacific Gas and Electric Company (PG&E) Conductor Risk Model (CRM) is a planning tool developed to set priorities for system hardening in PG&E territories on a time scale of one or more years. The CRM estimates the risk associated with conductor triggered electric grid infrastructure-caused ignitions. In principle, this framework allows for an integrated approach involving model scoping (planning), data intake, risk identification, risk assessment, risk management, and risk mitigation.

The Local Conditions Audit focuses on the 2021 version of the CRM which is the conductor component of the 2021 Wildfire Distribution Risk Model (referred to as WDRM v2). For the duration covered by this audit (2021 and 2022 PG&E WMP), the GIRS-RT finds that overall CRM exceeds industry standards and is fit for use. CRM, and WDRM v2 incorporate significant improvements over the previous PG&E WDRM v1 model in both the ignition and consequence models, allowing risk scores to be compared across territories.

The CRM consists of three main components: the conductor ignition probability model (LoRE),[74] the wildfire consequence model (CoRE),[75] and the risk model, which fuses the first two components to compute a risk score for each geographical location within the vicinity of PG&E's distribution network under Tier 2 and Tier 3 High Fire Threat Districts (HFTDs).[76] Locations near the distribution lines are rasterized in a grid comprised of 100m x 100m "pixels" covering distribution lines and their surroundings. This section focuses on the conductor ignition probability model (LoRE). The wildfire consequence model (CoRE) is the subject of the fourth tool in the audit sequence and will be reviewed in Section II.E.

The ignition probabilities are calculated using the machine learning model MaxEnt. The model uses four information sources: historical ignition records, local environmental conditions, local weather conditions, and local asset attributes related to the conductors. The data used to fit the model covers the fire seasons (Jun. 1 – Nov. 30) from 2015 to 2018, while data from 2019 fire season was utilized for model testing and performance reporting.

The model is trained on CPUC-reportable ignitions resulting from conductor failures. MaxEnt is a presence-only model, i.e. it is based only on positive observations of the dependent variable. Each pixel is characterized by a vector of features derived from local conditions (weather, environmental, and asset related). The features represent linear and non-linear transformations

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[74] LoRE stands for "Likelihood of a Risk Event".
[75] CoRE stands for "Consequence of a Risk Event".
[76] As determined by the California Public Utilities Commission (CPUC), available at https://www.cpuc.ca.gov/industries-and-topics/wildfires/fire-threat-maps-and-fire-safety-rulemaking.

of the original covariates. Meteorological and environmental data are either combined over the training period or represented by a single snapshot in time, resulting in a single value for each feature per pixel. For asset data, information was retrieved from PG&E's internal databases.

This section has four primary sections: the covariate data, representation and use of covariate data in MaxEnt, additional data analysis, and applications of CRM for system hardening.

II.D.2 CRM Covariates

Covariate vectors characterize local conditions throughout the distribution grid, including pixels that host the conductor-caused CPUC-reportable ignitions used to calibrate parameters in MaxEnt. Table II.D-1 summarizes the pool of covariates used in the CRM ignition probability model.

Table II.D-1: Covariate data used in the CRM.[77]

Covariate	Category	Source	Brief description
Unburnable areas	Environmental data	2016 LANDFIRE surface fuel model	The portion of pixel identified as unburnable
Maximum tree height		Salo Sciences	30m, scaled to 100 m
100-hour dead fuel moisture		gridMET	Daily, 4 km All gridMET data averaged over fire seasons (Jun 1 to Nov 30) from 2014 to 2016
Coastal indicator		EDGIS	A binary feature
Precipitation	Meteorological data	gridMET	Daily, 4 km. All gridMET data averaged over fire seasons (Jun 1 to Nov 30) from 2014 to 2016
Specific humidity			
Vapor pressure deficit			
Maximum temperature			
Wind average		RTMA	Hourly, 2.5 km. All RTMA data averaged/assessed over fire seasons from 2016-2018
Age	Conductor attributes	EDGIS/STAR model dataset	Identified by outages subject matter experts (SMEs)
Material (Al, Cu, ACSR)		EDGIS	
Size (2, 4, 6)		American Wire Gauge (AWG) standardized wire gauge system	
Splices		Reliability Program splice records	

[77] *PG&E 2021 WDRM Overview, p. 73.*

II.D.2.1 Environmental data

a. The feature "unburnable" includes surfaces that typically would not ignite even when a spark occurs. It is defined as the fraction of the 100m x 100m pixel identified as unburnable derived from the 2016 LANDFIRE surface fuel model. The unburnable land use types include urban, perennial snow/ice, agriculture, water, and barren.
b. Maximum tree height data was calculated for each 100m x 100m pixel along the distribution grid based on Salo Sciences satellite imagery collected in November 2019.
c. 100-hour dead fuel moisture data is from gridMET (see Meteorological data below).
d. The coastal indicator is a binary feature serving as a tag on conductor geometries from EDGIS since the coastal marine layer weather promotes conductor corrosion.

II.D.2.2 Meteorological data

The meteorological data used for covariates are from the Gridded Surface Meteorological dataset (gridMET) produced by the University of Idaho over fire seasons from 2014 to 2016 and the Real-Time Mesoscale Analysis (RTMA) produced by NCEP over fire seasons from 2016 to 2018.

a. Precipitation: The average daily total precipitation from gridMET.
b. Vapor pressure deficit (VPD): The average daily VPD from gridMET.
c. Specific humidity: The average daily specific humidity from gridMET.
d. Temperature: The average daily maximum temperature from gridMET.
e. Wind: Daily means of hourly average wind velocity and gust velocity at 10 m from RTMA.

II.D.2.3 Conductor attributes

a. Conductor material: The materials (Aluminum, Copper, ACSR)[78] were defined as binary model features (i.e., 1= True, 0=False, separately for each material).
b. Conductor size: The sizes (2, 4, 6) were defined using the American Wire Gauge (AWG) standardized wire gauge system and were defined as binary model features.
c. Conductor age: The number of years since the installation. If the installation data is missing or invalid, use the estimated age in the STAR model dataset.
d. Splices: Whether a splice record existed for a conductor was defined as a binary feature. Only the Reliability Program Splice records, which only included spans with more than three per phase, were used to prevent splice locations from introducing bias. The splices were mapped to conductors using a spatial joint and validated using the circuit name.

II.D.3 Assessment: Covariate Datasets

The model inputs are obtained from high quality databases and include variables derived from meteorological, surface condition, tree, conductor, and HFTD data, which collectively capture the

[78] *Aluminum conductor steel reinforced (ACSR).*

many crucial factors affecting fire ignition. However, the GIRS-RT has identified the following issues related to the covariates for further investigation.

II.D.3.A1 Masking of unburnable areas

The unburnable feature represents surfaces that do not ignite when a spark occurs, including urban, perennial snow/ice, agriculture, water, and barren surfaces. It is ranked as the feature with highest predictive value in the CRM (anticorrelated with ignition likelihood). In regions where it is possible, the GIRS-RT recommends masking unburnable areas to focus on the area where ignition may occur and on the predictive values of features that are more meaningful for mitigation. PG&E has partially accomplished this by restricting consideration to assets within HFTDs.

II.D.3.A2 Precipitation features and contrasting permutation importance between VRM and CRM

The precipitation feature has a high permutation importance of 29.8 in the CRM, which is only surpassed by unburnable at 30.8 and is followed by the third important feature conductor_material_acsr at 9.7 (WDRM Overview Table 5).[79] To explain this result, PG&E notes, "The precipitation feature shows correlation to the maximum tree height feature and may be an indicator of where trees are located that can fall into a conductor."[80] The GIRS-RT has concerns about this justification since the precipitation covariate is averaged over the fire season when precipitation is typically low. It may be of interest to include precipitation during rainy seasons (correlated with fuel growth) as an additional covariate. Also, the permutation scores for precipitation and max tree height are very different in VRM (3.1 and 26.1) and CRM (29.8 and 4.3). For future versions of WDRM the GIRS-RT recommends comparison studies of the covariates across the different ignition sources.

II.D.3.A3 Integration of satellite fuel data

The fire monitoring and modeling community has shifted to satellite-derived vegetation water content to evaluate the fuel load and vegetation dehydration (Abdollahi, Dewan, and Hassan 2019; Fu et al. 2023). The GIRS-RT suggests PG&E consider these data sources for future versions of WDRM.

II.D.4 Maximum Entropy Model for Estimation of Ignition Probabilities in the Conductor Risk Model

Using the covariate data described above, PG&E trains a machine learning model based on the Maximum Entropy principle to estimate ignition likelihood in the distribution network. This model is heavily inspired by works such as Elith et al. (2011) and Phillips, Anderson, and Schapire (2006) from the ecological subfield known as species distribution modeling. MaxEnt aims to identify a geospatial distribution for the probability of ignitions of maximal information entropy which still agrees with the observed data. The data are incorporated into the model through constraints imposed on the maximization problem. These constraints can be stated as follows: for each feature used to train the model, its empirical mean, computed from the sample data, must be equal to its estimated mean, as computed from the maximum entropy distribution. Since an equality restriction is likely to be overly restrictive and may lead to overfitting in the final model

[79] *PG&E 2021 WDRM Overview, p. 83.*
[80] *PG&E 2021 WDRM Overview, p. 83.*

jeopardizing its generalization capabilities, the formulation used by PG&E relaxes these constraints from equality to closeness (within a distance for each feature) z_j.

This entropy maximization formulation was shown to be equivalent to minimizing the negative log-likelihood of a Gibbs distribution by Della Pietra, Della Pietra, and Lafferty (1997). The result of this minimization problem is a function that represents ranking scores over the locations of interest that are ordered with respect to the ignition probability. However, these scores do not represent a valid probability distribution and as such, cannot be used directly in the conductor risk assessment. To resolve this shortcoming, PG&E transforms these scores into a valid probability distribution using the methodology stated by (Elith et al. 2011) by a process PG&E refers to as τ calibration in the related documentation.[81] Through this process, the average yearly count of ignitions over the training data is used to turn the output of the MaxEnt model into a valid probability distribution that can be used in posterior risk calculation tasks.

II.D.5 Assessment: Application of MaxEnt to Calculate Ignition Probabilities in CRM

The GIRS-RT finds that MaxEnt is an appropriate model for estimating the ignition probability due to conductor failures. Three issues regarding its implementation for this application are listed below for consideration in future versions of CRM.

II.D.5.A1 <u>Permutation importance calculation for binarized, mutually exclusive categorial variables</u>

PG&E uses Permutation Importance to assess the significance of each covariate. This technique involves randomly shuffling the values of a variable among the training samples, disrupting its correlations with other variables. Subsequently, the model is retrained using this altered dataset, and the performance difference between the original and modified models is recorded. The higher the performance loss, the more important the variable is. However, this method introduces internal inconsistencies when applied to binarized categorical data.

The CRM includes asset attributes for the estimation of ignition likelihood in MaxEnt:

- Conductor Size: categorical variable (gauge size 2, gauge size 4, or gauge size 6).
- Conductor Material: categorical variable (Aluminum, Copper, or ACSR).
- Conductor Age: continuous variable.
- Existence of Splice Record: binary variable.

The conductor's size and material are categorical variables, each with three mutually exclusive classes (e.g. a conductor cannot be both Aluminum and Copper at the same time). However, for MaxEnt, PG&E split these two variables into six binary covariates: each conductor material and size class is represented as a binary covariate with a 1 for true and 0 for false. While in principle permutation importance can be performed for models with binary variables, transformation of categorical variables into a set of binary variables can induce errors. When the values of one of the binarized variables is randomly shuffled across pixels, the outcome is that some pixels will be assigned "true" for more than one of the mutually exclusive values (e.g. randomization will create

[81] *PG&E 2021 WDRM Overview, p. 102.*

pixels that are classified as both Aluminum and Copper, or both size 2 and size 4). This error will show up in permutation importance scores when categorical variables are binarized.

The GIRS-RT notes that PG&E also reports alternative metrics that are not affected by this issue, such as Jackknifing. The GIRS-RT recommends retaining the original categorical variables for permutations tests rather than binarizing individual attributes that are mutually exclusive.

II.D.5.A2 Missing data/incomplete datasets for certain asset-related covariates

MaxEnt uses presence-only information to estimate the likelihood of an ignition given local information. The GIRS-RT reviewed the data used to calibrate MaxEnt and found that, at the ignition sites, all aluminum conductors were missing size information. Locations containing aluminum conductors account for 16% of the training ignitions. Size is relevant for numerous failure modes, such as a tree falling into a line or line sagging due to high environmental temperatures.

Table II.D-2 summarizes the missing data for ignition sites. Each cell represents the number of ignition sites falling into each combined category (conductor size and material). Note that all cells containing aluminum conductors are categorized as Missing Information for the size variable.

Table II.D-2: Distribution of HFTD ignition sites among material and size categories, including missing information.

	Missing Information	**Size 2**	**Size 4**	**Size 6**
ACSR	19	40	108	0
Al	47	0	0	0
Cu	3	5	13	44
Missing Information	3	0	0	0

The same issue arises when the full set of pixels is considered (i.e. for the complete set of pixels in the Tier 2 and Tier 3 distribution grid). An aluminum conductor is almost always paired with missing information regarding its size. The GIRS-RT recommends updating the dataset used in the training and prediction processes of the MaxEnt model, since incomplete data for one type of material can produce a bias in the outputs.

II.D.5.A3 Additional conductor variables for future consideration

The conductor risk model uses the following asset attributes for the estimation of ignition likelihood:

- Conductor Size.
- Conductor Material.
- Conductor Age.
- Existence of Splice Record.

While these features are important, there are additional features that are worthy of consideration. These are:

1. **Current density** in the conductor impacts internal temperature and therefore how much it sags under its own weight. Including a variable such as the Average of daily max current density over the fire season for each pixel may be informative for future models.
2. **Size** (missing as noted above in (3), especially for aluminum conductors) influences the strength of a conductor and, consequently, its resistance to damage from a falling trunk. Additionally, size plays a role in determining the weight of the conductor, which is essential for calculating sag under high-temperature conditions.
3. **Average distance between poles in each pixel**, since it impacts the weight of the line and therefore how much it sags under high-temperature conditions. Sagging is a critical phenomenon in distribution networks, as it has the potential to bring a conductor into contact with nearby vegetation, increasing the risk of ignition.
4. **Cleaning frequency of distribution insulators** is an important factor since accumulated dust and dirt in the insulators can generate a conductive layer, decreasing performance and increasing likelihood of a failure in the conductor-pole system. Including a variable such as the Frequency of cleaning distribution insulators for each pixel may be informative.

The GIRS-RT recommends that PG&E explore the inclusion of these variables for future versions of the conductor ignition likelihood estimation model.

II.D.6 Additional Analysis of CRM Covariate Data

The GIRS-RT analyzed covariate data to produce ROC and PR-Curves, statistical distributions of covariate values (ignition site and background distributions), and covariate correlations.

II.D.6.A1 Independent validation of metrics for model performance

Using the ignition training and test data and MaxEnt outputs provided by PG&E, the GIRS-RT reproduced the ROC curve reported by PG&E for the CRM.[82] The AUC score is greater than 0.7 which indicates that conductor-related ignitions are predicted significantly better than random chance (AUC=0.5). As with the VRM ignition model, the precision corresponding to the adopted recall threshold is low (<0.001), indicating that thousands of false positives are predicted for every true positive. Due to the low prevalence of ignitions and necessity of a high recall threshold, low precision is expected in this context. The GIRS-RT concludes that the model is sufficient to identify regions of elevated ignition probability and risk for long-term planning.

II.D.6.A2 Analyzing statistical distributions of individual covariate values

PG&E used covariate data for 226 conductor-related ignitions to train MaxEnt for the official run.[83] For the sake of parsimony, covariates were included or rejected based on their influence on the predictive power of the model and PG&E covariate preferences.[84]

MaxEnt internally generates importance rankings for the individual covariates using permutation importance (performance degradation from randomizing the covariate) and

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[82] PG&E 2021 WDRM Overview, p. 85.
[83] Information from file titled "ignition_equipment_summer_samplePredictions.csv" provided by PG&E as part of the documentation for this audit.
[84] PG&E 2021 WDRM Overview, p. 74; communication with the PG&E Modeling Team about including covariates that capture influences pertaining to ignitions.

jackknifing, which computes performance based using only on the single covariate, and on leaving the covariate out and using all others.[85]

To directly visualize the impact of individual covariate values in ignition likelihood estimates, the GIRS-RT computed the distributions of values of the non-binarized covariates for both the ignition pixels and the complete set of pixels for the distribution network in Tier 2 and Tier 3 HFTD regions. Results are shown for a subset of the covariates Figure III.D.1.

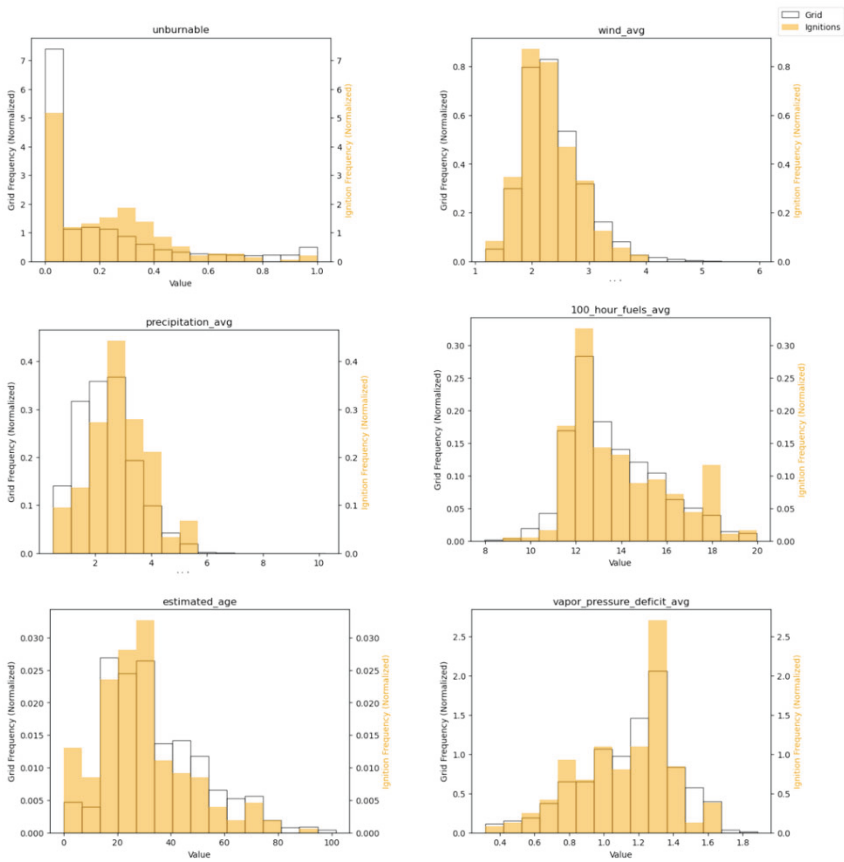

Figure II.D.1: Histograms for a subset of the covariate data for the full distribution grid (white) and the ignition sites used to train the conductor ignition model (orange) normalized to unit area for comparison.

PG&E's jackknifing results revealed that individually removing the unburnable, precipitation_avg, and estimated_age covariates (while retaining all other covariates) decreased the predictive power of the model most significantly.[86] For these covariates the distributions of covariate values corresponding to ignition pixels also differ most visibly from the corresponding distributions across the entire grid (Figure II.D.1). The values recorded in the unburnable distributions demonstrate that while it is likely that ignitions will occur in regions where the unburnable value is low (indicating more of the region is burnable), ignitions tend to occur more in regions with unburnable values ranging between 0.03-0.5 and less so for lower unburnable values ranging from 0 to 0.03 compared to the background distribution. The distribution of

[85] *PG&E 2021 WDRM Overview, p. 28-29.*
[86] *PG&E 2021 WDRM Overview, p. 84.*

precipitation_avg values corresponding to ignition pixels is slightly skewed towards higher values compared to the full distribution. The distribution of estimated_age values corresponding to ignitions tends to be skewed towards younger ages than compared to the grid. Other covariates used to train the model show a lower degree of systematic offsets (e.g., wind_avg, 100_hour_fuels_avg, specific_humidity, and vapor_pressure_deficit_avg in Figure II.D.1).

A statistically significant difference between a covariate distribution at ignition sites compared to the background distribution indicates that a covariate has predictive power. The Kolmogorov-Smirnov (KS) test is a routine statistical method to evaluate the likelihood that one distribution is sampled from another (Berger and Zhou 2014). The KS test is used below to determine whether the individual covariate distributions for ignition pixels are statistically distinct from the corresponding distributions for the entire grid.

*Table II.D-3: Results from the Kolmogorov-Smirnov test of non-binary covariates. Covariate distributions corresponding to ignition sites that are statistically significant (p-value<0.05) from the covariate distribution across the entire grid are in bold. The * symbol indicates the covariate was not used to train the CRM.*

Non-Binary Covariate	KS Statistic	p-value
windy_summer_day_pct*	7.02E-02	2.05E-01
wind_max*	5.71E-02	4.36E-01
wind_avg	6.49E-02	2.84E-01
vapor_pressure_deficit_avg	6.72E-02	2.48E-01
unburnable	**1.64E-01**	**9.02E-06**
tree_height_max	**1.70E-01**	**3.37E-06**
tree_height_avg*	**1.34E-01**	**5.04E-04**
specific_humidity	5.96E-02	3.84E-01
precipitation_avg	**2.18E-01**	**6.43E-10**
max_temperature_avg	**1.08E-01**	**9.87E-03**
local_topography	**1.08E-01**	**9.16E-03**
gusty_summer_day_pct*	7.04E-02	2.03E-01
estimated_age	**1.43E-01**	**1.62E-04**
1000_hour_fuels_avg*	**9.70E-02**	**2.66E-02**
100_hour_fuels_avg	8.20E-02	9.05E-02

Table II.D-3 lists the Kolmogorov-Smirnov Statistic (KS Statistic) and the p-value for the non-binarized covariates. The KS Statistic is the maximum vertical distance between the cumulative distribution function of the covariate values corresponding to the ignition sites and those of the entire grid. The p-value measures the statistical significance of the difference between the two distributions (a p-value below 0.05 indicates that the difference between the covariate distribution corresponding to the training ignition sites and the entire grid is significant).

Covariates with the lowest p-values are unburnable, tree_height_max, precipitation, and estimated_age, which were also identified as significant in the PG&E jackknifing results.[87] While 1000_hour_fuels_avg was not used to train the ignition model, it is statistically significant (p-value=0.0266<0.05) compared to 100_hour_fuels_avg (p-value=0.0905>0.05), which was used to calibrate the CRM. Another covariate not used to train the model that is statistically significant is tree_height_avg, which was correlated with tree_height_max. Note that none of the wind-related covariates are statistically significant by the criteria of this test.

II.D.7 Correlations Between Covariates

PG&E reports correlations between the CRM covariates as a heatmap of Pearson correlation coefficients between each pair of features.[88] There are strong correlations observed between conductor attributes and meteorological variables (see Figure 48 in PG&E 2021 WDRM Overview).[89] The meteorological variables representing the environmental dryness have strong correlations, including the specific humidity, 100-hour dead fuel moisture, vapor pressure deficit (VPD), maximum temperature, and the coastal indicator. It is not surprising that there are strong correlations among those variables since the fuel moisture and VPD are derived variables from humidity and temperature, and humidity over coastal areas is usually higher than the interior.

To visualize these correlations, the GIRS-RT produced scatter plots of covariate pairs. A subset is illustrated in Figure II.D.2. 1000_hour_fuels_avg and 100_hour_fuels_avg are highly correlated, which justifies using only one of the two to calibrate the CRM (Figure II.D.2.A). While many other covariates are correlated Figure II.D.2.B-D), for some covariate pairs the covariate values that correspond to training ignition locations are more strongly correlated that those of the entire grid based on the Pearson correlation coefficient (Figure II.D.2.B&C). This indicates that even for correlated covariate pairs, inclusion of both covariates may facilitate the predictive power of the model if the ignition sites are even better correlated than the background distributions.

The GIRS-RT recommends a more systematic analysis of the influence of correlations among the covariates in MaxEnt outputs, including comparison runs in which covariates are sequentially added or removed to maximally improve the predictive power of the model while continually monitoring the quality of the fit to avoid overfitting. This could be achieved by repeated, randomly sampling training data for test and calibration prior to the addition of each covariate.

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[87] PG&E 2021 WDRM Overview, pg. 84.

[88] PG&E reports correlation between conductor_material_cu and conductor_size_6 and between conductor_material_acsr and conductor_material_cu as strong. Of course, the material types ACSR and Cu are mutually exclusive, so the (anti)correlation should be 100%. The fact that correlations between pairs of material (or size) covariates are reported reflects the choice to binarize the material and size data, and any deviation from 100% (anti)correlation reflects incompleteness in the data.

[89] PG&E 2021 WDRM Overview, p. 82.

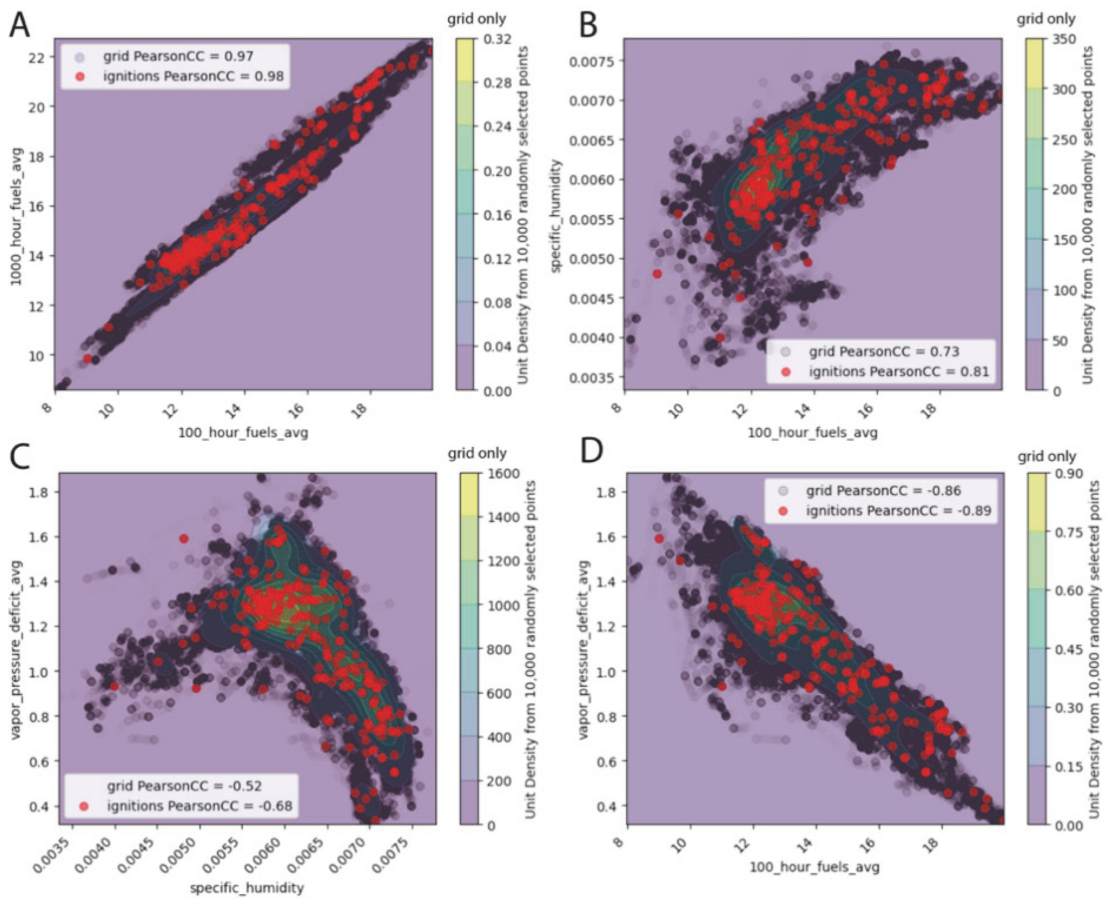

Figure II.D.2: Scatter plots of a subset of gridMET-derived covariate pairs corresponding to the entire grid (dark purple) and the ignitions used to train the conductor ignition model (red), along with the corresponding Pearson Correlation Coefficients for the training ignitions and the entire grid. Recall that 1000_hour_fuel_avg was not included in the model. Kernel density contours correspond to the distribution of covariate values across the entire grid (not the ignitions) and were generated from a random sample of 10,000 pixels out of the >600,000 pixels on the grid.

II.D.8 System Hardening: Overview

The CRM is used to inform the scoping and prioritization of System Hardening (SH) work in PG&E's distribution network. Recall that the CRM consists of two parts: an ignition probability model (LoRE) and a consequence model (CoRE). The risk output is the product of the two (LoRE × CoRE), calibrated via the Multi-Attribute Value Function (MAVF) developed by PG&E. These risk values are discretized along the distribution network by Circuit Protection Zones (CPZ). The risk model's output is therefore a risk score for each CPZ. These scores are used not only to rank but also to absolutely quantify the risk associated with a given CPZ.

Unlike vegetation management, which occurs widely across the distribution network, system hardening work is extremely limited in scope due to its cost and the long lead times associated with the projects. Work must therefore be effectively allocated to a reduced subset of CPZs. In the 2021 WMP, PG&E's stated goal is to use the CRM to prioritize work on the highest risk CPZs, which are defined to satisfy one of the three following criteria: 1) the CPZ is among the top 20%

of CPZs by MAVF risk score, 2) the CPZ is located in a fire rebuild area, and 3) the CPZ was previously affected by a PSPS event.[90]

Once the highest-risk CPZs are identified, a team of subject matter experts and public safety specialists reviews a set of possible workplans for each CPZ. Based on quantitative and qualitative factors the team provides a recommendation to the Wildfire Risk Governance Steering Committee (WRGSC). Projects are approved by the WRGSC and are aggregated into a workplan for the year. This workplan may include new SH projects, projects currently in progress, or projects associated with previously existing repair tags on the distribution network.

II.D.9 Development of the 2021 SH workplan

The prioritization of system hardening work is made difficult by the limited resources available to perform the work and the extended lead time required to complete projects.

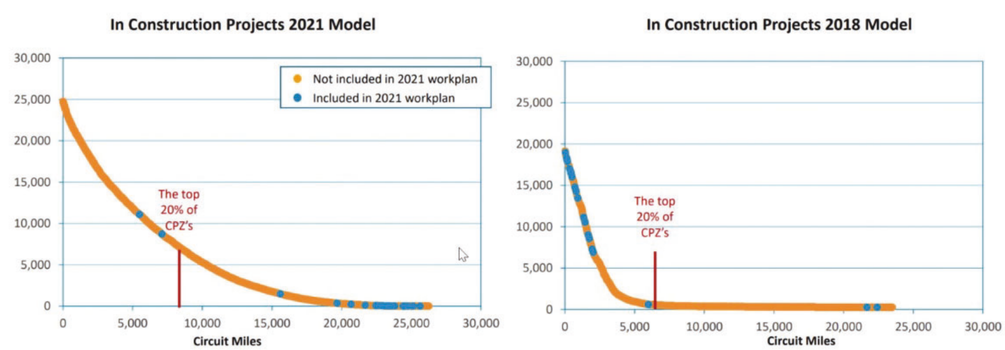

Figure II.D.3: In construction projects (blue) and their location on the CPZ risk spectrum (orange) for WDRM v1 and v2. The risk spectrum is represented by curves relating to the cumulative MAVF risk (y-axis) versus circuit miles (x-axis) for each CPZ considered.[91]

These facts represented a significant challenge when designing a portfolio of system hardening projects in 2021. By comparing risk scores across CPZs, it was found that the 2018 risk model (WDRM v1) had very little overlap with the 2021 risk model (WDRM v2).[92] Motivated by limited resource availability and cost considerations, many projects proposed for the 2021 workplan were already in construction, having been scheduled under the v1 model results. As a result, the portfolio of system hardening projects selected based on the v1 model did not align with the highest-risk circuits according to the v2 model. This is shown in Figure II.D.3, with the v2 model results on the left and the v1 model results in the right, and the projects in construction shown in blue.

In the initial workplan for 2021 (developed in late 2020), in construction projects, ECOP projects (electric corrective optimization program; the set of regular repair tags for issues on the network), and PSPS mitigation projects were prioritized over CPZs in the top 20% by risk. As a result, the top 20% of circuits by CRM risk constituted only 25% of the total mileage scoped for 2021, despite constituting a plurality of the risk reduction. GIRS-RT notes that the CRM risk

[90] *PG&E 2021 WMP, p. 608.*
[91] *WDRM V2 – Timeline and Key Decisions, PG&E WRGSC.*
[92] *WDRM V2 – Timeline and Key Decisions, PG&E WRGSC.*

rankings are only one facet of the highest risk designation. Despite the fact CPZs prioritized due to their rankings from the CRM were only a small percentage of scoped mileage, a large majority of scoped mileage fell under the highest risk designation, consistent with PG&E's stated goal.

However, this workplan was amended in early 2021: in the 2021 WMP, PG&E states, "PG&E needed to change course, stop previously selected projects, and start different projects that are in alignment with our updated risk model." The GIRS-RT agrees with this assessment and supports the decision to pivot from the initial 2021 workplan. The amended workplan represents 40% less mileage of scoped work but corresponds to a 68% increase in MAVF risk reduction due to its more direct use of the outputs of the WDRM v2 risk model. Retrospectively, the mileage goal for 2021 was exceeded, with PG&E performing over 200 miles of SH work. In addition, in 2021 over 1,300 miles were identified and scoped for future work, with 646 miles scoped for system hardening in 2022.[93] PG&E's stated goal was to for 80% of SH work to be performed on highest risk miles over a three-year period, a benchmark which was met by the amended workplan.

The GIRS-RT notes the initially scoped workplan (consisting of many in-construction projects) was not consistent with PG&E's stated goal of reducing wildfire risk as a primary concern. The GIRS-RT strongly supports the amended work plan and increased scope of work for 2021 and beyond.

II.D.10 System hardening decision workflow

Once the highest-risk circuits are identified, PG&E must decide on a specific system hardening workplan for each circuit. These include a baseline plan (no work done), line removal, overhead hardening, undergrounding, or hybrid plans. Each plan is evaluated across a set of basic metrics: the total risk reduction resulting from the work, the total capital costs, and operating and maintenance costs (discounted to the net present value). These variables are used to construct the primary filters for decision making: the risk-spend efficiency (cost per unit of risk reduction) and the Public Safety Specialist (PSS) preference. Other secondary decision factors include tree strike potential, ingress/egress availability, PSPS mitigation effect, and the operational timeline. Extra information is included, which may contain input from local first responders, subject matter experts, and analysis of local environmental hazards.[94] All these variables are considered by the scoping team, which recommends a specific plan for approval by the WRGSC. Once approved, the plan is added to the portfolio of SH work.

II.D.11 Assessment: system hardening prioritization

In the GIRS-RT assessment, with CPZs prioritized by the WDRM v2 risk model, the SH decision workflow integrates the most important aspects of work prioritization and, retrospectively, accomplished its goals in 2021. The workflow incorporates quantitative and qualitative variables. While this allows holistic consideration of projects, it also introduces subjectivity and variability to decision making. The GIRS-RT recommends the introduction of quantitative analysis to this process on two fronts.

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[93] *PG&E 2022 WMP, p. 589.*
[94] *PG&E 2022 WMP, p. 585.*

II.D.11.A1 Consider a retrospective analysis of SH decisions

Of all highest-risk CPZs, specific plans were chosen based on a set of numerical and categorical variables; by analyzing all projects considered, PG&E could quantitatively analyze which variables were the strongest predictors of chosen projects. Understanding which variables tend to influence the subjective decisions most would either validate the decision process (if consistent with PG&E's goals) or suggest new filters.

II.D.11.A2 Apply an optimization process to design an entire portfolio of SH projects

PG&E states that in future iterations, it intends to better incorporate PSPS mitigation into system hardening prioritization. Given a set of SH projects and workplans, the optimal overall workplan may not necessarily consist of the optimal workplan for each individual highest-risk CPZ. Instead, projects which address concerns on multiple fronts (PSPS mitigation, ECOP work) may be paired with projects addressing the highest-risk miles to form a portfolio of projects with improved overall RSE, timeline, or overall failure mitigation. As with the retrospective analysis of decision predictors, quantitative support of the total SH portfolio will serve to either correct or validate the existing decision process which relies heavily on SME and PSS individual decision making.

In conclusion, PG&E's system hardening framework leverages the results of the risk model effectively to prioritize and actualize mitigation work, scoping, and execution. After amending the initial workplan for 2021, the mileage goals for SH work were surpassed and the work completed was consistent with PG&E's stated goals. The GIRS-RT approves of the system hardening workflow and decision process and suggests developing supplementary quantitative analysis and support as a means of validation of the currently existing decision process.

II.D.12 Summary of GIRS-RT Findings for CRM

The GIRS-RT finds that the CRM model was fit for use and exceeded industry standards at the time of deployment. The CRM model is a significant improvement over the previous analogous used in WDRM v1, allowing probability scores to be compared across PG&E territories.

Features:

- CRM provides spatially resolved risk scores across PG&E Tier 2 and Tier 3 HFTD regions for vegetation driven wildfires.
- It combines data-driven ignition likelihood with Technosylva wildfire simulations and MAVF consequence values into a risk score.
- CRM was used to set priorities for SH.

Summary of Assessments:

II.D.3.A1 Masking of unburnable areas

The GIRS-RT recommends masking unburnable areas to focus on the area where ignition may occur and on the predictive values of features that are more meaningful for mitigation.

II.D.3.A2 Precipitation features and contrasting permutation importance between VRM and CRM

The GIRS-RT recommends including rainy season precipitation as a covariate and conducting comparison studies of covariates across different ignition sources.

II.D.3.A3 Integration of satellite fuel data

The GIRS-RT suggests PG&E consider satellite-derived vegetation water content to evaluate the fuel load and vegetation dehydration in future versions of WDRM.

II.D.5.A1 Permutation importance calculation for binarized, mutually exclusive categorial variables

The GIRS-RT recommends retaining the original categorical variables (such as conductor size or material) for importance tests rather than utilizing binarization.

II.D.5.A2 Missing data/incomplete datasets for certain asset-related covariates

The GIRS-RT reviewed the data used to calibrate the MaxEnt model and found missing data associated with aluminum conductors. The GIRS-RT recommendation is to complete the dataset to avoid bias in future models.

II.D.5.A3 Additional conductor variables for future consideration

The GIRS-RT recommends that PG&E explore the inclusion of additional variables, such as current density, average distance between poles, or cleaning frequency of insulators, for future versions of the conductor ignition likelihood estimation model.

II.D.6.A1 Independent validation of metrics for model performance

The GIRS-RT confirms that the CRM model's AUC score is above 0.7, indicating effective prediction of conductor-related ignitions despite low precision due to the low prevalence of ignitions and the necessity of a high recall threshold.

II.D.6.A2 Analyzing statistical distributions of individual covariate values

The GIRS-RT recommends that PG&E identify and utilize more covariates in which ignition values are statistically distinct from the background distribution of the covariate across the entire grid as this will facilitate the improvement of the predictive power of the model.

II.D.11.A1 Consider a retrospective analysis of SH decisions

With historical data of system hardening project approval, execution, risk reduction, and cost, analyzing which factors in the decision process led to successful risk mitigation projects could validate or inform the existing system hardening decision workflow.

II.D.11.A2 Apply an optimization process to design an entire portfolio of SH projects

The existing decision process for system hardening process involves factors such as MAVF risk, existing repair tags on the network, project cost; with only a finite amount of resources for system hardening work each year, creating a quantitative system to optimize a systemwide workplan could result in overall improved work efficiency.

II.E CoRE: Consequence of Risk Event

II.E.1 CoRE Overview

The Pacific Gas and Electric Company (PG&E) Wildfire Distribution Risk Model (WDRM v2) is a planning tool developed to set priorities for vegetation management (VRM) and system hardening (CRM) in PG&E territories on a time scale of one or more years. WDRM v2 estimates the risk $R(E)$ of an event E as the product of the likelihood of a risk event LoRE (i.e., the ignition probability $P(E)$) and the consequence of the risk event $CoRE = C(E)$:

$$R(E) = P(E) \times C(E)$$

The CoRE model assigns a consequence score to electric grid infrastructure-caused ignitions in high fire-risk regions of PG&E service territory.

This section focuses on the wildfire consequence model (CoRE). For the period covered by this audit (2021 and 2022 PG&E WMPs), the GIRS-RT finds that the CoRE model exceeds industry standards and is fit for use. WDRM v2 incorporates improvements over the previous model used by PG&E (WDRM v1) with respect to both the ignition likelihood and consequence models used to calculate risk scores.

The CoRE model consists of two components: the Technosylva wildfire simulation platform FireSim and the mapping of Technosylva outputs and other statistical and geospatial information to consequence scores. The CoRE scores are multiplied by ignition probability model values (LoRE) throughout the distribution grid to produce the WDRM v2 risk scores in Tier 2 and Tier 3 HFTDs.[95] While the fire simulations are only conducted in a grid of 200m x 200m pixels, for modeling purposes each of these pixels was subdivided into four 100-meter by 100-meter pixels in which CoRE scores are determined.

This section covers four topics: (i) use of the Technosylva wildfire simulation platform FireSim, (ii) mapping Technosylva and other geographical and statistical information to consequence scores using MAVF, (iii) a review of data used to obtain the consequence scores, and (iv) a geospatial comparison of Technosylva outputs and consequence scores to the historical record of fires which took place in the same locations obtained from the PG&E ignition database.

II.E.2 Consequence modeling: Technosylva

Technosylva, a wildfire modeling and risk mitigation company with over 25 years of experience, supplied fire simulation tools to all large California investor-owned utilities (IOUs) in 2021. Previously, in WDRM v1, PG&E used simulations from REAX Engineering but switched to Technosylva for WDRM v2. This decision was validated in part by comparing consequence scores generated by REAX and Technosylva based on inputs for a set of historically destructive fires,[96] where Technosylva resulted in a better correspondence of scores to historical outcomes than REAX. Additionally, the 2021 WDRM overview states that Technosylva offered improved fuel

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[95] *As determined by the California Public Utilities Commission (CPUC), available at https://www.cpuc.ca.gov/industries-and-topics/wildfires/fire-threat-maps-and-fire-safety-rulemaking.*

[96] *PG&E 2021 WDRM Overview, p. 132.*

models and incorporated a more comprehensive structure data set than REAX.[97] These are both valid reasons for PG&E to prefer Technosylva. Additionally, consistency with the modeling approaches of other CA IOUs is a step towards the development of a more unified risk assessment framework for utilities in CA.

Technosylva offers a suite of products for fire simulation. For the CoRE model, PG&E uses FireSim.[98] The software runs a fire simulation of specified duration for a given ignition point, resulting in a set of metrics characterizing fire behavior. The basic structure of the consequence model begins with running an ensemble of simulations under different weather conditions at each potential ignition point, computing the consequence score for each simulation, and calculating the average score over all weather scenarios for each ignition point. This furnishes a consequence score for each Tier 2 and Tier 3 location along the PG&E distribution network. These scores are subsequently combined with the LoRE model to produce a spatial map of risk scores.

II.E.3 Technosylva: modeling approach

To compute consequence scores, ignition points are placed across the PG&E distribution network in the 200m x 200m pixels amounting to just over 250,000 locations across the grid for wildfire spread simulations given the occurrence of ignitions in the pixels. At each location, a set of simulations are run for historical, worst-case weather scenarios. These scenarios are drawn from PG&E's 30-year historical record ranked by Fosberg Fire Weather Index, a commonly used metric for fire danger which incorporates temperature, humidity, and wind speed.[99] It should be noted that these worst-case conditions do not correspond to the conditions used to compute and model the probability of ignition (LoRE) at each ignition point. This mismatch between the conditions used to compute LoRE and CoRE was discussed in the GIRS-RT review of WDRM v2, Section II.B.7.A6.

Given ignition points and weather scenarios, Technosylva simulates 8 hours of fire progression. Fire simulations utilize data that describes local conditions, infrastructure, and population as inputs. Local conditions are characterized by weather data (wind, humidity, live fuel moisture), modeled fuel distribution, topography, and canopy density and height; the source and nature of these fuel data are reviewed below. Infrastructure data includes building footprints, population counts, distance to urban boundaries, and encroachment factors. The encroachment factors are developed by Technosylva to effectively reduce the rate of spread in urban fuel areas without a detailed urban fuel model.[100]

Technosylva uses a standard set of fuel models developed by the National Interagency Fire Center (Scott and Burgan 2005). The fire modeling approach is consistent with historical approaches based on the fire spread model of Rothermel (1972). Rothermel models are semi-empirical, utilizing a set of input data and sub-models to capture basic and more advanced aspects of fire propagation. Technosylva uses this basic model and standard sub-models while also integrating their own proprietary additions for features like rate-of-spread adjustment,

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[97] *PG&E 2021 WDRM Overview, p. 132.*
[98] *PG&E 2021 WDRM Overview, p. 120.*
[99] *Technosylva Historical Wildfire Risk Analysis (2020), p. 2-5.*
[100] *Technosylva Historical Wildfire Risk Analysis (2020), p. 6-8.*

evacuation/exposure mode, urban encroachment, and spotting.[101] The GIRS-RT notes that the majority of Technosylva's modeling approach is standard and validated by its common implementation across fire management agencies and simulation software. Due to their proprietary nature, GIRS-RT was unable to thoroughly review the design and performance of certain sub-models, and such evaluation is beyond the scope of the present audit.

For each weather scenario and ignition point, the 8-hour fire simulation outputs metrics characterizing the severity of the fire which include: the acres impacted (after 2h, 8h), the average flame length, the average rate of spread, the buildings impacted, and the population impacted. PG&E only uses the size of the fire, the fire behavior index (a combination of rate of spread and flame length), and the number of buildings impacted to place each outcome in certain consequence tranche to which a fixed consequence score is assigned.[102]

II.E.4 Assessment: Technosylva

Technosylva utilizes conservative, vetted models that are consistent with standard fire modeling approaches. In addition, they introduce proprietary sub-models to address more complicated dynamics. Overall, the GIRS-RT finds the approach is appropriate for fire simulation and is consistent with all other large California Investor-Owned Utilities (IOUs).

In documents produced by Technosylva, concerns are raised about averaging flame length and rate of spread across the fire, the use and development of encroachment parameters, and details of spotting and fuel moisture models.[103] External review by E3 raised concerns about using binned consequence scores and averaging consequence over all weather scenarios.[104] The GIRS-RT agrees with these concerns and suggests the following points for improvement or further analysis with respect to using Technosylva for the CoRE model.

II.E.4.A1 <u>Consider the distribution of consequences, not only the average</u>

When computing the consequence for a given ignition point, the only score utilized is the average consequence over all 452 simulations. Similarly, in computing the Fire Behavior Index (FBI), the flame length and rate of spread are averaged over the spatial extent of the fire. The behavior of these variables is not expected to be uniform, so the average is not expected to characterize the distribution of outcomes. The GIRS-RT recommends PG&E consider measures other than simple averages to better characterize the distribution of outcomes of both individual fire simulations and the ensemble of simulations. For example, at a given ignition location, the mean plus or minus one standard deviation of the consequence distribution could provide an estimate of the most likely range of consequence scenarios. Additionally, computing the arithmetic average of consequence scores, which are binned effectively on a logarithmic scale, may not be the correct aggregate statistic, and should be compared with, e.g., a geometric mean.

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[101] Technosylva Historical Wildfire Risk Analysis (2020), p. 11-13.
[102] PG&E 2021 WDRM Overview, p. 122-126.
[103] Technosylva Historical Wildfire Risk Analysis (2020), p 10.
[104] E3 Review of PG&E's Wildfire Risk Model Version 3 (2022), p. 14.

II.E.4.A2 Provide a benchmark for, or validation of, the urban encroachment factors

In computing the consequence for a specific simulation, the number of structures damaged can change the consequence tranche and subsequently drastically affect the consequence score. Therefore, the simulation of fires moving in the Wildland Urban Interface (WUI), with unique and varied fuel types, strongly affects the consequence scores of fire simulations. While basic documentation of the urban encroachment factor exists, the details and development are proprietary and inaccessible. The GIRS-RT recommends that PG&E determine a degree of confidence in the accuracy of these models especially as they pertain to WUI areas historically affected by California wildfires.

II.E.5 CoRE MAVF model

The wildfire consequence model (CoRE) used by PG&E for the WDRM v2 uses a Multi-Attribute Value Function (MAVF) methodology to estimate the spatial consequences of wildfire events within PG&E's Tier 2 and Tier 3 HFTD territory. The MAVF, developed in the RAMP proceedings, combines the consequences of various risk attributes associated with a risk event to create a single quantification of risk value. The MAVF is constructed based on several principles and reflects PG&E's risk modeling priorities. It uses a scaling function that converts a range of natural units (such as number of persons, billion dollars, etc.) associated with the risk attributes into a common, comparable, unitless risk score.[105]

The consequence model utilizes as inputs the following information at a pixel level: the local environmental conditions (described in Section II.E.7), the 452 worst historical fire weather days, the red flag warning (RFW) event records from 2015 to 2019, and a High Fire Threat District (HFTD) binary indicator.

The local environmental conditions and weather conditions are used in Technosylva FireSim to execute a series of fire simulations, as described in II.E.3. Each simulation is given a fire severity classification in accordance with Section 38 of the PG&E 2021 WDRM Overview.[106] The fire severity depends on fire size and damage to infrastructure, data which are output by FireSim. This fire severity classification is used in conjunction with the RFW records and the HFTD indicator to determine a pre-calibrated consequence value for the simulation from a look-up table (Table 8 of the PG&E 2021 WDRM Overview[107]). At a given ignition point, for specific values of the RFW and HFTD indicators, there are four possible consequence tranches for different levels of fire severity. Example MAVF values from this lookup table are listed below in Table II.E-1.

Finally, the average statistical risk-per-event, obtained from the WMP, is used to calibrate the consequence values obtained in the previous step. After the calibration process, the output of the model is a calibrated, dimensionless, consequence value for every pixel in the surroundings of the distribution network.

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[105] *Application of Pacific Gas and Electric Company (U 39 M) to Submit Its 2020 Risk Assessment and Mitigation Phase Report, p. 3-11.*
[106] *PG&E 2021 WDRM Overview, p. 125-126.*
[107] *PG&E 2021 WDRM Overview, p. 125.*

II.E.6 Assessment: CoRE MAVF Model

While the design and implementation of the MAVF scoring system is not included in the scope of the Local Conditions Audit, there are aspects of MAVF that impact the CoRE scores obtained in WDRM v2. Overall, the GIRS-RT finds that the CoRE MAVF model is appropriate for estimating the consequences of a wildfire ignition attributed to PG&E's distribution network during the period covered by this audit. However, three shortcomings are noted below, with suggested opportunities for improvements in future implementations.

II.E.6.A1 <u>MAVF assignment does not incorporate the local conditions except implicitly through consequence scoring</u>

The CoRE MAVF model incorporates a large amount of local information through the RFW records, the HFTD zoning, and local environmental covariates used as FireSim inputs. Furthermore, FireSim generates 452 detailed spatiotemporal simulation runs at each location resolving the details of potential fire spread behavior. However, the CoRE MAVF model uses the same, coarsely structured MAVF look-up table for all pixels to map consequence to numerical values. This potentially sacrifices a wealth of local information which may be useful in estimating risk and prioritizing mitigation. The GIRS-RT recommends that PG&E considers construction of multiple MAVF tables to better characterize the extent of consequences over the territory.

II.E.6.A2 <u>Extreme discontinuities in MAVF determination due to binning of consequence values</u>

The MAVF lookup table contains four categories of fire severity. The GIRS-RT finds these categories to be excessively broad, with large discontinuities in scoring between adjacent categories. As a result, very different fires can have a similar consequence attributed to them or very similar fires can result in vastly different consequence scores. Additionally, the use of the arithmetic mean to average consequence scores that differ by orders of magnitude may skew results towards higher consequence values.

Table II.E-1: CoRE lookup table for HFTD, RFW fire events.[108]

Category	Criteria	MAVF CoRE
Small fire	< 300 acres burned	0.06629
Large fire	> 300 acres burned	5.8599
Destructive fire	> 300 acres and 50+ structures, or FBI > 2	7110.2
Catastrophic fire	Destructive fire & serious injury	12825.4

Concrete examples are included below to illustrate these issues. Table II.E-1 lists consequence values for fires of each category (small, large, destructive, catastrophic) in HFTD areas under red flag warnings.[109] The categories are defined by sharp boundaries in the fire size and other metrics.

[108] *PG&E 2021 WDRM Overview, p. 125.*
[109] *PG&E 2021 WDRM Overview, p. 125.*

The MAVF CoRE values differ by orders of magnitude, e.g., large fires receive a fixed consequence score approximately 100x larger than that of small fires. This implies that fractional differences in the burned area of a given fire may result in enormous differences in the associated consequence scores. For example, consider a pair of outcomes where fire A burns 299 acres and fire B burns 301 acres. The burned areas differ by less than 1% while the consequence values differ by a factor of over 100. The coarseness of the consequence values also means that fires of drastically differing scope may receive identical consequence scores: a fire which burns 301 acres with an FBI of 3 has the same CoRE score as a fire which burns 1000 acres and 100 structures. While these outcomes seem intuitively different, the lookup table (above) may give them identical CoRE values.

Another issue that arises from the different orders of consequence magnitudes assigned to each fire severity category stems from using the arithmetic mean (the normal additive average) to aggregate the MAVF derived from each simulation into the pre-calibrated consequence for each pixel. To illustrate this, consider a location where 100 simulations are conducted in an RFW, HFTD pixel. Out of these, 90 result in small fires (MAVF = 0.06629) and 10 result in large fires (MAVF = 5.8599). Consequently, calculating the arithmetic mean across all events would give an average MAVF = 0.6457, which is 100 times larger than the consequence of 90% of the events. Alternatively, utilizing the geometric mean yields a result of MAVF = 0.103, which may provide a more accurate estimate of the true consequence carried by the pixels in the model, being much closer to the MAVF value of most events. The geometric mean is the *n*th root of the product of *n* numbers. When the values of a set of numbers are volatile and differ by orders of magnitude, as they do for the consequence scores, the geometric mean is a better measure of central tendency.

The MAVF calculation uses a nonlinear scaling function that is designed to amplify the consequences of catastrophic events.[110] The aim of this strategy is to prioritize low-frequency, high-consequence events, but not neglect the risks associated with high-frequency, low-consequence events. Though the intention behind choosing a nonlinear scaling function is appropriate, it results in disproportionate MAVF scores among the fire severity categories. Ideally, the choice of a nonlinear scaling function should not overly influence the MAVF score calculation.

The GIRS-RT recommends that PG&E consider the use of a continuous model to link the outputs of fire simulations to MAVF values. Alternatively, PG&E could expand the number of fire severity categories to address the issue of large discontinuities in the scores. Additionally, the averaging procedure for consequences scores, and sensitivity of the final risk score to the nonlinear scaling function in the MAVF calculation should be thoroughly evaluated.

II.E.6.A3 <u>Lack of considerations for the relative importance of different structure categories and egress procedures</u>

The CoRE model only considers the number of structures that were affected in each simulation, disregarding their relevance or criticality for the neighboring communities. Additionally, the model does not consider how a fire may affect the evacuation of an affected

[110] *Application of Pacific Gas and Electric Company (U 39 M) to Submit Its 2020 Risk Assessment and Mitigation Phase Report, p. 3-12.*

zone. Both these considerations are expected to impact the consequence value associated with a given fire.

The GIRS-RT recommends that PG&E considers the use of a weighted model that can incorporate the importance or criticality of different buildings. Additionally, the GIRS-RT recommends considering the interaction between wildfire behavior and the evacuation effort in the area to identify hazardous situations that would warrant a higher consequence score.

II.E.7 CoRE Datasets

This section reviews the datasets used in the CoRE model, which includes Technosylva FireSim covariates (weather, fuel, terrain, building, and demographic data), and some additional risk-per-event and geographical data for Red Flag Warning days (frequency statistics by location), and HFTD Tier 2 and Tier 3 designations.

II.E.8 Technosylva Covariates

Technosylva uses weather, fuel, terrain, and building data as input to FireSim. Fire simulations are conducted across the PG&E territory during the worst weather scenarios: a list of historical worst weather days selected from the past 30 years (1989-2018), primarily based on having a higher Fosberg Index.[111] The selection involves ranking days based on the Fosberg Fire Weather Index, calculated using temperature, wind, and humidity from the North American Regional Reanalysis.[112] The list of worst weather days is further supplemented by considering the occurrence of Diablo Winds from PG&E's Diablo Wind analysis. This list is further reviewed and compared with the fire data, resulting in a final list of 607 days, comprising a mix of traditional hot and dry days and strong Diablo and Santa Ana wind event days.

II.E.8.1 Weather data

Table II.E-2: Weather data used in the fire simulation.[113]

Parameters	Resolution	Source
U10: horizontal wind speed at 10 meters (m/s)	2 km and 1 hour	WRF (Weather Research and Forecasting Model) derived
V10: vertical wind speed at 10 meters (m/s)		
Mean_wtd_moisture_1hr (g/g)		
Mean_wtd_moisture_10hr (g/g)		
Mean_wtd_moisture_100hr (g/g)		
Live Fuel Moisture		

[111] *Technosylva – Historical Risk Analysis Technical Report (2020), p. 3.*
[112] *E3 Review of PG&E's 2021 Wildfire Distribution Risk Model, p. 107.*
[113] Technosylva, Wildfire Analyst: models & inputs. Technosylva (2022). https://www.sdge.com/sites/default/files/regulatory/OEIS-2022-04%20Attachement.pdf

The weather data are derived from the Weather Research Forecasting (WRF) model simulation, that uses initial and boundary conditions from Global Forecast System (GFS) model analysis. These weather data have a spatial resolution of 2km and a temporal resolution of one hour, which is further interpolated to a 30m raster size to provide input to FireSim.[114] This interpolation is conducted to reduce edge effect of the source 2km gridded data that enables a more realistic fire perimeter simulation. Table II.E-2 lists weather variables used in FireSim.

II.E.8.2 Fuel, terrain, and building data

Technosylva creates surface and canopy fuel data (Table II.E-3) using high-resolution imagery, available LiDAR & GEDI, and other imagery sources such as NAIP, Sentinel-2, and Landsat.[115] This is supplemented with field survey data to verify the fuels and to validate the fuels classification. The initial surface fuel data has been enhanced by Technosylva using an updated dataset from LANDFIRE 2016 to 2020.[116] This improvement aims to represent current fuels more accurately in California and enhance understanding of urban encroachment.

Table II.E-3: Fuel, terrain, and building data used in the fire simulation.[117]

Parameters	Resolution	Source
Herbaceous moisture content for 40 PFT calculate using weather data and flammability of the PFT	30m raster and yearly	(Scott and Burgan 2005)
Topography		High resolution imagery, LiDAR & GEDI, Sentinel 2 and Landsat, LANDFIRE 2016-2020
Canopy Cover (CC)		
Canopy Base Height (CBH)		
Canopy Bulk Density (CBD)		
Canopy Height (CH)		
Distance to urban boundary		
Building footprint	Polygon Footprints and yearly	Microsoft buildings data
Population count	90m and yearly	Oak Ridge National Laboratory LandScan data

[114] *Technosylva, Wildfire Analyst: models & inputs. Technosylva (2022). https://www.sdge.com/sites/default/files/regulatory/OEIS-2022-04%20Attachement.pdf*
[115] *Technosylva, Wildfire Analyst: models & inputs. Technosylva (2022). https://www.sdge.com/sites/default/files/regulatory/OEIS-2022-04%20Attachement.pdf*
[116] *Technosylva – Historical Risk Analysis Technical Report, p. 5.*
[117] Technosylva, Wildfire Analyst: models & inputs. Technosylva (2022). https://www.sdge.com/sites/default/files/regulatory/OEIS-2022-04%20Attachement.pdf

FireSim uses population count data from the Oak Ridge National Laboratory LandScan dataset at a 90 m spatial resolution. LandScan uses spatial data, imagery analysis, and dasymetric modelling to disaggregate census counts within administrative boundaries. The integration of nighttime imagery makes LandScan the preferred choice for accurate population data, especially in defining residential patterns in wildland and rural areas. In addition, Technosylva utilizes the Microsoft Buildings Footprint Dataset and enhances it by incorporating local high-resolution imagery data sources.[118] Table II.E-3 lists fuel, terrain, and building variables used in FireSim.

Additional consequence model covariates

In addition to the fire severity score determined from Technosylva outputs, the CoRE model utilizes various additional covariates to calculate the consequence score. These include HFTD (true or false) and red flag warnings (RFW). The HFTD shapefiles provided by CPUC and RFW shapefiles spanning from 2015 to 2019 are obtained from the National Weather Service.

II.E.9 Assessment: CoRE Datasets

II.E.9.A1 Usage of a robust and enhanced vegetation dataset

Technosylva creates a proprietary surface fuel dataset, incorporating a rich source of imagery data validated with field surveys for potential areas of concern. These data are further enhanced by integrating LANDFIRE data, generating a surface fuel and canopy dataset that is valuable for wildfire modelling and risk mitigation.

II.E.9.A2 Selection of worst weather days for simulation

PG&E's selection of worst weather days based on temperature, humidity, and winds is appropriate. The final list comprises 607 days, including a mix of hot and dry days and strong Diablo and Santa Ana wind events, chosen for fire simulations. These are down sampled for the consequence model, which utilizes only 452 of these worst weather days when calculating the consequence score.

II.E.10 Comparison of Technosylva and MAVF with Historical Ignition Fire Size Data

As a coarse evaluation of the CoRE model consequence scores, The GIRS-RT compared historical fire sizes obtained from PG&E ignition records with 1) modeled fire sizes derived from Technosylva simulations and 2) MAVF CoRE values.[119] Records of the 2014-2022 CPUC reportable ignition locations and corresponding fire sizes were provided by PG&E and CPUC.[120] PG&E also provided raster files with bands corresponding to different Technosylva fire size fractions and MAFV CoRE values.[121] Fire size fraction raster bands include 1) small fire fraction (<300 Acres), 2) large fire fraction (>300 Acres), and 3) destructive fire fraction (>300 Acres burning 50 or more

[118] Technosylva, "Wildfire Analyst Help Center". Technosylva (2023); https://help.wildfireanalyst.com/wfae/.
[119] PG&E 2021 WDRM Overview, p. 19-20, 119-133.
[120] PG&E, PGEFire Incident Data Collection2014 Report20150401.xlsx, PGEFire Incident Data Collection2015 Report20160401.xlsx, PGEFire Incident Data Collection2016 Report20170401.xlsx, PGEFire Incident Data Collection2017 Report20180401.xlsx, PGEFire Incident Data Collection2018 Report20190329.xlsx, PGEFire Incident Data Collection2019 Report20200401.xlsx, 2021_PGE Fire Incident Data Collection Report.xlsx, PGE 2022 CPUC Fire Incident Data.xlsx, PGE audit ignition data 20142020.csv.
[121] PG&E, pre_calibrated_mavf_core_2020_fbi_v2.1.tif, fire_size_probability_2019_fbi_v2.tif.

structures), which were each calculated from fire simulations.[122] In the table, the destructive fire fraction is included in the large fire fraction value (large fire fraction and small fire fraction sum to one).

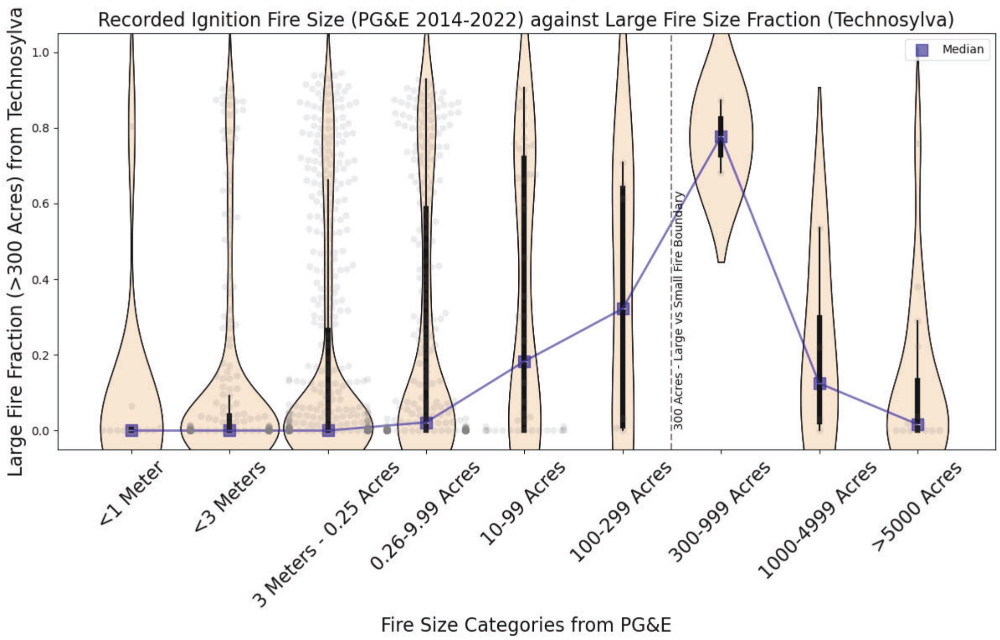

Figure II.E.1: Violin plots comparing large fire fraction from Technosylva with Fire Size categories for 2014-2022 ignitions. The blue squares, which represent median values at each fire size category, are connected by blue line to highlight trends with fire size. Light grey dots represent the ignition data. Darker grey dots at the edges of the violin plots indicate where data is most concentrated, and data points overlap. For example, the darker grey dots at the edges of the violin in the 0.26-99.9 Acres fire size category indicate that a sizable portion of the data have large fire fraction values that are near zero. The blue line marks the median large fire size fraction (Technosylva) for each fire size category (historical), and shows a consistent, increasing trend up to fires of intermediate size, but decreases, suggesting inconsistency, at the largest fire sizes. Ignitions of 2020 are solely from the PGE audit ignition data 20142020.csv file so 2020 ignitions may be underrepresented. Annual ignition reports were also provided for 2014-2022.[123]

The MAVF CoRE raster bands include 1) Safety CoRE, 2) Financial CoRE, 3) Reliability CoRE, and 4) Total CoRE scores. Total MAVF CoRE scores are calculated from scaled Safety, Reliability, and Financial CoRE values.[124] Safety CoRE constitutes 50% of the total MAVF CoRE score with values that are in natural units of equivalent fatalities. Reliability CoRE, which constitutes 25% of the total MAVF CoRE score, includes gas reliability (5%) with natural units of customers affected, and electric reliability (20%) with natural units of customer-minutes interrupted. The natural units of Financial CoRE, which constitute 25% of the total MAVF CoRE score, is the dollar amounts that correspond to the financial consequences associated with the modeled fires. Natural units of

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[122] *PG&E 2021 WDRM Overview, p. 19, 126; Historical Wildfire Risk Analysis (Technosylva) p. 3.*
[123] *PG&E Fire Incident Data Collection, retrieved from DRU12565.001.*
[124] *PG&E 2021 WDRM Overview, p. 19-20, 122-123.*

Safety, Reliability, and Financial CoRE are mapped to scaled units using scaling functions to calculate total MAVF CoRE scores for each pixel.

MAVF CoRE raster pixels are used to filter the ignition data to identify ignitions that lie within the MAVF CoRE pixels. The historical fire sizes associated with those ignitions are compared with the large fire size fraction obtained from the Technosylva fire simulations (Figure II.E.1). Median large fire fractions (blue line) from Technosylva outputs tend to increase with ignition size for fires <1000 acres, indicating successful estimation of fire size for the smaller burns (Figure II.E.1). However, the median large fire fractions decrease for fires >1000 Acres, which indicates that model outputs may underestimate the potential fire sizes in pixels that host ignitions that led to the largest fires.

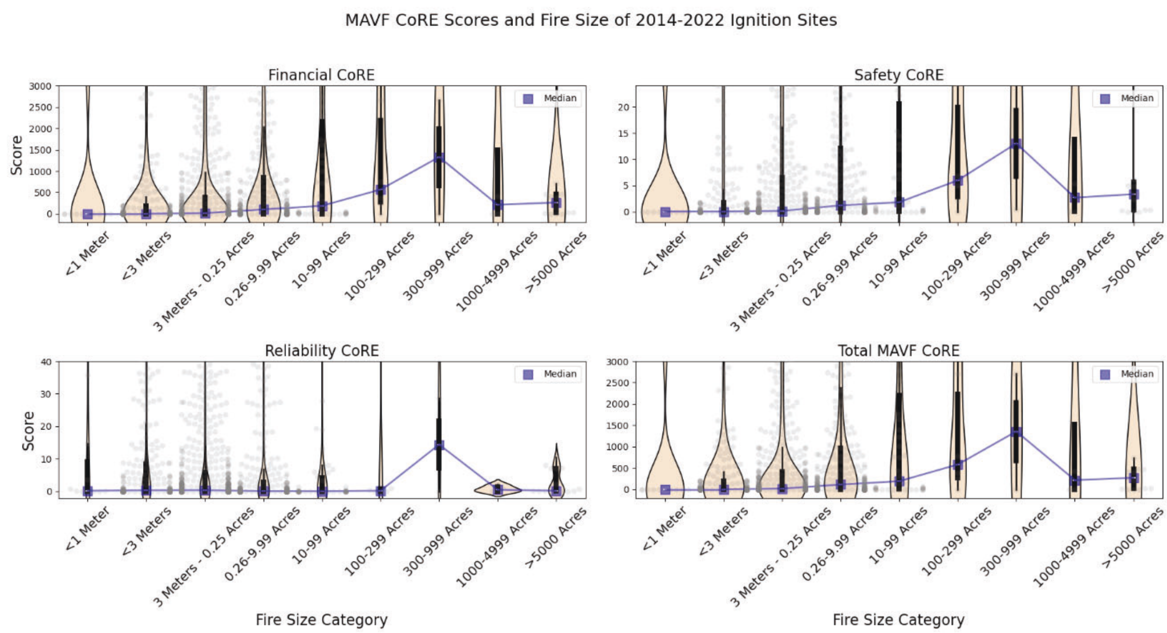

Figure II.E.2: Financial, Safety, Reliability, and Total MAVF CoRE values as a function of fire size for 2014-2022 ignition sites.[125] The blue squares, which represent median values at each fire size category, are connected by blue line to highlight trends with fire size. Portions of the violin plots and the ignition data (grey dots) extend beyond the range of the vertical axis to better display the median trend. Ignitions of 2020 are solely from the PGE audit ignition data 20142020.csv file so 2020 ignitions may be underrepresented. Annual ignition reports were provided for other years from 2014-2022.

The 8-hour run time of the fire simulations may underestimate fire size for larger fires.[126] While this run time may be sufficient for modeling fires that burn <1000 acres, increasing the duration of the simulations may better identify pixels that are more susceptible to hosting the largest fires.

As Technosylva model outputs are used to calculate MAVF CoRE scores,[127] the extent to which the MAVF CoRE values change with historical fire size (2014-2022 ignitions) is of interest. Median

[125] *PG&E Fire Incident Data Collection (2014-2022) and CoRE Data.*
[126] *PG&E 2021 WDRM Overview, p. 19,133.*
[127] *PG&E 2021 WDRM Overview, p. 19-20, 119-133.*

Financial and Safety CoRE values tend to increase with increasing fire size for ignitions that burn <1000 acres but drop for ignitions that burn larger areas, peaking in the 300-999 acres fire size category (Figure II.E.2). Similarly, median Reliability CoRE values peak in the 300-999 acres fire size category, which are otherwise close to zero for both larger and smaller fires (Figure II.E.2). Median Safety CoRE values show little relationship with fire size and all around zero (Figure II.E.2). By fire size category, median total MAVF CoRE values (Figure II.E.3) closely resemble the trend of median large fire size fraction values from Technosylva (Figure II.E.1). This indicates that the underperformance of the fire simulations, with respect to the largest fires, could downweigh MAVF CoRE consequence scores used to calculate risk.

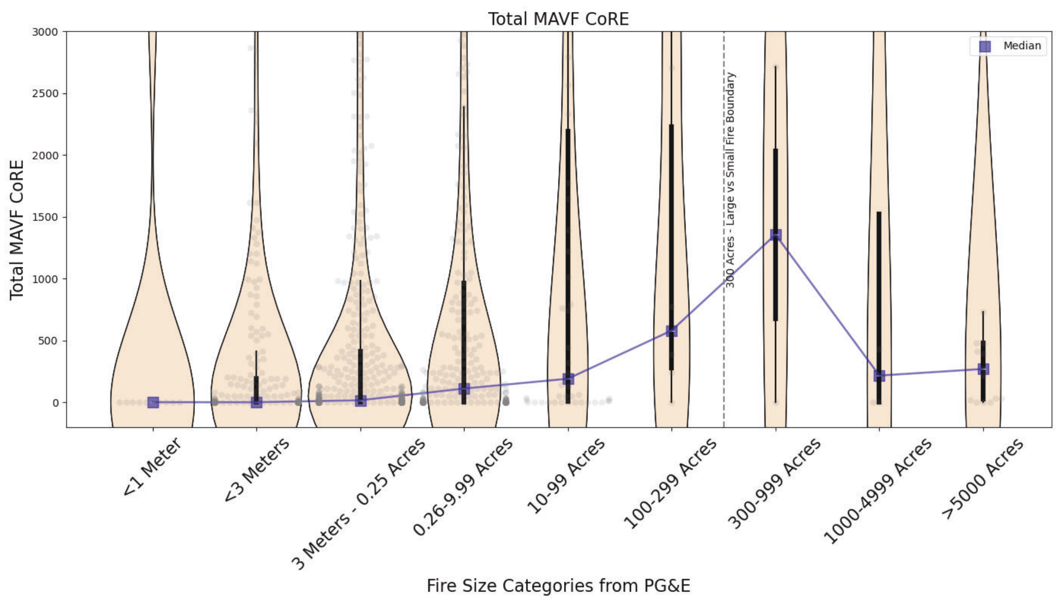

Figure II.E.3: Violin plots comparing statistics for the total MAVF CoRE values with historical fire sizes for 2014-2022 ignitions sites.[128] The blue squares representing median values for each fire size category are connected by a blue line to highlight trends with fire size. Portions of the violin plots and the ignition data (grey dots) extend beyond the range of the vertical axis to better display the median trend (blue curve). Ignitions of 2020 are solely from the PGE audit ignition data 20142020.csv file so 2020 ignitions may be underrepresented. Annual ignition reports were provided for other years from 2014-2022.

II.E.11 Assessment: MAVF scores and historical fire data

II.E.11.A1 Comparison of Technosylva and MAVF with historical ignition fire size data

Technosylva outputs are consistent with historical fire sizes for small to intermediate size fires (<1000 acres) but fail to capture trends associated with the largest historical fires (>1000 acres) (Figure II.E.1). The MAVF Financial CoRE, Reliability CoRE, and total MAVF CoRE scores also increase on average in regions with increasing historical fire size up to intermediate fire sizes (Figure II.E.2; Figure II.E.3) but decrease in regions which historically exhibited the largest fires. Longer Technosylva runs and/or data driven methods to pair modeled initial fire growth with

[128] *PG&E Fire Incident Data Collection (2014-2022) and CoRE Data.*

estimates of fire size on longer time scales are recommended to capture fire sizes and consequences of the largest fire sizes.

II.E.12 Summary of GIRS-RT Findings for the CoRE Model

The CoRE model assigns a consequence score to electric grid infrastructure-caused ignitions in high fire-risk regions of PG&E service territory. These consequence scores are numerical values specific to locations at 100-meter intervals along the distribution network. This approach simplifies the calculation of the overall risk score.

Features:

- WDRM v2 provides spatially resolved risk scores across PG&E Tier 2 and Tier 3 HFTD regions for vegetation and conductor driven wildfires.
- It combines data-driven ignition tools (LoRE) with Technosylva wildfire simulations and MAVF consequence scores (CoRE). Risk=LoRE x CoRE.
- The consequence (CoRE) model combines outputs from Technosylva with other geospatial information and data to compute numerical risk scores using generic MAVF lookup tables, which do not include local geospatial, demographic, egress, or infrastructure priority rankings.

Summary of Assessments:

II.E.4.A1 <u>Consider the distribution of consequences, not only the average</u>

The GIRS-RT recommends PG&E consider measures other than simple averages to better characterize the distribution of outcomes of both individual fire simulations and the ensemble of simulations.

II.E.4.A2 <u>Provide a benchmark for, or validation of, the urban encroachment factors</u>

Technosylva uses numerical factors to account for the slowing of fire spread in urban areas with heterogeneous fuels, but no data is shown to demonstrate that these factors faithfully represent fire spread through wildland-urban interface zones within the PG&E service area.

II.E.6.A1 <u>MAVF assignment does not incorporate the local conditions except implicitly through consequence scoring</u>

The CoRE MAVF model incorporates a large amount of local information through RFW records, HFTD zoning, and local environmental covariates for the FireSim inputs but uses a single, coarse MAVF look-up table for all pixels to map consequence values. The MAVF assignment does not include local geospatial, demographic, egress, or infrastructure priority rankings.

II.E.6.A2 <u>Extreme discontinuities in MAVF determination due to binning of consequence values</u>

The MAVF fire severity categories are found to be excessively broad. The GIRS-RT recommends using a continuous model, or additional categories, to more accurately link fire simulations with MAVF values.

II.E.6.A3 Lack of considerations for the relative importance of different structure categories and egress procedures

The CoRE model considers the number of structures affected in each simulation, disregarding their relevance or impact on community evacuation. The GIRS-RT recommends a weighted model that accounts for the criticality of different buildings and the interaction between wildfire behavior and evacuation efforts to better assess consequence scores.

II.E.9.A1 Usage of a robust and enhanced vegetation dataset

Technosylva creates a proprietary surface fuel dataset, incorporating a rich source of imagery data validated with field surveys, and is further enhanced by integrating LANDFIRE data, generating a surface fuel and canopy dataset that is valuable for wildfire modelling and risk mitigation.

II.E.9.A2 Selection of worst weather days for simulation

The selection of worst weather days follows a rigorous procedure, involving the ranking of historical days from the past 30 years (1989-2018) based on the Fosberg Fire Weather Index and supplementing this with Diablo Wind occurrences from PG&E's analysis. The final list includes both traditional hot and dry days as well as strong Diablo and Santa Ana wind event days, making it appropriate for fire simulation applications.

II.E.11.A1 Comparison of Technosylva and MAVF with historical ignition fire size data

The GIRS-RT recommends implementing longer Technosylva runs and/or data driven methods to pair modeled initial fire growth with estimates of fire size.

II.F Service Territory Fire-Threat Evaluation and Ignition Risk Trends

II.F.1 CPUC Guidelines for Service territory fire-threat evaluation and ignition risk trends

The CPUC provides a set of guidelines for the development of Wildfire Mitigation Plans (WMPs) by each California IOU. The three largest IOUs are: PG&E, SCE, and SDG&E. Within this audit, as a means of evaluating PG&E's approach, GIRS-RT has compared the approach of each of these utilities to evaluate aspects of PG&E's Local Conditions tools as they compare to industry standards in the state of California.

Service territory fire-threat evaluation and ignition risk trends is Section 4.2.1 of the WMP for each CA IOU. In this section CPUC asks for two principal responses: 1) discuss the fire-threat evaluation of the utility's service territory and evaluate whether an extension beyond the CPUC HFTD is warranted, and 2) list and describe any macro-trends impacting ignition probability and estimated wildfire consequence within the utility service territory. Each utility is asked to respond to these same prompts (*CPUC*, 2020).

For the first prompt, regarding extension of the HFTD classification, CPUC asks any modification to the HFTD to be supported by an assessment process and explanation of climatological or meteorological studies which support the HFTD modification.

For the second prompt, CPUC provides a list of 8 macro-trends:

1. Change in ignition probability and estimated wildfire consequence due to climate change.
2. Change in ignition probability and estimated wildfire consequences due to relevant invasive species, such as bark beetles.
3. Change in ignition probability and estimated wildfire consequences due to other drivers of change in fuel density and moisture.
4. Population changes (including Access and Functional Needs population) that could be impacted by utility ignition.
5. Population changes in HFTD that could be impacted by utility ignition.
6. Population changes in WUI that could be impacted by utility ignition.
7. Utility infrastructure location in HFTD vs. non-HFTD.
8. Utility infrastructure location in urban vs. rural vs. highly rural areas.

In this section, the GIRS-RT evaluates PG&E's response to these prompts and considers additional trends which may be worthy of future consideration. Modifications to the HFTD map are developed in the PG&E High Fire Risk Area (HFRA) map, used in operational considerations related to PSPS. The consideration of macro-trends consists of a well-thought out, science-supported analysis of key drivers of wildfire risk. In addition, since the responses of each CA IOU are publicly available, PG&E's responses are contextualized in comparison to the responses furnished by SCE and SDG&E in their 2020-2022 WMPs.

II.F.2 Construction of the HFRA Map

The PG&E High Fire Risk Area (HFRA) map is intended to inform scope, mitigation, and decision-making involving Public Safety Power Shutoffs (PSPS) under conditions of extreme fire hazard to mitigate the risk of utility triggered catastrophic wildfire within PG&E's service territory. Development and implementation of the HFRA map began in 2020[129] and continued through annual updates made during the period covered by this audit.

The HFRA map identifies regions of elevated risk of utility infrastructure ignition of catastrophic wildfires in wildfire season. The HFRA map builds on the California Public Utilities Commission (CPUC) High Fire Threat District (HFTD) map developed in 2018. The HFRA map makes incremental changes to the HFTD map by adding regions where the risk of utility-triggered catastrophic wildfire from an offshore wind event is high and removing regions where it is not.

The HFRA map is constructed via a detailed evaluation of polygons, referred to as candidate edit units (CEUs), in or adjacent to Tier 2 and Tier 3 regions of the High Fire Threat District (HFTD) map. Adjustments to the HFTD map to produce the HFRA map were made to 1) ensure that catastrophic wildfire risk is captured by the company's public safety power shut off (PSPS) program, 2) to remove areas that do not pose the risk of a catastrophic wildfire, 3) to account for changes in land use, climate, and PG&E's infrastructure, and 4) to inform internal teams to ensure PSPS project workplans are consistent with existing HFRA boundaries.[130]

All CEUs are reviewed for consistency by six criteria for removal or six criteria for addition. While a CEU will be removed if it meets at least two of the removal criteria, a CEU will be added by meeting one or more of the addition criteria.

Criteria for removal are as follows:

1. Is the area consistent with surrounding areas outside of the HFTD?
2. Does the area have low slopes / limited potential for an uphill fire propagated by an offshore wind event?
3. Does the area have low fuel loads?
4. Is the area isolated and does it have limited fire risk?
5. Is the area highly developed or comprised of low-risk land use?
6. Are there natural or anthropogenic fire breaks downwind of a potential fire driven offshore wind event?

Likewise, the criteria for addition are as follows:

1. Is the area consistent with surrounding HFTD areas?
2. Does the area have significant slopes / potential for an uphill fire propagated by an offshore wind event?
3. Does the area have a high fuel load?
4. Is the area in proximity to wildland fuels?
5. Is there development in high-risk land use areas?
6. Are there insufficient firebreaks given the exposure?

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[129] *Wildfire Mitigation Plan Update - PG&E 2022 Wildfire Mitigation Plan, p. 75.*
[130] *2020 HFRA Mapping Project, p. 1*

Each CEU was evaluated by four independent teams: (1) Internal (PG&E) Interdisciplinary Team, (2) Internal (PG&E) Wildfire Expert Integrated Assessment, (3) External (non-PG&E employees) Remote Assessment, (4) External (non-PG&E employees) Wildfire Simulation Assessment to review to assess the CEU for catastrophic wildfire potential.[131]

The HFRA map and annual updates have been implemented as part of the PG&E Wildfire Mitigation Plan since 2020. The updates resulted in some additions to the HFRA map, and some removals. The net change in the number of customers added/removed to/from potential PSPS for 2020 and 2021 is listed in the table below, taken from PG&E's 2022 Wildfire Mitigation Plan, Section 4.2.1.a.

TABLE PG&E-4.2-3:
SUMMARY OF PG&E HFRA MODIFICATIONS IN 2021

	2020 Modifications	2021 Modifications
Area (square miles)	+3,280	-30
Overhead Transmission Circuit Miles	+230	-30
Overhead Distribution Circuit Miles	+610	-170
Customers in PSPS Scope	+3,000	-36,000

Figure II.F.1: Net change in the area, transmission and distribution circuit miles, and number of customers added/removed to/from potential PSPS for 2020 and 2021. Source: PG&E's 2022 Wildfire Mitigation Plan, Section 4.2.1.a.

II.F.3 Assessment: HFRA Map

The GIRS-RT concludes that the approach used to construct the HFRA Map is sound and thorough. The criteria focus on the risk of catastrophic wildfire spread given an ignition and cover important features including slope, fuel load, proximity to wildland fuels, and the presence of sufficient firebreaks. PG&E increased the number of customers in the PSPS scope by 3,000 in 2020 and decreased by 36,000 in 2021. The reduction of approximately 33,000 customers from the PSPS scope contributed to significantly reducing the number of customers affected by the PSPS outages.

II.F.3.A1 Incorporation of ignition probability to HFRA addition/removal

The GIRS-RT suggests that future modifications to the HFRA map also incorporate ignition likelihood as one of the addition/removal criteria. The existing criteria are based on the risk of catastrophic wildfire spread, and do not consider ignition likelihood. The GIRS-RT recommends consideration of factors related to ignition probability, such as the presence of utility assets, fire history, wind patterns, tree height, and other covariates used in VRM and CRM to make the criteria more comprehensive. However, to avoid double counting, incorporation of ignition-

[131] *Revising the High Fire Risk Area (HFRA), Utility Bulletin: PSPS-1000S-B001, Published 08/03/2023, p. 2.*

related criteria into HFRA must consider the ways ignitions are factored into other PSPS-related operational models.

II.F.4 Fire Threat Evaluation and Ignition Risk Macro-Trends

As part of the preparation for PG&E's 2021 and 2022 Wildfire Mitigation Plan (WMP) report, CPUC requested consideration of macro-trends impacting ignition probability and estimated wildfire consequence within the service territory. PG&E responded with extensive, thoughtful, and well referenced comments on factors that will impact the ignition probability and wildfire consequences within the service territory in the upcoming years. PG&E's response to CPUC's list of macro-trends is summarized below.

Regarding the effect of climate change on ignition probability and wildfire consequences, several trends are mentioned. For example, the prevalence of warmer winters in California is reducing snowpack, consequently decreasing the water available during early summer. Reduced water availability induces stress on vegetation and increases the amount of dry fuel. This is compounded with warmer, and dryer fall and winter months, resulting in an extended fire season. Moreover, northeast winds in northern California during fall and winter can now increase the ignition probability if coupled with stressed vegetation and dryer conditions, even if temperatures are low.

Regarding the presence of invasive species, bark beetles are mentioned as an important factor in decreasing forest health and therefore increasing both the ignition probability and the estimated wildfire consequence. Other native insects are also mentioned as risk factors, since under conditions of environmental stress they may create similar hazardous situations. In addition to insects, invasive plants are considered due to their capacity to displace more weather-resistant native vegetation and therefore increasing the density of more flammable fuels in the service territory.

In trends related to population changes, PG&E's response mentions that it is likely for population to grow in Wildland Urban Interface (WUI) and/or HFTD areas within their service territory in the upcoming years. In relation to electrical infrastructure, the net-addition of infrastructure or the breakdown of assets between HFTD and non-HFTD areas is not likely to change significantly in the near future. However, when new or current infrastructure is added or repaired in or near HFTD territory, the implementation decisions will be made in agreement with existing resilience and mitigation programs within the company.

II.F.5 Assessment: Fire Threat Evaluation and Ignition Risk Macro-Trends

The GIRS-RT agrees that the list of macro-trends captures many important factors that will be relevant in the upcoming years for the estimation of ignition probability and wildfire consequence, and concludes that PG&E provided a thorough, well-referenced, science-based review.

In addition, for future versions of the WMP, the GIRS-RT suggests the following macro-trends may also be of interest to CPUC and the IOUs.

II.F.5.A1 New demand from electromobility and associated risk of conductor failure

The number of electric cars in California is steadily increasing (EIA 2024). This will certainly lead to an increase in household electricity usage, as the population replaces traditional fuel sources with electricity for commuting. Much of this energy will be delivered through the existing utility networks. Demand contributes to conductor failure rates (Vasquez and Jayaweera 2018), so it is useful to consider the effect of increased electromobility on wildfire risk.

The GIRS-RT suggests considering the effect of increased electromobility for ignition probability. This factor becomes particularly important if it is considered in conjunction with the expected population increase in fire-prone areas.

II.F.5.A2 Variability in fuel maps due to environmental changes

Vegetation on the landscape is in a constant state of change due to many factors, including seasonal growth patterns, changes in land use, past wildfires, regeneration, and climate change. For purposes of risk assessment and mitigation, the GIRS-RT recommends consideration of the impact of the changes in fuel conditions over time on both short- and long-term wildfire risk.

The GIRS-RT recommends the revision and update of fuel maps taking into consideration past fires, ecological factors, and changing land use.

II.F.5.A3 Risk induced by new monitoring approaches

The adoption of new monitoring approaches to inspect electric infrastructure and surrounding vegetation could increase the ignition probability if the risks associated with these methods are not properly assessed. An example of this is the use of unmanned aerial services (UAS), such as drones, for aerial inspection tasks. The use of drones near powerlines constitutes a relevant risk factor towards conductor-induced ignitions. While PG&E does mention[132] that there are currently initiatives to assess conductor strike associated risks, this risk should be explicitly considered in future ignition probability models.

Additionally, the dependence on novel remote monitoring approaches, such as satellite imagery or LIDAR captured through UAS, may replace current inspection performed on the ground. While remote monitoring approaches present several advantages, it is necessary to consider the potential risks derived from increased dependence on technology, the decrease in local, in-person awareness, and potential hazardous situations that may be left undetected.

The GIRS-RT recommends the assessment of risks derived from new, technological monitoring approaches and their explicit inclusion in the ignition probability model for future versions of the WMP.

II.F.6 Comparison to Other IOUs: Response of Southern California Edison

SCE's service territory borders the PG&E service territory, encompassing the southern transverse ranges, parts of the Central Valley, Owens Valley, Mojave Desert, and greater Los Angeles area. Historically, SCE developed its own fire danger maps. These were subsequently combined with the HFTD maps alongside CAL FIRE hazard zone maps to create an amalgamated

[132] *PG&E 2022 Wildfire Mitigation Plan, p. 834.*

fire danger map across the SCE service territory. However, in 2018, SCE conducted a review of its non-CPUC high-fire risk areas. The review ran REAX fire simulations on these areas to determine whether they represented an equivalent fire risk to Tier 2 or 3 HFTD. The result was a recommendation to remove 99% of all non-HFTD areas. Areas targeted for removal were principally located in the high Sierra and Inyo ranges, along with the northern escarpment of the San Gabriel range. As of the 2020-2022 WMP, SCE's high fire risk map was essentially equivalent to the CPUC HFTD tier 2 and 3 map (Southern California Edison 2020).

In their analysis of trends influencing ignition probability (Table 19 in SCE WMP; *SCE 2020-2022 WMP*), SCE highlights climate change as a main driver of increased wildfire risk. This link is supported by multiple cited studies. They claim that despite correlations between wildfire risk and other factors (such as invasive species), climate change is the primary driver of risk and root cause of these correlations. In particular, a *Proceedings of the National Academy* study is cited (Hart et al. 2015) which proposes that bark beetles are not a direct driver of increased burned area but are instead correlated with climate factors like increased temperatures and evapotranspiration. SCE does not identify any specific population trends in HFTD or WUI areas other than a 2% overall population growth rate from US census data. They do not model changes in ignition probability or consequences under future climate scenarios, but account for normal load growth as it affects their standard mitigation practices in HFTD areas.

II.F.7 Comparison to Other IOUs: Response of San Diego Gas & Electric

SDG&E monitors areas in its service territory outside HFTD for increased wildfire risk. In their 2020-2022 WMP, they find no areas in which fire risk is elevated to the level of Tier 2 HFTD. SDG&E therefore does not operate with any amendments to the CPUC HFTD classification.

In discussing macroscopic trends, SDG&E reports that the summer of 2020, being the hottest on record, led to decreased fuel moisture and accordingly elevated wildfire risk across its service territory. SDG&E mentions the role of invasive beetles weakening trees as well as the prevalence of the invasive and highly flammable eucalyptus trees in their service area. They claim that the main danger posed by these species is tree strikes on electric lines, mitigation of which is handled by the line inspection and hardening procedures already established in their WMP. SDG&E notes that HFTD population territory increased 13% across their service territory and includes data summarizing the growth of electric assets in HFTD, WUI, and non-HFTD areas of the service territory, but do not identify specific trends in their written WMP (San Diego Gas & Electric Company 2020).

II.F.8 Assessment: Service territory fire-threat evaluation and ignition risk trends and comparison to other IOUs

II.F.8.A1 <u>Robust HFTD classification framework</u>

In the GIRS-RT's assessment, PG&E's development of a robust framework for modification of the HFTD classification exceeds industry standards for updates to the CPUC HFTD map during the period of this review. Notably, PG&E's service territory encompasses a wider range of climatological regions when compared to the service areas of other IOUs (which cover a much larger area of arid, rocky desert). Other IOUs do not report any significant modifications of the HFTD classification as of 2021, while PG&E developed the HFRA map.

II.F.8.A2 Science-supported analysis of risk trends

PG&E also responds with an in-depth, science-supported analysis in their reporting of macroscopic ignition risk trends. All utilities identify climate change as a driver of reduced fuel moisture, but PG&E provides the most support for their analysis. Both SCE and SDG&E do not analyze changes in population distribution beyond basic population growth provided by census data; PG&E presents a thorough analysis of modern trends due to multiple factors (housing prices, COVID-19, etc.) and provides support for these claims.

The GIRS-RT finds that the robust methodology and in-depth, science-backed response provided by PG&E in their 2021 WMP exceeds industry standards for the tool under review. The GIRS-RT notes that these utilities face differing levels and concentrations of risk due to the environmental, climatological, and demographic differences in their service areas, but that regardless of these differences, the fire-threat evaluation laid out by PG&E represents an excellent evaluation of fire threat and ignition risk macro-trends.

II.F.9 Summary of GIRS-RT Findings for the Service Territory Fire-Threat Evaluation and Ignition Risk Trends

CPUC asked PG&E for two principal responses: 1) discuss the fire-threat evaluation of the utility's service territory and evaluate whether an extension beyond the CPUC HFTD is warranted, and 2) list and describe any macro-trends impacting ignition probability and estimated wildfire consequence within the utility service territory. The GIRS-RT asserts that the construction of the HFRA map from the HFTD map and subsequent revisions are warranted. The process behind this refinement to the HFTD map involves detailed evaluations of each adjustment based on sound criteria, and a rigorous approval process from both internal and external teams. Adjustments beyond HFTD better capture areas that are more prone to catastrophic wildfires and reject regions that are not. PG&E has additionally identified macro-trends associated with ignitions such as climate, invasive species, fuel density, moisture, population changes, infrastructure location, and more. PG&E has incorporated these influences in their decision-making for wildfire risk mitigation.

Features:

- The Service Territory Fire-Threat Evaluation model provides a robust approach for HFRA construction involving multiple teams and independent validation of results.
- The HFRA map construction enables PG&E to include catastrophic wildfire risk zones in the company's public safety power shut off (PSPS) program, remove areas that do not pose the risk of a catastrophic wildfire, account for changes in land use, climate, and PG&E's infrastructure, an inform internal teams to ensure PSPS project workplans are consistent with existing HFRA boundaries.
- The responses from PG&E to the Ignition Risk Macro-Trends posed by CPUC present an extensive, thoughtful and well-referenced understanding on factors that may impact the ignition probability and wildfire consequence within the service territory in the upcoming years.

Summary of Assessments:

II.F.3.A1 Incorporation of ignition probability to HFRA addition/removal

The current criteria mainly focus on the risk of catastrophic wildfire spread, and the GIRS-RT recommends incorporating ignition probability factors to make them more comprehensive.

II.F.5.A1 New demand from electromobility and associated risk of conductor failure

As electromobility increases in California, electricity demand, and stress over the existing network is bound to increase as well. The GIRS-RT suggests considering the effect of increased electromobility for ignition probability.

II.F.5.A2 Variability in fuel maps due to environmental changes

The GIRS-RT recommends regularly updating fuel maps to account for the impact of changing fuel conditions, past fires, ecological factors, and land use changes over time on both short- and long-term wildfire risk.

II.F.5.A3 Risk induced by new monitoring approaches

The use of drones, remote monitoring units, and other novel system monitoring approaches may introduce new risk factors with the potential to lead to line failures, such as a drone impacting a conductor or a monitoring device failing and leading to undetected outages or ignitions.

II.F.8.A1 Robust HFTD classification framework

PG&E's development of a robust framework for modification of the HFTD classification exceeds industry standards for updates to the CPUC HFTD map during the period of this review.

II.F.8.A2 Science-supported analysis of risk trends

The GIRS-RT finds that the robust methodology and in-depth, science-backed response provided by PG&E in their WMP for analyzing fire threat and ignition risk macro-trends exceeds industry standards.

II.G Transmission Operability Assessment (TOA)

Reliable assessment of the resilience of the transmission network to wind is critical for PG&E's risk-informed decision-making process. The Transmission Operability Assessment Model (TOA Model) is an operational model applied to PG&E's transmission network that estimates the probability of an asset failure with the presumption that a failure leads to an ignition. The methodology is derived from the performance-based engineering framework supported by the Pacific Earthquake Engineering Research (PEER) program, which is comprised of research and industry experts who have extensively published peer-reviewed technical papers related to asset resilience.[133]

As part of the development of the PG&E Wildfire Safety Plan, PG&E contracted the consulting firm Exponent to develop a framework to perform and support Asset Management (AM) and Operability Assessment (OA) of the transmission network within its service territory. The framework consists of two distinct models that can be used to perform operability assessment and asset management. The first model estimates the fragility curves of assets in the network with a given demand. The fragility curve represents the probability of failure of the asset (y-axis) when subjected to a demand (x-axis). In this case, the demand is the local 3-second wind gust speed. The second model is the hazard curve, which estimated annual frequency of gust events (y-axis) as a function of wind speed (x-axis). The hazard curve is unique for each location of interest within the service territory and is developed by using daily wind speed percentiles provided by PG&E Meteorology, fitted to extreme value (Gumbel) distributions by Exponent.

The 2021-2022 framework has two use cases:

Operability Assessment (OA): The fragility curve of an asset can be used in combination with the weather forecast to compute the probability of failure over the scope of the forecast. This can be further combined with the Fire Potential Index (FPI) to form a model that PG&E denotes as the Catastrophic Fire Probability model (CFP_T). The CFP_T model is reviewed in Section 0. The purpose of the TOA Model is to scope Electric Transmission Public Safety Power Shutoff (PSPS) events.[134]

Asset Management (AM): The fragility and hazard curves of an asset can be combined[135] to compute its annual probability of failure, which can be multiplied by a consequence value to compute the annualized risk associated with the asset. The consequence value is derived from the same model used in the distribution network (CoRE model, reviewed previously in Section II.E). This annualized risk is then compared among assets in the transmission network to guide inspections and help prioritize repairs. In accordance with PG&E, the risk ranking methodology is not used to start new projects (i.e., replacement of infrastructure). The AM application is the focus of this section.

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[133] *PG&E 2021 Wildfire Mitigation Plan Report (Rulemaking 18-10-007; February 5, 2021), p. 139.*
[134] *PG&E 2021 Wildfire Mitigation Plan Report (Rulemaking 18-10-007; February 5, 2021), p. 136-138.*
[135] *The combination of the fragility and hazard curves is done through a mathematical operation known as "convolution".*

II.G.1 Modeling Framework

The transmission OA and AM models make use of a fragility curve, representing the probability of failure based on a given wind gust speed. Figure II.G.1 depicts examples of fragility curves for a new, degraded and repaired assets.

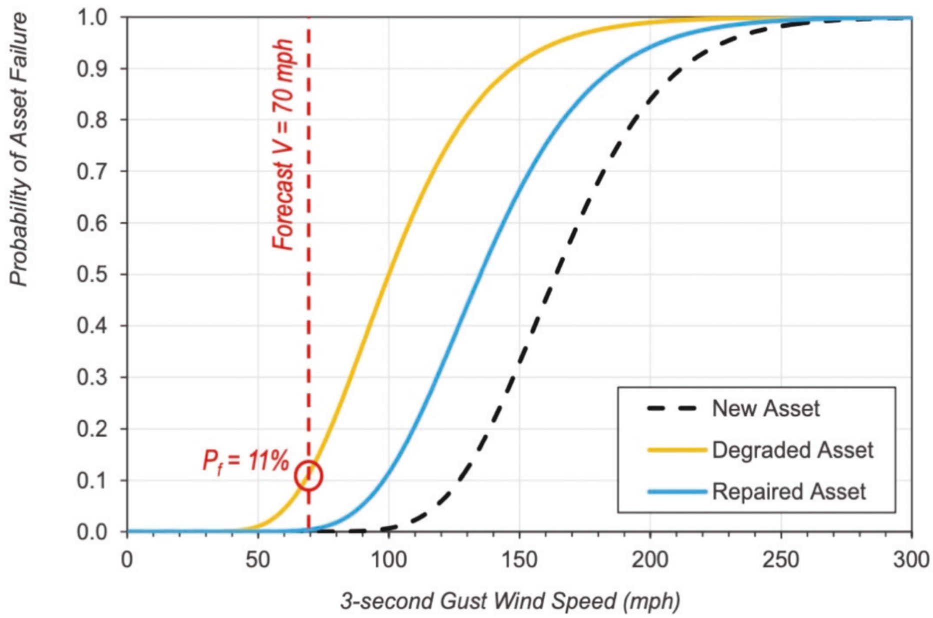

Figure II.G.1: Fragility curves for a new, degraded, and repaired asset. The probability of failure may be read off the curves at any given wind speed. The OA/AM framework provides a procedure for adjusting these curves based on asset data.[136]

In this section, the construction of the fragility curves associated with assets and sub-assets is reviewed and assessed. The model framework provides a method to construct baseline fragility curves, adjust them according to historical performance data, and translate qualitative and quantitative inspection data into numerical adjustment of each sub-asset's associated fragility curve. Figure II.G.1 shows example fragility curves of new, degraded, and repaired assets. The red line denotes a given wind speed, from which the probability of failure may be read directly off the value of the fragility curve.

The framework defines fragility curves as functions of wind gust speed which depend on two parameters: the median strength and the uncertainty (or dispersion).[137] These parameters define a lognormal distribution of strengths whose cumulative distribution function forms the fragility curve. The modeled fragility curves are constructed by the following procedure and in the order given below:

1. Baseline fragility curves are computed for each sub-asset of a larger asset in the transmission network. These curves are calibrated to match the expected design strength.
2. Bayesian updating is performed on the fragility curves, powered by the empirical wind/outage data available for the asset in question.

[136] *Operability Assessment Model Overview (2021), p. 2.*
[137] *Operability Assessment Model Overview (2021), p. 3.*

3. For a given sub-asset, the median strength parameter and uncertainty parameter are updated according to inspection results, environmental information, and other asset data.
4. Sub-asset fragility curves are combined into a composite fragility curve for an entire asset.

In the following sections, each step of the procedure is reviewed, and the framework is assessed.

II.G.1.1 Generation and calibration of baseline fragility curves (step 1)

Baseline values for the median strength and uncertainty must be chosen before adjustments are made either by Bayesian updates or by the explicit, physical degradation models. The initial values of the uncertainty parameters are fixed, constant values which depend only on the material type (either wood or steel).

In contrast, the initial values of the median strengths are calibrated based on the annual failure probability of the asset type, resulting in calibrated values for, e.g., steel or wood structures. Annual failure rates are computed by a convolution of the fragility curve (defined by the median strength and uncertainty), and the wind hazard curve. The calibration step selects the median strength such that the annual failure rate of the asset matches a predefined value. These values are determined from publicly available literature on reliable electric grid design. The framework documentation cites two such references: "Reliability-Based Design of Transmission Line Structures: Final Report, Publication EL-4793" (Electric Power Research Institute), and "Reliability-based Design of Utility Pole Structures" (American Society of Civil Engineers). This calibration step requires convolving the fragility curve with some wind hazard curve. PG&E indicated that all steel and wood structures have a common calibrated baseline, which means the same wind hazard curve was used to generate all calibrated annual failure probabilities. The specific wind hazard curve used for calibration was associated to an asset in Red Bluff, CA, the same location used to develop the reliability index in the Electric Power Research Institute study.

The calibration step ensures that the median strength baselines are consistent with commonly accepted design standards. However, these baseline values are generally less conservative than what would be computed if baseline values were chosen in strict adherence to CPUC General Order 95 (GO 95). Published in 2020, GO 95 details regulatory requirements for overhead line construction by California utilities and forms the backbone for all compliance requirements on PG&E's transmission network hardware.[138] According to GO 95, asset strength is generally computed as the required strength multiplied by the prescribed, regulatory safety factor. The framework documentation notes that this procedure results in overly conservative estimates and instead uses this calibration step to generate more accurate baselines.

II.G.1.2 Bayesian updating (step 2)

Bayesian updating is the process used to refine the fragility curves of a sub-asset based on the past performance of a sub-asset. The wind fragility curve originally assigned to each sub-asset is based on the performance expectation of a new, healthy asset. However, PG&E's wind-induced

[138] *Rules for overhead electric line construction: General Order No. 95, California Public Utilities Commission.*

outage record suggested that some circuits may have performed better or worse than expected, necessitating modifications to the original fragility curve.

Bayesian updating begins with the formulation of prior probability distributions to describe the state of knowledge about the unknown quantities of interest before accounting for available data.[139] In assessing the vulnerability of structures to wind loads, the unknown quantities of interest are the median strength and the uncertainty/dispersion parameter, which together define the fragility curve. In the TOA framework, the prior distributions of median strength and uncertainty characterize a new and healthy asset calibrated to design standards. These prior distributions are updated based on the historical wind and outage data. Note that asset specific wind data is used in the Bayesian updating, while outage data is used at line level (a lower resolution than the asset level).

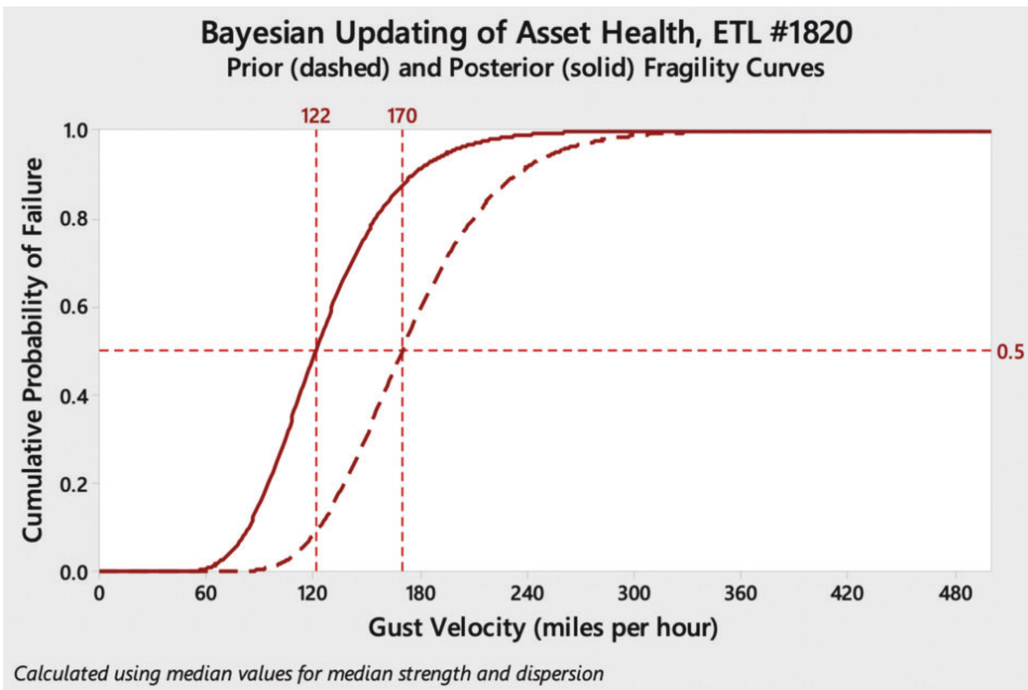

Figure II.G.2: An example of Bayesian updating performed on the prior (dashed) curve for wind/outage data with some observed outages. The resulting curve (solid) demonstrates generally increased probability of failure, reflecting the known performance of the asset.[140]

Statistically, asset response to demand (i.e., maximum daily 3-second wind gust) is modeled as a binary event: an asset/sub-asset either fails or does not. The probability of failure is the value of the fragility curve at the given wind gust speed. For a given asset, PG&E has collected historical wind and outage data. Viewing each day as another potential failure event, the historical record of failures and associated wind speeds contains information about the empirical failure probability of a given transmission network asset at the wind speed for that day. Historical data are viewed as samples from the true fragility curve of the asset and are used to bring the modeled fragility curve closer to observational truth. In practice, Bayesian updating takes in a calibrated

[139] *Operability Assessment Model Overview (2021), p. 22.*
[140] *A Framework for Risk-Based Transmission Line Asset Managements and Operability Assessment prepared by Exponent, p. 42*

fragility curve for a given sub-asset (the prior) as well as the historical wind/outage data from the specific asset. The framework then carries out a series of mathematical operations to define and maximize a likelihood function, a common object in Bayesian statistics. The output of the mathematical process is a new, updated fragility curve (the posterior) which is understood to be more consistent with the observed failures (or lack thereof) for the specific asset and the historical wind profile it experienced. An example of a prior fragility curve and its adjusted posterior is included in Figure II.G.2.

In the version of the framework considered in the audit, this updating step is performed on the calibrated fragility curves associated with new assets. There is no mathematical reason why the updating could not be performed after applying the physical models, but the present ordering was chosen by the modelers. The GIRS-RT recommends reviewing and validating the location of this updating step.

II.G.1.3 Adjustment of fragility parameters through degradation models (step 3)

After baseline, calibrated, fragility curves are constructed, the Bayesian updating process further adjusts fragilities based on outage/wind data for specific assets. The final adjustment uses field information: asset inspection data, environment data, and asset age/repair data, to again adjust both the median strength and uncertainty.

The median strength adjustment is comprised of two types of analysis: 1) visual inspection results and 2) a design check. Visual inspections give a condition code—a number between 1 and 5—to each sub-asset. These codes are converted into multiplicative adjustment factors for the median strength. An additional model for wood poles analyzes the remaining healthy wood cross section and provides an auxiliary adjustment.

The design check principally involves compliance with GO 95. The adjustment factor is computed as a ratio of the designed asset strength to the minimum required strength for GO 95 compliance. The quantification of the designed asset strength requires a detailed engineering analysis (sag-tension) combined with the GO 95 prescribed safety factor. This ratio, once computed, is multiplied by the median strength.

Median strength adjustments therefore incorporate basic field inspection results (condition codes, wood pole diameters) alongside design strength relative to regulatory requirements. As GO 95 regulations are not involved in the calibration step, their integration in the median strength adjustment is crucial to ensure that the model penalizes assets which border on non-compliance and rewards those whose strength exceeds the regulatory requirements.

The uncertainty parameter adjustment is a function of asset age. Any given asset has a design life: the age at which the uncertainty in asset strength is so high that it should be replaced or re-certified. The framework models uncertainty as increasing with age at an increasing rate. At zero age, the uncertainty has a fixed value, while the rate of increase is calibrated to GO 95 compliance. In particular, the uncertainty at the design life is set such that the corresponding fragility at a specific wind pressure (8 psf) is equivalent to the fragility for baseline uncertainty but with a 33% reduction in median strength. GO 95 requires asset replacement or reinforcement if strength deteriorates by 33% or more, so the uncertainty model is calibrated in such a way that at the design life, the uncertainty reaches a value which requires replacement under GO 95.

While each asset has a nominal design life, adjustments to design life are made according to the aggressiveness of the asset environment. Multiple corrosion sub-models are used which compute design life reductions; these and other reductions are aggregated to adjust the design life and hence evolution of uncertainty over the asset's lifespan. Additionally, outage and splice density on a given line contributes to design life degradation.

II.G.1.4 Sub-asset fragility curve estimation (step 4)

In the TOA framework, an asset may be composed of multiple sub-assets, each of which have an independently computed fragility curve. In this context, sub-asset refers to components of similar functionality, such as insulators or conductors. On the other hand, assets refer to the combination of these sub-assets at a single tower or pole structure to form the system in consideration. Consequently, to compute the aggregate asset fragility, the sub-asset curves must be combined in a statistically sound manner. The approach used by PG&E is to compute the average between two candidate aggregate asset curves.[141]

The first candidate curve is computed, assuming the failure of any sub-asset will cause the failure of the asset. Consequently, the asset probability of failure at a given wind speed can be computed as $p_f^I = 1 - \prod_j (1 - p_{f,j})$ where j is an index over the sub-assets and $p_{f,j}$ is the failure probability of sub-asset j. The resulting probability of failure for the combined asset will be higher than any independent sub-asset's failure probability. This represents a conservative approach to modeling the system's failure, and it is recommended when the interaction between the components failure and the status of the system is not well understood.

The second candidate curve is computed by taking the highest sub-asset failure probability at each wind-speed interval as the combined asset failure probability, $p_f^{II} = \max_j p_{f,j}$. This candidate curve produces lower probabilities of failure than the first candidate curve, and therefore it can be considered as less conservative. This means of combining probabilities is commonly used in the literature when two conditions are fulfilled: (i) all sub-asset probabilities are close to 0, and (ii) a single sub-asset has a considerably higher probability of failure than all others.

The framework computes the asset fragility curve as the average of both candidate curves.

II.G.2 Assessment: TOA Modeling Framework

The TOA modeling framework described by Exponent and PG&E thoroughly integrates asset data and makes reasonable assumptions about the parameters governing the fragility of transmission assets. The detailed quantitative models employed in the framework integrate field data, environmental data, and asset performance data to construct simple models which track the evolution of fragility curves over the lifespan of an asset. These models are calibrated to acceptable design standards in the literature and to the regulatory requirements of CPUC GO 95,

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[141] *Operability Assessment Model Overview (2021), p. 23.*

demonstrating that PG&E has integrated the regulatory backbone into their modeling. The GIRS-RT strongly approves of this consistency with CPUC guidelines.

In general, the framework developed by PG&E and Exponent is based on well-known engineering principles and is a suitable modeling choice for situations in which observational data is scarce. It integrates a large amount of available data and uses both physics-based engineering models as well as statistical models to capture the response of transmission assets to wind. However, the GIRS-RT notes a few shortcomings and suggests potential modifications of the framework. In general, GIRS-RT sees the framework as soundly constructed and reasonable. However, the predictions of the model are not validated against empirical outcomes. Specific assessments are included below.

II.G.2.A1 <u>Lack of data-driven validation procedures for the failure model</u>

While the methodology is used to assess both short- and long-term risk in the transmission network, the documentation provided by PG&E does not contain references to the testing process used to validate the results of the model. As with any physics-based or statistical model, the outcomes of the framework approximate what can be expected to occur in the future. From these outputs, it is essential to validate such models using existing data. In addition, the framework makes several assumptions that are well-justified from a theoretical point of view. However, adjustments made from these assumptions should be confirmed for the specific use cases of PG&E. For this purpose, the GIRS-RT suggests future execution of the following two tests to increase confidence in the proposed framework and evaluate areas where it can be improved to reflect reality more accurately.

- Compare the expected and observed number of failures in the transmission network for a given year. The expected number of failures can be computed using the annualized failure probability for assets in the network, while the observed number of failures can be retrieved from historical data. This comparison should indicate how sound the modeling assumptions are, and whether the Bayesian updating process is capturing the fragility and hazard curves for assets regionally.
- Perform a statistical analysis to verify the correlation between the location of observed transmission network failures and zones where the model assigns a higher annualized probability of failure. The correlation should be significant, i.e., failures should be observed where the model estimates a higher probability of failure.

In response to questions about validation procedures, PG&E reported that the addition of the Bayesian updating step constituted a validation step, as it adjusted the fragility curves to be closer to the empirical fragility of the asset. While this is mathematically true, it may still be the case that the updated curves do not demonstrate strong agreement with outcomes. Instead, Bayesian updating constitutes additional refinement or training of the model, rather than a validation test of the model. The GIRS-RT does not view the Bayesian updating procedure as constituting model validation and suggests validating the model performance using formal validation parameters in the context of model evaluation, as has been done in Wildfire Distribution Risk Model (VRM and CRM) validation procedures (e.g. with the construction of a receiver operating characteristic (ROC) curve).

II.G.2.A2 Underestimation of the asset fragility curve when aggregating sub-assets

The methodology used by PG&E and Exponent to compute the asset fragility curve can result in an underestimation of asset failure probability. PG&E computes the fragility curve of an asset as the average of two candidate curves:

- Candidate curve #1: $p_f^I = 1 - \prod_j \left(1 - p_{f,j}\right)$
- Candidate curve #2: $p_f^{II} = \max\limits_j p_{f,j}$

where $p_{f,j}$ is the failure probability of sub-asset j at a certain wind speed demand.

From a system reliability perspective, candidate curve #1 makes two fundamental assumptions. The first assumption is that the failures of sub-assets are mutually independent (i.e., the failure of one sub-asset does not affect the failure probability of another sub-asset). The second assumption is that the logical relationship between asset and sub-assets failure can be understood as an OR logical expression: if any of the sub-assets fail, then the asset fails as well.

On the other hand, the fundamental assumption taken by candidate curve #2, according to PG&E's framework, is the full correlation between sub-assets. Since failures are modeled as binary random variables, in practice this means that if one sub-asset fails, all the other sub-assets fail, and thus the entire system fails. Note that this is the same logical relationship between assets and sub-assets as the one used in candidate curve #1: an OR logical gate. Consequently, the failure of any component in either candidate curve #1 or #2 implies the failure of the system, regardless of the status of the other sub-assets.

With this conclusion in mind, candidate curve #2 is not a different model than candidate curve #1, but simply an approximation of it that is obtained when the following condition is fulfilled:

- All the sub-assets failure probabilities are very close to zero, except for one of them that is significantly higher.

Under this condition, $1 - p_{f,j} \approx 1$ for all sub-assets except for the most failure-prone, and therefore $p_f^I \approx 1 - 1 + \max\limits_j p_{f,j} = \max\limits_j p_{f,j} = p_f^{II}$. For the case where all but one of the failure probabilities are zero, then $p_f^I = p_f^{II}$, i.e., both candidate curves match exactly.

However, if the prior condition is not met, candidate curve #2 will heavily underestimate the failure probability of an asset, resulting in an average asset fragility that is underestimated as well.

Moreover, it is important to notice that both candidate curves are not two different models: they represent the same logical relationship between sub-assets and asset failure (OR gate). The only difference between them is that one represents an approximation of the other under special conditions. Because of this, the approach used by PG&E to compute an overall asset fragility curve is not taking into consideration two models of different levels of conservatism, but a model and an approximation (which may not be valid) instead.

The GIRS-RT recommendation is for PG&E to define the system's failure via a suitable reliability model, for example, a Fault Tree (Rausand, Barros, and Høyland 2020). This would allow combination of the failure likelihood of multiple sub-assets in a principled manner. In case this is not feasible, the GIRS-RT suggests a conservative approach, which is to assume that any failure in the sub-assets will cause a failure in the asset, i.e., curve #1, and not average with curve #2.

II.G.2.A3 Robustness and sensitivity of the Bayesian updating process

The Bayesian updating method used to adjust the initial fragility function is appropriate and serves to bring the model closer to the ground truth. It provides a way to continually adjust the OA/AM model as new outage data becomes available, which is a great benefit, especially to a model which may be deployed at a higher than annual frequency and can integrate newly obtained wind/outage data.

The Bayesian updating process depends on the initial fragility curve as well as the specified prior distributions of the median strength, uncertainty, and wind speeds. Different choices of prior distributions may have a large effect on the output from the Bayesian updating process. In the OA/AM framework, the Bayesian updating step precedes the application of the physical degradation models.

However, it is unclear how sensitive the Bayesian updating method is, given the wind/outage data. In the context of Bayesian updating, sensitivity analysis refers to measuring how strongly the final, updated (posterior) distribution depends on the specified initial (prior) distributions. If the process is very sensitive, different choices of prior distributions may result in very different updated fragility curves. In this case, the choice of prior matters strongly for the predictions of the model and should be chosen as carefully as possible. On the other hand, if the updating process is not sensitive, different choices of priors may lead to essentially the same updated fragility curve, and so the choice of prior is less important to modeling outcomes.

GIRS-RT recommends that a basic sensitivity analysis of the Bayesian updating process be carried out. This would involve choosing different priors, for e.g. the median strength and uncertainty distributions and performing the updating process on each. The results may then be compared across priors to observe how strongly the updating process changes the distribution.

Doing this type of analysis may lead to re-evaluation of order of operations in the TOA framework. If the updating process depends strongly on the priors, the degradation models could be applied before the Bayesian updating step, thereby building a more informed prior. If instead, the Bayesian updating is very insensitive to the prior distributions, the current order of operations would be validated.

II.G.3 Information and data used to calibrate the TOA Model

The TOA Model incorporates a comprehensive set of data types capturing four major categories: 1) age of the assets and sub-assets, 2) environmental hazards, 3) the physical condition of the asset, and 4) know asset characteristics associated with past performance.[142]

[142] *Operability Assessment Model Overview (2021) Local Conditions GIRS Meeting Data 9/28/23*

Table II.G-1: A summary of TOA Model Data Elements from the PG&E's 2022 Wildfire Mitigation Plan.[143]

OA MODEL DATA ELEMENTS

Input Data	Collection Period	Collection Frequency	Spatial Granularity	Temporal Granularity	Description
PLS-CADD	2019 - present	Bi-monthly	N/A	Bi-monthly	Advanced analysis of assets
Corrosion	2020 - present	Yearly	N/A	Daily	Air and soil* corrosivity factors
Inspection results	2019 - present	Daily	N/A	Daily	Current condition of assets
Outage	2007 - present	Yearly	N/A	Daily	Historical outages and causes
Structure details	1899 - present	Daily	N/A	Daily	Age, material, GIS
Pole test and treat	2006 - present	Yearly	N/A	Daily	Wood pole analysis
Repairs	2019 - present	Daily	N/A	Daily	Repair details
Asset feature list data	2021 - present	Once	N/A	Daily	Enhanced asset records
Bayesian updating	2019 - present	Yearly	N/A	Daily	Historical data
Wind gust percentile	2019 - present	Yearly	N/A	Daily	Wind gusts data
Wind speed analysis	2019 - present	Yearly	N/A	Daily	Analyzed wind data
Structure material	2019 - present	Yearly	N/A	Daily	Analyzed structure data

Age data consists of assets and sub-asset (parts of an asset) age, type, and materials (e.g., wood, steel), each of which influence the design life. Design life is also influenced by local environmental factors. Environmental information used for model calibration included historical wind conditions, corrosion hazards, historical weather patterns, and wood decay zones. Corrosion hazards are modeled by location as anticipated from atmospheric corrosivity or soil corrosivity, and wear and fatigue hazards are modeled for environmental subtypes (e.g., grazing land, freshwater pond, etc.).[144]

The information pertaining to the physical condition of each asset is derived from component testing data, annual updates from inspection data (ground and flyover), and the expected overstrength/understrength from structural analysis. Information related to the past performance of an asset includes the results of Failure Modes and Effects Analysis (FMEA), historical outages, failures, and repairs. This information is used for calibration during 1) the construction of the initial fragility curves for individual assets and sub-assets, 2) the Bayesian updating step, and 3) model revisions from field inspections as described in other sections in this report.

As discussed in Section II.G.1.2, the Bayesian updating process relies on historical wind/outage data for each asset in the PG&E transmission network. The historical wind data is provided by PG&E for the past 30 years. Each PG&E transmission line structure is located within the meteorology model grid cell. PG&E has summarized the extreme wind profile for each grid cell by calculating percentiles of the distribution of maximum daily wind speeds, ranging from the

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[143] *PG&E 2022 Wildfire Mitigation Plan (072622-wmp-update-redline.pdf), p. 219.*
[144] *A Framework for Risk-Based Transmission Line Asset Managements and Operability Assessment prepared by Exponent, p. 51*

historical minimum (0th) to maximum (99.99th) percentile, where the highest percentiles have higher resolution binning. Each percentile—corresponding to a certain wind speed at the specific asset—has associated with it a number of structure-days (days of operating that asset at that wind gust speed) and an outage record. All these data are input to the Bayesian updating procedure and used to bring the modeled fragility curves closer to the true behavior of the asset.

A total of 321 wind-related transmission line outages that occurred from 2007-2020 were used for the Bayesian updating process.[145] Of these outages, only 43 (~15%) occurred during wildfire season (June-November) in California (Figure II.G.3A). From 2007-2020, total annual wind-related outages vary from none in 2018 to eighty-six in 2008 but occur at a rate of ~23 outages per year on average (Figure II.G.3B). The wind speeds associated with these outages range between 10 and 60 mph and tend to occur below 50 mph (Figure II.G.4A). Even at the high end of these wind speeds, system failure occurred in regimes of low failure probability for typical TOA Model fragility curves (Figure II.G.4B). The maximum wind velocities documented by PG&E over 30 years generally lie on the very low probability (left) side of the fragility curves (Figure II.G.4A & B). For many transmission line assets, the 90th percentile wind velocities are of order a factor of two lower than the historical maxima.

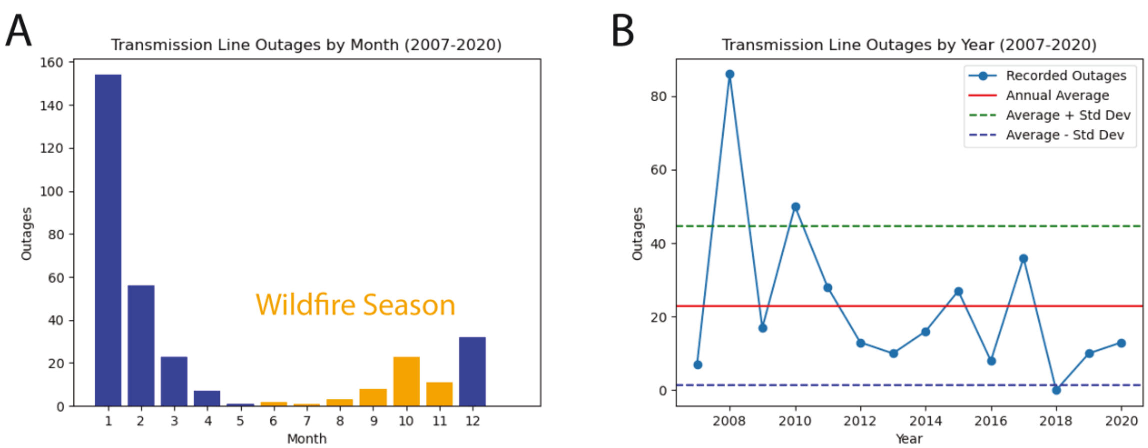

Figure II.G.3: Timing of historical wind-driven transmission line outages (2007-2020). Panel A is the distribution of outages by month. Orange columns indicate wildfire season months (June-November) and blue columns do not. Panel B is the annual ignition counts from 2007-2020 coupled with the annual average (~23 outages per year).

[145] *Internal Data from PG&E - DRU13290.002_Atch02_List of wind outages and associated wind speeds for BU.xlsx.*

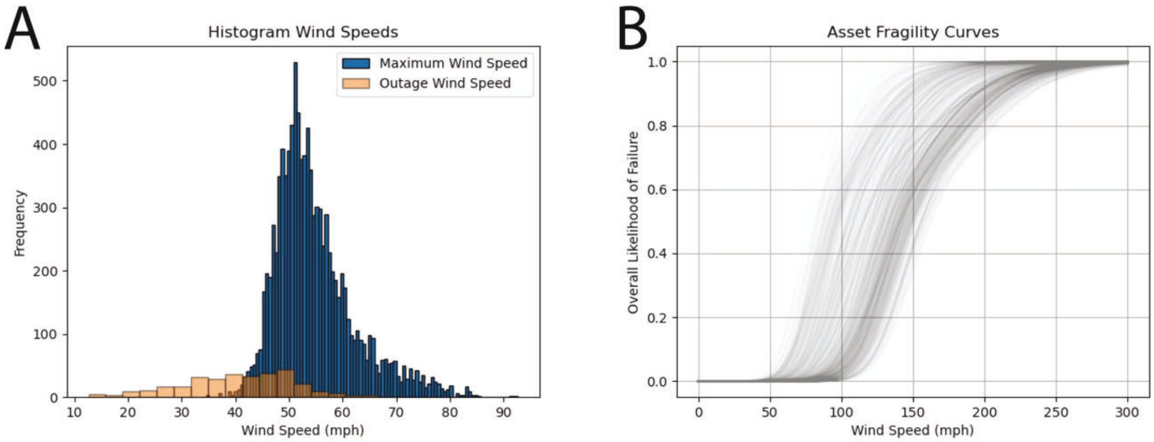

Figure II.G.4: Relationships between historical wind velocities and TOA Model range. Two histograms are plotted in Panel A that characterize historical wind conditions. The blue histogram is the distribution of the maximum windspeeds associated with each asset.[146] The orange histogram displays the wind conditions associated with historical transmission line outages spanning 2007-2020.[147] Panel B is a random sample of 10,000 fragility curves taken from the >100,000 transmission line assets. These fragility curves were calculated from model parameters of sub assets (themes) as described in PG&Es internal documentation.[148] Comparing Panels A and B illustrates that even the most extreme wind conditions typically sample only the relatively low probability, far left portion of the fragility curves for most of the assets. However, in some cases, the likelihood of failure increases appreciably in the range of 50-100 mph winds.

II.G.4 Assessment: TOA Model Data

II.G.4.A1 Comprehensive integration of field data

The comprehensive suite of information used to generate and run the transmission AM and TOA tools is adequate and fit for use to assess the likelihood that a transmission line will fail under windy conditions. While modes of failure that are independent of wind are not directly captured, influences associated with corrosion, effects of loading from ice, and other environmental factors are inherent in the information used for model calibration and degradation estimates. These data are obtained from a variety of reliable sources both external and internal to PG&E.

II.G.4.A2 Annualized vs. fire season-restricted datasets

Unlike the Vegetation Risk Model and the Conductor Risk Model, which each forecast ignition likelihood only during the fire season, the transmission AM model relies on annualized data to build the model framework. A key assumption in the model is that the failure of a transmission line leads to an ignition with absolute certainty. Historical wind-related transmission line outages mostly occurred during the winter months from 2007-2020 (Figure II.G.3A). High winds during such storms that lead to transmission line failures would certainly be less likely to lead to an ignition under rainy conditions as opposed to conditions in the wildfire season (June-November).

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[146] Internal Data from PG&E - DRU13290.002_Atch03_tline-ecgust-climo-percentile-daily-max-2007-2020.csv.
[147] Internal Data from PG&E - DRU13290.002_Atch02_List of wind outages and associated wind speeds for BU.xlsx.
[148] Internal Data from PG&E - DRU13290.003_Atch01_theme_mu_and_beta_2021_09_23_22_40.xlsx; A Framework for Risk-Based Transmission Line Asset Management and Operability Assessment, p. 4-27.

While this model may adequately inform PG&E about regions where transmission lines need service or are more likely to fail under windy conditions, its capacity to forecast ignition likelihood during winter months may be limited, and its forecast for summer months may be adversely affected by including annualized data not restricted to fire season.

II.G.5 Summary of GIRS-RT Findings for the Transmission Operability Assessment (TOA) Model

The TOA framework, grounded in established engineering principles, is effective for scenarios with limited observational data. It integrates extensive data with physics-based engineering and statistical models to predict the response of transmission assets to wind. This approach greatly benefits the operational and planning aspects of the PG&E transmission network.

Features:

- The Transmission Operability Assessment (OA) and Asset Management (AM) models provide PG&E with the technical capability of estimating short-term and long-term failures probabilities for assets related to their transmission network in the service territory.
- Through a combination of physics-based modeling, subject matter experts (SME) inputs and Bayesian modeling, the TOA can update the fragility curves associated to each asset to reflect the local conditions in an accurate manner.

Summary of Assessments:

II.G.2.A1 Lack of data-driven validation procedures for the failure model

For future iterations of the model, the GIRS-RT recommends using a data-driven approach for the TOA model validation, testing its performance against historical data.

II.G.2.A2 Underestimation of the asset fragility curve when aggregating sub-assets

The methodology used by PG&E and Exponent to compute the asset fragility curve can result in an underestimation of asset failure probability. The GIRS-RT suggests the use of a formal reliability model, such as a Fault Tree, to define the relationship between component failure and system failure.

II.G.2.A3 Robustness and sensitivity of the Bayesian updating process

The Bayesian updating method effectively adjusts the initial fragility function, improving the OA/AM model by incorporating outage data, but its sensitivity to the choice of prior distributions needs to be evaluated. GIRS-RT recommends performing a basic sensitivity analysis to determine the impact of different priors on the updated fragility curves, which may influence the order of operations in the TOA framework.

II.G.4.A1 Comprehensive integration of field data

The transmission TOA model uses a wide variety of high-fidelity datasets which expand the sensitivity of the wind-based fragility framework to a large range of asset failure modes.

II.G.4.A2 Annualized vs. fire season-restricted datasets

The capacity for the transmission TOA model to forecast ignition likelihood during winter months may be limited, and its forecast for summer months may be adversely affected by including annualized data not restricted to fire season.

III. Technical Findings: Design & Construct Tools

III.A Design and Construct Overview

Section III covers the GIRS-RT findings for the Design & Construct Category of the PG&E Local Conditions tools in the 2021-2022 WMPs. This includes System Hardening Decision Making for Design and the Resulting Construction Standards and Procedures, Fire Rebuild Design Guidance for System Hardening: Utility Bulletin TD-9001B-009, and Mitigation Checklist Decision Framework (TD-9001B-009 Attachment 3).

Tools in the Design & Construct Category have been developed to provide a framework for decision making, design, and construction for system hardening of the distribution and transmission systems and equipment upgrades, and replacement related to safety and reliability within the PG&E service territory. System hardening includes procedures to increase the resilience of the grid to ignition risk, asset failure, and improvement of the associated management or response to equipment failures. This section covers updates to grid topology to minimize ignition risk in HFTD areas, maintenance of distribution and transmission systems for both electrical and mounting equipment, and upgrades related to public safety power shutoffs. System hardening initiatives are directed at PG&E assets in HFTD Tier 3 and Tier 2 areas only.

This section provides an overview of PG&E's framework for System Hardening Decision Making for Design and the Resulting Construction Standards and Procedures, as well as the specific construction guidelines contained in Fire Rebuild Design Guidance for System Hardening: Utility Bulletin TD-9001B-009 and the Mitigation Checklist Decision Framework described in Utility Bulletin TD-9001B-009 Attachment 3 (dated 7/2/2019) along with 2021-2022 updates to the Decision Framework. Utility Bulletin TD-9001B-009 and supporting documents govern PG&E's 2021 and 2022 framework for decision making, design, and construction for system hardening of the distribution and transmission systems and equipment upgrades, and replacement related to safety and reliability within the PG&E service territory. The checklist in Utility Bulletin TD-9001B-009 Attachment 3 was an interim step prior to development of the Wildfire Risk Governance Steering Committee in October 2020, which supplanted the more abbreviated flowchart that appears in Utility Bulletin TD-9001B-009.

Overall, the GIRS-RT finds that these tools comply with the relevant General Orders and other design protocols, consider PG&E's wildfire risk-models where appropriate, meet or exceed industry standards, and are fit for use. More detailed assessments and suggestions for future upgrades are provided within the individual tool review sections. Overall, the Design & Construct Category tools are formulated to provide robust guidance for system hardening decision making and construction that mitigates wildfire risk across PG&E's broad and diverse service territories.

PG&E tools have continued to move forward since the period covered by the audit. The recommendations made in this review are intended to guide the ongoing development of these modeling tools.

III.B System Hardening Decision Making for Design and the Resulting Construction Standards and Procedures

III.B.1 System Hardening Overview

This section covers PG&E's 2021 and 2022 framework for decision making, design, and construction for system hardening of the distribution and transmission systems and equipment upgrades, and replacement related to safety and reliability within the PG&E service territory. System hardening includes procedures to increase the resilience of the grid to ignition risk and asset failure, and to improve the associated management or response to equipment failures. This section covers updates to grid topology to minimize ignition risk in HFTD areas, maintenance of distribution and transmission systems for both electrical and mounting equipment, and upgrades related to Public Safety Power Shutoffs. System hardening initiatives are directed at PG&E assets in HFTD Tier 2 and Tier 3 areas only.

This section tracks PG&E's compliance with key CPUC General Orders and regulatory procedures for equipment design and construction, PG&E's annual goals set and met, and key changes that occurred during the period covered the audit, which include increased attention to wildfire risk, changes to the inspection process and the associated backlog of tags, risk-based prioritization schemes, a change in the risk model from WDRM v1 to WDRM v2, and grid modification to minimize service disruptions during Public Safety Power Shutoffs.

III.B.1.1 Updates to Grid Topology to Minimize Risk of Ignitions in HFTDs

This section is centered on the initiatives undertaken by PG&E during 2021 and 2022 to update the Grid Topology of its service system, with the objective of minimizing operational risks in High Fire-Threat District (HFTD) Tiers 2 and 3.

Within the context of Grid Topology, six initiatives were reported by PG&E,[149] primarily addressing the risks associated with wildfires and customer reliability due to Public Safety Power Shutoff (PSPS) events. The initiatives encompass a wide range of measures including system hardening, equipment replacement, and infrastructure upgrades across various geographical locations. The initiatives are listed below.

- **Updates to the Distribution System**: This initiative applies a series of strategies such as line removal, undergrounding of lines, installing covered conductors, pole and equipment replacements, protective framing, and vegetation clearing to mitigate potential catastrophic wildfire risk induced by the distribution system. The prioritization of work is done primarily on the outputs of PG&E's 2021 WDRM v2.[150]
- **Updates to the Transmission System**: Unlike the distribution system hardening program, PG&E does not have a single initiative containing all mitigation strategies for the transmission system. Rather, a set of independent programs focus on mitigating risk.[151] This set includes maintenance notifications, sectionalizing devices, vegetation clearing, conductor replacement, line de-energization, grounding and removal, among

[149] PG&E 2022 WMP, p. 579.
[150] PG&E 2022 WMP, p. 581.
[151] PG&E 2022 WMP, p. 591.

others. Each program uses its own prioritization strategy. Some use local information and a risk-informed approach, while others use static procedures and rules.

- **Non-exempt Surge Arrester Replacement**: This initiative is a PG&E program that replaces existing non-exempt surge arresters with CAL FIRE approved surge arresters, decreasing ignition risk. All non-exempted arresters within HFTDs were expected to be replaced by the end of 2022, and no other prioritization strategy was implemented.
- **Rapid Earth Fault Current Limiter (REFCL)**: This initiative installs protective devices, known as Rapid Earth Fault Current Limiters (REFCLs), which detect high-impedance faults and limit the fault current below ignition thresholds. Prioritization for the installation of these devices is governed by PG&E's 2021 WDRM v2 and facility feasibility. However, the technology was not fully evaluated for the 2022 WMP due to a combination of substation failure and supply chain issues due to the COVID-19 pandemic effects on overseas suppliers.[152]
- **Remote Grid**: This initiative installs stand-alone, decentralized energy generation and distribution infrastructure for communities that require small loads and are in remote locations. Remote grids eliminate reliance on long distribution segments that feed only a small percentage of the public. The criteria for selecting locations are multi-dimensional, involving the risk to be mitigated, and other factors such as economic and technical feasibility.
- **Butte County Rebuild Program**: This program focuses on rebuilding and undergrounding electric infrastructure in the town of Paradise and surrounding areas in Butte County. These areas were heavily affected by the 2018 Camp Fire.

Following CPUC requirements, for each initiative PG&E reports a series of indicators such as the risk being mitigated, prioritization strategy, goals for the next years, future improvements and lessons learned. These are summarized in Table III.B-1.

[152] *PG&E 2022 WMP, p. 600*

Table III.B-1: Summary table of the initiatives used to mitigate risk through updates to grid topology.

Initiative	*Risk to be mitigated*	*Work Prioritization*	*Goals met in 2021?*	*Actual progress (2021)*	*Current Goals (2022)*	*Notes and future improvements*
Distribution Network	**Wildfire risk** caused by distribution overhead assets. **Customer reliability** due to PSPS events	**WDRM 2021,** in addition to fire rebuild, PSPS mitigation, and PSS identification.	**Yes, exceeded**	**Goal 2021**: 180 miles **Completed**: 210.5 miles	**470 miles** including overhead hardening, undergrounding, and removal	Increase pace of hardening. Incorporate data to refine hardening strategy
Transmission Network	**Multiprogram strategy. Wildfire risk** caused by asset failure. **Customer reliability** due to PSPS events	**Multiple factors,** depending on the program: **CoRE**, **TOA**, **PSPS lookback**, **inspections**, etc.	**N/A**	**93.8 miles** of conductor replacements **10 miles** of conductor removal	Remove or replace 32 circuit miles	Further inclusion of risk-based modeling in prioritization. Cost efficiency improvements
Non-Exempted Surge Arrester Replacement Program.	**Ignitions** caused by non-exempted surge arresters	**No risk model** HFTD Tier 2&3 optimizing use of available crews	**Yes, exceeded**	**Goal 2021**: 15,000 replacements **Completed**: 15,465	**Replace all remaining** non-exempted surge arresters in HFTD (4,590)	Expansion of program to non-HFTD areas
Rapid Earth Fault Current Limiter (REFCL)	**Ignitions** caused by high impedance faults (wire down, veg. contact)	**WDRM 2021** Ranked by risk, given substation feasibility for REFCL	**N/A**	**Project stalled** due to incomplete evaluation (equipment failure) and supply chain issues (COVID19)	Completing evaluation of program. No plans for installing additional REFCL at the time	Given successful evaluation, PG&E will work towards future deployment
Remote Grid	**Ignitions** caused by long segments crossing HFTD areas to supply small, remote loads	**WDRM 2021**,in addition to location, constructability, customer outreach, solar access	**N/A**	**One remote grid** operational as of June 2021. Multiple other engineering and design milestones	**Two new remote** grids Standalone Power Systems units	**Standardize** development, design, operation and monitoring
Butte County Rebuild Program	**Ignition** risk, **customer reliability** (PSPS events), **egress** route blockage	Minimizing disruption to inhabitants of Town of Paradise and lower Magalia	N/A	**31.5 UG miles**	**55 UG miles**	Expected to complete all work in 2025

III.B.1.2 Distribution System Prioritization Scheme

The prioritization and decision scheme followed by PG&E to determine the hardening strategy to employ for a circuit segment in the distribution system is summarized graphically in Figure III.B.1.

First, the circuits are prioritized following the outputs of the PG&E's 2021 WDRM v2, in addition to other factors such as whether circuits belong to a Fire Rebuild program, the impact of hardening on the frequency of PSPS events, and whether the circuits are recommended by the Public Safety Specialists (PSS) Team.[153]

Once a circuit segment has been selected as a candidate for mitigation, four strategies are evaluated in parallel: overhead hardening (OH), undergrounding the line (UG), a combination (hybrid strategy), or line removal (LR). The evaluation is based on the local and environmental conditions of the zone, the effect on PSPS and ingress or egress routes, employee safety, costs, and other factors. For this evaluation, PG&E involves several agencies and subject matter experts within the company.

The evaluation produces a series of metrics to compare the alternatives. Among them, the Risk Spend Efficiency (RSE) is highlighted in the WMP 2022 report as a key metric for decision-making. A final recommendation is issued to the Wildfire Risk Governance Steering Committee (WFGSC),[154] which provides guidance and approval for projects. Once approved, the projects are scheduled for final design, permitting, and execution.

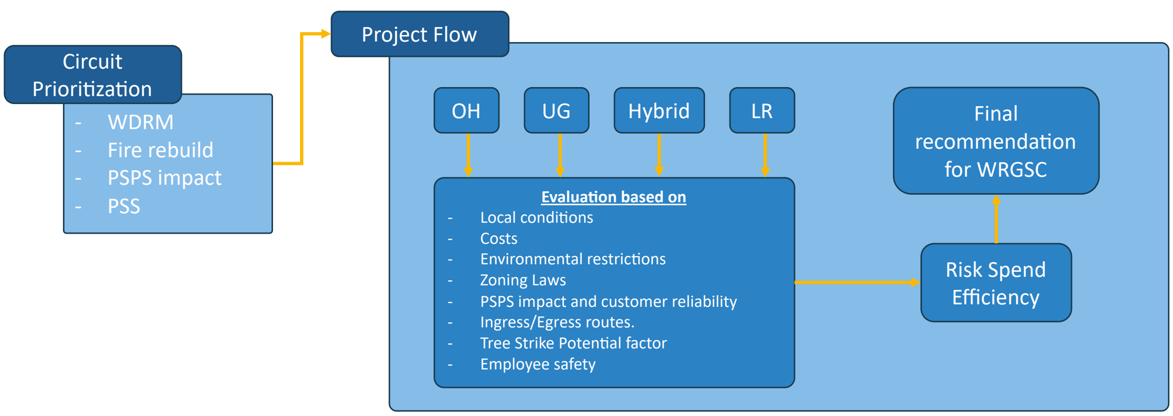

Figure III.B.1: Prioritization and decision scheme followed by PG&E to determine which mitigation strategy is used in each prioritized circuit. The alternative strategies are overhead hardening (OH), undergrounding (UG) or a hybrid approach. Line removal (LR) is also considered.

III.B.1.3 Assessments of Updates to Grid Topology

III.B.1.A1 Achievements of Milestones established by PG&E

The GIRS-RT finds that where milestones were applicable to establish, they were met or exceeded by PG&E for the years 2021 and 2022.

[153] *PG&E 2022 WMP, p. 583 & 584.*
[154] *PG&E 2022 WMP, p. 586.*

III.B.1.A2 Use of risk-based strategies for prioritization of work

The GIRS-RT finds that PG&E uses local conditions, through the various risk-based models reviewed in the Identify Category section of this report (Section II), for the prioritization of most of the system hardening initiatives. Decision-making for system hardening implementation in the distribution system is holistic and considers wildfire risk as a main element in its prioritization.

III.B.1.A3 Potential Redundancy in Transmission System Grid Updates

Decision making for the transmission system is subdivided among different teams and initiatives at PG&E. While each initiative is sound and can have a positive effect in decreasing wildfire risk in the transmission system, the division into separate initiatives may cause inefficiencies and/or redundancies in the overall mitigation strategy.

III.B.1.A4 Emphasis on real-time monitoring strategies

The GIRS-RT recommends additional emphasis on real-time monitoring strategies for future WMPs. These strategies provide both accurate information about the location and local conditions where hazardous situations occurred for future models, and real-time capabilities for mitigation under abnormal circumstances.

III.B.1.4 Primary General Orders and Utility Standards and Procedures involved in Grid Design and System Hardening

General Orders (GO), as established by CPUC, cover regulatory requirements for different types of services and infrastructure in the state. The GOs involved in Grid Design and System Hardening (Section 7.3.3 WMP 2022), as indicated by PG&E,[155] are listed below.

- GO 95: Rules for overhead electric line construction.
- GO 128: Rules for Construction of Underground Electric Supply and Communication Systems.
- GO 165: Inspection and maintenance requirements for electric distribution and transmission facilities.

Utility procedures and standards are internal documents that serve as instruction manuals for the correct execution of services within the company. The following is a list of the Utility Procedures and Standards referenced by PG&E in Grid Design and System Hardening (Section 7.3.3 WMP 2022).

- Utility Procedure TD-2302P-05: Electric Distribution Maintenance Requirements for Miscellaneous Overhead and Underground Equipment.
- Utility Procedure TD-3322M: Substation Maintenance and Construction Manual Circuit Breakers Booklet.
- Utility Procedure TD-2459P-01: Idle Facility Program.
- Utility Procedure TD-1003P: Management of Idle Electric Transmission Line Facilities Procedure.
- Utility Standard TD-3322S: Circuit Breaker Maintenance Template.

[155] *PG&E 2022 WMP, Section 9.2.*

III.B.1.5 Assessments of General Orders and Utility Standards and Procedures

III.B.1.A5 Update to General Order 128 and 165

Maintaining up to date GOs is the responsibility of CPUC and outside of the scope of this audit. General Order 95 was last revised in 2020. However, General Order 128, which covers the rules for construction of underground electric supply was last revised in 2005, and General Order 165, which covers inspection cycles for electric distribution facilities, was last revised in 2017. GIRS-RT recommends CPUC review and potentially update GOs 128 and 165 to reflect changes due to significant wildfire events that have occurred in California since the most recent updates.

III.B.2 Distribution and transmission system maintenance

A significant focus of the system hardening program is the creation, planning, and remediation of maintenance projects on the distribution and transmission systems. Maintenance issues are flagged with tags, i.e., notifications of failure or expected failure of an asset or sub-asset on the system. Once identified through inspections, these maintenance tags are prioritized by their time window for correction and wildfire risk. Electric Corrective (EC) refers to maintenance tags on the distribution system and Line Corrective (LC) to tags on the transmission system. An offshoot of the general maintenance program, PG&E's Electric Corrective Optimization Program (ECOP) proposes and initiates system hardening projects in areas of the distribution system with a high concentration of EC tags.

III.B.2.1 Comparison of GO 95 and PG&E maintenance tag urgency rankings

GO 95 lays out a 3-level priority hierarchy for maintenance or repair projects on the electric grid. Level 1 projects are regarded as immediate high impact risks to safety or reliability and should be completed or corrected promptly. Level 2 projects have moderate risk, and the required correction timelines depend on the HFTD classification of the project location. Level 2 projects must be corrected within 6 months for HFTD Tier 3, 1 year for HFTD Tier 2, and 3 years in non-HFTD areas (HFTD Tier 1). Level 3 (lower risk) maintenance projects require completion within 5 years.[156]

During inspections, hardware issues requiring corrective actions on the distribution system generate corrective tags. PG&E ranks these tags on a time-to-completion hierarchy like CPUC GO 95, but with different categorizations. PG&E priority A tags are GO 95 level 1 and pose immediate risk, requiring immediate correction. Priority B tags require correction in 3 months. Priority E tags require correction in 6 months for those in HFTD Tier 3 but 1 year otherwise. Priority F tags, which are low risk, require correction in 5 years on the distribution system and 2 years on the transmission system.

A final class, priority H, refers to class E tags which are scheduled for repair or correction through the system hardening program.[157] Reclassifying these tags is an important step PG&E takes to ensure that corrective actions already planned through system hardening are not creating redundancies with the standard maintenance work on the grid.

[156] *CPUC – General Order 95, Rule 18.*

[157] *PG&E 2022 WMP, Table RN-PG&E-22-05-01, p. 680.*

Priority A/B tags are corrected quickly to maintain safety and compliance with GO 95. E/F tags, being lower risk, tend to have longer lead times until correction; these are also the most prevalent tags generated during inspections. As of Q1 2022, A/B tags accounted for about 1% of open distribution tags in HFTDs in 2022 while E/F tags constituted almost 95%.

In 2018-2019, PG&E introduced the Wildfire Safety Inspection Program (WSIP), which enhanced inspections and increased inspection frequency along the distribution grid HFTD/HFRA areas. WSIP used a "failure modes and effect analysis" (FMEA), a quantitative tool to analyze the ignition risk of a given component. On the distribution network, the FMEA tool gave an estimate of the likelihood of failure, while FMEA on the transmission network identified any component which could be associated with an ignition, regardless of failure likelihood. Appropriate EC tags were generated if necessary. With a 5-fold increase in inspection frequency and the new use of the FMEA system, tag identification increased to 4 times the previous annual non-conformance find rate.[158] The high tag identification rate resulted in a volume of EC tags far greater than PG&E's annual corrective capability.

III.B.2.2 Rescoping and development of the 2021 workplan

PG&E tends to organize, scope, and approve maintenance and inspection workplans in the quarters leading up to the year of their deployment. Lead times for planning may cause the workplan organization to lag behind PG&E's most up-to-date risk models. This situation occurred in late 2020 after the approval of WDRM v2. Reviewed in the Identify Section of this audit (Section II), WDRM v2 was the successor to the first of PG&E's distribution risk models. It uses a different fire simulation tool and different ignition probability modeling strategies from its predecessor. The spatial MAVF risk map generated by WDRM v2 described a very different spectrum of risk from WDRM v1, both in magnitude and geospatial distribution.

This presented an immediate challenge for the 2021 workplan, which had already been planned and scoped under the risk map generated by WDRM v1. Analysis of the top 100 circuit protection zones (CPZs) by risk showed that there was zero overlap between the two models.[159] Additionally, projects originally scoped for the 2021 workplan had little correlation with the new risk scores. The scoped projects were broadly distributed throughout the WDRM v2 risk spectrum, meaning that the originally scoped workplan was not consistent with maximum risk reduction according to WDRM v2.

In November 2020, the PG&E Wildfire Risk and Governance Steering Committee (WRGSC) approved a new workplan colloquially titled "No Regrets". This revised workplan would create a new portfolio of scoped and planned projects which would align much more closely with the new risk model results. While some previously scoped projects would remain on the plan, PG&E ended up removing numerous vegetation management and system hardening projects (108 and 55 projects, respectively) from the workplan scope, and would pivot the focus to the 1000 riskiest miles on the system according to WDRM v2.

[158] *PG&E 2022 WMP, p. 678.*
[159] *PG&E WRGSC Meeting, 11/13/2020.*

As a result, 2021 would become the first year in which the PG&E inspection plan was shaped by risk/consequence rather than GO 165 compliance. The new inspection plan focused more heavily on HFTDs. The GO 165 inspection system, governed only by time-to-correction for compliance, would have directed a plurality of inspection efforts to non-HFTD areas, whereas the risk-informed inspection plan assigned a plurality to HFTD Tier 3 areas. The "No Regrets" workplan focused on four principal areas: 1) fire rebuild, 2) PSPS mitigation, 3) the electrical corrective optimization program (ECOP), and 4) any projects in the top 20% of CPZs by risk. Through December 2020 and into early 2021, the WRGSC approved new enhanced vegetation management, distribution PSPS mitigation, ignition component replacement, and ECOP projects to constitute and extend the "no regrets" workplan.[160]

III.B.2.3 <u>Origin and handling of the maintenance tag backlog</u>

Despite a greater reduction of risk, because of the rescoping of the workplan, the magnitude of work done on the system was lower in 2021 than earlier years. This was strongly reflected in the development of a backlog of maintenance tags on the PG&E system. The increased inspection frequency and detail associated with WSIP led to a large backlog of unaddressed tags on the distribution and transmission system across its service territory. A backlog of around 195k distribution EC tags was expected at the end of 2022.

While some tags were scoped under the 2021 workplan, the majority remained out of reach. The tag backlog issue was directly addressed in the 2022 WMP, where PG&E laid out 3-year and 7-year plans to remediate the backlog for ignition-related non-pole and pole-related distribution HFTD tags. The goal of these plans was to reach a steady state of tag identification and correction for HFTD tags. However, the prioritization of ignition-related HFTD tags only exacerbated the backlog among non-ignition HFTD EC tags. PG&E expects to reach a steady state for all HFTD tags by 2033, though LC (transmission) tags reached a steady state by the end of 2023.[161]

The tags that are scoped to be addressed are risk-prioritized in the E/F tier (A/B tags are addressed promptly and completely for compliance and so do not receive a risk ranking). Different decision processes are used for transmission and distribution tags (reflecting the differing risk models) and for pole and non-pole tags (reflecting the view that non-pole tags are more likely to lead to ignition). Specific, quantitative goals are set in the 2022 WMP: by the end of year 2022, PG&E aims to close at least 55k distribution HFTD tags and 18k transmission HFTD tags. 55,000 tags represent 27% of the open distribution HFTD tag backlog in Q1 2022.[162]

III.B.2.4 <u>Assessments of distribution and transmission system maintenance</u>

III.B.2.A1 <u>Rescoping of 2021 workplan supports risk-reduction objectives</u>

The GIRS-RT supports the rescoping efforts made by PG&E to align their workplans with a primary objective of risk reduction. Despite a potential reduction in mileage worked in 2021, aligning the workplan with the risk rankings is the best possible way to directly address wildfire risk in the system. Documentation made available for this review through the WRGSC proceedings

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[160] PG&E WRGSC Meeting, 11/20/2020, 12/4/2020.
[161] PG&E 2022 WMP, p. 685-688.
[162] PG&E 2022 WMP, p. 690.

shows a detailed decision process leveraging input from multiple sources and thorough analysis of each project added to scope.

III.B.2.A2 The significant backlog of EC tags presents a challenge and persistent risk factor on the distribution and transmission system

The consequences of the risk prioritization are reflected in the development of the backlog of EC tags. With resources directed to specific projects in high-risk areas, some proliferation of a backlog of lower-risk projects is inevitable. However, the backlog of E/F tags both within and outside HFTDs is significant, and under best circumstances, will not be rectified until 2033 at the earliest (only for the HFTD tags). This estimate does not consider the introduction of new risk models and potentially new re-prioritizations of work, which played a part in developing the current backlog.

GIRS-RT is concerned with the magnitude of the tag backlog and the long-term horizon scheduled for its rectification. PG&E intends to increase the overall work volume, but even with significant increases, the backlog will persist for years, causing some E/F tags to potentially go out of compliance. As some tags pose ignition risk on failure, promptly and effectively reducing the tag backlog is an essential aspect of system hardening. However, the general management of tags and the planning of corrective actions for tags is not explicitly part of the system hardening program. While system hardening of individual circuits may include the correction of some tags, system hardening projects are not scoped based purely on a goal of tag correction.

III.B.3 Grid electrical equipment maintenance and replacement

PG&E's initiatives, procedures, and progress on grid electrical equipment are addressed in Section 7.3.3 of the 2021 and 2022 PG&E WMPs. This includes poles, conductors, and other electrical equipment on the distribution and transmission grid, as well as the EC/LC tag system for distribution and transmission maintenance items.

III.B.3.1 Non-pole, non-conductor electrical equipment

PG&E maintains inspection and replacement programs for (non-conductor) electrical components on the distribution and transmission system. Some components (like expulsion fuses and transformers) are regarded as ignition-related and receive extra attention or specific ranking based on risk/consequence. Others, like capacitors and circuit breakers, do not receive region-specific risk prioritization.

Generally, PG&E inspects equipment in HFTDs at a higher frequency, as required for GO 165 compliance. Distribution/transmission systems and power substations receive higher inspection frequency and maintenance work in vegetation management and system hardening programs.

Table III.B-2 characterizes the way in which specific grid electrical components are addressed by PG&E. Notably, transformer and expulsion fuses receive risk or consequence prioritization, while the others do not. Capacitor banks, for example, are exhaustively inspected annually, so prioritization is not necessary. Similarly, circuit breakers receive monthly inspections and have their own risk ranking system by condition. For all equipment, the higher frequency of inspections in HFTDs acts as a baseline regional prioritization. The table shows that in terms of actual progress, PG&E met or exceeded its targets, where made.

Table III.B-2: Risks, prioritization, and progress on non-pole, non-conductor grid electrical equipment.

Equipment	*Risk to be mitigated*	*Inspection Schedule*	*Work Prioritization*	*Goals met in 2021?*	*Actual progress (2021)*	*Notes and future improvements*
Capacitor banks	Low voltage sag C-bank failure	Annual	**No risk model** High-load circuits	Yes	100% inspected	2% of ignitions Adding SCADA devices
Circuit breakers	Failure -> no control of line current	Monthly, condition trigger	**No risk model** Ranked by condition	Yes (exceeded)	971/946 HFTD breaker tasks completed	Future replacements prioritized by condition
Connectors/hotline clamps	Failure -> wires down	1-3 yrs (HFTD) 5 yrs (non-HFTD)	**No risk model** Part of SH program	N/A	Continued inspections	Infrared inspections, focus in HFTD buffer zones
Distribution Transformers	GO 165 compliance	1-3 yrs (HFTD) 5 yrs (non-HFTD)	**WDRM risk**	N/A	81 replacements	Risk model deployed for 2022 workplan
Expulsion fuses	Replace non-exempt fuses	N/A	**CoRE model** (by circuit)	Yes (exceeded)	1429/1200 replacements	All non-exempt replaced in 5 years

Beyond specific electrical components, PG&E completes inspections and maintenance along the distribution/transmission systems. For the distribution and transmission system, this is reflected in the generation of EC/LC tags, addressed earlier. PG&E inspects lines annually in HFTD 3 and every 3 years in HFTD 2 along the distribution system. Transmission inspections are risk-ranked using the TOA model. EC/LC tags are generated and placed in the A/B/E/F hierarchy.

For distribution and transmission substations, the main risk factor is an arc flash event into surrounding wildlands.[163] The primary risk mitigation actions undertaken for substations are the establishment of defensible space perimeters and animal abatement work. Maintenance tags generated on the substation through enhanced inspections are addressed as needed. Substations in HFTDs receive enhanced inspections, prioritized by HFTD tier and station criticality.[164]

Progress in 2021 for HFTD substations was as follows. For distribution substations in HFTDs, 96% achieved defensible space.[165] In 2020, 37% of distribution substations were inspected[166] and an additional 56% of were inspected in 2021.[167] 69% of tags on HFTD substations were closed, and the animal abatement targets were exceeded (27 completed, with the target set of 26) for a total of 75 completed animal abatement projects across distribution substations.[168] On the transmission system, 100% of substations achieved defensible space and 48% were inspected by

[163] PG&E 2021 WMP, p. 577.
[164] PG&E WRGSC Proceedings, 12/4/2020.
[165] PG&E 2021 WMP, p. 578.
[166] PG&E 2021 WMP, p. 578.
[167] PG&E 2022 WMP, p. 669.
[168] PG&E 2022 WMP, p. 528-529.

the end of 2020, with additional inspections planned for 2021.[169] 74% of HFTD tags were closed and 10/11 abatement targets were met.[170] 584 maintenance tags on distribution substations and 300 on transmission substations were in progress at the end of 2021.[171]

III.B.3.2 Assessments of Grid electrical equipment maintenance and replacement

III.B.3.A1 Goals met on non-pole, non-conductor grid equipment

In 2021 PG&E met or exceeded its goals, where made, with respect to equipment replacement and inspection and substation hardening. The risk models were leveraged to rank some components, and those that were not ranked are reasonably prioritized by other means or no prioritization is relevant. With higher inspection frequency in HFTDs, PG&E maintains GO 165 compliance and generally focuses resources on higher-threat areas.

III.B.3.A2 Continue the development and installation of novel technologies to manage grid equipment with reduced reliance on inspection and inspection personnel

PG&E comments on some new approaches to inspections and the addition of more automated equipment for remote monitoring and reduced workload for field personnel. GIRS-RT agrees that more advanced monitoring technology will help PG&E accomplish a higher volume of inspections and have a better “bird’s eye” view of the status of the system. For example, in WRGSC proceedings, an update is given on the DTS-FAST system for transmission towers. The array of remote monitoring sensors allows this technology to give PG&E a remote, high fidelity and real time view of equipment function and condition.[172] PG&E states in Section 7.1 of the 2022 WMP that this system is being expanded to distribution poles. Since the prioritization of inspection and maintenance resources is of primary concern, especially given the extreme and growing backlog of EC tags on the transmission system, any technology that allows a reallocation of resources is an opportunity to increase the risk buydown per year on the PG&E system.

III.B.4 Electric Poles and Towers

Electric poles and towers are integral parts of PG&E’s system, supporting overhead power lines and other equipment needed to deliver electricity to end users. Both poles and towers exist on the distribution and transmission systems, though the bulk of structures on the distribution system are poles and most towers are part of the transmission system. Failure of these systems poses a significant threat of wildfire ignition, customer safety, and system reliability. To address these issues, PG&E has preventive maintenance programs including Electric Transmission Line Inspection and Preventive Maintenance Program[173] and CPUC regulatory requirements.[174] These maintenance protocols reduce the potential for component failures and facilitate a proactive approach to repairing or replacing abnormal components. Regular inspections and patrols are conducted to check for damage or wear, and necessary repairs or replacements are made to ensure the integrity of the system. Deficiencies identified during inspections are prioritized based on condition and system impact, then scheduled for repair or replacement. Routine inspections

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[169] PG&E 2021 WMP, p. 581.
[170] PG&E 2022 WMP, p. 532.
[171] PG&E 2022 WMP, p. 529, 532.
[172] PG&E WRGSC Meeting, 12/4/2020.
[173] TD-1001S: Electric Transmission Line Inspection and Preventive Maintenance Program.
[174] TD-1001M: Electric Transmission Preventive Maintenance Manual, 2020, p. i.

reduce the potential for component failures and facility damage and facilitate a proactive approach to repairing or replacing identified abnormal components. Inspections encompass detailed visual observations of individual structures, components, and equipment, along with operational readings and component testing (e.g., hammer tests) to identify abnormalities or conditions that could negatively impact safety, reliability, or asset life.[175] Patrols supplement these inspections, including visual observations to identify abnormalities (e.g., obvious structural problems or hazards) or conditions that could negatively impact safety or reliability. The inspections trigger Electric Corrective (EC) / Line Corrective (LC) tag notifications. The work prioritizations are followed based on the EC/LC tag notifications.

III.B.4.1 <u>Distribution Pole Replacement and Reinforcement</u>

Electric pole and equipment inspections initially followed the Wildfire Safety Inspection Program, spanning three levels, the bottom, middle, and top thirds of the pole. These inspections include checks such as vegetation clearance, pole integrity, animal activity, signs of reduced circumference, ground condition, and other equipment checks. These inspections have evolved into standard distribution pole inspections and patrols with a higher frequency in HFTD areas compared to non-HFTD areas as per GO 165 compliance.[176] Additionally, PG&E conducts intrusive inspections every 10 years to identify internal or below-ground decay.

Table III.B-3 provides a summary of detailed inspection and maintenance work progress for electric distribution poles and transmission towers. These inspections may trigger EC tags, which are prioritized upon creation. Priority B EC tags are considered urgent and given higher priority over E tags. The E tags are prioritized using the Wildfire Distribution Risk Model (WDRM v2), where pole replacements are prioritized based on wildfire ignition likelihood and consequence.[177] In addition, other regulatory conditions are also considered for pole replacements. Through inspections and patrols, PG&E assesses where and what decay or degradation mechanisms poles are experiencing, which helps build a risk profile leading to mitigation efforts. Poles identified for reinforcement are generally in good condition, except for decay around the ground line, and typically receive reinforcements in the following calendar year.

III.B.4.2 <u>Crossarm Maintenance, Repair, and Replacement</u>

PG&E conducts electric pole crossarm inspections as part of the overhead inspection based on GO 165 inspections and patrols, with repairs or replacements performed at identified locations. Prioritization of crossarm replacement is determined by the severity of field conditions and EC tags. Additionally, PG&E crossarm work prioritization is based on risk ranking, which includes evaluating Facility Damage Action (FDA).[178] PG&E conducts post-job reviews for crossarm maintenance work to ensure work matches the job order and complies with GO 95. Composite crossarms have increased longevity and are considered as replacements for wooden crossarms.

[175] *TD-1001M: Electric Transmission Preventive Maintenance Manual, 2020, p. 1.*
[176] *PG&E WMP, 2021, p. 533.*
[177] *PG&E WMP, 2022, p. 474.*
[178] *PG&E WMP, 2021, p. 531.*

III.B.4.3 Pole Loading Infrastructure Hardening and Replacement Program Based on the Pole Loading Assessment Program

PG&E’s pole loading program aims to reduce the risk of potential fire ignitions from pole failures by evaluating poles throughout their service life, from initial installation to in-service conditions, maintenance impacts, attachment additions, and potential wood strength degradation. Pole loading calculations are performed in O-Calc software during the design phase to ensure poles are correctly sized to meet GO 95 requirements. These calculations cover the entire electric distribution pole from top to bottom, including conductors, communication attachments, and guy wires, ensuring sufficient strength.[179] The data used is derived from Electric Distribution GIS (EDGIS) along with a series of algorithms and conservative assumptions to fill any data gaps. Additionally, wood pole condition data from PG&E’s "Test and Treat" inspection is incorporated to enhance accuracy and reliability.[180] PG&E has various pole replacement programs, with the reliability (rerouting/reconfiguring distribution lines) and emergency and maintenance (inspection and patrol) programs contributing to a higher number of pole replacements. Furthermore, PG&E’s enhanced inspection program resulted in decreased equipment outages.

III.B.4.4 Transmission Tower Maintenance and Replacement

The transmission tower maintenance, repair, and replacement program focus on high-risk steel structures. The determination of high-risk steel structures is based on prior inspection conditions, environmental factors (such as HFTD area or corrosion zone), age, structure design, prior outages, and prior repairs. Through standard inspection and patrol, the Transmission tower Maintenance tag is created. As conditions are identified, they are given a time-based priority based on guidance in PG&E’s Electric Transmission Preventive Maintenance Manual. The prioritization of maintenance tags is based on the severity of the issues found, fire ignition potential (e.g., asset-conditions impacting issues associated with HFTD areas and HFRA map), probability of failure (annualized OA), and wildfire consequence (Multi Attribute Value Function).[181]

III.B.4.5 Assessments for Electric Distribution Poles and Transmission Towers

III.B.4.A1 Electric pole inspections exceed GO165/GO95 compliance and PG&E's pole risk assessment practices continue to incorporate novel technology

PG&E pole inspection programs are GO 165 compliant, with higher frequency in HFTD and regularly scheduled intrusive inspections. Use of quantitative pole loading assessment through tools like O-Calc ensures that PG&E is both compliant with GO 95 and capable of reliably identifying maintenance issues on poles. The associated EC tags are risk-prioritized in HFTDs. GIRS-RT approves PG&E's pole program, and, as the prevalence of remote monitoring devices proliferates on the distribution and transmission systems, encourages the adoption of these new technologies in high-risk areas to improve failure response and corrective issue identification.

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[179] *TD-8105: Distribution Line Overhead Asset Management Plan, p. 19.*
[180] *TD-8105: Distribution Line Overhead Asset Management Plan, p. 19.*
[181] *PG&E WMP, 2021, p. 593.*

Table III.B-3: Summary of the distribution pole and transmission tower maintenance work progress.

Equipment	*Risk to be mitigated*	*Inspection Schedule*	*Work Prioritization*	*Goals met in 2021?*	*Actual progress (2021)*	*Notes and future improvements*
Crossarm	Failure-> energized conductor falls to the ground	1-3 yrs (HFTD) 5 yrs (non-HFTD) Annual (urban) Bi-annual (rural)	Based on risk ranking	N/A	10,946 replaced/ repaired.	continue to inspect/ monitor
Distribution pole	Failure -> risk of a potential wires down	1-3 yrs (HFTD) 5 yrs (non-HFTD) Annual (urban) Bi-annual (rural) Intrusive Inspections: 10 yrs	replacements follow risk-based approach	Yes (exceeded)	16,359/3,012 replaced/ reinforced. composite pole replacement	no plan to expand composite pole except extreme conditions
Transmission Tower	Wildfire risk, customer safety and reliability	1-3 yrs (HFTD) 5 yrs (non-HFTD)	based on severity of the issue, HFTD/ HFRA, TOA model and MAVF	Yes	5,770 tags were completed (goal of 4,000)	additional inspection and asset-life extension technology
Pole loading	GO 95 compliances	1-3 yrs (HFTD) 5 yrs (non-HFTD) Annual (urban) Bi-annual (rural)	HFTD regions	No	61,000 poles	check multiple pole models at once

III.B.5 PSPS System Updates

In 2018, PG&E began implementing Public Safety Power Shutoffs (PSPS) to reduce the risk of catastrophic wildfires during extreme weather events. Because this was a new initiative, PG&E's infrastructure was not designed to minimize impacts of these events on customers and communities. During 2021-2022 PG&E prioritized system work to minimize PSPS impacts using historical climate records (PSPS 10-Year Lookback Model), areas of elevated wildfire risk (e.g., HFTDs), number of customers impacted, locations of critical facilities, supply chain and logistical constraints, presence of faulty equipment, and more.

III.B.5.1 PSPS 10-Year Lookback Model

The PSPS 10-Year Lookback Model is an analysis of 10 years of historical weather events (completed in the Fall of 2020).[182] The model evaluates whether actual weather events would have triggered PSPS events in PG&E's transmission and distribution systems. The model has identified ~30 weather events across the past 10 years that would have triggered PSPS events. PG&E prioritized circuits that show up most frequently in the model and in actual events while considering the impacts derived from the cumulative circuit risk and median customer impacts.[183] Circuits with elevated risk do not necessarily experience elevated PSPS frequency. Additional drivers that motivate the prioritization of work are addressed in the following sections.

III.B.5.2 Improvements to Mitigate or Reduce the Scope of PSPS Events

PG&E has installed and operated electrical equipment to sectionalize and island parts of the grid, microgrids, and local generators.

III.B.5.2.1 Distribution Line Sectionalization

Installation of remotely operable Supervisory Control and Data Acquisition (SCADA) sectionalizing devices and manually operated sectionalizing devices on the distribution system support PG&E's ability to segment distribution circuits near PSPS areas.[184] The initiative reduces potential ignitions by isolating high risk areas from safe-to-energize zones minimizing scope and customer impacts of PSPS events. Work is prioritized by 1) using the PSPS 10-year Lookback Model to identify conditions that would have led to PSPS events in the past and 2) identifying locations where work would most optimally minimize the number of customers impacted.[185] Permit requirements, the capacity to complete work before September 1st ("peak" PSPS season), and sections of the grid with "Viper" branded reclosers that suffer from moisture intrusion issues also drive work prioritization. In 2021, PG&E exceeded their goals for this initiative (Table III.B-4).

III.B.5.2.2 Transmission Line Sectionalization

PG&E installed remote-operated SCADA sectionalizing devices on the transmission system to allow segmentation of the transmission circuits in HFTD areas to enable operational flexibility, reducing the scope and customer impact of PSPS events.[186] Work is prioritized by 1) using the PSPS 10-year Lookback Model to identify conditions that would have led to PSPS events in the

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182 PG&E WMP 2021, p. 849.
183 PG&E WMP 2021, p. 849; WRGSC Summary Slides 12/11/2020; WRGSC Summary Slides 12/18/2020.
184 PG&E WMP 2022, p. 450.
185 PG&E WMP 2022, p. 451.
186 PG&E WMP 2022, p. 454.

past by 2) circuit HFTD location.[187] Switch upgrades are often identified at line junctions and substations, where operational flexibility may be most beneficial. Access challenges, permitting issues, and clearance restrictions also influence the order switches may be installed. PG&E achieved their work goals for this initiative in 2021 (Table III.B-4).

III.B.5.2.3 Distribution Line Motorized Switch Operator (MSO) Pilot

MSO switches were installed on PG&E's distribution system in 2019 as sectionalizing devices to reduce the scope of PSPS events. While MSOs were understood to meet CAL FIRE's criteria for not posing an ignition risk during operation, PG&E crews observed MSOs that exhibited arc flashes during operation.[188] PG&E halted installation of MSO switches in late 2019, and all operation of the MSOs was done while the devices were de-energized. All MSOs that are located within HFTD areas, or which serve line sections that feed into HFTD areas have been tagged for replacement. The first locations to be replaced will be those that can be replaced with SCADA-enabled reclosers and have limited permitting restrictions, which will also influence replacement timelines for MSOs. Device availability limitations also influence work completion in some locations. MSOs with Viper reclosers, which are susceptible to moisture intrusion issues, are also used to inform work prioritization. No risk model was used for the initiative.

III.B.5.3 Installation of System Automation Equipment

PG&E has installed and replaced equipment with remote operational capabilities enabling PG&E to control and monitor circuits.

III.B.5.3.1 Installation of System Automation Equipment

High impedance faults are conditions where line-to-ground faults do not draw fault current that a protective device can reliably sense and trip the circuit offline creating a potential ignition source. Installation of the SCADA equipment in Tier 2 and Tier 3 HFTD areas enables protection that address high impedance fault conditions.[189] This automation equipment is integrated into PG&E's centralized distribution control system and communication protocols. No risk model was used to prioritize work.[190] PG&E achieved their work goals for this initiative in 2021 (Table III.B-4).

III.B.5.3.2 Single Phase Reclosers

A single phase recloser is a flexible, intelligent device that can replace fuses and act as a single phase recloser with the capability to trip all phases. PG&E has initiated installation of these devices to reduce the risk associated with a wire down event if the downed wire remains energized due to a back-feed condition from another phase of the circuit.[191] Work is prioritized by whether the target 1) is in Tier 2 or Tier 3 HFTD areas, 2) has experienced one or more wire down outages in the last 10 years, and 3) has fuse cut-outs that have experienced elevated fire potential.[192] PG&E achieved their work goals for this initiative in 2021 (Table III.B-4).

[187] *PG&E WMP 2022, p. 455.*
[188] *PG&E WMP 2022, p. 457.*
[189] *PG&E WMP 2022, p. 462.*
[190] *PG&E WMP 2022, p. 463.*
[191] *PG&E WMP 2022, p. 465.*
[192] *PG&E WMP 2022, p. 465.*

III.B.5.4 Reducing PSPS Impacts on Customers and Residents

PG&E has taken action to improve access to electricity for customers during PSPS events including operation and installation of generation equipment for impacted communities.

III.B.5.4.1 Generation and Deployment

Temporary Generation (TG) organization and the TG Project Management Office (PMO) focus together on the acquisition of equipment and operational preparedness for substation microgrids, back-up power support, and community resource centers (CRC) during PSPS events.[193] The benefit of this initiative is to establish an organizational structure to ensure consistency of safety procedures, operations, program management, and reporting status to reduce customer impacts. Work is prioritized using the PSPS 10-year Lookback Model to identify conditions that would have led to PSPS events in the past.[194] The potential effects of circuits from this model also inform decision making for the installation of TG units.

III.B.5.4.2 Temporary Substation Microgrids

PG&E has acquired temporary generators and staged them at substations to keep customers online when upstream substations are impacted by de-energization.[195] This reduces the impacts of PSPS events on customers and improves the customer notification process. Work is prioritized using the PSPS 10-year Lookback Model to identify conditions that would have led to PSPS events in the past to inform which substations may be best for positioning TG units.[196] Planned utility improvements that impact transmission operability during high wind events and input from SMEs also inform work prioritization.

III.B.5.4.3 Temporary Distribution Microgrids

PG&E aims to keep communities and main street corridors energized to help mitigate risks during PSPS events by 1) installing devices to disconnect the distribution microgrid from the larger electrical grid, 2) determining space for back-up generators and equipment to allow rapid connection, and 3) using TGs allowing PG&E to shorten the design and construction time required for installation of a permanent microgrid.[197] Temporary distribution microgrids are designed to reduce the number of customers impacted by PSPS events and support community resilience by powering shared resources. Work is prioritized using the PSPS 10-year Lookback Model to identify conditions that would have led to PSPS events in the past and the identification of communities and clusters of shared services (food, fuel, healthcare, and shelter) and critical facilities that would be safe to energize during PSPS.[198]

III.B.5.4.4 Back-Up Power for Individual Critical Customer Facilities, Small Essential Businesses, and Residential Customers

PG&E coordinates with critical facilities, such as hospitals, telecommunication providers, and transportation agencies, among others, to further understand and more effectively plan for the impacts of PSPS events on the ability to safely operate these facilities. PG&E developed and

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[193] PG&E WMP 2022, p. 470.
[194] PG&E WMP 2022., p. 471.
[195] PG&E WMP 2022, p. 472.
[196] PG&E WMP 2022, p. 473.
[197] PG&E WMP 2022, p. 475.
[198] PG&E WMP 2022, p. 476.

patented the Backup Power Transfer Meter (BPTM) to provide temporarily power to the homes of customers from a generation source when power is off.[199] PG&E also assists small essential business and residential customers through programs that provide backup power options such as the Generator and Battery Rebate Program, Disability Disaster Access and Resources Program, and the Portable Battery Program. Work prioritization for critical facilities is governed by the request of ad-hoc back up power upon request and the presence of pre-staged sites.[200] No risk model is used for work prioritization.

III.B.5.4.5 <u>Community Resource Centers (CRC)</u>

PG&E opens CRCs to provide access to electricity during PSPS events. CRCs are equipped with backup power throughout the PSPS season for access to electricity.[201] Pre-identified CRC sites are present in the service territory where PSPS events are likely to occur. PG&E consults with regional, local, and tribal governments, county offices of emergency services, advisory councils, public safety partners, representatives of at-risk groups, business owners, community-based organizations, and public health and healthcare providers to identify potential CRC locations.[202] No risk models are used for work prioritization.

III.B.5.4.6 <u>Substation Activities to Enable Reduction of PSPS Impacts</u>

The installation or upgrade of protection equipment and automatic sectionalizing devices at various substations improve operating flexibility thereby minimizing the frequency, scope, and duration of PSPS events.[203] This effectively reduced the impacts of PSPS events on customers by both reducing the durations of events and the number of customers impacted. Work is prioritized using the PSPS 10-year Lookback Model to identify conditions that would have led to PSPS events in the past affecting substations.[204] The System Protection group and Substation Maintenance groups (internal groups at PG&E) conduct additional analyses to determine the work needed. PG&E identified one substation for system upgrades to mitigate PSPS impacts in 2021.[205]

III.B.5.4.7 <u>Emergency Back-up Generation – PG&E Service Centers and Materials Distribution Centers</u>

PSPS events impact PG&E Service Centers and Materials Distribution Centers, which affected PG&E's ability to efficiently restore power to customers. The Emergency Back-up Generation project aims at equipping sites with an emergency generation system capable of backing up PG&E Service Centers and Materials Distribution Centers allowing full operation on generator power during PSPS events.[206] Work prioritization is driven by 1) the proximity or presence of a service center in HFTD areas and 2) the population of PG&E employees

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[199] PG&E WMP 2022, p. 479.
[200] PG&E WMP 2022, p. 480-481.
[201] PG&E WMP 2022, p. 484.
[202] PG&E WMP 2022, p. 484.
[203] PG&E WMP 2022, p. 486.
[204] PG&E WMP 2022, p. 487.
[205] PG&E WMP 2022, p. 487.
[206] PG&E WMP 2022, p. 489.

corresponding to a given service center.[207] By the end of 2021, 37 sites were completed (5 of these sites were completed in 2020).[208]

Table III.B-4: Completion of PSPS Mitigation Related Work Goals by Initiative.[209]

Work Initiative	*Purpose of Work*	*Goal for 2021*	*Progress by 2022*
Installing SCADA-enabled distribution sectionalizing devices	Sectionalizes distribution circuits to reduce the impact and scope of PSPS events	Installing 250 SCADA-enable distribution sectionalizing devices	Installed 257 before Peak PSPS – Installed 269 by the end of 2021
Installing Transmission Switches for PSPS Mitigation	Allows operational flexibility to reduce the scope and impact of PSPS events	Installing 29 SCADA-enable distribution sectionalizing devices	41 were installed by the end of 2021
Replacement of Motorized Switch Operators (MSO) switches	MSO switches were reported to exhibit an arc flash during the opening (de-energizing) operation – ignition risk	Pilot Year	In 2021 PG&E replaced 50 MSO Switches
Replacement of Legacy 4C Controllers in HFTDs	Addresses high impedance fault conditions and integrated with communication protocols	Replacing all ~80 legacy 4C controllers in HFTDs	Replaced all 81 known legacy 4C controllers by the end of 2021
Installing Single Phase Reclosers to Replace Fuses	Decreases risk from wire down events where wire remains energized	Installing 70 single phase reclosers to replace fuses	Installed 71 by the end of 2021

[207] *PG&E WMP 2022, p. 489-490.*
[208] *PG&E WMP 2022, p. 490.*
[209] *PG&E WMP 2022, p. 450-465.*

III.B.5.5 Assessment of PSPS-related Updates

III.B.5.A1 Modification of Grid Infrastructure and Work Prioritization

PG&E has taken steps to modify grid infrastructure to minimize customer impacts during PSPS events and reduce wildfire risk, exceeding industry standards. Prioritization is driven by meteorological models derived from historical data, areas susceptible to high wildfire risk, customer impacts, logistical constraints, feedback from experts, and more.

III.B.5.A2 Meeting PSPS-related Work Goals

From 2021-2022, PG&E has met or exceeded their goals for PSPS-related line maintenance and system updates.

III.B.5.A3 Internal Risk Identification and Equipment Development

PG&E has identified grid components (e.g., MSO switches) that increase catastrophic wildfire risk and have independently undergone efforts to replace the faulty components. PG&E also developed equipment (e.g., BPTM) that reduced the impact of PSPS events on customers.

III.B.6 Summary of GIRS-RT Findings for System Hardening Decision Making

The GIRS-RT finds that the strategies used for system hardening decision making for the 2021 and 2022 WMPs were fit for use at the time of deployment. Moreover, the strategies take into consideration the main general orders established by CPUC, in addition to a series of utility standards and procedures designed for the maintenance and management of electric infrastructure.

Features:

- PG&E presents a variety of strategies for system hardening decision making across different scale levels in their service territory. The models used for this process are in general informed by an underlying risk metric and take into consideration local environmental and weather conditions.
- PG&E took action to revise a large amount of scoped work to align the system hardening and inspection plan with maximum risk reduction according to the outputs of WDRM v2. Due to the rescoping of the workplan and the specific allocation of resources, a backlog of maintenance issues was accumulated.
- Updates have been made to grid topology to minimize risk of ignitions in HFTDs.
- PG&E has complied with the relevant General Orders, procedures, and standards involved in Grid Design and System Hardening of pole and non-pole assets.
- Prioritization was reassessed to reflect the change in risk models (WDRM v2) which occurred during the audit period.
- Workplans have been constructed to address the backlog of tags.
- Updates to the grid were prioritized to minimize PSPS impacts on customers and critical infrastructure.

Summary of assessments:

III.B.1.A1 Achievements of Milestones established by PG&E

The GIRS-RT finds that where milestones were applicable to establish, they were met or exceeded by PG&E for the years 2021 and 2022.

III.B.1.A2 Use of risk-based strategies for prioritization of work

The GIRS-RT finds that PG&E uses a risk-based approach the prioritization of most of the system hardening initiatives.

III.B.1.A3 Potential Redundancy in Transmission System Grid Updates

The decision-making process for hardening in the Transmission System is subdivided among different teams and initiatives in the company. The GIRS-RT suggests generating a unified process to prevent redundancy and inefficiencies in risk mitigation.

III.B.1.A4 Emphasis on real-time monitoring strategies

The GIRS-RT recommends additional emphasis on real time monitoring strategies for future WMPs, as these types of strategies can provide both enhanced information for future models, as well as real time capabilities for mitigation under abnormal circumstances.

III.B.1.A5 Update to General Order 128 and 165

General Order 128 and General Order 165 were last revised in 2005 and 2017, respectively. GIRS-RT recommends that CPUC review and potentially update these orders to reflect changes due to significant wildfire events that have occurred in California since the latest update.

III.B.2.A1 Rescoping of 2021 workplan supports risk-reduction objectives

GIRS-RT supports the rescoping and revision of the 2021 workplan done to align the focus of work with the results of the 2021 risk model, a decision which increased the scoped risk reduction despite decreasing the magnitude of work.

III.B.2.A2 The significant backlog of EC tags presents a challenge and persistent risk factor on the distribution and transmission

PG&E states that the backlog of EC tags in HFTDs will not be remediated until 2033; increased work and targeted initiatives must be put in place to remediate this significant and persistent source of risk.

III.B.3.A1 Goals met on non-pole, non-conductor grid equipment

PG&E met or exceeded its goals, where made, with respect to the maintenance, replacement, and inspection of electrical equipment on the grid and in grid substations.

III.B.3.A2 Continue the development and installation of novel technologies to manage grid equipment with reduced reliance on inspection and inspection personnel

The introduction of more remote monitoring equipment will assist both in emergency preparedness and accurate identification of risk on the PG&E system; some programs, like DTS-FAST, are in development, and GIRS-RT strongly supports the proliferation of similar programs across the system.

III.B.4.A1 Electric pole inspections exceed GO165/GO95 compliance and PG&E's pole risk assessment practices continue to incorporate novel technology

PG&E satisfies GO 165 compliances in its pole inspection programs. GIRS-RT approves PG&E's pole program and encourages the adoption of these new technologies in high-risk areas to improve failure response and corrective issue identification.

III.B.5.A1 Modification of Grid Infrastructure and Work Prioritization

PG&E has modified grid infrastructure to minimize customer impacts during PSPS events and prioritized work by considering historical data, consequences, risk, customer impacts, and related other variables.

III.B.5.A2 Meeting PSPS-related Work Goals

PG&E has met or exceeded work goals for PSPS-related line maintenance and system updates.

III.B.5.A3 Internal Risk Identification and Equipment Development

PG&E independently identified grid components that pose ignition risks and developed equipment to minimize PSPS impacts on customers.

III.C Fire Rebuild Design Guidance for System Hardening: Utility Bulletin TD-9001B-009

III.C.1 Fire Rebuild Design Guidance Overview

Utility Bulletin TD-9001B-009 and supporting documents detail PG&E’s Fire Rebuild Design Guidance for System Hardening. This includes comprehensive instructions for standard overhead design guidance for all new construction and reconstruction work in Tier 2, Tier 3, and Zone 1 (tree mortality) areas. Utility Bulletin TD-9001B-009 is not intended for required maintenance or emergency work. The target audience includes Service Planning, Estimating, Capacity & Reliability Planning Engineering, Electrical and M&C personnel and contractors associated with fire rebuild areas.

This section includes 25 requirements with associated reference documents (covered in Section III.C.2 of this report) and instructions for how and when to apply guidance (Section III.C.3 of this report).

III.C.2 Overhead Design and Construction Requirements

III.C.2.1 New Construction Conductor Standards

- Description: Summarizes the type, size, and usage of approved conductors for up-to-date construction protocols. Generally, reinforced conductors like ACSR (aluminum conductor steel reinforced) or AWAC (alumoweld-aluminum conductor) are preferred over copper or pure aluminum conductors.

- Importance: Improved conductor tensile strength decreases the risk of mechanical failure and wire down faults.

PG&E Documents 059690[210] and 059626[211] list the specifications for the approved conductor types by load and region and the associated approved amperage. The amperage bounds, derived from IEEE standards 738−1993 and 835−1994 are season dependent. Historical temperature data is combined with sag calculations to compute the maximum allowed load for a given circuit under normal and emergency operation.

The only exception to the use of reinforced conductors is in areas of high corrosion, where copper is preferred; ACSR is more susceptible to corrosion than copper. Generally, high corrosion areas are coastal areas where the risk of ignition is lower, so this restriction is reasonable. All the construction guidelines presented meet or exceed GO 95 compliance and are intended to supersede GO 95 in the use of reinforced conductors more generally. GIRS-RT notes that ACSR conductors suffer from relatively high thermal sag compared to other reinforced conductor types (CTC Global, 2011). PG&E SMEs indicated that the higher tensile strength of ACSR allows higher tension in the line which can mitigate sag concerns.

III.C.2.2 Distribution pole construction standards

- Description: Provides electric pole construction requirements for installing and replacing wooden poles, including material specifications, setting depths, and vertical load capacities. Additionally, the guidelines include the use of intumescent-coated wooden poles.
- Importance: The pole construction guidelines ensure the safety and structural integrity of wooden poles within PG&E's service area. The use of intumescent-coated wooden poles enhances fire resistance.

Document 015203[212] outlines the basic engineering design and construction requirements for the installation and replacement of wooden poles. These requirements include the pole setting depth, which varies with soil conditions and pole length, and should be adequate to withstand wind loading. Additionally, GO 165 inspections and patrols are in place to address potential soil erosion and landslides due to extreme environmental conditions.

The wooden poles are commonly treated near the ground line using through-bore holes to extend their service life by protecting against internal decay. If a pole needs to be set deeper than usual, a pole treated over its entire length should be used rather than one that is only treated at the butt. Moreover, the requirements also include the vertical strength of utility poles that varies depending on their type of restraint, with guyed and effectively restrained poles offering greater strength compared to tangent line poles. The allowable vertical loads, which include the weight of the pole itself, are determined by the minimum dimensions for each pole class. For existing

[210] *PG&E Internal Document #059690, "General applications of conductors for overhead distribution lines", Rev. 9.*
[211] *PG&E Internal Document #059626, "Conductors for overhead lines", Rev. 14.*
[212] *PG&E Internal Document #015203, "Construction requirement for wood distribution pole", Rev. 14.*

poles, both groundline and vertical strengths are calculated based on the actual circumference at the groundline, with necessary adjustments for any damage or decay.

The intumescent material, infused onto fiberglass mesh and wrapped around wooden poles, acts as an insulating barrier when exposed to fire, protecting the poles from burning or charring during wildfire events. These poles are non-hazardous, non-conductive, and ideal for use in High Fire Threat Districts (HFTD Tier 2 and Tier 3).

III.C.2.3 Pole loading calculation

- Description: Pole loading calculations are performed prior to the construction of a new pole or when any changes are made to an existing pole.
- Importance: Pole loading calculation enhances fire ignition risk reduction.

Pole loading calculations are performed in O-Calc software during the design phase to ensure poles are correctly sized to meet GO 95 requirements.

III.C.2.4 Evaluation of pole loading calculation

- Description: Pole loading calculations are evaluated with a special load case designed for HFTD Tiers 2 & 3.
- Importance: Ensures poles are sufficiently robust to withstand high wind speeds.

PG&E's Utility Bulletin TD-9001B-010[213] reports the use of a 3-second wind gust value instead of a 1-minute average for evaluation of pole loading calculations in HFTD Tier 2 and Tier 3 areas. The discrepancy in the pole loading calculation ensures selection of the appropriate load case when there is a change in the pole construction grade.

The Utility Procedure TD-2951P-01[214] outlines procedures to request changes in the design, installation, and materials of electric distribution system that do not comply with PG&E's defined standards in the electric distribution manuals and documents. This variance is permitted for site-specific scenarios, depending on local conditions.

III.C.2.5 Non requirement for increasing pole class size

- Description: Standard requirement to increase the class size of wood poles is no longer necessary. Instead, new criteria have been proposed to increase the wood pole class.
- Importance: Reduce the probability of wildfires due to wind-related pole failures in areas of known high wind speeds.

The Utility Bulletin TD-015203B-002[215] introduces a new requirement to increase the wood pole class in designated fire protection areas subject to high winds. These new requirements will apply when historical peak wind speeds exceed 70 mph. The affected areas include Santa Barbara County, Urban Wildland Fire (UWF) Areas, and Other Wildland Fire (OWF) Areas.

[213] PG&E Utility Bulletin TD-9001B-010, "PG&E historical peak wind in GIS", Rev.0.
[214] PG&E Utility Procedure TD-2951P-01, "Request for variance from electric distribution standards", Rev.0.
[215] PG&E Utility Bulletin TD-015203B-002, "High wind area criteria for distribution wood poles", Rev.0.

III.C.2.6 Use of composite pole

- Description: Use of fire rated composite pole in high fire risk areas.
- Importance: Eliminate wood poles that provide a fuel source during wildfires.

The Utility Bulletin TD-066202-B001[216] provides guidance for use of Shakespeare fire rated composite poles.

III.C.2.7 Standard triangular crossarm construction

- Description: Provides guidelines and design specifications for triangular crossarm construction on distribution poles in non-raptor concentration zones.
- Importance: Reduce outages caused by birds.

Document 06619[217] outlines structural configurations for tangent and light-angle construction on distribution pole lines. It details designs for triangular crossarm construction, including component parts for assemblies, angle limitations, and tree wire angle restrictions specific to this construction type. These standards are intended to prevent outages caused by birds.

III.C.2.8 Angle washers

- Description: All insulators and insulator pins that support span wires and slack spans that support span wires and slack spans (excluding jumper supports) must have angle washers installed at the top and bottom of the composite arm.
- Importance: This requirement is for wind loading reinforcement purposes.

Internal Document 068180[218] is revised to reflect this requirement.

III.C.2.9 Trees are not to be used for wire attachments, anchoring, or guying of any poles

- Description: Attaching any type of service drop cable to trees is no longer allowed. Trees are also not an approved means for anchoring or guying of any poles.
- Importance: These measures decrease the ignition risk from vegetation contact.

Internal Document TD-2999B-044[219] elaborates on the updates to PG&E's protocols and internal document 0250202[220] was updated to reflect the updates to the construction protocols.

III.C.2.10 Trees are not to be used for guy support in heavily wooded areas

- Description: In heavily wooded areas, trees are not to be used for guy support. Field technicians and maintenance workers are to consider the increased vegetation clearance planned for HFTD Tiers 2 and 3 and determine if the newly available lead length is enough to support the pole.
- Importance: These measures decrease the ignition risk from vegetation contact.

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[216] *PG&E Utility Bulletin TD-066202-B001, "Use of Shakespeare composite poles", Rev. 0.*
[217] *PG&E Internal Document #066196, "Standard framing for tangent construction distribution pole lines", Rev.10.*
[218] *PG&E Internal Document #068180, "Composite Crossarms for Distribution Lines", Rev. 12.*
[219] *PG&E Utility Bulletin (TD—2999B-044), "Prohibiting the Attachment of Conductors and Distribution Facilities to Trees", Rev. 0.*
[220] *PG&E Internal Document #0250202, "Methods of Attaching Services to Customer Premises", Rev. 5.*

III.C.2.11 New un-guyed poles may require larger class sizes than historically designed

- Description: Storm guys may be used to offset the need for larger pole classes. Field technicians and maintenance workers are to consider changing the route, using shorter span lengths, or increasing the pole class and set depth as needed until the pole loading model shows a passing safety factor.
- Importance: These measures increase grid resilience under elevated wind speeds.

III.C.2.12 Ensure clearances are met with the greater sags of tree wire

- Description: Sags for tree wire can be much greater than bare wire and set depths are deeper leaving less room for clearances. Thus, it is essential to verify adequate clearance.
- Importance: These measures decrease the ignition risk from ignitions driven by sagging wires.

III.C.2.13 Limitations on span length

- Description: The previous 200-foot span requirement is now a recommendation.
- Importance: Limiting spans to 200 feet or less reduces the total wire sag and reduces the chance of vegetation contact, especially during high winds.

Limiting span length reduces sag and the chance of vegetation contact. Per discussions with PG&E SMEs, previous span length requirements were overly restrictive, causing practical engineering issues. Relaxing the requirement to a recommendation was done to maintain reasonable standards for span length while not creating unnecessary engineering challenges in practice.

III.C.2.14 Splices on the line

- Description: No new in-line splices are to be installed.
- Importance: Splices form a failure point in lines and were used in the WDRM v2 conductor risk model as a failure covariate. Installing new lines instead of inline splices improves overall conductor mechanical strength.

Utility Bulletin TD-022487B-003[221] lists two requirements: no new inline splices are to be installed, and no splices are permitted over major crossings. Major crossings include freeways and G0 95 grade A crossings, which are major railways with powered locomotives. PG&E rebuild guidance indicates that in emergencies, "on the spot" corrective action should be considered to eliminate 3 or more splices on a given line.

III.C.2.15 Replacement of open-wire secondaries with reinforced conductors

- Description: Secondaries—post-transformer low-voltage lines—which are open wire are to be replaced with ACSR or AWAC reinforced conductors.
- Importance: Secondaries deliver lower voltage power to local circuits and residences. With greater proximity to vegetation and built infrastructure, their impact on an object is more likely than elevated distribution lines. Replacement with reinforced conductors

[221] *PG&E Utility Bulletin TD-022487B-003, "Maximum number of splices in an overhead distribution conductor", June 2013.*

decreases the chance of mechanical failure or ignition due to tree or other object contact.

Standards for secondary wires are specified in Document 059690,[222] which addresses conductor standards more generally.

III.C.2.16 Insulating fluid for transformers

- Description: Only transformers that use the insulating fluid denominated as FR3 are allowed in Tier 2 and Tier 3 fire areas.
- Importance: FR3 insulating fluid has advantageous properties that decrease the likelihood of an ignition caused by a transformer. It has a lower flash point and fire point when compared to traditional insulating fluids such as mineral oil.

This requirement indicates the use of high fire-point natural ester insulating fluids, from which FR3 is one of the most common brand names in the market (Zimmerman and Bass 2014). The use of these novel insulating fluids was implemented as a standard in 2014 and included in the latest Department of Energy (DOE) high-efficiency standards in 2016.

The requirement is in line with external research (Zimmerman and Bass 2014; Srivastava, Goyal, and Saraswat 2021) that demonstrates that these insulating fluids provide utilities with significant advantages. These include 1) improved resistance to environmental factors (e.g., reduction in biodegradability), 2) reductions in health-related hazards resulting from the non-toxicity and non-carcinogenic qualities, and 3) safety factors (e.g., decreased ignition risk).

III.C.2.17 Prevention of animal-caused ignitions

- Description: All transformer locations must be fully guarded to prevent interaction with birds and other animals and must include insulated jumpers.
- Importance: The interaction between animals and the electric system is a relevant failure mode that increases wildfire risk and decreases customer reliability in the service territory.

This requirement follows PG&E Internal Document number 061149.[223] This document covers techniques used to construct or modify electric infrastructure to reduce the electrocution risk to all wildlife. Due to the increased protection, the risk of outages and ignitions is reduced.

Increased animal protection is achieved by mainly two strategies: 1) provide safe places for birds to land, and 2) prevent birds and other animals from occupying space between closely spaced phases.

III.C.2.18 Animal protection

- Description: All transformer locations must be fully guarded to prevent interaction with birds and other animals and must include insulated jumpers.
- Importance: The interaction between animals and the electric system is a relevant failure mode that increases the risk of ignition in the service territory.

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[222] *PG&E Internal Document #059690, "General Applications of Conductors for Overhead Distribution Lines" Rev 9.*
[223] *PG&E Internal Document #061149, "Raptor Safe Construction and Wildlife Protection", Rev. 14.*

This requirement follows the same internal document as requirement 1.17, described in Section III.C.2.17 of this report.

III.C.2.19 Inclusion of SCADA in electrical installations

- Description: All regulator installations must be closed delta with SCADA capabilities.
- Importance: SCADA capabilities shorten the response and restoration time in an outage emergency, increasing customer reliability, and enables data collection for quantitative modeling.

This requirement follows PG&E Internal Utility Bulletin TD-015239B-003,[224] which describes the installation of Supervisory Control and Data Acquisition (SCADA) communication on closed-delta line voltage regulators. The document is intended for new installations and work planned as Critical Operating Equipment (COE).

PG&E expects that the installation of SCADA capabilities in the electric system will enhance operational flexibility, work efficiency, and customer reliability through the new remote capabilities. The GIRS-RT agrees with this statement and encourages the inclusion of existing and novel monitoring technologies in the service territory.

III.C.2.20 Installation of CAL FIRE exempt surge arrestors

- Description: Install CAL FIRE exempt surge arrestors following PG&E internal Document 031822.[225]
- Importance: This is in line with current standards for equipment in high-fire areas. It reduces the wildfire risk produced by equipment operation and failure.

This requirement follows PG&E Document number 031822. The document provides information related to ordering and applying surge arresters on overhead distribution circuits. This information includes zones where surge arrestors are recommended, installation details, and instructions. Importantly, the criteria outlined in the document apply only to new installations.

III.C.2.21 Installation of CAL FIRE exempt equipment

- Description: Only CAL FIRE exempt equipment can be installed, no new, non-exempt equipment shall be installed.
- Importance: This is in line with current standards for equipment in high-fire areas. It reduces the wildfire risk produced by equipment operation and failure.

This requirement follows PG&E Document number 015225.[226] The document provides information regarding the ordering and application of these electrical devices and states the following two requirements: first, the installation of ELF or Fault Tamer Fuses for transformer protection; second, E-power Fuses for lateral and riser protection.

[224] PG&E Utility Bulletin TD-015239B-003, "Installation of SCADA communication and External PTs on Line Voltage Regulators", Rev. 1.
[225] PG&E Internal Document #031822, "Application of Surge Arresters on Overhead Distribution Lines", Rev. 17.
[226] PG&E Internal Document #015225, "Cutouts, Fuses, And Disconnects for Overhead Distribution Line", Rev. 25.

III.C.2.22 Armor rods, ties, and tree wire considerations

- Description: Use PG&E approved materials and installation procedures for Ties, Rods, and Tree Wires.
- Importance: The correct installation of carefully designed equipment that is fit for the application at hand can reduce the failures in the system, increasing customer reliability and decreasing wildfire risk.

The requirement cites three PG&E Internal Documents: 015195,[227] 028853,[228] and 021439. [229]

These documents extensively cover the procedures to select and install armor rods, ties, and tree wires in the electric system. This requirement also states three additional regulatory remarks. First, connections shall not be made under conductor covers. Second, piercing hot line connectors are not allowed to be used. Third, and finally, all skinned conductors must be covered with approved raptor covers or taped up.

III.C.2.23 Use of automated devices

- Description: The use of automated equipment (e.g., switches and regulators) is generally encouraged.
- Importance: Automated devices allow remote control and monitoring of electrical infrastructure. Automated switches and reclosers can address faults as they occur.

GIRS-RT strongly supports the continued adoption of automated technology across the grid. Automated grid control can mitigate faults and provide a second layer of resilience to the grid.

III.C.2.24 Adding SCADA to the system

- Description: SCADA should be added to existing switches or, where no switch is present, a SCADA MSO switch should be installed when lines transit HFTD or HFRA boundaries.
- Importance: SCADA and other automated devices allow remote control and monitoring of electrical infrastructure. By installing SCADA on existing switches, remote management centers can better control the line and surrounding circuit infrastructure. Adding switches at HFRA boundaries allows easier and more precise isolation of circuits during failures or PSPS events.

SCADA devices allow both control and data acquisition by remote monitoring centers on the PG&E system. Greater remote-control capability means less reliance on slow in person response and more effective emergency management. More data on electrical performance increases PG&E's targeting capabilities. GIRS-RT strongly supports the continued adoption of automated technology across the grid.

III.C.2.25 Phase balancing in transformers

- Description: Single-phase wire taps should be staggered within transformers to ensure the load is phase balanced.

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[227] PG&E Internal Document #015195, "Installation Details for Aluminum, ACSR, and Copper Covered Tree Wire", Rev. 5.
[228] PG&E Internal Document #028853, "Armor Rods and Ties for Aluminum Conductors", Rev. 6.
[229] PG&E Internal Document #021439, "Ties and Armor Rod for Copper Distribution Line Conductors", Rev. 6.

- Importance: Electric power is often delivered in three AC phases. Unbalanced power across phases can lead to device failures and lowered efficiency. Phase balancing refers to the practice of ensuring that phases are adequately connected between transformers and single-phase residential taps to ensure the system equipment functions as designed.

Phase balancing is a common issue in electric system construction and management. Unbalanced phases can damage and cause failure in motors running off a multiphase signal. Unbalanced phases can also signal ground faults. Maintaining proper phase balancing in new construction is essential so that the system functions as expected, and so ground faults can be properly detected if they occur.

III.C.3 Application of New Requirements for Reconstruction

Utility Bulletin TD-9001B-009[230] specifies a series of guidelines regarding how and when the new requirements, listed in Section III.C.2, should be applied. This section presents a summarized version of the most relevant guidelines.

- All tasks initiated after 9/1/19 must follow the requirements established by the Utility Bulletin. This includes tasks that require revisions after that date.
- Reconstruction jobs that involve 4 or more spans must comply with the requirements established by the Utility Bulletin.
- The Utility Bulletin is not intended for maintenance or emergency work nor for temporary construction. Review of additional documents provided by PG&E (Utility Standard TD-2006S[231] and Utility Standard EMER-4004S[232]) verifies that the company has implemented a solid and established procedure to monitor and complete repair work that was initiated during an emergency, including those corresponding to system hardening tasks. The documents describe in detail the steps that the utility must follow to complete emergency work, including compliance requirements, documentation of work, roles, and responsibilities, and importantly, how to address system hardening during emergency response.

III.C.4 Summary of GIRS-RT findings for Fire Rebuild Design Guidance for System Hardening

Overall, the GIRS-RT finds that the TD-9001B-009 Rev. 2 exceeds industry standards regarding fire rebuild design guidance, and complies with relevant guidelines, such as GO 95 and GO 165.

Features:

PG&E's Utility Bulletin TD-9001B-009 Rev. 2 provides detailed specifications for fire rebuild design guidance across the following asset categories in HFTD Tier 2 and Tier 3 and Fire Zone 1 areas:

- Poles and other mounting equipment
- No tree mounting

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[230] PG&E Utility Bulletin TD-9001B-009, "Fire Rebuild Design Guidance for System Hardening", Rev. 2.
[231] PG&E Utility Standard, "Emergency Electric Corrective Documentation Standard", Rev. 2.
[232] PG&E Utility Standard, "Requirements for System Hardening During Emergency Response", Rev. 0.

- Animal protection
- Conductors: wires, transformers, SCADA devices
- ASCR Cables
- No new splices
- Use of CAL FIRE exempt equipment
- Switching devices

Summary of Assessments:

III.C.4.A1 Consideration of alternative reinforced conductors in high load or high temperature areas

PG&E's standards focus on the use of ACSR reinforced conductors in rebuild areas, and ACSR has functioned as a standard choice for PG&E construction for many years. However, ACSR conductors are known to experience higher thermal sag than other types of reinforced conductors. In areas with high temperature and high winds, increased thermal sag can lead to unintended vegetation contact as the wind blows the sagging wire into nearby vegetation. This issue is exacerbated in high temperature areas where load is regularly correlated with temperature due to the use of air conditioning.

While amperage in high temperatures is considered in the PG&E rebuild standards, GIRS-RT recommends PG&E to evaluate the feasibility and potential impact of using alternative reinforced conductor types in high-temperature, high-wind areas. Such areas also represent increased fire danger, and the consequence of failure due to excessive thermal sag is high. Conductors like ACCC (Aluminum Conductor Composite Core) and ACCR (Aluminum Conductor Composite Reinforced) are also reinforced but exhibit less thermal sag than ACSR (CTC Global, 2011).

III.C.4.A2 Use of FR3 insulating fluid decreases the likelihood of an ignition caused by a transformer

This requirement is in line with external research that demonstrates several advantages for the FR3 fluid, including improved resistance to environmental factors (e.g., reduction in biodegradability), reductions in health-related hazards resulting from the non-toxicity and non-carcinogenic qualities, and improved safety (e.g., decreased ignition risk).

III.C.4.A3 The installation of SCADA capabilities increases the potential for data collection

Most of PG&E's Wildfire Mitigation Plan strategies incorporate at least one quantitative component, necessitating the collection of high-quality data. The installation of SCADA devices in the electric infrastructure increases the potential for capturing such data sources. While the GIRS-RT acknowledges PG&E's efforts in this regard, the team recommends the standardization of the data collection process for future sensor installations, with the objective of enhancing capabilities over time.

III.C.4.A4 Design guidelines for poles and triangular crossarms

The design guidelines for the poles and triangular crossarms ensure the safety and structural integrity of distribution poles and are useful for reducing wildfire risks. Depending on local conditions, modifications to PG&E's standard design, installation, and materials for the electric distribution system may be appropriate on a case-by-case basis.

III.D Mitigation checklist decision framework (TD-9001B-009 Attachment 3)

III.D.1 Checklist Decision Framework Overview

This section reviews the Mitigation Checklist Decision Framework described in Utility Bulletin TD-9001B-009 Attachment 3 (dated 7/2/2019) along with 2021-2022 updates to the Decision Framework. The checklist in Utility Bulletin TD-9001B-009 Attachment 3 was an interim step prior to development of the WRGSC in October 2020. Based on considerations enumerated in the checklist, a preliminary design decision is made by the PG&E System Hardening team. The decision and supporting documentation are presented to the WRGSC for approval. If the decision is overhead hardening, then the design follows the Fire Rebuild Design Guidance in Utility Bulletin TD-9001B-009.

Additionally, Section III.D.4 summarizes available data for system hardening progress during the review period. Finally, III.D.5 contains a summary of the central features of the mitigation checklist decision framework and the GIRS-RT assessments.

III.D.2 Decision Flowchart

For each potential project, PG&E's system hardening team submits an economic analysis to the Wildfire Risk Governance Steering Committee (WRGSC). In this analysis, the first consideration is whether the circuit segment can be eliminated because it is identified as an idle facility that is not required by design standards. If that is not the case, the economic analysis compares the costs of three risk-reduction alternatives against a common baseline:

- No system hardening (baseline)
- Overhead hardening
    - Umbrella term for varying techniques used to mitigate risk in primary distribution overhead lines located in HFTD area (Tiers 2 and 3) that serve large sections of customers and critical facilities.
- Undergrounding
    - While this strategy reduces risk significantly with respect to others, its feasibility and cost efficiency present logistical and economic drawbacks.
    - PG&E is currently focused on improving the RSE (Risk Spend Efficiency) of undergrounding through the implementation of varying strategies to reduce the implementation cost.
- Hybrid approach, combining both overhead hardening and undergrounding

The economic analysis is conducted with a specialized software named *Economic Analysis Software Package*, also known as EASOP. The scope of each project is usually a circuit segment or a portion of a circuit segment.

The inputs for the analysis consider a variety of sources of information, including construction and operational costs, projected service life, inflation rates, and projected risk values, among others. The analysis's primary outputs include 1) the total costs of each alternative and 2) the risk reduced by each, enabling the computation of the Risk Spend Efficiency (RSE).

If the EASOP analysis favors an overhead or hybrid hardening strategy and the risk reduced by those alternatives is within 100% margin of the risk reduced by under grounding, then PG&E uses the decision chart shown in the Wildfire Mitigation Plan Revision 6,[233] to account for additional factors that are not included in the EASOP. These factors are the tree fall-in risk, PSS judgement, Ingress and Egress considerations, and PSPS mitigation. The result of this decision tree can influence the project to still choose under grounding over alternative strategies even if the EASOP output indicates a higher RSE for overhead or hybrid hardening.

If the WRGSC decides to execute an overhead hardening strategy, then the design follows the Fire Rebuild Design Guidance in Utility Bulletin TD-9001B-009.

III.D.3 Mitigation Checklist

The Community Wildfire Safety Program (CWSP) Risk Mitigation Checklist is designed to methodically analyze the project to determine the final scope to eliminate or mitigate the wildfire risk to the maximum extent.[234] This Checklist served as an interim tool before the establishment of the Wildfire Risk Governance Steering Committee (WRGSC) in October 2020.[235] In 2021, during WRGSC proceedings, modifications were gradually made to aspects of the decision flow, with a focus on undergrounding.[236] While no explicit decision tree is included in the 2022 WMP, the system hardening process is described to have a structure extremely similar to the decision flow outlined in the mitigation checklist. However, the complete decision process, as outlined in the 2022 WMP, includes many factors beyond the scope of the checklist, including public safety specialist input and the EASOP economic analysis.

The Checklist outlines a series of design alternatives. The flexibility of the checklist, with its blank spaces, allows for adaptability in addressing specific project requirements. For each alternative, several key considerations are considered. These alternatives are:[237]

1. Overhead (OH) Line Elimination

- The implementation of Distributed Generation (DG) or the establishment of a Remote Grid to provide power independently from the main grid, particularly in high-risk, less-populated areas.
- The need to leverage alternate circuits within proximity, including the determination of circuit tie-in points and the assessment of the need for additional spans.
- The acquisition of new land rights.

2. Undergrounding Line

- The availability of viable routes for undergrounding and dedicated streets or easements.
- The feasibility of the conversion of existing infrastructure, including service drops, tap-lines, and overhead equipment, to an underground system.

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[233] *Wildfire Mitigation Plan Revision 6, dated July 5, 2024, Figure SRN-PG&E-23-05-06*
[234] *PG&E Utility Bulletin TD-9001B-009 Attachment 3, Process Flowchart, p. 2.*
[235] *PG&E response DRU14096.001.*
[236] *PG&E WRGSC Proceedings, 11/17/2021.*
[237] *PG&E Utility Bulletin TD-9001B-009 Att 3 Process Flowchart, p. 2-3.*

- The analysis of soil conditions to determine the appropriate installation method, including trenching, boring, or plow-in techniques.
- The feasibility and acquisition of new land rights.

3. Hybrid Overhead & Underground

- A combination of overhead and underground solutions.

4. Circuit Reconfiguration/Relocation/Reinforcement

- The identification of alternate routes that are accessible to construction and maintenance crews.
- The feasibility of acquiring necessary land rights or easements.
- The need for vegetation clearing along the selected routes.

5. Overhead Hardening or a combination of all above

- According to TD-9001B-009 or a combination of the alternatives above.

6. Microgrid

- Although the potential for microgrids to disconnect from the main grid during outages or emergencies had been identified, PG&E had not yet initiated this alternative in 2019, leaving this part of the checklist pending.

III.D.4 System Hardening Outcomes

PG&E has made significant progress in both system hardening and undergrounding initiatives. Table III.D-1 showcases the historical completed miles under the WMP GH-01 System Hardening Initiative. This initiative focuses on improving the resilience of powerlines against wildfires by either removing existing lines, hardening overhead lines, or transitioning them to underground installations. From 2018 to 2023, 1,664 miles were completed, including overhead and underground projects. Table III.D-2 details the historical completed miles for the WMP GH-04 10K Undergrounding Initiative. This Initiative is part of the broader system hardening efforts, focusing on undergrounding powerlines. From 2018 to 2023, 664 miles of underground lines were completed across different segments like System Hardening UG, Butte Mainline, Butte Short Main, and Community Rebuild. Notably in 2023, PG&E significantly increased the number of underground miles and decreased the number of overhead hardening miles relative to prior years.

In conjunction with the increase in underground efforts, there has been a targeted focus on reducing underground costs. PG&E illustrates the targeted cost reduction per mile for undergrounding from $3.75 million in 2022 to $2.5 million by 2026. This reduction is aimed to be achieved through optimizing design and construction standards, bundling work strategically, and deploying new technology and equipment. This focus on cost efficiency is crucial as the scale of undergrounding projects expands, ensuring that the utility can achieve its wildfire risk reduction goals while managing financial sustainability.

Table III.D-1. WMP GH-01 System Hardening Initiative including non-08W/3UG.[238]

	Historical Completed Miles												
	Base Projects			Fire Rebuild			Idle Facilities			Other			Total
Year	OH	UG	Removal	OH	UG	Removal	OH	UG	Removal	OH	UG	Removal	
2023	131.279	227.342	4.935	1.627	57.640	1.530	-	-	5.538	11.875	4.065	0.382	446.213
2022	327.828	59.681	2.258	5.654	57.099	5.258	-	-	17.077	1.256	2.358	-	478.470
2021	95.112	2.909	4.307	45.334	37.349	0.478	-	-	17.859	6.334	0.099	-	209.781
2020	139.375	2.913	-	191.815	2.354	-	-	-	3.222	3.314	-	-	342.994
2019	109.808	1.483	-	32.516	5.281	7.270	-	-	11.966	2.678	-	-	171.001
2018	15.773	-	-	-	-	-	-	-	-	-	-	-	15.773
Total	819.175	294.328	11.501	276.945	159.724	14.536	-	-	55.662	25.457	6.523	0.382	1,664.232

Table III.D-2. WMP GH-04 10K Undergrounding Initiative (System Hardening including non-08W/3UG, Butte, & Community Rebuild).[239]

	Historical Completed Miles					
	SH UG	Butte Mainline	Butte Short Main	Community Rebuild	Other	Total
Year						
2023	284.982	72.237	1.698	1.799	4.065	364.781
2022	116.319	58.178	2.379	-	2.820	179.695
* 2021	40.258	29.879	2.928	-	0.099	73.164
2020	2.913	32.591	2.571	-	2.354	40.430
2019	6.764	-	-	-	-	6.764
2018	-	-	-	-	-	-
Total	451.237	192.885	9.575	1.799	9.338	664.835

* Start Year of 10k UG Program

To assess whether PG&E's mitigation efforts correspond to decreases in annual ignitions, the GIRS-RT examined the annual number of ignitions initiated by specific drivers from 2019-2022 and compared those values to forecasted ignition numbers estimated by PG&E taking mitigation efforts into consideration. The WMP 2020 presents estimates for the numbers of ignitions stemming from different ignition drivers (e.g., vegetation contact) would be mitigated due to planned System Hardening, Enhanced Vegetation Management, and tag repair work from 2020-2022. These estimations used ignitions from 2019 as a baseline and assumed weather patterns were consistent with the 5-year historical average.[240] Note that the volatility of weather conditions and climate change influences can impact the number of ignitions that occur annually.

Forecasted annual shifts in ignitions triggered by specific ignition drivers from WMP 2020 (estimated for mitigation efforts)[241] and ignitions from fire event data provided by PG&E for 2019, 2021, and 2022 are compared to assess the response of ignitions to the influences of mitigation efforts (Figure III.D.1).[242]

In WMP 2020 (Tables 31-1 and 31-2), the top four divers of ignitions in 2019 summed across the transmission and distribution grid were 1) vegetation contact, 2) conductor equipment failure, 3) animal contact, and 4) transformer equipment failures. Slight differences in the 2019 ignition numbers from the data provided by PG&E and WMP 2020 may be related to updated ignition event data used to classify ignition drivers following the publication of WMP 2020. By 2021, PG&E started to classify ignition drivers into six categories (D1 – Equipment Failure; D2 –

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[238] *WMP GH-01 System Hardening Initiative including non-08W and 3UG.*
[239] *WMP GH-04 10K Undergrounding Initiative (System Hardening including non-08W and 3UG Butte and Community Rebuild)*
[240] *PG&E 2020 WMP, p 5-277.*
[241] *PG&E 2020 WMP, p 5-277 - 5-282.*
[242] *PG&E response DRU12565.001_Atch02_PGE Fire Incident Data Collection.*

Vegetation; D3 – Third-party Contact; D4 – Animal; D5 – Unknown or Other; and D6 – Seismic Scenario (Cross Cutting)),[243] which differ from the ignition driver classification scheme used in WMP 2020.[244] Details in the fire incident data enable comparison of 2019 ignition drivers (as classified in the WMP 2020) to the same drivers in later years.

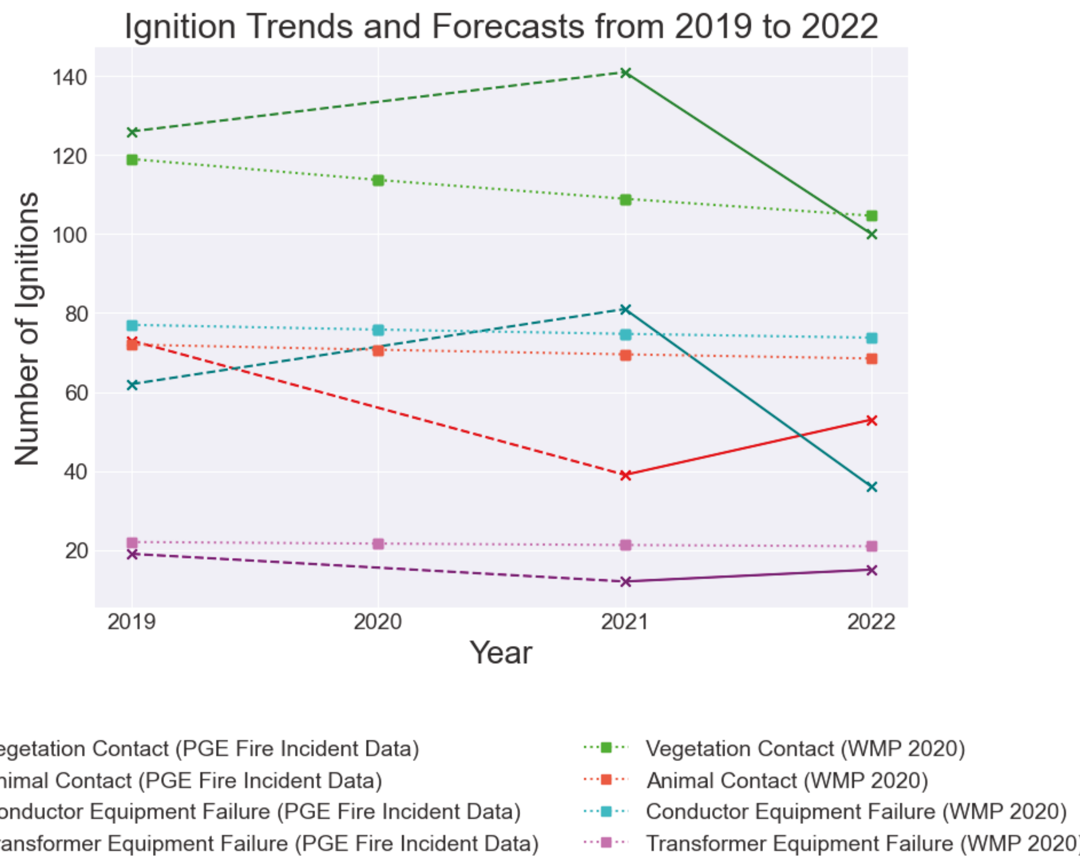

Figure III.D.1: Data used to produce this figure were acquired from Tables 31-1 and 31-2 in WMP 2020, and Fire incident data provided by PG&E for 2019, 2021, and 2022 (2020 fire incident data was not provided). Dashed line segments indicated that data for 2020 is absent from the plot. The 2019 data plotted from WMP 2020 are reported ignitions and values for all subsequent years from WMP 2020 are forecasted values estimated from mitigation efforts.

In 2021, ignition events increased compared to 2019 values for those driven by vegetation contact and conductor equipment failure but were lower when compared to ignitions driven by animal contact and transformer equipment failures. In 2022, ignitions for the top four drivers decreased to occurrences below the forecasted ignition numbers derived from Table 31-1 and 31-2 in WMP 2020. Annual fire incident data provided by PG&E reports 463 ignitions in 2019, 479 in 2021, and 467 ignitions in 2022. This shows that the total number of ignitions has slightly risen from 2019-2022 despite the decrease in ignitions driven by the top four drivers of ignitions in 2019 dropping in 2022. On an annual basis, the total number of ignitions are within counting-

[243] *PG&E 2021 WMP, p 94-96.*
[244] *PG&E 2020 WMP, p 5-279 – 5-282.*

statistics-error (one standard deviation) of each other indicating that there is no statistically significant difference between the total numbers of ignitions that occur year by year. In conclusion, while total numbers of annual ignitions have not changed significantly between 2019, 2021, and 2022, by 2022, ignitions driven by the top four drivers in 2019 did decrease as forecasted by PG&E. used in WMP 2020.

III.D.5 Summary of GIRS-RT findings for Mitigation Checklist Decision Framework

Mitigation Checklist Decision Framework provides updates to the Decision Framework from which a preliminary design decision is made by the PG&E System Hardening team. The checklist, dated 2019, was an interim step prior to development of the Wildfire Risk Governance Steering Committee (WRGSC) in October 2020 and the associated protocols for work reporting and approval.

Features:

Utility Bulletin TD-9001B-009 Attachment 3 provides a flowchart and checklist for deciding between design options that include

- Elimination of the overhead line
- Undergrounding the line
- Relocation of the line
- Hardening in place

The flowchart has been updated, as presented in PG&E 2023-25 WMP.[245] The design decision is made by PG&E's system hardening team and presented to the WRGSC for approval along with risk-spend efficiency estimates. If the decision is to harden in place, then rebuild follows the rebuild design guidance in Utility Bulletin TD-9001B-009.

Assessments:

III.D.5.A1 <u>Economic analysis of hardening strategies is fit for purpose</u>

The GIRST-RT considers the economic analysis that PG&E carries out to identify the Risk Spend Efficiency of each mitigation strategy fit for purpose. It considers a wide variety of relevant inputs and returns suitable outputs that inform decision-making processes. Moreover, the company has implemented correct safeguards to identify when additional considerations, such as PSPS mitigation, should override the EASOP analysis in favor of an underground strategy.

III.D.5.A2 <u>Recommendation for incorporating more factors in undergrounding assessment</u>

The GIRS-RT recommends the inclusion of additional factors for undergrounding lines that are mentioned in the 2022 WMP but were not incorporated into the current checklist. These factors include geological conditions, such as soil stability, and geomorphological conditions, like the risk of mudslides, as well as broader land and environmental considerations, including the presence

[245] *Wildfire Mitigation Plan Revision 6 dated July 5, 2024, Figure SRN-PG&E-23-05-06.*

of protected and endangered plants and species. These elements are critical given the significant variation across PG&E's service territory and should be systematically evaluated.

IV. Technical Findings: Operate Tools

IV.A Operate Overview

Section IV covers the GIRS-RT findings for the Operate Category of the PG&E Local Conditions tools in the 2021-2022 WMPs. This includes the Fire Potential Index (FPI), the Catastrophic Fire Probability Model for Distribution (CFP_D), the Catastrophic Fire Probability Model for Transmission (CFP_T), and Enhanced Powerline Safety Settings (EPSS).

Tools in the Operate Category have been developed to provide a framework for real-time operational decision-making and mitigation during periods of extreme wildfire hazard in PG&E High Fire Threat District (HFTD) Tier 2, Tier 3 territories and select adjacent buffer zones. The Fire Potential Index is a machine learning model. Given an ignition, FPI predicts fire severity (small, large, or catastrophic) on a 2 x 2 km scale based on weather, fuel moisture, fuel type, and topography. The model is trained using historical data for the covariates and fire detection data drawn from the Visible Infrared Imaging Radiometer Suite (VIIRS) satellite. The FPI model has many applications within the 2021 and 2022 PG&E WMPs, including the minimum Fire Potential Conditions (mFPC), the Catastrophic Fire Probability Model for Distribution (CFP_D), the Catastrophic Fire Probability Model for Transmission (CFP_T), Public Safety Power Shutoffs (PSPS), and the Enhanced Powerline Safety Settings Program (EPSS).

CFP_D and CFP_T combine FPI with models for ignition likelihood on the distribution and transmission networks, respectively. For CFP_D, the Ignition Probability Weather (IPW) model computes the probability of an ignition as the product of the machine learning Outage Producing Wind (OPW) model and the probability of an ignition given an outage (a statistical ratio). Like the FPI model, the OPW model is defined on a 2 x 2 km grid. The CFP_D model predicts outage probabilities for six different classes of outages. For CFP_T the methods used to determine the ignition probabilities combine observations and physical models and are separated into two classes—one for assets using the Transmission Operability Assessment (TOA) model, and the other for vegetation using the Transmission Vegetation Risk Model (VRM_T). CFP_D and CFP_T are both used to inform PSPS decision-making. The Enhanced Powerline Safety Settings (EPSS) Program is a mitigation strategy which enables powerlines to be turned off automatically within one tenth of a second when there is a hazard, like a branch falling into a powerline. EPSS was first implemented as a fixed Hot Line Tag (HLT) setting on a portion of PG&E's HFTD territories in a pilot study in 2021, followed by complete coverage across the Tier 2 and Tier 3 HFTD areas and selected buffer zones in 2022, with more selective enablement criteria to reduce impacts on customer reliability.

Overall, the GIRS-RT finds that these tools meet or exceed industry standards and are fit for use. More detailed assessments and suggestions for future upgrades are provided within the individual tool review sections. Overall, the Operate Category tools are designed to address the challenging problem of real time decision-making during periods of extreme wildfire risk, in a manner that balances actions (PSPS and EPSS) that reduce wildfire risk with customer reliability across PG&E's broad and diverse service territories. The suite of tools in this category provides PG&E with frameworks that allow for an integrated approach involving high quality data, physical and machine learning model-based risk assessments, risk management, and risk mitigation. For the period covered by this audit (2021 and 2022 WMP), geospatial, risk-based, methodologies for operational use were a new and rapidly developing approach for public utilities. PG&E tools have continued to move forward since the period covered by the audit. The recommendations made in this review are intended to guide the ongoing development of these modeling tools.

IV.B Fire Potential Index Model

This section covers PG&E's 2021 and 2022 framework for the design, validation, and utilization of the Fire Potential Index (FPI) model employed in various operational tasks within the PG&E service territory. The section is structured to provide a comprehensive review of the FPI model and its applications within PG&E's operational framework. Section IV.B.1 gives an overview of the FPI model, including its core concepts and a brief history of its development. Sections IV.B.2 and IV.B.3 focus analyzing and assessing, respectively, the data sources and methodology used in developing and training the FPI model, including satellite-derived fire occurrence data, meteorological data, terrain data, and fuel data. Section IV.B.4 analyzes the mathematical formulation of the FPI model, with an emphasis on the machine learning techniques employed, particularly the use of a Balanced Random Forest algorithm to account for class imbalance. Section IV.B.5 presents the assessments of the mathematical formulation. Section IV.B.6 discusses model validation practices, covering the cross-validation process and the AUC-ROC metric, while section IV.B.7 presents its assessments. Section IV.B.8 reviews the practical applications of the FPI Model, highlighting its role in daily operational decisions and PSPS guidance. Section IV.B.9 describes the assessments of the applications of the FPI Model. Section IV.B.10 summarizes the findings and assessments from the GIRS-RT.

IV.B.1 Fire Potential Index Model Overview

The 2021 FPI model takes in a set of features coarsely divided into four classes: weather, fuel moisture, fuel type, and topography. The PG&E service territory is divided into 2 x 2 km grid cells, and the FPI model predicts the class of the resultant fire severity, given an ignition, as a function of the features of the grid cell. The severity classes considered in the model are *small, large,* and *catastrophic*. Consequently, the FPI model is a multi-class classifier.

The datasets for the model consist of all 2 x 2 km grid cells that contain a detected fire event and associated features. Fire detection data is drawn from the Visible Infrared Imaging Radiometer Suite (VIIRS) satellite. The VIIRS mission detects thermal anomalies on Earth's surface from polar orbit; the satellite passes over the PG&E service area about once every 12 hours. This dataset is enhanced by cross-referencing with agency data, an initiative supported by private firm Sonoma Technologies, Inc. The precise features considered in the model and their origins are discussed in more detail in Section IV.B.2.

IV.B.1.1 <u>Brief history of the Fire Potential Index Model</u>

PG&E's Fire Potential Index (FPI) identifies the most likely class of fire given an ignition in a specified area of the PG&E service territory. Other fire danger indices have been developed by public and private agencies. Another example is the Wildland Fire Potential Index, developed by the USGS, which incorporates data such as fuel moisture, wind speed, temperature, and rainfall (USGS 2024).

Until 2014, PG&E used the CAL FIRE produced Fire Potential Index in their risk assessment practices. In 2015, after the index generation was discontinued by CAL FIRE, PG&E developed its first FPI model integrating weather and fuels data. The approach was supported by fire danger rating experts from the National Wildfire Coordinating Group and the model was benchmarked against San Diego Gas and Electric's own FPI model.[246]

In 2019, the PG&E FPI model was enhanced by adding fire occurrence data. Instead of generating an index based on domain knowledge of fire behavior given fuel and vegetation conditions, the new FPI model was developed as a binary classifier. The 2019 model incorporated inputs including live fuel moisture, dead fuel moisture, land use classes, and meteorological fire indices such as the Fosberg Fire Weather Index.[247]

The 2021 PG&E FPI model is the subject of this section. It improved on the 2019 model by including additional features, an enhanced fire occurrence dataset, and a machine learning framework for predicting fire severity.[248]

IV.B.2 Datasets used in the FPI Model

IV.B.2.1 Enhanced Fire Occurrence Dataset

In 2019, the FPI model was trained using a United States Forest Service (USFS) Fire Occurrence Dataset. This dataset includes information on each fire, such as the ignition location and the final fire size. In 2021, to improve the FPI model performance, PG&E switched to the Enhanced Fire Occurrence Dataset which utilizes sub-daily fire growth data extracted from satellite data, an initiative which involved partnering with Sonoma Technology, Inc. (STI). The VIIRS satellite fire detections used by PG&E were combined with agency fire occurrence data to derive sub-daily fire growth statistics. The sample rate of VIIRS over California is approximately once every 12 hours, enabling the assessment of fire growth between each pass. The VIIRS satellite data was combined with agency datasets including CAL FIRE's Fire and Resource Assessment Program (FRAP), ICS-209, GeoMAC, USFS FIRESTAT, and USFS FPA-FOD datasets to provide growth metrics for large fires.

Each detected fire event is labeled as small, large, or catastrophic depending on the size of the fire at its first detection by VIIRS. Because of the cadence of VIIRS passes, this does not guarantee a uniform time since ignition for all detections. The classes are delineated by their VIIRS first detect size as follows: small (<70 acres), large (70-500 acres), and catastrophic (>500 acres). According to documentation, the origin of this class delineation is from observed fire size data, where catastrophic fires (>500 acres at first detect) grew to 20,000 acres on average.[249]

PG&E SMEs emphasized that fast initial spread is often more strongly correlated with fire danger and consequent fatalities than the final burned area. While generally consistent with data and experience, no specific documentation was provided to support the precise choice of cutoffs (70 acres, 500 acres) that define classes from the first detect sizes.

IV.B.2.2 Weather, fuel, and topography data

The features used in the FPI model build upon the traditional "fire behavior triangle," incorporating the effects of weather, fuel, and topography on fire behavior. They can be grouped

[246] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, p. 17.*
[247] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, p. 17.*
[248] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, p. 18.*
[249] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, p. 22.*

into four categories: weather, fuel moisture, topography, and fuel type. Each model feature used is listed in Table IV.B-1.

Table IV.B-1: 2021 FPI model features.[250]

Feature	Group	Altitude(s)	Description	Source	Update Cadence	Spatial Granularity	Temporal Granularity
Temperature	Weather	surface	Temperature at the surface in Fahrenheit	POMMS	4x per day	2 km	hourly
Wind speed (sustained)	Weather	surface, 300m	Wind speed in mph	POMMS	4x per day	2 km	hourly
Vapor pressure deficit	Weather	surface	Measure of lack of water vapor relative to saturation in millibars	POMMS	4x per day	2 km	hourly
Turbulent kinetic energy	Weather	50m	Kinetic energy per unit mass observed in eddies characteristic of turbulent flow in Joules/kg	POMMS	4x per day	2 km	hourly
Ustar friction velocity	Weather	surface	Wind shear stress in velocity terms.	POMMS	4x per day	2 km	hourly
Dead fuel moisture – 1000hr	Fuel moisture	surface	1000-hour fuel moisture content	POMMS & ADS	4x per day	2 km	hourly
Dead fuel moisture – 100hr	Fuel moisture	surface	100-hour fuel moisture content	POMMS & ADS	4x per day	2 km	hourly
Dead fuel moisture – 10hr	Fuel moisture	surface	10-hour fuel moisture content	POMMS & ADS	4x per day	2 km	hourly
Live fuel moisture – Chamise new	Fuel moisture	surface	Live fuel moisture content of Chamise (new growth) species	POMMS & ADS	daily	2 km	daily
Live fuel moisture – Herbaceous	Fuel moisture	surface	Live fuel moisture content of herbaceous species	Technosylva	daily	30 m	daily
Live fuel moisture - Woody	Fuel moisture	surface	Live fuel moisture content of woody species	Technosylva	daily	30 m	daily
Alignment vector	Topography	surface	Alignment between wind direction and terrain	POMMS & DEM	4x per day	2 km	hourly
Slope degree mean	Topography	surface	Slope of terrain averaged over POMMS grid cell	DEM	NA	2 km	NA
Terrain rugged mean	Topography	surface	Measure of ruggedness in POMMS grid cell	DEM	NA	2 km	NA
Urban	Fuel type	surface	Proportion of the fuel category in POMMS grid cell attributed to urban	Technosylva	Sub-annual	2 km	Sub-annual
Grass-Shrub	Fuel type	surface	Proportion of the fuel category in POMMS grid cell attributed to grass-shrub	Technosylva	Sub-annual	2 km	Sub-annual
Shrub	Fuel type	surface	Proportion of the fuel category in POMMS grid cell attributed to shrub	Technosylva	Sub-annual	2 km	Sub-annual
Timber Litter	Fuel type	surface	Proportion of the fuel category in POMMS grid cell attributed to timber litter	Technosylva	Sub-annual	2 km	Sub-annual

[250] *2022 WMP, Page 198-200.*

Feature	Group	Altitude(s)	Description	Source	Update Cadence	Spatial Granularity	Temporal Granularity
Temperature	Weather	surface	Temperature at the surface in Fahrenheit	POMMS	4x per day	2 km	hourly
Grass	Fuel type	surface	Proportion of the fuel category in POMMS grid cell attributed to grass	Technosylva	Sub-annual	2 km	Sub-annual
Timber Understory	Fuel type	surface	Proportion of the fuel category in POMMS grid cell attributed to timber understory	Technosylva	Sub-annual	2 km	Sub-annual

IV.B.2.2.1 Weather and fuel moisture data

The weather data originates from the hourly 2 x 2 km PG&E Operational Mesoscale Modeling System (POMMS) weather forecast model, which is a specialized configuration of the Weather Research and Forecasting (WRF) model version 4.1.2.[251] PG&E collaborated with external partners, Weather Decision Technology (WDT) and Atmospheric Data Solutions (ADS), to implement the POMMS model, which provides key fire weather parameters, including wind speed, temperature, relative humidity (RH), and precipitation.[252]

The model uses a nested grid configuration with 18 km, 6 km, 2 km, and 0.67 km grids.[253] The outer coarse grid covers a broad area with lower resolution, while finer grids are embedded within it to provide detailed focus on areas of interest. The vertical grid configuration consists of 51 levels, with an upper boundary set at 2,000 Pa.[254] Each grid is run four times daily, except for the 0.67 km domain, which is run on demand during high-risk events.

Model forecasts are initialized using the 0.25° output from the National Centers for Environmental Prediction (NCEP) Global Forecast System (GFS) model and the 1/12° Sea Surface Temperature (SST) analysis.[255] In case of an NCEP data outage, data from the European Centre for Medium-Range Weather Forecasts (ECMWF) serves as a backup.

A 31-year climatology dataset was generated to train the Fire Potential Index (FPI) model, covering the period from August 1, 1998, to April 1, 2021. This dataset spans approximately 40,000 grid cells within the PG&E territory, including around 10,000 cells in High Fire Risk Areas (HFRAs). To construct the climatology, the NCEP Climate Forecast System Reanalysis (CFSR) data is used to initialize and force the WRF model.[256] The coarse CFSR data is dynamically downscaled to 2 km resolution, using the same model physics as applied in the forecasts.

Outputs from POMMS are used as inputs for the Nelson Dead Fuel Moisture (DFM) model, as well as proprietary Live Fuel Moisture (LFM) models developed by ADS, to derive 1-hour, 10-hour, 100-hour, and 1000-hour DFM and LFM values for Chamise (new growth).[257] New live fuel moisture metrics sourced from Technosylva are incorporated into the Fire Potential Index (FPI).

[251] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 7.*
[252] *2022 WMP, Page 196.*
[253] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 7.*
[254] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 7.*
[255] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 7.*
[256] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 8.*
[257] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 6.*

Technosylva utilizes remote sensing to estimate the available moisture in woody and herbaceous plant species, enhancing the accuracy of moisture assessments.

IV.B.2.2.2 Fuel Data used for FPI

Fuels Data for FPI were derived from Technosylva, who updated LANDFIRE fuel maps (produced ≥ annually)[258] for burn scars and vegetation regrowth. PG&E and Technosylva fire scientists consolidated the >50 fuel model types into six parent categories that consist of 1) urban, 2) grass, 3) grass-shrub, 4) shrub, 5) timber-litter, and 6) timber-understory. As the native resolution of the data source is 30 x 30 m, the fraction of each of the six fuel categories is computed for all six categories in each 2 x 2 km cell.[259]

IV.B.2.2.3 Terrain data used for FPI

Terrain data used for FPI training include slope, ruggedness, and hourly alignments factors for interactions between wind and topography. Metrics for terrain ruggedness are assessed via changes in slope and aspect in each 2 x 2 km grid cell from a digital elevation model (DEM).[260] Slope, which has been shown to have a positive effect on wildfires was used for FPI calibration (mean values were computed for each grid cell).[261] Hourly wind-terrain alignment factors are calculated to provide an assessment of the wind-terrain alignment in each 2 x 2 km grid cell using wind data from POMMS and DEM data.

IV.B.3 Assessment: Datasets used in the FPI Model

IV.B.3.1 Assessments of Enhanced Fire Occurrence Dataset

IV.B.3.A1 Development of novel and model-appropriate fire occurrence dataset

The Enhanced Fire Occurrence Dataset used for training FPI is an aggregated dataset that combines agency data and satellite fire detection to describe fire growth, final fire size, and approximate ignition locations at sub-daily timescales. This utilization of combined satellite data and agency data to assess sub-daily fire growth metrics exceeds industry standards. However, linear fire spread rates calculated from a first detection that occurs in ~12-hour intervals can vary substantially. For example, the spread rate for a fire that is first detected after burning for 11 hours would be about an order of magnitude slower than a fire of the same size that is first detected after burning for 1 hour.

As a potential solution, the GIRS-RT suggests the exploration of two alternatives. First, estimation of the rate of spread may be enhanced by cross-referencing agency time of ignition data with the VIIRS detection timestamp. Second, instead of using the size at first detection to categorize fires, PG&E may consider the *growth ratio*, computed as the difference in fire areas between two consecutive measurements divided by the time between those measurements.

[258] *Fuel data releases from* https://landfire.gov/data
[259] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev 4., Page 23-24.*
[260] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev 4., Page 23-24.*
[261] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev 4., Page 24.*

IV.B.3.A2 Rationale for dividing fire size classes could be more robust

The FPI model, as a classifier, depends strongly on how fire data is divided into the three classes of small, large, and catastrophic. Model performance varies greatly between these classes (as measured by the ROC-AUC), which suggests reconsideration of the class divisions may be useful.[262] Since initial detect size is known in addition to other metrics about the fire event (final fire size, average rate of spread), a data-driven approach could be taken to define natural classes of fire events. One option would be to use an unsupervised method (clustering of first-detect sizes); alternatively, a supervised method may be employed (regression of first detect size to final fire size). Regardless of the method chosen, testing an identical model on different class divisions would demonstrate robustness of the FPI model.

A particular concern arises with the small fire size class, defined as <70 acres at first detection. The VIIRS data has a spatial resolution of 375m. 70 acres is approximately two 375m x 375m grid cells, which means that most of the fires in the small class likely constitute 2 or fewer individual VIIRS detections. Documentation from Sonoma Technologies notes that 70 acres is the minimum fire area for VIIRS detections, and that agency records frequently do not match up with these small detections (McClure et al. 2023). These practical challenges suggest that the <70 acres definition for small fires should be revisited in future work.

IV.B.3.2 Assessments of weather, fuel, and topography data

IV.B.3.A3 Advancing wildfire research through collaboration and open data access

The collaboration with San Jose State University (SJSU) Wildfire Interdisciplinary Research Center (WIRC) enhances wildfire research through joint publications and operational efforts. Researchers now have access to over 30 years of climatological weather, fuels, and fire occurrence datasets, which promote open science and enable broader research into fire behavior, risk assessment, and climate impacts.

IV.B.3.A4 Improvement in weather and fuel moisture data used for FPI

The FPI utilizes weather data and fuel moisture models that have been enhanced over the years. With improved POMMS model spatial resolution from 3 km to 2 km with on-demand simulations available at 0.67 x 0.67 km and the integration of live fuel moisture data from Technosylva, the FPI can better predict fire behavior and make operational decisions.

IV.B.3.A5 Benefits of integrating satellite-derived fuel moisture data

Incorporating satellite-derived fuel moisture data improves the precision and timeliness of fuel moisture data, as opposed to model-derived fuel moisture data that relies on historical patterns or interpolated weather data. PG&E has incorporated this type of information into the current FPI model. The Technosylva live fuel moisture herbaceous model includes satellite observations. The GIRS-RT encourages continued incorporation of more satellite-based features to reduce potential bias introduced in model-derived data due to parameterization or weather inputs, such as through the NCAR fuel moisture content products providing hourly retrievals over CONUS.[263]

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[262] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, p. 25.*
[263] *From NCAR, "Fuel Moisture Content Retrievals", Available at: https://ral.ucar.edu/tool/fuel-moisture-content-retrievals*

IV.B.3.A6 While fuel data incorporates up-to-date conditions such as burn scars and vegetation regrowth, fine-scale controls on wildfire spread may be lost to data coarsening efforts for FPI

FPI utilizes fuel data sourced from LANDFIRE that has been modified to include recent burn scars and vegetation regrowth, indicating that PG&E is calibrating FPI with fuels that represent the most up-to-date conditions in their service territory. Because the source data is 30 x 30 m resolution, the 2 x 2 km FPI pixels include the proportions of each fuel type within each pixel. Fine-scale spatial relationships between the distributions of fuel types, which can impact fire growth, are lost when coarsening the resolution of the fuel data.

IV.B.3.A7 While terrain data used for FPI adequately incorporates parameters for wildfire spread, alternative metrics for ruggedness could be tested to improve performance

Terrain data used for FPI captures the influences of 1) terrain ruggedness, 2) slope, and 3) topographic influences on wind parameters. However, FPI may benefit from inclusion of other topographic parameters such as Topographic Position Index (TPI) or Terrain Ruggedness Index (TRI), which are metrics that capture ruggedness and characteristics of topographic features such as valley bottoms, ridge lines, and hilltops. TPI and TRI are calculated differently from the metric for terrain ruggedness used by PG&E, which is derived from the shifts in slope and aspect in each grid cell. Incorporation of these parameters may improve model performance.

IV.B.4 Mathematical Formulation of the FPI Model

The Fire Potential Index model is based on a machine learning technique known as Random Forest (Breiman 2001).[264] A Random Forest model, portrayed in Figure IV.B.1, is best described as an *ensemble learning method* commonly used for classification or regression tasks. Random Forest models work by producing a global output through the combination of multiple independent decision trees. Decision trees incorporate input features of arbitrary modality and make a series of decisions to arrive at a classification for the input. Each tree may incorporate different subsets of the input data and have a different structure. Each individual decision tree is generally a low-bias, high-variance predictor. When aggregated in an ensemble, the variance is decreased, and the predictions are generally robust to overfitting. In the case of a classification task over K classes, each decision tree produces a *vote* for a given class, and the global prediction is taken as the class with the largest number of votes.

[264] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 21.*

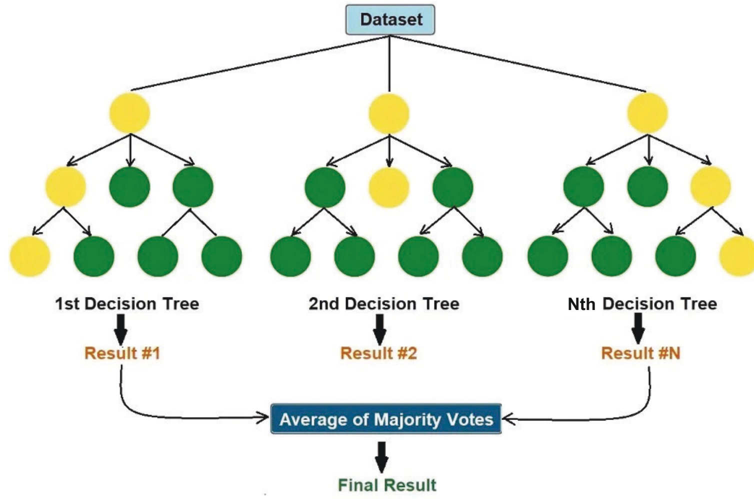

Figure IV.B.1: Diagram portraying a Random Forest model composed of N independent Decision Trees. Note how the model output is given by the class that receives most of the votes.

Random Forests are generally accepted as a good model choice for tabular data, given their non-parametric nature, robustness against noise in the data and overfitting, and ability to deal with both numerical and categorical data.

However, in the context of the FPI model, catastrophically severe fires are rare events. Specifically, in the dataset used for training and testing the FPI model, only 2% of observed fire events fall into the catastrophic class.[265] This class imbalance can make effective modeling difficult and decrease the performance of the final model. This is because, in its traditional formulation, each decision tree is trained on a uniformly sampled subset of the original dataset (with replacement). Consequently, class imbalance is also present, on average, over the subsets used for the training of each decision tree. This generates a global bias over the Random Forest prediction. The data science team at PG&E was aware of this limitation and, after experimentation, chose a modified model which is both robust to class imbalance and robust to overfitting: a Balanced Random Forest (BRF) classifier (Chen 2004).[266] In a BRF, instead of uniformly sampling a subset of the training dataset to train each decision tree, the algorithm first draws a bootstrap sample of n elements from the minority class and then samples with replacement the same number of elements from each one of the other classes.

Generation of this alternative subset ensures that each decision tree is trained on a balanced dataset. Therefore, the bias over the global model is minimized. Due to the class imbalance present in the Enhanced Fire Occurrence Dataset, described in Section IV.B.2.1, PG&E uses a Balanced Random Forest algorithm for the Fire Potential Index model.

[265] *Conversation with PG&E data science SME, 9/19/24.*
[266] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 21.*

IV.B.5 Assessment: Mathematical Formulation of the FPI Model

The following is a series of assessments regarding the mathematical formulation of the FPI model.

IV.B.5.A1 Appropriate use of balanced Random Forest variant

From a data science perspective, the characteristics of this dataset can be summarized in three key points:

- The data is tabular and high dimensional, where for each cell in the service territory there is knowledge about numerous variables described in Section IV.B.2.
- The dataset is highly imbalanced, with approximately 2% of the data points corresponding to the category denominated *catastrophic.*
- The dataset contains variables of different nature: some of them are continuous, while some others are categorical.

Under these characteristics, the GIRS-RT considers the use of the Balanced Random Forest model an **appropriate choice** given the generalization capabilities of Random Forests, their resistance to overfitting, their capability to combine data of different natures, and the disparity in class count present in the dataset.

IV.B.6 Model Validation

The PG&E data science team trained and evaluated models using cross-validation on a subset of the dataset to tune model parameters and architectures. Models were evaluated based on their ROC curves and associated area under the ROC curve (AUC-ROC). As predictions are made for multiple classes, this evaluation was done in the one-vs-rest fashion.[267]

The dataset was randomly split into train (70%) and test (30%) sets, and the performance, from PG&E documentation, is reported for the unseen test dataset. The performance of the catastrophic class was strong with AUC = 0.88. The performance of the large class was comparatively weak, reaching only AUC = 0.55. The small class had good performance with AUC = 0.68, close to the macro-average AUC = 0.70 for the model across classes.[268] The disparity in performance between the catastrophic and large classes is significant. PG&E SMEs suggested that likely explanations include the impact of suppression on the size classification for large fires may be more significant than it is for catastrophic fires and a difficulty in distinguishing class boundaries between the large and small classes.[269]

AUC-ROC is a standard evaluation metric for classification models but does not provide a complete characterization of the classifier. Other metrics, like the model precision, are not affected by the presence of true negatives. If the minority class is very rare, a model which almost always predicts the absence of the minority class will correctly predict many negative occurrences, leading to an artificially inflated false positive rate. The precision of such a model

[267] Conversation with PG&E data science SME, 9/11/24.
[268] Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, p. 24-25.
[269] Conversation with PG&E Data Science SME, 9/11/24.

will be low. A corollary of this fact is that AUC values for minority classes in highly imbalanced datasets will in general have large confidence intervals.

For imbalanced datasets, metrics other than the AUC-ROC can and should be reported to more holistically characterize the performance of the model. Despite this, the general performance of the 2021 FPI model on the catastrophic class is still very strong and is testament to the modeling efforts of the PG&E team.

As part of the model development and evaluation procedure, PG&E's data science team generated feature importances for each class of the model. Feature importances, reported in this case as the Shapley Additive Explanation (SHAP) value, characterize the effect of an input feature on the model's output. Analyzing feature importances is a crucial step in understanding what the model is learning in addition to selecting an informative set of features for optimal performance. PG&E SMEs indicated that the total feature selection process combined model performance evaluations, feature importance calculations, and domain knowledge to arrive at the final set of features integrated into the FPI model.[270]

The feature importance results are consistent with intuitive expectations about informative data for each class, serving to validate the model's predictive capability. For example, the dominant feature in predicting the small class is the "urban" feature, representing developed land cover. For the catastrophic class, the dominant features are the live and dead fuel moistures, quantities which are well-known to contribute to fire spread.[271] The interpretability of these important features, and their consistency with more traditional fire indexing techniques, such as the USGS WFPI, supports the feature selection and model development process carried out by the PG&E team.

IV.B.7 Assessment: Model validation

IV.B.7.A1 <u>Thorough feature analysis and model validation practices</u>

PG&E's FPI model displays strong performance on the catastrophic class, where correct prediction of fire danger is most consequential. Throughout the model development process, good data science practices, including cross-validation and feature importance analysis, were performed.[272] Both the validation results of the model on the held-out test set and the feature importance values reported to GIRS-RT by the PG&E data science team demonstrate a successful model development and deployment process. Most importantly, the 2021 FPI model was operationally validated and performed satisfactorily.[273]

IV.B.7.A2 <u>Use of robust metrics for imbalanced data</u>

The primary metric used in the model development process, and the only metric reported for the model's performance on the test set, was the ROC curve and associated AUC-ROC value.[274] This metric is standard for use in describing classifiers and characterizes model performance in

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[270] Conversation with PG&E Data Science SME, 9/11/24, 9/19/24.
[271] Conversation with PG&E Data Science SME, 9/11/24, 9/19/24.
[272] Conversation with PG&E Data Science SME, 9/11/24.
[273] Conversation with PG&E Data Science SME, 9/11/24, 9/19/24.
[274] Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 24.

an interpretable fashion. However, when the underlying dataset is highly imbalanced by class, the AUC-ROC can be misleading or fail to characterize all aspects of performance of the classifier.

In the present case, the catastrophic class makes up only 2% of the test dataset.[275] The ROC curve is constructed in part by the false positive rate, defined as the ratio of false positives to true negatives and false positives. Since 98% of the data are not in the catastrophic class, a model with little discriminatory ability may still demonstrate a small false positive rate as it makes many (correct) true negative predictions. This may cause the AUC-ROC value to be inflated compared to a dataset with approximately balanced classes.

To counteract this, other metrics which do not depend on the true negative count should be reported. The precision-recall curve (PR) is like the ROC curve but is unaffected by true negatives. The area under the precision recall curve (AUC-PR) is analogous to the AUC-ROC but captures a different aspect of model performance. GIRS-RT recommends that PG&E report the AUC-PR value or a similar metric, both to demonstrate consideration of the effect of class imbalance in model evaluation and to provide a helpful benchmark as models are iterated and improved upon in coming years.

IV.B.8 Applications of the Fire Potential Index Model

The scope considered in this section covers two main categories of operational uses for the FPI model.

IV.B.8.1 <u>Fire Potential Index Rating</u>

PG&E reviewed the FPI model outputs for historical fires during 2008-2020 and converted the outputs for the catastrophic and large fire categories to a discrete scale composed of five categories. These categories are designated as R1, R2, R3, R4, and R5, with R1 and R5 representing the lowest and highest fire risk rating, respectively. This representation of the FPI model outputs is known as the Fire Potential Index Rating.

The Fire Potential Index Rating is used as an input for multiple internal processes within the company. Notably, the FPI index results are aggregated in a daily manner across multiple **Fire Index Areas** (**FIA**) within the service territory to inform the mitigation of risk derived from field work.[276] This aggregation is performed by considering the FIA FPI rating as the daily maximum of the hourly FPI average across the 2 x 2 km cell in each FIA. Guidelines and requirements for field work are described in an internal document titled Utility Standard TD-1464S.[277] Examples of the FPI aggregation across multiple FIAs are shown in Figure IV.B.2.

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[275] Conversation with PG&E Data Science SME, 9/19/24.
[276] Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 17.
[277] Preventing and Mitigating Fires While Performing PG&E Work, Utility Standard: TD-1 464S Rev7, June 2022.

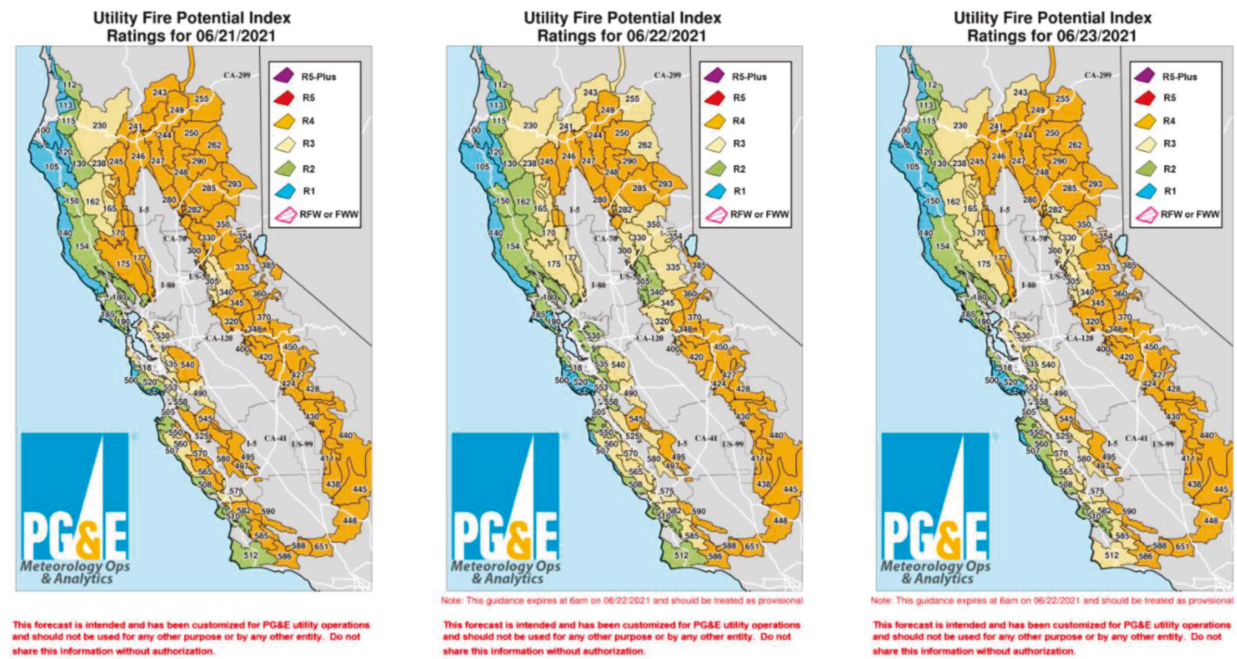

Figure IV.B.2: Example of Fire Potential Index for three-consecutive days.[278]

IV.B.8.2 <u>PSPS Guidance</u>

In addition to defining Fire Index Areas, the FPI model is used in two core stages within the PSPS guidance framework.[279] For both these stages, the final output of the FPI model is reduced to a single value between 0 and 1 by selecting a subset of fire severities. In other words, while the full FPI model described the probability of a fire evolving towards a small, large or catastrophic severity, the use cases related to PSPS guidance only use some of these categories.

IV.B.8.2.1 <u>Minimum Fire Potential Conditions, mFPC</u>

The first stage in which the FPI model is used is the minimum Fire Potential Conditions (mFPC).[280] For this application, both the *large* and *catastrophic* categories for fire severity are used. In other words, the FPI model is reduced to the following output: $P(large\ or\ catastrophic|ignition)$.

The mFPC stage is best understood as a checklist that serves as a filter to identify environmental and weather conditions that should be exceeded to consider issuing a PSPS event. These conditions were derived from a historical examination of fire occurrences within PG&E service territory, as well as information released by federal agencies.

Table IV.B-2 contains a list of variables that PG&E considers for the determination of mFPC. As shown, the logic imposed by the mFPC model indicates that all these conditions must be met for PSPS to be considered as a possible wildfire mitigation measure. In particular, the probability of

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[278] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 29.*
[279] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 25.*
[280] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 16.*

an ignition evolving to a catastrophic fire needs to be at least 0.7 for the FPI condition to be met, as indicated in the last row of Table IV.B-2.

Table IV.B-2: Minimum Fire Potential Conditions for PSPS Guidance.[281]

Logic	Variable	Sign	Value
AND	Sustained Wind Speed [mph]	>	19
AND	Dead Fuel Moisture @ 10 hr.	<	9%
AND	Dead Fuel Moisture @ 100 hr.	<	11%
AND	Dead Fuel Moisture @ 1000 hr.	<	11%
AND	Herbaceous Live Fuel Moisture	<	65%
AND	Shrub Live Fuel Moisture	<	90%
AND	Relative Humidity	<	30%
AND	2021 Fire Potential Index (FPI)	>	0.7

IV.B.8.2.2 Catastrophic Fire Probability models, (CFP_D and CFP_T)

The second component of the PSPS guidance where the FPI model is applied is the calculation of the Catastrophic Fire Probability models for both the distribution and transmission models, abbreviated as CFP_D[282] and CFP_T[283], respectively.

Catastrophic Fire Probability model for Distribution, CFP_D

The CFP_D is computed as a function of time at a 2 x 2 km cell resolution. It corresponds to the time-dependent probability that the cell will generate a catastrophic wildfire. A conditional probability model is used for the calculation:

$$P(catastrophic\ fire) = P(catastrophic\ fire|ignition) \times P(ignition).$$

The second factor on the right of the previous equation corresponds to the Ignition Probability Weather (IPW) model, a component of PSPS guidance that determines the probability that a cell will generate an ignition, given local environmental and weather conditions. The first factor on the right of the previous equation corresponds to the conditional probability that an initial ignition will grow into a catastrophic fire. From Section IV.B.4, this quantity is recognized as the output of the FPI model. Consequently, the previous equation is reformulated as:

$$CFP_D = FPI \times IPW.$$

The PSPS guidance model specifies a $CPF_D > 9$ to execute a PSPS event.

Catastrophic Fire Probability model for Transmission, CFP_T

For the transmission counterpart, PSPS guidance follows two sub-models: one that describes the fire probability induced by assets ($CFP_{T\text{-}Asset}$) and another that describes the fire probability induced by vegetation ($CFP_{T\text{-}Veg}$). Both models use the FPI model in a similar fashion to their

[281] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 16.*
[282] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 38.*
[283] *2022 WMP, Page 1032.*

distribution counterpart: as an approach to determine the conditional probability of observing a catastrophic fire given an initial ignition.

The Catastrophic Fire Probability models, for both distribution and transmission, and the Ignition Probability Weather model are reviewed in detail in Section IV.C and Section 0, respectively.

IV.B.9 Assessment: Applications of the Fire Potential Index Model

The following assessment pertains to application of the FPI model.

IV.B.9.A1 Recommendation to explore the use of a Binary Classification model

The application of the FPI model for PG&E's operational tasks is sound. However, in applications related to PSPS guidance, only the catastrophic and large fire severity probability are used as an input, disregarding the output that corresponds to the small fire severity. While having a multi-class model has the benefit of using the same model for different applications, it raises the question of whether better results could be achieved by redefining the FPI model as a binary classification model (Class 1: catastrophic or large severity, Class 2: small severity) for its use in the determination of fire potential indexes. This change would enable training the model as an *anomaly detection* technique, utilizing methods that are easier to train and validate than those typically used for multi-class classification. For future applications, the GIRS-RT suggests comparing the current model against a binary classification version to determine whether better results are obtained following this alternative approach.

IV.B.10 Summary of GIRS-RT findings for the Fire Potential Index Model

The Fire Potential Index (FPI) model is a machine learning-based classification model that aims to predict how likely it is that an initial ignition results in a wildfire with a small, large, or catastrophic severity using weather, fuel, and topography variables. The FPI model has many applications within the 2021 and 2022 PG&E WMPs, including the minimum Fire Potential Conditions (mFPC), the Catastrophic Fire Probability Model for Distribution (CFP_D), the Catastrophic Fire Probability Model for Transmission (CFP_T), Public Safety Power Shutoffs (PSPS), and the Enhanced Powerline Safety Settings Program (EPSS).

Features:

- The FPI is a machine learning model which predicts the size class (small, large, catastrophic) of a wildfire, given an ignition.
- The FPI size class is determined from the VIIRS first-detect size.
- FPI uses a suite of well established, reliable datasets to predict fire size classes obtained from POMMS, ADS, LANDFIRE/Technosylva, and DEM.
- The FPI is updated daily, and uses weather, fuel moisture, fuel type, and topography to predict fire size. Satellite fire detections and agency fire occurrence data were combined to create a sub-daily fire growth dataset. This new dataset, integrated with the 2 x 2 km weather and fuels climatology, enhanced the FPI model.
- The FPI model uses a Balanced Random Forest classifier to predict the probability that a given 2 x 2 km cell presents the conditions to grow an initial ignition towards a small, large, or catastrophic fire. As such, it is a classification into three classes.

- The FPI model is operationally used in three key applications. First, it is used in the definition of Fire Index Areas. Second, within PSPS guidance, it is used in the determination of minimum Fire Potential Conditions (mFPC). FPI is used in PG&Es Catastrophic Fire Probability Models (CFP_D and CFP_T) for operational decision making in PSPS Guidance.

Summary of Assessments

IV.B.3.A1 Development of novel and model-appropriate fire occurrence dataset

The Enhanced Fire Occurrence Dataset used for training the FPI model exceeds industry standards. However, linear fire spread rates calculated from a first detection that occurs in ~12 hour intervals can vary substantially. The GIRS-RT suggests either the incorporation of agency time of ignition data to the dataset, or the development of a novel metric to measure the rate of fire spread.

IV.B.3.A2 Rationale for dividing fire size classes could be more robust

Fire classes are divided by VIIRS first detect size, but the small class size is at the resolution limit for VIIRS detections (70 acres), and the method of choosing the boundary between the large and catastrophic classes (500 acres) could be more strongly supported by existing fire data.

IV.B.3.A3 Advancing wildfire research through collaboration and open data access

The collaboration with SJSU WIRC expands wildfire research by providing access to extensive datasets, fostering joint publications, and promoting open science.

IV.B.3.A4 Improvement in weather and fuel moisture data used for FPI

The FPI has been improved by enhancing weather and fuel moisture data, including higher spatial resolution and live fuel moisture integration.

IV.B.3.A5 Benefits of integrating satellite-derived fuel moisture data

Integrating satellite-derived fuel moisture data enhances the reliability of fuel moisture-related features. The GIRS-RT encourages PG&E to continue advancing in this direction, prioritizing the use of satellite-based data.

IV.B.3.A6 While fuel data incorporates up-to-date conditions such as burn scars and vegetation regrowth, fine-scale controls on wildfire spread may be lost to data coarsening efforts for FPI

While a portion of the original data used in the FPI model was generated at a resolution of 30 x 30 m, the final dataset used for the FPI model training is aggregated in 2 x 2 km pixels. Due to this data preprocessing approach, fine-scale spatial relationships between the distributions of fuel types, which can impact fire growth, can be lost when coarsening the resolution of the fuel data.

IV.B.3.A7 While terrain data used for FPI adequately incorporates parameters for wildfire spread, alternative metrics for ruggedness could be tested to improve performance

While the data used in the FPI model includes terrain features, its performance may increase by including other topographic parameters such as Topographic Position Index (TPI) or Terrain Ruggedness Index (TRI). These parameters are magnitudes capturing ruggedness and characteristics of topographic features.

IV.B.5.A1 Appropriate use of balanced Random Forest variant

The GIRS-RT considers the use of the Balanced Random Forest model an appropriate choice given the generalization capabilities of Random Forests and the disparity in class count present in the dataset.

IV.B.7.A1 Thorough feature analysis and model validation practices

Throughout the model development and evaluation process, good data science practices and a thorough feature selection process were performed, leading to a performant, operationally validated model consistent with traditional fire modeling practices despite leveraging modern statistical tools.

IV.B.7.A2 Use of robust metrics for imbalanced data

Model evaluation metrics should be robust to the class imbalance in the data in the same way as the model architecture was chosen to be robust to the data. GIRS-RT recommends PG&E report values like the area under the precision-recall curve (AUC-PR) in addition to the AUC-ROC, as the latter is potentially affected by class imbalance and does not completely capture the performance of a classifier.

IV.B.9.A1 Recommendation to explore the use of a Binary Classification model

The GIRS-RT suggests the exploration of a modified FPI using a binary classification model to inform the steps involved in PSPS guidance, leveraging the advantages associated with anomaly detection models.

IV.C Catastrophic Fire Probability Distribution (CFP_D) Model

This section covers PG&E's 2021 and 2022 framework for the design, validation, and utilization of the Catastrophic Fire Probability (CFP_D) model employed for PSPS guidance on the distribution network within the PG&E service territory. The section is structured to provide a comprehensive review of the CFP_D model and its applications within PG&E's operational framework. Section IV.C.1 gives an overview of the CFP_D model, including its core concepts and a brief history of its development. Sections IV.C.2 and IV.C.3 focus on analyzing and assessing, respectively, the data sources and methodology used in developing and training the CFP_D model, including meteorological data, fuel data, and local performance data. Section IV.C.4 analyzes the mathematical formulation of the CFP_D model, with an emphasis on the machine learning techniques employed, particularly the use of a Categorical Boosting algorithm and time ensemble approach to account for changing environmental conditions through the years. Section IV.C.5 presents the assessments of the mathematical formulation. Section IV.C.6 discusses model validation practices, covering the metrics and techniques used to assess the applicability of the model. Section IV.C.7 presents the assessments of the model validation. Section IV.C.8 reviews the practical applications of the CFP_D model, highlighting its role in PSPS guidance. Section IV.C.9 summarizes the findings and assessments from the GIRS-RT.

IV.C.1 Catastrophic Fire Probability Distribution Model Overview

The core objective of CFP_D is to predict, at a local level, the probability of experiencing a catastrophic fire produced by the interaction between the environment and PG&E's assets in the distribution network. The model is subdivided into two components, as described the following equation:

$$CFP_D = P(Catastrophic\ Fire) = P(Catastrophic\ Fire|Ignition) \times P(Ignition)$$

This equation follows a conditional probability model. The first component, $P(Catastrophic\ Fire|Ignition)$, is recognized as one of the outputs of the Fire Potential Index (FPI) model, reviewed in Section IV.B. The second component, $P(Ignition)$, is the output of a data-driven model known as the Ignition Probability Weather (IPW) model. The IPW model is the primary focus of this section.

Like the FPI model, the IPW model is defined using local 2 x 2 km grid cells, enabling its outputs to be easily combined with the outputs of the FPI model. The precise features considered in the IPW model and their origins are discussed in more detail in Section IV.C.2. The mathematical concepts behind the IPW model are described in Section IV.C.4.

IV.C.1.1 Brief Timeline of the Catastrophic Fire Probability Distribution (CFP_D) Model

The development of the CFP_D model in general, and the IPW model in particular, can be traced back to the year 2008 when PG&E started the Storm Outage Prediction Project (SOPP). The SOPP's objective was to predict outage activity within the service territory in response to any type of weather, including rain, snow, wind, lightning, and others.

Then, in 2019, the SOPP was used as a basis to generate the first version of the Outage Producing Wind (OPW) model, which aimed to inform the local probability of an outage as a function of wind speed. Operationally, the OPW model output—the probability of an outage given weather and asset conditions—was used as a proxy for the probability of ignitions. The second version of the OPW model was released in 2020. This updated release included an enhanced mathematical model and the adoption of the 2 x 2 km weather model grid. In 2021, a third version of the OPW model was released. This version of the model makes use of a Categorical Boosting machine learning algorithm to predict outage probability across several failure modes, granting the ability to predict outages of different classes. In addition, the OPW model output is converted into an ignition probability—and thus into the IPW model—using historical ignition to outage ratios. This version of the model is the focus of this section.

IV.C.2 Datasets used in the CFP_D Model

The 2021 IPW model was trained on windspeeds and other weather features from the 31-year downscaled climatology data at 2 × 2 km resolution and approximately 500,000 sustained and momentary outages occurring on the distribution grid from 2008 to the end of 2020.[284] Asset damage and hazards observed during PSPS events were also included in the training set. Certain outage records—those from underground circuits or those occurring on non-weather-driven major event days—were excluded to ensure model specificity to weather-related conditions.

The IPW model maintains the same 2 × 2 km resolution as the POMMS, which is configured with the Weather Research and Forecast (WRF) model version 4.1.2. Key features utilized in the IPW model are outlined in Table IV.C-1.

IV.C.2.1 Weather, vegetation, and local performance data

The weather variables used to train the IPW model include wind speed at the surface and 50 m, turbulent kinetic energy at 50 m, friction velocity, vapor pressure deficit at the surface, temperature at the surface, and precipitation. The model includes additional features beyond weather variables: the aerial LiDAR tree overstrike data. This dataset provides the IPW model with insights into tree density and proximity to power lines within each grid cell. The value for each tree is summed per 2 x 2 km grid cells. The tree overstrike is calculated by measuring the tree's point of contact with a conductor to the top of the tree if it were to fall directly toward the conductor.

"Node," a key categorical variable in the model, captures outage trends specific to each location, reflecting factors such as asset condition, vegetation stress, materials, soils, cars, balloons, animals, and other exogenous factors. The Nodes were created to divide the distribution system into roughly equal sections of approximately 50-line miles, ensuring spatial contiguity. This process began by aggregating 1.4 million individual line segments into vertices spaced every 200 meters along the lines. These vertices were then grouped into Nodes using a genetic growth algorithm to ensure an approximately equal number of features per Node. After evaluating various clustering algorithms and methodologies, the Build Balanced Zones tool from the ArcGIS Pro Spatial Statistics toolbox was employed to finalize the Node creation. Finally, the weather

[284] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, p. 30.*

model grid cells and the Nodes were spatially linked to establish a relationship between the two datasets. This approach ensures that the Nodes reflect nuanced spatial patterns in outage occurrences across varying service areas.

Table IV.C-1: IPW model features.[285]

Predictor	Altitude	Description	Source	Update Cadence	Spatial Granularity	Temporal Granularity
Temperature	Surface	Temperature at the surface in Fahrenheit	POMMS	4 × per day	2 km	Hourly
Wind speed	Surface, 50 m	Wind speed at the surface (50 m) in mph	POMMS	4 × per day	2 km	Hourly
Vapor pressure deficit	Surface	Measure of lack of water vapor relative to saturation in millibars	POMMS	4 × per day	2 km	Hourly
Turbulent kinetic energy	50 m	Kinetic energy per unit mass observed in eddies characteristic of turbulent flow in Joules/kg	POMMS	4 × per day	2 km	Hourly
Friction velocity	Surface	Wind shear stress in velocity terms	POMMS	4 × per day	2 km	Hourly
Precipitation	Surface	Precipitation in mm per hour	POMMS	4 × per day	2 km	Hourly
Tree overstrike	Surface	The length in ft of tree overstrike	Vegetation Management Aerial LiDAR	Updated when new Aerial LiDAR data is available	Point tree data, aggregated to 2 km	Static until next Aerial LiDAR update
Node	Surface	A categorical variable representing outage trends	PG&E	NA	NA	NA

IV.C.3 Assessment: Datasets used in the CFP$_D$ Model

IV.C.3.A1 Feature selection and future enhancements

The 2020 IPW model was limited to using wind speed as the only predictive feature. The 2021 IPW model expanded the feature set to include wind speed, turbulent kinetic energy, vapor pressure deficit, surface temperature, tree overstrike, and Node ID, which provided a more comprehensive representation of outage-driving factors. However, machine learning was a new

[285] *PG&E 2022 Wildfire Mitigation Plan, p. 209.*

approach for estimating outage probability, and the feature selection process in 2021 was constrained by computational expenses and the substantial size of the training data. In the future, the GIRS-RT recommends that PG&E consider implementing statistically driven feature selection methods. Additional features, such as fuel moisture derived from satellite observations and field measurements, should be tested for inclusion.

IV.C.3.A2 Node as a critical predictor of localized outage trends

The inclusion of the Node feature in the 2021 IPW model represents a thoughtful design choice. This feature captures local outage trends, incorporating influences such as asset condition, vegetation stress, materials, soils, and exogenous factors like animal activity and external interference. The creation of Nodes using a genetic growth algorithm and the spatial clustering of vertices ensures that each Node reflects nuanced, localized conditions. The Node feature has demonstrated importance, achieving the highest mean feature importance values among all features. This approach highlights the value of incorporating geographically informed categorical variables to improve the model's predictive performance.

IV.C.4 Mathematical Formulation of the CFP_D Model

As stated in Section IV.C.1.1, the CFP_D model is a composite model. At a high level, it consists of 3 core components. These components are shown in Figure IV.C.1.

The FPI component was reviewed in the previous report. This section focuses on the *OPW* and *conditional* models (shown in Figure IV.C.1 in blue), which together compose the IPW model. The next subsection describes the mathematical background of the OPW component.

$$CFP_D = FPI \times IPW$$

$$CFP_D = FPI \times \underbrace{P(ignition|outage)}_{\text{Conditional Model}} \times \underbrace{P(outage)}_{\text{OPW Model}}$$

Figure IV.C.1: High level structure of the CFP_D Model.

IV.C.4.1 Outage Producing Wind Model

The Outage Producing Wind (OPW) model predicts the probability that a 2 x 2 km cell will experience one of six outcomes[286] described in Table IV.C-2. Note that five of these outcomes

Table IV.C-2: Types of Outages predicted by the OPW model.[287]

Class
Vegetation
Equipment – Structural
Equipment – Electrical
3rd party – Animal
Unknown
No Outage

[286] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, p. 32.*
[287] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, p. 32.*

correspond to outage types while the sixth outcome corresponds to “No Outage,” a modeling choice used to ensure a complete set of possible outcomes by incorporating the possibility that no outage events occur in the cell for the period of analysis considered. It is worth noting that most data points correspond to the “No Outage” class.

The technique used for the OPW model is a gradient boosting inspired approach known as Categorical Boosting, or CatBoosting for short.[288] CatBoosting provides enhanced support for categorical variables of high cardinality when compared to other gradient boosting models, a relevant feature in this application considering the nature of the input variable *Node*. Gradient boosting is a general ensemble machine learning technique in which the objective is to train a sequence of simple learning models. In this sequence, the model m_{i+1} is trained to predict the residuals (or errors) produced by the previous model, instead of the original independent variable. In this iterative scheme, the predictions on residuals are used to correct the errors produced by previous models. After all models are trained, they are joined together to achieve a minimization of the total predictive error.

While any model that is trained via the minimization of a loss function can be used within the gradient boosting methodology, the model chosen by PG&E is decision trees, following the original paper on CatBoosting (Prokhorenkova *et al.* 2019). The main drawback of gradient boosting that CatBoosting attempts to solve is the encoding of categorical variables into numerical counterparts. Commonly used approaches, such as one-hot encoding and target statistics, are either too computationally intensive or induce bias into the prediction. CatBoosting proposes an alternative methodology, following an ordered principle between training datapoints that is demonstrated to decrease bias and to be computationally tractable.

The data used in the training of the model includes the years 2008-2020. However, it is expected that recent years may contain more valuable information than older years within the data interval. This is particularly relevant in this application, where environmental changes can occur from one year to the next. To enhance the predictive power of the model, PG&E proposes the use of an ensemble approach that constructs a separate model for each year weighing the data in accordance with the year it was collected. This approach is described in the next subsection.

IV.C.4.2 Time Ensemble

The OPW model is an amalgamation of thirteen outage models trained for each year separately from 2008 to 2020 for each outage class (Vegetation, Equipment-Structural, Animal-3rd Party, Equipment-Electrical, and Unknown Cause). A time-weighted approach is implemented to weigh recent years more heavily in the final model output to address trends in grid performance and reliability over time. An example of the OPW model’s weighted formulation of the probability P of the vegetation outage class is:

[288] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, p. 31.*

$$P(vegatation\ outage) = \frac{1}{\sum_{i=2008}^{2020} w_i} \sum_{i=2008}^{2020} w_i P_i(vegetation\ outage)$$

where the index i runs over the years 2008-2020, P_i is the model for each year i, and the weights for each year w_i are defined as:

$$w_i = e^{b(i-2008)}$$

The value of b in the previous equation is set to 0.1 based on a grid search of values used to optimize predictions for 2020 based on the ensemble of models trained with 2008-2019 data.

These exponential weights are designed to incorporate annualized changes in local conditions. These may include negative trends such as increased tree mortality and asset degradation as well as positive trends such as conductor and pole replacement and vegetation management.

IV.C.4.3 Conditional Model

The conditional model, $P(Ignition|Outage)$, is simply defined using the ratio of the mean number of CPUC reportable ignitions to the mean number outages observed within the years 2015-2020, excluding months outside of the fire season[289] and days with rain, winter storms, low snow, and lightning conditions. This calculation, shown in the following equation, is done for each one of the outage classes described in Table IV.C-3:

$$P(Ignition_{\boldsymbol{c}}|Outage_{\boldsymbol{c}}) = \frac{\#\ CPUC\ ignitions\ due\ to\ \boldsymbol{c}}{\#\ outages\ of\ class\ \boldsymbol{c}}$$

Table IV.C-3: Data used to compute the conditional probability of an ignition given an outage, for each one of the outage classes.[290]

Cause Class	Ignition Count	% of Ignitions	Outage Count	% Total Outages	Estimated $\boldsymbol{P(Ignition|Outage)}$
3rd-Party-Animal	165	22.9%	3,202	16.2%	5.15%
Equipment-Electrical	46	6.4%	2,988	15.1%	1.54%
Equipment-Physical	160	22.3%	3,022	15.3%	5.29%
Unknown	12	1.7%	6,712	34.0%	0.18%
Vegetation	336	46.7%	3,844	19.4%	8.74%
Total per Cause	719		19,768		3.60%

[289] In this case, the fire season is defined as the period between May 1st and November 30th.
[290] Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, p. 32-33

IV.C.5 Assessment: Mathematical Formulation of the CFP_D Model

IV.C.5.A1 Categorical Boosting is deemed ideal considering the high cardinality of the Node variable

The Node variable, which encodes geospatial information through assigning a category to each location in the dataset, has an extremely high cardinality. Most machine learning models, such as random forest or logistic regression, would not be recommended under these conditions. For this reason, the choice of Categorical Boosting by the PG&E team is deemed an ideal solution for enabling the development of a classification model, and at the same time, being able to incorporate geospatial information through the Node variable.

IV.C.5.A2 Time weighted ensemble would benefit from a sensitivity analysis and annual recalibration

The time-weighted ensemble approach uses an exponential weight factor that favors more recent years, rather than a metric based on physical principles. As such, it may fail to account for cyclical patterns in weather and fire events (e.g., 2- to 5-year cycles), where a hot and dry year might precede a cooler and wetter year.

The method used to determine the weight parameter *b* for the time weighted ensemble is *ad hoc*, inherently time dependent, and lacks systematic validation. The GIRS-RT recommends that PG&E evaluate the sensitivity of results to the choice of weight functions and time-dependence of the weights.

The GIRS-RT suggests that PG&E's modeling team perform a sensitivity analysis of the weighting scheme with respect to calibration and forecasting power over a range of years (not just training on 2008-2019 data and assessing performance with 2020 data to calibrate b). If the calibrated weights show strong sensitivity to different calibrations over different years, annual recalibrations of weights may increase predictive power.

IV.C.5.A3 Lack of spatial and temporal considerations in conditional model

The conditional model, described in Section IV.C.4.3, is a simple ratio, derived solely from available data spanning 2015–2020, without considering the statistical significance, reliability, or uncertainty of this ratio. It does not incorporate temporal or spatial information in the estimation of the conditional probability of an ignition given an outage, other than the elimination of winter months. This is particularly relevant when compared with the OPW model, which incorporates both spatial and temporal information through use of data distributed in 2 x 2 km cells and the time weighed ensemble, respectively.

Since the IPW model is the product of the OPW model and the conditional model, the IPW model and CFP_D predictions may lose local and temporal sensitivity, and therefore diminished accuracy in operational tasks. This drawback was corrected in subsequent versions of the model.

IV.C.6 Model Validation

The IPW model was validated in two ways: a statistical train/test evaluation and a climatological validation of the model's predictions around historical high wind ignition events.

For the statistical evaluation, the IPW model was trained on data from the years 2008-2019 and tested on the year 2020. As a multiclass classifier, the model's discriminative ability was evaluated per class in a one-vs-rest fashion.[291] The performance for each class was evaluated by the AUC-ROC score, a threshold-independent metric which is well-suited to multiclass evaluation especially for the dataset in question where there is not a severe class imbalance (except for the cause class 'unknown'). The results for the testing data in each class are included in Table IV.C-4.

Table IV.C-4: AUC-ROC scores by class for the IPW model, evaluated on data from the year 2020.[292]

Cause class	AUC-ROC score
Vegetation	0.81
Equipment-Structural	0.69
3rd-party-animal	0.68
Equipment-Electrical	0.67
Unknown	0.64
No Outage	0.67
Macro-average	*0.70*

The model performs best on the vegetation class, which also accounts for the largest share of ignitions. The AUC values indicate good performance across classes and are relatively balanced, which suggests good model generalizability.

It should be noted that different models are trained for each year and combined, via the time-weighted ensemble, to produce the final scores.[293] Individual models for each year were trained using an 80/20 train/test split to monitor their fit, but these AUC scores are not reported. The skill of the aggregated model, using the time-weighted ensemble, is assessed by the AUC scores presented here.

Alternatively, the final model could have been weighted by year by explicitly assigning a weight variable to each year during training, rewarding correct predictions in more recent years more heavily than correct predictions in prior years. In this approach, the year would become a feature of each datapoint. Including a comparative AUC score for this procedure would serve to validate the time-weighted ensemble approach, which is otherwise not directly statistically tested in the current framework. PG&E data scientists indicated that this approach was not attempted due to the large size of the dataset.[294] However, CatBoosting does support batched training, which can be utilized to sequentially train a model on an arbitrarily large dataset.

The IPW model was also evaluated using a back-cast approach: specific high-wind events associated with historical ignitions were identified and the model's predictions were compared with historical ignition and wind data. The IPW model, trained on all available years 2008-2020, was deployed using the historical weather and fuel data. Its predictions were evaluated by the

[291] Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, p. 34.
[292] Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, p. 35.
[293] Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, p. 33.
[294] Conversation with PG&E data science SMEs, 11/18/24.

PG&E Operational Meteorology team to assess whether the predicted IPW probability increased contemporaneously with the onset of wind events and whether the relative probability on days with observed ignitions was higher than on days without ignitions. The model was judged to perform well both spatially and temporally.[295] However, this evaluation is purely in-sample: the model was trained on the data used to evaluate it in this fashion and is therefore calibrated to produce the correct predictions on these data. With machine learning models, in-sample evaluations can only indicate whether the model's training has proceeded as desired. However, this procedure unequivocally does not determine its predictive or out-of-sample capabilities.

As with other models covered in the Local Conditions Audit, GIRS-RT compared the approach taken by PG&E to operational risk modeling—both the FPI and IPW components of the CFP_D model—to the approaches taken by the other two large CA investor-owned utilities, Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E). While SCE uses a machine-learning model to predict ignition probability and fire severity across its service territory (analogous to PG&E's WDRM models),[296] neither SCE nor SDG&E utilize a real-time machine learning approach to develop FPI or catastrophic fire probability predictions. For example, SDG&E has both a Santa Ana wind index and fire potential index framework which compute values based on deterministic formulae involving data such as wind speed and fuel dryness.[297] These formulae were developed in 2016 and are used as of the publication of SDG&E's 2022 WMP. However, SDG&E's service territory is significantly smaller and is historically associated with fewer wildfires than PG&E's. Regardless, PG&E's approach integrates a much wider suite of datasets and offers a finer-grained spatial and temporal prediction, utilizing more complex and modern methods. GIRS-RT commends PG&E for establishing the state of the art in operational risk modeling for large CA utilities.

IV.C.7 Assessment: Model Validation

IV.C.7.A1 <u>IPW model exceeds industry standards and demonstrates good performance across cause classes</u>

The machine learning powered IPW model, and the aggregated CFP_D model, represent the state of the art in utility operational risk modeling in California. In statistical train-test evaluation of the IPW model, AUC-ROC scores indicate good performance across outage cause classes. Performance is best for vegetation-caused outages, which are associated with the highest probability of an ignition given an outage. Additionally, climatological evaluation of the model in its training set demonstrates consistency of model predictions with historical weather and ignition events. However, there is a general lack of documentation of model validation procedures.

IV.C.7.A2 <u>Lack of independent validation of the time-weighted ensemble method</u>

The current IPW model is based on a time ensemble approach, where an independent model is trained for each year from 2008 to 2020, and then these models are joined together using exponential weighting. This modeling choice assumes that recent years have better information

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[295] *Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, p. 35.*
[296] *Southern California Edison 2020-2022 WMP, p. 42-46.*
[297] *San Diego Gas & Electric 2020-2022 WMP, p. 93-97.*

than past years when it comes to outage prediction. Alternatives techniques, directly compatible with the CatBoosting architecture, exist to focus the model's training on more recent years, including a direct specification of training weights by year. These alternative approaches were not evaluated by PG&E. Consequently, the time-weighted ensemble approach cannot be independently validated as a method of encoding temporal focus to the model. GIRS-RT encourages PG&E to consider such an approach to create a baseline or potentially improve model performance, as more data can be integrated into the model training procedure.

IV.C.7.A3 Climatological evaluation is carried out in-sample, offering no guarantee of predictive performance

While validating the trained model's performance on historical data and observing good performance indicates that model training has proceeded satisfactorily, PG&E's climatological validation process is an in-sample test. That is, the machine learning models have seen the data on which they are evaluated and are instructed to correctly predict it. A completely overfit model with no generalization capability will perform well on such a test but will fail to predict out-of-sample IPW probabilities.

Since PG&E performed a train/test evaluation holding out data from the year 2020, GIRS-RT strongly recommends that climatological evaluations be performed on the out-of-sample holdout data (i.e. wind and ignition events in 2020). From a statistical learning perspective, the results of in-sample evaluations do not indicate in any way the out-of-sample performance of the model, which is the only relevant performance when the model is operationally deployed.

IV.C.8 Applications of the CFP_D Model

The IPW model, and consequently the CFP_D model, is executed four times a day, for every 2 x 2 km grid cell within the distribution network in the service territory. Each prediction represents a forecast for both the outages and ignition probabilities of the cell for 129 hours ahead.

The main operational application of the CFP_D model is for PSPS guidance. It represents one of the three main conditions that would, on its own, trigger a PSPS event given that minimum Fire Potential Conditions (mFPC) are met. As seen in Figure IV.C.2, the threshold used for the CFP_D is 9.0 (the output of the CFP_D model is scaled by 10^3 for ease of communication).

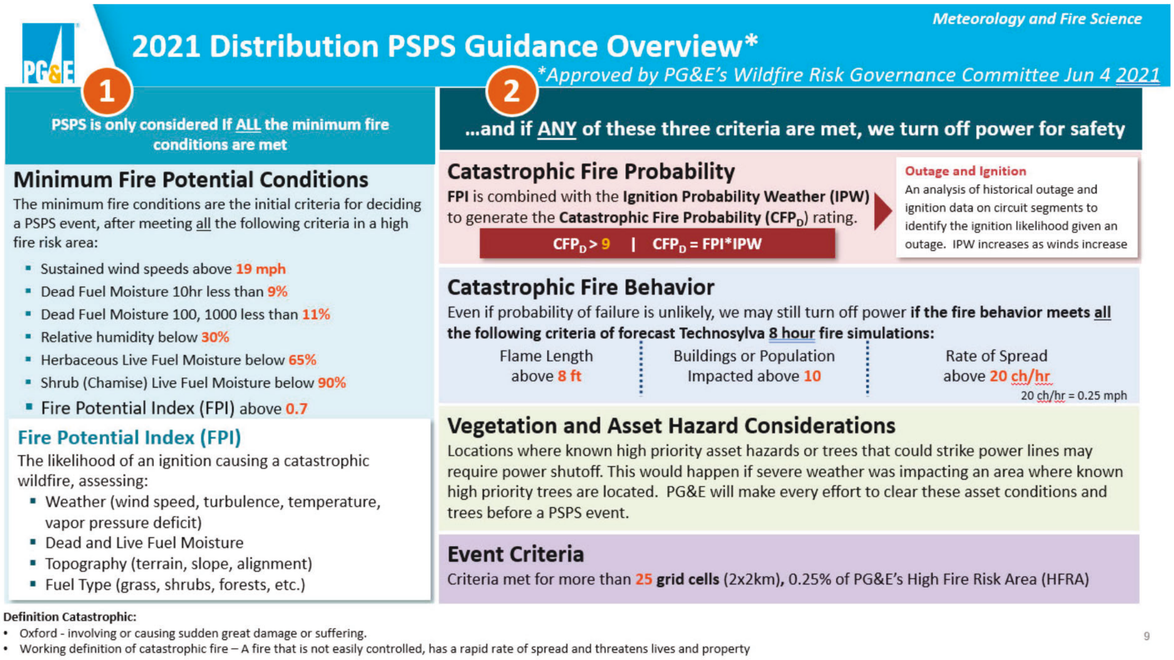

Fig. 32. 2021 distribution PSPS guidance overview

Figure IV.C.2: 2021 PSPS Guidance for the distribution network. The framework is divided into two steps (symbolized by the numbers 1 and 2 in the figure). In the first step, the Minimum Fire Potential Conditions are validated. If these conditions are fulfilled, Step 2 checks whether one of multiple conditions occurs to trigger a PSPS event.[298]

IV.C.9 Summary of GIRS-RT findings for the CFP_D Model

The CFP_D model effectively predicts the probability of catastrophic wildfire on distribution networks by integrating extensive environmental data within a conditional probability model, exceeding industry standards. By combining ignition probability with the FPI model in a highly localized context, it is used for operational decision making in PSPS guidance.

Features:

- CFP_D is a composite model, formed by the product of the Fire Potential index (FPI) and the Ignition Probability Weather (IPW) model. The IPW model is also a composite model, formed by the product of a conditional probability and the Outage Producing Wind (OPW) model.
- PG&E's IPW model leverages weather data, including wind speed, temperature, and precipitation, alongside vegetation data from aerial LiDAR to predict hourly outage and ignition probabilities.
- PG&E incorporated localized risk factors by integrating a categorical "Node" variable that captures location-specific outage trends and summing tree overstrike values within 2 km grid cells.

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[298] Calculating Meteorological and PG&E Fire Risk PG&E PSPS Decision-Making for Distribution, Rev. 4, Page 51.

- PG&E's IPW model is composed of two sub-models. The first one predicts the probability of outages (OPW model), while the second one predicts the conditional probability of an ignition given an outage.
- PG&E's OPW model preferentially weights outage probabilities to favor predictions from the most recent annual models.
- PG&E's IPW model demonstrates good performance in statistical evaluation using the AUC-ROC metric.
- PG&E's approach to FPI and IPW modeling integrates more data and uses more modern methods than similar models at other large CA IOUs, exceeding industry standards.
- PG&E's CFP_D is used for PSPS guidance as one of the three conditions that would trigger a PSPS event given that minimum Fire Potential Conditions (mFPC) are met.

Summary of Assessments

IV.C.3.A1 Feature selection and future enhancements

The 2021 IPW model significantly improved the 2020 version by expanding the feature set beyond wind speed. The GIRS-RT recommends stricter statistically driven feature selection and model validation for future versions, including assessments of reliability and robustness of the model and consideration of additional features like fuel moisture.

IV.C.3.A2 Node as a critical predictor of localized outage trends

The Node feature effectively captures localized outage trends by incorporating geographic and contextual factors, making it the highest feature importance in the model and a key contributor to improved predictive accuracy.

IV.C.5.A1 Categorical Boosting is deemed ideal considering the high cardinality of the Node variable

The Node variable has an extremely high cardinality. For this reason, the choice of Categorical Boosting by the PG&E team is deemed as an ideal solution for enabling the development of an outage classification model under these conditions.

IV.C.5.A2 Time weighted ensemble would benefit from a sensitivity analysis and annual recalibration

The GIRS team suggests that the PG&E's modeling team perform a sensitivity analysis of the weighting scheme with respect to calibration and forecasting power over a range of years. If the calibrated weights show strong sensitivity to different calibrations over different years, annual recalibrations of weights may benefit predictive power.

IV.C.5.A3 Lack of spatial and temporal considerations in conditional model

The conditional component of the IPW model, described in Section IV.C.4.3, does not incorporate temporal or spatial considerations into the estimation of the conditional probability of an ignition given an outage. This drawback was corrected in later versions of the model.

IV.C.7.A1 <u>IPW model exceeds industry standards and demonstrates good performance across cause classes</u>

Statistical evaluation of the IPW model shows good performance across size classes, and the data-driven approach exceeds industry standards in operational risk modeling. However, there is a general lack of documentation of model validation procedures.

IV.C.7.A2 <u>Lack of independent validation of the time-weighted ensemble method</u>

PG&E combines independent models, trained on different years, by explicitly weighing their predictions to emphasize data from more recent years. Such a weighting can be achieved directly in model training, allowing for a larger training dataset, and offering a comparable baseline in model performance, which could have been compared to the approach chosen by PG&E.

IV.C.7.A3 <u>Climatological evaluation is carried out in-sample, offering no guarantee of predictive performance</u>

PG&E compares model predictions near historical wind events to observe whether the model correctly predicts the onset of higher ignition probabilities alongside the historical onset of weather events. However, this evaluation is performed in the training set, violating a basic tenet of statistical learning practice: an in-sample evaluation does not indicate anything about a model's predictive performance on unseen data.

IV.D Catastrophic Fire Probability Transmission (CFP_T) Model

This section covers PG&E's 2021 and 2022 framework for the design, validation, and utilization of the Catastrophic Fire Probability for Transmission (CFP_T) model employed for PSPS guidance within the PG&E service territory. Construction of the CFP_T model was a challenging task utilizing new methodologies which evolved significantly over the period of the audit. PG&E teamed with consulting agencies (e.g., Formation Environmental, NV5, and Exponent) to formulate, calibrate, and assess numerous sub-models (e.g., TOA, FPI, & VRM_T) for the CFP_T. Sub-model evaluation from PG&E and consulting companies resulted in improvements in feature selection and identification of inadequacies (e.g., issues with imbalanced averages).

The section is structured to provide a comprehensive audit of the CFP_T model and its applications within PG&E's operational framework. Section IV.D.1 gives an overview of the CFP_T model, focusing on listing all the sub-models that compose it. Section IV.D.2 focuses on the data sources and methodology used in developing and training the CFP_T model, including meteorological data, asset data, local environmental data, past performance data, and LiDAR tree data, while Section IV.D.3 presents an assessment of these findings. Sections IV.D.4 and IV.D.5 presents the findings of the mathematical formulation of the CFP_T model and its assessments, respectively. Section IV.D.6 discusses model validation practices, covering the metrics and techniques used to assert the applicability of the model. Section IV.D.7 presents a review of the statistical testing of the model, while IV.D.8 presents the corresponding findings. Section IV.D.9 reviews the practical applications of the CFP_T model, highlighting its role in PSPS guidance. Section IV.D.10 summarizes the findings and assessments from the GIRS-RT.

IV.D.1 Overview and timeline of the Catastrophic Fire Probability for Transmission (CFP_T) Model

In 2021, operational risk within the transmission network was calculated using the Large Fire Probability for Transmission (LFP_T) model. Its main objective was to "identify and quantify areas of the PG&E territory where there is concurrence in space and time of high potential for large fires to occur and increase failure probabilities."[299] This model was specifically designed to consider only fires caused by asset-related failures. This model was upgraded to also include vegetation-related ignitions in 2022, when the Catastrophic Fire Probability for Transmission (CFP_T) was introduced.

The CFP_T expands on its previous iteration by incorporating an additional failure mode: vegetation-related incidents. With this, the CFP_T assesses the catastrophic fire probability in the transmission network for two potential causes: fires related to the failure of an asset, and failures related to contact with nearby vegetation. The CFP_T is a composite model created by combining multiple sub-models developed within the company. Figure IV.D.1 provides a diagram illustrating the relationship between the CFP_T and its constituent models.

[299] *2021 PG&E Wildfire Mitigation Plan Report Revised, Table PG&E-4.5-1, p. 126.*

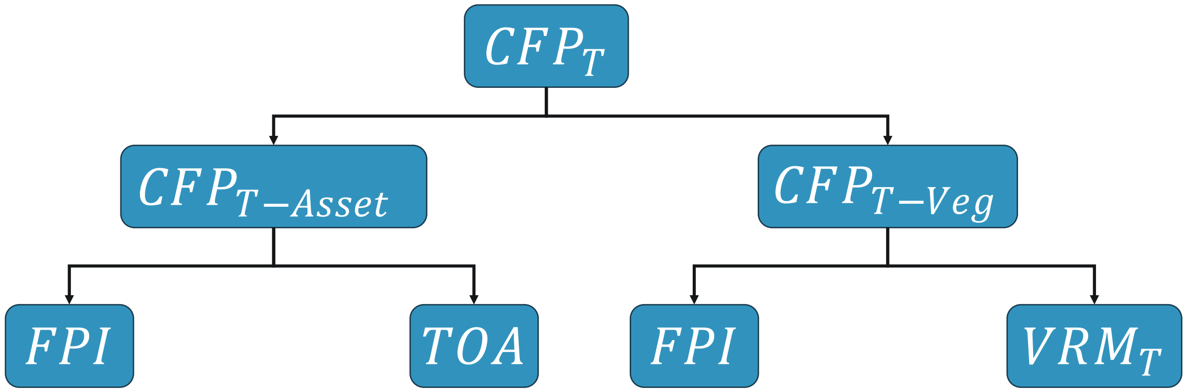

Figure IV.D.1: Composite structure of the CFP_T model, portraying how the global model, CFP_T, is separated into two branched depending on the failure mode.

As shown in Figure IV.D.1, the CFP_T has two main sub-models: one for asset-related failures and one for vegetation-related failures. The asset-focused model combines the Fire Potential Index (FPI) model and the Transmission Operability Assessment (TOA) model to quantify the probability of an asset generating a catastrophic fire because of its failure. The FPI and TOA models are reviewed in Section IV.B and Section II.G, respectively. This section includes abbreviated summaries of previous findings for these models as needed here. The reader is directed to the aforementioned sections if additional details are of interest.

The vegetation-focused model combines the FPI model, and a component called *Transmission Vegetation Risk Model* (VRM_T) to quantify the probability of an asset generating a catastrophic fire due to its interaction with nearby vegetation. The VRM_T was designed for use in both vegetation management and PSPS guidance and was integrated into the CFP_T framework in 2021. The 2021 version of VRM_T, which is the version assessed in this section, represents an enhanced model derived from a series of recommendations issued by the consulting company Formation Environmental, tasked with the development of a validation report[300] for the 2020 VRM_T model. Since the VRM_T is the only component in Figure IV.D.1 that has not been reviewed in a previous section within this audit, it constitutes the primary focus of this section.

IV.D.2 Datasets used in the CFP_T Model

IV.D.2.1 Data used in the TOA Model

The TOA Model integrates data from four major categories: asset and sub-asset age, environmental hazards, asset physical condition, and asset characteristics linked to past performance.[301]

The age, type, and materials (e.g., wood, steel) of assets and sub-assets are critical factors influencing design life. Local environmental factors, such as historical wind conditions, corrosion hazards, weather patterns, and wood decay zones, also play a significant role. Corrosion hazards

[300] *Tree Risk Score Back-Test Analysis Transmission Vegetation Management Final Report (Phase II & III), Formation Environmental.*
[301] *Operability Assessment Model Overview (2021) Local Conditions GIRS Meeting Data 9/28/23.*

are modeled based on atmospheric and soil corrosivity, while wear and fatigue hazards are assessed for specific environmental subtypes, such as grazing land and freshwater ponds.[302]

The physical condition of assets is evaluated using component testing, annual inspection updates from ground and aerial surveys, and structural analysis results. These assessments provide valuable insights into overstrength or understrength factors that influence asset reliability. This information is crucial for understanding current asset conditions and informing model calibrations.

Past performance data, including Failure Modes and Effects Analysis (FMEA), historical outages, failures, and repairs, are also incorporated into the model. This information is used to construct initial fragility curves, perform Bayesian updates, and revise models based on field inspection data. These steps ensure the model is continuously refined to reflect real-world asset behavior accurately.

Historical wind data spanning 30 years is a key component of the model, with each PG&E transmission structure mapped to a meteorological grid cell. PG&E summarizes wind profiles by calculating percentile distributions of maximum daily wind speeds, ranging from the 0th to 99.99th percentiles. These wind profiles are combined with structure-days and outage records, forming the basis for Bayesian updates. The updates align modeled fragility curves with observed asset performance under varying wind conditions.

IV.D.2.2 Data used in the VRM_T Model

Since 2010, PG&E's Transmission Vegetation Management (TVM) team has utilized Light Detection and Ranging (LiDAR) technology to supplement its ground inspections. For the 2018-2019 and 2019-2020 inspection years, LiDAR data was collected across the entirety of the 18,200 miles of transmission line right-of-way (ROW).[303] The LiDAR data collected annually from NV5 provides the 3D position (x, y, elevation), height, and crown information of trees.

Three test groups of tree populations, "All Trees", "Failure Trees", and "Ghost Trees," were defined. The size of the All Trees population varied depending on the parameter that was analyzed, using the largest number of trees available for each based on the availability of the dataset(s) used in the calculation of each respective parameter. The All Trees population was geographically distributed across the PG&E service area and statistically robust with population size ranging from 429,636 to 839,399, based on the availability and spatial extent of the underlying datasets.[304]

The identification of Failure Trees relies on multiple datasets and a systematic approach.[305] Key inputs include the PG&E outage investigation report, which provides details on vegetation-related outages, and NV5 vegetation segmentation polygons, derived from LiDAR data, to identify

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[302] *A Framework for Risk-Based Transmission Line Asset Managements and Operability Assessment prepared by Exponent, p. 51.*
[303] *Overview of Statistical Testing, p.1-3; Tree Risk Score Back-Test Analysis Transmission Vegetation Management Final Report (Phase II & III), Formation Environmental, p. 4.*
[304] *Overview of Statistical Testing, p.1-3; Tree Risk Score Back-Test Analysis Transmission Vegetation Management Final Report (Phase II & III), Formation Environmental, p. 9.*
[305] *Overview of Statistical Testing, p.1-3; Tree Risk Score Back-Test Analysis Transmission Vegetation Management Final Report (Phase II & III), Formation Environmental, p. 9-10.*

vegetation clusters within the transmission ROW. High-resolution LiDAR point clouds are essential for detecting structural changes in vegetation before and after outages. Additionally, the vegetation management work history database helps exclude previously removed trees. At the same time, Formation Environmental WRF-generated wind data provides critical information on weather conditions, such as wind speed and direction, that may have contributed to tree failure.

The failure tree identification process begins by mapping each vegetation-caused outage using GIS tools.[306] Pre- and post-outage LiDAR data are then compared to detect missing or altered vegetation, identifying potential Failure Trees. Supporting evidence, including vegetation work history and wind conditions, is analyzed to validate the findings. Finally, NV5 vegetation polygons that align with the probable failure tree(s) are selected, ensuring consistency with observed data.

The selection of Ghost Trees is based on a combination of PG&E's transmission vegetation management work history database and airborne LiDAR datasets provided by PG&E's LiDAR vendor.[307] Ghost Trees refer to trees that failed but did not contact transmission lines, making them more challenging to identify. The primary goal of the methodology is to pinpoint vegetation that disappeared between the 2018-2019 and 2019-2020 LiDAR data while ensuring that previously worked or intentionally removed trees are excluded.

The Ghost Tree selection process involves several steps.[308] First, vegetation that existed in the 2018-2019 LiDAR data, but was absent in the 2019-2020 LiDAR data, is flagged as potential Ghost Trees. Next, transmission vegetation work records from 2019 are used to eliminate worked trees from the analysis. To further refine the selection, digital surface models (DSMs) and canopy height models (CHMs) derived from LiDAR data are utilized to detect and confirm reductions in the tree canopy, removing false positives. Due to the spatial uncertainty associated with the GPS coordinates from the transmission work history database and observed classification errors in the preliminary ghost tree dataset provided by the LiDAR vendor, a manual review of potential Ghost Trees was conducted. Finally, field verification at a sample of 33 locations ensures the accuracy and reliability of the identified Ghost Trees.

IV.D.3 Assessment: Datasets used in the CFP_T Model

IV.D.3.1 Assessment of the data used in the TOA model

IV.D.3.A1 Comprehensive integration of field data in TOA

The comprehensive suite of information used to generate and run the TOA model is adequate and fit for use to assess the likelihood that a transmission line will fail under windy conditions. While modes of failure that are independent of wind are not directly captured, influences associated with corrosion, effects of loading from ice, and other environmental factors are inherent in the information used for model calibration and degradation estimates.

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[306] *Overview of Statistical Testing, p.1-3; Tree Risk Score Back-Test Analysis Transmission Vegetation Management Final Report (Phase II & III), Formation Environmental, p. 10-13.*
[307] *Overview of Statistical Testing, p.1-3; Tree Risk Score Back-Test Analysis Transmission Vegetation Management Final Report (Phase II & III), Formation Environmental, p. 13.*
[308] *Overview of Statistical Testing, p.1-3; Tree Risk Score Back-Test Analysis Transmission Vegetation Management Final Report (Phase II & III), Formation Environmental, p. 13-14.*

IV.D.3.A2 Annualized vs. Fire-season-restricted data in TOA

Unlike the Vegetation and Conductor Risk Models, which focus on fire season in the Wildfire Distribution Risk Model, the TOA model uses annualized data, assuming all line failures cause ignitions. However, most wind-related outages from 2007 to 2020 occurred in winter, where wet conditions reduce ignition risk compared to the dry wildfire season. While the TOA may be effective at identifying failure-prone regions, incorporation of an ignition likelihood model given environmental conditions may improve the accuracy of the model.

IV.D.3.2 Assessment of the data used in the VRM_T model

IV.D.3.A3 Correct integration of multiple data sources in VRM_T

The methodology effectively integrates various datasets, including LiDAR data, weather conditions, and outage reports, to identify Failure Trees and Ghost Trees. While each dataset has inherent limitations, the approach compensates for these by incorporating a manual review of each outage event from PG&E's transmission vegetation-caused outage database. Furthermore, field verification was conducted to ensure the reliability and accuracy of the findings.

IV.D.3.A4 Opportunities for incorporating operational updates in VRM_T

While the integration of multiple datasets provides a reliable base of population selection for the VRM_T, the responsiveness of the tool to changing conditions could be improved by incorporating real-time or recent operational data. Incorporating operational data, such as records of trees worked, removed, or identified as fallen during events, would improve the accuracy of risk assessment effectively.

IV.D.3.A5 Expanding exploration on environmental factors in VRM_T

There is potential to broaden the scope of environmental factors included in the analysis, such as wind exposure, soil moisture, tree species, and vegetation health indices.[309] Wind exposure is a critical factor influencing vegetation stability and failure risk, and both excessively dry and overly saturated soils can compromise tree stability. Certain tree species are inherently more flammable, making them higher risk during fire-prone conditions. Similarly, species with shallow root systems or brittle wood are more likely to fail during high winds or storms. Additionally, unhealthy or stressed trees often have weakened structural integrity, making them more susceptible to breakage. Incorporating vegetation health indices could help identify such trees early, enabling proactive management to reduce the risk of failure or fire in vulnerable areas.

IV.D.4 Mathematical Formulation of the CFP_T Model

As shown in Figure IV.D.1, the CFP_T model is composed of two sub-models. The first one, denoted as $CFP_{T\text{-}Asset}$, estimates the catastrophic failure probability due to asset-related failures in the transmission network. The second model, denoted as $CFP_{T\text{-}Veg}$, performs a similar task, but focused on vegetation-related failures. This section begins by describing the mathematical formulation of the former.

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[309] *Overview of Statistical Testing, p.1-3; Tree Risk Score Back-Test Analysis Transmission Vegetation Management Final Report (Phase II & III), Formation Environmental, p. 28-34.*

IV.D.4.1 Catastrophic Fire Probability for Transmission: Asset Related Failures ($CFP_{T\text{-}Asset}$)

The $CFP_{T\text{-}Asset}$ model is the product of the FPI and TOA models. The TOA model is evaluated at the asset level, whereas the FPI model is evaluated using the location of the asset as the input. This is shown in the following equation.

$$CFP_{T-Asset} = FPI(asset's\ location) \times TOA(asset)$$

In the previous equation, FPI and TOA stand for the Fire Potential Index and Transmission Operability Assessment models, respectively. The following paragraphs briefly describe these components. For a more in-depth review, the reader is referred to Section IV.B and Section II.G for a detailed review of the FPI and TOA models, respectively.

The FPI model is a multi-class classifier model that takes in a set of features coarsely divided into four classes: weather, fuel moisture, fuel type, and topography. For this model, the features are distributed spatially into 2 x 2 km grid cells. The output of the FPI model is the expected fire severity given an ignition for each grid cell across the service territory. The severity classes considered in the model are *small, large,* and *catastrophic*. Mathematically, the FPI model estimates the following probability distribution: $P(severity|ignition)$, where $severity \in \{small, large, catastrophic\}$.

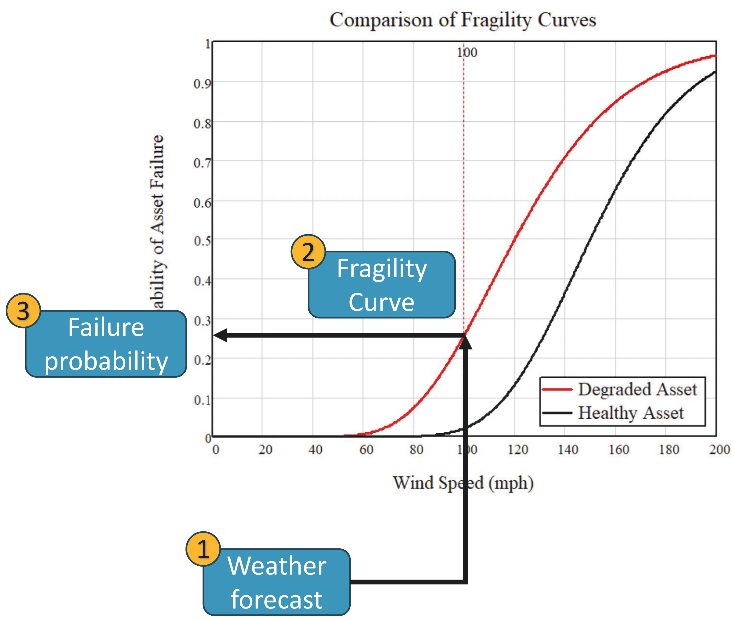

Figure IV.D.2: Three-step methodology to obtain failure probabilities from an asset's fragility curve. In the first step, the weather forecast is used to identify the corresponding wind speed in the x-axis. In the second step, the fragility curve is evaluated at the wind speed identified in step 1. Finally, in step 3, the failure probability is read from the fragility curve.

The Transmission Operability Assessment model is a framework collaboratively developed by the consulting company Exponent and PG&E. The framework informs construction of fragility curves, which are models that describe the relationship between the failure probability of an asset for given structural demand. In the case of the TOA, the assets are elements within the transmission network, and the structural demand is the local 3-second wind gust speed. Given a meteorological prediction for wind speed at the location of a given asset, its failure probability can be read directly from the fragility curve. This process is represented in Figure IV.D.2. The TOA framework generates fragility curves for each asset in the transmission network. This process involves several steps, including, but not limited to, the characterization of a two-parameter probability distribution and a Bayesian updating step. For more details on the TOA framework, including the GIRS-RT assessment, the reader is referred to Section II.G.

IV.D.4.2 Catastrophic Fire Probability for Transmission: Vegetation Related Failures ($CFP_{T\text{-}Veg}$)

This section describes the second branch of the CFP_T model: the vegetation-related model. The $CFP_{T\text{-}Veg}$ model is defined as the product of the FPI model, evaluated at a given asset's location, and the Transmission Vegetation Risk Model (VRM_T), evaluated at the asset level. This formulation is shown in the following equation. The FPI model was reviewed in detail in section IV.B, and a summary is included in Section IV.D.4.1 of the current section. This section focuses on describing the VRM_T mathematically.

$$CFP_{T-Veg} = FPI(asset's\ location) \times VRM_T(asset)$$

The Transmission Vegetation Risk Model assigns a risk score to every tree located near the 18,200 miles of transmission lines within the service territory. This assessment is based on a combination of LiDAR data, environmental variables, and historical vegetation-related failures. The model has been under continuous development since 2018 and is currently used to support both PSPS (Public Safety Power Shutoff) scoping and Vegetation Management tasks.

The version of the model that was used during the period covered by this audit was developed by a consulting company, *NV5,* and includes modifications based on feedback from *Formation Environmental* which performed a review of the previous version of the model that had also been developed by NV5. The Formation Environmental review was thorough, and among other changes, motivated a reduction in the number of parameters in the model from seven to four. The VRM_T model was delivered to PG&E by NV5 as a *black-box model*. Consequently, instead of receiving model specifications, PG&E receives directly from NV5 the final risk scores computed for each tree in the transmission network. While PG&E does not have direct access to the model or its configuration, the following mathematical description was determined based on a series of interviews the GIRS-RT held with PG&E personnel.

The VRM_T model uses LiDAR data to compute four key variables for every tree in the transmission network Right of Way (ROW). These variables include:

- **Fall Distance Percentage**, which measures the potential conductor overstrike distance relative to tree height—higher percentages indicate greater risk.
- **Slope to Wire**, which measures the degree of slope from the tree to the conductor, with greater upslope presenting higher risk.
- **Unobstructed Fall Paths**, which measures the number of unobstructed paths for a tree to fall onto a conductor, with more paths signifying greater risk.

- **Tree Exposure**, which measures the relative height difference between a tree and its surroundings, with greater exposure indicating increased risk.
- Once the coefficients are defined, the VRM_T can be used to compute the corresponding risk score for every tree near PG&E's transmission network.

Figure IV.D.3 provides a graphical description of the variables.

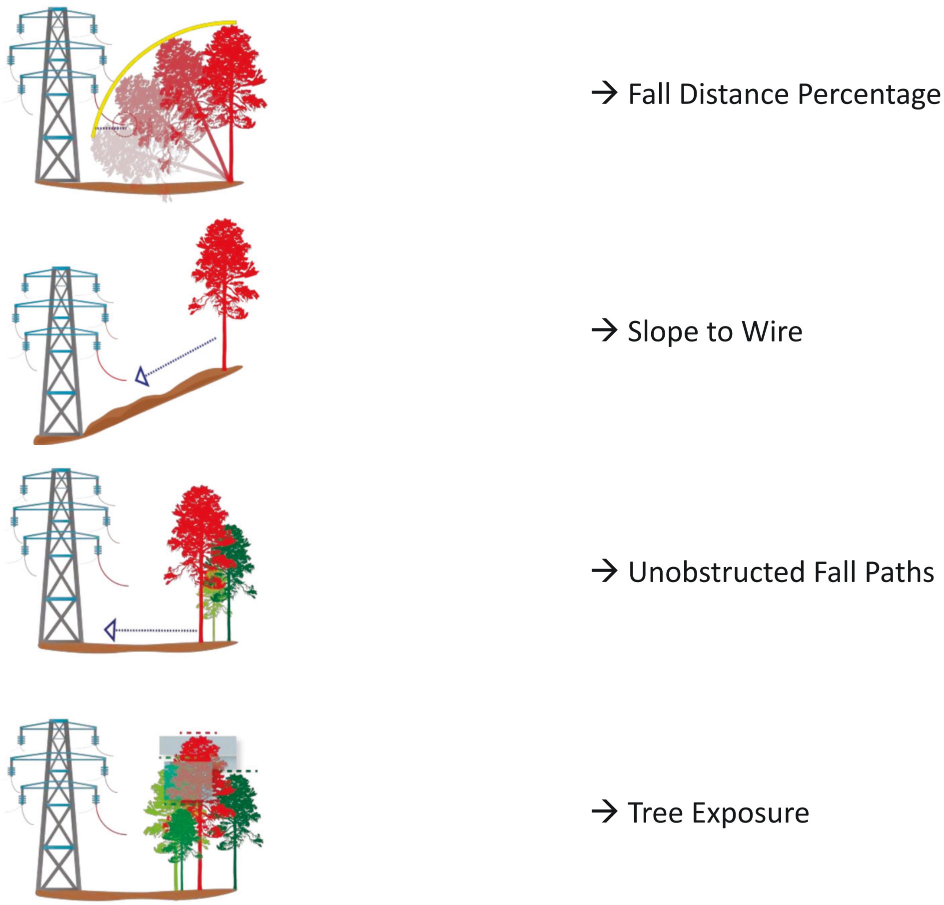

Figure IV.D.3: Graphical description for each LiDAR-informed variable considered in the VRM_T model.

Each one of the LiDAR variables is transformed into a score ranging from 0 to 100 using a methodology known as the *Frequency Ratio.* The methodology is defined by the following steps:

1. The range of a given variable within the population of the *All Trees* group is divided into N bins.
2. Then, for each bin, the relative frequency (RF) of trees with values in that bins are computed.
3. The same is done with the population of *Failure Trees*, using the same bin limits.
4. The frequency ratio for each bin is computed as $FR = \frac{RF\ Failure\ Trees}{RF\ All\ Trees}$.
5. The final frequency ratios are normalized to a 0-100 scale.

Figure IV.D.4, taken from PG&E documentation,[310] provides a concrete example of the Frequency Ratio calculation for *Fall Distance Percentage*. The frequency ratio is a variable that quantifies how significant a certain range is within the Failure Trees group compared to the All Trees group. Generally, higher frequency ratio values indicate variable ranges that are more prone to a negative outcome.

Fall Distance Percent

All Trees (365,006)			Failure Trees (77)			FR
Bin of % of tree capable of overstrike	Count	Rel. Freq	Bin of % of tree capable of overstrike	Count	Rel. Freq	
10	103,006	28.2%	10	7	9.1%	0.3
20	81,228	22.3%	20	7	9.1%	0.4
30	66,718	18.3%	30	16	20.8%	1.1
40	50,795	13.9%	40	16	20.8%	1.5
50	36,446	10.0%	50	11	14.3%	1.4
60	18,953	5.2%	60	9	11.7%	2.3
>60	7,860	2.2%	>60	11	14.3%	6.6

Figure IV.D.4: Table portraying a graphical example of the Frequency Ratio methodology. Step 5, which consists of the normalization of the frequency ratios, is not included in the table.

As seen in Figure IV.D.4, a potential issue arising from the small sample of Failure Trees is the lack of monotonicity in the frequency ratios. For example, one would expect that a higher Fall Distance Percentage would always correspond to a higher frequency ratio, but this pattern is not observed in Figure IV.D.4: note how the frequency ratio increases up to 1.5, and then decreases to 1.4, then continues to increase. PG&E attributes this anomaly to the fact that the sample size for Failure Trees is small, resulting in noisy data. The GIRS-RT agrees with this explanation. As a solution, PG&E established an intermediate step between steps #4 and #5 in the methodology, where the frequency ratios obtained, which may not exhibit monotonicity, are then fit to a logarithmic curve to adjust the values and ensure monotonic behavior.

Once all variables have been transformed into scores ranging from 0 to 100, a "risk score" is calculated using the following equation.

$$\begin{aligned} Risk\ Score = \quad & Fall\ Distance\ Score \times \mathbf{0.43} \\ & + Unobstructed\ Path\ Score \times \mathbf{0.32} \\ & + Slope\ to\ Wire\ Score \times \mathbf{0.13} \\ & + Tree\ Exposure\ Score \times \mathbf{0.12} \end{aligned}$$

Due to the black-box nature of the VRM_T model, PG&E was unable to fully explain the process used to define the bold-faced coefficients in the previous equation. However, they were able to offer an educated guess. It is believed that the bold parameters are iterated to maximize the AUC-ROC score of a binary classification experiment. This binary experiment can be described as follows:

[310] *Wildfire Risk Governance Committee, June 2nd, 2021, p. 27. Document code: DRU14659.001_Atch04.*

1. Select a set of bold-faced coefficient values.
2. Compute the risk score for all trees in the database.
3. Compute the ROC curve, and the corresponding AUC, taking as the binary classification task the separation of failing and not failing trees.
4. Iterate the values of the bold coefficients to maximize this AUC metric.

While this is a reasonable procedure, PG&E is not certain whether this is how the bold coefficients were determined by NV5. Once the coefficients are defined, the VRM_T can be used to compute the corresponding risk score for every tree near PG&E's transmission network.

IV.D.5 Assessment: Mathematical Formulation of the CFP_T Model

IV.D.5.A1 General Remarks regarding the $CFP_{T\text{-}Asset}$

Since the $CFP_{T\text{-}Asset}$ model is the product of the FPI and TOA model outputs, the GIRS-RT assessment of its mathematical formulation is directly inherited from its constituents. While those assessments and recommendations can be reviewed in detail in their respective sections, a summary of assessments most relevant to Operational use is included in this section.

a) The FPI and TOA frameworks are based on sound and well-justified engineering and probabilistic principles and represent suitable models. In particular, the approach used for the TOA model is found particularly useful in situations where observations are scarce, such as the case of outage assessment in transmission networks.
b) However, for the TOA model, the documentation provided did not include a section to validate results obtained from the TOA framework. As with any physics-based model, the results obtained from it should be compared to a set of trustworthy observations to assess its predictive power. The GIRS-RT recommends PG&E conduct a directly data driven validation of the model in future iterations, i.e., a validation study that compares observed outage rates on the transmission network to TOA predictions of the outage probabilities. Unlike updating the fragility curve based on observations, (which is a form of training and refining the model), the data-driven approach provides an independent test of the model's performance.
c) Similarly, the TOA model documentation does not provide a sensitivity analysis for the priors used in the Bayesian update step. The GIRS-RT recommends that PG&E conduct a sensitivity analysis (i.e., determine the extent to which the predicted failure probabilities are sensitive to the initial values) for future iterations to assess the influences of small changes in initial conditions. A stable Bayesian approach minimizes the sensitivity and converges to a prediction that does not depend on the priors. Confirming this is an important step in the validation of the procedure.
d) The use of fragility curves is widely accepted in the reliability community to assess the failure probability of assets. However, in this application the range of failure probabilities predicted under realistic conditions (extreme forecasts or historical peak wind speeds) is very small, limiting the operational range at which the fragility curve is used in practice to only its left side tail. The GIRS-RT recommends a more thorough analysis of the functional form and sensitivity in the range of wind speeds observed in practice (i.e. in the left tail of the fragility curves) to determine how accurately the failure probability is related to demand (wind speed in this case) in this range.

IV.D.5.A2 Use of $CFP_{T\text{-}Veg}$ to model the outage probability could be enhanced

The CFP_T model, in both the asset and vegetation applications, aims to estimate the catastrophic fire probability within the transmission networks. This probability is formulated by disaggregating the probability of a catastrophic fire into a series of conditional components:

$$P(catastrophic) = P(catastrophic|ignition) \times P(ignition|outage) \times P(outage)$$

The GIRS-RT finds that the asset version of the model is well justified as a model estimating a probability measure for the following reasons:

- The FPI model, which estimates a probability, is correctly used as the $P(catastrophic|ignition)$ component.
- The TOA model, which also estimates a probability, is correctly used as the $P(outage)$ component.
- The term $P(ignition|outage)$ is set equal to one, which is a conservative assumption based on the relatively low number of failure events in the transmission network, which constrains the ability to generate a statistical model for this quantity.

By considering all these modeling choices, it is determined that the asset version of the CFP_T represents a valid estimation of a probability measure, since it is itself composed of several probability sub models (the multiplication of probabilities is also a probability).

However, the vegetation version of the CFP_T does not represent a valid probability model: it uses the VRM_T to estimate the $P(outage)$ component, which is not a probability model. The VRM_T is a model that estimates the degree of association between past failures and tree characteristics. While this association will likely be related to the probability of outages, it does not represent a direct replacement for the $P(outage)$ term and therefore jeopardizes the main purpose of the CFP_T model, which is to estimate a catastrophic fire probability. Our suggestion is to consider reformulating the VRM_T as a probability model in future iterations of the $CFP_{T\text{-}Veg}$. PG&E reported that this issue has been rectified in the current version of the model.

IV.D.5.A3 Black-box models and lack of documentation VRM_T

While the GIRS-RT recognizes the potential value of utilizing consultants for aspects of model development and understands that this approach may limit internal knowledge regarding the models used in the CFP_T, the GIRS-RT is concerned about the lack of documentation on VRM_T that PG&E obtained from NV5. The GIRS-RT found that certain key elements, such as the origin of the coefficients used in the computation of the Risk Score, were not understood at PG&E. The VRM_T documentation for its 2022 iteration was limited and disorganized, hindering both the investigation and validation of the model during this audit and limiting its usefulness for future tasks within the company.

The GIRS-RT acknowledges and applauds the fact that following the period covered by this audit, as of the 2023 iteration of $CFP_{T\text{-}Veg}$ PG&E internalized the VRM_T and $CFP_{T\text{-}Veg}$ model development, ensuring comprehensive knowledge of the model within the company.

IV.D.5.A4 Monotonic adjustment for the Frequency Ratios in VRM_T is deemed appropriate

The lack of monotonicity in the frequency ratios due to small samples is found to be a relevant drawback of the technique. The ad-hoc solution used by PG&E to solve this issue, which consists of applying a logarithmic fit to the curve, is accepted as a valid approach to ensure monotonicity in the final frequency ratios.

IV.D.6 Model Validation

Both the TOA model and VRM_T considered in this audit lack adequate documentation for statistical testing, validation, and sensitivity analysis.

Tree risk score back testing for the previous iteration of the VRM_T (the version prior to the version considered in this audit) was performed in a thorough review by Formation Environmental. That version of the model is summarized in Figure IV.D.5. Note that it is composed of seven risk-informed variables (instead of four), which are divided into two categories:

- "Outage" variables, which describe the propensity of a tree to cause an outage in the transmission network.
- "Descriptive" variables, which describe the relative position of the tree with respect to the surrounding environment.

These variables were normalized and grouped together using a weighted average to formulate the final risk score for each tree in the network.

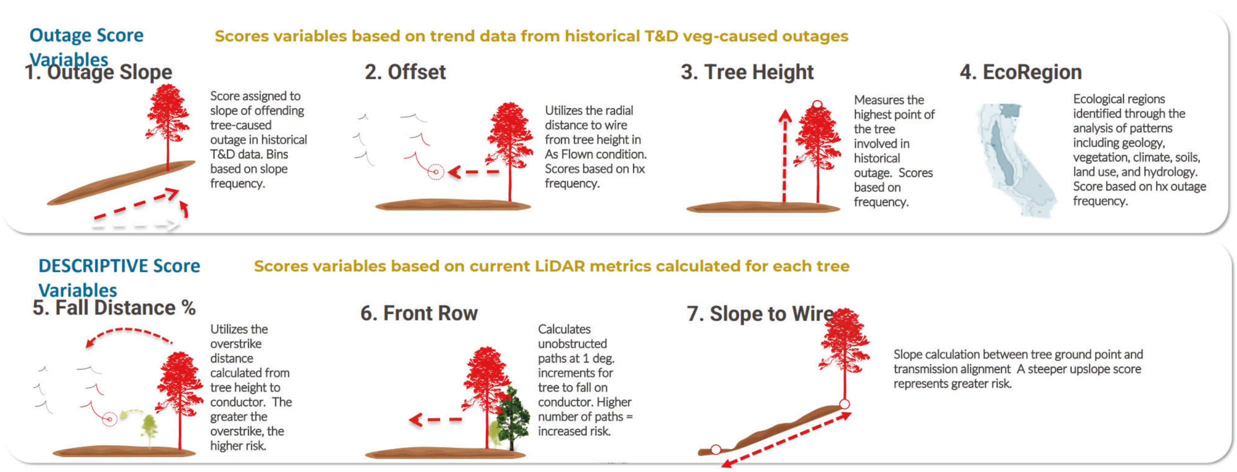

Figure IV.D.5: Risk-informed variables used for the previous version of the VRM_T. The variables are divided into two categories, "Outage" variables and "Descriptive" variables.[311]

The review addressed the following questions:

- How well do each of the tree metric variables capture tree failures associated with outages and non-outages?
- Do the Tree Risk Scores reflect risk of line impact upon tree failure?

[311] *Transmission Vegetation Management, Tree Risk Scores, p. 4.*

- Do the Tree Risk Scores reflect probability of failure regardless of line impact?

Results of the Formation Environmental review were used by NV5 to make updates to VRM_T for the version considered in this audit. Among other changes, the number of parameters used in the model was reduced from seven to four, and the way individual parameter risk scores were combined was revised. The methods used by Formation Environmental to evaluate VRM_T included and Assessment of the LiDAR Score Assignments, Statistical Trend Analysis, Cluster Analysis (PCA), and Machine Learning.

IV.D.7 Statistical Testing

This section summarizes the statistical testing to interrogate the VRM_T scores from the prior 2020-2021 model.

IV.D.7.1 <u>Statistically Significant Differences Between the Tree Categories, as Measured by the LiDAR Parameters</u>

The Formation Environmental external review of VRM_T includes an assessment of the LiDAR tree scoring process that found that the methods used to categorize individual trees and determine the values of the VRM_T parameters (as described in the VRM_T data in Section IV.D.2.2) and a three-step statistical evaluation.[312] The first step tests if there are statistically significant differences between the three tree categories: All Trees, Failure Trees, or Ghost Trees as measured by the distribution of the seven parameter shown in Figure IV.D.5 (reduced to four parameters after the Formation Environmental Review). The second step is to determine whether the three groups exhibit statistically significant differences via a post-hoc test. The third step is to quantify the amount of difference (the measure). The test identified significant differences for a subset of the parameters, which contributed to the reduction from the original seven parameter model to the four-parameter model.

IV.D.7.2 <u>Absence of Normalization and Issues with Imbalanced Averaging</u>

Formation Environmental identified issues associated with normalization and averaging that arose in the previous version of VRM_T. In the earlier model, the seven parameters (shown in Figure IV.D.5) were divided into separate Outage and Descriptive categories. Scores were computed for each category, and then the Outage and Descriptive scores were averaged. Formation Environmental showed that the lack of normalization and imbalanced averaging could lead to uneven weighting, cancelations, and dilution of certain parameters.[313] In the updated risk formulation, the earlier method of combining scores was replaced with the weighted combination of the normalized parameter values.

IV.D.7.3 <u>Positive Correlates</u>

The next step in the analysis involved classification of positive correlates, which are identified as parameters that exhibit increasing normalized risk scores for Failure Trees. Statistical trend analysis identified four positive correlates, which are 1) Fall Distance Percent Scores, 2) Front Row

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[312] *Overview of Statistical Testing, p.1-3; Tree Risk Score Back-Test Analysis Transmission Vegetation Management Final Report (Phase II & III), Formation Environmental, p. 35-37.*

[313] *Tree Risk Score Back-Test Analysis Transmission Vegetation Management Final Report (Phase II & III), Formation Environmental, p. 22.*

Scores, 3) Slope to Wire Scores, and 4) Ecoregion Scores. Slope, Offset, and Tree Height were not characterized as positive correlates and were thus excluded from further analysis in the Formation Environmental review.

IV.D.7.4 Principal Components Analysis of Positive Correlates

Principal Components Analysis (PCA) was used to create the most differentiated variability clusters for the positive correlates. PCA assesses the extent to which linear combinations of the positive correlates can account for the variance between the three categories (All Trees, Failure Trees, and Ghost Trees). The 95% confidence ellipse for Failure Trees substantially overlaps those of Ghost Trees and All Trees. (Note that well separated ellipses are indicative of a successful explanatory model.)

IV.D.7.5 Machine Learning with Positive Correlates

Random Forest machine learning was used to assess the extent to which nonlinear combinations of the positive correlates can account for the differences between the three categories (All Trees, Failure Trees, and Ghost Trees).[314] The model used 90% of the data for training and 10% of the data for testing and differentiated 80% of the Failure Trees accurately, and 89% when the Failure Trees and Ghost Trees were combined. Parameter importance indicated that the Front Row Score was of highest importance among the four positive correlates followed by Slope to Wire and Fall Distance Percentage. Ecoregion exhibited minimal importance.

IV.D.8 Assessment: Statistical Testing

IV.D.8.A1 Statistical Validation of VRM_T

While statistical tests, including PCA and machine learning-based analyses, were performed on the previous version of the VRM_T, these primarily serve as validation for parameter selection rather than for the overall model performance. For the updated version of VRM_T, model-level validation is documented via the ROC-AUC curve (AUC = 74%),[315] with no similar statistical tests performed on the parameters.

IV.D.8.A2 Formation Environmental Review of VRM_T

The Formation Environmental Review of the previous version of VRM_T was thorough, providing detailed analysis of the data collection, tree group classifications, and risk parameters for the original, seven parameter model. The report justifies reduction to the four-parameter model and suggests additional risk parameters based on environmental parameters.

IV.D.8.A3 Formulation of the Previous VRM_T Model

Imbalanced averaging of risk scores coupled with parameters that were not normalized may have resulted in overweighting and underweighting of parameter influences in the previous 2020-2021 VRM_T. This was replaced in the updated model. However, as mentioned before, the updated model lacks documentation for the method used to set the weights.

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[314] Tree Risk Score Back-Test Analysis Transmission Vegetation Management Final Report (Phase II & III), Formation Environmental, p. 55.

[315] DRU14659.001_Atch02_Transmission VM Lidar Risk Tool 2022 Risk Score Update_NV5_06.13.2022_CONF, p. 8.

IV.D.9 Applications of the CFP_T Model

This section describes how both versions of the CFP_T model are used operationally by PG&E. It begins with the asset version, $CFP_{T\text{-}Asset}$, which is summarized in Figure IV.D.6. Note that the TOA model output is computed at the asset level, and the FPI component is evaluated at the location of the given asset.

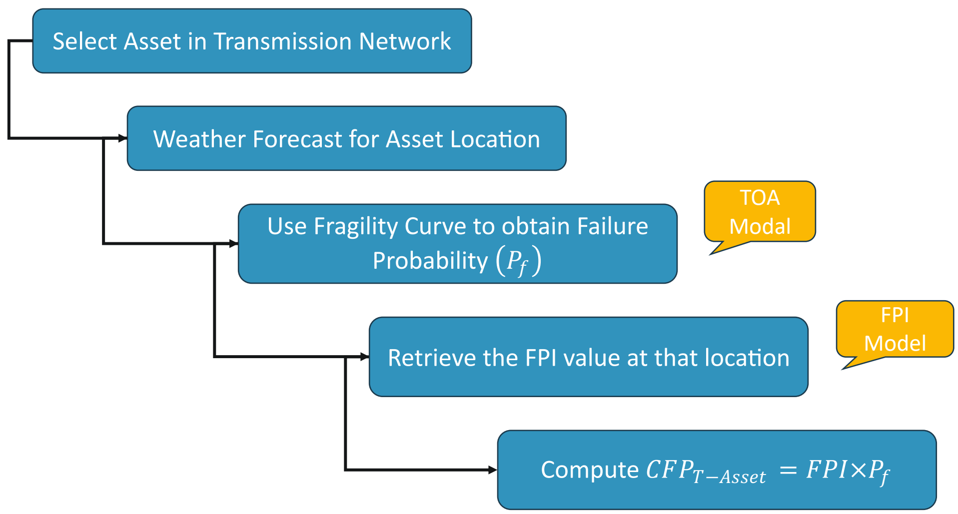

Figure IV.D.6: Methodological steps for the application of the $CFP_{T\text{-}Asset}$ for a given asset within the transmission network.

The application of the $CFP_{T\text{-}Veg}$ model is described in a similar manner in Figure IV.D.7. Note that in this case, the application is at the line level: the risk scores for all trees in the vicinity are averaged over line segments.

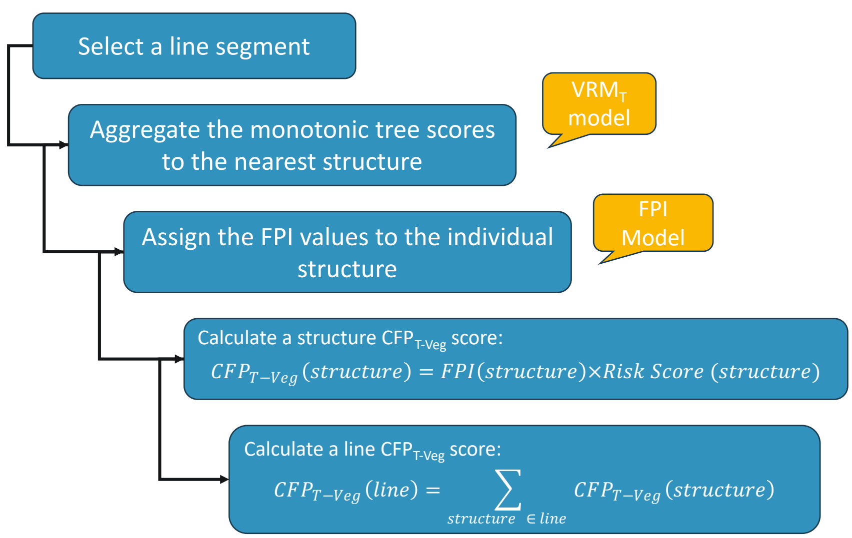

Figure IV.D.7: Methodological steps for the application of the $CFP_{T\text{-}Veg}$ for a given asset within the transmission network.

Finally, the $CFP_{T\text{-}Asset}$ and $CFP_{T\text{-}Veg}$ models are used to inform the scope of PSPS application. This application is seen in Figure IV.D.8, where the model outputs are directly incorporated as one of the three sufficient conditions to trigger a PSPS event.

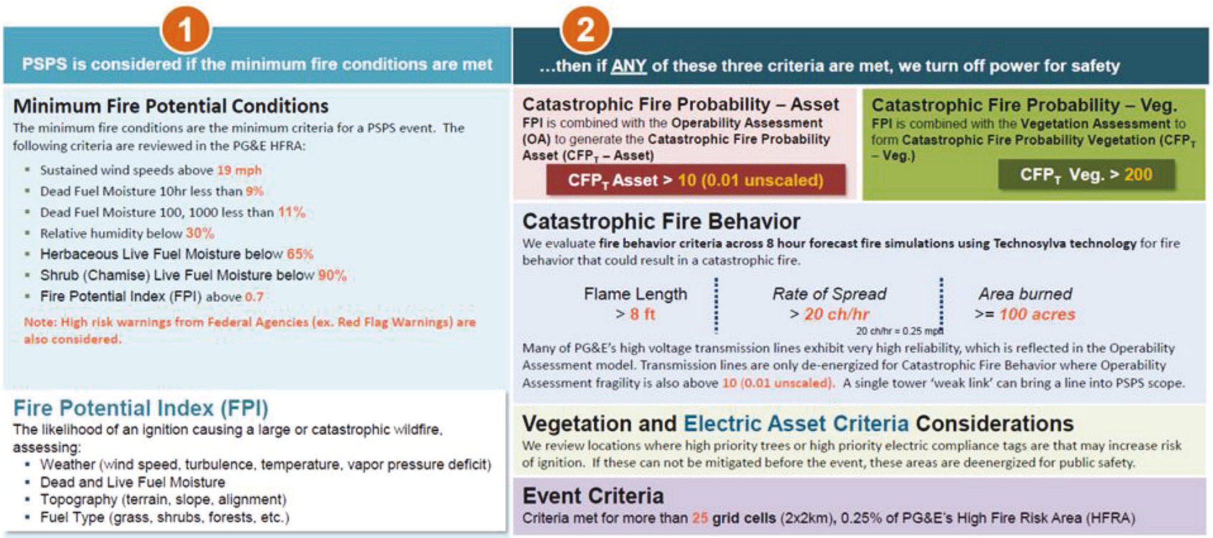

Figure IV.D.8: PSPS event decision map.[316] The framework is divided into two steps (symbolized by the numbers 1 and 2 in the figure). In the first step, the Minimum Fire Potential Conditions are validated. If these conditions are fulfilled, then step 2 checks whether one of multiple conditions occurs to trigger a PSPS event. Note how the CFP_T models are used in the step 2 of the PSPS decision map.

IV.D.10 Summary of GIRS-RT findings for the CFP_T Model

The CFP_T model integrates two sub-models to assess the probability of asset- and vegetation-related catastrophic wildfires in transmission networks. It provides frameworks to translate quantitative and qualitative data into failure probabilities for assets and trees. It exceeds industry standards and is used for operational decision making in PSPS guidance.

Features:

- The CFP_T model is subdivided into two model variants: $CFP_{T\text{-}Asset}$ for asset related failures, and $CFP_{T\text{-}Veg}$ for vegetation related failures.
- The $CFP_{T\text{-}Asset}$ combines the Fire Potential Index (FPI) model with the Transmission Operability Assessment (TOA) model to assess (at the asset level), the probability of a catastrophic fire.
- The $CFP_{T\text{-}Veg}$ combines the Fire Potential Index (FPI) model with the Transmission Vegetation Risk Model (VRM_T) to assess large fire propensities in transmission lines.
- The VRM_T model uses annual LiDAR data, providing spatially aware tree information. Tree populations are classified into All Trees, Failure Trees, and Ghost Trees. Failure and Ghost Trees are identified by comparing pre- and post-outage LiDAR data with validations using vegetation work history, weather conditions, and field checks.

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[316] *2022 PG&E Wildfire Mitigation Plan Update Revised, p. 1033.*

Summary of Assessments:

Overall, the GIRS-RT finds that the CFP_T model, while early in its development, is fit for its use in estimating the catastrophic fire probability in the transmission network. The models are based on solid principles and make good use of the available data. However, the GIRS-RT strongly recommends that PG&E emphasize the statistical validation and testing of upcoming iterations of the model.

IV.D.3.A1 <u>Comprehensive integration of field data</u>

The TOA model uses a wide variety of high-fidelity datasets which expand the sensitivity of the wind-based fragility framework to a large range of asset failure modes.

IV.D.3.A2 <u>Annualized vs. Fire-season-restricted data</u>

The TOA model uses annualized data and assumes all failures cause ignitions, overlooking that many wind-related outages occur in low-risk winter conditions. Incorporation of an ignition likelihood model given environmental conditions would be beneficial.

IV.D.3.A3 <u>Integration of multiple data sources</u>

The methodology used for VRM_T combines LiDAR data, weather conditions, and outage reports with manual reviews and field verification to identify Failure and Ghost Trees, ensuring accuracy and reliability.

IV.D.3.A4 <u>Opportunities for incorporating frequent updates</u>

Implementing frequent operational updates, such as records of worked, removed, or fallen trees, would improve the timeliness and accuracy of the VRM_T by better reflecting changing conditions.

IV.D.3.A5 <u>Expanding exploration on environmental factors</u>

There is potential to include additional correlates for vegetation risk, such as wind exposure, soil moisture, tree species, and vegetation health indices, to improve the VRM_T performance.

IV.D.5.A1 <u>General Remarks regarding the $CFP_{T\text{-}Asset}$</u>

The $CFP_{T\text{-}Asset}$ model's formulation inherits its strengths and limitations from the FPI and TOA models, which are based on sound engineering and probabilistic principles.

IV.D.5.A2 <u>Use of $CFP_{T\text{-}Veg}$ to model the outage probability could be enhanced</u>

The CFP_T model, in both asset and vegetation variants, estimates catastrophic fire probability within transmission networks using a conditional probability framework. While the asset variant is mathematically sound with well-defined components, the vegetation variant compromises the model's integrity by using a risk score as a proxy for outage probability. This undermines its ability to accurately estimate catastrophic fire probability within a broader risk mitigation context.

IV.D.5.A3 Black-box models and lack of documentation VRM_T

The audit revealed that PG&E lacked complete understanding of key elements in externally developed models, particularly the bolden parameters of the VRM_T model. Since the 2023 iteration of the $CFP_{T\text{-}Veg}$ model, PG&E has internalized its development, ensuring full knowledge within the company.

IV.D.5.A4 Monotonic adjustment for the Frequency Ratios in VRM_T is deemed appropriate

The lack of monotonicity in the frequency ratios due to small samples is a key drawback, but PG&E's ad-hoc solution of applying a logarithmic fit to the curve is accepted as a valid approach to ensure monotonicity in the final ratios.

IV.D.8.A1 Statistical Validation of VRM_T

Statistical tests on the previous VRM_T version focused on parameter selection, while the updated version includes model-level validation (ROC-AUC = 74%) but lacks similar parameter-level analyses.

IV.D.8.A2 Formation Environmental Review of VRM_T

The Formation Environmental Review was thorough, providing detailed analysis of the data collection, tree group classifications, and risk parameters for the original, seven parameter VRM_T model. The report justifies reduction to the four-parameter model and suggests additional risk parameters based on environmental parameters.

IV.D.8.A3 Formulation of the Previous VRM_T Model

Imbalanced averaging of risk scores coupled with parameters that were not normalized may have resulted in overweighting and underweighting of parameter influences in the 2020-2021 VRM_T.

IV.E Enhanced Powerline Safety Settings Program

IV.E.1 Overview of the Enhanced Powerline Safety Settings Program

The Enhanced Powerline Safety Settings (EPSS) program was developed and implemented by Pacific Gas & Electric (PG&E) as a proactive approach to rapidly adapt to evolving weather and environmental conditions, as outlined in their 2022 Wildfire Mitigation Plan.[317] The program began with a pilot phase conducted between July and October 2021. Following the pilot, during the first half of 2022, EPSS was deployed across all distribution circuits in HFTD/HFRA areas, along with a buffer zone in targeted non-tiered regions.

A key distinction between the EPSS program and other wildfire mitigation strategies, such as system hardening, is that EPSS can be activated or deactivated on demand at the circuit level. Consequently, EPSS enables PG&E to dynamically enhance wildfire mitigation efforts in response to forecasted weather conditions. This flexibility is particularly valuable, as local conditions can deviate significantly from their yearly or seasonal averages, which are typically used to determine the application of static strategies.

EPSS mitigates wildfire risk by modifying protection settings in circuit devices, increasing the circuit's sensitivity to fault currents and enabling faster safety shutdowns compared to non-EPSS conditions. By reducing the time required for the system to de-energize, the energy released into the environment during a fault decreases. This reduction in released energy is expected to lower the likelihood of an ignition. Since wildfire risk is defined as the product of likelihood and consequence, EPSS is also expected to reduce overall risk.

This section evaluates two fundamental questions regarding the impact of EPSS on PG&E's network. The first question concerns the effectiveness of the EPSS program in reducing the ignition rate across the service territory, which is critical for understanding the level of mitigation EPSS can achieve. The second question examines the potential negative effects of EPSS when enabled, particularly its impact on customer reliability. It was found during the pilot period that increasing the network's sensitivity to fault currents can lead to longer outages. Assessing PG&E's approach to addressing both questions is essential, as it directly informs the cost-benefit analysis of this mitigation program.

To this end, this section is organized as follows. Section IV.E.2 outlines the implementation timeline of the EPSS project, while section IV.E.3 presents the corresponding findings. Section IV.E.4 details the various enablement criteria PG&E used in 2021 and 2022 to determine when and where to activate EPSS capabilities within their service territory, with section IV.E.5 presenting the corresponding findings. Section IV.E.6 and IV.E.7 analyzes PG&E's approach to evaluating the positive effects of the EPSS program, and an assessment of this evaluation approach, respectively. Section IV.E.8 examines PG&E's approach to assessing the negative effects of EPSS on customer reliability, along with the mitigation measures implemented to address these externalities. IV.E.9 presents the assessments of the Reliability Impact methodology. Finally, Section IV.E.10 summarizes the GIRS-RT findings and provides recommendations for future

[317] *PG&E's 2022 Wildfire Mitigation Plan (WMP), p. 837.*

iterations of the program. Assessments are included at the end of each section to maintain thematic organization.

IV.E.2 Timeline of the EPSS program

The implementation of EPSS during the period covered by this audit (2021–2022) can be divided into two stages: the pilot period, which took place between July and October 2021, and the implementation period, which occurred during the first half of 2022.

During the pilot period, an early version of the EPSS program was implemented across approximately 11,500 miles of distribution networks, covering 45% of the circuit mileage in HFTD areas.[318] To select the circuits for the EPSS pilot, PG&E primarily chose circuits in HFTD Tier 2 and 3, along with other situational awareness criteria such as terrain accessibility, the frequency of PSPS events, identified high-risk assets or vegetation areas,[319] among other factors.

The pilot's initiation is referred to by PG&E as the "Pre-Optimization Stage," during which existing safety settings already implemented in protection devices were leveraged to quickly deploy the pilot on the selected circuits. These safety settings, known as *Hot Line Tag* (HLT) settings, are typically used for worker safety when operators conduct work on energized primary conductors. After the initial two months of the pilot, an enhanced set of settings modified the *Fast Trip Settings* (FTS) which were implemented across selected EPSS circuits, with the goal of reducing outage duration and improving restoration time. This period, from September 2021 to the end of the pilot, is referred to by PG&E as the "Post-Optimization Stage." Additional details regarding the pre- and post-optimization stages are included in Section IV.E.8.1.

The pilot officially ended in October 2021. However, due to heightened ignition potential detected in certain areas, FTS were kept enabled on approximately 40 circuits across the HFTD/HFTA zones. Metrics regarding the positive and negative effects of the EPSS program on ignition rate reduction and customer reliability, respectively, are inferred from the pilot period.

The pilot period timeline is depicted graphically in Figure IV.E.1.[320,321]

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[318] *PG&E's 2022 Wildfire Mitigation Plan (WMP), p. 838.*
[319] *PG&E's Wildfire Risk Governance Committee, November 10th, 2021, p. 15.*
[320] *PG&E's 2022 Wildfire Mitigation Plan (WMP), p. 842.*
[321] *PG&E's Wildfire Risk Governance Committee, November 3rd, 2021, p. 10.*

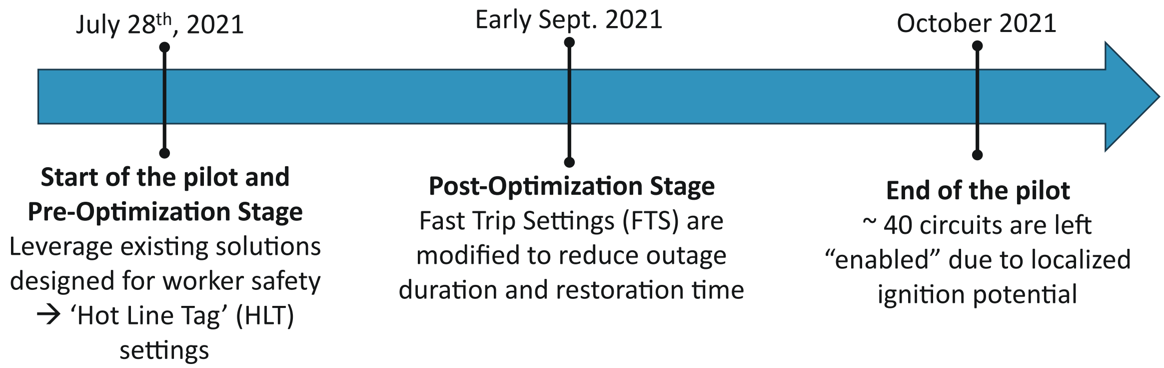

Figure IV.E.1: Timeline for the Pilot Period of the EPSS Program, spanning from July 2021 to October 2021.

The second stage, depicted graphically in Figure IV.E.2, involved implementation of the EPSS program across the HFTD/HFRA zones (consisting of approximately 25,000 miles), along with targeted areas designated as "buffer" zones.

For the implementation stage, PG&E began loading the Enhanced Powerline Safety Settings into circuit protection devices at the beginning of 2022. This process is manual, requiring an operator to physically visit each protection device location to modify its operational settings and install EPSS capabilities. Given the time required for this operation and the large number of devices to be updated, PG&E developed a circuit prioritization scheme that functioned as a work order. This prioritization was built based on the outputs of various wildfire risk models, with special consideration given to ensuring that circuits had EPSS capabilities before the expected onset of risk-prone weather conditions. Additionally, PG&E established implementation deadlines for the enhanced settings: May 2022 for 80% of the devices and August 2022 for 100% of the devices included in the program. However, the implementation process was completed ahead of schedule, with all circuits having EPSS enabled before the corresponding deadlines.[322]

An important distinction highlighted in PG&E documentation is the difference between implementation and enablement. The implementation of EPSS refers to the process of loading the program settings into the circuit protection device, which, as previously mentioned, is performed manually on-site. Once EPSS has been implemented on a circuit, the circuit can switch between two modes of operation: EPSS on or EPSS off. Enablement, on the other hand, refers to the activation of EPSS on the circuit (EPSS is on). This process can be done remotely, following an

[322] *PG&E's 2022 Wildfire Mitigation Plan (WMP), p. 844.*

operational framework known as the "Enablement Criteria." More details regarding the enablement criteria are provided in Section IV.E.4.

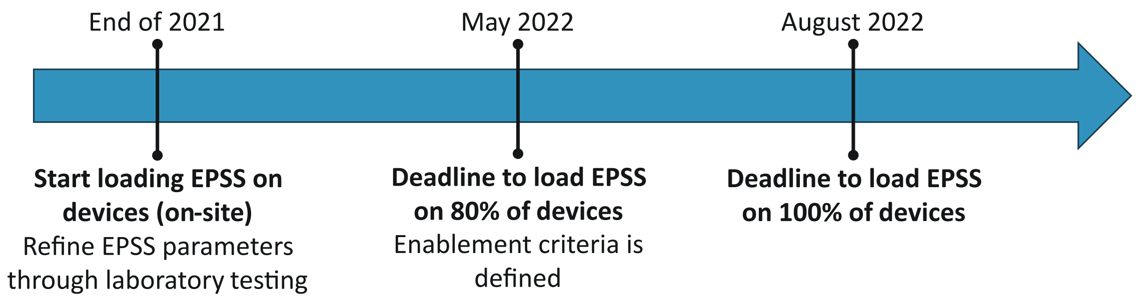

Figure IV.E.2: Timeline for the Implementation Period of the EPSS Program, spanning from the end of 2021 to August 2022.

IV.E.3 Assessment: EPSS Timeline

IV.E.3.A1 EPSS implementation was performed in a timely manner

PG&E established a series of deadlines for the implementation of EPSS throughout 2022, all of which were met on time. Given that the implementation process is manual and requires physical visits to the circuit protection devices, this achievement represents a significant logistical success for PG&E. Furthermore, the company developed a prioritization strategy to ensure that higher-risk circuits would be addressed first, in case deadlines could not be met. Although the prioritization strategy ultimately proved unnecessary, as all circuits were implemented within the prescribed timelines, it remains a good safety practice, which is recommended to continue for future implementations or changes.

IV.E.3.A2 Remote capabilities for the implementation of new settings are being adopted

The implementation of EPSS requires that an operator physically visits each protection device every time settings need to be updated. This is because the devices, in general, cannot allow the incorporation or modification of settings remotely. Physically visiting each protection device is time consuming, particularly given that the EPSS program is continuously updated to improve its effectiveness and reduce negative impacts on reliability for customers. However, it is encouraging to see that PG&E is actively working to incorporate novel remote capabilities for updating settings, like the remote functionalities already in place for EPSS enablement. This effort could significantly streamline the process and enhance overall program efficiency. The GIRS-RT recommends that these efforts continue into future versions of the EPSS program.

IV.E.4 Enablement Criteria Definition

As mentioned in Section IV.E, the "Enablement Criteria" refers to the operational framework PG&E follows to determine when and where to activate EPSS. During the pilot and implementation periods, PG&E employed different enablement criteria, which are described and reviewed in this section.

During the pilot period, the enablement criteria were defined uniformly: EPSS was enabled on all circuits with EPSS capabilities for the entire duration of the pilot. While this approach maximized circuit protection, it had a negative impact on customer reliability. Consequently, beginning in 2022, PG&E introduced several refined enablement criteria.

In February 2022,[323] PG&E established that EPSS would be enabled for circuits that fulfill either one of the following conditions: (1) a Fire Potential Index (FPI) of R3 or higher, or (2) all the minimum fire potential conditions set by the PSPS program are met. These minimum fire potential conditions (mFPC) are as follows:[324]

- Wind speed above 19 mph
- Dead fuel moisture 10hr < 9%
- Dead fuel moisture 100hr, 1000hr < 11%
- Relative humidity < 30%
- Herbaceous live fuel moisture < 65%
- Chamise live fuel moisture < 90%
- FPI above 0.7 (on the "probability scale," instead of the categories).

This criterion is based on a historical analysis that indicates that R3+ conditions capture approximately 95% of acres burned, and almost the totality of historical consequences.

In March 2022,[325] the enablement criteria were updated to also enable EPSS under R1 or R2 FPI conditions if the following weather conditions—considered particularly risky within those FPI levels—were met.

- For FPI R1 level conditions: wind speed over 25 mph, relative humidity under 20%, or dead fuel moisture under 9%.
- For FPI R2 level conditions, wind speed over 22 mph, relative humidity under 25%, or dead fuel moisture under 9%.

In May 2022,[326] the enablement criteria were updated once again to enable EPSS on a set of circuits within a non-tiered area, referred to as the "buffer zone," when conditions fell under a Red Flag Warning (RFW), a Fire Weather Watch (FWW) Warnings, or PSPS-adjacent conditions.

Then, in June 2022,[327] the enablement criteria were overhauled to capture even more expected consequences. The new criteria always enabled EPSS on all circuits, unless they meet one of the following two low risk sets of conditions:

- CALM conditions, for circuits under FPI R1 level and wind speeds below 19 mph.
- DAMP conditions, for circuits with a relative humidity above 75% and dead fuel moisture above 9%.

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[323] PG&E's Wildfire Risk Governance Committee, February 2nd, 2022, p.11.
[324] PG&E's Wildfire Risk Governance Committee, September 7th, 2022, p.8.
[325] PG&E's Wildfire Risk Governance Committee, March 2nd, 2022, p.5.
[326] PG&E's Wildfire Risk Governance Committee, May 11th, 2022, p.15.
[327] PG&E's Wildfire Risk Governance Committee, June 6th, 2022, p.10.

Additionally, a trawling method was implemented, where the number of forecast days referenced to make EPSS enable/disable decisions was expanded, anchoring the decision on the most conservative forecast. The enablement criteria for buffer zone circuits were maintained.

Finally, in September 2022,[328] the criteria were once again updated. This time, the enablement of EPSS in the buffer zone was determined to follow mFPC conditions in addition to RFW, FWW, or PSPS adjacent conditions.

IV.E.5 Assessment: Enablement Criteria

IV.E.5.A1 Enablement Criteria are designed following a data-driven approach

During 2022, PG&E updated the enablement criteria a total of four times. For each of these updates, they followed a data-driven approach to justify the changes to EPSS criteria. These data-driven approaches included analyzing ignition propensity in relation to the Fire Potential Index and examining the correlation between RFW, FWW, or PSPS-adjacent conditions and past events in the service territory. Overall, the GIRS-RT finds that all the changes are well justified and based on sound evidence.

IV.E.5.A2 Enablement Criteria could integrate an optimization-based approach

The enablement of EPSS is a fundamental component in determining how effective this technology is in mitigating wildfire risk. If the technology is not enabled, its practical effectiveness is 0%, as expected. However, if it is enabled at all times, its effectiveness in mitigating wildfire risk could be offset by its detrimental impact on customer reliability, particularly on days with low-risk environmental conditions. As such, a complex trade-off is at play, involving local environmental and weather conditions, the expected wildfire risk mitigated, and the effects on customer reliability. Currently, the enablement criteria is the tool PG&E has chosen to balance these trade-offs. However, this problem could be formally treated as an optimization problem by defining an appropriate objective function and developing an algorithm to determine the optimal enablement criteria. Moreover, this enablement criteria could be dynamic, considering the Fire Potential Index (FPI), weather variables, and even the population affected by each EPSS enablement action. The GIRS-RT suggests that PG&E research this alternative to evaluate its potential advantages.

IV.E.6 Wildfire Mitigation Effectiveness

IV.E.6.1 Records and Reporting

For 2021, PG&E reports a 74% drop in ignitions on EPSS circuits (i.e., on circuits corresponding to the EPSS pilot study in 2021 compared to ignitions on the same circuits from 2018-2020 during the same period (July 28 – October 17)), and a ~40% drop on all HFTD circuits for the corresponding period.[329,330,331] The GIRS-RT obtained ignition data from PG&E and reviewed these calculations. The records include ignition locations, timing, whether ignitions were primary or secondary, ignition failure drivers, and information about the county and circuit where the

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[328] PG&E's Wildfire Risk Governance Committee, September 7th, 2022, p.7.
[329] PG&E's Wildfire Risk Governance Committee, November 10th, 2021, p 15.
[330] PG&E's 2022 Wildfire Mitigation Plan (WMP), p. 6.
[331] PG&E's initial documentation reported an 80% decrease in ignitions, but this number was later revised to a 74% decrease in ignitions upon reevaluation on the data.

ignition occurred.[332] PG&E's reliability records for EPSS outages include data pertaining to the circuits, the outage timing and duration, the schools and hospitals impacted, the customer minutes, the cause of the outage, and the EPSS outage type for assessment of risk drivers and reliability impacts.[333]

In general, PG&E's EPSS record keeping was adequate. However, the GIRS-RT review revealed discrepancies in the location information for 2018, with some ignitions labelled as HFTD which were outside HFTD Tier 2 and Tier 3 territories.[334] These do not significantly impact PG&E's EPSS effectiveness calculations for the pilot circuits because they either occur outside the pilot dates or on circuits that are well separated from the pilot circuits. For the overall reduction, the impact of the 2018 mislabeled data is estimated to be potentially as high as ~9% based on the total number of HFTD ignitions reported in this period.

PG&E's reported reductions are tied to choices made in how the data was filtered. To complement PG&E's assessments, the GIRS-RT evaluated 1) pilot period ignition changes compared to historic ignition trends in regions inside and outside the 2021 EPSS pilot, 2) ignition changes before and after implementation in HFTDs in 2022, 3) comparison of annual fire season FPI variations in 2021 and 2022 to seasonal averages before EPSS, and 4) the impacts of EPSS outages on critical facilities and reliability.

IV.E.6.2 <u>Effectiveness of EPSS during the 2021 Pilot Period</u>

From July 28 to October 17, 2021, PG&E implemented the EPSS pilot program to test its capabilities on a subset of HFTD Tier 2 and 3 circuits. As shown in Figure IV.E.3, for these circuits, ignitions dropped 71% compared to the same circuits during the same dates (July 28-October 17) in 2015-2020. In comparison, on HFTD circuits that were not included in the pilot, ignitions increased by 76%. The contrasting 71% decrease on circuits with EPSS enablement compared to the 76% increase on unchanged circuits is a strong indicator of success for EPSS's effectiveness in ignition mitigation. Note that EPSS pilot circuits exhibited fewer ignitions during the pilot period than all other years from 2015 to 2020.

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[332] EPSS outage data from PG&E, 2021-2022 (Retrieved from "EPSS outage data from DRU15106.001_Atch01_EPSS Analysisv2_R1_K3BP_2.26.25_CONF.xlsx" and "DRU15106.003_Atch01_PGE - EPSS Outages Monthly Report 20220117_CONF.xlsx.").

[333] EPSS Monthly Outage Reports for 11/2021 to 12/2022 (Retrieved from "DRU15075.001_Atch01_EPSS Monthly Outage Reports for 11.2021 to 12.2022_CONF.zip").

[334] Roughly one third of the 336 ignitions in 2018 were mislabeled as in HFTDs. Some of these are far from HFTD boundaries. Of the mislabeled ignitions, the ones on or adjacent to pilot circuits (approximately 4% are close to HFTD boundaries) did not occur during the pilot period dates, so do not impact effectiveness calculations.

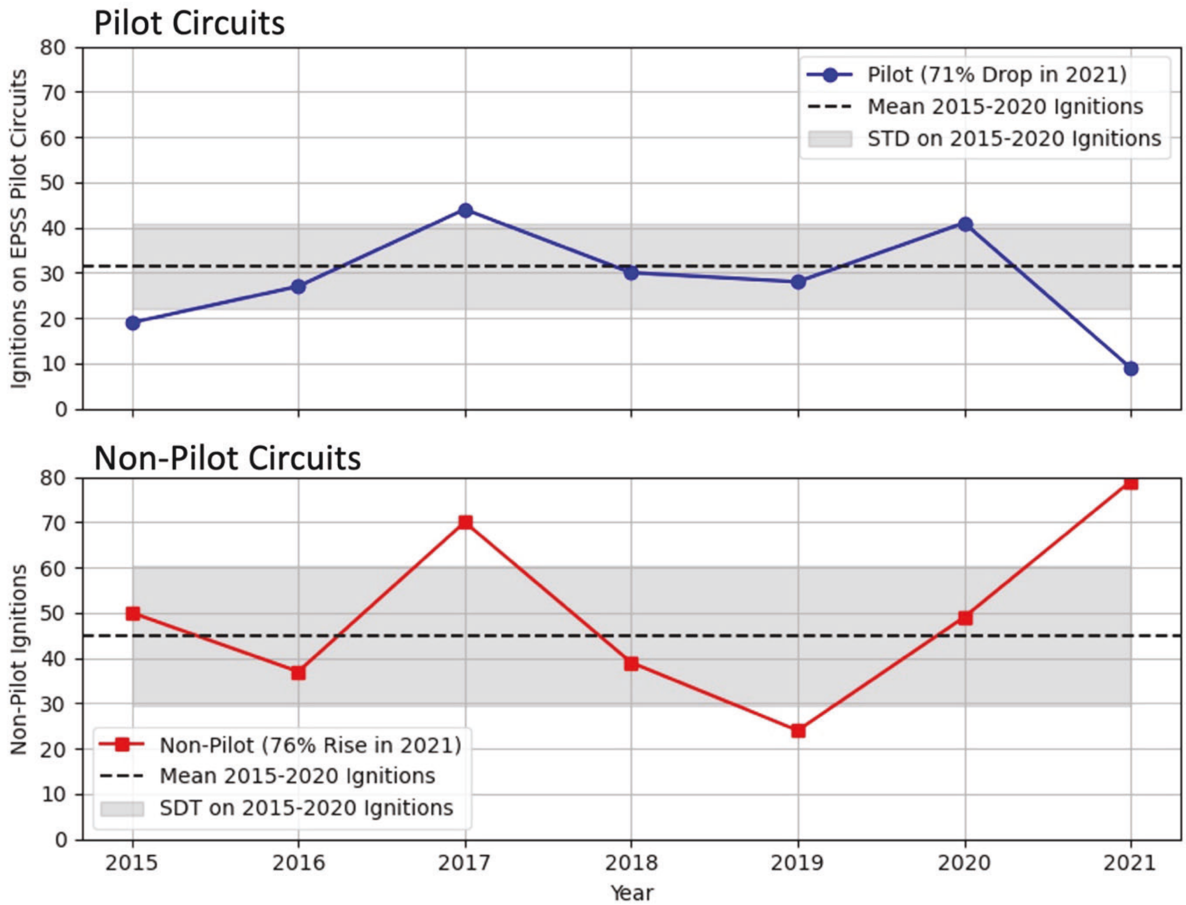
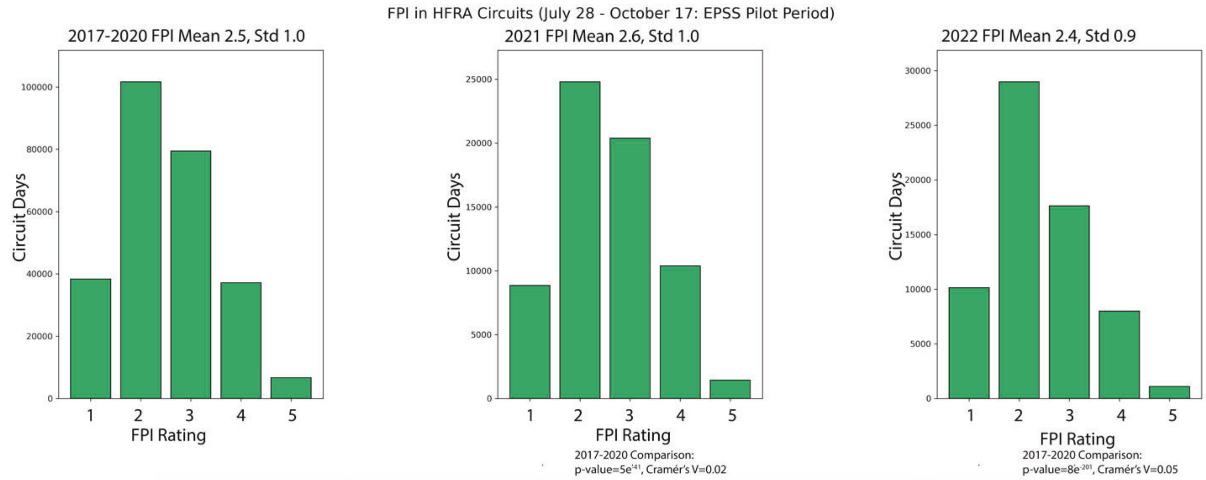


Figure IV.E.3: Ignition trends in HFTDs from 2015-2021 for July 28 – October 17 (dates of the 2021 EPSS pilot period). Ignition trends in HFTDs for circuits with EPSS enabled during the pilot period in 2021 (upper blue trend), and ignition trends in HFTDs for circuits that were not part of the EPSS pilot (lower red trend) as shown. The black dashed line is the mean annual ignition rate from 2015-2020 and the grey shading encapsulates one standard deviation from the mean.

Because shifts in ignitions rates can be explained by shifts in meteorological conditions, the GIRS-RT evaluated distributions of FPI ratings in HFRA areas in PG&E's service territory from 2017-2020 (pre-EPSS), 2021 (EPSS pilot year), and 2022 (full EPSS implementation in HFTDs by August) to complement the evaluation of annual ignition rates. By FPI ranking, circuit days were tabulated from July 28th to October 17th (EPSS pilot period time window) for circuits in HFRA areas (Figure IV.E.4). Compared to 2017-2020, average FPI rankings increase slightly in 2021 and decreased slightly in 2022, but exhibit overlap within one standard deviation.



	2017–2020 Annualized Rate	2021 Rate	2021 vs 2017–2020	2022 Rate	2022 vs 2017–2020
FPI 1	9591	8849	-7.7%	10138	5.7%
FPI 2	25409	24793	-2.4%	28968	14.0%
FPI 3	19864	20383	2.6%	17625	-11.3%
FPI 4	9305	10382	11.6%	8007	-13.9%
FPI 5	1677	1439	-14.2%	1108	-33.9%

Figure IV.E.4: Comparison of FPI conditions across HFRA circuits in PG&E's service territory from 2017-2020, 2021, and 2022 during the EPSS pilot period dates (July 28 – October 17).[335] Means and standard deviations of FPI values are shown above the bar plots for each duration. The p-values and Cramér's V values from the chi-squared analyses comparing the 2017-2020 FPI distribution to 2021 and 2022 are reported for the 2021 and 2022 bar graphs. The table shows changes in the annualized rates of circuit days for each FPI ranking from July 28 to October 17.

Despite the overlap and similar appearance of the FPI rank versus circuit day distribution, a chi-squared test demonstrated that the distributions in 2021 and 2022 were statistically distinct from the 2017-2020 distribution. Evaluation of shifts in annualized rates of circuit days from this analysis by FPI ranking show that on average the FPI conditions of HFRA circuits in PG&E's service territory during the 2021 pilot period were similar to conditions in previous years with slight increases in FPI 3 and FPI 4 and decreases in other FPI scores (see table in Figure IV.E.4). In 2022 the highest FPI rankings (3, 4, and 5) each decreased by over 10% compared to rates in 2017-2020 with FPI 5 circuit days dropping by 33.9%. Despite these statistically significant differences, it is extremely unlikely that the shifts in ignition rates during the pilot study in 2021 or 2022 were driven by changes in FPI rankings given the magnitude of ignition decreases. Nonetheless, the GIRS-RT recommends that meteorological conditions be considered in future evaluations of the success of wildfire mitigation efforts.

[335] *Daily Circuit FPI Data (2017-2022).*

IV.E.6.3 Effectiveness of EPSS in 2022

By August 2022, the implementation of EPSS on all HFTD circuits was complete. A 61% drop in annual HFTD ignitions in 2022 was observed when compared to the average annual ignition rate from 2015 to 2021 (Figure IV.E.5). During the fire season (June-November), HFTD ignitions decreased 65% compared to the average annual ignition rate from 2015-2021 (Figure IV.E.5 and Figure IV.E.6). Both annual and fire season HFTD ignition rates were lower in 2022 than any other year. Findings indicate the EPSS implementation resulted in lower ignition rates in high-risk areas.

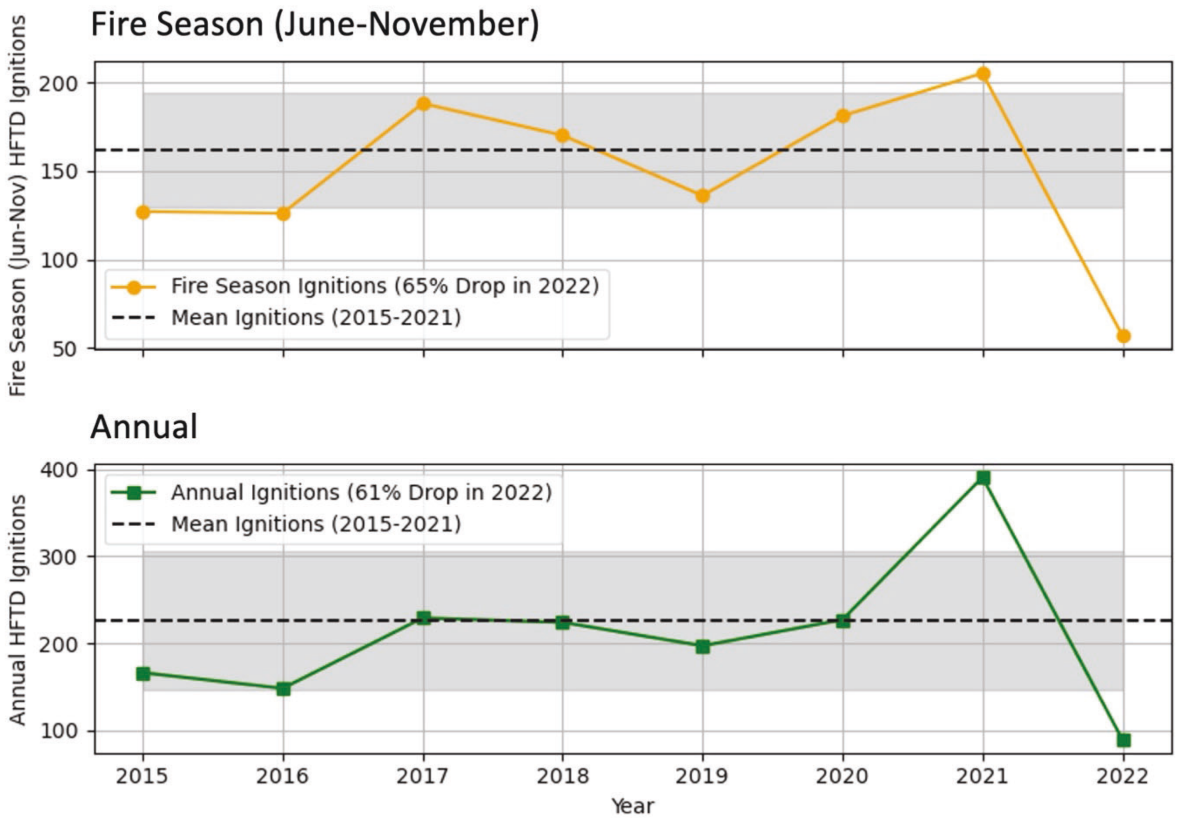


Figure IV.E.5: Fire Season (June-November: top - orange) and annual (bottom - green) PG&E ignitions rates in HFTDs from 2015-2022.[336] *The black dashed line is the mean annual ignition rate from 2015-2021 and the grey shading encapsulated one standard deviation from the mean. Note the 61% drop on annual ignitions and 65% drop in fire season ignitions in 2022 compared to the 2015-2021 mean values.*

[336] *2022 Ignitions from PGE Fire* Incident Data Collection and others from EPSS Analysisv2_R1_K3BP_2.26.25_CONF with *2018 HFTD GIS correction.*

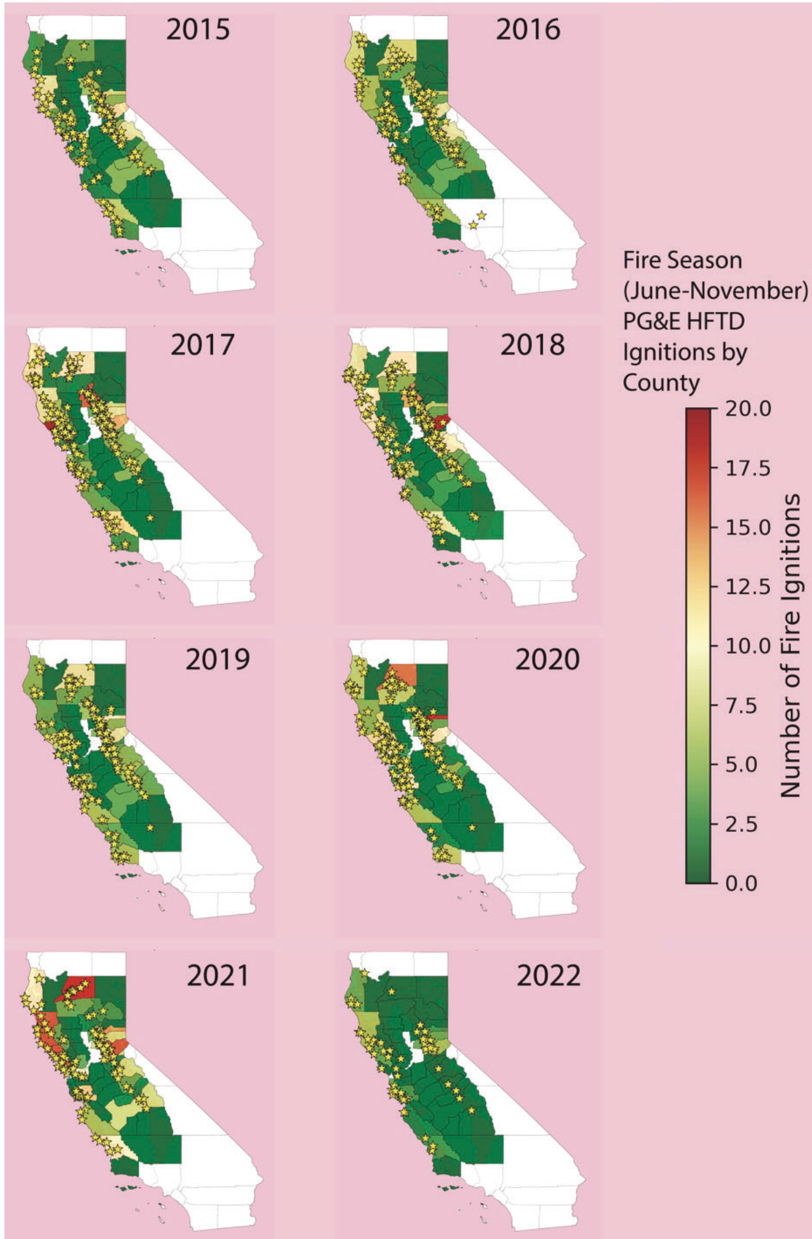


Figure IV.E.6: PG&E fire season (June-November) ignitions in HFTDs[337] (opaque grey shading) by county[338] from 2015-2022 by year. Individual ignitions (yellow stars) and county ignitions (color coded county polygons) are shown. Only counties with HFTDs in PG&E's service territory are shown.

To evaluate changes in the spatial distribution of fire season ignitions in HFTDs, the GIRS-RT calculated fire season ignitions by county in California attributed to PG&E from 2015-2022. In 2022 by county ignitions attributed to PG&E's infrastructure during fire season in HFTDs were extremely low compared to historical rates (Figure IV.E.6). No county exhibited ten or more ignitions in HFTDs in the 2022 fire season associated with PG&E's infrastructure. The low uniform

[337] *High Fire Threat District (HFTD) GIS Data: https://files.cpuc.ca.gov/safety/fire-threat_map/2021/GIS_Files/.*
[338] *California County Boundaries https://gis.data.ca.gov/datasets/CALFIRE-Forestry::california-county-boundaries/about.*

fire season ignition rates by county in 2022 contrast to historical ignition rates from 2015-2021 fire seasons. Collectively, findings indicate that EPSS implementation dampens ignition likelihood in high-risk environments.

While findings indicated that EPSS implementation can reduce ignition likelihood, and thus wildfire risk, implementation can impact reliability and critical infrastructure such as schools and hospitals (Figure IV.E.7). The GIRS-RT examined EPSS impacts by county on reliability and impacts on critical facilities. In 2022, schools in PG&E's service territory experienced hundreds of outages due to EPSS enablement. Critical facilities such as hospitals were also impacted by EPSS outages. The GIRS-RT suggests that PG&E implement strategies to mitigate customer impacts. This could be accomplished by the installation of substation microgrids that can provide backup power to critical facilities.

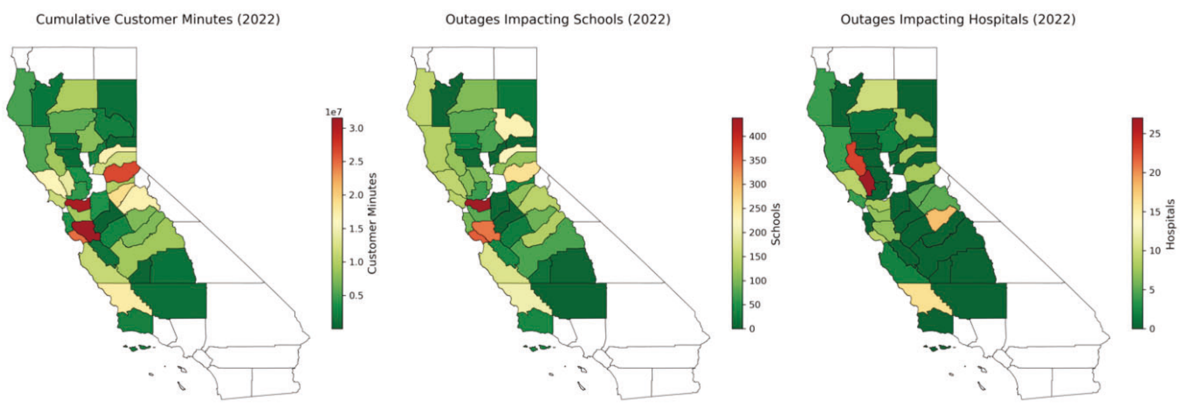


Figure IV.E.7: Cumulative customer minutes and outages experienced by schools and hospitals by county in PG&E's service territory associated with EPSS outages. Only counties with HFTDs in PG&E's service territory are shown.

IV.E.7 Assessment: Wildfire Mitigation Effectiveness

IV.E.7.A1 <u>EPSS implementation resulted in lower ignitions rates</u>

EPSS implementation resulted in significant decreases in ignitions in HFTDs and CPUC reportable ignitions in PG&E's service territory. During the 2021 EPSS pilot period, ignitions in HFTDs on circuits with EPSS enablement decreased 71% while ignitions increased by 76% for unchanged circuits compared to annual ignitions over the same period from 2015-2020. In 2022, when EPSS became fully implemented in HFTDs, HFTD ignitions decreased by 61% annually and 65% in the fire season compared to 2015-2021.

IV.E.7.A2 <u>FPI should be controlled for when measuring EPSS in ignition rates</u>

While it is highly unlikely that the decrease in ignition rates following EPSS implementation was driven by annual variations in the weather as reflected by lower FPI rankings, the GIRS-RT recommends that FPI be accounted for in future analyses of the efficacy of wildfire risk mitigation efforts.

IV.E.7.A3 EPSS implementation adversely impacts reliability

While EPSS enablement corresponded to decreases in ignitions, EPSS outages adversely impact reliability and critical facilities such as hospitals and schools. These effects could be minimized by installation of substation microgrids that can provide backup power to critical facilities.

IV.E.8 Reliability Impact

This section examines the impact of EPSS on system reliability and the efforts undertaken to improve it. It begins with the 2021 optimization efforts aimed at reducing the size of affected territory and the length of restoration time, followed by reliability assessments and improvements in 2022. These include vegetation management and equipment repairs to reduce related outages, strategies to improve restoration efficiency, and expanded customer support, communication, and utility collaboration.

IV.E.8.1 EPSS optimization process

The pre-optimization phase (July to September 2021), previously referred to as *Hot Line Tag* (HLT), involved manual adjustments to circuit breakers (CB) and line reclosers (LR) on high-risk circuits to enable preliminary safety settings.[339] However, due to a lack of coordination among the protective devices, outages affected a larger territory due to the potential for multiple devices to detect the same fault and having a longer duration due to visual inspections and patrolling.

To reduce the outage size and decrease the outage duration, two methods were used in the post-optimization phase (early September to October 2021), previously referred to as *Fast Trip Settings* (FTS).[340] Engineering reviewed circuits from source to load to coordinate device response timing to fault detection. By isolating the fault as close to its location as possible instead of shutting down larger grid sections, this reduced the number of customers affected. The control center implements coordinated device settings from Engineering into SCADA (Supervisory Control and Data Acquisition) scheme settings, which ensure device responses are automated and synchronized and quickly detected and isolated faults.

With the post-optimization settings, PG&E could adjust the patrol strategy to focus only on the impacted Circuit Protection Zone rather than needing to patrol the full circuit, which reduced the time required to restore service. Through the optimized EPSS circuit settings, the average affected customer count per outage reduced from 1,095 to 841, and the average outage duration decreased from 10.4 to 8.7 hours.[341]

IV.E.8.2 Reliability improvements

Throughout 2022, PG&E implemented targeted reliability improvements to mitigate outage impacts and enhance system resilience. In January 2022, PG&E conducted a Preliminary Reliability Study, analyzing historical outage data, identifying upstream EPSS protection devices,

[339] *PG&E's Wildfire Risk Governance Committee, November 3rd, 2021, p.9.*
[340] *PG&E's Wildfire Risk Governance Committee, November 3rd, 2021, p.9.*
[341] *PG&E's Wildfire Risk Governance Committee, November 3rd, 2021, p.13.*

and assessing the potential impact of EPSS activation.[342] The findings guided the prioritization of reliability mitigation efforts, particularly for circuits most affected by the EPSS expansion.

To mitigate vegetation-related outages, which accounted for 33% of EPSS outages in 2021, PG&E reassessed its Vegetation Management strategy.[343] This involved integrating the EPSS circuit work into its 2022 Vegetation Management programs and deploying dedicated crews to proactively inspect and clear vegetation on 12 high-risk circuits with a history of frequent vegetation-related outages.

In addition, equipment failures contributed to 25% of EPSS outages in 2021, prompting PG&E to launch targeted repair programs prioritizing 50 high-impact EPSS circuits based on the highest projected Customer Experiencing Sustained Outage (CESO) metrics.[344] These circuits accounted for 27% of the projected customer reliability impact. Repairs included replacing cross-arms, structures, and conductors, as well as improving animal and bird protection. While prioritizing these circuits for reliability improvements, PG&E continued to expand and execute repairs across its broader system.

IV.E.8.3 Restoration response and resource

To ensure efficient outage restoration, PG&E adopted a multi-layered response strategy. The Standard Outage Response Protocol prioritizes dispatching local crews to address outages, with additional support from neighboring divisions when needed. PG&E aims to restore EPSS outages within 240 minutes, using the Customer Average Interruption Duration Index (CAIDI) to monitor and adjust resource allocation.[345]

Incorporating advanced forecasting methods, the Storm Outage Prediction Project (SOPP) was enhanced to predict outage activity up to four days in advance. By integrating 2022 EPSS outage data, SOPP enables division leadership to anticipate service disruptions and allocate resources proactively.[346]

To improve patrol efficiency, PG&E deployed 16 rapid response helicopters in nine strategic locations across its service territory.[347] These helicopters provide aerial patrols in difficult-to-access areas, significantly reducing restoration times. Additionally, when field resource shortages arise, PG&E supplements its workforce by deploying system inspection personnel and contracting external resources to maintain EPSS operations without impacting regular system inspections. These initiatives enhance PG&E's ability to respond quickly and effectively to EPSS-related outages.

IV.E.8.4 Customer outreach and support

PG&E has continued to enhance customer engagement and outreach to ensure customers are well-informed about EPSS-related outages. Special attention has been given to Medical Baseline (MBL) customers and individuals with Access and Functional Needs (AFN), many of whom were

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[342] *PG&E's 2022 Wildfire Mitigation Plan (WMP), p. 854.*
[343] *PG&E's 2022 Wildfire Mitigation Plan (WMP), p. 855.*
[344] *PG&E's 2022 Wildfire Mitigation Plan (WMP), p. 855.*
[345] *PG&E's 2022 Wildfire Mitigation Plan (WMP), p. 862.*
[346] *PG&E's 2022 Wildfire Mitigation Plan (WMP), p. 863.*
[347] *PG&E's 2022 Wildfire Mitigation Plan (WMP), p. 863.*

previously unaware of emergency preparedness resources. To strengthen communication, PG&E has coordinated with hospitals, telecommunications providers, and schools, while also leveraging automated outage alerts, community partnerships, and direct customer engagement efforts.[348]

In 2022, PG&E expanded resiliency program eligibility to include customers outside High Fire-Threat Districts (HFTDs) affected by EPSS outages. Additionally, emergency preparedness training was strengthened through partnerships with 211 services and disability support organizations. Other improvements to communication efforts include refining the notification system to provide more accurate restoration estimates, increasing outreach via email, direct mail, and social media, investing in paid advertising, and enhancing the EPSS webpage with updated resources. These initiatives aim to ensure that all impacted customers, especially vulnerable populations, have the necessary information and support to prepare for and respond to EPSS outages effectively.[349]

PG&E has also introduced customer support programs to help mitigate the impacts of EPSS-related outages.[350] These include the Portable Battery Program, which provides backup battery solutions for MBL customers and individuals with AFN, ensuring that critical medical devices remain operational during power outages. The Generator & Battery Rebate Program offers financial assistance for customers purchasing backup power solutions, helping them maintain essential services during disruptions. Additionally, the Backup Power Transfer Meter Program enables customers with generators to safely connect backup power without requiring complex electrical modifications.

IV.E.8.5 <u>Industry benchmarking and collaboration</u>

PG&E actively benchmarks its protective device settings and wildfire risk reduction strategies in collaboration with other utilities.[351] PG&E leads monthly meetings with San Diego Gas & Electric (SDG&E) and Southern California Edison (SCE), focusing on system protection practices and wildfire risk mitigation. Additionally, PG&E engages with utilities outside California, including PacifiCorp, Avista, and BC Hydro, to exchange insights and best practices.

In April 2022, PG&E hosted a deep dive session with SDG&E and SCE to explore EPSS strategies, including sensitive relay settings and fast-acting fuse technologies. A comprehensive benchmarking report was also completed, documenting FTS and relay technologies across multiple utilities. PG&E's benchmarking plan includes regular collaboration efforts, such as biannual deep dive sessions, ad-hoc discussions with external utilities, and participation in industry conferences on protective relaying and wildfire mitigation.

IV.E.9 Assessment: Reliability Impact

IV.E.9.A1 <u>Comprehensive strategies implemented by PG&E to mitigate reliability impact</u>

To improve customer preparedness and awareness, PG&E has refined its notification systems, expanded direct outreach through email, mail, and social media, and provided specialized

[348] PG&E's 2022 Wildfire Mitigation Plan (WMP), p. 859-860.
[349] PG&E's 2022 Wildfire Mitigation Plan (WMP), p. 861-862.
[350] PG&E Fast Trip Unplanned Outages and Distribution Reliability Workshop Presentation, p.24.
[351] PG&E's 2022 Wildfire Mitigation Plan (WMP), p. 864.

assistance for MBL and AFN customers. In addition, PG&E has broadened its backup power support programs to ensure customers have access to reliable power solutions during outages.

On the technical and operational front, PG&E has optimized protective device settings, implemented targeted vegetation management on high-risk circuits, and upgraded infrastructure through equipment repairs and replacements. The SOPP enhances outage forecasting, while rapid response helicopters and surge personnel deployments improve restoration times and resource efficiency.

IV.E.9.A2 Suggested future improvements in reliability mitigation and customer support

The GIRS-RT recommends that PG&E continue to refine the outage notification systems to provide more accurate estimated restoration times. To support customers experiencing frequent EPSS-related outages, PG&E could introduce financial assistance programs to alleviate the burden on those disproportionately affected.

Expanding infrastructure upgrades, including the installation of more fault indicators and line sensors, would improve fault detection and isolation. Additionally, advancements in real-time decision-making for outage response and power restoration could further optimize PG&E's ability to manage service disruptions quickly and efficiently.

IV.E.10 Summary of GIRS-RT Assessments

Overall, the GIRS-RT finds that the EPSS Program is fit for its application as a wildfire risk mitigation strategy within PG&E's service territory. Additionally, the GIRS-RT finds that great effort and correct data analysis practices were applied to the definition of enablement criteria and additional mitigation strategies to reduce EPSS impact on customer reliability. Nonetheless, the GIRS-RT strongly recommends that PG&E enhance the approach used to measure the effectiveness of the program in reducing ignitions. Incorporation of the FPI into the estimation is an especially promising approach to differentiate years with a different baseline risk profile.

The following is a list of features of the EPSS program:

Features:

- The Enhanced Powerline Safety Settings (EPSS) program is a wildfire mitigation tool used by PG&E.
- EPSS mitigates wildfire risk by modifying protection settings in circuit devices, increasing the circuit's sensitivity to fault currents and enabling faster safety shutdowns compared to non-EPSS conditions.
- The program began with a pilot phase conducted between July and October 2021. Following the pilot, EPSS was deployed across all distribution circuits in HFTD/HFRA areas, along with a buffer zone in targeted non-tiered regions, during the first half of 2022.
- The pilot phase pre-optimization phase began with Hot Line Tag (HLT) settings. The post-optimization phase introduced modified Fast Trip Settings (FTS) in selected circuits and devices to improve device coordination and reduce outage size and duration.

- EPSS *Enablement Criteria* refers to the operational framework PG&E follows to determine when and where EPSS should be activated.
- Vegetation management and equipment repairs on 50 high-impact EPSS circuits were prioritized to reduce customer impact.
- PG&E adopted a multi-layered response strategy to improve restoration efficiency and expanded customer support, communication channels, and utility collaboration.

Summary of Assessments:

IV.E.3.A1 <u>EPSS implementation was performed in a timely manner</u>

PG&E successfully met all EPSS implementation deadlines in 2022 despite the manual process requiring physical visits to circuit protection devices. Although their prioritization strategy for high-risk circuits was not needed, it remains a valuable practice for future implementations.

IV.E.3.A2 <u>Remote capabilities for the implementation of new settings are being adopted</u>

EPSS implementation currently requires manual visits to protection devices, making the process inefficient, especially with ongoing program updates. PG&E's efforts to incorporate remote update capabilities, like existing remote enablement, have the potential to greatly improve efficiency.

IV.E.5.A1 <u>Enablement Criteria are designed following a data-driven approach</u>

In 2022, PG&E updated the enablement criteria four times using a data-driven approach to justify the changes. The GIRS-RT finds these updates well justified, based on analyses of ignition propensity, environmental conditions, and past events.

IV.E.5.A2 <u>Enablement Criteria could integrate an optimization-based approach</u>

EPSS enablement is crucial for wildfire risk mitigation but enabling it always may harm customer reliability, requiring a balance based on environmental conditions. GIRS-RT suggests PG&E explore a formal optimization approach to dynamically adjust enablement using factors like the Fire Potential Index, weather variables, and affected populations.

IV.E.7.A1 <u>EPSS implementation resulted in lower ignitions rates</u>

EPSS implementation resulted in significant decreases in ignitions in HFTDs and CPUC reportable ignitions in PG&Es service territory. During the 2021 EPSS pilot period, ignitions in HFTDs on circuits with EPSS enablement decreased 71% while ignitions increased by 76% for unchanged circuits compared to annual ignitions over the same period from 2015-2020. In 2022, when EPSS became fully implemented in HFTDs, HFTD ignitions decreased by 61% annually and 65% in the fire season compared to 2015-2021.

IV.E.7.A2 <u>FPI should be controlled for when measuring EPSS in ignition rates</u>

It is highly unlikely that decrease in ignition rates following EPSS implementation was driven by annual variation in weather related to wildfire risk as, e.g., reflected by in FPI rankings. The

GIRS-RT recommends that FPI be included in future analyses of the efficacy of EPSS and other wildfire risk mitigation efforts.

IV.E.7.A3 EPSS implementation adversely impacts reliability

While EPSS implementation corresponded to decreases ignition rates, EPSS outages adversely impact customer reliability and critical facilities such as hospitals and schools.

IV.E.9.A1 Comprehensive strategies implemented by PG&E to mitigate reliability impact

PG&E has enhanced customer communication, expanded backup power programs, and optimized protective device settings to improve outage preparedness and response. Infrastructure upgrades, vegetation management, improved forecasting models (SOPP), and rapid response deployments have further strengthened system resilience and minimized service disruptions.

IV.E.9.A2 Potential future improvements in reliability mitigation and customer support

Future enhancements could include more accurate outage notifications, financial assistance for frequently affected customers, and expanded infrastructure upgrades such as more fault indicators and line sensors. Additionally, advancements in real-time decision-making for outage response and power restoration could further optimize reliability and service efficiency.

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Appendix: The Institute and Review Team Members

The B. John Garrick Institute for the Risk Sciences (GIRS)

Founded in 2014, The B. John Garrick Institute for the Risk Sciences (GIRS) is the umbrella organization for the risk, safety, reliability, and resilience research and related educational activities at UCLA and many affiliated universities in California. Over 80 Core, Adjunct, and Affiliate Faculty and research staff provide a rich multi-disciplinary intellectual core of the Institute, contributing to fulfilling its vision to advance the theory and application of the risk sciences to save lives, protect the environment, and improve system performance.

The Institute research focuses on a wide array of topics in risk, reliability, and resilience related areas. Examples of our current work are medical device reliability, AI enabled health monitoring (prognostics) of complex physical systems, and safety of autonomous systems. The Institute also studies the effects of natural hazards – such as earthquakes, wildfire, and tsunamis – and how systems and society can best withstand and recover from them.

The overarching premise is that to manage the risk of complex systems and processes, the risk must be understood in terms of what can go wrong, how likely it is to go wrong, and what are the consequences if it does go wrong. This requires an interdisciplinary approach to research, technology development, and continuity of effort by a distinguished and dedicated group of scientists, engineers, economists, social scientists, and practitioners. GIRS was established to provide the intellectual and organizational environment to achieve this.

The institute's activities are organized and conducted through six major units:

Center for Reliability Science and Engineering focuses on advancing methods for prognostics and health management of complex systems, resilience engineering, reliability of cyber-physical-human (CPH) systems, quantum computing and deep learning for reliability and risk.

Center for Natural Hazards Risk and Resiliency Research is a multidisciplinary and multi-university research center with the goal of reducing the risk of natural hazards from becoming natural disasters.

Center for SMART Health is dedicated to research, development, and application of technology for predicting and reducing risk, improving precision, enhancing resilience, and improving quality in healthcare.

Safety and Reliability of Autonomous Systems Research Unit is an interdisciplinary organization focusing on autonomous system Safety, Reliability, and Security, including human-system interaction, risk-informed decision-making regarding technology development and deployment, and legal and regulatory aspects.

Energy Systems Resilience Unit aims is to equitably solve energy transition risks through actionable research to support the industry and policymakers.

Projects of these units fall into the following broad categories:

- Collaboration on research projects with federal agencies, industry partners and researchers at international universities.
- Independent technical review and assessment of the performance of complex systems.
- Provision of a world-class repository of risk sciences information.
- Promotion, distribution and commercialization of methods and technologies developed by institute researchers.
- Organization and sponsoring workshops and conferences and publishing fundamental research on theoretical foundations and applications of risk management.

The B. John Garrick Institute for the Risk Sciences Review Team (GIRS-RT)

PI: Professor Jean Carlson

- **Appointments**
  - Distinguished Professor of Physics at the University of California, Santa Barbara (UCSB).
  - External Faculty, the B. John Garrick Institute for Risk Sciences, University of California, Los Angeles (UCLA).
  - External Faculty, Santa Fe Institute for Complex Systems Science.
- **Awards**
  - Fellow of the American Physical Society.
  - Packard Foundation Fellow.
  - McDonnell Foundation 21st Century Science Award.
  - Chair Elect, American Physical Society, Statistical and Nonlinear Physics.
- **Relevant Expertise**
  - Over 30 years of experience modeling wildfires and other hazards, and combining model outputs with scenarios involving resource allocation, human factors, and risk assessment (NSF, NIH, ARO, ONR, EPRI, DARPA, UCOP).
  - Carlson has served as an external review team member for several projects related to the PG&E Wildfire Mitigation Plan, specifically the High Fire Risk Area Mapping Project and Public Safety Power Shutoff Descoping.

Professor Ali Mosleh

- **Appointments**
  - Distinguished University Professor of Engineering at University of California, Los Angeles (UCLA).
  - Director, The B. John Garrick Institute for the Risk Sciences, University of California, Los Angeles (UCLA).
- **Awards and Honors**
  - Member of the National Academy of Engineering.
  - Fellow, Society for Risk Analysis.
  - Fellow, American Nuclear Society.

- **Relevant Expertise**
  - Over 40 years of experience in risk, reliability and safety assessment and risk-informed regulatory analyses for public and private sectors, with many projects related to natural hazards such as fire, flooding, and seismic.
  - Project lead for the wildfire risk model and software platform development for electric power grid, under a collaborative R&D agreement between UCLA and PG&E.
  - Mosleh has served as an external review team member for several projects related to the PG&E Wildfire Mitigation Plan, specifically, Operability Assessment, High Fire Risk Area Mapping Project and Public Safety Power Shutoff Descoping.

Professor Yongkang Xue

- **Appointments**
  - Distinguished Professor of Geography and Atmospheric & Oceanic Sciences at University of California, Los Angeles (UCLA).
  - Affiliated Members of the UCLA Natural Hazards Risk and Resiliency Research Center, the UCLA Joint Institute of Regional Earth System Science and Engineering, and the UCLA Institute of the Environment and Sustainability.
- **Honors**
  - Fellow of American Meteorological Society.
- **Relevant Expertise**
  - Development of four generations of the "SSiB" land surface scheme under NSF, NOAA, and NASA support, which include fire, ecosystem, urban, and land surface water, carbon, and energy balances.
  - Development of the SSiB-Fire model including the meteorological forcing, fire ignition, fuel load, and fire spread processes, as well as fire impact on vegetation and carbon emission. The model has participated in the international fire model intercomparison project.
  - Xue served on external review teams for several projects related to the PG&E Wildfire Mitigation Plan.
  - Researching and teaching remote sensing and GIS.

Abas Goodarzi, PhD

- **Appointments**
  - CEO, Magmotor Technologies, Founder US Hybrid.
  - Technical Director General Motor EV1 Program (Lead).
  - SAE, IEEE Various Committee member (conductive, inductive and catenary overhead Charging, Hydrogen Safety).
  - BOD, “West Coast Center of Excellence in Zero Emission Technology and Renewable Energy Workforce.
- **Awards and Honors**
  - 2021 IEEE PELS Vehicle and Transportation Systems Achievement Award.

    - Plenary Speaker for Applied Power Electronic Conference "APEC" 2019.
    - Keynote Speaker, Panelist, and speaker, IEEE, SAE, ARPA-e, TARDEC, NSF, DARPA.
    - Various Outstanding, Superior and Team performance award, Hughes Aircraft, SAE, IEEE.
- **Relevant Expertise**
    - Over 38 years of experience in renewable distributed energy and EV drives and charging infrastructures, deployment and maintenance.
    - PI for "Power System disruption caused by metallic balloons", SB1990, SB1499 legislation.
    - PI for development, fabrication and operation US Airforce renewable Energy System (Hicham Air Force base, Honolulu Hawaii).
    - Technical advisor member for SAE charging standards (J1772, J2954, J3105).
    - Professional Engineer since 1985. Eight Patents issued and 11 in process.
    - Author "Electric Powertrain, Energy Systems, Power Electronics and Drives for Hybrid, Electric and fuel cell vehicles" Wiley, Textbook and Work Force Training (English & Chinese).

Eddie Dehdashti, Ph.D., P.E.

- **Appointments**
    - Founder and Chief Technology Officer of Power Applications and Research Systems, Inc.
    - Independent Engineer to Resolve interconnection disputes for the Public Utility Commission of Hawaii.
    - Expert Witness for Public Utility Commission of Virginal (SCC) on a 765 kV transmission line proposal by PJM.
    - Consultant to Public Utility Commission of Texas on ERCOT's wholesale electricity markets.
    - Consultant to the San Francisco Public Utility Commission during the Energy Crisis of 2000 and 2001 and beyond.
- **Awards and Honors**
    - Winner of President George Maneates of PG&E for innovation.
    - Invited Speaker and panelist on various power system related issue at IEEE, CIGRE etc.
    - Industry Advisor and Consultant to EPRI Research on many power system related research Projects.
- **Relevant Expertise**
    - Over 41 years of experience in electric power systems including transmission planning, design and operation.
    - Participated in the design of the Third Pacific AC Intertie linking Oregon to California.
    - Participated in the design of Mah Moh to Bangkok 500 kV transmission line in Thailand.

    - Former PG&E Engineer and current trainer to PG&E Transmission Planning and Operations Departments.
    - Trainer to Reliability First on power systems design and analysis.
    - Designed over 11,000 MWs of wind, solar, and storage battery power plants in California, Arizona etc.
    - Participated in USTDA funded Smart Grid research for the countries of Mexico and Turkey.

Carl Swindle, PhD

- Appointments
    - Postdoctoral Researcher at the B. John Garrick Institute for the Risk Sciences and the Department of Materials Science and Engineering at University of California, Los Angeles (UCLA).
    - Ph.D. (2023) in Geology at California Institute of Technology.
- Awards
    - Graduate Research Fellowship, National Science Foundation (2020-2023).
- Relevant Expertise
    - Dr. Swindle has expertise in Risk Analysis, Fire Modeling, Machine Learning, Data Science, Computer Programing, Statistical Analysis, and GIS.

Hara Prasad Nayak, PhD

- **Appointments**
    - Postdoctoral Scholar, Department of Geography, University of California, Los Angeles.
- **Professional engagements:**
    - Life member of India Meteorological Society (IMS).
    - Member of American Geophysical Union (AGU).
- **Relevant expertise:**
    - Over five years of experience in biophysical modeling, including vegetation and soil moisture feedback to surface meteorological parameters, which are critical for wildfire modeling.
    - Development surface meteorological analyses.
    - Expertise in statistical data analysis, data visualization, and numerical modeling of extreme weather events.

Zhijiong Cao

- **Appointments**
    - PhD Candidate, Department of Geography, University of California, Los Angeles.
- **Professional Engagements**
    - Member of the American Geophysical Union.
- **Relevant Expertise**

- Experience in developing machine learning models to estimate wildfire ignition probability across California, with a focus on analyzing temporal variations in the influence of key drivers.
- Participation in the external review team for PG&E's High Fire Risk Area Mapping Project.

George Hulsey

- **Appointments**
  - PhD Candidate, Department of Physics, University of California, Santa Barbara (awarded June 2024).
- **Relevant expertise**
  - Theoretical and practical experience in machine learning, research on applied convex optimization, and multiple publications on wildfire models and risk analysis.

Gabriel San Martin Silva

- **Appointments**
  - PhD. Candidate, Department of Civil and Environmental Engineering, University of California, Los Angeles (awarded May 2025).
- **Awards and Honors**
  - Summer Mentored Research Fellowship, University of California, Los Angeles (UCLA).
- **Relevant Expertise**
  - San Martín has over 6 years of experience developing data-driven models for Risk and Reliability applications in the context of complex engineering systems. During his doctoral studies, he studied the impact of different wildfire mitigation techniques, developing varied causal inference-based models to estimate their effectiveness.