A Catastrophe Bond Design for the Financial Resilience of Electric Utilities Against Wildfires

Saeed Nematshahi, *Graduate Student Member, IEEE*, Behrouz Sohrabi, *Member, IEEE*, Ali Arabnya, *Senior Member, IEEE*, Amin Khodaei, *Senior Member, IEEE*, and Erin Belval

***Abstract*—The scale of wildfires, in terms of acreage burned and mortality rates, is rising due to climate change. There are various causes for wildfire ignition; however, power lines are one of the most significant factors, leading to some of the most devastating wildfire events over the past decade and even bankrupting electric utilities. Traditional insurance strategies are often not applicable for providing financial resilience to electric utilities against such catastrophic events. This paper quantifies the associated risk and proposes a catastrophe bond (CAT bond) as a form of parametric insurance to cover a portion of the risk. Vegetative fuel, weather, power grid, and historical wildfire ignition data are integrated into a proposed simulation-based methodology to accurately price the risk of the third-party wildfire liability, transmission line reconstruction, and the cost of load-shedding. The proposed methodology offers a useful tool for transmission system owners to transfer a portion of the risk of wildfire ignition to CAT bond investors. In addition, the premium calculation is analyzed through a sensitivity analysis to calibrate the indemnity-based CAT bond parameters.**

***Index Terms*—Catastrophe bonds, climate risk financing, parametric insurance, resilience, wildfire.**

Nomenclature

X	Payout function.
L	Total loss amount.
a	Attachment point.
h	Bond range.
P	Principal amount.
$X(t,P)^{Bin}$	Binary loss function with threshold point of t and principal amount of P.
l	Certain total loss.
t	Threshold for binary Cat bonds.
$F_L(l)$	Cumulative distribution function.
$Pr(l)$	Probability function of loss.
$S_L(l)$	Decumulative distribution function.
$L(a,a+h]$	Total loss amount within the bond.
y	Random variable within the loss layer.
$E(L)$	Expected absolute loss.
PFL	Probability of first loss.
CEL	Conditional expected loss rate.
EL	Expected loss.
$\rho(l)$	Premium function associated with loss.
Λ	Risk loading.

Received 12 June 2024; revised 13 September 2024 and 22 October 2024; accepted 14 November 2024. Date of publication 18 November 2024; date of current version 17 March 2025. This work was supported by the U.S. Forest Service under Grant 22-CS-11221636-12. Paper no. TEMPR-00121-2024. *(Corresponding author: Amin Khodaei.)*

Saeed Nematshahi, Behrouz Sohrabi, and Amin Khodaei are with the Department of Electrical and Computer Engineering, University of Denver, Denver, CO 80208 USA (e-mail: saeed.nematshahi@du.edu; behrouz.sohrabi@du.edu; amin.khodaei@du.edu).

Ali Arabnya is with the Quanta Technology, Raleigh, NC 27607 USA, and also with the Department of Electrical and Computer Engineering, University of Denver, Denver, CO 80208 USA (e-mail: aarabnya@quanta-technology.com).

Erin Belval is with the Rocky Mountain Research Station, U.S. Forest Service, Fort Collins, CO 80526 USA (e-mail: erin.belval@usda.gov).

Digital Object Identifier 10.1109/TEMPR.2024.3501012

I. Introduction

LARGE-SCALE wildfires can severely impact critical infrastructures, natural and built environments, and put communities at risk [1]. Over the past several decades, the size and intensity of large wildland fires in the United States have increased due to climate change [2] and fuel accumulation [3]. The changes in fire activity and behavior, in concert with growth in the wildland-urban interface (WUI), have led to increased damages from wildland fires [4]. The ignition drivers of these wildfires can be categorized into two categories: a) climate-related drivers and b) human-related drivers. In the U.S., 84%–90% of wildfires are ignited by human activities. This includes but is not limited to, arson, campfires, debris burning, smoking, fireworks, and power lines-related incidents [5], the latter of which is the focus of this research.

While wildfires ignited by power grids are not very common in terms of occurrence, they have been associated with several large-scale and highly damaging wildfire events. For example, among the ten most destructive wildfires in California prior to 2024, four have been attributed to power systems, namely: the Camp Fire (2018), Woolsey Fire (2018), Tubbs Fire (2017), and Witch Fire (2007) [6]. The cost for each of these disasters amounts to billions of dollars [7]. The incidence of wildfires ignited by power grid failures is increasing both in the western regions, such as California, Colorado, and Oregon, as well as in other states [8]. One recent grid-ignited wildfire, Smokehouse Creek in Texas on February 26, 2024, burned over 1 million acres and destroyed an estimated 500 structures [9].

If an electric utility is determined responsible for igniting a fire, it may be exposed to litigations to three categories of liability: a) damage to properties; b) costs related to firefighting efforts by government agencies; and c) additional economic and environmental losses, such as business interruption, long-term health impacts from smoke, and reduced air and water quality [10]. When an electric utility becomes liable for triggering a wildfire event, its financial exposure can threaten its solvency.

A recent World Bank Group study emphasizes the crucial role of operational and financial preparedness as the two key elements of building resilience in managing power infrastructure against climate-related risks [11]. Operational resilience is crucial to prevent utility-caused ignitions. This includes trimming trees and vegetation [12], burying power lines underground [13], and installing covered power lines in wildfire-prone areas. In 2019, the three major investor-owned utilities in California – Pacific Gas & Electric, Southern California Edison, and San Diego Gas & Electric – collectively reported about $4.7 billion in expenditure on system hardening, vegetation management, and equipment inspection [14]. The primary reason for the limited adoption of these mitigation methods is the high cost, with undergrounding averaging $1.9 million per kilometer and conductor covering averaging around $350000 per kilometer as of 2022 [15]. Financial resilience, which is the focus of this study, incorporates designing a mechanism that ensures quick access to sufficient financial resources to execute a prescheduled plan to restore electricity in case of failure caused by any kind of disasters. Meanwhile, it is necessary to carry out risk modeling to understand the potential cost of climate-related disruptions. Then, the electric utility can take advantage of risk transfer mechanisms and insurance options to cover the potential financial losses.

The contribution of this paper is twofold: first, it develops a novel framework for the risk pricing of grid-ignited wildfires, and second, it proposes the design of a catastrophe bond (CAT bond) scheme to provide an immediate financial mechanism for recouping wildfire-related costs.

The remainder of this paper is organized as follows. Section II demonstrates the necessity of wildfire risk financing and reviews existing research and the existing gap. Then, Section III describes the CAT bond premium calculation. Section IV presents a wildfire spread simulation, followed by numerical results and discussion. Finally, Section V provides the concluding remarks.

II. Wildfire Risk Financing

Wildfire risk financing is essential for utilities facing potential economic losses, and various mechanisms exist to help manage this risk. Funded self-insurance involves setting aside reserves to cover losses to reduce post-disaster financial burdens, while commercial insurance, as a traditional strategy, can become expensive due to heightened wildfire risks. CAT bonds transfer the risk to investors, with payouts upon defined triggering events, and captives allow utilities to establish insurance entities to cover difficult-to-insure risks like wildfires. Risk pooling sees participants sharing financial resources to cover losses, which is particularly useful in wildfire-prone areas, while recovery bonds offer a post-disaster financing mechanism for acquiring capital to pay for reconstruction expenses, recently legislated for wildfires in California. These mechanisms collectively aim to bolster utilities' resilience and financial stability in the face of wildfire threats [16].

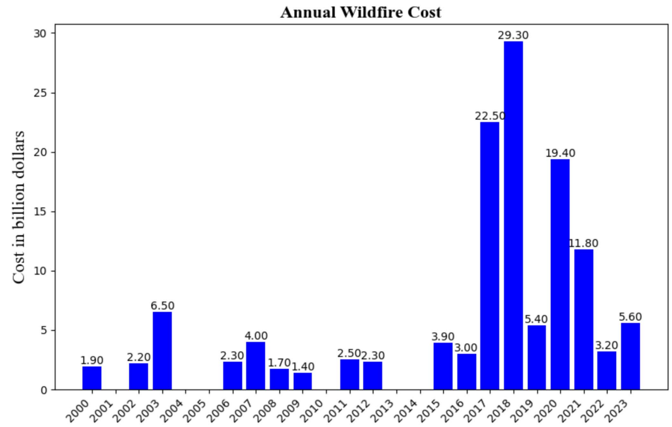

Fig. 1. Annual cost of "billion-dollar wildfires" across the nations from 2000 to 2023.

Since the frequency and intensity of disasters such as wildfires have grown in recent years, insurance companies have adjusted their premiums in response to the increasing risk factors [17]. In this regard, insurers have increased premiums or stopped issuing traditional insurance policies altogether in some states (e.g., Allstate and State Farm in California) due to wildfire risk [18]. Thus, utilities urgently require a new financial instrument to effectively manage and mitigate the substantial risks posed by high-consequence events such as wildfires.

To put this trend into perspective, Fig. 1 shows the annual cost of wildfires in recent years based on the data from the National Centers for Environmental Information [19]. Zero values for certain years indicate the absence of data for those specific years.

A. Catastrophe Bond

The rationale behind the CAT parametric insurance for grid-ignited wildfires is driven by several key factors: the escalating frequency and intensity of wildfires, the substantial financial impact on utilities and communities, and the urgent need for innovative risk management solutions that can deliver swift financial support. This insurance scheme benefits a wide array of stakeholders, including utility companies, local governments, affected communities, insurance companies, investment banks, broker-dealers, utility shareholders, utility management, ratepayers, and regulators such as utility commissions. Utility companies and local governments gain a reliable and swift financial tool to address wildfire costs, while utility shareholders and management benefit from reduced financial risk and increased organizational stability. Affected communities benefit from faster recovery and stabilization. Insurance companies and investors, including those in investment banks and broker-dealers, find a unique opportunity to diversify their portfolios, as this investment has no correlation with financial market volatility and economic downturns. Additionally, ratepayers benefit from more stable utility rates, and regulators ensure that the financial burden of wildfires is managed in a way that aligns with the public interest.

CAT bonds, while not a new tool for disaster risk financing, can be an effective instrument for electric utilities to mitigate

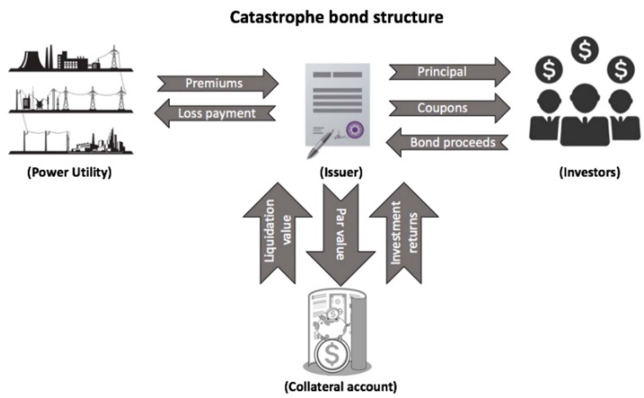

Fig. 2. CAT bond structure for wildfire risk transfer by electric utilities.

the financial risk of large-scale wildfires. Generally, CAT bonds belong to the category of Insurance-Linked Securities (ILS), facilitating the transfer of risk from the sponsor (in this case, the electric utility) to investors who, in some way, wager on the non-occurrence of the disaster. In the meantime, these events hold significant appeal for investors since their likelihood is entirely independent of other risks like stock market fluctuations, credit risk, and interest rate variations [20]. The second appeal for investors is that the CAT bonds offer them higher interest rates, including the regular interest from the Treasury money market fund and the premium received from the sponsor. While CAT bonds are generally more attractive to risk-seeking investors, their structural features can also make them appealing to risk-averse financiers. Investors with low risk tolerance typically prefer investments with stable, albeit lower, returns. However, by investing in CAT bonds, they can add a unique asset class to their portfolios that is uncorrelated with any other investments that can help to reduce overall portfolio risk. In addition, CAT bonds can offer structured payouts based on the severity of events, allowing for partial or tiered payments. This feature significantly reduces the risk of total loss for investors, making the bonds more attractive to risk-averse parties.

To facilitate the CAT bond transaction, sponsors typically establish a Special Purpose Vehicle (SPV), a legally separate financial entity. This SPV serves as an intermediary, collecting principal from investors and making premium payments in return. The premium spread depends on the expected loss for investors. If a triggering event with previously defined specifications in a defined timeframe occurs, the principal is transferred to the sponsor (power line owner in this case) to cover their losses; otherwise, the principal, along with return on investment, is returned to the investors [17]. Fig. 2 illustrates the major components and cash flows associated with CAT bonds. Note that the initial investment will be placed in an extremely secure account, such as a U.S. Treasury money market fund, to ensure that there is no risk associated with it.

There are various methods for triggering CAT bonds, including but not limited to parametric, industry loss, modeled, and indemnity triggers. Parametric insurance, an index-based trigger, is well situated for securing utilities against grid-induced wildfires due to its fast-track process. For example, wind speed, temperature, and precipitation are potential indices for assessing wildfire risk. This type of trigger accounts for only three percent of the market. Industry loss index triggers activate 20 percent of outstanding CAT bond capital, while modeled loss triggers represent six percent of issuances [21]. However, this research specifically focuses on wildfires ignited by power lines, where the power line owner bears responsibility for all subsequent losses. The indemnity trigger emerges as the most appropriate type for this study which also made up 70 percent of outstanding capital [21]. Based on this, electric utilities can leverage CAT bonds to insure themselves against the risk of grid-ignited wildfires. CAT bonds with indemnity triggers typically require two to three years to disburse payments following a triggering event, whereas CAT bonds utilizing industry-loss or parametric triggers generally complete payouts within three months [22].

Our main contribution in this paper is to incorporate geographical, weather, and power grid data (including historical grid ignition data) to provide a risk pricing framework for grid-ignited wildfires and integrate it into CAT bonds. Our goal is to demonstrate it as a viable disaster risk financing mechanism for utilities to mitigate the financial risk of wildfires.

B. State of the Art

In the wake of devastating wildfires in recent years, power system owners and operators are taking action to enhance their resilience against wildfires and reduce their losses from catastrophic events [23]. Electric utilities can employ a wide range of measures to mitigate the adverse effects of wildfires on the power grid during their daily operations. Authors in [24] present a review of wildfire mitigation plans (WMPs), encompassing grid design and system hardening, asset management and inspection, situational awareness and forecasting, operational response, vegetation management, public safety power shutoffs, and cost-effective risk mitigation. Preemptive de-energization and recloser disablement programs, also known as Public Safety Power Shut-off (PSPS), have become a commonly used last resort to reduce the risk of fire ignition. This approach seeks to address the dual risks associated with wildfire prevention—specifically, the threat of wildfire ignitions caused by electrical infrastructure—while simultaneously considering the socioeconomic and health impacts that extended power outages impose on at-risk populations [25]. In the use of PSPS, specific grid sections are intentionally de-energized by utilities, leading to planned blackouts [26], [27], [28]. Authors in [29] present a novel preemptive de-energization planning approach through a two-step stochastic program, solved via an enhanced Lagrangian decomposition method. A mathematical model to help utilities decide where and when to proactively shut off power during fire weather and how to restore it efficiently afterward is presented in [30]. Authors in [31] propose an optimization tool that helps operators manage PSPS events by reducing wildfire risk and operational costs while increasing service. In [32], a plan for expanding electricity grids in areas with persistent wildfire ignition risks is outlined, with the goal of enhancing resilience against wildfires. Authors in [33] proposed a proactive strategy using dynamic heat balance equations to improve operational efficiency and decision-making for power distribution networks during progressing wildfires. In [34], a quasi second-order stochastic dominance (Q-SSD) measure is developed to mitigate wildfire risk while minimizing the economic impact of PSPS-induced outages. Despite these efforts, there is still a significant gap in theory and practice to manage wildfire risk by electric utilities. This calls for developing enhanced risk management frameworks and interdisciplinary approaches to address this emerging risk landscape.

Commercial insurance plays a crucial role in distributing and reducing financial risks associated with adverse events in power infrastructure, aiding in managing remaining catastrophe risks. It is explored as a risk management tool for enhancing energy infrastructure security and resilience, as presented in [36]. The insurance industry can play a crucial role in reducing the vulnerability of communities to weather-related natural disasters while simultaneously advancing its market goals and promoting sustainable development [36]. CAT bonds have demonstrated success in mitigating insurance catastrophe risks such as floods, hurricanes, and earthquakes. In [37], a CAT bond scheme is proposed as a risk mitigation strategy for power system cyber insurance providers, specifically designed to address the tail risk associated with power system cybersecurity incidents. It is important to highlight that the aforementioned CAT bonds are specifically issued to cover first-party property losses and do not encompass coverage for third-party liability [17]. In [16], CAT bonds are described as a potential solution for wildfire risk financing in electric utilities. Authors in [38] present a statistical framework for modeling wildfire losses using state-level data from the United States between 1989 and 2019. However, their model overlooks significant spatial variations in wildfire risk within the state. Notably, the proximity of power lines to High Fire-Threat Districts (HFTDs) plays a critical role in wildfire risk, which is not accounted for in their analysis. Although recent efforts have been devoted to the topic, a compatible research on financial resilience for an specific power system risk management is still in its early stages. To address this gap, in this paper we present a framework to use CAT bonds to address grid-ignited wildfires by electric utilities. We aim to bridge disciplinary gaps and offer a set of practical financial resilience-building solutions for electric utilities in the face of wildfire events. This novel method not only considers liability but also accounts for the outages and the reconstruction cost of the power grid. To that end, we introduce a risk pricing model that encompasses both third-party losses and power grid losses.

III. Problem Formulation

To formulate the CAT bond structure, it is imperative first to quantify the damage costs associated with wildfires. Therefore, the loss variable (L), which is intrinsically linked to the extent of the burned area, the impacted power infrastructure, and the total outages must be precisely defined. To achieve this, a wildfire simulator is employed to model the behavior and spread of the fire, utilizing landscape data, meteorological conditions, and ignition coordinates. This simulation provides estimates of the damage scale, including total burned acreage, the length of affected power lines, and the lost loads which directly influence the financial loss captured in the payout functions, adopted from [39]:

The variable associated with the environmental damage cost caused by wildfires ignited along transmission lines is denoted as LBE (Loss from Burned Environment) and is calculated as follows:

$$LBE = \frac{\sum_{i=1}^{N}\sum_{c=1}^{C} S_c^i . \propto . CBE}{N} \tag{1}$$

where i and c represent the indices for the ignition point and cell, respectively. The size of each cell is determined by the resolution selected for the analysis. N denotes the total number of ignition events, while C represents the total number of cells in the study area. The cell status, indicated by S, takes a value of 1 when the cell is burned and 0 when it remains unaffected by the wildfire. The symbol $\propto$ represents the conversion factor used to convert the cell size into acres, and CBE refers to the average cost associated with one acre of burned environment.

The variable representing the loss due to the reconstruction of damaged transmission lines, denoted as LBL (Loss from Burned Lines), is given by:

$$LBL = \frac{\sum_{i=1}^{N}\sum_{j=1}^{J} l_j^i . X_j . CBL}{N} \tag{2}$$

where J is the total number of transmission lines, l indicates the status of each affected line, and X_j represents the length of line j. Furthermore, CBL denotes the average cost of restoring a damaged transmission line per mile.

The variable representing the cost of outages due to downed power lines is denoted as LLL (Loss from Lost Loads), and is calculated using the following formula:

$$LLL = \frac{\sum_{i=1}^{N}\sum_{k=1}^{K} ENS_k^i . VOLL}{N} \tag{3}$$

where k denotes the bus number, ENS_k^i is the Energy Not Supplied at bus k due to ignition event i, and $VOLL$ represents the Value of Lost Load per MWh.

Finally, the model integrates financial losses to assess transmission line risk, introducing a metric that quantifies the risk associated with the transmission system. The total wildfire loss variable resulting from ignition at transmission lines, represented by the variable L, is defined as:

$$L = LBE + LBL + LLL \tag{4}$$

Incorporating this loss model ensures a perfect representation of wildfire risk, a critical factor in the design of the CAT bond payout mechanism. The simulation process and algorithm flow are presented in Table I.

CAT bonds are financial instruments developed by insurance companies and reinsurers to transfer the risks associated with natural disasters to the capital markets. These bonds can offer either excess-of-loss (XOL) or binary (Bin) payouts, depending on the situation. Note that the following equations in this section are adopted from [40] and [41], and modified to be compatible with the context of grid-ignited wildfires. The payout function

TABLE I
ALGORITHM FLOW

Algorithm 1: Catastrophe bond design for grid-ignited wildfire.	
Input	Landscape data, weather data, and transmission grid map.
Step-1:	Create potential ignition points along power lines at regular intervals.
Step-2:	**for** ignition point ∈ {1,…,N}
Step-3:	Simulate wildfire propagation using landscape, weather, and ignition point data.
Step-4:	Extract the corresponding burned area.
Step-5:	Map the burned area onto the transmission grid to identify impacted power lines.
Step-6:	Run the power flow and determine the ENS.
Step-7:	Estimate the financial losses from environmental damage and grid impacts.
Step-8:	**end for**
Step-9:	Establish the attachment and exhaustion points for the catastrophe bond.
Step-10:	Set the risk loading factor.
Step-11:	Set the probability of an ignition in the study area
Step-12:	Determine the insurance premium based on calculated risks.
Step-13:	Set the return rate for the catastrophe bond investors.
Step-14:	Calculate the coupon payment based on the bond principal.

for XOL (also known as layered) is:

$$X\left(a,a+h\right] = \begin{cases} 0, & \text{if } L \le a, \\ L-a, & \text{if } a < L \le a+h, \\ h, & \text{if } L > a+h, \end{cases} \tag{5}$$

where L is a positive random loss variable representing total loss linked to a layer beginning at point a (attachment point) and extending to point $a+h$ (exhaustion point). According to this definition, if the wildfire loss is less than or equal to a, the utility cannot receive any funds from the collateral account. In the second scenario, if the total loss falls within the range greater than a and less than or equal to $a+h$, the utility can access a portion of the principal. Finally, if the total loss surpasses the exhaustion point, the entire bond amount is allocated to the utility to offset the wildfire losses. It is important to note that the total loss comprises liability claims, power infrastructure losses, and outages. The total financial loss from wildfires is detailed in Section IV, taking into account the scenarios where wildfires were ignited on power lines, and the resulting damages to the environment and the power grid.

In practice, for wildfire CAT bonds, the bandwidth represented by h is not equal to the principal amount. Therefore, we modified the payout function to (6) to accurately represent the relationship between loss and the total principal, as follows:

$$X\left(a,a+h\right] = \begin{cases} 0, & \text{if } L \le a, \\ \left(\left(L-a\right)/h\right) * P, & \text{if } a < L \le a+h, \\ P, & \text{if } L > a+h, \end{cases} \tag{6}$$

Similarly, the payout function for binary form is:

$$X(t,P)^{Bin} = \begin{cases} 0, & L \le t, \\ P, & L > t, \end{cases} \tag{7}$$

where the payout will be either full or none. When the total loss is less than or equal to the threshold, i.e., t in (7), the utility will receive nothing; however, if the total loss exceeds the threshold, the utility will receive all the money in the collateral account.

To calculate the expected loss, the Cumulative Distribution Function (CDF) for the loss is defined as follows:

$$F_L\left(l\right) = Pr\left(L \le l\right) \tag{8}$$

CDF presents the probability of total loss being less than or equal to l, which is a certain amount of total loss. Based on this definition, the probability of total loss greater than l is Decumulative Distribution Function (DDF), which is defined as follows:

$$S_L\left(l\right) = 1 - F_L\left(l\right) = Pr(L > l) \tag{9}$$

Given the existing DDF for stochastic variable L, it is straightforward to articulate the DDF for the loss layer within the interval $(a, a+h]$ in the following manner:

$$S_{L(a,a+h]}\left(y\right) = \begin{cases} S_L\left(a+y\right) = Pr(L > a+y), & \text{if } 0 \le y < h, \\ 0, & \text{if } y \ge h, \end{cases} \tag{10}$$

where $L(a, a+h]$ is the total loss amount within the bond layer from a (exclusive) to $a+h$ (inclusive) and y is a random variable between 0 and h. This implies that if the loss amount falls within the specified layer, the corresponding DDF represents the probability of total loss exceeding a given threshold. Conversely, if the total loss amount falls outside this layer, the DDF is set to 0.

Determining the anticipated loss of an insurance product involves computing the expected loss of the related layer. This is because the expected absolute loss for any arbitrary loss variable L (with a minimum value of 0) is provided by the below equation:

$$E\left(L\right) = \int_0^\infty S_L\left(l\right) dl \tag{11}$$

The expected value of the absolute loss layer within the interval $(a, a+h]$ directly follows from:

$$\begin{aligned} E\left(L\left(a,a+h\right]\right) &= \int_0^\infty S_{L(a,a+h]}\left(y\right) dy \\ &= \int_0^h S_L\left(a+y\right) dy = \int_a^{a+h} S_L\left(l\right) dl \end{aligned} \tag{12}$$

which refers to the integration of the DDF from the point of attachment to the point of exhaustion. Subsequently, the Expected Loss (EL) of the layer can be defined as a function of the Probability of First Loss (PFL) and the Conditional Expected Loss Rate (CEL) as follows:

$$PFL = S_L\left(a\right) = Pr(L > a) \tag{13}$$

$$CEL = \frac{E\left(L\left(a, a+h\right] | L > a\right)}{h} \tag{14}$$

$$\begin{aligned} EL &= \frac{E\left(L\left(a, a+h\right]\right)}{h} \\ &= Pr\left(L > a\right) . \frac{E\left(L\left(a, a+h\right] | L > a\right)}{h} \\ &= PFL \cdot CEL \end{aligned} \tag{15}$$

Based on a thorough comparison among several premium calculation models in [41], we use the linear premium principle. Therefore, the premium $\rho(l)$ for the interval (a, $a+h$] is expressed as:

$$\rho\left(l\right) = EL + \Lambda = PFL \cdot CEL + \Lambda \tag{16}$$

The risk loading (Λ) ensures that investors receive fair compensation for assuming the risks linked to catastrophic events. This involves multiple factors including investors' appetite for CAT bonds, legal fees, and SPV's fees.

In the following, the precision of wildfire scenarios outlined in Section IV will furnish us with a proper assessment of total loss within the designated area of inquiry. Subsequently, this information will serve as the foundation for executing premium calculations.

IV. Numerical Results and Discussion

A. Wildfire Simulation

We aim to quantify the risk of grid-ignited wildfires and propose an indemnity-based CAT bond for electric utilities. Therefore, the initial step is to calculate an accurate pricing of the associated risk. As we consider third-party liability, damages to the power infrastructure, and lost loads, it is necessary to integrate geographic data and weather data as inputs to simulate wildfire spread in the study area.

We use the U.S. Forest Service's open-source package, FARSITE [42], for wildfire simulation. It predicts wildfire spread and intensity over time, considering weather, fuel, and topography. Inputs include ignition files, weather data, burn periods, and fuel moisture, covering landscape parameters like elevation, slope, aspect, fuel models, and canopy characteristics. Weather data includes temperature, humidity, and wind direction and speed. FARSITE processes these to generate outputs such as arrival time, spread direction, and rate of spread, which are then used to determine the burned area for each scenario.

The transmission grid's GIS map is needed to precisely place the ignition point on the power line. Subsequently, we will transmit the ignition point to FARSITE, as the last input. The information on the burned area is then overlaid onto the GIS map, allowing us to assess both liabilities and damages to the transmission system in the affected area.

This simulation provides a proper approach to modeling grid-ignited wildfires by offering three key advantages: first, it generates ignition points on power lines, representing the origin of grid-related wildfires; second, it integrates real landscape and weather data from the study area into the wildfire simulator, enabling precise predictions of wildfire spread and intensity; third, it overlays the resulting burned areas, illustrating the extent of wildfire damage to both third-party properties and power grid assets.

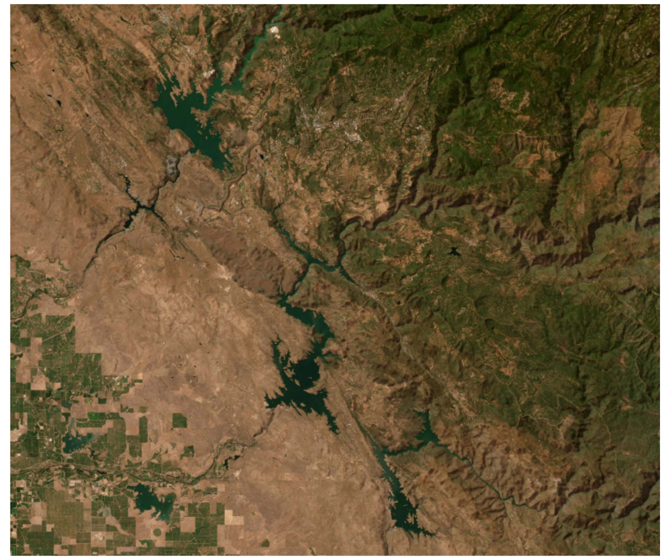

Fig. 3. Geographic map for the study area.

In this section, we provide a detailed demonstration of the four sources of data required for the modeling process and how we modeled them. These four inputs to FARSITE are explained in the following subsections.

1) Geographic Data: The study region, located approximately 100 miles to the east of San Francisco Bay, is situated within the latitudes of 37.6° to 38.1° and longitudes of −120.7° to −120°, covering an area of around 800000 acres, as illustrated in Fig. 3.

Landscape data is extracted from LandFire [43], comprising 8 layers: elevation, slope, aspect, fuel model, canopy cover, stand height, canopy base height, and canopy bulk density.

2) Meteorological Data: The weather data stream includes wind speed, wind direction, temperature, and humidity, each significantly impacting wildfire spread. Historical data for the study region is retrieved from the National Solar Radiation Database (NSRDB) [44] at hourly intervals. To ensure comparable wildfire scenarios, identical weather data beginning October 1, 2023, is used for all scenarios. Each wildfire scenario is run once with these consistent weather conditions.

3) Power Grid Data: To initiate a wildfire scenario, we establish a geographic representation of the transmission system using the IEEE 30-bus test system along with the geospatial map, as provided by the authors in [45]. Fig. 4 displays the power lines in black and the buses as red points for a clearer understanding of the transmission system's configuration.

4) Ignition Points: Our focus in this study is solely on wildfires ignited by power lines. In these cases, a single point typically triggers the wildfire, whereas wildfires caused by other factors, such as natural phenomena, may have multiple ignition points occurring simultaneously or with a delay. In this study, each ignition point, situated specifically along the power lines, represents a distinct wildfire scenario. As shown in Fig. 5, these

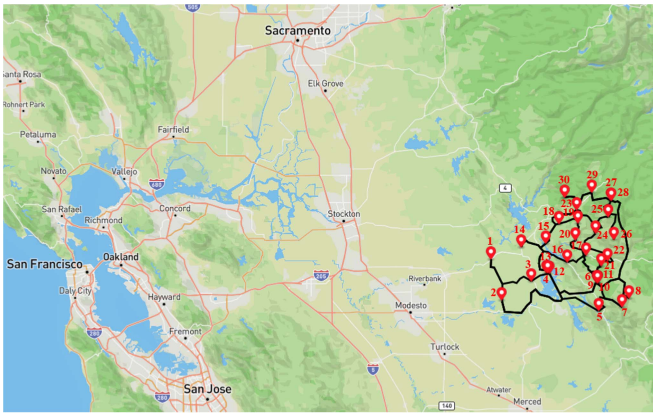

Fig. 4. Geographic visualization of the IEEE 30-bus test system.

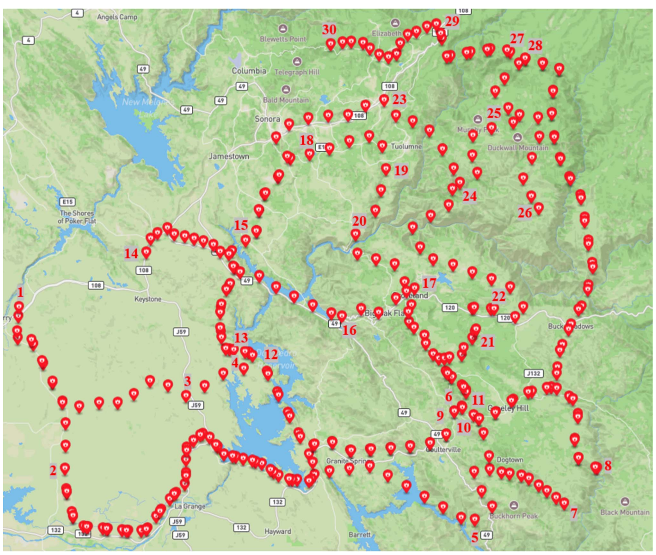

Fig. 5. Spatial distribution of ignition points originating from power lines.

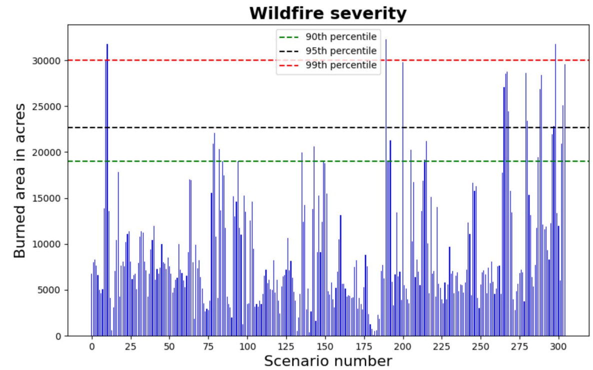

Fig. 6. Corresponding burned area for each scenario.

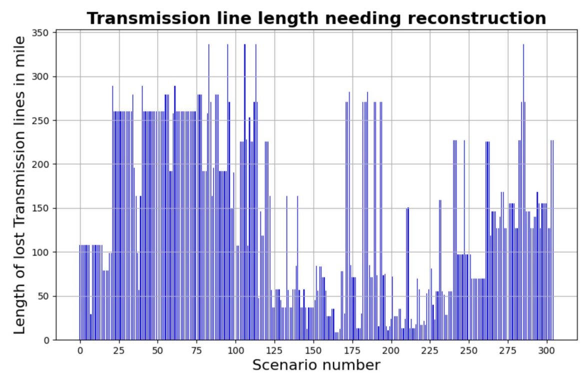

Fig. 7. Length of power transmission lines needing reconstruction.

ignition points are distributed approximately 2 km apart along the power lines. In total, 305 ignition points are established, resulting in 305 distinct wildfire scenarios. The resolution in this study is 120 m $\times$ 120 m, and we assume that each wildfire is fully contained in a maximum of 96 hours. Afterward, the status of each cell within the study area is determined as either 1 (burned) or 0 (unaffected).

Now, we are able to analyze each grid-ignited wildfire scenario to assess the associated risks. With 305 distinct scenarios defined, it is crucial to evaluate the total damage distribution, including liability, power line reconstruction costs, and outages, in order to thoroughly estimate the associated risk.

B. *Total Damages*

By integrating geographical and meteorological data with specific ignition points, we first obtain distinct burned areas for each scenario. The burned area is calculated by multiplying the number of cells with a burned status by the actual size of each cell. Fig. 6 compares the total burned area, measured in acres, for each scenario.

The distribution of burned areas in our small-scale power system demonstrates a notable dispersion from the average. It ranges from a minimum of 85 acres to an expansive maximum of 32291 acres, with an average of 9142 acres. This dispersion is even more pronounced in large-scale power systems due to significant variations in geographic and weather conditions. Consequently, the standard deviation in such cases tends to be higher, underscoring the importance of understanding and accounting for these diverse environmental factors.

Next, by overlaying the burned area with the existing power lines, we can identify the affected lines and calculate the length of power lines requiring reconstruction for each scenario. Fig. 7 illustrates the specific lengths of power lines necessitating reconstruction in each scenario.

In certain extreme scenarios, restoring the power system may necessitate replacing over 300 miles. At first glance, one might anticipate a high correlation between the size of the affected area and the length of the failed lines. However, delving deeper into the details of Figs. 6 and 7 reveals no correlation. Instead, each is influenced by the unique spatial relationships between the burned area, the proximity and orientation of power lines, and the varying local vegetation and fuel conditions.

To quantify the impact of downed power lines on operation, we calculate the exact amount of lost load, referred to as Energy

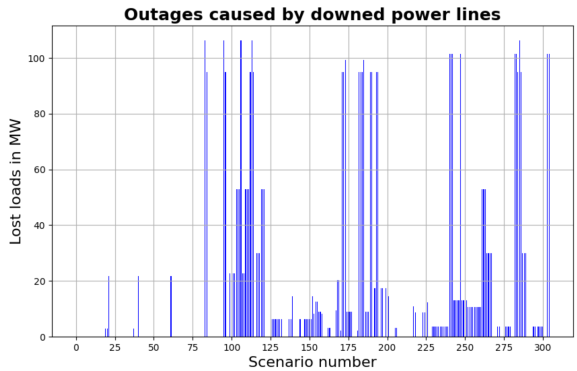

Fig. 8. Load-shedding amount caused by wildfire.

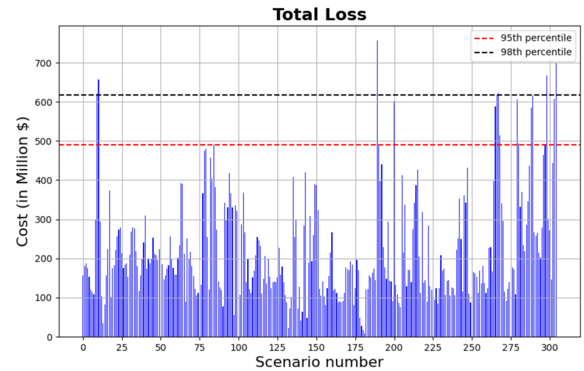

Fig. 9. Comparison of total loss for each grid-ignited scenario.

Not Supplied (ENS). In this study, we define lost load as the portion of demand that is either disconnected from the grid or is only partially met because of transmission line capacity constraints. The latter occurs when the connected transmission lines are unable to fully supply the load. Specifically, we simulate removing downed power lines and run a power flow analysis to identify the affected loads. Fig. 8 shows the ENS for the 305 scenarios. It is important to note that we assumed power outages persist for 24 hours following full containment of the wildfire.

C. Total Cost

The total cost is calculated by summing the burned acres for each scenario and multiplying by the average liability associated with grid-ignited California wildfires. Additionally, it involves adding the sum of failed line lengths for each scenario, multiplied by the average cost of transmission line reconstruction. The final component is the cost of outages, determined by multiplying the amount of lost load by the VOLL. Note that the selected region is considered as a low-density population area, which translates to a low number of affected structures and fatalities. In this study, we assumed a liability cost of $20000 per acre, a reconstruction cost of $200000 per mile for power lines, and a general VOLL of $5000 per MWh.

The liability cost can vary significantly depending on several factors, such as the extent of damage to structures, the number of fatalities, and the impact on resources within the wildfire zone [46]. For example, in densely populated urban area, costs can increase dramatically due to the higher density of structures, the greater property value, and more complex infrastructure. Additionally, urban areas often have more affected resources, such as businesses, schools, and hospitals, further escalating the economic impact.

Regardless of these variables, the proposed model is adaptable and can be used to estimate costs under various scenarios and assumptions. This provides a flexible tool for different wildfire-related financial assessments. Based on our assumptions, the total cost is calculated for each scenario and depicted in Fig. 9.

The total loss ranges from $9 million to $757 million, with the highest total loss associated with scenario number 190, representing a wildfire originating from line 27 between buses 10 and 21.

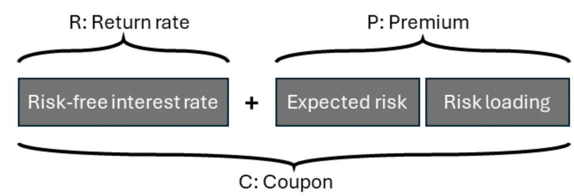

Fig. 10. Composition of CAT bond yield components.

TABLE II
DERIVED PREMIUMS FOR WILDFIRE IGNITION

The probability of an ignition in the study area	Premium: EL (%) + Risk Loading
0.05	1.27% + 2 %
0.10	2.54% + 2 %
0.15	3.81% + 2 %
0.20	5.08% + 2 %
0.25	6.35% + 2 %
0.30	7.62% + 2 %

D. Premium Calculation

Parametric insurance acts as a complementary component to conventional insurance models. The total bond yield, or coupon, transferred from the issuer to investors comprises two primary components: a) a risk-free interest rate, typically based on the latest US Treasury notes, and b) a premium, which encompasses the expected risk along with a risk loading factor. Fig. 10 illustrates these components of the coupon.

In our risk transfer strategy, we tailor the CAT bond to extend coverage for aggregate losses exceeding the 95th percentile but falling below the 98th percentile threshold, as delineated in Fig. 9 (between the red dashed line and the black dashed line). The attachment point is set at $491 million, and the exhaustion point at $618 million. The preferred duration for CAT bonds often spans from 3 to 5 years, offering an adequate timeframe for risk assessment and investor yield.

Applying a risk loading of 2%, Table II delineates the premium calculation according to the probability of ignition for grid-ignited wildfires within the designated study area. The probability of ignition on power lines is strongly influenced by

TABLE III
THE PRINCIPAL AMOUNT AND CORRESPONDING MONTHLY PAYMENTS FOR LOW-RISK WILDFIRE AREA

Principal	Return	Premium	Coupon
$25M	$84k	$95k	$179k
$50M	$168k	$189k	$357k
$75M	$252k	$284k	$536k
$100M	$336k	$378k	$714k
$125M	$420k	$473k	$892k
$150M	$504k	$568k	$1.07M
$175M	$588k	$662k	$1.25M
$200M	$672k	$757k	$1.43M

TABLE IV
THE PRINCIPAL AMOUNT AND CORRESPONDING MONTHLY PAYMENTS FOR HIGH-RISK WILDFIRE AREA

Principal	Return	Premium	Coupon
$25M	$84k	$200k	$284k
$50M	$168k	$400k	$568k
$75M	$252k	$601k	$853k
$100M	$336k	$802k	$1.14M
$125M	$420k	$1M	$1.42M
$150M	$504k	$1.2M	$1.7M
$175M	$588k	$1.4M	$1.99M
$200M	$672k	$1.6M	$2.27M

factors such as line loading, maintenance plans, and the extreme weather conditions in the region under study. To illustrate this, two scenarios are analyzed: a low-risk area with a wildfire occurrence probability of 0.1, and a high-risk area where the probability increases to 0.3, as indicated by previous studies in the literature [47]. These contrasting cases highlight the variability of ignition risks based on localized conditions.

As a case of low-risk wildfire area, we designate a 0.1 probability of a grid-ignited wildfire occurrence within the study area over the term of the CAT bond. As demonstrated in Table II, this potentiality can significantly influence the premium. Consequently, for utilities with a higher concentration of power lines inHFTDs, the premium is substantially greater compared to those with power lines situated in lower-risk areas. Also, the return rate of 4.03% is assumed, aligning with the certified interest rate for 2024 as determined by the U.S. Department of the Treasury. According to these assumptions, Table III provides insights that help electric utilities strategically balance the principal amount against the monthly coupon.

For a high-risk wildfire area, we adjusted the wildfire occurrence probability to 0.3; Table IV shows the values of return, premium, and the corresponding coupon for different principal amounts.

Since the return rate remains constant for both high-risk and low-risk wildfire areas, any variation in coupon payments is driven by changes in the premium. Assuming a fixed risk loading, the effect of wildfire probability in the study area on the premium is linear.

For example, if the electric utility located in the low-risk wildfire zone selects the CAT bond worth $100 million, it will

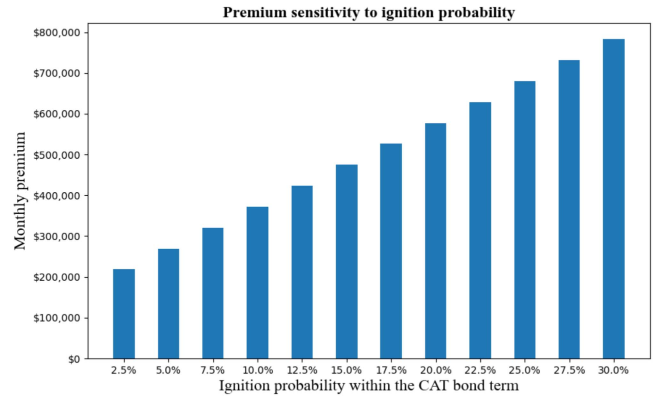

Fig. 11. Monthly premium for different ignition probability.

need to pay $714k monthly. Once a wildfire occurs within the CAT bond term and total losses exceed $618 million, the utility will receive the full $100 million, and no further coupon payments will be required. If total losses reach $550 million, only $46.46 million of the bond is delivered to the utility, and the coupon needs to be paid for the remaining $53.54 million before the CAT bond term ends.

In the following, we also conduct a sensitivity analysis to assess the impact of ignition probability. Various factors directly affect the likelihood of a grid-ignited wildfire and its subsequent spread. The proximity of vegetation to power lines and meteorological conditions are the most influential factors in determining the probability of ignition. Given the significance of this risk in determining premiums, Fig. 10 presents a sensitivity analysis comparing different probabilities of ignition caused by the power grid. The monthly premium is calculated for a $100 million CAT bond.

In Fig. 11, a clear linear relationship exists between the risk of ignition within the CAT bond term and the corresponding monthly premium. This indicates that for every 1% increase in ignition probability, the monthly premium rises by $21200. Therefore, electric utilities operating in high-risk zones experience higher payments to shift the risk of grid-ignited wildfire to CAT bond investors.

V. CONCLUSION

In this paper, a novel parametric insurance solution is proposed, specifically designed for electric utilities to transfer the risk of wildfire ignition to investors in capital markets. Geographic, meteorological, and power grid data are overlaid to model the risk of grid-induced wildfires. This facilitates a more accurate pricing of the damages within the designated study area. Third-party liability, power lines reconstruction cost, and load-shedding cost are integrated into calculating losses. A catastrophe bond with an indemnity-based trigger was designed to enhance the financial resilience of power infrastructure against wildfires ignited by the grid. This tailored model, designed specifically for electric utilities, offers a unique perspective on the susceptibility of their power lines to trigger wildfires and subsequent financial consequences. Premium calculation is discussed separately to provide utilities with a higher level of information symmetry on their underlying risk and the expected cash flows involved in the CAT bond contracts.

In a follow-up work, we aim to increase the accuracy and practicality of our analyses by broadening our weather dataset to encompass multiple years across all four seasons. This expanded approach will facilitate more comprehensive scenario simulations. Furthermore, we will incorporate suppression assumptions to evaluate the impact of fire response strategies more precisely.

References

[1] M. Milne, H. Clayton, S. Dovers, and G. J. Cary, "Evaluating benefits and costs of wildland fires: Critical review and future applications," *Environ. Hazards*, vol. 13, no. 2, pp. 114–132, 2014.

[2] J. T. Abatzoglou and A. P. Williams, "Impact of anthropogenic climate change on wildfire across western US forests," *PNAS*, vol. 113, no. 42, pp. 11770–11775, 2016.

[3] M. R. Kreider et al., "Fire suppression makes wildfires more severe and accentuates impacts of climate change and fuel accumulation," *Nat. Commun.*, vol. 15, 2024, Art. no. 2412, doi: 10.1038/s41467-024-46702-0.

[4] J. Bayham, J. K. Yoder, P. A. Champ, and D. E. Calkin, "The economics of wildfire in the United States," *Annu. Rev. Resour. Econ.*, vol. 14, pp. 379–401, 2022, doi: 10.1146/annurev-resource-111920-014804.

[5] K. C. Short, "A spatial database of wildfires in the United States, 1992-2011," *Earth Syst. Sci. Data*, vol. 6, pp. 1–27, 2014, doi: 10.5194/essd-6-1-2014.

[6] CalFire. Accessed: Apr. 30, 2024. [Online]. Available: https://www.fire.ca.gov/our-impact/statistics

[7] K. Barrett, "The full community costs of wildfire," Headwaters Economics, 2018. Accessed: Mar. 15, 2024. [Online]. Available: https://headwaterseconomics.org/wp-content/uploads/full-wildfire-costs-report.pdf

[8] P. Arbaje, "Wildfires and power grid failures continue to fuel each other," The EQUATION. Accessed: Jun. 4, 2024. [Online]. Available: https://blog.ucsusa.org/paul-arbaje/wildfires-and-power-grid-failures-continue-to-fuel-each-other/

[9] P. Helsel, "Broken power pole and downed wires caused largest fire in Texas history, investigator says," NBCNEWS. Accessed: Apr. 31, 2024. [Online]. Available: https://www.nbcnews.com/news/us-news/broken-power-pole-downed-wires-caused-smokehouse-creek-fire-rcna142579

[10] C. Kousky, K. Greig, B. Lingle, and K. Kunreuther, "Wildfire cost in California: The role of electric utilities," *Changes*, vol. 114, pp. 4582–4590, 2018.

[11] World Bank Group, "Financial protection of critical infrastructure services," World Bank, Washington, DC, USA, 2021. Accessed: Mar. 15, 2024. [Online]. Available: http://hdl.handle.net/10986/36902

[12] S. Kandanaarachchi, N. Anantharama, and M. A. Muñoz, "Early detection of vegetation ignition due to powerline faults," *IEEE Trans. Power Del.*, vol. 36, no. 3, pp. 1324–1334, Jun. 2021.

[13] S. Jazebi, F. de León, and A. Nelson, "Review of wildfire management techniques—Part II: Urgent call for investment in research and development of preventative solutions," *IEEE Trans. Power Del.*, vol. 35, no. 1, pp. 440–450, Feb. 2020.

[14] J. Horing, I. S. Wing, and M. Lisk, "Economic consequences of wildfire adaptation: Public safety power shutoffs in California." Accessed: Apr. 15, 2024. [Online]. Available: https://ssrn.com/abstract=4417805

[15] J. W. Mitchell, "Analysis of utility wildfire risk assessments and mitigations in California," *Fire Saf. J.*, vol. 40, 2023, Art. no. 103879.

[16] A. Arab, A. Khodaei, R. Eskandarpour, M. P. Thompson, and Y. Wei, "Three lines of defense for wildfire risk management in electric power grids: A review," *IEEE Access*, vol. 9, pp. 61577–61593, 2021.

[17] C. Kousky, K. Greig, and B. Lingle, "Financing third party wildfire damages: Options for California's electric utilities," Wharton Risk Manaagement and Decision Processes Center, Philadelphia, PA, 2019.

[18] R. Koury, "Allstate also halting home insurance policies in California due to wildfire risk," ABC7NEWS. Accessed: Apr. 30, 2024. [Online]. Available: https://abc7news.com/farmers-insurance-state-farm-allstate-home-wildfire/13335307/

[19] NOAA National Centers for Environmental Information (NCEI), U.S., "Billion-dollar weather and climate disasters," 2024. Accessed: Apr. 30, 2024. [Online]. Available: https://www.ncei.noaa.gov/access/billions/

[20] M. Edesess, "Catastrophe bonds: An important new financial instrument," *Alternat. Invest. Anal. Rev.* vol. 4, no. 3, 2015.

[21] A. Braun and C. Kousky, "Catastrophe bonds," in *Risk Management and Decision Processes Center*, Philadelphia, PA, USA: Univ. of Pensylvania, 2021.

[22] W. Fan and R. Mamon, "A hybridized stochastic SIR-vasiček model in evaluating a pandemic emergency financing facility," *IEEE Trans. Comput. Social Syst.*, vol. 10, no. 3, pp. 1105–1114, Jun. 2023.

[23] X. Y. Jiang, J. Chen, M. Chen, and Z. Wei, "Multi-stage dynamic post-disaster recovery strategy for distribution networks considering integrated energy and transportation networks," *CSEE J. Power Energy Syst.*, vol. 7, no. 2, pp. 408–420, 2021.

[24] D. A. Z. Vazquez, F. Qiu, N. Fan, and K. Sharp, "Wildfire mitigation plans in power systems: A literature review," *IEEE Trans. Power Syst.*, vol. 37, no. 5, pp. 3540–3551, Sep. 2022.

[25] C. Huang et al., "A review of public safety power shutoffs (PSPS) for wildfire mitigation: Policies, practices, models and data sources," *IEEE Trans. Energy Markets, Policy Regulation*, vol. 1, no. 3, pp. 187–197, Sep. 2023.

[26] 2020 Wildfire Mitigation Plan Report; Pacific Gas and Electric Company: San Francisco, CA, USA, 2020.early access: Sep. 8, 2023. [Online]. Available: https://energysafety.ca.gov/what-we-do/electrical-infrastructure-safety/wildfire-mitigation-and-safety/wildfire-mitigation-plans/2020-wmp/

[27] Wildfire Mitigation Plan; San Diego Gas & Electric Company: San Diego, CA, USA, 2020. Early access: Sep. 8, 2023. [Online]. Available: https://energysafety.ca.gov/what-we-do/electrical-infrastructure-safety/wildfire-mitigation-and-safety/wildfire-mitigation-plans/2020-wmp/

[28] Wildfire Mitigation Plan Update; Southern California Edison Company: Rosemead, CA, USA, 2022. early access: Sep. 8, 2023. [Online]. Available: https://energysafety.ca.gov/what-we-do/electrical-infrastructure-safety/wildfire-mitigation-and-safety/wildfire-mitigation-plans/2020-wmp/

[29] H. Yang, N. Rhodes, H. Yang, L. Roald, and L. Ntaimo, "Multi-period power system risk minimization under wildfire disruptions," *IEEE Trans. Power Syst.*, vol. 39, no. 5, pp. 6305–6318, Sep. 2024.

[30] N. Rhodes and L. A. Roald, "Co-optimization of power line shutoff and restoration under high wildfire ignition risk," in *Proc. IEEE Belgrade PowerTech*, 2023, pp. 1–7.

[31] R. Bayani, M. Waseem, S. D. Manshadi, and H. Davani, "Quantifying the risk of wildfire ignition by power lines under extreme weather conditions," *IEEE Syst. J.*, vol. 17, no. 1, pp. 1024–1034, Mar. 2023.

[32] R. Bayani and S. D. Manshadi, "Resilient expansion planning of electricity grid under prolonged wildfire risk," *IEEE Trans. Smart Grid*, vol. 14, no. 5, pp. 3719–3731, Sep. 2023.

[33] M. Rostamzadeh, M. H. Kapourchali, L. Zhao, and V. Aravinthan, "Optimal reconfiguration of power distribution grids to maintain line thermal efficiency during progressive wildfires," *IEEE Syst. J.*, vol. 18, no. 1, pp. 632–643, Mar. 2024.

[34] J. Su, S. Mehrani, P. Dehghanian, and M. A. Lejeune, "Quasi second-order stochastic dominance model for balancing wildfire risks and power outages due to proactive public safety de-energizations," *IEEE Trans. Power Syst.*, vol. 39, no. 2, pp. 2528–2542, Mar. 2024.

[35] U.S. Department of Energy, "Insurance as a risk management instruction for energy infrastructure security and resilience," 2013. Accessed: Apr. 10, 2024. [Online]. Available: https://www.energy.gov/sites/prod/files/2013/03/f0/03282013_Final_Insurance_EnergyInfrastructure.pdf

[36] E. Mills, "Synergisms between climate change mitigation and adaptation: An insurance perspective," *Mitigation Adapt. Strategies Glob. Change*, vol. 12, pp. 809–842, 2007.

[37] Z. Liu, W. Wei, and L. Wang, "An extreme value theory-based catastrophe bond design for cyber risk management of power systems," *IEEE Trans. Smart Grid*, vol. 13, no. 2, pp. 1516–1528, Mar. 2022.

[38] H. Li and J. Su, "Mitigating wildfire losses via insurance-linked securities: Modeling and risk management perspectives," *J. Risk Insurance*, vol. 91, no. 2, pp. 383–414, 2024.

[39] S. Nematshahi, A. Khodaei, and A. Arabnya, "Risk assessment of transmission lines against grid-ignited wildfires," in *Proc. IEEE PES Grid Edge Technol. Conf. Expo.*, 2025, pp. 1–5.

[40] M. O'Toole and S. Hasan, "Catastrophic events impacting transportation infrastructure: Understanding funding and risk management approaches, *Federal Res. Div., Library Cong.*, 2022.
[41] M. Galeotti, M. Gürtler, and C. Winkelvos, "Accuracy of premium calculation models for CAT bonds—An empirical analysis," *J. Risk Insurance*, vol. 80, no. 2: pp. 401–421, 2013.
[42] M. A. Finney, "FARSITE: Fire area simulator-model development and evaluation," U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, 1988.
[43] M. G. Rollins, "LANDFIRE: A nationally consistent vegetation wildland fire and fuel assessment," *Int. J. Wildland Fire*, vol. 18, no. 3, pp. 235–249, 2009.
[44] National Renewable Energy Laboratory (NREL), "National Solar Radiation Database." Accessed: Mar. 15, 2024. [Online]. Available: https://nsrdb.nrel.gov/
[45] B. Sohrabi, A. Arabnya, M. P. Thompson, and A. Khodaei, " A wildfire progression simulation and risk-rating methodology for power grid infrastructure," *IEEE Access*, vol. 12, pp. 112144–112156, 2024.
[46] N. Rhodes, L. Ntaimo, and L. Roald, "Balancing wildfire risk and power outages through optimized power shut-offs," *IEEE Trans. Power Syst.*, vol. 36, no. 4, pp. 3118–3128, Jul. 2021.
[47] B. Chen and Y. Jin, "Spatial patterns and drivers for wildfire ignitions in California," *Environ. Res. Lett.*, vol. 17, no. 5, 2022, Art. no. 055004.

Saeed Nematshahi (Graduate Student Member, IEEE) received the M.Sc. degree in electrical engineering from the Ferdowsi University of Mashhad, Mashhad, Iran, in 2017. He is currently working toward the Ph.D. degree in electrical and computer engineering from the University of Denver, Denver, CO, USA. He continued his scholarly pursuits from the Center of Excellence in Soft Computing and Intelligent Information Processing, Ferdowsi University of Mashhad, Mashhad. His research interest include but are not limited to power system economics, power system operation, electricity markets, deep reinforcement learning, and wildfire risk management.

Behrouz Sohrabi (Member, IEEE) received the Master of Science degree in computer engineering focusing on data science applications in power systems and the energy industry from the University of Denver, Denver, CO, USA. His thesis, "Data-driven Solutions for Transmission and Distribution Networks in Modern Power Grids," highlights his interest in integrating computational techniques with energy systems. His research interests focuses on innovative strategies to enhance the efficiency and resilience of modern power grids.

Ali Arabnya (Senior Member, IEEE) received the Ph.D. degree in industrial engineering from the University of Houston, Houston, TX, USA. He was with the Electric Power Analytics Consortium in Houston, Texas. He was a Data and Analytics Manager with Protiviti in New York City. He was a consultant climate economist with The World Bank in Washington, Washington, DC, USA. He is the Director of Infrastructure Finance and Climate Risk with Quanta Technology and a research professor of electrical and computer engineering with the University of Denver, Denver, CO, USA. He is a Senior Member of the IEEE's Power and Energy Society.

Amin Khodaei (Senior Member, IEEE) is a Professor and Past Chair of the Electrical and Computer Engineering department with the University of Denver, Denver, CO, USA. He has authored over 200 peer-reviewed technical papers and has advised over 40 graduate students and postdoc associates. He is the co-author of the book, the Economics of Microgrids, published by IEEE/Wiley in 2023. His research interests include climate crisis, grid of the future, and advanced technologies to modernize the grid, including artificial intelligence and quantum computing.

Erin Belval is a Research Forester within the Wildfire Risk Management Science Team, housed in the Human Dimensions Program with the Rocky Mountain Research Station, USDA Forest Service, Fort Collins, Colorado. She specializes in suppression resource movement, assessment and planning, decision support, and performance measurement in wildland fires. She recently led modeling efforts exploring COVID-19 spread among the firefighting population and model analyses to support wildfire incident management and prioritization.