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Journal

IEEE Transactions on Power Systems, 41(1)

ISSN

0885-8950

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Publication Date

2026

DOI

10.1109/tpwrs.2025.3599431

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Probabilistic Resilience-Oriented Assessment Approach for Transmission Networks under Wildfires

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Abstract—The rising threat of wildfires poses significant challenges to power transmission networks, particularly in areas prone to such disasters. Traditional approaches for wildfire risk assessment neglect some potential wildfire scenarios. This paper introduces a probabilistic resilience-oriented assessment approach for power transmission networks to address this gap. Initially, a probabilistic wildfire model is developed to capture uncertainties in ignition, intensity, and fire spread. Next, a spatiotemporal fragility model is constructed to assess the impact of wildfires on transmission corridors, incorporating Thermal Aging (TA) and Dynamic Thermal Rate (DTR) change. Finally, a comprehensive resilience metric is defined to evaluate system performance, leveraging the fragility model to determine component and system-level resilience. The approach employs a combinatorial enumeration method to generate potential wildfire scenarios, enhanced by an impact-increment-based state enumeration (IISE) method for computational efficiency. The proposed method provides critical insights for identifying system vulnerabilities and developing robust strategies to protect transmission networks from wildfires. The efficacy of this approach is validated through extensive scenarios of the RTS-GMLC system across Southern California, Nevada and Arizona.

Index Terms—Probabilistic resilience assessment, spatiotemporal fragility modeling, wildfire probabilistic modeling, thermal aging, dynamic thermal rating.

I. INTRODUCTION

Climate change has significantly intensified severe weather events, presenting a substantial threat to power systems across the United States. In 2023, the impact of extreme weather, including wildfires and heatwaves, resulted in 28 billion-dollar disasters and numerous fatalities [1]. These challenges are exacerbated by increasing exposure, heightened vulnerability, and the worsening effects of climate change [2]. Among these, the projected rise in wildfire frequency and severity, driven by warmer and drier conditions, poses a unique risk to power systems [3]. Long-distance transmission corridors, including lines and towers, are particularly susceptible to such environmental extremes, yet wildfire impacts are often overlooked in power transmission system planning, revealing a critical gap in addressing climate-related threats.

Recent studies have increasingly focused on enhancing power system resilience and developing mitigation strategies in

response to natural disasters like wildfires [3]–[12]. The interaction between wildfires and electric infrastructure is distinct, involving a two-way relationship different from other disasters, such as hurricanes [4]. While many efforts have concentrated on Wildfire Risk Reduction (WRR) strategies—such as vegetation management, asset inspections, situational awareness, forecasting, and Public Safety Power Shutoffs (PSPS)—they primarily aim to mitigate the risk of wildfires ignited by power lines [3]–[13]. Although wildfires are often triggered by natural events like lightning, spontaneous combustion, or volcanic eruptions, as well as routine human activities [14], limited attention has been given to the direct impact on power systems, frequently overlooking potential wildfire damage and the importance of proactive system preparation.

Transmission networks are particularly vulnerable to wildfires, especially as transmission lines are frequently located near fire-prone wildland areas. Wildfires can damage transmission towers and poles, leading to line failures. Among power grid components, transmission lines are especially prone to damage [15]. When wildfires occur, factors such as physical infrastructure damage, breakdown voltage due to smoke and soot, thermal aging faults causing conductor sag and strength loss, and line tripping due to changes in dynamic line rating contribute to increased failure rates and probabilities in transmission components [15], [16]. Such failures often lead to significant load shedding, emphasizing the need to model wildfire impacts to assess the ongoing effects on power systems. Various studies have developed wildfire behavior models, which can be categorized into theoretical, empirical, and semi-empirical types [13]. For instance, the model in [17] calculates fire spread and flame length, prioritizing radiation as the primary heat transfer mechanism. Other studies, such as [18] and [19], analyze surface fire spread using first-order partial differential equations. Despite these efforts, existing models struggle to account for the probabilistic nature of wildfires, making it challenging to predict long-term wildfire events and implement preventive measures during the planning period.

Incorporating wildfire impacts into system resilience assessments involves understanding how specific wildfire characteristics—such as ignition probability, intensity, spread rate, temperature, spatiotemporal profile, and severity—influence the likelihood of failure in power system components. A comprehensive model combining wildfire heat transfer and Dynamic Thermal Rating (DTR) of power lines was intro-

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duced in [13], [20], [21] to assess the temperature effects of wildfires on overhead lines. Additionally, [22] integrated spatiotemporal wildfire behavior into an optimization framework for improved network management during wildfires. However, these models still do not evaluate the probability of power system component failure during wildfires. To address this gap, [15] applied the dynamic heat balance equation and Weibull distribution to assess the impact of wildfires on power line aging. Other studies, such as [23], developed line outage models based on air gap voltage breakdown, considering wildfire predictions to estimate line failure probabilities. Recently, a combined line outage probability model was developed in [16], incorporating dynamic heat balance-based aging failure, voltage breakdown, and line tripping. Nevertheless, these models assume an infinite flame width parallel to the transmission line, which is impractical given that transmission systems typically cover large areas. Therefore, it is crucial to develop a model that reflects the temporal and spatial failure probabilities of different transmission corridors as wildfires spread.

Existing resilience indices primarily provide a system-wide perspective [24]–[27], lacking the ability to pinpoint specific vulnerabilities, such as transmission corridors. Analyzing wildfire impacts on individual transmission corridors is essential for identifying system weaknesses and optimizing resilience strategies [28], [29]. This paper aims to develop a probabilistic resilience-oriented assessment approach to evaluate power system resilience against wildfires and identify its weak points. By analyzing potential wildfire impacts on each transmission corridor, the resilience of the power system can be comprehensively assessed, and vulnerabilities can be accurately identified. The proposed framework consists of three key components:

- A probabilistic wildfire model, developed using key wildfire parameters and their probability distributions, to emulate various potential wildfire scenarios.
- A spatiotemporal fragility model for transmission systems to quantify the cumulative effects of wildfire duration on transmission corridor failure probabilities.
- Resilience indices designed to evaluate both overall system and component resilience, enabling planners to identify weak points in transmission systems.

II. OVERVIEW OF THE PROPOSED FRAMEWORK

The proposed framework, shown in Fig. 1, is structured into three stages. In Stage 1, a spatio-temporal wildfire analysis is conducted using the solid flame model [13]. By estimating probability distributions for key parameters—such as wind speed, direction, ambient temperature, and wildfire ignition probability—based on historical data and spatial datasets [30], multiple potential wildfire scenarios and their probabilities are generated using combinatorial enumeration [31].

Stage 2 assesses the spatio-temporal fragility of transmission corridors for each scenario, focusing on line aging and line tripping as the wildfire progresses. Transmission corridors, consisting of multiple lines and towers, are particularly susceptible to wildfire damage [15]. A long corridor is modeled as connected line segments, with overall failure probability treated as a series system.

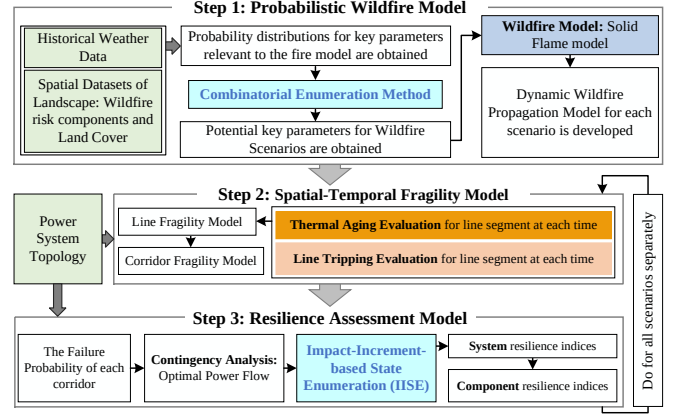


Fig. 1. The proposed resilience assessment framework

Wildfires can significantly raise transmission line temperatures, leading to conductor annealing and reduced tensile strength, which is evaluated through Line Aging [15], [16]. Additionally, high temperatures lower the thermal rating of lines, increasing failure risk [15], [16], [20]–[22]. Line tripping is modeled by considering the Dynamic Thermal Rating (DTR) of lines, using nonsteady-state heat balance equations [13].

Stage 3 develops a resilience assessment model to quantify system and component resilience. The system model estimates expected load shedding from wildfire disruptions, while the component model identifies vulnerable transmission corridors. Contingency analysis and optimal power flow are used to evaluate load shedding [32]. To balance efficiency and accuracy, the Impact-Increment-based State Enumeration (IISE) method [33] is applied in the resilience assessment.

III. WILDFIRE MODELS AND CONDUCTOR IMPACTS

This study utilizes the solid flame model as outlined in [13] and [34]. In this model, the visible flame is treated as a geometric shape that emits heat flux uniformly across its surface. The heat transfer is primarily radiative (Φ^r), which dominates over convective heat transfer (Φ^c). Neglecting the interaction between radiation and convection, the total heat flux (Φ^{wf}) received by the target is defined as [13], [35]:

$$\Phi^{wf} = \Phi^r + \Phi^c \quad (1)$$

Fig. 2 depicts the flame geometry, where a planar surface has flame length L , width W , tilt angle γ , and spread rate V^f , moving towards the l -th line segment of the m -th transmission corridor at a height h_m above the ground. The radiative heat flux reaching the target at time t can be calculated as:

$$\Phi_{\omega,m,l,t}^r = \begin{cases} \tau \varepsilon^{wf} \sigma T^{f4} \left[F_{vf}(r_{\omega,m,l,t}^{inf}, \beta_{\omega,m,l,t}^{inf}) + F_{vf}(r_{\omega,m,l,t}^{sup}, \beta_{\omega,m,l,t}^{sup}) \right], & L > h_m \\ \tau \varepsilon^f \sigma T^{f4} F_{vf}(r_{\omega,m,l,t}^{inf}, \beta_{\omega,m,l,t}^{inf}), & L \leq h_m \end{cases} \quad (2)$$

where F_{vf} is the view factor as detailed in [34]. The parameters τ , ε^f , and σ represent the atmospheric transmissivity, flame emissivity, and Stefan–Boltzmann constant, respectively.

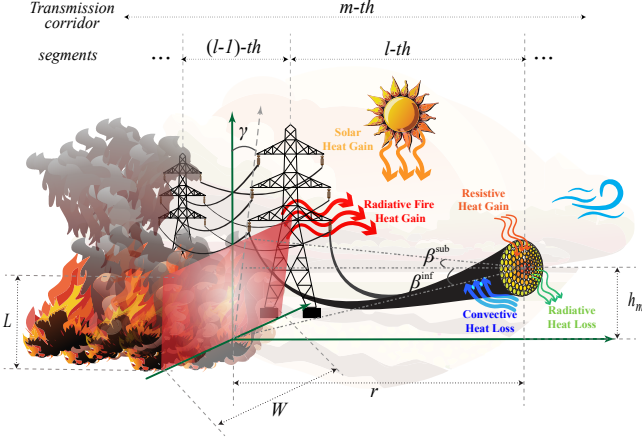


Fig. 2. Schematic diagram of fire geometry and heat dynamics in a power line conductor (sketched based on [13], [22]).

T^f denotes the flame temperature. The view angles $\beta_{\omega,m,l,t}^{\text{inf}}$ and $\beta_{\omega,m,l,t}^{\text{sup}}$, along with the view distances $r_{\omega,m,l,t}^{\text{inf}}$ and $r_{\omega,m,l,t}^{\text{sup}}$, are defined as follows:

$$\beta_{\omega,m,l,t}^{\text{inf}} = \tan^{-1} \left(\frac{h_{m,l}}{r_{\omega,m,l,t}^{\text{inf}}} \right) \quad (3)$$

$$\beta_{\omega,m,l,t}^{\text{sup}} = \tan^{-1} \left(\frac{L \cos(\gamma) - h_{m,l}}{r_{\omega,m,l,t}^{\text{sup}} - L \sin(\gamma)} \right) \quad (4)$$

$$r_{\omega,m,l,t}^{\text{inf}} = r_{\omega,m,l,t} \quad (5)$$

$$r_{\omega,m,l,t}^{\text{sup}} = r_{\omega,m,l,t} - h_{m,l} \tan(\gamma) \quad (6)$$

The distance $r_{\omega,m,l,t}$ between the wildfire center, defined by coordinates $y_{\omega,t}^{\text{wf}}$ and $x_{\omega,t}^{\text{wf}}$, and the affected line segment l of the m th transmission line, denoted by $y_{m,l}^c$ and $x_{m,l}^c$, is computed using the Haversine formula (in meter):

$$r_{\omega,m,l,t} = 1000 \times R_{\oplus} \times 2 \times \text{atan2} \left(\sqrt{a_{\omega,m,l,t}}, \sqrt{1 - a_{\omega,m,l,t}} \right) \quad (7)$$

$$a_{\omega,t,m,l} = \sin^2 \left(\frac{\Delta y}{2} \right) + \cos(y_{\omega,t}^{\text{wf}}) \cos(y_{m,l}^c) \sin^2 \left(\frac{\Delta x}{2} \right) \quad (8)$$

Here, $R_{\oplus}$ is the Earth's radius (6371 km), and Δy^1 and Δx^2 represent the differences in latitudes and longitudes, respectively. The wildfire spread rate V_{ω}^{wf} is influenced by wind speed V_{ω}^{wind} , fuel bulk density ρ_{ω}^b , and a constant k (set to 0.07 kg/m³ for wildfires) [13]:

$$V_{\omega}^{\text{wf}} = \frac{k \cdot (1 + V_{\omega}^{\text{wind}})}{\rho_{\omega}^b} \quad (9)$$

Given the spread rate, the coordinates of the wildfire center at time $t + 1$ can be updated as follows:

$$y_{\omega,t+1}^{\text{wf}} = \sin^{-1} \left(\sin(y_{\omega,t}^{\text{wf}}) \cdot \cos(A) + \cos(y_{\omega,t}^{\text{wf}}) \cdot \sin(A) \cdot \cos(\theta_{\omega}^{\text{wind}}) \right) \quad (10)$$

$$^1 \Delta y = (y_{m,l}^c - y_{\omega,t}^{\text{wf}}) \times \frac{\pi}{180}$$

$$^2 \Delta x = (x_{m,l}^c - x_{\omega,t}^{\text{wf}}) \times \frac{\pi}{180}$$

$$x_{\omega,t+1}^{\text{wf}} = x_{\omega,t}^{\text{wf}} + \tan^{-1} \left(\frac{\sin(\theta_{\omega}^{\text{wind}}) \cdot \sin(A) \cdot \cos(y_{\omega,t}^{\text{wf}})}{\cos(A) - \sin(y_{\omega,t}^{\text{wf}}) \cdot \sin(y_{\omega,t+1}^{\text{wf}})} \right) \quad (11)$$

$$A = \frac{V_{\omega}^{\text{wf}} \times 3.6}{R_{\oplus}} \times \frac{180}{\pi} \quad (\text{in degree}) \quad (12)$$

Here, $\theta_{\omega}^{\text{wind}}$ represents the wind direction relative to the north. Thus, the primary factors influencing wildfire behavior include wind speed V_{ω}^{wind} , wind direction $\theta_{\omega}^{\text{wind}}$, fuel bulk density ρ_{ω}^b , and the coordinates of the ignition point $(y_{\omega,0}^{\text{wf}}, x_{\omega,0}^{\text{wf}})$.

The convective heat transfer flux at a height of h_m above the fire is determined by the following equation [13], [35], based on the assumption that the fire is beneath the object:

$$\Phi_{\omega,m,l,t}^c = 22h_c \left(\frac{(300L^2)^{2/3}}{h_m^{5/3}} \right) \quad (13)$$

where h_c denotes convection heat transfer coefficient (W/m²). Thus, the total heat flux received by the target is:

$$\Phi_{\omega,m,l,t}^{\text{wf}} = \begin{cases} \Phi_{\omega,m,l,t}^r, & L > h_m \\ \Phi_{\omega,m,l,t}^r + \Phi_{\omega,m,l,t}^c, & L \leq h_m \end{cases} \quad (14)$$

A. Wildfire Impact Model on Power Conductor

This section examines the effects of wildfires on power transmission lines, particularly focusing on thermal aging (loss of tensile strength due to high temperatures) and line tripping (changes in dynamic thermal rating). A unified model is proposed, integrating wildfire behavior with conductor temperature changes and the consequent decrease in line rating. Since wildfire progression cannot be directly expressed as a continuous time function, the total wildfire duration T is divided into shorter periods. The temperature change in a conductor during the t -th interval $\Delta T_{\omega,m,l,t}$ is determined by the heat sources (warming the conductor Φ^{source}) and sinks (cooling the conductor Φ^{sink}) [13], [15], [20], as per the thermal balance model in IEEE Std 738 [36]:

$$\Delta T_{\omega,m,l,t} = \frac{\Delta t}{MC_p} \cdot (\Phi_{\omega,m,l,t}^{\text{source}} - \Phi_{\omega,m,l,t}^{\text{sink}}) \quad (15)$$

Here, Δt is the time interval, M the mass per unit length (kg/m), and C_p the heat capacity (J/kg °C). Heat sources include radiative heat from the fire Q^{wf} , solar radiation Q^{sun} , and ohmic losses Q^{line} (referring to Fig. 2):

$$Q_{\omega,m,l,t}^{\text{wf}} = D_{m,l} \Phi_{\omega,m,l,t}^{\text{wf}} \quad (16)$$

$$Q_m^{\text{sun}} = D_m \alpha^{\text{sun}} \Phi^{\text{sun}} \quad (17)$$

$$Q_{\omega,m,l,t}^{\text{line}} = R (T_{\omega,m}^{\text{line}} |I_m|^2) \quad (18)$$

$D_{m,l}$ denotes the outer diameter (m) of the l -th conductor in the m -th line. Φ^{sun} is the solar radiation (W/m²) while the solar absorptivity represented by α^{sun} ranges between 0.27 and 0.95 depending on the type of conductors (If no information is available, it can be set to 0.5 [22]). Conductor current is denoted by I_m in Ampere. Temperature variations result in changes to the conductor's resistance, as described in [37]:

$$R(T_{\omega,m}^{\text{line}}) = R_m^{\text{norm}} \cdot (1 + \zeta_{m,l} \cdot (T_{\omega,m}^{\text{line}} - T^{\text{amb}})) \quad (19)$$

Where R_m^{norm} represents the conductor resistance at the standard ambient temperature T^{amb} (20°C), and $\zeta_{m,l}$ is the temperature coefficient of conductor resistance at T^{amb} .

The heat sinks, Φ^{sinks} , include the convective heat loss rate, Q^{chl} , for non-zero wind speeds (W/m), and the radiative heat loss rate, Q^{rhl} (W/m) [13].

$$Q_{\omega,m,l,t}^{\text{chl}} = \max \left(\begin{aligned} &K_{\omega,m}^{\theta} \left[1.01 + 1.35 (N_{\omega,m,l,t}^{\text{Re}})^{0.52} \right] k^{\text{air}} (T_{\omega,m}^{\text{line}} - T_w^{\text{amb}}), \\ &K_{\omega,m}^{\theta} 0.754 (N_{\omega,m,l,t}^{\text{Re}})^{0.6} k^{\text{air}} (T_{\omega,m}^{\text{line}} - T_w^{\text{amb}}), \\ &3.67 \rho_a^{0.5} D_m^{0.75} (T_{\omega,m}^{\text{line}} - T_w^{\text{amb}})^{1.25} \end{aligned} \right) \quad (20)$$

$$Q_{\omega,m}^{\text{rhl}} = 17.8 D_m \epsilon^{\text{line}} \left[\left(\frac{T_{\omega,m}^{\text{line}} + 273}{100} \right)^4 - \left(\frac{T_w^{\text{amb}} + 273}{100} \right)^4 \right] \quad (21)$$

Where k^{air} denotes the thermal conductivity of air (W/mK), ϵ^{line} is the conductor emissivity (dimensionless), $\rho_a^{0.5}$ is the air density (kg/m³), T_w^{amb} is the actual air temperature (°C), N^{Re} is the Reynolds number, and K^{θ} is the wind direction factor, calculated as follows:

$$N_{\omega,m,l,t}^{\text{Re}} = \frac{D_m \rho_a V_{\omega}^{\text{wind}}}{\mu^{\alpha}} \quad (22)$$

$$K_{\omega,m}^{\theta} = 1.194 - \cos(\varphi_{\omega,m,l,t}^{\text{wc}}) + 0.194 \cos(2\varphi_{\omega,m,l,t}^{\text{wc}}) + 0.368 \sin(2\varphi_{\omega,m,l,t}^{\text{wc}}) \quad (23)$$

Where ρ_a represents the air density (kg/m³), μ^{α} is the dynamic viscosity of air (Pa-s), and φ^{wc} denotes the angle between the wind direction and the conductor axis (degrees).

Thermal Aging: Elevated temperatures lead to conductor annealing, which diminishes tensile strength. When the cumulative loss of tensile strength exceeds a critical limit, the transmission line fails. Wildfires exacerbate this aging process by raising the conductor temperature (see (15)). Morgan [38] proposed a life equation ($\Delta L(\Delta T)$) for transmission lines based on experimental data, which is adapted here to account for the temperature change during the t -th time interval as follows:

$$\Delta L(\Delta T_{\omega,m,l,t}) = \exp \left(\frac{\Phi^{\text{life}}(\Delta T_{\omega,m,l,t})}{\kappa_n^{\text{lf}}} \right) \quad (24)$$

$$\begin{aligned} \Phi^{\text{life}}(\Delta T_{\omega,m,l,t}) = &\ln \ln \left(\frac{1}{1 - \left(\frac{W^{\text{max}}}{W^{\text{a}}} \right)} \right) - \kappa_a^{\text{lf}} \\ &- \kappa_b^{\text{lf}} (T_{\omega,m}^{\text{line}} + \Delta T_{\omega,m,l,t}) - \kappa_c^{\text{lf}} \ln \left(\frac{\kappa_r^{\text{lf}}}{80} \right) \end{aligned} \quad (25)$$

The $\Delta L(\Delta T)$ implies the proportional time with respect to the operational period that a conductor can withstand the new temperature ($T_{\omega,m}^{\text{line}} + \Delta T_{\omega,m,l,t}$). The initial maximum tensile strength of the ACSR conductor is denoted by W^{max} , while W^{a} refers to the tensile strength loss due to annealing. The material properties of the conductor are defined by κ_a^{lf} , κ_b^{lf} , κ_c^{lf} , κ_r^{lf} , and κ_n^{lf} . The updated conductor temperature at time t is denoted as T^{line} .

Line Tripping: During a wildfire, line tripping can occur primarily due to the elevated conductor temperatures resulting from the fire's heat [16]. This heat reduces the rated current, or the maximum allowable current, that the conductor can safely

carry. Tripping happens when the rated current drops below the line current. To accurately evaluate the impact of wildfires on the thermal rating of an overhead transmission line, it is essential to factor in the heat transferred from the fire into the line's Dynamic Thermal Rating (DTR) [13]. Consequently, Eq. (26) accounts for both radiative and convective heat transfers from the fire:

$$\underbrace{R(T_{\omega,m}^{\text{line}}) |I_m|^2 + Q_{\omega,m,l,t}^{\text{wf}} + Q_m^{\text{sun}}}_{\Phi_{\omega,m,l,t}^{\text{source}}} = \underbrace{Q_{\omega,m,l,t}^{\text{chl}} + Q_{\omega,m}^{\text{rhl}}}_{\Phi_{\omega,m,l,t}^{\text{sink}}} \quad (26)$$

The rated current is then calculated as:

$$I_{\omega,m,l,t}^{\text{rated}} = \sqrt{\frac{Q_{\omega,m,l,t}^{\text{chl}} + Q_{\omega,m}^{\text{rhl}} - Q_{\omega,m,l,t}^{\text{wf}} - Q_m^{\text{sun}}}{R(T_{\omega,m}^{\text{line}})}} \quad (27)$$

IV. SPATIO-TEMPORAL FRAGILITY MODEL

The aim is to quantitatively assess the resilience of a transmission system during wildfires by examining the relationship between wildfire characteristics and the likelihood of failure for each transmission corridor, considering both temporal and spatial factors. To achieve this, a spatio-temporal fragility model is developed, accounting for the movement of wildfires across the transmission system. This model enables the calculation of the cumulative probability of failure over the wildfire duration T , considering both line aging and line tripping.

Thermal Aging: It is assumed that the line segment between two adjacent towers experiences uniform wildfire impacts. The failure rate λ^{TA} of the l -th line segment in the m -th transmission corridor at the t -th time interval, due to Thermal Aging, is expressed as follows:

$$\lambda_{\omega,m,l}^{\text{TA}}(t) = \begin{cases} 0, & \tilde{T}_{\omega,m,l,t}^{\text{line}} \in [0, T_m^{\text{max}}] \\ \left(\frac{\Delta t}{\text{OP} \times \Delta L(\Delta T_{\omega,m,l,t})} \right)^{\beta}, & \tilde{T}_{\omega,m,l,t}^{\text{line}} \in [T_m^{\text{max}}, \infty] \end{cases} \quad (28)$$

In this context, OP denotes the operational period, typically representing a specific timeframe during which operations, tasks, or activities are conducted. For this analysis, the operational period is assumed to span 8760 hours per year over 30 years (262,800 hours). The shape parameter β is set to 5 [15], and the maximum allowable conductor temperature T_m^{max} is established at 75°C in this model [36]. The equation $\Delta L(\Delta T)$ implies the proportional time relative to the operational period that a conductor can withstand at the temperature T_m .

As discussed earlier, the total wildfire duration T is divided into several shorter intervals. The wildfire heat transfer to the lines and their failure rates during these intervals are treated as constants. The cumulative failure probability (CFP) of the l -th line in the m -th transmission corridor over the duration T is calculated as:

$$p_{\omega,m,l}^{\text{TA}} = 1 - \exp \left\{ - \sum_{i=0}^{N^{\text{sp}}-1} \lambda_{\omega,m,l}^{\text{TA}}(t) \Delta t \right\} \quad (29)$$

where N^{sp} is the total number of shorter intervals.

Line Tripping: The failure rate λ^{LT} of the l -th line segment in the m -th transmission corridor at the t -th time interval due to Line Tripping is given by:

$$\lambda_{\omega,m,l}^{LT}(t) = \exp \left[\alpha_1 - \alpha_2 \times \frac{I_{\omega,m,l,t}^{\text{rated}}}{I_m} \right] \quad (30)$$

Empirically, α_1 and α_2 are set to 8 and 15, respectively. The CFP of the l -th line segment in the m -th transmission corridor over the wildfire duration T is expressed as:

$$p_{\omega,m,l}^{LT} = 1 - \exp \left\{ - \sum_{i=0}^{N^{\text{sp}}-1} \lambda_{\omega,m,l}^{LT}(t) \Delta t \right\} \quad (31)$$

A. Aggregated Line Failure Probability

Since the transmission line segments are connected in series, the failure of a single line segment due to either line aging or tripping can lead to the tripping of the entire transmission corridor. These failures are considered independent of each other. The equivalent failure probability of the m -th transmission corridor is the aggregated failure probability of all line segments due to line aging or tripping, calculated as:

$$p_{\omega,m} = 1 - \prod_1^{N_m^{\text{line}}} (1 - p_{\omega,m,l}^{\text{TA}}) (1 - p_{\omega,m,l}^{LT}) \quad (32)$$

where N_m^{line} represents the total number of line segments in the m -th transmission corridor.

V. RESILIENCE ASSESSMENT MODEL

This section presents a resilience assessment model designed to quantify system resilience and identify vulnerable transmission corridors. By evaluating spatiotemporal cumulative failure probabilities, planners can pinpoint the transmission corridors most susceptible to wildfire impacts.

A. System Resilience Assessment

In wildfire-prone regions such as the southwestern United States [39], planners must account for a range of potential wildfire scenarios. These scenarios vary in location, path, and intensity, resulting in different failure scenarios and levels of load shedding. The system resilience index, R^{sys} , is defined as the expected load shedding resulting from various potential wildfires during the planning period and is calculated as:

$$R^{\text{sys}} = \sum_{\omega=1}^{N^{\text{wf}}} P_{\omega}^{\text{wf}} E[L_{\omega}] \quad (33)$$

where P_{ω}^{wf} represents the probability of wildfire ω , N^{wf} is the total number of potential wildfire scenarios, and $E[L_{\omega}]$ is the expected load shedding caused by wildfire ω .

B. Component Resilience Assessment

While enhancing system resilience against wildfires is essential, it is also costly. Strengthening all transmission corridors is impractical, so it is crucial to identify the most vulnerable ones. The component resilience index, R_m^{corr} , identifies these critical corridors by evaluating their potential impact on system resilience:

$$R_m^{\text{corr}} = R^{\text{sys}} - R^{\text{sys}}|_{p_{\omega,m}=0} \quad (34)$$

where $R^{\text{sys}}|_{p_{\omega,m}=0}$ represents the system resilience assuming that the m -th transmission corridor does not fail under any wildfire scenario. This index reflects the significance of a component's failure to overall system resilience. A higher R^{corr} value indicates a more critical component, guiding targeted enhancement measures to reduce the system's vulnerability to wildfires.

VI. ALGORITHM IMPLEMENTATION

This section outlines the framework used to evaluate transmission system resilience against wildfires, as depicted in Fig. 1. The framework integrates two key methodologies: the Combinatorial Enumeration Method and the IISE Method, providing a comprehensive and efficient approach to resilience analysis.

A. Combinatorial Enumeration Method

The Combinatorial Enumeration Method generates various wildfire scenarios using probabilistic parameters such as wind speed, wind direction, ambient temperature, and initial ignition point coordinates. These parameters follow specific probability distributions: Rayleigh for wind speed, Mises for wind direction [13], and normal for ambient temperature. The probability distribution of ignition point coordinates is determined based on regional wildfire risk data [40].

The parameters are discretized into segments, and wildfire scenarios are generated by enumerating combinations within each segment [28]. For example, the probability of wind speed V_{ω}^{wind} in segment c_H is calculated as:

$$P(V_{\omega}^{\text{wind}}) = \int_{V_{\omega}^{\text{wind}} - c_H/2}^{V_{\omega}^{\text{wind}} + c_H/2} f(V^{\text{wind}}) dV^{\text{wind}}, \quad (35)$$

where $P()$ denotes the probability, and c represents the segment length.

Similar probabilistic calculations are applied to wind direction $\theta_{\omega}^{\text{wind}}$, ambient temperature T_{ω}^{amb} , and initial wildfire ignition coordinates $(x_{\omega,0}^{\text{wf}}, y_{\omega,0}^{\text{wf}})$. The overall occurrence probability of wildfire ω in a specific area is computed as:

$$P_{\omega}^{\text{wf}} = P(V_{\omega}^{\text{wind}}) P(\theta_{\omega}^{\text{wind}}) P(x_{\omega,0}^{\text{wf}}, y_{\omega,0}^{\text{wf}}) P(T_{\omega}^{\text{amb}}) \quad (36)$$

These parameters are then input into the wildfire model to compute heat sources Φ^{source} and sinks Φ^{sink} using the thermal balance model (Eq. 15) across the affected region. The Cumulative Failure Probability (CFP) for each transmission corridor during a wildfire event is derived from the spatiotemporal fragility model.

B. Incorporating Environmental Characteristics

Environmental data layers, such as Annual Probability of Wildfire Ignition, Flame Length, and Canopy Bulk Density, are collected and integrated to assess their intersection with power lines. The region of interest is divided into equal cells with a specified resolution (here, that is 2 km), as shown in Fig. 3. These non-utility data layers are scaled and aggregated

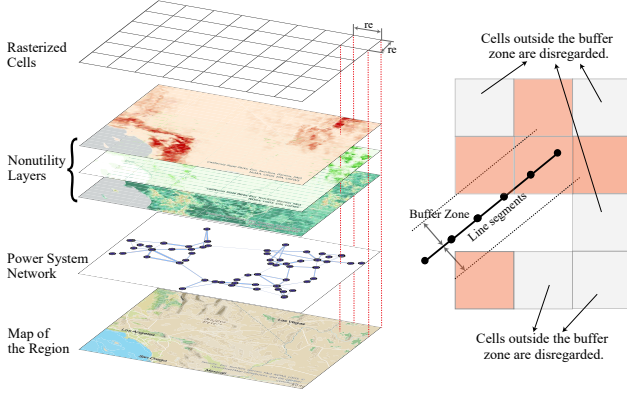


Fig. 3. Integration layers of environmental characteristics with the power grid and landscape.

to match the rasterized map of the region, with each cell represented by its central point.

A buffer zone is defined to identify cells that could potentially affect transmission lines if a wildfire ignites within them, excluding cells outside this zone from the analysis. This ensures that only relevant areas are considered when evaluating the impact of wildfires on power transmission networks, as illustrated in the accompanying figure.

C. IISE Method

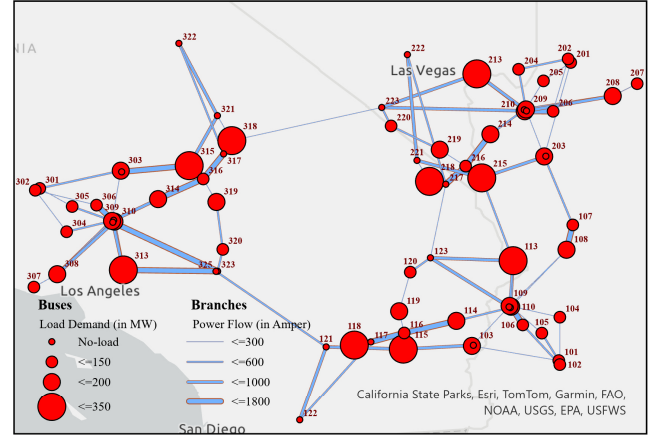
To optimize computational efficiency and accuracy in resilience assessment, the IISE Method [28] is employed. This method evaluates system resilience indices by iterating through failure scenarios and considering the impact of transmission corridor failures under wildfire conditions:

$$R^{\text{sys}} = \sum_{\omega=1}^{N^{\text{wf}}} P_{\omega}^{\text{wf}} \sum_{j=1}^J \sum_{s \in \Omega_j^A} \left(\prod_{m \in s} p_{\omega,m} \right) \Delta I_{\omega,s}. \quad (37)$$

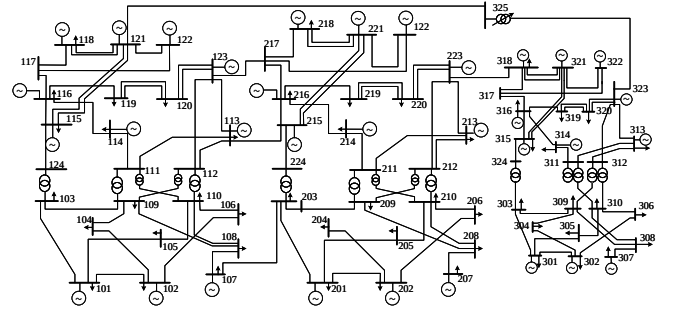
Here, Ω_j^A represents the j -th order subset A, s denotes a failure scenario involving a set of transmission corridor failures, J is the default order of enumerated failure scenarios, $p_{\omega,m}$ is the corridor failure probability under wildfire ω (obtained using the proposed spatiotemporal fragility model), and $\Delta I_{\omega,s}$ denotes the impact increment due to load shedding in scenario s under wildfire ω , as per the methodology in [33]. The impact of transmission corridor cuts is determined through contingency analysis proposed in [32], which involves calculating line flows and bus voltages following one or more component failures and identifying any overloading, voltage violation, isolated bus, or split island. AC power flow is employed in this work.

Similarly, component resilience indices (Eq. 38) are calculated to assess the resilience of individual transmission corridors:

$$R_m^{\text{corr}} = \sum_{\omega=1}^{N^{\text{wf}}} P_{\omega}^{\text{wf}} \sum_{j=1}^J \left[p_{\omega,m} \sum_{\substack{s_m \in \Omega_j^A \\ m \in s_m}} \left(\prod_{m \in s_m} p_{\omega,m} \right) \Delta I_{\omega,s_m} \right], \quad (38)$$



(a)



(b)

Fig. 4. (a) The network layout of the RTS-GMLC attached on the geographic map of three regions (southern California, Nevada, and Arizona) with steady-state Power Flow through each corridor/power line demonstration (generated using ArcGIS Pro [43]), (b) The schematic diagram for RTS-GMLC.

The results from this assessment inform targeted resilience enhancement measures, such as adding redundant transmission routes or reinforcing vulnerable corridors with more robust materials.

VII. NUMERICAL RESULTS

To validate the proposed framework, the RTS-GMLC system [41], an updated version of the RTS-96 system [42], was used. It has 73 buses across Southern California, Nevada, and Arizona, covering approximately 402 x 402 km, see Fig. 4a. This figure also provides details on load demand per bus, power flow across the branches, and the system's schematic diagrams. The RTS-GMLC includes 120 branches, with circuit lengths of 1128 km for 138 kV and 2125 km for 230 kV, as well as 16 transformers with a total rating capacity of 6400 MVA. The system's total load capacity is 2850 MW. Further details can be found in [41].

In this analysis, only transmission line damage is considered, with transformers assigned a risk value of zero. Transmission towers are assumed to be spaced every 50 meters, effectively dividing the lines into 50-meter segments. The cell resolution is set at 2 km. According to [44], the locations of all line segments and towers can be estimated. Historical weather data, including wind speed, direction, and ambient temperature, are sourced from the National Centers for Environmental Information [45]. Additional data on weather, conductors, and

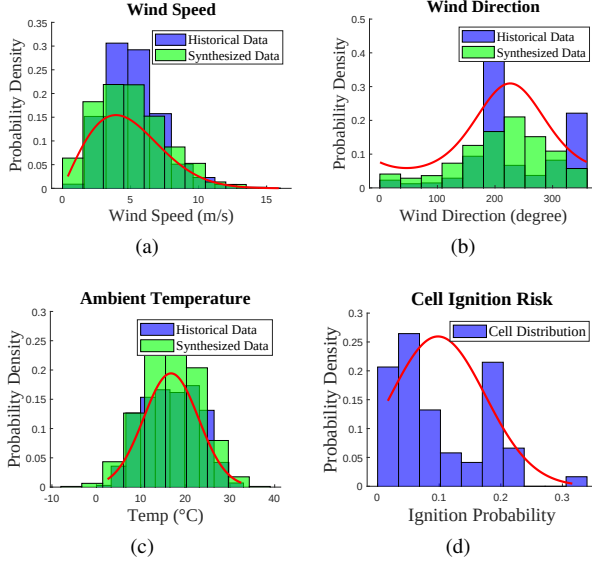


Fig. 5. (a) Wind speed distribution fitted to the Rayleigh distribution, (b) Wind direction represented with a Von Mises distribution fit (c) Ambient temperature distribution fitted to a Normal distribution, (d) Spatial distribution of wildfire ignition probability across the study area

wildfire front properties are provided in [13], [15], [36], [37], with conductors assumed to be aluminum conductor steel reinforced (ACSR) [13]. Flame length (in meters) and canopy bulk density (in kg/m^3) are obtained from the LANDFIRE Project [46], while the annual wildfire likelihood for the region is derived from [40].

Using historical weather data, the probability density functions (PDFs) for key parameters are generated, as shown in Fig. 5. These PDFs, which include wind speed, direction, and ambient temperature, are verified against synthetically generated data. The red line in Fig. 5 represents the fitted distribution based on actual historical data, which closely aligns with the assumed distribution.

The probability of wildfire ignition does not adhere to a specific distribution. Instead, wildfire likelihood is mapped to cells, with probabilities scaled to a range between 0 and 1 to define bands for ignition probability. These bands classify cells, which are then used in the Combinatorial Enumeration Method. By dividing the PDF of each key parameter into ten equal portions and defining ten equal bands for ignition probability, approximately 8000 wildfire scenarios, each with its associated probability, are generated. Each unique combination of key parameters results in a distinct wildfire scenario.

The simulation is conducted over a 72-hour period, with a time step of 30 minutes. It is assumed that affected lines will remain out of service for the entire duration. The numerical analysis is performed using MATLAB R2021a on a standard PC equipped with a 2nd Gen Intel Core i9-12900KF 3.19 GHz processor and 128 GB RAM.

A. Spatial-Temporal Impact of Wildfire on Transmission Corridor

This subsection illustrates the importance of spatial-temporal wildfire characteristics and their effects on transmis-

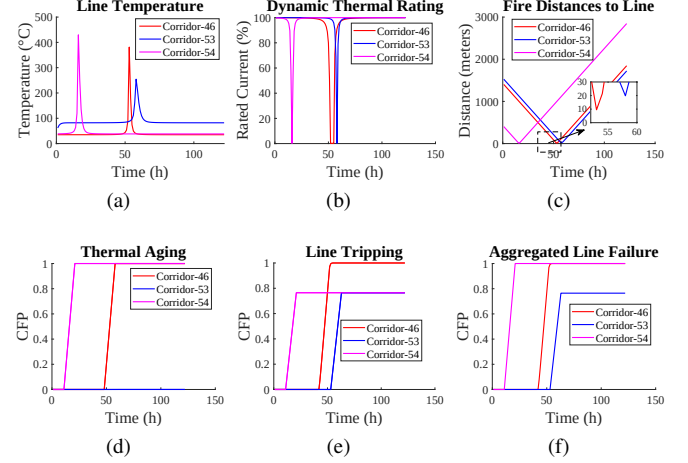


Fig. 6. Analysis of the spatio-temporal fragility model in a specific wildfire scenario. (a) Line temperature distribution; (b) Dynamic thermal rating of conductors; (c) Distances to fire sources; (d) Cumulative failure probability (CFP) due to thermal aging; (e) CFP for line tripping; (f) Aggregated CFP. Corridor-46 (bus 202 to 206), Corridor-53 (bus 208 to 209), and Corridor-54 (bus 208 to 210).

sion line fragility. We begin by assessing resilience under a single wildfire scenario, where a wildfire ignites at coordinates 35.8335° N , $-113.8726^\circ \text{ E}$. This location is approximately 400 meters from branch 54 and 1500 meters from branch 53-54. The initial flame length and bulk density are chosen based on the specific cell where the wildfire occurs, and the wildfire spreads in a south-to-north direction with an average wind speed of 5 m/s.

Fig. 6(a)–(c) show how the line segment most affected by the wildfire is impacted as it approaches. These figures present the conductor failure probability (CFP) for the corridors in Fig. 6(d)–(f). As the wildfire moves through the system, the temperatures of the corridors fluctuate. In Corridor-54, for example, the conductor temperature steadily increases, peaking at approximately 400° C as the wildfire center nears, resulting in a 98% reduction in conductor capacity. As the wildfire moves farther away, the distance increases, allowing the conductor's ampacity to recover.

Fig. 6(d)–(f) illustrate the cumulative failure probabilities (CFP) for the affected corridors over time. As the wildfire approaches Corridor-54, the rising temperatures cause cumulative tensile strength loss to reach a critical threshold, leading to transmission line failure when the thermal aging probability equals 1 (Fig. 6(d)). Simultaneously, the CFP due to line tripping approaches approximately 0.78. The aggregated failure probability, which includes both thermal aging and line tripping effects, is displayed in Fig. 6(f).

B. Traditional Resilience Assessment Under Comprehensive Wildfire Risk

Traditional resilience assessments often focus on comprehensive wildfire risk, which includes several key factors to varying extents [5]: (i) the probability of ignition, (ii) the likelihood that an ignition will escalate into a wildfire, (iii) the size and intensity of the resulting wildfire, and (iv) the

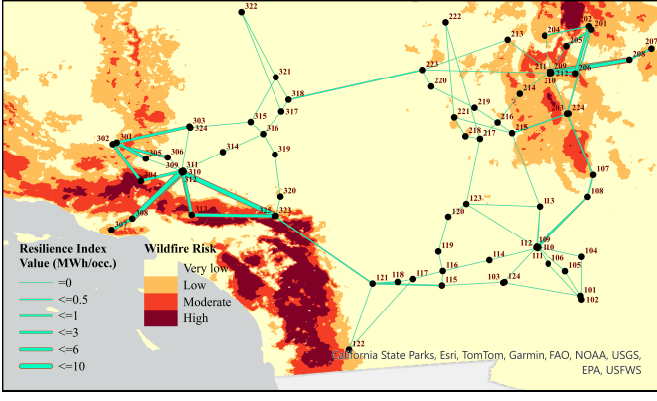


Fig. 7. Resilience assessment under comprehensive wildfire risk.

potential damage caused. Recent studies have adjusted these risk factors to consider the threats posed by electric grid infrastructure, with the goal of reducing ignition risks from these components [5], [8].

In this study, we define aggregated wildfire risk along transmission corridors[7]. By integrating geographical data from annual wildfire likelihood maps with the specific paths of these corridors, we calculate a cumulative risk metric normalized by corridor length as follows:

$$WR_m = \frac{1}{L_m} \int_0^{L_m} wr(x) dx \approx \frac{1}{L_m} \sum_{i=1}^{N_m^{\text{line}}} wr_i \cdot l_i \quad (39)$$

where WR_m represents the aggregated wildfire risk for corridor m , $wr(x)$ denotes the wildfire risk (ignition probability) at point x along the corridor, L_m is the total length of corridor m , N_m^{line} is the number of line segments along the corridor, wr_i is the wildfire risk at the i -th segment, and l_i is the length of the i -th segment.

By calculating the cumulative failure probability of the corridors using the derived equation, we generate a corresponding set of failure scenarios for resilience assessment. For illustration, we default to an order of three enumerated failure scenarios. A component-level evaluation is performed to identify corridors most susceptible to wildfire impacts. The cumulative failure probability for each corridor, along with the impact increment of each scenario, enables us to directly derive the component resilience indices without additional optimal power flow calculations.

The results, including only the seven most vulnerable corridors, are presented in Table I and illustrated in Fig. 7. This figure provides a comprehensive perspective on how the resilience indices related to the wildfire risk, as visualized on the raster map. Vulnerable corridors are highlighted based on their width; wider lines indicate greater fragility. Notably, Corridor-92 has the highest resilience index, suggesting that its failure would result in the most severe consequences under wildfire conditions.

TABLE I
OBTAINED RESILIENCY INDICES UNDER COMPREHENSIVE WILDFIRE RISK.

Resiliency Indices	Result (MWh/occ.)
R_{92}^{corr} (Bus 308 to 310)	9.6711
R_{91}^{corr} (Bus 308 to 309)	7.1957
R_{53}^{corr} (Bus 208 to 209)	7.0352
R_{100}^{corr} (Bus 312 to 323)	6.8903
R_{54}^{corr} (Bus 208 to 210)	5.8076
R_{101}^{corr} (Bus 313 to 323)	4.8325
R_{99}^{corr} (Bus 312 to 313)	3.8806

C. Resilience Assessment Under All Potential Wildfire Scenarios

Resilience indices were calculated across 8,000 potential wildfire scenarios by iteratively applying the proposed method to each generated scenario. The overall system resilience index results are presented in Table II and visualized in Figure 8. Throughout the process, the proposed component resilience indices, wildfire occurrence probabilities, cumulative failure probabilities for each transmission corridor, and impact increments for each failure scenario were determined.

Table II details the component resilience indices, focusing on the seven most vulnerable corridors. The data clearly indicates that Corridor-101 is the most susceptible to wildfire events followed by Corridor-90. In particular, Corridor-101 contributes about half of the system resilience index, dominating other corridors. The Corridor-190 and Corridor-153 have similar resilience indices. Fig. 8 visualizes the risks of different transmission lines from spatial perspectives. This allows the planners and operators to quickly locate the geographic locations of the assets for better preparedness and response. In summary, the ranked resilience indices show the vulnerabilities of each corridor and provide critical insights for developing strategies to enhance the system's resilience against wildfires.

D. Comparison Results with Traditional Approach

Traditional resilience assessments often do not account for the full range of potential wildfire scenarios and their spatio-temporal characteristics. Our proposed method addresses these limitations by incorporating these variables within a probabilistic and dynamic framework. Traditional approaches may overlook critical risk factors, leading to an underestimation of risks and insufficient preparedness for extreme wildfire events.

Fig. 9 compares the component resilience indices for critical corridors derived from both traditional and proposed methods, revealing notable discrepancies. For instance, Corridors-91 and -92, identified as the most vulnerable corridor by traditional methods, are ranked among the least vulnerable in our approach. Similar inconsistencies are observed for Corridors-90 and -101. Moreover, while traditional methods indicate that Corridor-53 is more vulnerable than Corridor-54, our proposed method shows nearly identical resilience indices for both.

These findings highlight the advantages of our approach, which captures a broader spectrum of potential risks, thereby

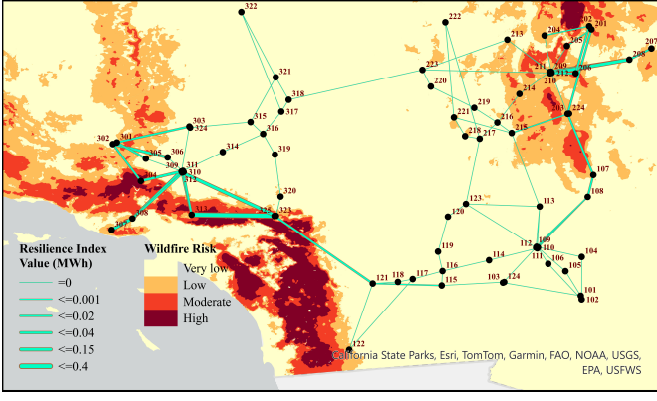


Fig. 8. Resilience assessment under all potential wildfire scenarios.

TABLE II
OBTAINED RESILIENCY INDICES UNDER ALL POTENTIAL WILDFIRE SCENARIOS.

Resiliency Indices	Result (MWh)
R_{sys}^{sys}	0.1538
R_{101}^{corr} (Bus 313 to 323)	0.0876
R_{90}^{corr} (Bus 307 to 308)	0.0361
R_{53}^{corr} (Bus 208 to 209)	0.0355
R_{84}^{corr} (Bus 302 to 306)	0.0273
R_{54}^{corr} (Bus 208 to 210)	0.0233
R_{87}^{corr} (Bus 304 to 309)	0.0180
R_{99}^{corr} (Bus 312 to 313)	0.0168

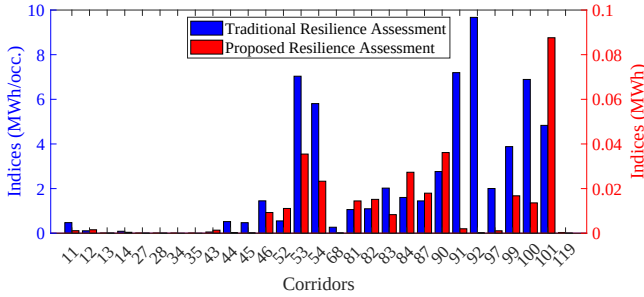


Fig. 9. Comparison of Traditional vs. Proposed Resilience Assessments.

providing a more robust and comprehensive resilience assessment.

VIII. CONCLUSION

This paper introduces a probabilistic resilience-oriented assessment approach to evaluate the resilience of power transmission networks against wildfires. Traditional methods often fail to capture the full range of wildfire scenarios and their spatio-temporal dynamics. Our approach addresses these gaps by incorporating these variables into a dynamic probabilistic framework.

Analyzing 8,000 wildfire scenarios, the proposed method reveals significant differences in vulnerability rankings of transmission corridors compared to traditional assessments. For instance, Corridor-92, previously considered highly vulnerable, is shown to be less susceptible, while Corridor-101 is identified as more critical.

The results highlight the importance of adopting a probabilistic, scenario-based approach for resilience assessments, especially as wildfire risks increase due to climate change. This method provides a more comprehensive evaluation, aiding in the development of strategies to enhance power system resilience. Future research could expand this approach to other natural hazards, further strengthening resilience assessments.

The methodology not only offers a more accurate depiction of transmission network resilience but also serves as a valuable tool for utility operators, policymakers, and researchers in mitigating wildfire impacts on critical infrastructure.

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