

Integrated Wildfire Impact Modeling on Urban-Suburban Distribution System Resilience

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Abstract—Wildfires pose increasing threats to modern power distribution systems through direct infrastructure damage and cascading effects, such as solar generation reduction and affected electric vehicle (EV) charging patterns during mass evacuations. This paper develops an integrated wildfire impact modeling framework that couples fire propagation simulation, aerodynamic-based smoke dispersion modeling, stochastic EV charging behavior during evacuation from wildfire, and power flow analysis to comprehensively assess distribution system resilience under compound wildfire stresses. The presented case study examines California’s Sonoma County electric power distribution system with high photovoltaic (PV) penetration and high EV adoption. The results show that fire damage can significantly influence the distribution system resiliency. Smoke-induced PV generation reductions and evacuation-related charging surges are also substantial contributors to system stress. The integrated modeling approach reveals compound stress patterns and critical vulnerability, enabling utilities to conduct comprehensive resilience assessments and develop coordinated infrastructure hardening and emergency response strategies for distribution systems serving urban-suburban communities.

Index Terms—Wildfire impact assessment, distribution system resilience, smoke dispersion modeling, electric vehicle evacuation

I. INTRODUCTION

Wildfires are increasingly threatening power distribution infrastructure across the western United States, with the frequency of large fires in California alone increasing fivefold since the 1970s and annual burned acreage exceeding 2 million acres in recent years [1]. The 2017 Tubbs Fire extensively damaged power distribution infrastructure serving Santa Rosa with reconstruction costs exceeding \$1 billion and around 100,000 people were evacuated during this wildfire [2]. Grid vulnerability is amplified by the continued expansion of the wildland-urban interface, where millions of homes now sit within high or very high wildfire hazard zones, exposing both communities and the electrical infrastructure serving them to direct risk. Modern power distribution systems, with high penetration of photovoltaic (PV) and increased adoption of electric vehicles (EV), face several concurrent threats from wildfires. First, the fire may directly damage the power distribution equipment, causing outages. Second, wildfire-induced evacuation of a large population of electric vehicles may result in a surge of charging activity that overwhelms the capacity of the local distribution grid. Finally, distributed generation, such as rooftop PV systems will

be impacted by smoke, greatly reducing the effectiveness of a potential tool for mitigating impacts from the surge in EV charging. These compounding stresses reach far beyond the electric power infrastructure, generating broad economic and social consequences, including critical facility outages and impaired evacuation logistics due to charging infrastructure failures [3], and voltage problems [4], [5]. For utilities to effectively select equipment for hardening and plan for the strain of a large-scale wildfire evacuation, a holistic modeling framework, capturing the full spectrum of direct and indirect grid impacts, is needed.

Existing research on wildfire impacts on power systems has primarily focused on transmission-level infrastructure vulnerability and direct physical damage assessment. Recent work has begun incorporating probabilistic damage models that account for heat flux intensity and exposure duration [6], yet these studies remain confined to assessing infrastructure loss without considering operational impacts on modern distribution systems. Critically, existing frameworks fail to capture the cascading effects of wildfires on converter-based resources and dynamic load patterns at the grid edge, treating the power system as a static network rather than an active system with intermittent generation sources, and time-varying demands that react to emergency conditions.

Smoke matter from wildfire significantly reduces irradiance through light scattering and absorption, with PM2.5 concentrations typical of wildfire smoke events causing 20-40% generation losses from PV systems [4]. This is a substantial reduction, especially in locations with significant rooftop PV generations, where such reductions may have a significant impact on power flow and voltage. Prior studies of EV charging behavior during emergencies have examined hurricane evacuations and planned power outages. These studies identified charging infrastructure availability, and state-of-charge at departure as critical factors influencing evacuation decisions [7], [8]. Several studies examine solar PV degradation and EV behavior as independent phenomena without integrating them into comprehensive wildfire impact frameworks [1], [9], [10]. No existing work couples real-time smoke dispersion modeling with spatially-resolved PV generation analysis or links stochastic evacuation charging demands to power flow constraints during active wildfire events [11]. Without such a holistic framework, critical gaps in our understanding of these simultaneous stress mechanisms and distribution system vulnerabilities remain.

This paper addresses these gaps by developing a holistic wildfire impact modeling framework. Beyond simple integration, this approach captures the non-linear coupling between fire propagation, atmospheric smoke dispersion, stochastic electric vehicle evacuation, and distribution system power flow. By modeling these interdependent layers simultaneously, the framework uncovers compounding stress of smoke-induced PV curtailment during peak evacuation charging that isolated models inevitably miss. The primary contributions include:

This work is supported by the US Department of Energy Office of Cybersecurity, Energy Security, and Emergency Response. (Email: junbo.zhao@dartmouth.edu) This article has been authored by an employee of National Technology & Engineering Solutions of Sandia, LLC under Contract No. DE-NA0003525 with the U.S. Department of Energy (DOE). The employee owns all right, title and interest in and to the article and is solely responsible for its contents. The United States Government retains and the publisher, by accepting the article for publication, acknowledges that the United States Government retains a non-exclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this article or allow others to do so, for United States Government purposes. The DOE will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan <https://www.energy.gov/downloads/doe-public-access-plan>. 979-8-3315-8138-1

- A unified framework that synchronizes Hybrid Single Particle Lagrangian Integrated Trajectory Model (HYSPLIT)-based smoke transport modeling [12] with fire perimeter evolution and network operational analysis that captures temporal correlations between physical wildfire phenomena and power distribution system stress;
- A probabilistic grid infrastructure damage model incorporating time-dependent failure rates based on thermal exposure duration from fire;
- An empirical smoke-to-PV model that spatially maps PM2.5 concentrations to PV generation curtailment across different locations and a stochastic EV evacuation charging model that distributes charging demand based on distance-dependent departure timing and battery state-of-charge requirements.

The framework is demonstrated in a large-scale case study in Sonoma County and the results demonstrate that, although direct fire destruction remains the dominant impact factor, indirect effects from smoke-induced solar reduction and evacuation charging become increasingly influential under high PV penetration scenarios, with compound effects extending service restoration times beyond predictions from fire-damage-only analysis.

II. INTEGRATED WILDFIRE IMPACT EVALUATION FRAMEWORK

A. Framework Workflow

The proposed integrated wildfire impact modeling framework consists of three layers, as illustrated in Fig. 1. (1) The integrated database layer incorporating GIS/parcel data, historical meteorology, and power distribution system information; (2) The center controlled, parallel running simulation engine comprising fire propagation, smoke dispersion using HYSPLIT, and EV evacuation modeling; (3) The power system analysis module that performs iterative power flow calculations accounting for topology changes, PV output reduction, and load profile updates to generate comprehensive impact assessment reports. The framework operates as a discrete-time simulation, capturing wildfire evolution and its cascading effects on distribution system operation at each time step.

The integrated database is built from three publicly available data sources. GIS and parcel data provide high-resolution spatial information on infrastructure locations, vegetation types, fuel loads, and traffic system, enabling precise geolocation of electrical assets relative to fire propagation paths. Historical meteorological data, including wind speed and direction, temperature, humidity, and atmospheric stability conditions, are processed to establish realistic fire weather scenarios and inform both fire spread dynamics and smoke transport patterns [13]. The power distribution system database encompasses network topology, line parameters, transformer ratings, substation configurations, distributed PV installation locations and capacities [14], EV registration statistics, all spatially coupled to enable impact assessment and analysis.

At each simulation time step, as the right box in Fig. 1 shows, the fire propagation module determines the advancing fire perimeter and identifies infrastructure elements at risk, the HYSPLIT-based smoke dispersion module calculates spatial concentration fields that quantify atmospheric transmission reduction affecting solar generation, and the EV evacuation module estimates departure patterns and charging demand distributions based on fire threat proximity. These parallel simulation outputs are synchronized by the central controller and fed into the power system analysis module. This simulates the physical damage, smoke-induced PV degradation, and evacuation-driven charging in the electrical system through

power flow calculations that reveal voltage violations, thermal overloads, and service interruptions. Thus, the impact of all three factors is finally integrated via the grid model, enabling the holistic analysis of effects due to fire damage, generation loss, and demand surge.

B. Wildfire Propagation and Element Damaging Model

The wildfire propagation model is built using the FlamMap tool [15] developed by the US Forest Service. This fire behavior simulation tool utilizes the landscape data, fuel moisture, canopy characteristics, ignition location and fire perimeter as inputs to provide a hypothetical fire propagation model. The outputs of this model include fire arrival time and fire spread rate through the landscape. To provide a realistic large fire perimeter relevant to the given area, Remote Automated Weather Stations (RAWS) data of the last decade from the nearest weather stations were used to obtain the fuel moisture content, and generate the static burn probability and associated fire perimeters by running thousands of large fire simulations.

Fire spread is mapped to grid equipment damage by assessing the failure risk of distribution system components based on their spatial location relative to fire-affected zones and exposure duration. For component i (distribution line, transformer, or substation equipment) that falls within a fire-impacted geographical region, the time-dependent failure probability at time t is modeled as:

$$p_i^{\text{fail}}(t) = \begin{cases} 0 & t < t_i^{\text{expo}} \\ 1 - \exp(-\lambda_i(t_i^{\text{expo}} - t)) & t_i^{\text{expo}} \leq t < t_i^{\text{expo}} + \delta^{\text{expo}} \\ 0 & t_i^{\text{expo}} + \delta^{\text{expo}} \leq t \end{cases} \quad (1)$$

where t_i^{expo} represents the time step when component i first enters the fire perimeter, and λ_i is the component-specific damage rate parameter (in units of hour^{-1}), which characterizes thermal vulnerability based on equipment type, construction materials, and hardening level. δ^{expo} represents the time period of which grid components exposed in fire burning. The damage rate λ_i varies significantly across component categories, such as overhead wooden pole lines, which could suffer rapid failure with $\lambda \in [0.5, 1.0]\text{h}^{-1}$, and transformers, which are assigned $\lambda \in [0.2, 0.4]\text{h}^{-1}$ [16].

At each simulation time step, the fire propagation model is used to identify elements that are exposed to the fire and the element damage model determines failure probability for all exposed components. During this step, for effected element, a random variable is drawn from a uniform distribution $U[0, 1]$. If the failure probability p_i^{fail} exceeds u as 1, the equipment is flagged as “damaged” and transitions to a failed state.

C. Smoke Dispersion and PV Output Reduction Model

The smoke dispersion simulation employs the HYSPLIT model, a widely-validated atmospheric transport and dispersion model developed by National Oceanic and Atmospheric Administration (NOAA)’s Air Resources Laboratory [12]. HYSPLIT simulates the advection and diffusion of smoke particulates emitted from active wildfire zones by tracking the trajectories of computational particles released from fire emission sources. The model integrates meteorological data from the NOAA High-Resolution Rapid Refresh (HRRR) dataset [13], which provides hourly atmospheric conditions including three-dimensional wind fields, temperature profiles, humidity, and planetary boundary layer height at 3 km spatial resolution.

At each simulation timestep, HYSPLIT calculates the spatial distribution of smoke particulate matter concentration (PM2.5)

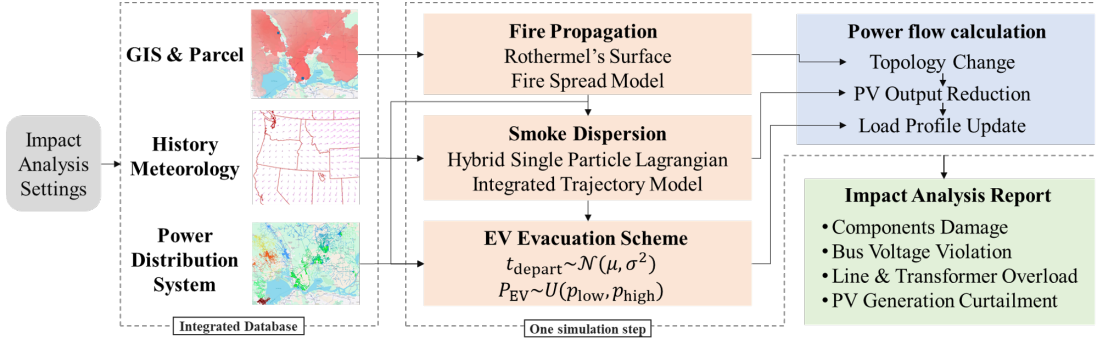


Fig. 1: Proposed integrated wildfire impact modeling on urban-suburban distribution systems.

across the region by solving the advection-diffusion equation under wind and atmospheric conditions [17]. Fire emission rates are estimated from the burned area growth rate provided by the fire propagation simulation, combined with fuel consumption factors and emission factors specific to the vegetation types obtained from GIS data. The resulting PM2.5 concentration can be obtained for at each small region.

The reduction in photovoltaic power output due to smoke-induced solar irradiance attenuation is quantified using an empirical relationship between atmospheric particulate concentration and solar transmissivity based on established research on aerosol impacts on PV performance [18]. For PV i at time t , the smoke-affected power output is calculated as:

$$P_i^{\text{smoke}}(t) = P_i^{\text{clear}}(t) \cdot \tau(\text{PM2.5}_i(t)) \quad (2a)$$

$$\tau(\cdot) = \exp(-\beta \cdot \text{PM2.5}_i) \quad (2b)$$

where $P_i^{\text{clear}}(t)$ represents the PV output under clear-sky conditions power output calculated by original weather condition; $\tau(\cdot)$ is the atmospheric transmissivity factor accounting for smoke obscuration. $\text{PM2.5}_i(t)$ denotes the smoke particulate concentration (in $\mu\text{g}/\text{m}^3$) from HYSPLIT dispersion results. β is the extinction coefficient (in $\text{m}^3/\mu\text{g}$) characterizing how smoke particles effect solar radiation based on Beer-Lambert law, that higher smoke concentrations exponentially reduce of solar irradiance. β is calibrated using historical data from wildfire regions where co-located PM2.5 measurements and PV generation records are available, accounting for the wavelength-dependent absorption characteristics of smoke particles and the spectral response of PV cells [19].

D. Wildfire-Driven EV Evacuation Scheme

The EV evacuation model quantifies the spatiotemporal charging demand resulting from population displacement during wildfire events. The number of evacuating EVs in each affected zone is estimated from census data on population and vehicle registration, multiplied by a predetermined EV adoption ratio reflective of regional market penetration, normally choose from [0.3, 0.4].

The temporal characteristics of EV evacuation model is build by vehicle owner departure model [20]:

$$t_i^{\text{start}} = t_i^{\text{ign}} + \frac{d_i}{v_{\text{avg}}} \quad (3)$$

where t_i^{ign} represents the ignition time of the fire. d_i is the distance from the vehicle's origin to the ignition point, and v_{avg} is the average fire spread speed [21].

Vehicle departure time is determined by the energy it needs. Each EV is assigned an initial state of charge ($\text{SOC}^{\text{initial}}$) randomly sampled from a uniform distribution $\mathcal{U}$ to represent realistic pre-evacuation battery levels, as drivers typically do not maintain full charge during normal operation. SOC^{tgt} for evacuation charging target is set to be 80% efficient range to reach safe zones beyond

the fire threat area based on emergency charging behavior studies [3], [5]. Then each EV's charging energy is:

$$E_i^{\text{chg}} = (\text{SOC}_i^{\text{tgt}} - \text{SOC}_i^{\text{initial}}) \cdot C_i \quad (4)$$

where C_i is the vehicle battery capacity.

Finally, to model charging behavior, the total charging power demand P^{chg} is set to level II charger only, then energy needed for each EV is uniformly distributed, so the vehicle stopped charging time t_i^{end} can be obtained:

$$t_i^{\text{end}} = t_i^{\text{start}} + \frac{E_i^{\text{chg}}}{P^{\text{chg}}} \quad (5)$$

This EV charging load is then added to the power distribution load profile by modifying the loadshape of the closest load to the driver's starting position.

III. CASE STUDY

A. Case Settings: Sonoma County, CA

Sonoma County was selected as the case study location due to its severe wildfire vulnerability and history of catastrophic fire events that caused extensive damage to electrical distribution infrastructure and communities. The region has experienced two particularly devastating wildfires in recent years. The 2017 Tubbs Fire burned 36,807 acres, destroyed 5,643 structures, and resulted in 22 fatalities [2].

Based on the state of California Division of Motor Vehicles and local government statistics data of [22]–[24], we assume there are around 11,463 EVs registered in Sonoma County. EV charging behavior parameters are selected such that $\text{SOC}_i^{\text{initial}} \in \mathcal{U}[30, 60]$, and $P^{\text{chg}} = 7.5 \text{ kW}$. The wildfire simulation scenario is configured based on historical fire weather conditions and ignition patterns of Sonoma County, which if extracted from the 2017 Tubbs Fire [2].

The power distribution networks for both case studies are extracted from the Smart-DS dataset developed by NREL [14], which provides realistic distribution system models based on actual utility data. Case 1 encompasses five regions, including P1R, P7U, P8U, P11U, and P12U, totaling 167,538 distribution line segments and 190,701 buses spanning urban, suburban, and rural areas. Case 2 focuses on a more concentrated two-region system comprising P1R and P5U sub-regions, with 230,113 line segments and 258,371 buses, representing a denser urban-suburban interface with higher infrastructure and population exposure. The networks include detailed medium-voltage and low-voltage systems, substation connections, and PV installations.

Both wildfire scenarios are configured to replicate extreme fire conditions similar to historical Tubbs fire event. In Case 1, the fire ignites at the geographic center of sub-region P8U and propagates to the southwest, driven by prevailing winds, with smoke dispersion following the same directional pattern to affect downstream sub-regions; the fire threat triggers evacuations in P12U, creating

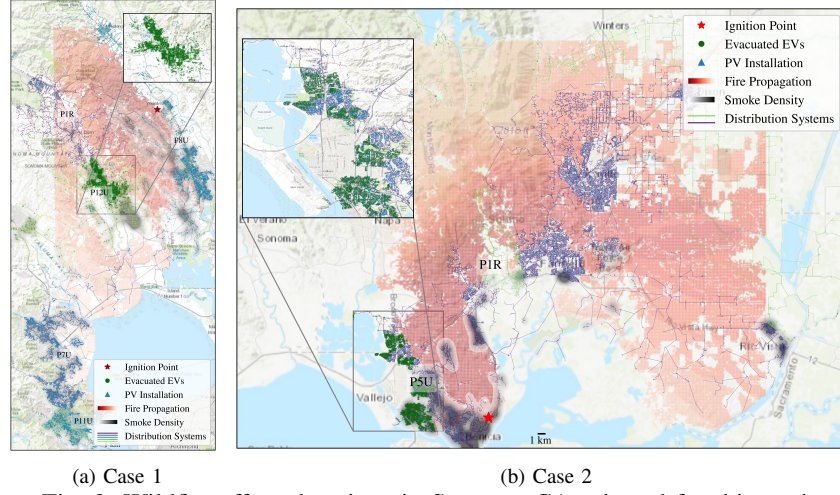


Fig. 2: Wildfire-affected regions in Sonoma, CA selected for this study.

an electric vehicle charging pattern based on distance-dependent departure timing.

Case 2 features ignition at the southern border of sub-region P5U, where geographic boundaries and terrain features constrain fire spread to the northeast, while smoke plumes continue to disperse southwestward due to wind patterns, creating spatial separation between direct fire-damage zones and areas experiencing smoke-induced solar generation degradation. Meteorological inputs for both cases are derived from NOAA HRRR model data at 1-hour temporal resolution, simulating atmospheric conditions of the initial hours of the 2017 Tubbs Fire that drove rapid fire spread and extensive infrastructure damage. The fire propagation and smoke dispersion simulation results are shown in Fig. 2.

B. Results Analysis

Fig. 3 presents the temporal evolution of voltage profiles across three representative sub-regions over a 24-hour simulation period. Sub-region P8U experiences immediate voltage perturbations during the initial hours due to its direct exposure to fire damage, as the ignition point is positioned within this feeder's service territory. This causes rapid disconnection of distribution line segments and transformers as they enter the fire perimeter. The voltage stress is most pronounced at the 0.48 kV secondary distribution level, where loss of upstream supply paths forces load transfer to adjacent feeders operating near capacity limits and the network settles into a post-reconfiguration topology.

Sub-region P12U follows a different pattern, with significant voltage deviations occurring during the 10:00 AM - 03:00 PM window, corresponding to the peak evacuation period when residents respond to fire threat warnings. The sharp voltage drops before fire arrives are caused by EV charging demand within the evacuation zone, creating load surges and voltage drops. The fire damages are represented by time-stamped count of infrastructure effected events, where each bar indicates the number of distribution system components that were affected during that interval.

Sub-region P11U demonstrates the compound effects of smoke dispersion and evacuation behavior, with voltage degradation manifesting in two distinct phases. The voltage decline beginning around 11:00 AM corresponds to the smoke arrival that reduces the distributed PV generation. This generation deficit is compounded by simultaneous evacuation charging demand. The voltage profile illustrates how indirect smoke effects can create prolonged operational challenges well beyond the immediate fire threat period.

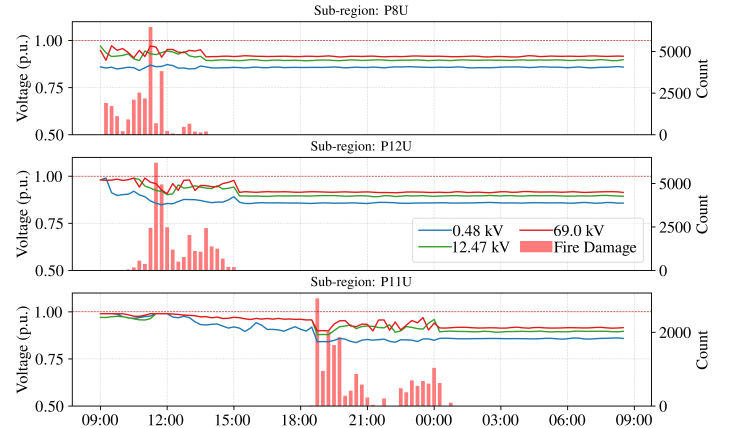


Fig. 3: Case 1: Voltage profile and element exposed to fire count.

To examine the spatiotemporal coupling between smoke dispersion dynamics and distributed PV generation degradation, we focus on sub-region P5U in Case 2, which experiences prolonged smoke exposure due to the southwestward plume trajectory following ignition at the P5U border. Fig. 4 illustrates the aggregate PV generation profile compared to smoke intensity, revealing a strong inverse correlation between particulate concentration and solar output. During the peak smoke period at afternoon, the aggregate PV generation experiences an instantaneous peak reduction of

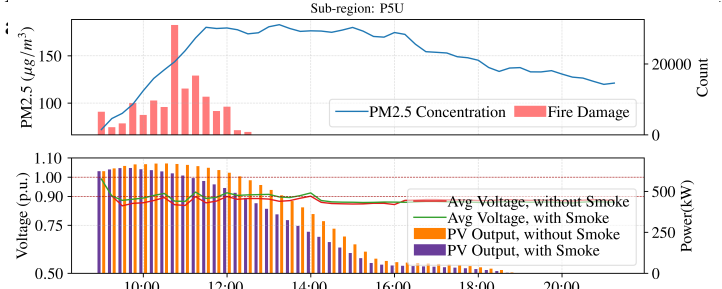


Fig. 4: Case 2: PV output reduction.

Table I summarizes the comprehensive impact metrics aggregated across all sub-regions for Case 2, quantifying the multi-dimensional effects of wildfire on distribution system operation. EV evacuation load impacts are quantified by aggregating stochastic charging demands across all evacuation zones, yielding a peak charging power of 4.3 MW and identifying 895 transformer overload instances. PV generation loss is assessed through the smoke dispersion model, with worst-case PM2.5 intensity reaching about $550 \text{ m}^3/\mu\text{g}$, causing maximum instantaneous power loss of 113 kW in a region as compared to a clear-sky baseline. Voltage

violations are evaluated from power flow results, showing that the post-fire voltage remains at a low level across affected buses, with the worst-case voltage at one bus lowered to 0.27 p.u.

TABLE I: Wildfire Impact Assessment Statistics for Fire 2

Impact Category	Metric	Value
Infrastructure Damage	Lines disconnected	3264 (14.8%)
	Transformers disconnected	271 (4.9%)
EV Evacuation Load	Peak charging power	4.3 MW
	Transformer overloaded	895
PV Generation Loss	Worst PM2.5 intensity	55%
	Max instant power loss	113 kW
Voltage Violations	Aftermath voltage range	0.83-0.9 p.u.
	Worst voltage	0.27 p.u.
Economic Losses	Infrastructure replacement	\$12.4 M
	Unserved energy cost	\$3.8 M
	Lost PV generation revenue	\$2.1 M
	Total direct losses	\$18.3 M

Infrastructure damage metrics are calculated by tracking component failure events from the probabilistic thermal exposure model. Economic impact assessment is calculated based on the model shown in [25]–[27], showing an estimated \$12.4 million in infrastructure replacement costs based on the standard utility equipment pricing, \$3.8 million in unserved energy costs calculated at \$5,000/MWh for residential load and \$10,000/MWh for commercial/industrial load integrated over outage durations, and \$2.1 million in lost solar generation revenue valued at wholesale electricity rates. This yields a total direct economic loss of \$18.3 million for this wildfire event scenario.

IV. CONCLUSION

This paper presents an integrated wildfire impact modeling framework that comprehensively assesses the multi-dimensional effects of wildfires on urban-suburban distribution systems by coupling fire propagation, smoke dispersion, and EV evacuation dynamics with power system operational analysis. Results obtained from the large-scale Sonoma County distribution system reveal that while fire-induced infrastructure damage remains the dominant impact mechanism, indirect effects from smoke attenuation of distributed solar and concentrated evacuation charging significantly amplify system stress.

The integrated modeling demonstrates that the compound effects of these simultaneous stressors extend service restoration timelines and result in widespread voltage violations, a trend that conventional single-factor analyses fail to capture. These findings underscore that as distributed energy resource penetration increases in wildfire-prone regions, resilience assessment frameworks must account for the coupled dynamics of fire damage, generation loss, and demand surges to accurately predict system vulnerability and inform targeted preparedness strategies. Future research directions include integrating real-time fire prediction models for proactive network reconfiguration, incorporating vehicle-to-grid capabilities as mobile resilience resources during evacuations, and extending the framework to evaluate long-term infrastructure planning in high-fire risk areas across broader geographic regions. In the future work, a more detailed economic analysis will be adapted with comparison between real-world wildfire cost benchmarks.

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