CHAPTER SEVENTEEN

Grid resilience against wildfire with machine learning

Machine learning based detection, localization and mitigation of the impact of forest fires on power grids

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17.1 Introduction

Wildfires are global phenomena that pose a huge threat to our way of life (Fig. 17.1). With rising temperatures across the globe, towering infernos of seemingly apocalyptic proportions have been ravaging our forests. From the Amazon forest in Brazil to Canada and the United States in the American continents, to Greece and the UK in the European continent, and all the way to Australia, extreme wildfires are causing enormous economic and human losses and vastly damaging ecosystems. These impacts are felt not only in the immediate surroundings but for hundreds of miles. Smoke and ash travel long distances and cause orange skies and terrible air quality, like in Northern California in 2020 [1] and New York in 2023 [2], affecting humans and animals alike. Owing to global warming, fire seasons are becoming longer and starting earlier. Globally the length of the wildfire season had grown by nearly 19% between 1978 and 2013 [3]. The general trend over the years can be seen in Fig. 17.2.

In January 2017, a highly destructive series of wildfires destroyed more than 500,000 ha in Chile. In June 2020, the Brazilian National Institute for Space Research detected 103,000 wildfires in the Brazilian Amazon with an annual increase of 16%. In 2019, the economic damage of wildfires was estimated at circa US$3.5 trillion for the Brazilian economy [4].

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Fig. 17.1 Firefighter fighting a wildfire. *(Courtesy: Fabian Jones on Unsplash.)*

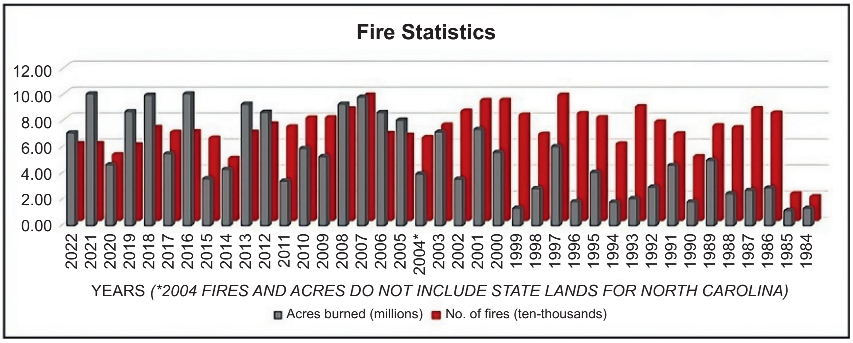

Fig. 17.2 Wildfires over the years.

The UK spends around £55m a year on fighting wildfires. Worldwide, an area equivalent to about 20 times the size of Great Britain is burnt by wildfires on average each year. By July 2018, the area burned in the UK that year was more than four times the average of the past decade [3]. In the United States, losses from the fires of 2018 in California are estimated at a record US$19 billion, making it the worst fire season in history. Of the 10 largest wildfires in California's history, eight have occurred since 2001 [5].

In the United States, 1289 large wildfires (fires that burn a minimum of 100 acres in timber fuel models or 300 acres in grass and brush fuel models, as defined by the National Mobilization Guide) were reported in 2022, which represented less than 2% of total wildfires reported nationally that year. There were 68,988 reported wildfires that consumed 7,577,183 acres in 2022 and 58,985 reported wildfires that consumed 7,125,643 acres in 2021 across the country (as shown in 1.3), which accounted for over $11.2 billion in damage [6,7] (Fig. 17.3).

Western United States, like the states of California, Nevada, and Arizona, face long stretches of arid climate with little rain, making them especially susceptible to wildfires. Statistics for the top 10 states for wildfires in 2021 have been provided in Table 17.1.

According to California's fire suppression agency, CalFire, prolonged periods of high temperatures and drought, record high winds and lightning storms, the significant buildup of dry fuel, and continued development in the wildland-urban interface are the main contributors to increasing the number of wildfires. Though a large number of wildfires are caused by nature, the majority of them have originated from human-related ignition sources such as arson, vehicles, outdoor activities, and transmission lines [9], as can be seen in Table 17.2.

As global temperatures continue to rise, it will have a significant impact on the frequency and intensity of catastrophic wildfires, creating a new norm that critical system operators will need to plan for. Proactive operational and investment planning against such disastrous and highly unpredictable events will require supporting and enabling policy and regulatory frameworks to incentivize operational and investment planning toward resilient infrastructure. Along with the physical impacts on critical infrastructure and the responses from network operators, planners, regulators, and policymakers, it is imperative to devise a set of prevention, mitigation, and adaptation measures aimed to hedge the risks of these wildfires.

According to the United Nations, artificial intelligence (AI)-based technologies, such as simulators, weather prediction models, autonomous systems, and the likes, will provide safer and efficient defenses against the exponential rise in the number of wildfires. The U.S. Forest Service is currently working toward using drone technology that can not only spot fires but also set controlled fires to barricade the spreading fire by cutting off its path to the vegetation that fuels it. The USDA Forest Service Missoula Fire Sciences Laboratory and the Colorado Division of Fire Prevention and Control use advanced visualization and virtual-world simulation platforms to forecast the progress of a wildfire, thereby helping governmental agencies ascertain where to direct resources to protect their citizens [10]. Integrating different types of robots along with drones into the firefighting plan can assist in transporting equipment, evacuating the wounded, as well as intervening

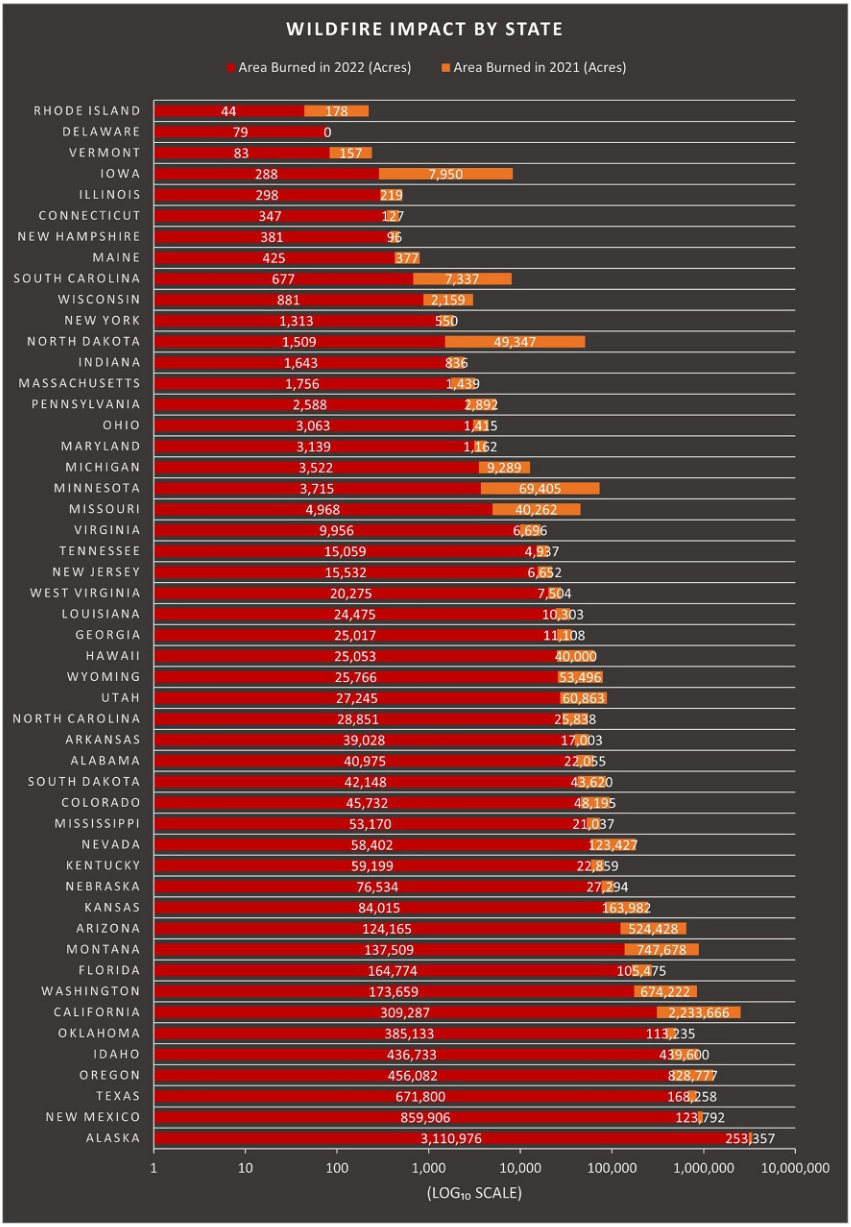

Fig. 17.3 Wildfires reported in the United States in 2021 and 2022.

close to the danger to protect their human counterparts. The LA Fire Department developed and implemented a drone program, integrated a firefighting robot, and purchased an electric fire engine since the devastating fires of 2020 [11].

Table 17.1 States ranked by number of fires and number of acres burned in 2021 [8].

Rank	State	No. of fires	Rank	State	Acres burned
1	California	9260	1	California	2,233,666
2	Texas	5576	2	Oregon	828,777
3	North Carolina	5151	3	Montana	747,678
4	Montana	2573	4	Washington	674,222
5	Florida	2262	5	Arizona	524,428
6	Oregon	2202	6	Idaho	439,600
7	Georgia	2139	7	Alaska	253,357
8	Minnesota	2065	8	Texas	168,258
9	Washington	1863	9	Kansas	163,982
10	Arizona	1773	10	New Mexico	123,792

Table 17.2 Top 10 most destructive California wildfires as of October 2022 [8].

Rank	Fire name	Cause	Date	Acres	Deaths
1	Camp Fire	Power lines	November 2018	153,336	85
2	Tubbs	Electrical	October 2017	36,807	22
3	Tunnel—Oakland Hills	Rekindle	October 1991	1600	25
4	Cedar	Human related	October 2003	273,246	15
5	North Complex	Lightning	August 2020	318,935	15
6	Valley	Electrical	September 2015	76,067	4
7	Witch	Power lines	October 2007	197,990	2
8	Woolsey	Electrical	November 2018	96,949	3
9	Carr	Human related	July 2018	229,651	8
10	Glass	Undetermined	September 2020	67,484	0

A real-time modeling and predictive analysis tool, known as WIFIRE, that uses live data from a public network of more than 1000 high-definition, pan-tilt-zoom cameras positioned across the state of California, and factors in dynamic changes in wind, moisture, terrain, and other constituents, was developed by scientists at the University of California, San Diego. It is part of Fire Integrated Real-Time Intelligence System (FIRIS), a public-private partnership in California that also uses an aerial infra-red platform for real-time information from an active wildfire, which sends a prescriptive analysis to frontline teams, as well as to a publicly accessible website called Firemap [12]. In Turkey, an interactive wildfire risk map was developed as part of a pilot program that leverages AI and machine learning (ML) algorithms on multiple data sources, including historical, meteorological, and geographical data, along with inputs from a global community of experts.

It was successfully implemented with an 80% accuracy rate in predicting wildfires 24 h before their outbreak [11,13].

By empowering detection specialists with enhanced visualization and rapid data analysis powered by AI, it will be possible to quickly identify and contain devastating wildfires, thereby protecting human lives, property, as well as wild animals and their habitats. This chapter focuses on the effect of fires on power networks, the mitigation plans developed by utilities to lessen the impact, and new AI-based techniques being developed by researchers for enhanced situational awareness and improved resiliency of the power grid.

17.2 Impact of wildfires on power systems

Critical infrastructures, like the power grid, are extremely vulnerable to wildfires. High-voltage lines influence wildfire risk by both causing them and being devastatingly affected by a passing wildfire, influencing risk to communities. Accidental wildfire ignitions caused by overhead lines involve an electrical fault resulting from a combination of wind and/or a foreign object (e.g., tree, wildlife, and so on) interacting with them. During high wind days with elevated temperatures, which cause lines to sag due to thermal expansion, if two conductors make contact, allowing current to flow between them, the power lines can be heated to the point of melting, and molten droplets of conductor material may then be ejected and ignite fine fuels if the conditions are conducive to a wildfire. Toppled trees or large broken branches can even break power lines, causing them to fall to the ground and ignite vegetation from the electrical discharge. Less forceful vegetation interactions, such as a tree leaning on a power line or a branch laying across conductors, may provide a path for electrical current to flow through and ignite the vegetation, thereby starting a fire. Another ignition method for wildfires is transformer oil fires and explosions, which are typically a consequence of electrical faults due to lightning, high wind, weather, or interactions with trees [14] (Fig. 17.4).

An increase in temperature does not affect every component associated with power grids, causing a decrease in efficiency. In case of natural-gas power plants, for every degree above 15°C, the nameplate capacity of open-cycle natural-gas-fired power plants decreases by 1.0% and that of

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The conventional multiperiod optimization method is based on perfect fire prediction by using a precalculated dataset, which is unrealistic but yields the best possible result, theoretically, given the fire impact on the power system.

17.5 Conclusion and future work

As climate change aids the increase in peak demands, while increasing the likelihood of wildfires, utility companies are being required to anticipate such changes and develop methods to harden the existing infrastructure and set up additional system capacity to offset this impact. Addressing wildfire risks requires enhanced designing, construction, operation, and maintenance of power systems, which enhances the safety of the system and makes it resilient during extreme events. These measures also improve fire agencies' ability to detect and accelerate response to emerging fires.

As wildfires combine complex meteorological scenarios, complicated topography, and complex fuel structures, their behavior is quite hard to predict and modeling becomes computationally challenging. Many research efforts have been conducted in order to monitor, predict, and prevent wildfires using AI techniques and strategies such as ML and remote sensing.

The testbed we developed by integrating a wildfire-propagation model with a power-system operation model was used to train and validate a DRL-based controller that can supplement traditional computationally intensive, forecast-driven power grid operations during wildfires. The proactive control agent was able to reduce the load loss and was also robust against different fire propagation scenarios. We plan to integrate state-of-the-art fire simulation models into our testbed with a more detailed proactive power control agent based on advanced DRL models for improved grid resilience. The ultimate goal is to leverage ML to predict wildfire danger and propagation with high confidence in fire-prone parts of the world and explainable AI to identify the contribution of different variables and pave the way for robust and trustworthy safeguards against wildfires.

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