Protecting the Grid from Wildfire through Data Analytics

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I. Abstract

With the planet heating up, extreme conditions favoring wildfires are becoming even more likely. Additionally, there is the danger of man-made wildfires, as the devastating one in California in 2018, which was sparked by a transmission line. Not only is the grid becoming a danger to communities, the grid itself is also threatened by raging wildfires. Therefore, a holistic approach is necessary to prevent wildfires caused by grid components, recognize threats early, and in the worst case, mitigate the impact of wildfires on the grid when disaster strikes.

The paper investigates promising data-driven approaches in those three areas and suggests a framework to be implemented for a safer, more alert, and more resilient grid.

II. Introduction

The increasing frequency and severity of wildfires has become a major concern for communities and ecosystems worldwide. In addition to natural causes, the risk of man-made wildfires has become evident in recent years. The devastating 2018 Camp Fire in California was caused by a transmission line, claiming 85 lives and causing damage of $16.5B [1]. This paper explores promising data-driven approaches and proposes a framework for a safer, more alert, and more resilient power grid. The proposed framework will involve a holistic approach that leverages remote sensing technologies such as LiDAR to address four main components: prevention, early warning, disaster relief and a framework to integrate them. Specifically, the paper investigates how to use remote sensing data to identify potential threats, establish collaborative networks for early warning and response, and develop strategies to mitigate the impact of wildfires on power grids and surrounding communities. The goal of this research is to provide a solution that is not only effective in reducing the risk of wildfire damage but also protect power grid infrastructure and communities that are dependent on it.

III. Prevention

Wildfire prevention is critical for ensuring the safety and reliability of the power grid. In this section, we will talk about various approaches that can be taken to make the grid and its surroundings more fire-resistant. A study [2] conducted between 2015 and 2017 of high fire threat districts in California, USA found key factors contributing to wildfires, as shown in table I. It can be noted, that contact of line conductors with vegetation and equipment failures were the primary causes of most wildfire events. Thus, the two topics explored in this section will be vegetation management and power line monitoring.

TABLE I
Key contributing elements for wildfire events [2]

Factors	Contribution (%)	Nature of the event
Vegetation contact	49	Contact of line conductor with vegetation
Equipment or other failure	27	Failure of equipment like power transformers, conductors
Other inadvertent contact	13	Accidents/sabotage
Animal contact	8	Bird flights and burrowing animal contact
Unknown	2	Causes of unknown origin
Fuse operation	1	Fire ignition from fuse blowout

A. Vegetation Management

Proper vegetation management plays a critical role in preventing wildfires. By regular inspection of the vegetation that surrounds a power grid, grid operators can reduce the risk of a wildfire spreading and becoming uncontrollable. In addition to traditional methods, the use of LiDAR technology has become an increasingly popular tool for vegetation management. It can be used to classify plants and, based on that, identify areas at risk.

The approach suggested by Fernández-Álvarez *et al.* is to use LiDAR point clouds to classify forest fuels for wildfire prevention [3]. The process flow diagram is shown in Fig. 1. The data is gathered with a UAV platform. Collected data was used to detect and characterize individual trees, estimate the cover and height of shrubs, and build decision trees to automatically verify the geometric parameters of the vegetation. Proposed method allows for the automatic verification of compliance with wildfire prevention legislation, helps avoid subjectivity, and is more efficient for evaluating large areas than conventional methods.

Biomass management strips are areas of land where trees and plants are managed to reduce the risk of fires [3]. The first step is to identify the strips according to the local wildfire prevention legislation.

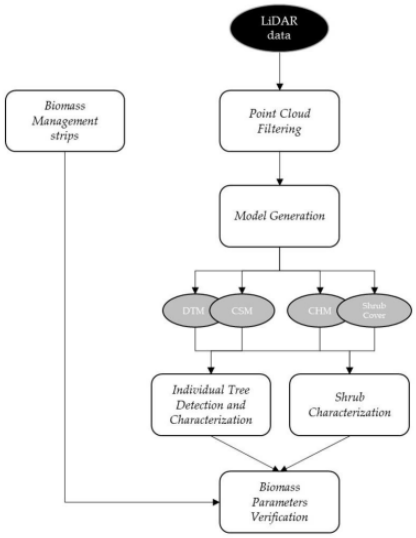

Fig. 1. Process flow diagram; figure taken from [3]

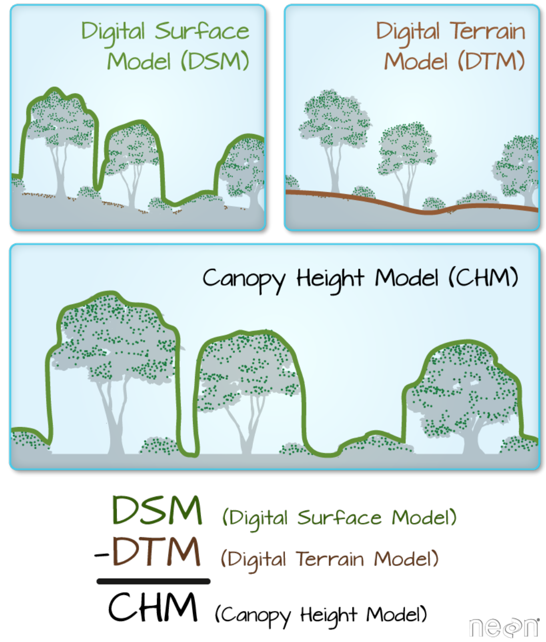

Fig. 2. DSM, DTM and CHM explanation; taken from [5]

LiDAR point cloud data is then filtered to separate ground points from non-ground points using a filtering algorithm based on Kraus and Pfeifer linear prediction [4].

Afterwards, digital terrain models (DTM), digital surface models (DSM), and canopy height models (CHM) are generated. DSM represents the top of the surface. DTM is the elevation of the Earth's surface. CHM is derived by subtracting DTM from DSM, as shown in Fig. 2. CHM is important as it shows the actual height of the objects.

Shrub cover (SC) model is used for shrub characterization. SC can be calculated as a function of the number of LiDAR returns. The heights of shrubs are assumed to fall within a range of 0.2m to 3m. The value for each cell was obtained using the following equation:

$$\text{SC (\%)} = \frac{\text{number of returns between 0.2 and 3 meters}}{\text{number of returns in 5 meters cell}} \tag{1}$$

The next step is to identify individual trees. There are various methods for individual tree detection (ITD), including the variable-sized window method (VSW), watershed delineation (WD), point cloud segmentation, and layer stacking. The accuracy of these algorithms can be affected by factors such as the type of forest (coniferous, broadleaved, or mixed), tree density and distribution, and crown morphology. Tree identification algorithms tend to be more accurate in coniferous forests than in broadleaved forests [3] due to the conical shape of coniferous tree crowns, which makes it easier to define local maxima. However, broadleaved trees may have branches that can be mistaken as separate crowns, leading to multiple trees being detected in the same crown.

The total height (H_t) is then calculated from CHM cells. For pruning height (H_{pr}) calculation Fernández-Álvarez *et al.* suggest the following model:

$$H_{pr} = -C + B \times H_t - A \times H_t^2 \tag{2}$$

where A, B and C are constant coefficients. Calculated parameters can then be compared with local wildfire restrictions to find potentially fire-prone vegetation (Table II).

The methodology described above allows for the automatic verification of vegetation compliance with wildfire prevention legislation, avoiding operator subjectivity and increasing efficiency in the evaluation of large areas. Geometric requirements, established by the Galician authorities (Table II), are an example of such legislation. This approach can be applied at a small scale to evaluate the wildland interface that surrounds the power grid. The information obtained can be used to design intervention priority criteria and connect with administrative punishment procedures. By identifying areas with a higher risk of wildfire and implementing prevention measures in those areas, it may be possible to reduce the likelihood of wildfires damaging the power grid.

This approach has several advantages. Firstly, the usage of LiDAR technology allows for high-resolution mapping of vegetation, which can provide detailed information on the structure and composition of forest fuels. Secondly, the use of UAVs allows for data collection in difficult-to-access areas, such as steep terrain or remote locations. And finally, the automation of the data processing and analysis can save time and resources compared to manual methods. However, there are also some disadvantages. LiDAR data collection can be expensive and may not be feasible for all areas or budgets. In addition, data processing and analysis can require

TABLE II
GEOMETRIC REQUIREMENTS, ESTABLISHED BY THE GALICIAN WILDFIRE PREVENTION LAW [3]

Strata	Distance between Trees	Geometric Conditions
Overstory	$> 7m$	$H_t \leq 11.4m$ $H_{pr} < 35\%$ of total height $H_t \geq 11.4m$ $H_{pr} \geq 4m$ above ground
Understory	-	Cover $< 20\%$ $H_t < 100cm$ Cover 20%–50% $H_t < 40cm$ Cover $> 50\%$ $H_t < 20cm$

specialized skills and software, which may not be available to all local authorities. Furthermore, this methodology is focused on wildland-urban interfaces, and may not apply to other types of landscapes or vegetation patterns.

Frank *et al.* examine the use of hyperspectral imagery in combination with LiDAR for vegetation management of utility corridors [6]. The study aims to identify various vegetation species by using two different classification methods, Support Vector Machines (SVM) and Spectral Angle Mapper (SAM).

The study acquired the data using a Cessna 402C (Fig. 3) aircraft, which flew over a power line right-of-way. It was flown at an altitude of 450m above ground level (AGL) resulting in a ground sample distance (GSD) of 50cm for the hyperspectral imagery, 6cm for the digital imagery, and 15cm for the LiDAR data (2 passes). The LiDAR data was collected with a pulse rate of 150 kHz resulting in an average point density of 14 points/m2. All sensors were operated with a full angle of around 35 degrees and connected to the same navigation data stream to avoid spatial distortions. The test site was an electric transmission line located in the northeast of Tampa, Florida.

The approach involves reconstructing and vectorizing each transmission line span using LiDAR data. To do this, the researchers locate the centers of transmission line towers in the pre-processed data and compute local models of the data to form individual transmission line spans. It is mentioned that the performance of the algorithm to classify and model transmission lines from laser point clouds depends on the quality of the LiDAR measurements, such as position accuracy, range separation, and point density. Some line spans couldn't be fully reconstructed due to a low point density, so extra line points had to be manually digitized.

After the line spans have been reconstructed and vectorized, the researchers calculated the clearances of transmission lines. The study then describes some pre-processing steps applied to the raw LiDAR data such as calibrating, geometrically correcting, classifying into different classes, and generating different LiDAR-derived layers. Then, a median filter was applied to the data, and input layers for the classification were extracted. Lastly, two different classification methods were used: Support Vector Machine (SVM) and Spectral Angle Mapper (SAM) for the final vegetation species classification.

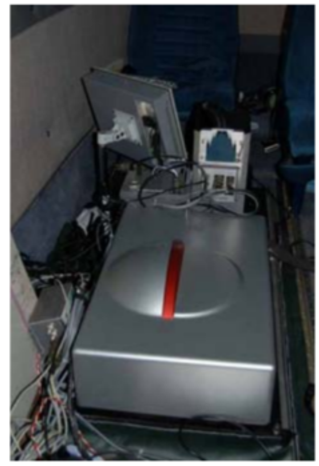

Fig. 3. Sensor setup on board a Cessna 402C; taken from [6]

The overall classification accuracy is shown in Tables III, IV. The SVM method had an overall classification accuracy of more than 10% better than SAM for every dataset. The greatest improvement was seen with LiDAR data at 17%. The combined dataset of hyperspectral and LiDAR data performed the best with an accuracy of 80% for SAM and over 92% for SVM. The integration of LiDAR data led to significant improvements in user accuracy for classes with different horizontal and vertical surface properties, but it also led to small declines in user accuracy for classes that have similar properties.

TABLE III
SAM ACCURACY [6]

SAM	Overall Accuracy	Kappa Coefficient
LiDAR	36.47%	0.2873
Hyperspectral	71.09%	0.6615
Hyperspectral+LiDAR	79.58%	0.7609

TABLE IV
SVM ACCURACY [6]

SVM	Overall Accuracy	Kappa Coefficient
LiDAR	54.24%	0.4859
Hyperspectral	83.26%	0.8039
Hyperspectral+LiDAR	91.75%	0.903

There are some advantages and disadvantages to this approach. The combination of hyperspectral imagery and LiDAR data allows for more accurate identification of "alert trees" and other vegetation that could pose a risk to power lines. The ability to map individual vegetation species provides the opportunity to calculate individual growth models for every species, and identify dead and unhealthy trees. Automating the process and using machine learning algorithms reduces the risk of human error and saves time and money compared to traditional methods. However, collecting the data can be expensive, which may limit the ability of utility companies to implement this approach across large areas regularly.

As a result, classification of the vegetation types that are located near a power grid can help detect potential fire-prone areas. For instance, pine and cypress trees, which can be identified using the described methodology, can endanger the area because they are easily flammable. Considering this, grid operators and local authorities can define areas where wildfire prevention and monitoring should be concentrated.

B. Power Line Monitoring

In this section, we will talk about power line monitoring with an aim of protecting the grid from wildfires.

Nguyen *et al.* present a new system for automatically inspecting power lines using a UAV equipped with cameras [7]. The system uses deep learning algorithms to analyze images taken by a UAV and identify various defects and issues in power line components. To improve the accuracy of the system, the authors create several training datasets, apply data augmentation techniques to balance the classes, and propose a multi-stage component detection and classification method.

Four datasets were created for training deep learning models. The images (Fig. 4) for the datasets were collected from helicopters using high-quality DSLR cameras and came from multiple power grids in Norway. The first dataset is annotated with bounding boxes and labels for 54 power line component classes. The second dataset is created by cropping and annotating top caps from the first dataset with two classes. The third dataset is created by cropping, dividing into squares, and annotating poles from the first dataset with three classes. The fourth dataset is created by rotating and cropping cross arms from the first dataset, dividing them into squares, and annotating with four classes.

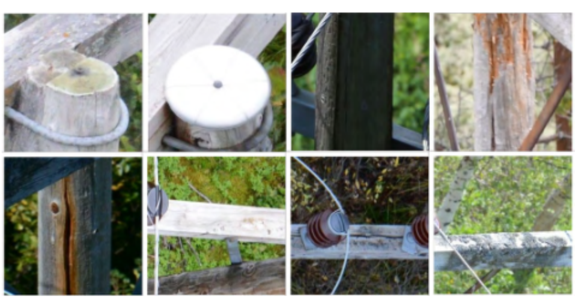

Fig. 4. Sample images from the dataset used in the study (from left to right, top to bottom): missing top cap, normal top cap, normal pole, woodpecker-damaged pole, cracked pole, normal cross arm, cracked cross arm, and rot-damaged cross arm; Taken from [7]

To address the class imbalance and the lack of training data the paper suggests using a series of data augmentation techniques. These techniques include padding and shifting bounding boxes, adding Gaussian noise and blur, performing zoom and rotation operations, and flipping images horizontally and vertically. These techniques are applied to the original training images to create a larger, more diverse training set and to balance the classes. The data augmentation techniques are implemented using the scikit-image library.

The authors propose a multi-stage component detection and classification pipeline (Fig. 5) to address the challenge of detecting small components and faults in power lines. The pipeline works by first detecting power masts in the input images, then using the detected masts to locate power line components, and finally identifying faults in the detected components. The pipeline allows for the detection of small faults, such as cracks and damage.

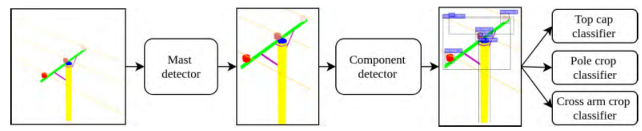

Fig. 5. The general structure of the proposed multi-stage component detection and classification pipeline. The pipeline consists of five components: a mast detector, a component detector, a top cap classifier, a pole crop classifier, and a cross arm crop classifier; Taken from [7]

This methodology is effective at addressing the challenges of detecting component faults and overcoming the lack of training data. Suggested data augmentation techniques are also effective at improving the performance of the component classification models in terms of weighted precision (wP), weighted recall (wR), and weighted F1 score, particularly in tasks with fewer training examples. When deployed in the Microsoft Azure cloud, the system can analyze over 180,000 images per hour. The system has demonstrated promising results in field tests and has the potential to play a valuable role in the intelligent monitoring and inspection of power line components.

This approach could potentially be used for wildfire prevention by detecting faulty power lines or other infrastructure that could cause fires, such as damaged power poles, cracked or rot-damaged cross arms, or missing top caps. By regularly inspecting power lines and other infrastructure, fire prevention agencies could proactively identify and fix potential fire hazards before they have the opportunity to cause a wildfire. Additionally, the system's ability to analyze large numbers of images quickly could allow for more frequent inspections and greater coverage of at-risk areas.

IV. Early Warning

In this chapter, we will examine the key components of effective early warning systems to predict fires and overheating in power lines, including both software (such as physical simulations, machine learning modeling, sensor communication, and cloud computing) and hardware (such as sensors and deployment infrastructure).

We begin by providing in subsection *A* an overview of current methods for modeling and predicting wildfire spread in regions surrounding power grids and for identifying faults within power transmission lines. And later in subsection *B*, we discuss the sensors in setup and data measurement aspects, as well as the data engineering and cloud computing elements that are essential for successful inference and modeling of the early warning systems.

A. Prediction and modeling of wildfire spread and real-time fault localization across the energy transmission lines

In this subsection, we will explore the use of prediction and modeling to minimize the damage caused by wildfires in the vicinity of power transmission lines. Wildfires can have a significant impact on power transmission infrastructure, and early warning is crucial for minimizing damage. We will first examine methods for predicting the likelihood of wildfire occurrence in the area surrounding power transmission lines. This will include an overview of historical data and physical simulations used to make these predictions. Furthermore, we will examine the use of fault localization as an early-warning instrument for detecting the probability of power transmission lines-induced fire. Finally, we will discuss the importance of dataset balancing and data mining in improving the accuracy of machine learning models used in wildfire predictions a.

1) Wildfires predictions by utilizing physical simulations and real-world data: Wildfire forecasting is crucial for minimizing damage to power transmission infrastructure, however current state-of-the-art modeling techniques such as computational fluid dynamics, statistical regression, or cellular automata, are not fast enough to produce real-time predictions for massive wildfires. There is a lot of successful research that has been conducted around the fire spread and probability, but, nevertheless, a lot of new state-of-the-art solutions being proposed every year. In this section we will cover a recent paper from 2022 [8] to address the problem of wildfires spread predictions, the authors of the paper introduce an efficient two-step parameter flexible fire prediction algorithm based on machine learning and reduced order modeling techniques. This approach uses a training dataset generated by physics-based fire simulations to forecast burned area at different time steps with a low computational cost.

The methodology is structured around the Latent Data Assimilation approach (specifically, the Generalised Data Assimilation algorithm), which is focused on the efficient parameter estimation for the wildfire forecasting models, by combining latent space representations.

The first step of the pipeline (see 6), which is also called *Forward Problem*, is focused on training a machine learning model that is based on the initial parameters of the wildfire simulation (and later the real world scenarios) can predict the latent space representation of the wildfire state at time *t*. For the encodings of such latent space representations, any potential dimensionality reduction model could be used. For instance, PCA, Convolutional Auto Encoders, or Singular Value Decomposition Autoencoders. For the prediction of the latent space representation based on the physics-based simulation parameters, one can use Random Forest Regression, K-Nearest Neighbour Regression, or Multi-Layer Perceptrons. Though, when speed of the predictions is at the highest priority, the operator of the infrastructure should evaluate the available computational power, while training and inferring the predictions with the Deep Neural Networks could be computationally expensive and not optimal.

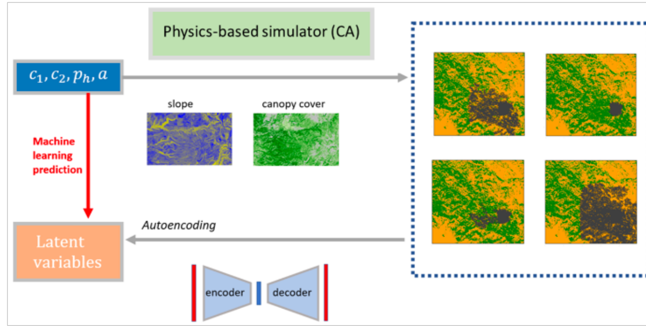

Fig. 6. Flowchart of the forward prediction model with Cellular Automata and Reduced-Order Modelling for a specific region. Figure taken from [8]

The second step of the pipeline (see 7), also coined as *Inverse Problem* by the authors, is focused on the calibration of the parameters using real-time observations. Here are they utilizing the Generalised Latent Assimilation (GLA) Algorithm [9] to combine latent space predictions (which were created by the model from the first step) to later analyze the state (i.e., the latent space representation that was assimilated with the help of GLA), and can forecast the next states at time *t* with machine learning models. Again, here is important to choose the model with inference speed and connectivity status. In the end, we suggest to develop two separate models: one to tackle in-time predictions and the second one that covers more complex predictions, like for instance the one that happens at the time $t > 3$ *days*.

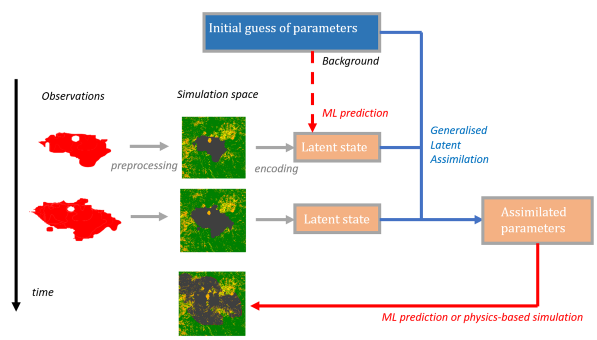

Fig. 7. Flowchart of the inverse problem. Figure taken from [8]

Because the approach is not focused on a specific location or structure of the vegetation, it makes it a superior candidate for the universal predictor of wildfire spread. On top of that, the sub-modules of this approach can be adapted to various power infrastructure locations.

2) Fault localization as an early-warning instrument for detecting the probability of transmission line-induced wildfire: Fault localization plays a crucial role in detecting the likelihood of transmission lines-induced wildfires. The increasing number of faults and incidents in power networks due to natural hazards and technical system issues have made the behavior and effects of faults in wildfires more complex. This can lead to the misoperation of circuit breakers and cause electrical equipment to fail and spark uncontrollable fire disasters, resulting in safety hazards for society. In recent years, electrical power problems have been identified as a leading cause of wildfires in California (see 8), making accurate fault localization and quick potential fire detection vital for power grids and surrounding areas.

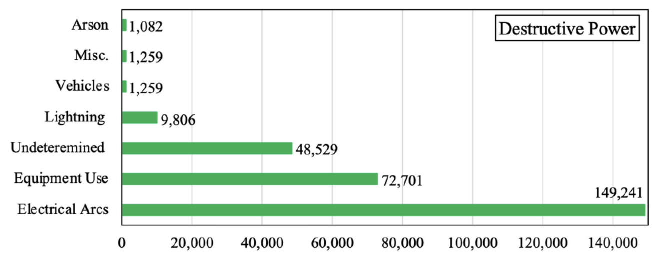

Fig. 8. Wildfire sparked by power lines and electrical equipment burned the most acreage in California in 2015. Figure taken from [10]

The backbone of such analysis is based upon Fault Determination and Localization (FDL) Algorithm which was coined in this paper [10]. The authors designed a 4-step approach to effectively determine and localize faults within the power transmission lines systems.

The main tools for classifying and localization are the Convolutional Neural Networks. Here, the authors present 2 CNN Models, namely, **Model-T** and **Model-L** (see figure 9). The Model-T uses feature vectors extracted from measured voltages and currents with real phases to determine fault types, while Model-L is used to locate faults and potential fires in the system by incorporating the positive, negative, and zero asymmetrical component sequences, which play a significant role in unbalanced faults.

The accuracy of the presented CNN models is ensured through training and testing on a dataset that is a function of the fault distance d (later used in the algorithm), leading to extensive and accurate fault localization. The method has the advantage of single observability in distribution systems, as the feature vectors are trained and tested using data from individual measurement devices.

$$\begin{aligned} \chi_{a0} &= \frac{\chi_a + \chi_b + \chi_c}{3} \\ \chi_{a1} &= \frac{\chi_a + \alpha\chi_b + \alpha^2\chi_c}{3} \qquad \chi \in \{V, I\} \\ \chi_{a2} &= \frac{\chi_a + \alpha^2\chi_b + \alpha\chi_c}{3} \end{aligned} \tag{3}$$

$\alpha = \angle 120° = -0.5 + i0.866, \alpha^2 = \angle 240° = -0.5 - i0.866$ and $\chi_{a0}, \chi_{a1}, \chi_{a2}$ are zero (Z), negative (N) and positive (P) sequences on phase voltages and phase currents.

Algorithm 1 The FDL Algorithm proposed by []

Input:
Voltages V_{abc}^{pref}, V_{abc}^{f}, currents I_{abc}^{pref}, VI_{abc}^{f} and corresponding phase angles $\theta_{(V/I)abc}^{pref}$, $\theta_{(V/I)abc}^{f}$

Step 1 (Feature vector φ_t):
Calculate the voltage differences $\Delta V_{abc} = V_{abc}^{f} - V_{abc}^{pref}$, current differences $\Delta I_{abc} = I_{abc}^{f} - I_{abc}^{pref}$, and phase angle differences $\Delta\theta_{(V/I)abc} = \theta_{(V/I)abc}^{f} - \theta_{(V/I)abc}^{pref}$.
Create feature vector
$\varphi_t = \{|\Delta V^{abc}(d)|, |\Delta I^{abc}(d)|, \Delta\theta_V^{abc}, \Delta\theta_I^{abc}\}$

Step 2 (Fault Type Classification):
Insert the feature vector φ_t and fault type labels as the input of the CNN fault type model (Model-T), and obtain the fault types' information.

Step 3 (Feature vector φ_l):
Calculate the zero, negative, and positive (Z, N, P) sequences of voltages and currents of each phase as defined in 3 and augment them into φ_t as the feature vector $\varphi_l = \{|\Delta V^{abc}(d)|, |\Delta I^{abc}(d)|, \Delta\theta_V^{abc}, \Delta\theta_I^{abc} V^{ZNP}, I^{ZNP}\}$.

Step 4 (Feature localization):
Insert the feature vector φ_l and fault location labels as the input of the CNN fault localization model (Model-L), obtain the information of the fault locations.

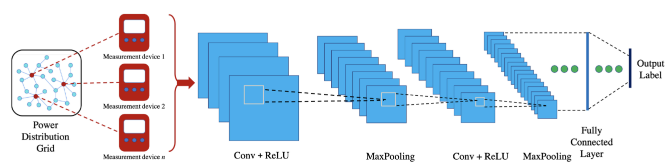

Fig. 9. Architecture for the Convolution Neural Network used in Model-T and Model-L

The authors also suggest performing classification and localization by having information only for a single measurement device, arguing that this is more economical and practical for power distribution systems, especially when the number of measuring devices and sensors is limited.

As a remark, according to the latest developments and specifically to Graph Convolutional Networks (GCNs) are showing outstanding performance [11], and are on track to become state-of-the-art when applied to the graph-structured data and graph-like systems. Therefore, a potential improvement for the current proposed Models could be by switching from Convolutional Neural layers to Graph Convolutional layers.

To determine the most crucial factors of the Power Lines-induced Wildfires, the authors of the paper also propose to analyze drivers of the wildfire occurrence probability. In order to numerically evaluate the probability, we are going to construct a logistic regression for the probability of wildfire events. For this, in the original paper authors decided upon 34 parameters. The hypothesis of the regression line is constructed as follows: $\Theta(E_v) = \theta^T E_v = \theta_0 + \theta_1 E_{v,1} + \theta_2 E_{v,2} + ... + +\theta_{34} E_{v,34}$. The probability of the wildfire occurrence (p_w) is defined as follows:

TABLE V
FIRST 26 NON-ZERO PARAMETERS OF
THE WILDFIRE OCCURRENCE PROBABILITY

Feature	Parameter θ_i	Feature	Parameter θ_i
Conductor Failure – Wires Down	0.9357	Voltage Regulator Failure	0.1148
All types of Equipment Failure	0.5849	Crossarm Failure	0.0803
Equipment Failure Other	0.5161	Conductor	0.0786
Animal	0.4607	Connector/ Hardware	0.0786
Vegetation Contact	0.4537	Contact from other Objects	0.0738
Car Pole	0.3145	Vegetation	0.0676
Animal Contact	0.2636	Transformer	0.0676
Insulator or Bushing	0.2138	Balloon Contact	0.0574
Pole Failure	0.1605	Conductor Failure – All	0.0437
Third-Party Agents	0.1572	Transformer Failure	0.0121
Vehicle Contact	0.1516	Capacitor Bank Failure	0.0041
Insulator Failure	0.1493	Lightning Arrester Failure	0.0023
Other Overhead Line Equipment	0.1462	Switch Failure	0.0021

$$p_w = \frac{2}{1+\exp(-\Theta(E_v))} - 1 \tag{4}$$

In **Table V** we gathered 26 most influential parameters in regard to the Wildfire Occurence, induced by Power Transmission Lines.

3) Datasets Balancing and Data Mining for improvements in predictions: In the paper *Prediction of Wildfire-induced Trips of Overhead Transmission Line based on data mining* [12] the authors investigate the risks for wildfire-induced trips by utilizing and overviewing data mining techniques, such as Support Vector Machine (SVM), Random Forests, Neural Networks; and data balancing approaches, like the Synthetic Minority Oversampling Technique (SMOTE), Random Undersampling and EasyEnsemble methods.

The data for the evaluations is based upon observation from 2014 to 2019 in the Chinese provincial power grids. The dataset covers two classes: fire samples that did not induce trips of transmission line, and fire samples that induced trips of transmission line. There were total 20 selected features for the experiments, including meteorological, topographic, anthropogenic, combustible, and vegetation. These features are highly intervened with the ones presented in the previous sub-section, which shows that these discoveries around the data gathering, mining and balancing could be applied to a substantial range of tasks within the fire management in electrical systems, and power transmission lines-induced fire predictions. In the evaluation in 10 we focused on SVMs, and specifically Kernel SVMs because they are a powerful tool for making fast predictions when the results inference time is crucial. Authors also compared the data balancing techniques for other machine learning models, like Neural Networks and Random Forests.

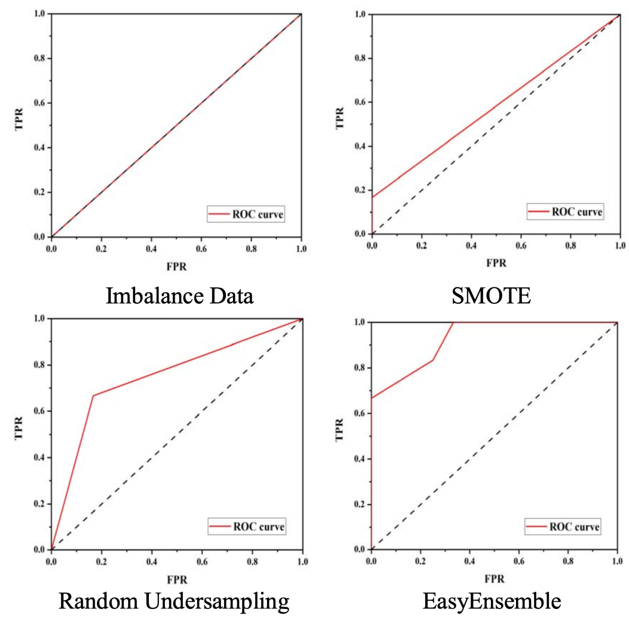

Fig. 10. ROC Curves of SVM models with different data balancing techniques. Figure taken from [12]

In figure 10 we can observe that tackling the data imbalance with synthetic data generation and undersampling methods like SMOTE, Random Undersampling and EasyEnsemble, especially the later one, can substantially improve the metrics of prediction.

B. Sensors and Data Engineering

In this section, we will examine the current state of sensor technology in transmission and distribution systems, with the focus on the components that directly influence fault detection covered in section *A.2)*. This will include a comprehensive overview of the latest sensors and their specific use cases in these systems. Additionally, we will explore the potential for future developments in this field, specifically in regards to the integration of modern sensor technology in transmission and distribution systems.

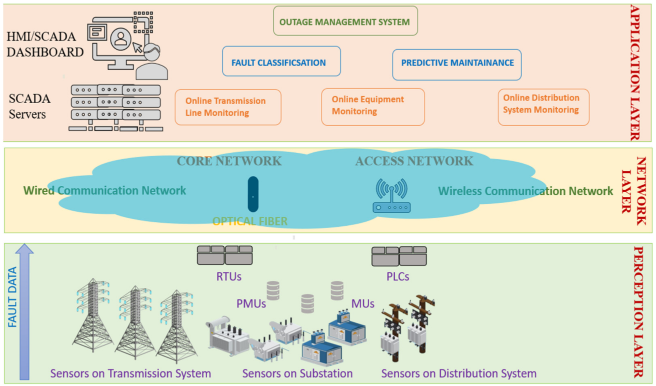

Fig. 11. Pervasive sensing network framework in a power system. Figure taken from [13]

The increasing use of sensors and wireless networks for monitoring power grid parameters generates large amounts of data, making data transmission, storage, and processing challenging. This is known as "data deluge" and can lead to higher costs for hardware and storage. To overcome this challenge, data preprocessing at the edge level can be implemented to reduce the amount of data that needs to be transmitted and stored. Distributed file systems, NoSQL databases and data processing tools such as Hadoop, Storm, Spark, and Grid Gain can also be used to avoid data deluge [13].

Additionally, it is difficult to create a unified protocol for the integration of advanced sensing technologies in the power grid due to the complexity and heterogeneity of power grid components and the diverse nature of power sources and environments. The deployment of new technologies is also capital, labor and knowledge intensive. The development of a single sensing technology or standard protocol is difficult as the technology is constantly evolving and advanced components, control methods, and interfaces are under rapid development. [13]

The trend in modern sensor technology is the integration of multiple sensors and connected devices to form wireless sensing networks (WSNs) in transmission and distribution systems. This advanced technology provides efficient real-time monitoring of the grid through data acquisition, transmission, and processing. WSNs consist of three layers: the perception layer (input layer) of multiple sensors deployed on various components, the network layer for data transmission through wired and wireless communication technologies, and the application layer for data analysis and fault detection. [13]

Current challenges in regards to integrating sensor in the current systems and introducing in the new generation of power grids (e.g. smart power grids) and power transmission systems include: credibility of data acquisition, heterogeneity issues, security issues, scalability issues. But recent development and research in cloud computing solves most of these issues.

The advent of cloud computing has led to a significant reduction in the costs of data storage and processing. With the increasing computational power and scalability of cloud services, it is now possible to store and process large amounts of data generated from the power grid in a cost-effective manner. Furthermore, cloud computing can be used to train machine learning models that can be applied to the power grid to enhance its efficiency and reliability. By leveraging cloud-based infrastructure, it is possible to perform real-time inference and data analysis, reducing the complexity and costs associated with data deluge. The use of cloud computing in the power grid is expected to grow in the coming years, as it offers an ideal platform for data storage and processing, enabling the development of advanced sensing technologies and control methods.

But despite the many benefits of using cloud computing in the power grid, it is important to note that connectivity in remote areas and between power line nodes can sometimes be disrupted or unreliable. This can impact the accuracy of machine learning models and the ability to perform real-time inference and data analysis. To address these challenges, it is crucial to consider the potential for connectivity issues when designing the inference and prediction algorithms for machine learning models. This can help to ensure that the models are robust and can still provide reliable information even in areas where connectivity is limited.

V. Disaster Relief

While there are several approaches to mitigating the impact of wildfire on the grid, the three most promising ones are closer investigated in this section.

A. *Serving Shut-Off Areas*

When areas of the grid have to be de-energized, one way to soften the blow is by trying to keep supplying parts of the grid that had to be separated from the main grid with alternative power sources as done in [14]. The paper introduces a tri-layer solution. The first layer uses AI to coordinate the local energy supply: before, during, and after a wildfire. The second layer senses the environment, identifies locations of outages caused by natural hazards, and stops power supply to that area. The third and final layer uses distributed storage and demand response to serve a severely affected area that had to be disconnected from the main grid. Not all parts of the tri-layer solution are discussed in detail; the paper focuses heavily on the last part, the energy exchange with a de-energized area of the grid. In order to keep serving power to an area of the grid that had to be separated from the main grid, an alternative, distributed power supply can be used. The approach is illustrated in figure 12.

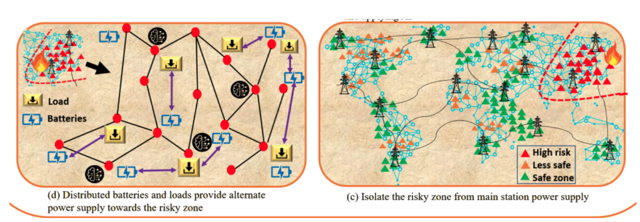

Fig. 12. Illustration of the mitigation approach; figure taken from [14]

The system is made up of two types of agents, Demand Response Agent (DRA) and Distributed Storage Agent (DSA) as well as the Resilience Management System (RMS). The DRAs know about the load of each region of the cut-off area and manage the distribution of energy it receives from DSAs. The DSAs on the other hand track the state of charge of distributed batteries and communicate with the RMS, e.g. to inform about the desire to share energy with another distributed area. Since the RMS talks to all agents, it passes on information between them and synchronizes them during an energy exchange.

To implement that system, it is necessary to equip each consuming node in the grid with a battery. In the event of an outage, each component can check its battery status, use the stored energy to keep operating and recharge its battery from a nearby DSA. To manage this decentralized energy exchange, the paper suggests a market-based trading solution.

The high-level idea is that as soon as an area is cut off, the RMS tries to maximize the power supply and minimize the loss due to the outage. This is formulated as a convex optimization problem with the control signals sent from RMS to DRA and DSA as decision variables and the loads and battery charges as feasibility requirements. In the first time step, each DRA i initializes a load profile from the connected appliances and each battery j initializes a charge profile. Note that a battery and a DSA are not the same thing; a DSA is a collection of one or more batteries. There is also a convergence condition based on a pre-defined convergence threshold ξ. The idea is that the system distributes power iteratively between DSAs and DRAs until it stabilizes and the absolute difference between all loads/battery charges $x(t)$ from timestep $m-1$ to m falls under the threshold ξ as shown in equation 5.

$$|x^m(t) - x^{m-1}(t)| \leq \xi \tag{5}$$

Until that condition is met, the same procedure is repeated: each DRA i and each battery j send their load/state of charge to the RMS. The RMS uses this information to obtain new values for the decision variables (control signals) based on the optimization task explained above and sends them back to the DRAs and batteries. Depending on whether a battery has more charge than the current maximum storage and is interested in sharing energy with a neighboring node, it is added to a DSA. The DRAs on the other hand send a request to the RMS if the charge of their battery falls under a minimum load threshold. The RMS then arranges and synchronizes the power supply from DSA to DRA.

Their simulation results show that this system can mitigate the sharp performance drop in the cut-off area of the grid.

Building on the work from [14], [15] approaches the problem with distributed machine learning. The main improvement over their previous work is that instead of centralized decision-making via the RMS they use distributed intelligence. To add to the system's robustness, all data is shared with all entities within one RMS, and failure of an entity does not hinder the communication of the rest. This is especially important given the likelihood of a wildfire destroying significant parts of the system.

Apart from the advantages mentioned above, the agents also do not have to engage in local decision-making anymore. Instead, the authors use collaborative learning to leverage the edge intelligence of the agents, leading to better outcomes. The shift from [14] to [15] is illustrated in figure 13.

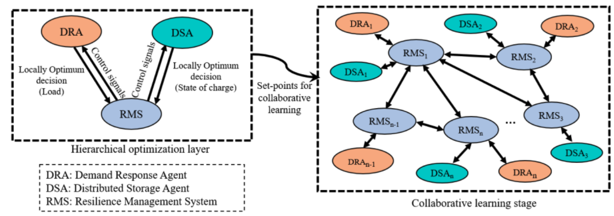

Fig. 13. Collaborative learning approach; figure taken from [15]

Again, the system is based on a Resilience Management System (RMS), a Demand Response Agent (DRA), and a Distributed Storage Agent (DSA). Just as in the previous work, a DRA measures the energy consumption of its connected entities and can request power, etc. A DSA informs the RMS about its connected entities' charge levels and their potential interest in sharing power. Instead of one single RMS, which consists of a DRA, DSA, or both, making local decisions, the RMS now also learns from neighboring RMS. With machine learning, an RMS can learn to infer the load profile requirements of a neighboring agent, its expected outage duration, and its battery charging state. Unfortunately, the details are missing in the paper, but the authors claim that this information leads to better results.

Eventually, the goal of the collaborating RMS agents is to minimize the number of loads that do not get served during an outage. This can be framed as an optimization problem similar to the one in [14].

B. Proactive Grid Control

In the event of a raging wildfire, there is also the risk that transmission lines may cause additional, secondary wildfires. Because the ambient temperature rises, the transmission lines sag, putting them at a higher risk of colliding with vegetation and sparking a secondary wildfire. It gets even worse when another risk factor comes into play: strong winds. Not only do they spread the wildfire but they also make the transmission lines swing. Therefore, a common strategy is to preemptively de-energize transmission lines when a wildfire approaches. To protect consumers from outages and to minimize the risk of secondary wildfires, [16] proposes a proactive approach to control line flows. It is intended to help human operators to reduce load loss, avoid infeasible power-flow solutions that would violate the thermal limits of transmission lines, and throttle power flow through lines that are to be de-energized.

To control the grid according to the wildfire threat, a fire propagation model is necessary. Therefore, the geographical region is represented as a set of grid cells X. The propagation model holds variables for ignition states and wildfire fuel for each grid cell. The probability of wildfire spread from cell to cell is based on a stochastic process using geographical and environmental data.

To bring the grid into this, each power system component is mapped to one or more cells depending on the location of the component. The power system is then represented as a graph with each of the nodes corresponding to a generation or transmission substation and each edge representing a transmission line. Each substation $i \in N$ and each transmission line $t \in T$ gets a binary variable $z^f_{i,k}$ or $z^f_{t,k}$ respectively. The variable is 0 in case at least one associated cell is on fire at the given timestep, and 1 if no associated cell is on fire. It is noteworthy that this information comes from the wildfire spread model. Deployed in the real world, the $z^f_{i,k}$ and $z^f_{t,k}$ variables also correspond to emergency calls when a fire is creeping up on the substation or when measured temperatures on the transmission lines indicate that a fire is close.

The paper distinguishes between a controller and an operator. The controller is basically the policy, obtained from a reinforcement learning algorithm. The controller suggests shut-off actions for the transmission lines and substations respectively, that the operator can carry out. In total, the operator updates the topology from timestep k to timestep $k+1$ based on three inputs: controller actions $z^e_{i,k}$ and $z^e_{t,k}$ for substations and transmission lines respectively, the current operational statuses $z^o_{i,k}$ and $z^o_{t,k}$, and the emergency responses $z^f_{i,k}$ and $z^f_{t,k}$ from either the wildfire simulation block or actual line monitoring of emergency lines. The new operating status $z^o_{i,k+1}$ and $z^o_{t,k+1}$ for each substation/transmission line is only 1 if all three inputs are 1. For the deployed real-world scenario that means that a power-system component will only be considered available if there is no emergency call, the previous status is "available", and the controller does not suggest shutting it off. The new operating status at $k+1$ for each component is called updated system topology.

As the next step, the operator tries to figure out the setpoints for all generators while minimizing the load loss at $k+1$. This problem is formulated as shown in equation 6. Φ_{k+1} is the set of decision variables, including (among others) the generated power outputs $P^g_{i,k+1}$, the state of the generators (some of those might also be affected/have to be shut down) $z^g_{i,k+1}$, critical and non-critical shredded loads $P^{c\_l}_{i,k+1}$ and $P^{nc\_l}_{i,k+1}$ and the flow through the individual transmission lines $P^{flow}_{t,k+1}$. $w^{c\_l}_i$ and $w^{nc\_l}_i$ represent the critical and non-critical loads respectively for each node $i \in N$. Note that one interesting feature in equation 6 is the last term $\epsilon \cdot (P^g_{i,k+1} - P^g_{i,k})^2$. One might think that the optimization could be done without that term because the two remaining terms represent load in the current time step multiplied by load shedding in the next time step (which is a decision variable). However, the last term makes sure that the generator outputs do not vary too much over time. Otherwise, multiple feasible solutions might exist with no regard to high variances in individual generator outputs, thereby leading to a constant ramping up and tuning down of generators.

$$\min_{\Phi_{k+1}} \sum_{i \in N} w^{c\_l}_i \cdot \Delta P^{c\_l}_{i,k+1} + w^{nc\_l}_i \cdot \Delta P^{nc\_l}_{i,k+1} + \epsilon \cdot (P^g_{i,k+1} - P^g_{i,k})^2 \tag{6}$$

The constraints to that objective function are upper and lower generator capacity limit and ramping capabilities. When generators have an outage, they are not considered anymore and will, in the current state of the software, not become available again. Apart from limitations on the generation part, the demand part also imposes some constraints. First and foremost, the operator needs to predict loads in order to make control decisions. Load prediction is usually based on historical data and the paper presumes the existence of such a system. Given those predicted loads, the potentially shredded critical and non-critical loads can be bounded. For each node $i \in N$, there is the binary operational status $z^o_{i,k+1}$ introduced earlier, and a fraction α_i indicating the share of critical load. Given the load prediction $P^l_{i,k+1}$, the bounding constraints for potential critical (see equation 7) and non-critical load shedding (see equation 8) can be derived.

$$0 \leq \Delta P^{c\_l}_{i,k+1} \leq \alpha_i \cdot z^o_{i,k+1} \cdot P^l_{i,k+1} \tag{7}$$

$$0 \leq \Delta P^{nc\_l}_{i,k+1} \leq (1 - \alpha_i) \cdot z^o_{i,k+1} \cdot P^l_{i,k+1} \tag{8}$$

Lastly, there are also constraints imposed by the load flow. As discussed previously, $P^{flow}_{t,k+1}$ represents the power flow through transmission line $t \in T$ at timestep $k+1$. There is more detail to this but in principle, for each transmission line, there is a certain $P^{maxflow}_t$.

Given the objective function in equation 6 and the constraints, the optimization problem can be solved, providing the operator e.g. with set points for the generators and an estimate (based on the predicted loads) of the critical and non-critical load shedding, which it is trying to minimize.

The special part of the paper is now the deep reinforcement learning aspect. As described earlier, the operator receives instructions from the controller. The operator by itself acts myopic as it will solve the optimization problem introduced in the previous paragraphs only considering the current point in time. To mitigate that problem, the idea is to make the controller more far-sighted by making it consider whole trajectories via reinforcement learning and take future scenarios into account.

The control problem is modeled as a Markov Decision Process (MDP) D with finite states S, a finite set of actions A, a transition probability function P, and a reward function R. While the paper discusses the MDP and the deep reinforcement learning algorithm in great depth, the full explanation is out of scope for this paper. Instead, a simplified description of the MDP and in particular the reward function R is instructive and sufficient to understand their approach.

The controller is capable of giving shut-off commands/suggestions z^e_i and z^e_t to all nodes and transmission lines. Moreover, it can select generators to be controlled and change power injections for those generators by a specified amount ΔP_i^e. This is in principle a setpoint adjustment and the operator will check for feasibility regarding the generator limits. The states of the MDP are all possible tuples consisting of wildfire state and power system state. Transition probabilities between states given a controller action are expressed by P. The stochasticity comes from the wildfire propagation model as well as the load predictions. The action alone does not determine the state of the fire or the power system in the next time step. Instead, the wildfire spread, expressed in probabilities by the propagation model, and the future load demand predicted by the load prediction model play an important role that is integrated into P. Most importantly, the reward function $R(s_k, a_k, s_{k+1})$ is composed of four weighted penalties $r1$, $r2$, $r3$, and $r4$.

$r1$ is called the "load loss penalty" and it is the sum of the load loss of all nodes $i \in N$. The load loss for one node i is either the whole predicted load $P_{i,k}^l$ in case the node had to be shut off ($z_{i,k}^o = 0$) or otherwise the added shredded critical and non-critical loads $\Delta P_{i,k+1}^{c\_l}$ and $\Delta P_{i,k+1}^{nc\_l}$.

$r2$ is the "Proactive Isolation of grid Assets with expected Wildfire" (PIAW) penalty. The idea here is that shutting off heavily loaded substations or transmission lines is highly undesirable. Therefore, the penalty in timestep k is the sum of power in all substations i and transmission lines t which are to be shut off in timestep $k+1$ through controller actions in timestep k.

$r3$ is presented as "Asset Damage and Isolation due to encroached Wildfire" (ADIW) penalty. The intuition is that this penalty scales with the number of substations i and transmission lines t that are still operating, although one of their associated cells is already on fire. This penalty should encourage timely shut-offs.

$r4$ depends on a variable that indicates non-convergence of the initial optimization problem, implying overload and failure of transmission lines. Therefore, this penalty is intended to guide the controller towards avoiding thermal overloading and eventually failure of transmission equipment.

This general idea of the MDP can be used by a deep reinforcement learning algorithm to learn an optimal policy that maximizes the expected rewards over some timeframe. The policy then determines the controller's actions.

Given the reward function, the policy should a) avoid load loss, b) slowly de-energize components in danger, c) initiate shut-offs in time, and d) distribute the energy flow in a way that does not lead to thermal overload on transmission lines.

C. Supporting Firefighters

Another possible mitigation technique is introduced in [17]. The paper is about equipping firefighters with augmented reality e.g. to highlight objects by displaying their segmentation masks in vivid colors. This can be helpful for firefighters to keep their orientation e.g. when operating in dense smoke. Even though the paper is not related to the grid in particular, the approach seems promising for firefighting around transmission lines, which is a dangerous and difficult task. First of all, electricity can pass through several meters of air gap. When a wildfire approaches a transmission line, the increased temperature causes the lines to sag closer to the ground, making those "electricity jumps" more likely. To add to the danger, smoke can act as a conductor and the lines themselves may come down when a pole is severely damaged, putting firefighters at heightened risk of electrocution. Apart from those so-called flashovers, downed power lines on the ground also put firefighters in danger. Therefore, firefighters are advised to stay about 25 meters away from transmission lines. The technology described in the paper can be easily adapted to highlight any kind of grid entities, in particular (downed) transmission lines, that may not be clearly visible in thick smoke. This is especially useful since the hose stream should never be pointed at the power lines or any adjacent burning vegetation. In conclusion, adapting the technology to visually highlight grid components could greatly increase firefighter safety when fighting wildfires around grid components and at the same time guide fire extinguishing efforts to protect those components under bad visibility. Understanding how their approach can be adapted requires an understanding of the underlying technology. Simplified, the idea is to capture an image from the firefighter's helmet, run inference on it using a neural network for instance segmentation, and send the augmented image back to the firefighter's Microsoft HoloLens, allowing him to see the segmented object(s) in real-time. To achieve the segmentation, a Mask R-CNN [18] is used.

The data that is being used for the networks is acquired by a depth and a thermal camera attached to the helmet. This gives RGB, thermal, and depth data, which are passed through the Mask R-CNN deployed on a GPU that the firefighter carries attached to his uniform. This setup is shown in figure 14.

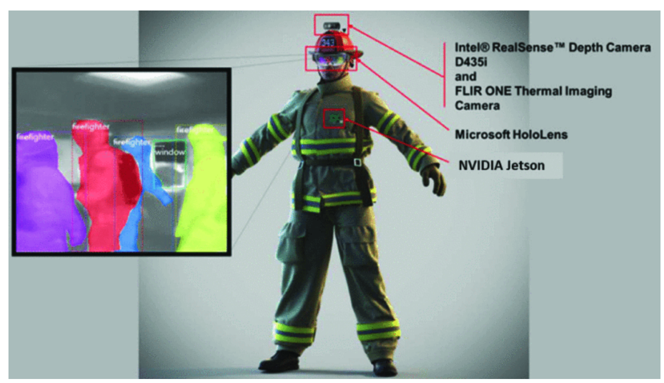

Fig. 14. Firefighter equipped with the necessary hardware. On the left an exemplary augmented image displayed on the HoloLens; figure taken from [17]

The raw and the augmented images are streamed to a server, where everything is available as a live video, e.g. for the commanding officer overseeing the operation. Most importantly, the augmented image is streamed in real-time to the firefighter's HoloLens. The pipeline as a whole is shown in figure 15.

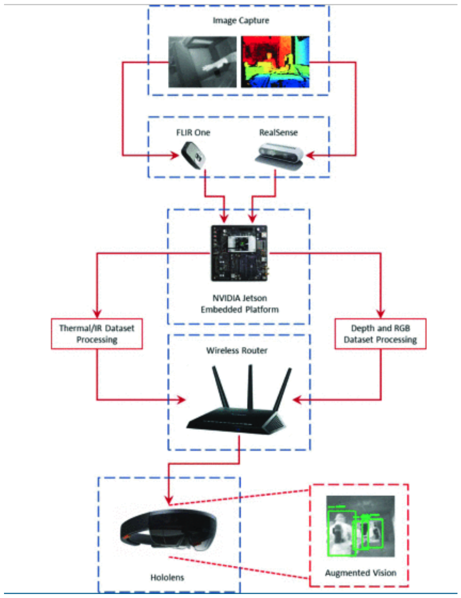

Fig. 15. Whole pipeline from data collection via sensors to augmented vision via HoloLens; figure taken from [17]

While the approach comes with major obstacles, in particular integrating all the hardware into the gear without creating discomfort or disadvantages for the firefighters, it seems feasible and most importantly, adaptable to different use cases such as the one motivated above. To achieve that, the Mask R-CNN has to be trained on a different dataset; instead of training on all sorts of objects, the training data has to be focused on grid components, in particular transmission lines. The necessary data could be obtained by attaching a depth and a thermal camera to helmets during the next wildfire season and annotating the data accordingly.

VI. Framework

A. Requirements

1) Prevention: Based on the prevention methodologies described above, there are two aspects of successful protection of the grid from wildfires:

- Vegetation Management
- Power Line Monitoring.

For vegetation management both reviewed papers [3] and [6] suggest using LiDAR technology to classify forest fuels. The first study focuces on classifying fire-prone vegetation based on its height. The approach described in second study is useful to detect areas that are generally more flammable based on vegetation types that grow there.

We propose a combined approach, which requires several steps. First, local governments are advised to develop proper legislation that defines allowed values, in which height parameters of individual trees and shrubs can range. An example for this are geometric requirements established by Spanish local authorities (Fig. II). Then UAVs with LiDAR sensors are needed to identify trees that do not comply with the proposed legislation.

To identify specific vegetation types, the optimal approach would be to equip a UAV with a LiDAR system and hyperspectral imaging equipment. In paper [6] researchers use AISA Eagle and ALS 50-II, mounted on a Cessna 402C (Fig. 3). As the study was conducted in 2010, more up-to-date devices and a smaller, less expensive UAV can be used.

Power line monitoring, as well as vegetation management, requires a UAV mounted with proper equipment. The study reviewed in this paper [7] suggests using digital single-lens reflex (DSLR) cameras (e.g., Nikon D810, Canon EOS 5D Mark III, Nikon D3X) with multiple resolutions (e.g., 7360x4912, 6048x4032, 5760x3840). Microsoft Azure cloud with access to GPU resources can then be utilized for image classification.

2) Early Warning: Reliable and rapid early warning systems could be examined from two perspectives:

1) Software – robust machine learning modeling and fast predictions; sensors communication, machine learning models training and availability, and data storage (covered in **IV-A** and **IV-B**).
2) Hardware – sensors and their state, and sensors-servers connectivity(covered in **IV-B** and **IV-B**).

In the end, we suggest a focus on three key areas to address the relationship between wildfires and power systems: predicting the spread of wildfires around power systems, accurately identifying faults in the power distribution systems, including their location and type, and utilizing the power of sensors and cloud computing to support these predictions. To improve the accuracy of these predictions, we recommend exploring techniques such as dataset balancing and data mining. We also suggest recognizing the importance of fault localization as an early-warning instrument, given the increasing number of faults and incidents in power networks and the potential for misoperation of circuit breakers and electrical equipment failure which can lead to uncontrollable wildfires.

3) Disaster Relief: The disaster relief methods described above can be separated into two parts: 1) making the grid more resilient under wildfire disasters and 2) making fire fighting around grid components more secure and effective. Both come with requirements. Since [15] is the successor of [14], the requirements are similar and are only discussed for [15] in the following. The strategy chosen in the paper is to keep a part of the grid operating that was severely affected and had to be cut off from the main power grid. The underlying idea is that consuming appliances are equipped with a battery. In case an area is being cut off, it can sustain itself for a short time on the batteries and when they fall under a certain threshold, they can be recharged from other batteries close by. This obviously requires the installation of many batteries at a significant cost. Moreover, having a large number of batteries in a danger zone can further fuel an ongoing wildfire, especially if those batteries were subsequently installed. Therefore, as a system to mitigate the impact of wildfire on the functionality of the grid, we recommend using the solution presented in [16]. However, this also comes with requirements. As in the other approaches, it is necessary for each grid component to be able to communicate e.g. its load/generator status, effectively requiring a smart grid. While the requirements and costs for this approach seem particularly high, the transition to a smart grid seems inevitable and will have to be made sooner or later anyways.

For the firefighting part, the requirements are shown in figure 14: for each firefighter, a depth camera, a thermal camera, a HoloLense, and a GPU are necessary. While this will amount to several thousand dollars, it is noteworthy that the primary cost driver is the HoloLense. However, with XR still in its infancy, there is a good chance for more affordable solutions in the future.

B. Recommendations

Based on the requirements for wildfire prevention, we recommend conducting regular inspections of power lines and the surrounding vegetaion. A UAV with LiDAR and imaging eqipment can be utilized for all the steps desribed in the prevention part. We also advise local policymakers to develop wildfire prevention legislation, as desribed above, that can then be used by powerline operators to identify potential threats.

We also urge policymakers to initiate a gradual conversion of the grid to a smart grid, while equipping firefighters in those areas with the necessary equipment. Additionally, we recommend finding pilot communities willing to implement those measures experimentally, as e.g. the integration into the current firefighting equipment is still an open issue and will require some trials. That way, the required initial budget can be reduced and in case the measures prove useful, they can be rolled out on a larger scale.

Given those recommendations, a possible deployed solution could work in the following way for any given community. Each month, UAVs fly over the relevant area and identify risks e.g. in form of vegetation or a cracked pole. The local authorities can then immediately initiate necessary maintenance measures.

From the early warning perspective, it is important to ensure having software solutions (here, machine learning models that focus on wildfire spread prediction and fault localization within the power distribution systems) that can make reliable in-time predictions and analysis. We also recommend utilizing computational power and availability of the cloud services and ensure that power nodes have a required wireless connection (though, developing models that can adapt to unstable wireless connections could also play a crucial role in adaptive early warning systems).

In case a wildfire breaks out, the grid operators are supported by a reinforcement learning based algorithm that guides them to avoid load loss, perform shut-offs in time, and avoid thermal overload of transmission lines. The firefighters on site are to be equipped with XR hardware, helping them to see and safely protect grid components.

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