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Review

Power Distribution System Faults and Wildfires: Mechanisms and Prevention

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Abstract: Wildfires are one of the most hazardous natural disasters in Australia in terms of fatalities, property damage and financial losses. Events of catastrophic wildfires are recorded across the world including in the United States and Canada. Failures along power distribution infrastructure and network faults have been identified as some of the causes for the initiation of wildfires. Thus, it is critical to better understand the mechanisms and the potential prevention strategies for wildfires caused by power distribution system faults. In this light, this paper presents how the power distribution network faults cause wildfires highlighting the main mechanisms. Further, this paper reviewed studies on recent advancements for the prediction, detection and prevention of wildfires. Condition assessment of power distribution infrastructure including poles, crossarms, overhead cables and other attachments are paramount to detect potential defects and to carry out timely replacements which can subsequently mitigate the possibility of wildfire initiation. Therefore, this paper summarized the studies on condition monitoring and surveillance techniques for power distribution infrastructure. Altogether, this paper aimed to enhance the awareness about the prevention strategies for wildfires caused by power distribution system faults.

Keywords: wildfire; power distribution; fire prevention; condition monitoring; surveillance

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1. Introduction

Wildfires are identified as one of the most hazardous and catastrophic natural disasters. Events of wildfires have been recorded around the world over the years [1,2]. Nevertheless, Australia, the United States and Canada are among the top in the list of countries prone to wildfires given their topography, climate and vegetation patterns [3–6]. Australia has a history of a long line of events of large-scale wildfires occurring in the days of elevated temperatures and extreme weather conditions as it is the driest continent in the world. Among these events are the 1939 wildfires in the states of Victoria and New South Wales, 1967 wildfires in Tasmania, 1977 wildfires in Victoria and "Ash Wednesday" and the 1983 wildfires in Victoria and South Australia [7–9]. More recent wildfires include the devastating "Black Saturday" 2009 wildfires in Victoria and the 2019–2020 wildfires in New South Wales [10,11]. These wildfires have collectively resulted in hundreds of fatalities, thousands of houses destroyed and millions of dollars in economic losses. The greatest tragedy of the Black Saturday wildfires in 2009 was that it alone destroyed over 1800 homes burning over 270,000 ha of land and causing death for 173 people [10]. Further, the catastrophic wildfires of New South Wales in the recent wildfire season (2019–2020) in Australia have damaged over 3000 homes, claimed 34 human lives, more than 1.25 animal lives and caused an economic loss of over $110 billion [10,11]. It is evident from these data that the persistence of wildfires in Australia continues to pose enormous socio-economic impacts.

The temperature and rainfall preceding a wildfire determines the size and duration of the wildfires [12]. Further, the wind speed is a crucial factor in determining the spread of wildfires [13]. There are numerous causes of the initiation of wildfires among which some are natural causes such as lightning, which are inevitable [14,15]. Deliberately lit fires and human errors also account for a significant portion of the known fire causes in Australia [16,17]. Some examples of human errors which can lead to wildfires include improperly discarded cigarettes, unattended campfires and the burning of debris [18]. Power distribution system faults and the failure of power distribution infrastructure, especially during elevated fire danger conditions, can result in the initiation of wildfires [19]. There is a wide variety of issues which might cause power distribution system faults. The root causes can be categorized as vegetation-related faults, electrical apparatus failures, pole and crossarm related failures and line failures [1,20]. Vegetation-related faults typically occur when a conductor in an electricity distribution system breaks and touches the ground or leans and touches an overgrown tree branch [21]. In addition, fallen trees or tree branches on conductors can result in faults. These faults are commonly known as High Impedance Faults (HIFs). Electrical apparatus failure refers to the failure of power network equipment such as overhead lines, switches, breakers and capacitors. Further, the explosion of transformers falls into this category. The failure of poles and crossarms is mainly due to their degradation over the service life resulting in the loss of structural integrity. Overlooked defects in this infrastructure can cause structural failures, leading to the loss of capability to support overhead conductors. Moreover, leakage current in wooden poles and insulator contamination can cause pole-top fires which can create severe safety concerns [22]. The detection and prevention of these faults is paramount to mitigate the threat of wildfire initiation and, thus, government authorities continue to pay attention to this. For example, the Victorian Bushfires Royal Commission [10], appointed after the devastating "Black Saturday 2009" wildfires in Victoria, provided special recommendations to prevent or at least to mitigate electricity-caused fires. Among these recommendations are to improve the monitoring and surveillance of power distribution infrastructure.

The main components in power distribution networks are overhead conductors (cables), utility poles, crossarms, transformers and substations [23]. Timber is a widely used material for utility poles and crossarms, due to its relative advantages compared with other alternative materials such as steel, concrete and composites [24]. Timber is a biodegradable material subject to deterioration and the main sources of degradation are weathering, decay and termite attack [25]. Therefore, routine inspections are carried out by the network managers to assess the condition of utility poles and crossarms. The conventional inspection techniques for timber poles and crossarms consist of visual inspection and sounding. Further, drilling operation at the ground level is also carried out in timber poles to assess their condition. Due to the shortcomings and limitations of conventional inspection techniques, there have been recent advancements in sophisticated Non-Destructive Testing (NDT) techniques which can provide accurate and reliable condition assessment [26]. Similar to the deterioration of poles and crossarms, overhead cables also degrade over time mainly due to corrosion and mechanical damage induced by aeolian vibration [27]. Alternating lift and drag forces induced by wind create aeolian vibration in overhead cables. Moreover, there is the possibility of having fine cracks in insulators due to weathering, thermal and mechanical cycling and due to other electro-thermal causes [28]. Given these deterioration mechanisms in overhead lines, monitoring and surveillance techniques are implemented to assess the condition for the purpose of achieving safe and reliable power distribution. Except for the conventional visual inspection, there are improved aerial inspection methods incorporating photography, videography and unmanned aerial vehicles. The main symptom of overhead cable defects is high frequency partial discharges and, thus, there are partial discharge detection techniques for the condition monitoring of overhead cables [29].

As power distribution system faults and the failure of related power infrastructure can cause the initiation of wildfires, it is critical to better understand the mechanisms of and potential prevention strategies for such fires. Therefore, this paper presents how the power distribution network faults cause wildfires, highlighting the main mechanisms. Further, a review was conducted on the recent advancements in the detection and prevention of wildfires caused by power distribution system faults. In addition, the latter part of this paper summarizes the studies on condition monitoring and surveillance techniques for power distribution infrastructure. The overall aim of this study was to enhance awareness about the prevention strategies for wildfires caused by power distribution system faults.

2. Wildfires and Consequences

The threat of wildfires has been continuously increasing for many Australian communities as a result of the population growth in vulnerable areas and due to changing climatic conditions [30]. Compared with other natural hazards, the incurred costs of wildfires are relatively low in Australia. Nevertheless, wildfires have resulted in the highest number of fatalities [31,32]. Table 1 provides a summary of the major events of wildfires occurring in different countries, highlighting the economic losses, number of fatalities and homes destroyed. The devastating Black Saturday wildfires in Victoria resulted in the highest number of fatalities and it is ranked as second among Australia's worst natural disasters. There was a total of 316 fires burning on this day, among which major fires occurred in 14 different geographical regions as illustrated in Figure 1. The spread of fire and its continuation over three weeks burned an area of approximately 400,000 hectares. The wildfire-related fatalities occur due to numerous causes such as flames, heat, smoke and over-exertion [9].

Table 1. Major events of wildfires [9,10,30,33–35].

Date	Location/State (Country)	Economic Loss	Fatalities	Homes Destroyed
14 February 1926	Victoria (Australia)	Not reported	39	550
8–13 January 1939 "Black Thursday"	Victoria and New South Wales (Australia)	~$750 million	79	650
Summer 1943–1944	Victoria (Australia)	Not reported	46	885
7 February 1967	Hobart, Tasmania (Australia)	~$14 million	64	1557
8 January 1969	Lara, Victoria (Australia)	Not reported	21	230
16 February 1983 "Ash Wednesday"	Victoria and South Australia (Australia)	~$400 million	75	2253
18 February 2003	Australian Capital Territory (Australia)	~$350 million	4	530
2003 wildfire season	Siberian Taiga Fires (Russia)	Not reported	17	1100
11 January 2005	Eyre peninsula, South Australia (Australia)	~$40 million	9	93
24–27 August 2007	South Greece	~$1.6 billion	84	1000
7 February 2009 "Black Saturday"	Victoria (Australia)	~$2.94 billion	173	2029
1 May, 4 July 2016	Horse river (Canada)	~$3.8 billion	none	2400
28 November, 9 December 2016	Gatlbinburg (USA)	~$2 billion	14	2500
17, 24 June 2017	Pedrogao Grande (Portugal)	~€500 million	66	263
September 2019 to March 2020	New South Wales (Australia)	~$110 billion	34	3000

Despite enormous efforts for prevention, wildfires in Australia continue to pose severe safety concerns and socio-economic impacts, which is evident from recent wildfires (2019–2020) in the state of New South Wales, which burned more than five million hectares of Eucalyptus forests [36]. Fire weather is generally expressed as a combination of rainfall, air temperature, relative humidity and wind speed [37]. The danger of wildfires has been increased by the changes in climatic conditions that favor the initiation and spread of wildfires [38,39]. The depletion of rainfall and the increase of temperature can create a vulnerable environment for wildfires and the danger can be amplified by higher wind speeds facilitating the spread of fire. By analyzing the Australian rainfall deciles from 1 January to 31 December 2018, it can be noticed that the lowest rainfall is recorded for south-east Australia and this region was subjected to numerous fires between September 2019 and March 2020, resulting in 34 fatalities [40]. Therefore, the climatic conditions preceding a wildfire are also paramount, since they govern the size and duration of the wildfire. Other than metrological conditions, the type/extent of vegetation and topography determine the potential for the spread of wildfires. In the Australian vegetation classification according to AS 3959:2018, there are seven vegetation categories: forest, woodland, shrubland, scrub, mallee, rainforest and grassland. Vegetation is the source of fuel for wildfire and the spread of fire relies on fuel type, fuel arrangement, and fuel load [36]. As an example, grasslands burn quickly compared to forest or scrub. However, forest or scrub burn at a much higher temperature and intensity. Further, considering the topography, a fire can burn much faster uphill and the opposite is true for a fire burning downhill [41]. When a wildfire is reaching uphill with an increasing slope, flames can reach more unburnt fuel and the speed of fire spread is faster.

There is a wide array of socio-economic consequences arising from catastrophic wildfires and the loss of lives is undoubtably the top of the list. Moreover, the trauma inflicted on the communities prone to wildfires is massive, which can even result in long lasting effects over a lifetime. Considering the economic implications, the cost of wildfires can be mainly categorized into three groups: cost in anticipation, cost as a consequence and cost of response [42]. Figure 1 illustrates this categorization. Cost in anticipation refers to the costs incurred for equipment, processes and services to mitigate the adverse effects of wildfires expected in the future. The second category is the cost as a consequence, which is mainly due to property losses, loss of business, injury costs and environmental costs. Costs in response refer to the costs incurred in responding to an event of wildfire (e.g., fire brigade costs).

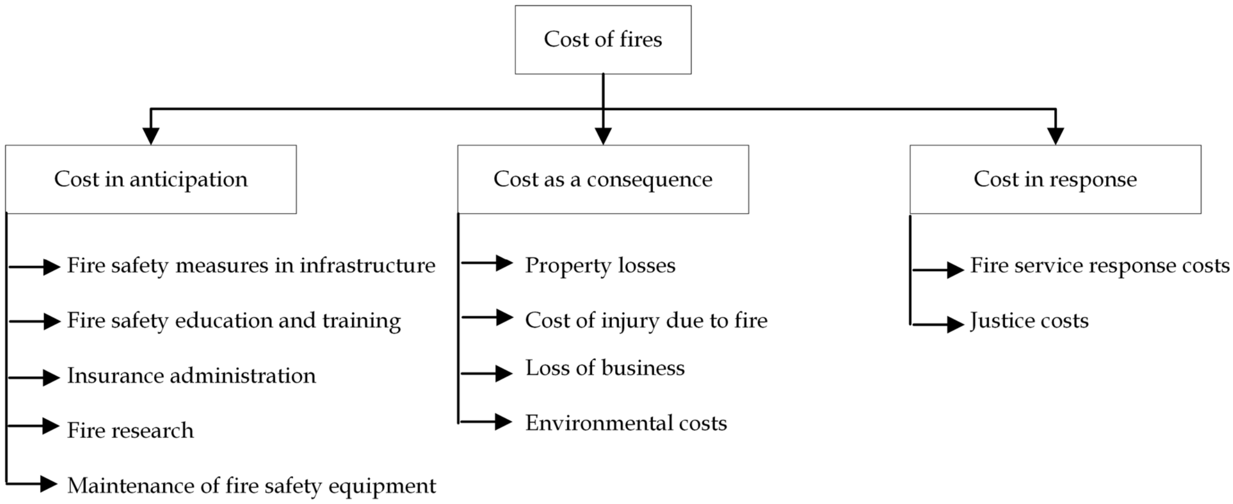


Figure 1. Categorization of the involved costs of wildfires [42].

3. Power Line Failures/Faults and Wildfire Initiation Mechanisms

The failure or faults in power distribution infrastructure can initiate wildfires. Multiple ignition mechanisms are possible considering different root causes. In this paper, the aforementioned mechanisms are broadly grouped as: vegetation related faults, electrical apparatus failures, overhead cable supporting infrastructure (poles and crossarms) failures and overhead cable failures. The following sections provide a brief overview of each mechanism.

3.1. Vegetation Related Faults

Wildfire initiation can take place in different ways due to overhead powerline vegetation-related faults. Characteristics of the vegetations and their ignition features dominate the potential of these faults [43]. The occurrence of vegetation-related faults is twofold. One way is by direct contact with conductors which results in high-impedance fault-to-ground and if this is continued for a reasonable time it can result in flashover. The other way is when fallen trees or broken tree branches land on the overhead cables causing conductors to make contact with each other [44]. Mechanical tear down of conductors by falling trees or branches has been estimated to cause about 80% of all vegetation-related power line failures [20]. Figure 2 illustrates photos of conductor flashover due to vegetation-related faults. These faults are crucial, especially under elevated wildfire danger conditions such as strong winds and high temperatures. Under these conditions, even a small spark can initiate a wildfire which can subsequently lead to a widespread catastrophic wildfire.

Figure 2. Vegetation-related faults and flashover in conductors [20].

A wildfire initiated by vegetation-related faults is driven by a few main factors such as: fuel and its availability to burn, sources of ignition and prevailing weather conditions [45,46]. Fuel and its availability are highly variable both spatially and temporally due to relying on complex physical and biological processes [47]. Fuel arrangement in vegetation can be divided into five main strata: overstorey fuel (trees), elevated fuel (young trees and shrubs), near-surface fuel (herbs and grasses), surface fuel (ground leaf litter and fallen bark) and bark fuel (bark on tree trunks and branches) [48]. The fuel arrangement also greatly varies from place to place, similar to fuel availability. For example, in Australia there are regions of dense rainforests, grassland savannas and open woodlands. Fuel quantity/fuel load relies on the type of vegetation and a dense forest has more fuel than an open forest. In western Australia, Jarrah forests accumulate fuel at a rate of around 1–2 tons per hectare per year whereas Karri forests have a fuel load around 3–4 tons per hectare per year [49,50]. In addition to the type of vegetation and corresponding fuel load, type of fuel also dominates the intensity and spread of wildfires. Fuel type can be characterized as fine or coarse [51]. Fine fuels are less than 6 mm wide and consist of dead leaves, dead grass and twigs. Coarse fuel consists of fallen logs and tree branches which are far less combustible than fine fuels. Fine fuels dry out fast and can catch a fire and burn easily. Despite fuel type, dryness of fuel is also a crucial factor determining the rate of ignition. The dryness or the moisture content of fuel is heavily influenced by climate and local weather conditions. Further, characteristics of the vegetation also affect the moisture content of fuel. Some plant species are relatively drier than others naturally [52].

3.2. Electrical Apparatus Failure

Power distribution networks consist of different electrical equipment such as transformers, breakers, switches, bushings, clamps, capacitors and many more. Faults in this equipment can lead to overheating which can ultimately end up with burning, arching or explosion. Falling down of the hot molten or burning parts on ground or vegetation can lead to the initiation of wildfires. Among different components, transformers have been identified to be more susceptible to explosions and fires [53]. In addition to transformer explosion, bushing flashover has been observed as another common example of electrical equipment failure [20].

3.3. Power Distribution Infrastructure Failure

Utility poles and crossarms are the structures supporting the overhead cables. Most of this infrastructure is made from timber which is a bio-degradable material subjected to deterioration over the service life. Failure of timber poles can take place under normal conditions due to overlooked defects resulting in false conclusions about the structural integrity. Their failure rates can be high, especially under low frequency extreme weather events such as hurricanes. Moreover, vehicle crashes can result in the failure of timber poles. The failure of poles or crossarms can result in the conductors being grounded or conductors coming into contact with each other leading to flashover or arching.

3.4. Conductor Failure

Conductor failure can take place, especially under high wind conditions. When the conductors are loose, high swinging can take place, resulting in the distension of cables and the bending of supporting structures. Arching can take place if contact occurs between energized conductors, and clashing power lines are likely to emit particles capable of causing wildfires [54]. In addition to high wind conditions, conductor clashing can occur due to short circuits in a power system leading to electromagnetic forces between conductors. These electromagnetic forces subsequently lead to conductor swinging which creates the possibility of arching.

The aforementioned mechanisms can occur alone or in combination with each other. For example, in the event of extreme wind conditions, there is a possibility of fallen trees or branches on conductors causing vegetation-related faults. Meanwhile, higher wind speed can lead to a higher probability of utility pole or crossarm failure. Thus, power distribution infrastructure failure is also possible under high winds. In addition, conductor flashing is another possibility due to the high swinging of cables and contact between energized conductors. Therefore, more than one mechanism can take place simultaneously under certain conditions. Among the different types of wildfire initiation mechanisms due to power line faults, vegetation-related faults are the most common and significant factor contributing to wildfires. This has been identified as the main cause for many large-scale wildfires spread in Australia [10,11]. In terms of the frequency of occurrence, the second dominant cause for wildfire initiation is the conductor failure. Conductor failures can generate sparks and these can initiate wildfires in elevated wildfire danger conditions. Electrical apparatus failure and power distribution infrastructure failure can be rated as the next influential mechanisms of wildfire initiation due to powerline faults. When assessing the risk of wildfire initiation due to power line faults, the aforementioned order of causes needs to be considered according to their significance.

4. Prediction, Detection and Prevention of Wildfires

Prediction, detection and prevention are important steps which are essential in wildfire management to prevent or mitigate catastrophic wildfires and their consequences. The following sections summarize previous research carried out to advance the prediction, detection and prevention of wildfires. A detailed explanation of condition assessment technologies for power distribution infrastructure to detect/predict potential power line faults is not presented here and it can be found in the previous works of the authors [23,26,55].

4.1. Prediction of Wildfires

The adverse effects of climate change are evidenced in most parts of the world where the intensity and duration of droughts are increased. Moreover, rainfall intensity in some regions has been drastically reduced. Therefore, advanced wildfire prediction tools are essential. Chaparro et al. [56] explored the climate–wildfire relationship by incorporating remotely-sensed soil moisture data to predict the extent of wildfires. Wildfires that occurred in the Iberian Peninsula between 2010 and 2014 were analyzed. It was observed that low surface temperatures and wet soils limited wildfire spread. The proposed model with moisture-temperature preconditions was improved by adding information on land cover and month of fire outbreak. Results indicated that the developed model has a wildfire extent prediction accuracy of around 83%. Catry et al. [57] used logistic regression models to predict the potential of wildfire ignitions in Portugal. More than 125,000 ignitions that occurred within a 5-year period were analyzed. Analysis results showed that the land cover, elevation, population density and human accessibility are the key parameters affecting the spatial distribution of fire ignitions. Predictions from this kind of model can facilitate the decision-making process of wildfire management. Fire occurrence probability mapping of northeast China was investigated by Zhang et al. [58] to better understand the spatial distribution of fires. A binary logistic regression model was developed by incorporating ten predictor variables. The proposed model was evaluated using inner testing and was validated independently. The results indicated better reliability and greater potential for fire management.

The conventional wildfire prediction techniques are mostly probability based or from statistical analysis. Nevertheless, machine learning algorithms such as neural networks have also been implemented recently for wildfire size and risk prediction [59,60]. Lall and Mathibela [59] developed an artificial neural network pattern recognition model for wildfire risk prediction for the city of Cape Town in South Africa. Vegetation, climate and location features were used as inputs to the model and the outputs were whether a particular region has low, moderate, high or extreme susceptibility to wildfires. The model was trained and tested on fire incidence data from 2009 to 2015. It was observed from the results that the developed model has an accuracy of 97% and a precision of 87%. A similar study was conducted by Storer and Green [60] to predict wildfire size using neural network models. A relatively small, highly skewed dataset from a national park in Portugal was selected for model development. A Particle Swarm Optimization algorithm was used to train the neural network regression model to predict the burned area from wildfires. The implementation of the Particle Swarm Optimization algorithm significantly reduced the root mean square error of the neural network model and provided accurate results.

4.2. Detection Techniques of Wildfires

After the initiation of a fire in a particular location, it can develop into a widespread wildfire in elevated temperatures and higher wind speeds. Therefore, early detection and response to wildfires is crucial to avoid widespread catastrophic wildfires. Some of the conventional techniques that are used for wildfire detection include mobile ground-based solutions, satellite imaging, aerial platforms and sensing techniques [1]. Fukuhara et al. [61] developed a technique whereby a thermal infrared camera mounted on a small satellite was used to detect wildfires. The developed apparatus was launched and has successfully detected considerable hotspots of wildfires. Further, the brightness temperature derived from the observation has been used to presume the scale/extent of the wildfire. Thus, it is evident that satellite observations in combination with infrared cameras can detect wildfires effectively. In other investigations [62], satellite-based fire observations were combined with ground-based lightning detections to identify lightning fires. In this study, an algorithm was developed and tested which combined Moderate Resolution Imaging Spectroradiometer (MODIS) fire detections with lightning detections from the National Lightning Detection Network (NLDN) to identify lightning fires in the USA. The algorithm successfully detected broad scale spatial patterns of lightning fire occurrences. However, the proposed technique had limitations in detecting smaller fires. Chen and Huang [63] designed and developed an intelligent fire-safety management system (FSMS) for electrical fire detection and emergency response. The integrated FSMS consisted of sensor nodes and an energy meter with a smart breaker and concentrator. This system was designed to continuously monitor the energy information and line losses to detect potential electrical fires. Moreover, the proposed system was capable of shortening the fire alarm delay, allowing for a quick emergency response. The detection of electrical fires facilitates the avoidance or mitigation of potential wildfires.

Polivka et al. [64] proposed a novel technique for detecting wildfires at night by incorporating visible light to the detection algorithm. The existing technique of satellite remote sensing of fires was improved with the Visible Infrared Imaging Radiometer Suite (VIIRS) day-night band. In the proposed algorithm, fire pixels were characterized based on visible light and infrared signatures at night. Compared with the VIIRS fire algorithm, the developed technique showed an increase up to 90% in the number of detected fire pixels for the study period. In a study by Dimitropoulos et al. [65], a real time video-based flame detection algorithm was proposed. Higher detection rates were achieved by modeling the behavior of the fire using various spatio-temporal features and the temporal evolution of pixels' intensities in an image block through dynamic texture analysis. A two-class support vector machine algorithm was employed as a supervised learning algorithm to classify the candidate regions. Experimental results of the proposed technique indicated that it outperforms the conventional fire detection algorithms. Smoke detection is another aspect that can be focused on for wildfire detection. Labati et al. [66] explored a novel approach to detecting wildfire smoke clouds from low-quality frame sequences. This approach was based on image processing and computational intelligence techniques, which could identify wildfire smoke from heterogenous sequences taken from a distance. Both real and simulated smoke frame sequences were used for the performance evaluation of the proposed approach. Accurate detection capability was observed in this technique for a wide array of environments and weather conditions.

Gunay et al. [67] developed an entropy-functional-based online adaptive decision fusion (EADF) framework for image analysis and computer vision for the application of wildfire detection in video. The proposed algorithm consisted of five main steps: slow moving object detection in video, smoke colored region detection, wavelet transform-based region smoothness detection, shadow detection and elimination and classification with decision functions. The experimental results of the proposed wildfire detection technique were satisfactory and it facilitated real-time intelligent video analysis. Recent advancements in data mining and machine learning techniques have been employed by researchers to improve the wildfire detection and classification algorithms [68,69]. In these studies, supervised learning algorithms such as artificial neural network models and unsupervised learning algorithms such as k-NN classifiers were implemented to facilitate wildfire detection while minimizing the false detections. Phan et al. [70] conducted a similar study to investigate the feasibility of using a multi-scale deep neural network model for detecting and locating wildfires. Satellite images and weather data were used for the neural network model. It was noticed that weather information with careful spatio-temporal alignment can effectively augment the imagery data. Experiments on real-world datasets showed that the proposed model had an accuracy of 93%. In [71], a machine learning based approach was proposed to learn the normal spatio-temporal behavior of the environmental data collected over one year. Then, possible wildfire detection was carried out by detecting anomalies in the real-time data (from field sensors) of the spatio-temporal pattern. In this framework, the Internet of Things was applied to ensure that the detected anomalies indicating possible wildfires were not due to sensor failure or security attack.

In addition to satellite images and sensing techniques, drones can also be employed for wildfire detection, monitoring and control (e.g., [72]). Drones can be used specifically to collect images, data on wind speed, direction and microclimate, which can be gathered to better understand the behavior of forest fires. Zhang et al. [73] developed a wildfire detection model based on drones and UAVs. Eastern Victoria, Australia was selected as the study area and in the proposed methodology, drones detect terrain automatically and send the information to emergency operations center. Radio repeater drones were employed to eliminate communication problems in firefighting. Estimation models were developed to predict the required optimum number of drones for future operations considering the increase of the fire density in the study area. Table 2 shows a summary of the studies on wildfire detection techniques.

Table 2. Summary of the studies on wildfire detection techniques.

Study	Category	Equipment, Methods, Analysis Techniques
[61]	Satellite imaging	Thermal infrared camera mounted on a small satellite, hotspot detection
[62]	Satellite imaging and ground-based solutions	Algorithm combining Moderate Resolution Imaging Spectroradiometer (MODIS) fire detections with lightning detections from the National Lightning Detection Network (NLDN)
[63]	Smart sensing	Sensor nodes, energy meter with a smart breaker and concentrator, Intelligent fire-safety management system (FSMS) for electrical fire detection and emergency response
[64]	Satellite imaging and sensing techniques	Visible Infrared Imaging Radiometer Suite (VIIRS) day-night band, thermal emission and reflection
[65]	Terrestrial systems based on video cameras	Video-based flame detection, computer vision, spatio-temporal modeling, dynamic texture analysis
[66]	Surveillance camera imaging	Wildfire smoke cloud detection, image processing, computational intelligence techniques
[67]	Surveillance camera videography	Entropy-functional-based online adaptive decision fusion (EADF) framework for image analysis and computer vision
[68,69]	Satellite imaging	Data processing and interpretation using machine learning algorithms, neural network models, k-NN classifiers
[70]	Satellite imaging and remote sensing	Satellite images and weather data for wildfire detection, multi-scale deep neural network model
[71]	Smart sensing	Anomaly detection of the spatiotemporal behavior to detect possible wildfires, Internet of Things
[72]	Drone-based network sensing	Drones to collect images, wind data and microclimate data to detect wildfires
[73]	Drone-based network sensing and controlling	Drones to collect information, communicate and control wildfires

4.3. Prevention of Wildfires Caused by Powerline Failures

Different approaches can be employed for the prevention of wildfires initiated by power line failures. The replacement of fire prone equipment in overhead lines is one possible option. Power system equipment, such as oil-filled transformers, have higher potential for the initiation of wildfires due to explosion or burning. This kind of device can be replaced with equivalent dry type fire safe equipment. Nevertheless, replacing all the fire prone equipment in a power distribution network is not always economically feasible.

Overhead line management is another option for wildfire prevention, in which the line design documents can be revisited. By modifying the design standards, there is the possibility of avoiding or minimizing power line failures such as clashing conductors. Extra length, extra sag and transitions are the common reasons for conductor clashing which are mainly due to incorrect designs of overhead lines. Revisiting the designs considering less frequent extreme weather events can enhance the integrity of power distribution networks. Another option for avoiding power line failures is by moving towards underground power systems. This approach has already been used in some cities around the world and it completely eliminates the wildfire risk due to power line failures. However, it is extremely costly and will only be feasible when designing and implementing new power distribution systems.

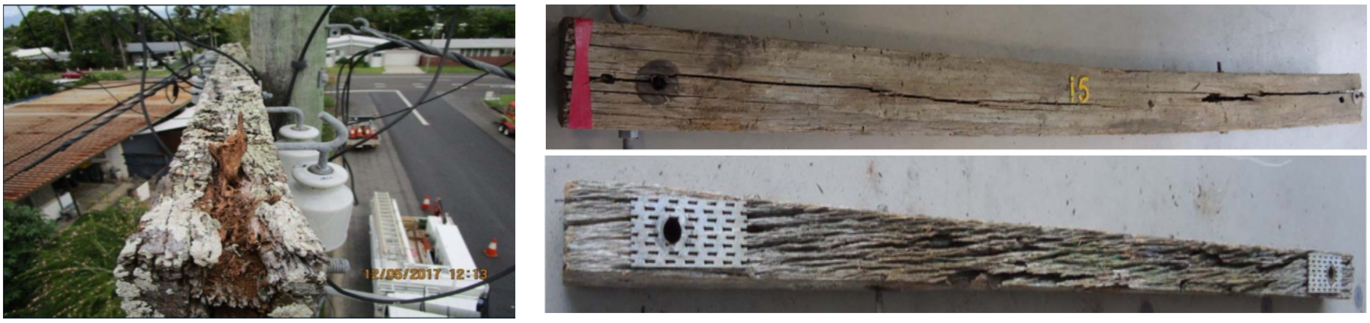
Replacing bare wires with covered conductors is another feasible option which can reduce or prevent the initiation of wildfires. In covered conductors, a weather resistant insulation cover is placed on top of the conductor. This insulation cover enhances the tolerance of overhead conductors against clashing and leaning trees. In addition, covered conductors enable reduced phase distances, making the power lines even more compact compared to bare conductors. Another wildfire prevention technique adopted by Australian power distribution companies is to use Rapid Earth Fault Current Limiters (REFCLs). REFCLs detect when one line out of a three-phase powerline has fallen and almost instantly reduces the voltage on the fallen line while it increases the voltage on the two remaining lines in service. Due to the reduced voltage on the fallen line, the resulting current flow will not be sufficient to spark a fire. Hence, it maintains power in the network but significantly reduces the fire risk [74]. Further, Automatic Circuit Reclosers (ACRs) are employed in power distribution networks to combat the wildfire risk. ACRs operate in such a way that, when a fault is detected, the circuit breaker trips. Then, the controller closes the circuit again under configured conditions. However, if a fault persists, the circuit breaker trips again [75]. The reclosing mechanism can be disabled on days of high wildfire risk. These guidelines are specified in national wildfire mitigation policies. Both REFCLs and ACRs have been identified as effective, reliable and feasible approaches to minimizing the risk of wildfire initiation.

All the aforementioned approaches for the prevention of wildfires initiated by power line failures are capital-intensive. Moreover, some of these techniques can be only implemented for new power distribution systems. On the other hand, timely inspection and maintenance of power distribution networks are economically feasible options for managing power lines, transformers, utility poles, cross arms, breakers, capacitors and other related equipment. Proper inspection cycles need to be determined based on the network. Shorter inspection cycles are required for wildfire prone regions. The reliability and accuracy of the inspection and maintenance techniques are paramount for effective condition assessment. Management decisions about the replacement of power distribution network equipment need to be taken based on the results of the condition assessment techniques.

5. Condition Monitoring and Surveillance Techniques for Power Distribution Infrastructure

Assessing the condition of power distribution infrastructure is essential to avoid component failures which might have severe safety concerns considering the initiation of wildfires. The main power distribution components include utility poles, cross arms, conductors and other related equipment. Timber is the material that is mainly used for utility poles and cross arms. Timber is a biodegradable material that is subject to deterioration over time due to weathering, decay and termite attacks. Weathering is the deterioration of the external surface of wood due to the exposure to sunlight and alternating wet and dry conditions. Decay is caused by fungal attack which consumes wood for its growth. Favorable conditions, such as the retention of moisture in wood, enhance the susceptibility to decay. In timber utility poles, the below ground section is the crucial part considering fungal attack, since moisture can be retained in the soil. Figure 3 shows the presence of defects in uprooted and sectioned timber poles condemned from service. As noticed in Figure 3, the defect has spread throughout the length of the pole and a significant portion of the sound wood is lost. Figure 4 illustrates the presence of defects in in-service and decommissioned timber cross arms. The cross arm in Figure 4a has been severely degraded by weathering and decay. Defects of splitting close to bolt holes and severe weathering of the exterior surface of cross arms are shown in Figure 4b. In timber cross arms, decay is significant close to the bolt holes where moisture can be retained for a long period of time. Termite attack can be anywhere in a utility pole and it is not limited to the below-ground region. Weathering, decay and termite attack are not the only issues related to ageing timber power distribution infrastructure. Leakage of current flow in wooden components can also be a source of the initiation of fires even though these infrastructures are in a structurally sound condition. Insulation degradation resulting in the leakage of current flow through high voltage insulators has been investigated and it was found that there is a significant ageing effect on timber components' resistance to the leakage of current flow [22]. The leakage of current flow in timber poles has the possibility to initiate fire at the pole top leading to a pole failure. Figure 5 shows a burning timber pole where the initiation of fire is within the pole due to leakage of current or electrical apparatus fault.

Figure 3. Defects in uprooted and sectioned timber poles condemned from service.



(**a**) (**b**)

Figure 4. Defects in timber cross arms (**a**) in-service cross arm (**b**) splitting and weathering in decommissioned cross arms.

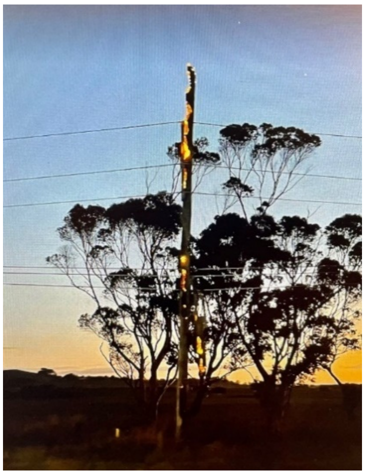
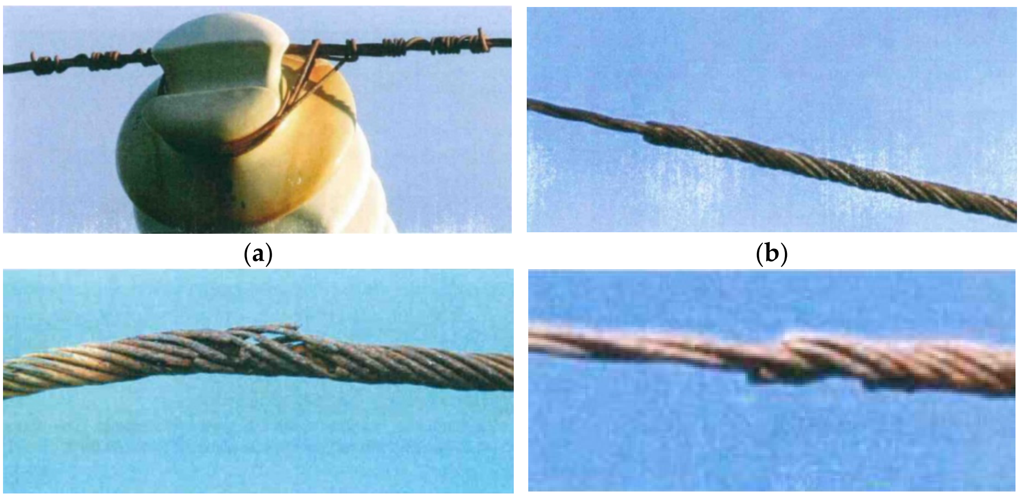


Figure 5. Burning pole—initiation of fire within the pole due to leakage of current or electrical apparatus fault.

Due to these modes of deterioration, routine inspections are carried out by network managers to assess the condition of timber poles and cross arms. Visual inspection, sounding and drilling are the conventional pole inspection techniques. However, the accuracy and the reliability of the obtained results using these techniques are questionable due to subjectivity. Therefore, advanced non-destructive testing techniques such as vibration-based techniques, stress wave propagation-based techniques, ultrasonic and tomography techniques have been explored to accurately predict the condition and the remaining service life of utility poles. Advanced machine learning algorithms are used in combination with these non-destructive testing techniques for post processing and result interpretation [76,77].

Performance comparison of these techniques has been carried out in the previous works of the authors, summarizing the relevant research works [26]. Therefore, they are not presented here. Similar to timber poles, visual inspection and sounding are the conventional inspection methods used for timber cross arms. However, drilling inspection is not very common for timber cross arms. Except for the visual inspection, advanced inspection techniques using aerial photographs have been developed for accurate inspection with the use of unmanned aerial vehicles. The condition assessment techniques for cross arms have been investigated and presented in the previous works of the authors [78]. The focus of this paper was mainly on condition monitoring and surveillance techniques for overhead cables, since overhead lines are a financially feasible and frequently-used option as carriers for electric energy. Assessing the condition of electrical equipment in networks such as transformers, breakers, capacitors and insulators is not within the scope of this work.

Compared with the early days of the power industry, the distances over which power is transmitted have continuously increased along with the system voltage levels [27]. Therefore, there is a higher chance of overhead cable failures given the increased transmission lengths. The main factors affecting the conductor degradation are the corrosion and vibration. Corrosion initiates at the exterior surface of the conductor and spreads towards the steel core, and the rate of corrosion relies on a number of factors such as environmental and climatic factors. For example, elevated levels of corrosion can be experienced in regions where sea salt aerosol or industrial halides influence the overhead cables [27]. The continuation of corrosion with time reduces the section of the metal strands in the conductor, which results in a reduction of the current-carrying capability and a loss of mechanical strength. In addition to corrosion, wind-induced alternate lift and drag forces acting on the conductor can cause conductor degradation. The type and intensity of the vibrations determine the magnitude of the bending stresses on the cables. Both corrosion- and vibration-induced defects need to be detected and the severity of these defects needs to be assessed to avoid conductor failures. Figure 6 shows photos of defects in overhead lines and these defects are identified in ties, conductor terminations and conductor joint/splices.



(**a**) (**b**)

(**c**) (**d**)

Figure 6. Defects in overhead lines. (**a**) ties (**b**) terminations (**c**,**d**) conductor joints/splices.

The aforementioned defects can be identified by a careful observation of potential symptoms. The generation of partial discharge has been identified as a major and sensitive symptom for the identification of conductor defects. Therefore, partial discharge detection is a major type of condition assessment technique for overhead cables.

5.1. Partial Discharge Detection of Overhead Cables

The detection of partial discharges (PDs) in overhead cables can reveal information about the presence of potential defects and their locations. Therefore, many researchers have explored different aspects of PD detection for the reliable and accurate condition assessment of overhead cables. Steiner and Reynolds [79] explored technical difficulties associated with the location identification of PDs. It was observed that the background noise in the system limits the PD detection if it is not properly dealt with. Further, it was noticed that a single minimum detectable level of PD in a cable cannot be defined since it was case dependent. It was proposed in this study to develop a portable apparatus with a signal processor with a PD-free power source for the system to detect PDs in overhead cables. Additionally, to use this apparatus in the field, it should have the capacity to capture and process thousands of PD events in a short period of time. In [80], an online PD detection technique was developed which can be applied to both wire screen and solid shielded cables. This technique used a spectrum analyzer at a very high frequency (VHF) and it was capable of checking the cable accessories such as splices and terminations. The performance of the proposed technique was evaluated and compared with the alternative PD detection techniques such as a pulse phase analyzer and a high-speed digital oscilloscope. It was observed that the online PD detection technique had good attributes similar to those of the two alternative PD detection techniques.

Gulski et al. [81] investigated advanced PD diagnostics of medium voltage power cables using an oscillating wave test system. PD measurements during service, as well as the on-site continuous energizing of medium voltage cables, were explored. It was noted that the sensitive detection of critical PD occurs by energizing the medium voltage cables at 50 Hz. The detection of discharges alone in a cable was not sufficient to determine in the seriousness of the defect and detailed investigation was required depending on the type of insulation. This study was extended in [82] by discussing some characteristic cases of time-based signals collected by onsite PD analysis techniques. The accurate techniques to extract correct discharging sites from these signals were explored. It was concluded that, with the use of advanced software, the PD analysis can be expedited and can be fully automated in certain cases. Nevertheless, some cases were identified which provided erroneous interpretations such as the cases of physical limitations or crossing pulses. It was found that some of the above cases can be addressed by further developments in data post processing. Quak et al. [83] explored different techniques that can be used to extract the maximum possible information from PD patterns for effective condition assessment of overhead cables. Wavelet transform was employed to differentiate noise and other possible disturbances from time domain signals. An example of the wavelet denoising of PD data obtained from field measurements was presented. It was noticed that the optimum mother wavelet should be selected depending on the cable length. Further, it was observed that, when interpreting results, the influence of different velocities on cable sections comprised of various cable parts needs to be considered. It was concluded that wavelet filtering is a useful technique for de-noising PD measurement data.

Practical experiences with the insulation condition assessment of power cables via PD diagnosis were presented in [84] considering different cases in the Netherlands. This study showed that selecting a proper advanced PD diagnosis technique in the field requires due consideration for both technical and economic aspects. In addition, it was noticed that PD diagnosis at digital-to-analogue converter (DAC) voltages can detect cable insulation defects in both cross-linked polyethylene (XLPE) and paper-insulated lead covered (PILC) cables. Database support was found to be very effective in extracting additional information, which was not shown by the measurements, to make maintenance and management decisions. Gulski et al. [85] presented an overview of the on-site testing and PD detection of high voltage (HV) power cables considering the aspects of energizing and diagnosis. Both newly-installed HV cables and service-aged cables were studied. From the field experience, it was noted that PD detection for new, repaired and service-aged cable systems is crucial for evaluating the overall condition, estimating the reliability and setting up maintenance/replacement schedules. Further, the test results of enhanced AC voltage testing higher than the overvoltage of defective insulation showed that it may have a destructive influence on the service life of the component in service even if a breakdown has not occurred. PD detection can be effectively employed to check whether an onsite test had a destructive impact on the insulation system. In [86], the influence of attenuation and the dispersive effects of cable characteristics for PD diagnosis was investigated. Energizing the PILC and XLPE cables with damped AC voltage demonstrated the relevant demands for field application of PD diagnosis. It was proposed to use statistical methods to determine the threshold levels and relevant condition indices, when a sufficient amount of PD diagnosis data for cables were available. It was concluded that PDs need to be measured and analyzed at voltages up to 1.7 times overvoltage to detect and localize weak spots in cable insulation and cable accessories.

There is a wide array of factors influencing the quality of the PD measurement and its interpretation. Specifically, when testing for long lengths of Power distribution cables the sensitivity and capability to locate the PD site is affected. Therefore [87], proposed to increase the PD measurement sensitivity by including an additional PD measuring unit at the end of the cable. This additional unit was measuring the PD activity with conventional PD detection synchronized with the damped AC test voltage. The test results indicated that this two-sided measurement provides higher detection sensitivity when this technique is applied for a long length of medium voltage cables. Shafiq et al. [88] explored the possibility of monitoring the entire feeder by installing integrated sensors at each critical location. The direction-of-arrival technique was used for PD diagnosis. The performance of the integrated sensors was evaluated by conducting simulations. The proposed electromagnetic PD measurements system was compatible with both continuous and periodic monitoring. Nevertheless, a hybrid monitoring system was proposed to overcome the shortcomings of conventional monitoring techniques. A permanently installed sensor network collected data at constant time intervals and this mitigated the drawback of missing hard events on the components which was impossible with periodic monitoring. Refaat and Shams [29] reviewed the PD diagnosis techniques considering both offline and online detection. Moreover, the common signal denoising techniques were presented, highlighting the relative advantages and shortcomings of each technique. Offline detection techniques such as direct detection circuit and bridge detection circuit were described summarizing the relevant studies. Online detection techniques summarized in this study were acoustic and ultrasonic sensors, high-frequency current transformer and transient voltage sensors. Under PD denoising techniques, the use of artificial neural networks, discrete wavelet transform and fast Fourier transform was presented. This study also highlighted the main challenges faced in the practical implementation of PD detection. Attenuation and dispersion, selection of the optimum position of the PD detection equipment and calibration of the detected signal to localize the defects and identify its severity were among the main challenges that were identified.

Wu et al. [89] proposed assessing the condition of high voltage XLPE cables through PD measurement using a high frequency current transformer through link boxes. These link boxes were used to facilitate on-site PD signal identification and they were placed in manholes since most of the overhead cables run along roadsides. A phase-resolved PD pattern was used to diagnose the insulation condition. This study described the method of locating the PD source on a cable circuit and the challenges faced when using PD measurement by a high frequency current transformer. The effectiveness of the proposed PD measurement technique was evaluated using real cases of monitoring 132 kV cables. Results from these cases demonstrated the capability of the proposed technique to detect cable defects. The conventional PD detection and analysis techniques for the condition assessment of power distribution cables can be improved by incorporating machine learning algorithms, specifically to automate the post processing. In [90], a deep learning approach was implemented to develop a PD detection framework. This framework did not require any feature extraction and very little pre-processing was needed. Convolution neural network models provided improved detection results at the power line and phase levels. Further, pulse activation maps were extracted to improve the interpretability of the results. Significant time saving was experienced by implementing neural networks in comparison with the conventional techniques. Another key feature of learning algorithms is its learning and generalization capability with access to more data. From all these studies, it is evident that the PD detection has a huge potential for the on-site condition assessment of overhead cables. Table 3 provides a brief summary of the studies on PD detection techniques for the condition assessment of power distribution cables.

Table 3. Summary of the studies on PD detection techniques.

Study	Content, Methods, Analysis Techniques	Remarks
[79]	Analysis of technical difficulties associated with location identification of partial discharges.	Background noise in the system was identified as the key factor which limits the PD detection
[80]	Development of an online PD detection technique by using a spectrum analyzer in VHF	Illustrated good performance in comparison with pulse phase analyzer and high-speed digital oscilloscope.
[81]	PD Diagnostic of medium voltage power cables using oscillating wave test system	It was found that sensitive detection of critical PD occurs by energizing the medium voltage cables at 50 Hz.
[82]	Explored accurate techniques to extract correct discharging sites from PD signals	Cases of physical limitations or crossing pulses provided erroneous interpretations. Further post-processing was encouraged
[83]	Wavelet transform was employed to differentiate noise and other possible disturbances from time domain signals.	The optimum mother wavelet should be selected depending on the cable length.
[84]	Presented practical experiences with insulation condition assessment of power cables via PD diagnosis summarizing case studies in the Netherlands	Database support was found to be very effective in extracting additional information to make maintenance and management decisions.
[85]	PD detection of High Voltage (HV) power cables considering the aspects of energizing and diagnosis	PD detection could be employed to check weather an onsite test had destructive impact on the insulation system.
[86]	Influence of attenuation and dispersive effects of cable characteristics for PD diagnosis was investigated	PDs need to be measured and analyzed at voltages up to 1. 7 times overvoltage to detect and localize weak spots in cable insulation
[87]	Inclusion of an additional PD measuring unit at the end of the cable for testing long length of cables	Two-sided measurement provided higher detection sensitivity when testing for long length of power cables
[88]	Monitored the entire feeder by installing integrated sensors at each critical location and a hybrid monitoring system was proposed	Permanently installed sensor network collected data at constant time intervals and this mitigated the drawback of missing hard events on the components
[29]	Reviewed the PD diagnosis techniques considering both offline and online detection. Presented common signal denoising techniques	Attenuation and dispersion, selection of the optimum position of the PD detection equipment and calibration of the detected signal were identified as main challenges
[89]	Assessing HV XLPE cables through PD measurement using high frequency current transformer through link boxes	Phase resolved PD pattern was used to diagnose the insulation condition
[90]	Deep learning approach was implemented to develop a PD detection framework in combination with pulse activation maps	Convolution neural network models provided improved detection results at the power line and phase levels

5.2. Inspection of Overhead Conductors

The inspection of overhead conductors is carried out using different techniques. Some of the conventional inspection techniques are ground patrol, photography and videography from the ground. In the ground patrol technique, power lines are inspected from the ground by travelling along the length of the distribution lines. This technique requires lot of time and manpower, and can be very challenging when the access to the line becomes difficult. To avoid the subjectivity of the ground patrol techniques, photography and videography techniques from the ground have been introduced [91]. Photography and videography provide useful information which can be used for documentation for future reference.

Nevertheless, limited access to the power lines creates difficulties in obtaining better sight, which hinders the observations. These techniques can provide better spot assessment for distribution cables where problems or defects have already been identified.

5.2.1. Airborne Inspection Techniques

To address the shortcomings and limitations of the conventional inspection techniques carried out from the ground, airborne inspection methods have been introduced such as airborne visual patrol, photography and videography. Airborne inspection provides better access and full sight of the distribution cables for better condition assessment. Airborne photography and videography techniques can achieve high speed line patrol and the critical locations can be captured by zooming in. High speed recording/picture shooting and wide-angle sight are some of the attributes which can provide enhanced performance for assessing the condition. The initiation of airborne inspection methods has been conducted through cameras and recorders mounted on helicopters. However, with the advancement of technology, airborne inspection has come to be performed using unmanned aerial vehicles and mobile robots. Further, automated image analysis techniques have been incorporated to facilitate improved aerial inspection of power distribution cables.

Whitworth et al. [92] investigated the feasibility of using a helicopter-mounted camera to capture and store visual information from a video inspection of overhead power lines. This technique required a helicopter flying at low levels adjacent to power lines to video record the condition of power lines. This paper presented the use of active vision techniques to automatically steer the camera's sightline to acquire and maintain the object to be observed in the camera's field of view. Further, challenges that need to be addressed in the airborne inspection of overhead cables using helicopters were highlighted. The low resolution of aerial images can hinder the condition assessment of power lines via airborne inspection. Therefore, automatic extraction of features from aerial images is paramount, especially with the spread of aerial photogrammetry technology and sensor technology. In [93], an automated algorithm for the extraction of power lines from aerial images was presented, which processed aerial images acquired from a digital camera mounted on a helicopter. This algorithm consisted of three steps—the extraction of line segments, a grouping method to link relevant segments and connecting segments with the application of Kalman filter technology to form the complete overhead cable. Experimental results indicated the capability of the proposed technique to extract power lines from aerial images irrespective of the background complexity.

With the advancement of data processing methods, deep learning algorithms have been used for the post processing of aerial images taken from airborne inspection [94–96]. Manual interpretation of the aerial images is challenging when power distribution lines are inspected for thousands of kilometers. Therefore, automating the data processing and interpretation is essential for accurate and efficient condition assessment. In addition, when more and more data are fed to learning algorithms, the prediction and generalization capacity of the model keeps on improving. Considering these attributes, different deep learning approaches, such as deep convolutional neural networks, have been successfully implemented for the condition assessment of power distribution cables. Once the data are collected, subsequent steps of data cleaning, data labelling, data augmentation, component detection, fault identification and finally model training and optimization need to be followed. Data cleaning, data labelling and data augmentation can be categorized as data preprocessing, and typically manual data preprocessing is carried out using conventional techniques. Automated data preprocessing, analysis and post processing can result in significant time saving while improving the prediction accuracy. Some of the challenges faced during the implementation of these deep learning algorithms are data quality problems, small object detection and embedded application. The pixel resolution of the images has to be sufficient enough to detect small objects and their defects. However, using high resolution aerial images and video recordings requires lot of storage capacity. Thus, it should be a balance between the resolution of the images, available devices for capturing images and the available data storage capability. Embedded application challenges refer to the problems, related to existing embedded computing devices, of not being able to handle high performance analysis methods. These areas need to be further studied and solutions have to be proposed to overcome the existing limitations.

5.2.2. Advanced Inspection Techniques (via Mobile Robots and Unmanned Aerial Vehicles)

Both the conventional inspection techniques of observing the power distribution lines from the ground and airborne inspection techniques such as photography and videography have limitations. Airborne inspection has mainly been carried out using cameras and recorders mounted to helicopters. Therefore, it requires properly trained human resources and these techniques can be quite expensive considering the cost of helicopters. With the advancement of technology, these issues have been addressed by incorporating mobile robots and unmanned aerial vehicles (UAVs) for airborne inspection.

Tavares and Sequeira [97] presented the development of a robot which is capable of moving on power distribution lines for the purpose of condition assessment. The proposed robot consisted of a main body and three arms. Two of the arms were used to provide motion and the remaining arm ensured the stability and facilitated overcoming obstacles in motion. Simulations were carried out to evaluate the performance of the robot. Simulation results indicated the kinematic structure of the proposed robot was capable of moving successfully on power distribution lines up to a slope of 10^0. A similar work was presented in [98], where a double conical wheels-based mobile robot was developed for the aerial inspection of power distribution lines. This robot consisted of three driven wheels, a distributed control system and a self-configuration frame. The shape of the wheels was designed to overpass the powerline devices and obstacles. In addition, this shape enhanced the self-steering capability of the wheels. The configurable frame was able to determine the wheel position based on the distance between the power distribution cables. Field tests were conducted using the developed robot prototype and it was capable of minimizing the inspection time and improving the inspection quality and the safety of electricians. Pouliat et al. [99] developed a teleoperated robotic platform called Line Scout to inspect and maintain high voltage power lines. This robot was capable of avoiding most obstacles found along grid lines. This study presented the mobile platform design and its mechatronics subsystems to introduce the main functions and potential applications of the proposed technology. The platform was comprised of a compact modular arm and a sensor network capable of conducting inspection and maintenance. A future research direction was shown to develop autonomous navigation and inspection using improved robotic platform.

Robotic applications have mostly been through robots that can travel along the power distribution lines for inspection and maintenance. However, there are robotic applications where robots are placed in vehicles which can travel along power distribution lines and these robots are teleoperated by human operators [100]. This kind of a system consists of an operator's cabin and a remote platform which is located on the top of an isolated telescopic boom. Inspection and maintenance of live power lines can be carried out in a safe and reliable manner with the use of these robotic systems. Oliveira and Lages [101] investigated the use of infrared vision for the robotized inspection of power lines. The normal air borne inspection uses images generated by the usual cameras in the range of visible light. In contrast, thermographic images are formed by electromagnetic waves in the infrared portion of the spectrum. Thermographic images of conductors in a power distribution network have to be acquired and these can be used for the automatic detection of faults. An infrared thermography anomaly detection algorithm was developed to process the images and to detect hotspots which correspond to faults in transmission lines. The experimental results of the tested aluminum cables indicated the capability of the proposed technique for defect identification and condition assessment of cables.

Katrasnik et al. [102] reviewed the application of mobile robots for power distribution line inspection, summarizing relevant studies. For the purpose of comparison, different aspects were considered such as design requirements, inspection quality, autonomy and universality of inspection. Specific benefits and drawbacks were highlighted in relation to the condition assessment. Mobile robots were found to be capable of performing different tasks besides powerline inspection. Routine tasks such as insulator cleaning, conduct deicing and even measuring important power line parameters can be carried out using mobile robots. Without mobile robots, these tasks can only be performed by workers on power distribution cables. It was concluded that there is a potential for mobile robots to be used for the automatic inspection and maintenance of overhead cables, possibly with future advancements and research.

UAVs is the other type of sophisticated equipment that can be used for improved inspection of power distribution lines. Montambault et al. [103] presented a review and summary of the attributes and requirements of vertical takeoff and landing UAVs considering its critical subsystems. Detailed descriptions were provided about the propulsion, power source and overall platform design of UAVS. These kinds of devices need to have efficient control systems considering the safety concerns and to ensure asset integrity preventing collisions with power distribution infrastructure. Another important aspect was identified as the inspection features that can be captured from UAVs. Different types of measurement and data such as high-quality visual information, electric field measurements, UV detection and infrared imaging can be obtained via UAVs. These collected data can be processed to draw conclusions about the condition of the assets. In [104], developments were carried out to fully automate the inspection system of UAVs without the need for any manual intervention for anomaly detection. This study developed techniques to process consecutive images taken from UAVs together with telemetry data obtained from the autopilot to determine the distance of vegetation and trees to the power lines. Further, infrared images were captured and processed to detect possible defects in overhead cables.

Vega et al. [105] implemented high voltage power line inspection through UAVs based on a quadrotor helicopter. The quadrotor helicopter was equipped with the required payload to conduct qualitative inspection of the overhead lines. This paper presented the hardware architecture of the aerial robotic system. Both a conventional color camera and an infrared camera were used to capture images to detect possible defects of overhead lines and to assess their condition. In [106], two approaches were proposed to achieve real-time tracking of power lines using quadrotor UAVs. In the first approach, solutions were made in the 2D image space. Image-based visual servoing formulation along with a linear quadratic approach were utilized to link the image features and the kinematics of the UAV. In the second method, partial pose-based visual servoing was used to solve the control in 3D cartesian space. Experimental results indicated that the second approach performed well in comparison with the first approach for the considered visual servoing problem.

One of the main challenges faced in analyzing images captured using unmanned aerial systems is the extraction of power lines from the existing natural background. To address this issue, filtering techniques, morphological operations and different mathematical techniques are implemented [107]. The performance of these techniques to suppress the background information and to extract power line can be evaluated by field testing. In this kind of framework, the detection of false positives should be minimized and additional post processing can be carried out for further refinement of the captured images. The data extracted from UAVs can be used to develop automated vision-based condition assessment techniques for power distribution lines by implementing learning algorithms [108–110]. Learning algorithms can be effective in preprocessing, analysis and post processing the data to draw conclusions about the overall condition. As noted previously, there are many advantages of incorporating learning algorithms for data processing such as avoiding the subjectivity of manual interpretations, saving time and the possibility of analyzing a lot of data simultaneously. Previous studies indicate that the use of deep learning approaches, such as conventional neural networks, and dimensionality reduction techniques, such as principal component analysis, can effectively interpret the data collected via UAVs for the accurate condition assessment of power distribution cables [108]. Table 4 provides a brief summary of studies on advanced inspection techniques for overhead lines by employing mobile robots and UAVs.

Table 4. Summary of the studies on advanced inspection techniques for overhead lines.

Study	Category	Content, Methods, Analysis Techniques
[97]	Mobile robot	Development of a kinematic structure of a robot capable of moving on powerlines avoiding obstacles for condition assessment
[98]	Mobile robot	Developed a double conical wheel based mobile robot with three driven wheels, distributed control system and a self-configuration frame
[99]	Teleoperated robotic platform	Presented the mobile platform design and its mechatronics subsystems describing the functions and the potential applications
[100]	Teleoperated robotic platform	Development of a robotic system which consists of operators cabin and remote platform which is located on the top of an isolated telescopic boom
[101]	Robotized inspection with infrared vision	Infrared thermography anomaly detection algorithm was developed to process the thermographic images and to detect hotspots in conductors
[102]	Mobile robot	Reviewed the application of mobile robots for power distribution line inspection. Robots were found capable of performing different other tasks beside powerline inspection
[103]	UAVs	Presented a summary of the attributes and requirements of vertical takeoff and landing UAVs considering its critical subsystems.
[104]	UAVs	Developed techniques to process consecutive images (both normal and infrared) taken from UAVs together with telemetry data for automated inspection of power cables
[105]	UAVs-based on quadrotor helicopter	Presented the hardware architecture of the aerial robotic system by providing required payload to conduct qualitative inspection of power lines
[106]	Quadrotor UAVs	Proposed two approaches to achieve real-time tracking of power lines (Image-based visual servoing formulation along with linear quadratic approach and partial pose based visual servoing to solve the control in 3D cartesian space)
[107]	UAVs	Implemented filtering techniques, morphological operations and different mathematical techniques to extract power lines from images suppressing the background
[108–110]	UAVs and deep learning techniques	Employed convolutional neural networks and other deep learning approaches for automated analysis of the data obtained from UAVs. Learning algorithms provided effective preprocessing, analysis and post-processing.

6. Conclusions

This paper presented a review of the mechanisms and prevention strategies for wildfires initiated by power distribution system faults. From the data of major events of wildfires in Australia, it can be noted that catastrophic wildfires have caused hundreds of fatalities and destruction to thousands of homes causing massive trauma for communities prone to wildfires. There are significant economic implications considering the cost of fires which can be identified as cost in anticipation, cost as a consequence and the cost in response. Among the wide array of causes of wildfire initiation, power line failures/faults have been identified as a root cause, having the possibility of multiple ignition mechanisms. In this study, power line failures were broadly categorized as vegetation-related faults, electrical apparatus failure, power distribution infrastructure failure and conductor failures. An overview of each wildfire initiation mechanism was provided. Then a comprehensive summary of the studies related to prediction and detection of wildfires was presented, highlighting the benefits and shortcomings of each technique.

From this review, it can be concluded that there is a huge potential for wildfire detection using satellite imaging and network sensing techniques. The implementation of machine learning algorithms for data processing and interpretation further enhanced the detection capability of the aforementioned techniques. Under the prevention strategies of wildfires caused by power line failures, accurate and reliable condition monitoring and surveillance techniques for power distribution infrastructure were identified as critical. The identification of potential defects in power distribution lines at an early stage facilitated the implementation of timely replacements and other remedial measures. Condition assessment techniques for power distribution lines such as partial discharge detection and improved inspection using mobile robots and unmanned aerial vehicles were presented, reviewing relevant literature.

From the conducted review of the condition assessment of power distribution lines, it can be concluded that the use of unmanned aerial vehicles along with advanced automated data interpretation techniques can overcome most of the challenges of the conventional inspection techniques, such as ground patrol or airborne inspection. Avoiding manual interpretation, saving time, processing large amount of data simultaneously, accuracy and reliability are among the main advantages possessed by advanced inspection techniques. Future research can be directed towards addressing the challenges faced when implementing learning algorithms for data processing and interpretation. The main challenges identified were data quality problems, small object detection and the problems related to existing embedded computing devices of not being able to handle high performance analysis methods.

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