Application of Artificial Intelligence in Pre-defect Identification and Hidden Danger Early Warning for Distribution Substation Fire and Flood Risks

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Abstract: In our modern day and age, how well the power distribution equipment works is connected with what we do every single day and even with just living. The endpoint of the power system, it is very important to make distribution stations run safely and healthily. Natural hazards like fires and floods that can directly cause dangers on power grids. Traditional prediction and disaster avoidance uses manual judgments which leads us to delays and not good early warning. AI tech developing speed brings up an option that could help spot substation danger signs before anything terrible happens with disaster protection. It systematically reviews the use of AI tech in finding substation equipment flaws and warning about fire and water risks in advance. Risk modeling and anomaly detection and decisions etc. The paper focuses on research achievements of such as mult-sourced data gathering, computer vision, time sequence forecast, multitype information fusion, knowledge graph. And analyze through typical example from home and abroad of practical effects brought by AI improvement on early warning correctness, decreasing answer time, minimizing false alarm frequency. Also, talk about current difficulties and restrictions for technology. Then look ahead towards where we hope it will go so we might have something to offer in terms of theory about how substations could grow healthily and stably.

Keywords: Distribution Substation; Fire Early Warning; Flood Risk and Hazard Early Warning; Multimodal Fusion; Artificial Intelligence

1. Introduction

Substation is part of the power system, where power is distributed and it is the last place before you get electricity at your house. Its safety running affects the whole system's stability and toughness very much. The equipment of substation working on severe weather have lots of risk. Recently, there has been more frequent occurrence of extreme weathers, especially fires and floods become big threat for the safety of substations. Such as cable overheating, insulation aging, partial discharge and so on and also cigarettes, open fire and lightning strikes etc. which will be very easy to cause fire. Because of the heavy rains, the floods, the sudden rises in slopes of the waters will lead to an entire facility becoming submerged in water and causing a circuit that results in many parts being cut off from the main power, thus suffering great financial harms.

Traditional risk control ways depend much on hand inspection and single-threshold alarms, which aren’t fast enough or correct in their early warnings, and can’t work well with multiple dangers at once, so they don’t meet how reliable and strong smart grids need to be. IoT and bigdata and AI has advanced very fast now there are various alternative technologies present on which we can apply our substation equipment defect and hazard early warning. Like use of Deep Learning based image recognition for fire, it detects if equipment starts getting heated up or if there's smoke, or combining an AI method that brings together Geography Information Systems along with Hydrologic models helps to find out how many places would get flooded during floods and how much higher than normal does the water rise [1,2]. In this paper I’ll briefly look through some papers on AI being used within power distrubution substations on fire and flood, looking mainly at advances in multiple datasets collection, Computer Vision and Time Series forecasting. Using examples like the ones above can give us an idea on whether those studies work out well in reality, also what we cannot do now by current technology and what should we

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focus more on building in the near future, providing some references for making intelligent safety protections and post-disasters recoveries in power distribution substations.

2. Literature Review

Fires can be caused by aging equipment, local overheating, and arc discharge during thunderstorms in power distribution substations. Currently, the mainstream prevention and detection methods are still based on single sensors, such as temperature and smoke detectors. These sensors are greatly affected by the environment, and improper sensitivity settings can easily lead to false alarms or missed alarms. In recent years, the application of artificial intelligence technology in the field of risk identification in power distribution networks has been continuously deepened. This paper selects some representative works for review and summary. In the direction of fire risk identification, some studies have proposed a method for intelligent inspection and defect identification of substation equipment based on deep learning [3], which can identify hot spots and insulation damage and other hidden dangers and judge the equipment status through infrared thermal imaging. Other scholars have designed an intelligent substation active fire early warning system [4], which integrates temperature sensing, smoke detection and image recognition technologies, and verified the feasibility of the system through simulation experiments. In the field of low-voltage arc fault detection, researchers have constructed a parallel neural network structure based on CNN and Transformer encoder [5], which effectively reduces network complexity and computational load. There are also works that, based on summarizing the causes of accidents and fire extinguishing behaviors in urban substations, propose an improved fuzzy Bayesian network method [6] and verify its effectiveness through case studies. Faced with the threat of wildfires, some studies have explored the application of deep reinforcement learning in intelligent wildfire recovery controllers [7] to achieve real-time monitoring and adaptive protection of power distribution system status and wildfire dynamics. Flood risk is characterized by its suddenness and huge spatiotemporal differences. However, compared with fire risk, flood risk is more controllable. Geographic information analysis and hydrological sequence data can be collected in a targeted manner to provide sufficient data support for artificial intelligence to play a role. In terms of flood dynamic assessment and prediction, some studies have combined fuzzy Bayesian networks with mixed integer linear optimization [1] to construct an adaptive flood control system suitable for substations, realizing dynamic risk assessment and emergency optimization decision-making. Other studies have proposed practical optimization strategies for flood scenarios [8] to improve the flood control capacity of power distribution stations and the resilience of the power grid. There are also studies that use graph neural network models to predict the power outage of power distribution networks caused by extreme weather [9] to achieve precise prediction of disaster impact. Related reviews systematically reviewed the application of artificial intelligence in intelligent flood control management [2], pointing out that time series prediction and spatial modeling are the current focus. The complex environment of power distribution stations brings high requirements for prevention and control, and single disaster early warning is difficult to meet the needs. The relevant literature systematically summarizes the application of artificial intelligence in enhancing the disaster resistance of power grids under extreme weather conditions [10], covering prevention technologies and challenges for multiple disasters such as fires and floods. Other studies have proposed a spatiotemporal artificial intelligence model that integrates geospatial and climate data [11] for renewable energy site selection and multi-hazard perception. And other work talks about how to make things better with the disaster tolerance of combined energy systems after bad weather in the nature [12], and there's also talk about mixing artificial smarts and doing things well. The kind of data-center-oriented disaster-natural-couple-analysis research too [13].

Techology makes hidden dangers easy for us to understand; it improves on prediction as well. And some works have made use of an AI based intelligent substation detection system [14] which is able to fully identify all equipment defects and environment hazards. Other work suggest we try cloud-edge collaborative smart substation inspection plan, by improving early warning reliability using multi model data [15,16]. Fusing multiple models and using knowledge inference can effectively eliminate data island problem, and they will be able to achieve joint perceiving, association judging and early warning cooperation against risk events such as fire and flood [7,14].

3. AI Technologies and Methodologies

We are going to go through the core technical pathways of A1 in substation disaster prevention and control. Split up into three layers - the first being our data gathering level, then we get into our A1 algorithms, lastly being our early alert system layer.

3.1 Data Acquisition Layer

Data serves as the ground work upon which all else in early warning systems comes to be. Substation usually has different kinds of sensors like the temperature sensor, the humidity sensor, the current sensor, smoke detectors and the water level detectors to gather info from their equipment and the environment around it [4,15]. HD visible light cam and IR therm imagers: Collect visuals such as the equipment's looks, heat zones, smokes, and fires, to spot hot areas, harmed spots, and those covered in water [3,14]. Through the Internet of Things to integrate many types of access, and through 5G, edge computing to reach ultra-low latency, on-site pre-processing to ease the load on cloud and enhance response times. At the same time, the external data such as weather forecast, rainfall, river water level and the geographical information system are also accessed [1,11] in order to give spatiotemporal support for the flood risk modeling.

3.2 AI Algorithms for Pre-defect Identification

For the two types of risks, fire and flood, a differentiated algorithm is used to realize defect detection, trend prediction and risk assessment. The fire risk identification process is as follows: First, image recognition and anomaly detection are performed. Based on deep learning models such as YOLO and CNN, target detection is performed on infrared and visible light images to identify fire precursors such as equipment overheating, joint erosion, insulation damage and smoke [3]. Combined with anomaly detection algorithm, unknown defects can be identified without labeled samples, thus improving generalization ability. Then, time series prediction and degradation trend analysis are performed. Models such as LSTM, GRU and Transformer are used to predict time series signals such as temperature, current and partial discharge to determine the aging trend and failure probability of equipment [5]. Using CNN-Transformer parallel network, MWSN multi-head wide kernel convolutional network and other structures, high-precision and anti-interference diagnosis of low voltage arc and residual current faults is realized to suppress electrical fires from the source [5,17]. Finally, combined with fuzzy logic, Bayesian network, random forest and other methods, a multi-factor fire risk model is constructed to consider data uncertainty and improve the reliability of complex scenario assessment [6].

Flood forecasting requires combining GIS data and historical records to build spatial models to predict the inundation range, and then using LSTM, Transformer or graph neural networks to simulate rainfall-runoff response and power outage probability to support flood control scheduling. In complex scenarios, multimodal fusion and knowledge graph technologies become key, achieving more stable risk identification by integrating image, sensor and meteorological data, and supporting causal reasoning and explainable decision-making [12,18].

3.3. Early Warning Systems

Based on previous parts in terms of data gathering as well as an algorithmic model layer, we may also create such kind of stacked early-warning structure especially focusing towards substations fire and flood danger risk. Figure 1 illustrates the layered architecture of this proposed system. System does not mean by pieces only, it is combined with the pieces so a complete chain from lower data to finally output decision could be achieved. The first is a data acquisition and pre-processing stage that gathers signal inputs from multiple kinds of sensors like temperature, humidity, smokes and liquid levels, along with visual imaging data obtained through visible-light and IR imaging devices, also data coming from external weather and geographical information database. After being cleaned aligned and temporarily saved as a base for more in-depth investigation. Data cleaning and arranging after that has been prepared. And the module can affect if all is right inside our main system; if there is bad preparation then it makes senseless any of the fancy algorithms you find at top.

Edge computing layer installed in the substation

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is next. This layer does a few important things really fast nearby: it looks at weird data and throws that away, shrinks images so we send less of them, and starts judging whether some numbers in real time have hit any lines. The good parts from doing this will be clear to you, it lowers the waiting time before something is sent up high on the clouds to get ready for the start, helps when things need to alert quicker because the internet can go wonky on us, and makes less stress on the cloud side. Upstairs is the core processing layer for AI algorithm in cloud, it includes very hard computational work of our system. Fire risk: A CNN image-recognizing method and a time-series analyzing method by using LSTM or Transformer to detect signs of overheating, smoke and the potential of equipment degradation by looking into time-sery changes of temperature and supply current. For flood, runs GIS-integrated flooding simulation + graph neural networks to predict regional outage chance. Images & sensor info + meteo/hydro: the multimodal fuser combines all these together. equipment & history & emergencies are organized as a knowledge base. This creates a much better logical flow for our reasoning around risks and much easier to follow what was actually done during this process. The risk assessment layer gets the results that were worked on up there, and figures out the chance the substation will have a fire right now, how flooded it'll be, and what's up with the danger overall – kind of like giving you some straightforward numbers to think about. Early Warning Decision Making Layer will automatically generate corresponding levels of early warning information according to these evaluation results and preset threshold value, push it to the person in charge of operation and maintenance via visualized terminal or mobile device. And it would be able to change if it needs to notify people more frequently, in different ways, if the risk got worse, instead of sending too much information at once.

Finaly it has been made to have a feedback loop which means that the system will get a signal that we have had a problem so we know when the next one will occur and that's why every real fault occurs in our model it would compare between the warning we gave and what happens on the floor right now and change things on our algorithms and knowledge graph at the cloud. This kind of thing leads to something like continuous learning process — perceiving, analyzing, early-warninging, confirming and adjusting constantly, getting increasingly accurate and responsive.

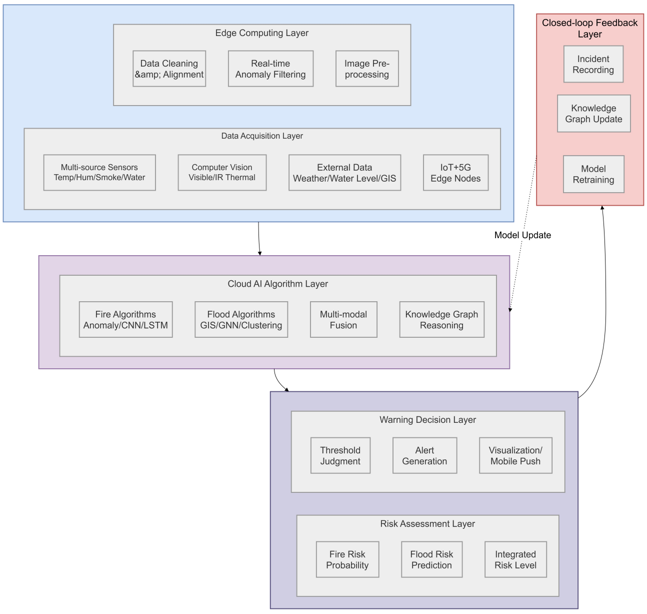

Figure 1. Layered Architecture of the AI-based Early Warning System

4. Case Studies and Applications

Artificial intelligence technology has been implemented in the early warning of fires and floods in power distribution substations. The following is a quantitative analysis of the application effectiveness based on typical cases.

Case 1: Intelligent inspection system for substations based on deep learning. Xing et al. deployed a deep learning-based intelligent inspection system in a 220kV substation [3]. This system uses both infrared thermal imaging and visible light cameras, along with an improved YOLOv5 target detection model, to automatically detect potential hazards such as equipment overheating, insulation damage, and foreign objects hanging on wires. In six months, a total of 37 equipment abnormalities were identified, of which 3 were early overheating hazards—all of which were later confirmed through subsequent maintenance. According to calculations, the accuracy rate of early warning by this system reached 91.9%. Compared with the traditional manual inspection method, the defect identification time was reduced from an average of 2.5 hours to 15 minutes, and the inspection efficiency and the ability to detect potential hazards were significantly improved. Chen Zhen et al. deployed an active fire early warning system that integrates temperature sensing, smoke sensing and image recognition in a smart power distribution substation [4]. The system adopts a multimodal data fusion strategy. When a single sensor triggers an alarm, it automatically calls nearby camera images for secondary confirmation, effectively reducing the false alarm rate caused by environmental factors such as dust and moisture. Actual test data shows that the system's false alarm rate has decreased from 12.6% in the traditional single-sensor method to 3.8%, and the average response time for early warning has been shortened from 45 seconds to 18 seconds.

Case 3: Deep reinforcement learning-driven anti-wildfire power grid protection. Shalaby et al. deployed a power grid autonomous dynamic protection system based on security deep reinforcement learning in high-risk areas of California, USA [7]. The system accesses meteorological data (wind speed, humidity, temperature), line status and historical wildfire records in real time, and dynamically adjusts the protection relay threshold and line switching strategy. In simulated wildfire scenario tests, the system can identify high-risk lines 12-18 minutes in advance and perform preventive power outages, avoiding the spread of fires caused by line faults, and the false alarm rate is controlled within 5%.

Case 4: Graph neural network-driven power grid extreme weather outage prediction Le et al. used a graph neural network model to model the historical outage data and meteorological data of a US power distribution company during the hurricane season, predicting the probability of line outages under extreme weather conditions [9]. The model embeds the power distribution network topology into the graph neural network, which can capture the spatial propagation characteristics of disasters. In the two hurricane events in 2024, the model's early warning accuracy for power distribution outages reached 87.3%, which is 14.2 percentage points higher than the traditional logistic regression model, with an average early warning lead time of 3.2 hours.

Based on the above cases and literature reports [10,12,13,19], the improvement effect of AI technology in early warning of fire and flood in power distribution can be summarized in Table 1. The above cases confirm that AI technology can significantly improve the accuracy and timeliness of early warning of fire and flood risks in power distribution, while reducing the false alarm rate, providing effective technical support for the disaster resilience construction of power distribution networks.

Table 1. Quantitative Comparison of AI-based vs. Traditional Methods for Fire and Flood Early Warning in Distribution Stations

Metric	Traditional Methods	AI-based Methods	Improvement
Fire warning accuracy	75–82%	88–94%	+10–15%
Flood warning accuracy	70–78%	83–90%	+12–15%
Average response time (fire)	30–60 sec	15–20 sec	Reduced by 30–60%
Average response time (flood)	Several hours	1–4 hours	Reduced by 50–70%
False alarm rate	8–15%	3–6%	Reduced by 50–70%

5. Discussion

As the case study in Chapter 4 demonstrates, the introduction of artificial intelligence (AI) technology has indeed significantly improved the disaster prevention and control capabilities of distribution substations, achieving substantial progress in early warning accuracy, false alarm control, and response speed. These improvements not only reduce unnecessary on-site inspections by maintenance personnel, saving considerable manpower and resources, but also significantly reduce the risk of equipment damage and large-scale power outages caused by fires or floods, thereby enhancing the overall reliability of the power

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grid. It can be said that AI has shown clear advantages in equipment defect identification and early risk warning, opening up new technological avenues for the safety protection of distribution substations.

However, practical implementation also faces several real-world challenges that require careful consideration. First, the performance of AI models is highly dependent on the quantity, quality, and diversity of training data. However, substation fires and floods are low-probability but severe events, and real-world disaster samples are very limited. This can lead to insufficient learning of typical disaster characteristics, affecting the model's generalization ability when encountering new and complex situations. Furthermore, the annotation of infrared thermal images, smoke images, and flooded scenes requires the long-term involvement of specialized technical personnel, which is not only costly but also prone to discrepancies in annotation standards among different personnel. Many current studies still rely heavily on simulation data or laboratory-built scenarios. These data differ significantly from real-world engineering conditions, further limiting the model's performance in practical deployments.

And another thing we might note is that fire and water flooding isn't so much something separate all on its own, often these things could kind of set off the other one and happen at the same time. But mostly of all current works consider these to be largely independent problem and they lack complete modeling for the entire cause-effect chain along with space–time relationship amongst disasters. We can achieve a joint early warning and a collaborative decision for multi hazards coupling but it’s really still a hard thing. From an engineering viewpoint, making our models lighter yet maintaining early warning precision, doing this on devices close to users (edges), which have very limited power, would also be big. 5G Networks & The huge investment needed in building out IOT Infrastructure makes it hard to put them up there in remote substation locations.

Moreover deep learning model itself is complicated and hard to understand. It would not have good result when it comes to maintenance people if it has no transparent reason that why it is going to warn something to us. If system cannot give an open and clear reason for early warning, then maintenance staff may stop trusting the early warning as soon as possible. As for Knowledge Graph Technology, although there is possibility to become more interpretable, but in the large scale of practice we’re still very much exploring it right now. The end part, old substation facilities plus surrounding environment and seasons causing distributions of information shifting around too. Offline trained model performs worse with each day passing and therefore requires a way to remain continuously updated to retain lasting reliability.

6. Conclusion

This paper systematically reviews the research progress and practical application effects of artificial intelligence (AI) technology in the fields of equipment defect identification in distribution substations and fire and flood risk early warning. It establishes a relatively complete technical framework and verifies the practical benefits through typical domestic and international case studies. Simultaneously, it objectively points out the main challenges and limitations currently hindering the large-scale engineering implementation of AI early warning systems.

To meet the practical needs of future smart grid disaster resilience construction, we believe that future research can focus on deepening the following directions: first, the integration of digital twin technology with physical information; second, edge intelligence and lightweight model design; and third, improving multi-hazard collaborative modeling and causal reasoning capabilities. Digital twin technology, by constructing a high-fidelity virtual model of the substation, can achieve real-time synchronization and two-way interaction between the physical entity and the digital space. In the future, dedicated digital twin systems can be developed for fire and flood scenarios, embedding AI early warning models within them to support real-time simulation, extrapolation, and early prediction of disaster evolution, providing more intuitive basis for decision-making.

In conclusion, with the deep integration of AI technology and power engineering, risk prevention and control in distribution substations will gradually move towards a new stage of intelligence, autonomy, and high resilience. Going forward, it is necessary to strengthen close cooperation among industry, academia, research and application parties to promote the application of more advanced artificial intelligence methods in real substation scenarios. This is expected to provide a solid technical guarantee for the disaster resilience construction of smart grids.

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