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A review on the impact of weather conditions on the reliability of medium voltage distribution substations

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Abstract
The reliability of medium voltage (MV) distribution substations is critical to the stability and resilience of modern power systems. However, their performance is highly susceptible to environmental and meteorological factors, particularly under extreme weather conditions such as rainfall, storms, wind, and snow. This paper presents a comprehensive review of research examining the influence of weather phenomena on the reliability of MV substations. It outlines the fundamental reliability indices, explores the mechanisms by which different weather conditions affect system components, and discusses the emerging role of machine learning (ML) techniques in predictive reliability assessment. The review further identifies major research gaps including the lack of integrated weather modeling, limited regional transferability of existing models, and the need for interpretable AI-driven approaches. The findings emphasize that combining meteorological data with ML-based predictive models offers a promising path toward resilient and adaptive power distribution networks.

Nomenclature and units

MV	Medium Voltage
ML	Machine Learning
SAIFI	System Average Interruption Frequency Index
SAIDI	System Average Interruption Duration Index
CAIDI	Customer Average Interruption Duration Index
MAIFI	Momentary Average Interruption Frequency Index
LOLP	Loss of Load Probability
EENS	Expected Energy Not Supplied

1. Introduction

Electric power systems are indispensable for economic and social development, yet they remain vulnerable to failures caused by natural and environmental disturbances. As highlighted by (Ward 2013), weather-related events such as high winds and heavy rainfall can critically affect grid components and thereby hamper electricity supply reliability. In the distribution context, medium-voltage (MV) substations function as critical nodes that link high-voltage transmission systems to low-voltage consumer networks; their failure undermines the continuity of service to many downstream customers. Therefore, ensuring that MV substations maintain high availability is central to overall power system reliability. Climate change has amplified the frequency and severity of storms, rainfall, wind events and other extreme conditions, posing significant challenges for grid operators. A report by Climate Central indicated that about 83 % of major outages in the U.S. between 2000 and 2021 were weather-related, with the number of such outages rising approximately 78 % in the 2011–2021 decade compared to 2000–2010. Moreover, studies show that compound weather phenomena (for example, antecedent rainfall combined with high winds) can increase the probability of outages by factors of three to five when compared to single-factor models. These trends emphasize the urgency of addressing weather impacts in reliability assessments and resilience planning for MV substations.

In response to these emerging risks, the literature has begun focusing on three key dimensions: the fundamental reliability concepts and indices used to evaluate power systems; the specific influence of distinct weather phenomena on distribution substations; and the potential of modern computational and machine learning techniques to forecast and improve reliability under varying meteorological conditions. For example, (Banasik & Chojnacki 2024) explored ambient temperature, humidity, wind speed and precipitation as influencing variables on the failure intensity of low-voltage cable lines, thereby linking weather conditions directly with reliability indicators. Additionally, generic studies (e.g., Ward, 2013) emphasize that distribution network reliability is sensitive to diverse weather modes and that traditional models may underestimate multi-hazard effects. Despite the growing body of work, several knowledge gaps remain. Many studies focus on transmission or high-voltage systems rather than MV distribution substations, limiting applicability in the distribution domain. Further, models often consider single weather phenomena in isolation, rather than the compounded or cascading effects of multiple weather stressors. There is also a need for greater use of real-time data and adaptive predictive techniques (e.g., machine learning) in reliability modelling, especially for MV substations in diverse geographic and climatic contexts. Addressing these gaps will support more resilient MV distribution systems that can adapt to increasing weather variability and changing infrastructure demands.

2. Review Methodology

This study adopts a structured and systematic literature review methodology to ensure transparency, reproducibility, and academic rigor in assessing the impact of weather conditions on the reliability of medium voltage (MV) distribution substations. The methodology consists of three main stages: database search, study selection, and thematic classification.

2.1 Literature Search Strategy and Databases

A comprehensive search of peer-reviewed literature was conducted using established scientific and engineering databases, namely IEEE Xplore, Scopus, and Web of Science. These databases were selected due to their extensive coverage of power systems engineering, reliability analysis, meteorology, and data-driven modeling techniques.

The search was performed using combinations of keywords and Boolean operators, including but not limited to: *"medium voltage substation reliability," "weather-related outages," "distribution network reliability," "meteorological impacts on power systems," "extreme weather events,"* and *"machine learning-based outage prediction."* To capture recent methodological advances, particular attention was given to studies published within the last 10–15 years, while seminal and highly cited earlier works were retained where relevant. Reference lists of selected papers were also manually screened to identify additional influential studies not captured through database queries.

2.2 Selection and Inclusion Criteria

To ensure relevance and quality, retrieved publications were filtered using predefined inclusion and exclusion criteria. Studies were included if they:
(i) addressed power system reliability with explicit consideration of weather or environmental factors;
(ii) focused on distribution systems, with emphasis on MV substations or closely related components;
(iii) employed quantitative reliability indices (e.g., SAIFI, SAIDI, failure rate, outage duration) or predictive modeling approaches; and
(iv) were published in peer-reviewed journals or reputable conference proceedings.

Studies were excluded if they:
(i) focused exclusively on transmission or generation systems without applicability to MV distribution substations;
(ii) discussed weather impacts only qualitatively without reliability implications; or
(iii) lacked sufficient methodological detail.
This screening process resulted in a refined set of publications that directly support the objectives of the review.

3.3 Thematic Classification and Analysis

The selected literature was analyzed and organized using a thematic classification approach. Three dominant themes emerged from the review. The first theme covers fundamental reliability concepts and indices, providing the theoretical basis for assessing MV substation performance. The second theme focuses on the impacts of specific weather phenomena such as rainfall, wind, temperature extremes, storms, and compound weather events on MV substation components and outage behavior. The third theme examines data-driven and machine learning-based approaches for reliability assessment and outage prediction under varying meteorological conditions.

Within each theme, studies were compared based on modeling techniques, data requirements, geographical context, and key findings. This structured classification enables the identification of methodological trends, limitations, and research gaps, particularly regarding integrated weather modeling, multi-hazard interactions, and the transferability of predictive models across different climatic regions.

3. Power System Reliability Overview

Power system reliability is broadly divided into two key dimensions: adequacy and security. Adequacy concerns the ability of a power system to meet forecasted demand and energy requirements under normal operating conditions meaning it has sufficient generation, transmission, and distribution resources available. For example, resource adequacy includes maintaining spare capacity and reserves so as to avoid load-shedding or energy (shortfall Chowdhury & Koval, 2009). On the other hand, security refers to the system's capability to withstand and respond to sudden disruptive events or contingencies (such as equipment failures, faults, or unexpected loss of generation) without widespread interruption of service.

3.1 Reliability Indices

Reliability in power systems is typically quantified using a set of standardized statistical indices that measure both the frequency and duration of power interruptions experienced by consumers. These indices such as the System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), and Customer Average Interruption Duration Index (CAIDI) are widely adopted by utilities and regulatory agencies for benchmarking distribution system performance (Billinton & Allan, 1996; Chowdhury & Koval, 2009). Table 1 summarizes the most commonly used reliability indices and their respective formulations. These metrics enable engineers and policymakers to assess service continuity, identify weak points in the distribution network, and develop targeted maintenance and resilience strategies to enhance system reliability under both normal and adverse operating conditions.

Table 1: Common Reliability Indices in Power Distribution Systems

Index	Definition	Formula
SAIFI	Average frequency of interruptions per customer	$SAIFI = \frac{\sum \lambda_i N_i}{\sum N_i}$
SAIDI	Average outage duration per customer	$SAIDI = \frac{\sum U_i N_i}{\sum N_i}$

CAIDI	Average restoration time per interruption	$CAIDI = \frac{SAIDI}{SAIFI}$
MAIFI	Average number of momentary interruptions (<5 min)	—
LOLP	Probability that demand exceeds available supply	—
EENS	Expected energy not supplied due to outages	—

3.2 Importance of Reliability

The reliability of power systems plays a crucial role in sustaining economic growth, technological progress, and public welfare across modern societies. Economically, frequent or prolonged power interruptions lead to significant financial losses by disrupting industrial operations, supply chains, and commercial productivity costing billions annually in lost output (Billinton & Allan, 1996; Kariuki & Allan, 1996). From a social perspective, electricity reliability is vital to maintaining essential services such as healthcare, water supply, and emergency response systems, directly influencing quality of life and societal stability (Aldhubaib et al., 2023). Technologically, a reliable grid provides the necessary foundation for integrating renewable energy sources, distributed generation, and smart grid technologies, which require stable and adaptive networks to function effectively (Panteli & Mancarella, 2015). Environmentally, improved reliability contributes to sustainable operations by minimizing waste, optimizing resource utilization, and enhancing the system's ability to withstand and recover from climate-induced disasters. The interdependence among these factors is illustrated in Figure 1, which conceptually links power system reliability with adequacy, security, and their multi-sectoral impacts across the generation, transmission, and distribution levels.

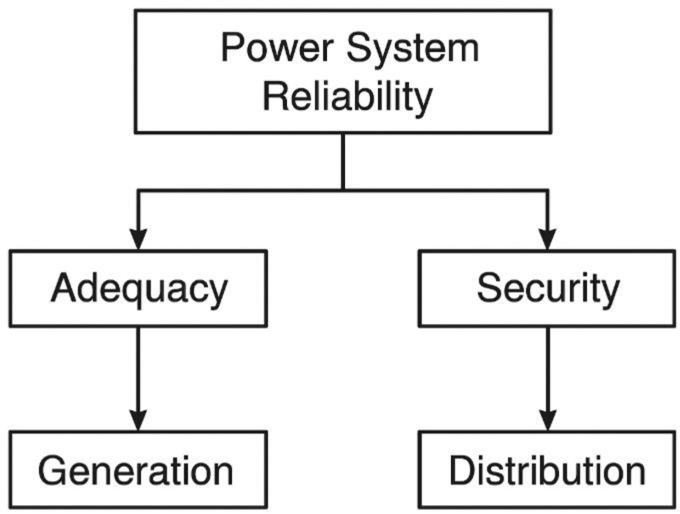

Figure 1: Conceptual Model of Power System Reliability

4. Impact of Weather Conditions on Distribution Substations

Weather conditions exert a profound influence on the reliability of medium-voltage (MV) distribution substations by imposing both mechanical and electrical stresses on critical infrastructure components. For instance, overhead equipment exposed to high winds, lightning, or large hailstones is more prone to structural damage, such as snapped poles, broken conductors, or failing insulators—events that directly increase failure rates and restoration times (Ward, 2013). Concurrently, flooding and moisture infiltration associated with heavy rainfall can degrade insulation, undermine substation foundations, and accelerate corrosion of outdoor apparatus, resulting in short-circuits and extended outages (Wu et al., 2020).

Moreover, weather-driven environmental extremes produce indirect but equally significant effects on MV substations. Elevated ambient temperatures can reduce transformer cooling capacity and accelerate aging of insulation and bushings, while ice and snow accumulation add dangerous mechanical loads leading to line sagging, conductor galloping, and structural collapse (Zhang et al., 2025). Underground distribution assets are not immune either: heavy precipitation and subsequent ground saturation raise the risk of cable faults, joint failures, and reduced restoration capability (Banasik & Łukasz Chojnacki, 2024). These combined stressors thereby reduce the reliability indices such as SAIFI and SAIDI for the substation feeder segments.

Finally, the changing climatological patterns longer heatwaves, more frequent intense storms, and amplified multi-hazard events pose increasing challenges for reliability modelling and resilience planning in MV distribution systems. Traditional models that treat weather as a single-state variable are insufficient, as evidenced by research showing that adverse weather states significantly elevate failure probabilities and prolong outage durations (Kirankumar & Vidya Sagar, 2025). This recognition underscores the importance of systematically integrating detailed weather-component interaction models into reliability assessments and operational planning for MV substations.

4.1 Rainfall and Flooding

Prolonged or heavy rainfall can severely impact medium-voltage (MV) distribution substations by causing inundation of switchyards, control rooms, and cable trenches, thereby compromising insulation and triggering short-circuit events. A geo-referenced statistical model developed by (Mathaios and Pierluigi 2015) highlights that floods result in extensive damage to both transmission and distribution infrastructure, contributing to high-impact, sustained interruptions. Additionally, a recent study by (Abdullah et al., 2023) demonstrated how flash floods and soil erosion in mountainous urban regions degraded the foundations of transmission towers and distribution poles, suggesting that similar mechanisms expose MV substations to structural risk under intense precipitation.

Further compounding the issue, flooding disrupts access roads, substation drainage systems, and underground cable corridors, which increases the probability of extended restoration time and elevated reliability indices such as SAIDI and SAIFI. A review of infrastructure climate risks by National Grid confirmed that erosion of tower foundations often a secondary effect of heavy rainfall and floodwater run-off can lead to foundation failure and elevated asset repair costs. These mechanisms underscore the need to integrate rainfall-driven hazard modelling into reliability assessments of MV distribution substations, especially under changing climate conditions that increase precipitation intensity and flood risk.

4.2 Storms and Lightning

Storms, and particularly lightning activity, represent major threats to the reliability of medium-voltage (MV) distribution substations due to the large surges and transient overvoltage they generate. For example, (Ward 2013) demonstrates that weather-related events especially storms and lightning are among the most significant causes of grid system failures in Europe and North America, and notes that lower-voltage distribution networks tend to be more vulnerable than high-voltage systems. When lightning strikes overhead lines or nearby equipment, the resulting electromagnetic pulse and surge currents can damage insulation, blind protective devices, or trigger fault clearing operations, thereby increasing interruption frequency (SAIFI) and duration (SAIDI).

Even when substation equipment is protected by surge arresters and grounding systems, the risk from induced surges and secondary effects remains substantial. Research shows that protection systems themselves may become failure points under extreme weather exposure, leading to “failure bunching” in substations and associated downstream feeders. For instance, an application-level study on transmission line failure modelling under extreme weather found both wind and lightning-induced failures to be significantly correlated with higher outage rates when protection system mis-operation was considered (Kiel & Kjølle 2020). These findings underscore the necessity of including lightning and storm effects explicitly in MV substation reliability models, emphasising component fragility, protection system resilience, and the cascading impact of weather events on distribution networks.

4.3 High Wind Events

High-wind events such as hurricanes, derechos, and strong storms significantly undermine the reliability of medium-voltage (MV) distribution substations by inflicting mechanical damage on overhead lines, poles, and towers. Research indicates that overhead power distribution systems are highly vulnerable during extreme wind hazards for example, falling trees or limbs caused by strong winds account for over half of failures in certain regions in the U.S. distribution infrastructure (Hou & Muraleetharan 2023). In these situations, the structural integrity of lines is compromised, leading to conductor breakage, pole collapse, or line interruption, which in turn increase reliability indices like SAIFI and SAIDI.

In arid or semi-arid regions, high winds often carry sand or dust, introducing an additional failure mechanism: insulator contamination and consequent flash-overs. For instance, a recent study found that wind–sand coupling loads increase structural responses of transmission towers by over 28% and 41% in displacement and axial forces respectively, compared to pure wind load conditions (Lu et al., 2025). Such contamination accumulates on insulator surfaces, especially when moist, creating conductive paths that reduce flash-over voltage and increase equipment failure risk. Together, these findings highlight that wind and wind-borne particulates pose both direct mechanical and indirect electrical threats to MV substation reliability, necessitating integrated mitigation strategies.

4.4 Snow, Ice, and Cold Weather

Severe winter conditions significantly impact the reliability of MV distribution substations by imposing excessive mechanical loads and inducing electrical stress. Ice accretion on overhead conductors can raise the weight and sag well beyond design limits; for instance, a case study in Inner Mongolia found that heavy snow and ice accumulation increased conductor loading by three to four times the normal conditions, leading to trip faults and structural failures (Zhang 2025). In parallel, freezing rain triggers ice build-up on wires and towers, altering aerodynamic characteristics and increasing mechanical stress from wind-ice interactions. Estimations of extreme ice accretion loads at Canadian sites show that freezing rain can cause loads sufficient to exceed standard design values for structural elements supporting power lines (Sheng & Hong 2023).

These combined mechanical and environmental stresses also degrade system performance and prolong restoration times, thereby increasing reliability indices such as SAIDI and SAIFI as shown Figure 2. In icy conditions, insulator contamination and galloping conductors become prevalent, which triggers flashovers and short-circuit events, further impairing service continuity. Experimental and simulation studies demonstrate that even moderate ice levels combined with wind can induce conductor galloping amplitudes up to 15 m, leading to phase-to-phase contact or grounding faults (Yan et al., (2019). These findings indicate that reliability assessments for MV substations must explicitly consider snow, ice and cold-weather hazards in the same framework as other weather events.

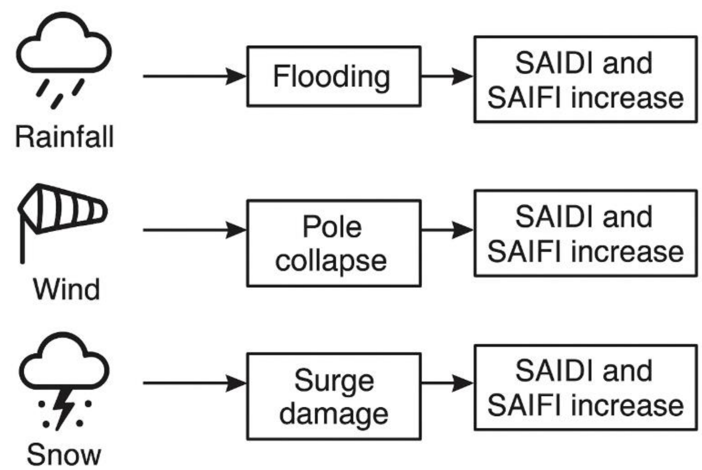

Figure 2: Weather-Related Threats to Distribution Substation Reliability

5. Machine Learning Approaches in Reliability Assessment

The increasing availability of high-resolution meteorological and operational datasets has spurred the adoption of machine learning (ML) techniques for assessing and forecasting the reliability of power systems. These data-driven models are particularly suited to capture complex, nonlinear relationships between weather variables and system failures relationships that traditional statistical models struggle to represent (Fu & Wu 2022). For example, recent research highlights that ML approaches such as support vector machines (SVM), artificial neural networks (ANN), and ensemble methods (e.g., random forests) outperform classical methods in forecasting reliability metrics and fault occurrence when weather data are included as input features.

In applications focused on distribution networks, ML has proven effective in predicting outage duration, failure likelihood, and component vulnerability under adverse weather conditions. A case-study by (Şah et al., 2020) illustrated how ML models using hurricane forecast inputs could estimate line congestion and fault risk in near-real-time, thereby offering utilities preventive and corrective decision support. In another study, a recent model developed for a Turkish utility incorporated weather and operational data to deploy decision trees, random forest, k-nearest neighbours and gradient-boosting techniques, achieving high accuracy in predicting outage durations (Pani & Gujjarlapudi 2025).

Despite these successes, several challenges remain for ML-based reliability assessment in MV (medium voltage) distribution substations. Firstly, data quality and completeness particularly regarding component-level fault records and high-granularity weather measurements limit model generalizability and transferability (Aslam & Majeed 2025). Secondly, many models treat weather variables and reliability outcomes as independent relationships, without fully capturing cascading effects or spatial–temporal dependencies (e.g., multi-component interactions in a substation during a storm). Recent work suggests that advanced architectures such as graph neural networks (GNNs) or hybrid ML-physical models may better capture these dependencies (Thilakarathne & Ahmad 2020).

5.1 ML Categories

Machine-learning approaches applied to power-system reliability typically fall into four practical categories: (1) supervised learning for classification and regression (fault classification, remaining-useful-life and load/price forecasting), (2) unsupervised learning for anomaly detection and clustering (early fault/anomaly discovery and condition grouping for maintenance prioritization), (3) semi-supervised and transfer learning to cope with limited labelled event data and domain shifts between substations, and (4) deep learning and hybrid models that combine physics-based models with data-driven layers for high-dimensional signal interpretation (Kumbhar 2021). Supervised and deep methods dominate load forecasting and fault classification tasks because of their strong predictive performance on labelled historical data, while unsupervised clustering and anomaly detection are widely used for condition monitoring and prioritising inspections see the summary in Table 2 for example algorithms and typical applications (Vivas, E., *et al.* 2020; Porawagamage *et al.* 2024).

In practice, each ML category brings distinct advantages and trade-offs for reliability engineering: supervised models give interpretable risk scores but require labelled failures, unsupervised methods reduce labeling burden but need careful thresholding to avoid false alarms, transfer/semi-supervised approaches help when data are scarce or nonstationary, and hybrid/deep architectures excel where rich sensor streams (SCADA/PMU/thermal) must be fused for real-time decision support (Payette 2023; Liu *et al.* 2025). Successful deployment also hinges on data quality, feature engineering, explainability, and integration with asset management workflows challenges repeatedly highlighted in the recent literature and summarized alongside algorithm–use-case mappings in Table 2.

Table 2: Machine Learning Categories and Applications in Power Reliability

Learning Type	**Description**	**Example Algorithms**	**Applications**
Supervised	Trains on labeled data to predict outcomes	Random Forest, Support Vector Machine, ANN	Outage prediction, failure classification
Unsupervised	Finds hidden patterns in unlabeled data	K-Means, PCA	Weather clustering, anomaly detection
Reinforcement	Learns through feedback-driven optimization	Q-Learning, Deep RL	Maintenance scheduling, control strategy optimization

5.2 Random Forest Models

The ensemble learning approach embodied by the Random Forest (RF) algorithm has become a mainstay in reliability-prediction frameworks for power systems, largely because of its robustness to nonlinearities, scalability to large data sets, and interpretability via feature importance ranking. In the reliability-prediction flow-chart depicted in Figure 3, RF sits at the modelling block where weather, asset condition, and operational features converge into a predictive model of failure risk or outage duration. For example, RF was employed to detect fault location and duration from high-resolution power-system phasor data, outperforming conventional methods in both accuracy and processing time (Sugunaraj et al., 2022). In another work applying RF to outage prediction from extreme weather events, wind speed, temperature and rainfall intensity emerged among the most influential variables, illustrating how RF identifies key environmental drivers of reliability risk (Arora & Ceferino 2023).

In applying RF within the framework of Figure 3, several practical advantages and caveats must be acknowledged. The algorithm’s built-in feature-importance metrics facilitate identification of the most impactful predictors (for example, thunderstorm winds, heavy rainfall, heat-wave temperature spikes), which in turn informs maintenance planning and sensor deployment. Yet RF also exhibits a fundamental limitation: while very good at interpolation within the training data domain, it struggles to extrapolate beyond it (e.g., ultra-high wind speeds in hurricane conditions) and may deliver overly conservative predictions in extreme conditions (Arora & Ceferino 2023). Therefore, when designing the prediction pipeline in Figure 3, one must ensure extensive and representative training data, careful feature selection (including weather-asset interaction terms), model validation under extreme conditions, and integration of explainability outputs for decision support by utility operators.

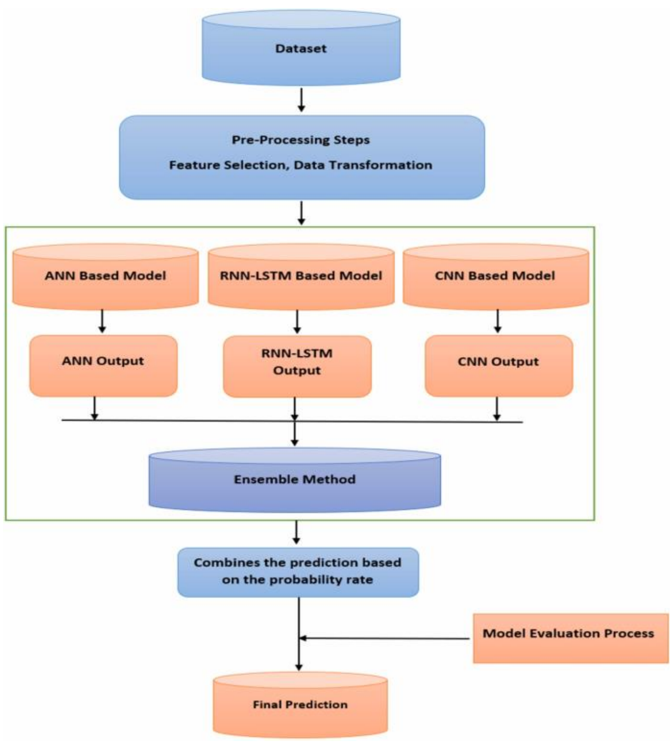

Figure 3: Flowchart of ML-Based Reliability Prediction Framework

6. Review of Related Literature

Table 3 provides a synthesis of key studies that have examined weather-related reliability modeling in electric power systems. These studies collectively explore how meteorological drivers including wind, precipitation, lightning, and temperature extremes affect outage frequency and duration across both transmission and distribution networks. Early empirical works established foundational statistical relationships between weather intensity and outage frequency (Lat, 1989; Zhou et al., 2006; Reed, 2008), while more recent studies have incorporated multi-factor, data-rich, and simulation-based approaches. Panteli and Mancarella (2015) advanced this line of inquiry by linking extreme weather and climate change to system reliability and resilience, emphasizing the need for probabilistic modeling under evolving climatic conditions. Similarly, Kong et al. (2020) demonstrated that big-data analytics can be used to develop predictive maintenance strategies for improving reliability metrics such as SAIDI and EENS.

Recent research has increasingly leveraged machine-learning (ML) and hybrid physics-based frameworks to enhance predictive accuracy. For instance, Watson et al. (2022) utilized random forest algorithms to forecast outage probability from multi-year weather data, achieving superior performance compared to regression-based baselines. Nayak (2023) extended this trend by employing deep learning architectures to improve fault prediction, though interpretability and computational demands remain ongoing challenges. Complementing these, Sharma et al. (2023) proposed a weighted ML ensemble approach that captures nonlinear effects of concurrent weather variables, while Hughes et al. (2024) developed a probabilistic hybrid model integrating physics-informed simulations with data-driven reliability assessment, improving resilience quantification.

Consistent with these findings, recent reviews (Panteli et al., 2020; Shield, 2021) and applied studies (Ghasemkhani et al., 2024) emphasize that weather accounts for the majority of large-scale outage events and customer-hour losses globally. Moreover, when trained on representative outage records and high-resolution meteorological inputs, ML techniques such as Random Forests and gradient-boosting deliver strong predictive performance (Ghasemkhani et al., 2024; Sharma et al., 2023). However, existing models often remain region-specific, rely on historical data rather than real-time observations, and lack transparency for operational decision-making underscoring the need for hybrid, interpretable frameworks capable of capturing rare or compound events and generalizing across climatic zones (Hughes et al., 2024; Panteli & Mancarella, 2015).

Table 3. Summary of Related Literature on Weather–Reliability Studies

Author(s)	**Year**	**Weather Focus**	**Indices Used**	**Key Findings**	**Limitations**
(Lat 1989)	1989	Lightning	SAIFI, SAIDI	Linked lightning density with faults	Ignored combined weather effects
(Zhou et al., 2006)	2006	Thunderstorms	SAIFI, CAIDI	Modeled lightning-induced faults	Limited to single condition
(Reed 2008)	2008	Wind	SAIFI, CAIDI	Defined wind thresholds for outages	Region-specific data
(Panteli & Mancarella 2015)	2015	Multi-factor	SAIDI, EENS	Related climate change to reliability	Static assumptions
(Kong et al. 2020)	2020	Big-data approach	SAIDI, EENS	Developed predictive maintenance model	Data bias issues
(Watson et al. 2022)	2022	ML	SAIFI, SAIDI	Forecasted outages using	Lacked explainability

				RF model	
(Nayak 2023)	2023	Deep learning	SAIDI, SAIFI	Improved fault prediction	High computational cost
(Sun et al. 2024)	2024	Typhoon simulation	SAIDI, EENS	FEM modeling of storm effects	Simplified structural parameters

7. Discussion and Research Gaps

Despite notable progress in applying data-driven and computational approaches to power system reliability, significant research gaps remain. A major limitation lies in isolated weather modeling, where most studies analyze the influence of single meteorological variables such as rainfall, wind, or temperature without accounting for the compound or cascading impacts of multi-hazard weather events. This simplification fails to capture real-world interdependencies, such as how wind-driven rainfall or freezing rain simultaneously affects multiple substation components. Furthermore, much of the current literature exhibits regional dependence, as reliability models and failure rates are calibrated using data from specific climatic or infrastructural contexts (e.g., North America or East Asia). This limits the global generalizability and transferability of such models to regions with different network topologies and environmental stressors. In addition, data quality poses a persistent challenge many models rely on historical averages or coarse-grained weather datasets, which reduce predictive fidelity under rapidly changing climate conditions.

Equally critical are methodological gaps related to interpretability and system resilience integration. Deep learning and ensemble methods, while powerful, often function as “black boxes,” making it difficult for utilities to understand model rationale and apply insights in operational decision-making. The lack of transparent, explainable AI frameworks hinders trust and adoption in reliability management processes. Moreover, few studies explicitly integrate predictive reliability assessment with adaptive control mechanisms, such as automated switching, demand response, or dynamic reconfiguration of feeders under extreme weather. Future research should therefore prioritize hybrid modeling frameworks that merge physical simulations with interpretable machine learning architectures such as physics-informed neural networks or graph-based models. These approaches can enhance generalization across climates and grid configurations, enabling robust, explainable, and resilient reliability forecasting for medium-voltage distribution substations in an era of intensifying weather extremes.

8. Conclusion

This paper provided a comprehensive review of the current state of research addressing the influence of weather conditions on the reliability of medium-voltage (MV) distribution substations. The literature consistently demonstrates that meteorological phenomena such as heavy rainfall and flooding, high winds, lightning, snow, and ice pose significant risks to substation equipment and system performance. These weather-induced stresses lead to insulation failures, conductor breakages, and prolonged restoration times, thereby increasing reliability indices such as SAIDI and SAIFI. The reviewed studies collectively highlight that climate change is amplifying the frequency and severity of these disruptive weather events, emphasizing the urgency of developing adaptive reliability models that can operate effectively under evolving environmental conditions. Advancements in machine learning (ML) have introduced powerful new tools for modeling and predicting reliability outcomes in weather-sensitive systems. Methods such as Random Forests, Gradient Boosting, and Deep Neural Networks have demonstrated superior predictive capability compared to traditional statistical approaches, primarily due to their ability to capture nonlinear relationships between weather variables and component failures. However, challenges remain regarding data quality, regional generalization, and the interpretability of complex models. Many deep learning frameworks function as "black boxes," limiting their practical utility for grid operators who require explainable insights to guide maintenance planning and operational decisions.

Looking forward, future research should prioritize the development of hybrid, interpretable reliability assessment frameworks that combine the strengths of physical simulations, high-resolution climate modeling, and machine learning. Integrating real-time meteorological data, remote sensing, and Internet of Things (IoT)–based monitoring can enhance situational awareness and enable predictive maintenance under dynamic weather conditions. Furthermore, embedding predictive reliability insights into adaptive grid control and resilience planning including automated switching, distributed energy resource coordination, and microgrid islanding will be essential to ensure the continued reliability of MV substations in a changing climate. In sum, the convergence of data science, engineering resilience, and climate adaptation represents a critical frontier for the sustainable and secure operation of modern power systems.

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