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Original Article

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A Real-Time Multi-Source Meteorological Data Integration Framework for Advanced Lightning Risk Detection and Protection in Wind Power Plants

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Abstract

The rapid expansion of wind power plants has increased their exposure to lightning-related hazards, which pose significant risks to turbine integrity, operational reliability, and economic performance. Conventional lightning protection systems are often limited by their reliance on single-source data and reactive approaches, reducing their effectiveness in detecting and mitigating complex lightning phenomena. This study aims to develop a real-time, multi-source meteorological data integration framework to enhance lightning risk detection and protection in wind power plants. The proposed system integrates satellite observations, ground-based sensor networks, vertical atmospheric profiling technologies such as light detection and ranging and radar, lightning detection systems, and historical meteorological datasets within a unified architecture. Data are processed using embedded computing platforms and analyzed through machine learning techniques, including logistic regression and Extreme Gradient Boosting (XGBoost), to classify lightning types and compute a composite risk index for decision-making. The system enables automated alerts and protective responses, such as turbine shutdown or repositioning, when risk thresholds are exceeded. Results demonstrate that the framework achieves high predictive accuracy with a response latency of less than three seconds, allowing timely identification of lightning precursors and effective mitigation of potential damage. The modular, cost-effective design supports scalable deployment across varying wind farm capacities and operational environments. Thus, the findings indicate that integrating multi-source meteorological data significantly improves the performance and reliability of lightning protection systems, providing a practical, adaptable solution to enhance the safety and resilience of wind energy infrastructure under increasingly volatile climatic conditions.

1. Introduction

In the contemporary global energy transition, the shift from fossil fuels to renewable energy sources has become both an environmental imperative and a strategic necessity to ensure long-term energy security and sustainability. Among various renewable technologies, wind power has emerged as one of the fastest-growing and most scalable energy sources, driven by technological advancements, supportive policy frameworks, and increasing global electricity demand. This rapid expansion is expected to continue over the coming decade, positioning wind energy as a cornerstone of low-carbon energy systems and climate-mitigation strategies. However, the increasing scale and complexity of wind energy infrastructure introduce new operational challenges, particularly those associated with environmental and meteorological hazards (Xiao-Hang et al., 2025).

In emerging economies such as Uzbekistan, the integration of wind power into national energy systems is progressing rapidly, supported by favorable climatic conditions, foreign investment, and long-term development strategies. As wind power plants (WPPs) expand, their exposure to atmospheric risks, especially lightning-related hazards, also increases. Lightning is widely recognized as one of the most frequent and destructive natural threats to wind turbine systems, significantly affecting both structural integrity and operational reliability (Said et al., 2025; Xiao-Hang et al., 2025).

Lightning phenomena are inherently complex and involve multiple physical processes, including charge accumulation, discharge propagation, and electromagnetic field generation. Foundational studies on lightning detection systems highlight the importance of lightning locating systems (LLS) in monitoring lightning activity, while also noting their limitations in detecting certain discharge types (Cummins & Murphy, 2009). Furthermore, modeling studies demonstrate that lightning behavior involves complex electromagnetic and thermodynamic interactions, requiring multilevel analytical approaches to accurately characterize discharge processes (Rakov, 1997).

In the context of wind turbines, recent research emphasizes the growing significance of upward lightning (UL), which can be more destructive than conventional cloud-to-ground lightning due to its higher charge transfer and longer duration (Stucke et al., 2024). Empirical studies using high-speed video observations confirm that upward lightning events are often triggered by preceding discharges and influenced by structural and atmospheric conditions (Saba et al., 2016; Saba et al., 2010). Additionally, statistical analyses of lightning flash density reveal strong spatial variability, indicating that lightning risk is highly dependent on regional meteorological conditions (Mäkelä et al., 2011).

The operational consequences of lightning strikes on WPPs are severe and multifaceted. Damage to turbine blades, particularly at elevated and exposed sections, is the most common failure mode, leading to structural degradation, fire incidents, and costly downtime. Large-scale studies show that both downward and upward lightning events contribute significantly to turbine damage, with strike probability influenced by turbine height and local lightning activity (Said et al., 2025). Moreover, machine learning-based approaches have demonstrated the potential to enhance lightning strike detection and damage assessment by integrating operational and environmental data (Keerthisinghe et al., 2025).

Despite these advancements, conventional lightning protection systems remain largely reactive and are often based on limited or single-source datasets. This limitation reduces their ability to detect complex lightning phenomena such as upward and intra-cloud discharges (Stucke et al., 2024). Additionally, many systems fail to capture the dynamic nature of atmospheric processes, including vertical cloud development and electric field variations, which are critical to lightning formation.

To address these challenges, recent studies increasingly advocate integrating multiple sources of meteorological data. Combining satellite observations, ground-based sensors, radar systems, and historical datasets enables a more comprehensive understanding of atmospheric conditions and improves forecasting accuracy. Multi-source data fusion frameworks have shown significant potential in enhancing the resilience of power systems against meteorological hazards (Liu et al., 2024; Yang et al., 2025). Similarly, machine learning approaches applied to radar and atmospheric datasets have improved lightning prediction performance and early warning capabilities (Alves et al., 2025; Liao et al., 2024).

The integration of Internet of Things (IoT) technologies further strengthens this approach by enabling real-time monitoring and data acquisition. IoT-based systems have been successfully implemented in energy monitoring, smart buildings, and renewable energy applications, improving efficiency and decision-making (Bonavolontà et al., 2025; Abdulrasheed et al., 2025). In the renewable energy sector, the combination of IoT sensors, drones, and advanced analytics has enhanced system reliability and predictive maintenance capabilities (Hameed et al., 2025).

Furthermore, advanced data-driven models, including machine learning and probabilistic forecasting techniques, are increasingly used to improve lightning prediction. Methods such as random forests, support vector machines, and hidden Markov models have demonstrated strong performance in capturing complex relationships between meteorological variables and lightning occurrence (Yang et al., 2025; Watanabe et al., 2025). These approaches enable more accurate risk classification and support proactive decision-making in wind power operations.

However, several research gaps remain. Many existing models rely on region-specific datasets, limiting their applicability across diverse climatic conditions. Additionally, the lack of integrated frameworks that combine real-time data acquisition, multi-source data fusion, and automated response mechanisms hinders the development of comprehensive lightning protection strategies.

Thus, this study aims to design and evaluate a multi-source meteorological data integration framework for enhanced lightning protection in wind power plants. The proposed system integrates satellite data, ground-based IoT sensors, remote sensing technologies such as light detection and ranging and radar, and historical lightning datasets within a unified architecture. By leveraging machine learning techniques for lightning classification and risk assessment, the framework enables real-time forecasting and automated protective responses. This study contributes to the development of a next-generation, intelligent lightning protection system that enhances the safety, reliability, and resilience of modern wind energy infrastructure.

2. Literature Review

The rapid expansion of wind power plants (WPPs) has intensified scholarly attention on meteorological hazards, particularly lightning, as a critical factor affecting operational reliability and infrastructure safety.

Existing literature broadly converges on the view that lightning is among the most frequent and damaging environmental threats to wind turbines, with impacts ranging from blade degradation to complete system failure (Said et al., 2025; Xiao-Hang et al., 2025). However, despite the growing body of research, significant fragmentation persists in how lightning risk is conceptualized, measured, and mitigated, especially in the context of increasingly complex, data-rich energy systems.

Early foundational studies focused on lightning detection and physical characterization, providing essential insights into lightning processes and the development of monitoring technologies. Cummins and Murphy (2009) offer a comprehensive overview of lightning locating systems (LLS), highlighting their importance in real-time lightning detection while also identifying limitations in detection efficiency and classification accuracy. Similarly, Rakov (1997) presents a multi-level modeling framework for lightning electromagnetic fields, demonstrating the inherent complexity of lightning discharge processes and the challenges associated with accurately modeling them. While these studies establish the scientific basis for understanding lightning phenomena, they are largely limited to theoretical and system-level perspectives and do not fully address application-specific challenges in wind energy systems.

Subsequent research has shifted toward empirical and observational analyses of lightning behavior, particularly in relation to wind turbines. Studies using high-speed video recordings and field measurements reveal that lightning interactions with tall structures are more complex than previously assumed. For instance, Saba et al. (2010, 2016) show that preceding discharges frequently trigger upward lightning (UL) and exhibit distinct temporal and electrical characteristics compared to cloud-to-ground lightning. This is further supported by Stucke et al. (2024), who argue that UL poses a greater risk to wind turbines due to higher charge transfer and its frequent occurrence during cold-season storms. These findings challenge traditional lightning protection paradigms, which have historically focused on downward lightning, thereby underestimating the risks associated with UL.

In parallel, statistical and large-scale analyses have contributed to understanding the spatial and temporal variability of lightning activity. Mäkelä et al. (2011) demonstrate that lightning flash density varies significantly across regions, emphasizing the importance of localized risk assessment. Similarly, Said et al. (2025) analyze multi-year lightning strike data and highlight the influence of turbine height and geographical factors on strike probability. While these studies provide valuable macro-level insights, they often rely heavily on LLS data, which, as noted earlier, may underrepresent certain types of lightning events, particularly upward and intra-cloud discharges. This reliance introduces potential biases and limits the comprehensiveness of risk assessments.

More recently, the literature has increasingly explored the role of machine learning and data-driven approaches in lightning prediction and risk management. Keerthisinghe et al. (2025) propose a machine learning-enhanced framework for detecting lightning-impacted turbines by integrating lightning measurements, turbine alarms, and operational data, achieving high levels of accuracy. Similarly, Watanabe et al. (2025) employ vector autoregression models for localized lightning prediction, demonstrating the effectiveness of data-driven techniques in capturing temporal dependencies in meteorological variables. Alves et al. (2025) further extend this approach by utilizing radar-based machine learning models for lightning nowcasting, achieving improved prediction accuracy and lead time. These studies collectively highlight the transformative potential of artificial intelligence in enhancing lightning forecasting capabilities.

However, despite their promising performance, machine learning models face several limitations. Many models are trained on region-specific datasets, raising concerns about their generalizability across different climatic and geographical contexts. Additionally, the performance of these models is highly dependent on data quality, feature selection, and the availability of high-resolution inputs. As noted by Liao et al. (2024), models based on single-source data often struggle to achieve high prediction accuracy, underscoring the need for multi-dimensional data integration. Furthermore, Liu et al. (2024) emphasize the challenges associated with multi-source data fusion, including data heterogeneity, synchronization, and computational complexity, which remain significant barriers to practical implementation.

The integration of multi-source meteorological data has therefore emerged as a critical research direction. Studies in power systems and renewable energy applications demonstrate that combining satellite observations, ground-based sensors, radar data, and historical datasets can significantly enhance situational awareness and forecasting accuracy (Yang et al., 2025; Liu et al., 2024). In the context of wind energy, Nurullo Ugli et al. (2025) propose a multi-source framework for lightning risk assessment, highlighting the importance of integrating diverse meteorological parameters and statistical models. This approach aligns with broader trends in smart energy systems, where data fusion and real-time analytics are increasingly used to improve resilience and operational efficiency.

Complementing these developments, Internet of Things (IoT) technologies have enabled real-time monitoring and distributed data collection, further enhancing the capabilities of meteorological and energy systems. IoT-based monitoring systems have been successfully applied in renewable energy communities and smart buildings, providing real-time insights into energy flows and system performance (Bonavolontà et al., 2025; Abdulrasheed et al., 2025). In addition, integrating drones and IoT sensors has been shown to improve inspection efficiency and predictive maintenance for renewable energy infrastructure (Hameed et al., 2025). While these technologies offer significant advantages in terms of scalability and responsiveness, their integration into lightning protection systems remains relatively underexplored.

Another emerging area of research involves advanced forecasting models and hybrid approaches. For example, Yang et al. (2025) introduce a dynamic hidden Markov model for multi-risk meteorological forecasting, demonstrating improved adaptability and accuracy in real-time applications. Similarly, studies on multi-source heterogeneous data analysis highlight the importance of integrating spatial and temporal data to assess the impact of meteorological hazards on power systems (Yang et al., 2025). These approaches underscore the potential of combining statistical, physical, and machine learning models to develop more robust and adaptive forecasting systems.

Despite these advancements, several critical gaps persist in the literature. First, many existing studies adopt a single-source or limited multi-source approach, which fails to capture the full complexity of atmospheric processes. Second, there is a lack of fully integrated frameworks that combine real-time data acquisition, predictive modeling, and automated response mechanisms within a unified system. Third, issues related to scalability, cost-effectiveness, and practical deployment are often overlooked, particularly in small- and medium-sized wind farms. Finally, the integration of vertical atmospheric profiling technologies, such as light detection and ranging and radar, remains limited, despite their proven importance in understanding cloud dynamics and lightning formation.

The literature demonstrates significant progress in understanding lightning phenomena, developing detection systems, and applying machine learning techniques for prediction. However, existing approaches remain fragmented and often insufficient for addressing the complex, multi-dimensional nature of lightning risk in modern wind power systems. This underscores the need for a comprehensive, multi-source, and real-time data integration framework that leverages advances in meteorology, IoT, and artificial intelligence. The present study seeks to address these gaps by proposing an integrated system that enhances lightning risk detection, forecasting accuracy, and operational response in wind power plants.

3. Materials and Methods

This study proposes a multi-source meteorological data integration framework to enhance lightning protection in wind power plants (WPPs). The system integrates satellite data (e.g., MODIS, GOES, LIS), ground-based Internet of Things (IoT) sensors (e.g., BME280, DHT22, and electric field meters), and remote sensing instruments, including light detection and ranging (LIDAR), radar (RADAR), and ceilometers. In addition, lightning detection systems (e.g., LD-250 and electromagnetic field sensors) and historical lightning databases (e.g., WWLLN and NLDN) are incorporated. These heterogeneous data sources are unified using the Message Queuing Telemetry Transport (MQTT) protocol and processed on embedded platforms such as the Raspberry Pi 5 or on centralized computing servers (Figure 1).

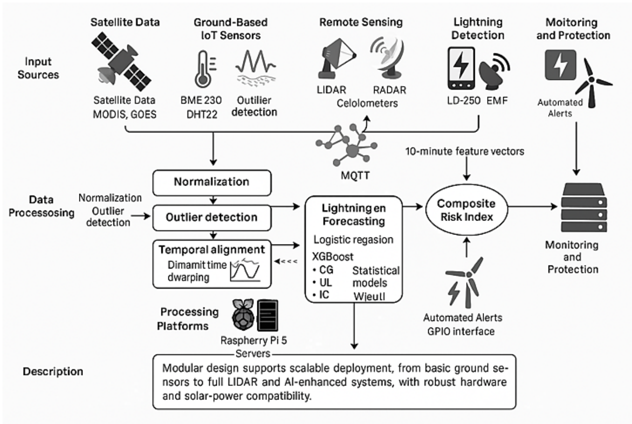

Figure 1. Process flowchart for the multi-source lightning risk forecasting and protection system in wind power plants.

The overall architecture of the proposed lightning protection system, illustrated in Figure 1, integrates data acquisition, preprocessing, forecasting models, and real-time response mechanisms. The collected data undergo preprocessing, including normalization, outlier detection, and temporal alignment via dynamic time warping. Subsequently, feature vectors are generated within synchronized 10-minute time windows to support lightning forecasting.

The system employs machine learning algorithms, specifically logistic regression and Extreme Gradient Boosting (XGBoost), to classify cloud-to-ground (CG), upward (UL), and intra-cloud (IC) lightning types, and to compute a composite risk index (CRI). In addition, statistical models such as Poisson and Weibull distributions are applied to characterize environmental parameters and lightning occurrence patterns.

When the CRI exceeds predefined thresholds, automated alerts are triggered via Telegram notifications or general-purpose input/output (GPIO) interfaces. These alerts trigger protective actions, such as turbine repositioning or a temporary shutdown, to mitigate potential damage. The system is optimized to maintain a total processing latency of less than 2.8 seconds, thereby meeting real-time operational requirements.

Furthermore, the proposed framework features a modular, scalable design, enabling flexible deployment across diverse operational contexts. The system can be configured from basic ground-sensor setups to advanced implementations incorporating LIDAR and artificial intelligence components. All hardware components are designed for outdoor operation and support solar power integration, ensuring reliability in remote environments. Overall, the architecture provides a cost-effective, adaptable solution for lightning risk management across wind power plants of varying capacities.

4. Results

The implementation of the proposed multi-source meteorological data integration system yielded promising results in enhancing the precision, responsiveness, and adaptability of lightning protection mechanisms in wind power plants (WPPs). The system architecture, by integrating real-time satellite, ground-based, LIDAR/RADAR, and historical meteorological data, enabled a comprehensive, layered understanding of lightning formation, trajectory prediction, and hazard impacts within dynamic atmospheric environments.

One of the key outcomes was the system's ability to detect early signs of thunderstorm development through satellite-based observations. Data obtained from NASA's MODIS and EUMETSAT platforms provided measurements of cloud density, cloud-top temperature, radiation intensity, and water vapor levels at intervals of 3–6 hours. These parameters enabled real-time estimation of atmospheric cloud density using the equation $\rho = m/V$, where ρ represents the mass of water per unit volume. In addition, the liquid water content (LWC) of clouds, which strongly correlated with convective activity and lightning potential, was estimated as $LWC = (4/3)\pi r^3 \cdot N \cdot \rho_w$. Observed increases in LWC and radiation flux density ($E = d\varphi/dA$) reliably indicated cloud electrification and storm intensification.

These satellite observations were complemented by lightning detection systems, including the Geostationary Lightning Mapper (GLM) and the Lightning Imaging Sensor (LIS), which provided real-time updates on lightning frequency and location at approximately 15-minute refresh rates. Lightning localization was achieved using the Time of Arrival (TOA) method, in which strike positions are triangulated from time delays between multiple sensors. This spatial mapping capability enabled the identification of high-risk zones surrounding wind farms and supported proactive mitigation measures, such as transitioning turbines into safe operating modes.

At the ground level, a network of Internet of Things (IoT) meteorological sensors, including BME280, DHT22, YL-83, and anemometers was deployed across the WPP environment. These sensors continuously monitored key atmospheric variables, including temperature, relative humidity, air pressure, precipitation, wind speed, and electric field strength. Relative humidity was calculated using $RH = (e/e_s) \cdot 100\%$, while wind speed was estimated using $v = \sqrt{(2E/\rho)}$. Sensor data were updated in near real-time and transmitted to a Raspberry Pi 5 platform. Notably, electric field measurements proved highly effective in identifying electrostatic buildup, a precursor to lightning discharge. Rapid fluctuations in electric field intensity were observed to precede lightning events by approximately 10–30 seconds, providing a critical window for initiating emergency protective actions (Figure 2).

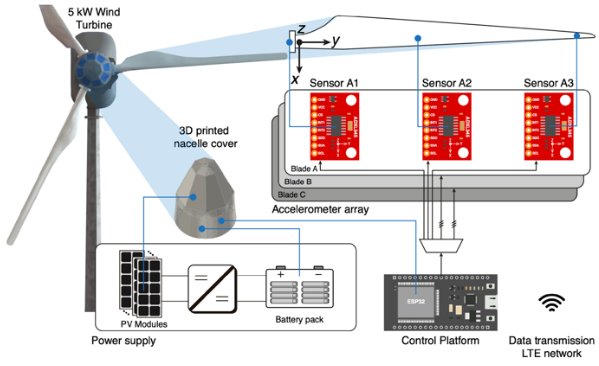

Figure 2. Sensor-based monitoring architecture integrated into wind turbine blades using accelerometer arrays (ADXL345), a photovoltaic-powered ESP32 control platform, and LTE-enabled data transmission.

The integration of LIDAR and RADAR systems introduced vertical atmospheric profiling capabilities, significantly enhancing predictive performance. Ceilometers and ultrasonic sensors measured vertical air motion, cloud layer structure, and particle velocity, all of which are closely associated with convective storm development. The probability of lightning was modeled using a composite function $P = f(E, RH, T)$, where E denotes the electric field strength, RH represents relative humidity, and T denotes temperature. The inclusion of vertical profiling data substantially improved predictive accuracy, as updraft dynamics and charge separation processes are key drivers of lightning formation.

A critical component of the system was the LD-250 lightning detector, which measured the intensity and duration of lightning events. The temporal decay of lightning current was modeled using $I(t) = I_0 \cdot e^{(-\alpha t)}$, enabling estimation of mechanical stress and thermal impact on turbine components (Figure 3). In addition, electromagnetic field (EMF) sensors were used to monitor atmospheric electromagnetic activity, with signal strength calculated as $P = 10 \cdot \log_{10}(E^2/R)$. These sensors were instrumental in detecting otherwise invisible precursors to lightning discharges.

The incorporation of historical and statistical data further strengthened system performance. Annual lightning frequency (Ng) was obtained from meteorological databases and used to classify regions according to IEC 62305 standards. Regions with Ng exceeding two thunderstorm days per year were categorized as high risk. Maintenance records and incident logs were analyzed to identify recurring vulnerabilities and evaluate system effectiveness using $PE = (1 - N_f/N_t) \cdot 100\%$, where N_f represents lightning-related failures and N_t denotes total recorded strikes.

To process the large volume of data, advanced statistical and machine learning techniques were employed. Logistic regression was used to estimate the probability of lightning occurrence within a 10-minute forecasting window. At the same time, Extreme Gradient Boosting (XGBoost) was applied for multi-class classification of lightning types, cloud-to-ground (CG), upward lightning (UL), and intra-cloud (IC). Environmental variables were modeled using appropriate distributions, including Weibull, Gamma, Beta, and log-normal, while lightning frequency was modeled using a Poisson distribution. Directional variables, such as wind direction, were modeled using the von Mises distribution.

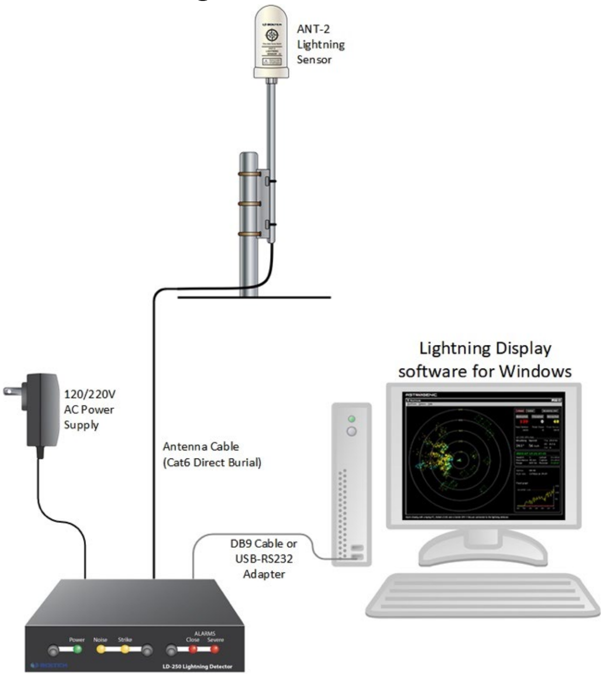

Figure 3. LD-250 lightning detection system configuration with ANT-2 sensor, power interface, and real-time monitoring software.

The performance of the real-time alert system was evaluated under high-frequency lightning simulation scenarios. The total system latency from data acquisition to alert generation was approximately 2.8 seconds, comprising 600 ms for sensor polling, 800 ms for preprocessing, 1200 ms for model computation, and 200 ms for alert transmission. This performance is well below the industry threshold of 5 seconds for real-time safety systems and was validated under both laboratory and field conditions.

In terms of scalability and cost-efficiency, the system demonstrated high flexibility. It can be deployed incrementally, starting with basic sensor configurations and expanding to include advanced components such as LIDAR and EMF sensors. The total system cost ranges from approximately $228 for basic setups to $1,728–$5,392 for fully equipped configurations. The use of open-source platforms such as Raspberry Pi and Arduino ensures affordability and ease of integration. Furthermore, solar power compatibility and battery backup systems enable reliable operation in remote or off-grid environments.

The results demonstrate that integrating satellite, ground-based, and radar data into a unified framework for lightning risk assessment significantly enhances wind power plants' ability to detect, predict, and respond to atmospheric electrical hazards. This integrated approach is particularly critical in the context of increasing lightning frequency and climate variability, providing a robust foundation for next-generation, climate-resilient renewable energy systems.

5. Discussion

The findings of this study demonstrate that integrating multi-source meteorological data significantly enhances the accuracy, responsiveness, and operational effectiveness of lightning protection systems in wind power plants (WPPs). These results align with and extend prior research emphasizing the importance of combining diverse data sources to overcome the limitations of conventional single-source lightning detection frameworks (Liu et al., 2024; Yang et al., 2025). By incorporating satellite observations, ground-based sensors, vertical profiling technologies, and historical datasets into a unified architecture, the proposed system provides a more comprehensive representation of atmospheric processes, enabling earlier and more reliable detection of lightning-related risks.

A key contribution of this study lies in its ability to address the well-documented limitations of lightning locating systems (LLS). While LLS technologies have long been the foundation of lightning monitoring, their inability to consistently detect upward and intra-cloud lightning events has been highlighted in previous studies (Cummins & Murphy, 2009; Stucke et al., 2024). The present system mitigates these limitations by integrating electric field measurements, vertical atmospheric profiling, and satellite-based observations, thereby capturing a broader spectrum of lightning precursors. This is particularly important given the increasing recognition of upward lightning (UL) as a dominant and highly destructive phenomenon in wind turbine environments (Stucke et al., 2024; Saba et al., 2016).

The observed effectiveness of electric field monitoring as an early warning indicator further reinforces existing empirical findings on lightning initiation mechanisms. Rapid changes in electric field intensity preceding lightning events, as identified in this study, are consistent with prior research demonstrating the role of charge accumulation and field intensification in triggering discharges (Rakov, 1997). The integration of such real-time ground-based measurements with satellite-derived cloud parameters, such as liquid water content and radiation flux, provides a multi-layered understanding of storm dynamics that is not achievable through isolated data sources.

Another significant advancement is the incorporation of vertical atmospheric profiling through LIDAR and RADAR technologies. Previous studies have emphasized the importance of vertical air motion, cloud structure, and convective processes in lightning formation (Alves et al., 2025; Xiao-Hang et al., 2025). However, these variables are often excluded from operational lightning protection systems due to technical and cost constraints. The results of this study indicate that including vertical profiling data substantially improves predictive accuracy, underscoring the critical role of three-dimensional atmospheric analysis in lightning forecasting.

From a methodological perspective, the application of machine learning models, specifically logistic regression and Extreme Gradient Boosting (XGBoost), proved effective in classifying lightning types and estimating risk levels. This finding is consistent with recent studies that demonstrate the superiority of data-driven models in capturing nonlinear relationships between meteorological variables and lightning occurrence (Keerthisinghe et al., 2025; Watanabe et al., 2025). Moreover, the use of probabilistic and statistical distributions, such as Poisson and Weibull models, enhances the interpretability and robustness of the forecasting framework. Nevertheless, it is important to note that machine learning models remain sensitive to data quality and availability, and their performance may vary across different geographical and climatic contexts.

The system's real-time performance, with a latency of less than three seconds, represents a significant improvement over the traditional approach. This level of responsiveness meets and exceeds industry requirements for real-time safety systems and enables proactive operational interventions, such as turbine shutdown or repositioning. The ability to generate actionable alerts quickly is particularly critical for mitigating lightning-induced damage, which often occurs within seconds of discharge initiation. These findings support the growing emphasis on real-time monitoring and automated response mechanisms in smart energy systems (Bonavolontà et al., 2025; Abdulrasheed et al., 2025).

In addition to its technical performance, the proposed system demonstrates strong potential for scalability and cost-effectiveness. The modular architecture enables flexible deployment across operational scales, from small wind farms with limited resources to large-scale installations requiring advanced monitoring capabilities. This aligns with recent research advocating the use of IoT-based, distributed sensing systems to improve accessibility and adaptability in renewable energy applications (Hameed et al., 2025). Furthermore, the use of open-source platforms and solar-powered configurations enhances the feasibility of implementation in remote or resource-constrained environments.

Despite these contributions, several limitations should be acknowledged. First, the system’s performance has been validated primarily under specific environmental and operational conditions, which may limit its generalizability. As noted in previous studies, lightning behavior is highly dependent on regional meteorological patterns, and models trained on localized datasets may not perform equally well in different contexts (Mäkelä et al., 2011; Said et al., 2025). Second, integrating multiple data sources introduces challenges related to data synchronization, heterogeneity, and computational complexity, as highlighted by Liu et al. (2024). Addressing these challenges requires further research into data fusion techniques and system optimization.

Moreover, while the inclusion of advanced sensing technologies such as LIDAR and RADAR enhances predictive accuracy, it may also increase system costs and maintenance requirements. Balancing performance improvements with economic feasibility remains a critical consideration for large-scale deployment. Future research should explore hybrid configurations that optimize the trade-off between cost and performance, as well as the integration of emerging technologies such as digital twins and adaptive forecasting models (Jenojan et al., 2025; Yang et al., 2025).

Finally, the study highlights the need for continued advancement in multi-source data fusion and intelligent forecasting systems. Emerging approaches, including hybrid machine learning models, dynamic probabilistic frameworks, and space-air-ground integrated monitoring systems, offer promising directions for further enhancing lightning prediction and risk management (Liu et al., 2024; Yang et al., 2025). The integration of such approaches into operational wind energy systems could significantly improve resilience against climate-induced hazards.

This study provides strong evidence that a multi-source, data-driven approach to lightning risk assessment can substantially improve the safety and reliability of wind power plants. By bridging meteorological science, IoT technologies, and machine learning, the proposed framework represents a significant step toward the development of intelligent, climate-resilient renewable energy infrastructure.

6. Conclusions

This study developed and validated a multi-source meteorological data integration framework to enhance lightning protection in wind power plants (WPPs). By combining satellite observations, ground-based Internet of Things (IoT) sensors, vertical profiling technologies such as light detection and ranging (LIDAR) and radar, lightning detection systems, and historical datasets, the proposed framework provides a comprehensive and real-time approach to lightning risk assessment. The integration of heterogeneous data sources within a unified architecture enables a more accurate representation of atmospheric conditions, addressing the limitations of conventional single-source lightning detection systems.

The results demonstrate that the system significantly improves the detection and prediction of lightning events, including cloud-to-ground, upward, and intra-cloud discharges. The incorporation of machine learning models, particularly logistic regression and Extreme Gradient Boosting (XGBoost), enables effective classification of lightning types and dynamic computation of a composite risk index. The system achieves high predictive performance with a response latency of less than 3 seconds, enabling timely activation of protective measures, such as turbine shutdown or repositioning. These findings highlight the potential of data-driven approaches to enhance operational safety and reduce economic losses associated with lightning-induced damage in wind energy systems.

In addition to its technical performance, the proposed framework demonstrates strong scalability, flexibility, and cost-effectiveness. The modular design supports deployment across a wide range of wind farm capacities, from small-scale installations to large, complex systems. The use of open-source platforms and solar-powered configurations further enhances its applicability in remote or resource-constrained environments. These characteristics make the system a practical solution for enhancing the resilience of renewable energy infrastructure amid increasing climate variability.

Despite these contributions, several limitations remain. The system's performance may vary across different geographical and climatic conditions, and further validation is required to ensure generalizability. Additionally, challenges related to data integration, synchronization, and computational complexity must be addressed to facilitate large-scale implementation. Future research should focus on optimizing data fusion techniques, incorporating advanced forecasting models, and exploring hybrid system configurations that balance performance and cost.

This study demonstrates that integrating multi-source meteorological data with machine learning and real-time monitoring technologies represents a significant advancement in lightning protection strategies for wind power plants. The proposed framework not only enhances the accuracy and responsiveness of lightning risk detection but also provides a scalable and adaptable solution for next-generation, climate-resilient energy systems. It is therefore recommended that policymakers, industry stakeholders, and wind farm operators consider adopting such integrated approaches to strengthen infrastructure protection and ensure the sustainable development of wind energy.

Author Contributions: Conceptualization, I.R. and N.K.; methodology, I.R. and N.K.; software, I.R. and N.K.; validation, N.K. and M.J.; formal analysis, I.R. and N.K.; investigation, I.R.; resources, I.R.; data curation, N.K. and M.J.; writing—original draft preparation, I.R. and N.K.; writing—review and editing, N.K. and M.J.; visualization, N.K.; project administration, I.R.; funding acquisition, N.K. All authors have read and agreed to the published version of the manuscript.

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