Yirik shamol elektr stansiyalarida chaqmoq xavfini baholash uchun sun’iy intellektga asoslangan markazlashtirilgan real vaqt rejimidagi monitoring va diagnostika tizimini ishlab chiqish

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Dolzarblik: Chaqmoq zarbalari yirik shamol elektr stansiyalarining ishonchliligi va ekspluatatsion xavfsizligini sezilarli kamaytiradi.
Maqsad: Ushbu tadqiqot murakkab elektromagnit va meteorologik sharoitlarda ishlovchi shamol turbinalari uchun real vaqtli chaqmoq toklarini tahlil qilish, ko‘p manbali ma’lumotlarni birlashtirish, anomaliyalarni aniqlash va qisqa muddatli prognozlashga mo‘ljallangan AI-asosidagi markazlashtirilgan monitoring tizimini ishlab chiqishga qaratilgan.
Usullar: Ko‘p sensorli ma’lumotlar fuzionlash, Bayesian modeli, XGBoost algoritmi, adaptiv normallashtirish va real vaqt signal tasniflash usullari qo‘llanildi.
Natijalar: Taklif etilgan tizim chaqmoq razryadlari va elektromagnit shovqinlarni ishonchli ajratib, real vaqt diagnostikasi hamda prognozlashda barqaror ishlashni namoyish etdi.
Kalit so‘zlar: shamol elektr stansiyalari; chaqmoq monitoringi; AI diagnostika; XGBoost; Bayesian modellari; ma’lumotlar fuzionlash; real vaqt monitoringi; prediktiv texnik xizmat

Интеллектуальная централизованная система мониторинга и диагностики в реальном времени на основе искусственного интеллекта для оценки риска поражения молнией крупномасштабных ветровых электростанций

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Актуальность: Отказы, вызванные ударами молнии, существенно снижают надежность и безопасность крупных ветроэнергетических установок.
Цель: В работе разработана централизованная система мониторинга и диагностики на основе искусственного интеллекта для анализа токов молнии в реальном времени, многоканального объединения данных, обнаружения аномалий и краткосрочного прогнозирования в ветроэнергетических системах.
Методы: Использованы многосенсорное объединение данных, байесовские модели, алгоритм XGBoost, адаптивная нормализация и классификация переходных сигналов в реальном времени.
Результаты: Предложенная система надежно разделяла сигналы молнии и электромагнитные шумы, обеспечивая устойчивую диагностику и прогнозирование в реальном времени при экспериментальных испытаниях.
Ключевые слова: ветроэлектростанции; мониторинг молнии; AI-диагностика; XGBoost; байесовские модели; объединение данных; мониторинг реального времени; предиктивное обслуживание

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Ai-based centralized real-time monitoring and diagnostic framework for lightning risk assessment in large-scale wind power plants

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Relevance: Lightning-induced failures significantly reduce operational reliability and safety in large-scale wind power plants worldwide.
Objective: This study develops a centralized AI-based monitoring and diagnostic framework for real-time lightning current analysis, multi-source data fusion, anomaly detection, and short-term forecasting in wind turbine systems operating under complex electromagnetic and meteorological conditions.
Methods: Multi-source sensor fusion, Bayesian inference, XGBoost prediction, adaptive normalization, and real-time transient signal classification were implemented.
Results: The proposed framework reliably distinguished lightning discharges from electromagnetic noise, achieving stable real-time diagnostics and predictive warning performance under experimental operating conditions.
Keywords: wind power plants; lightning monitoring; AI diagnostics; XGBoost; Bayesian models; sensor fusion; real-time monitoring; predictive maintenance

1. Introduction

The rapid expansion of global wind energy infrastructure has significantly increased the importance of operational reliability, predictive maintenance, and intelligent monitoring systems in large-scale wind power plants. According to the Global Wind Energy Council, worldwide installed wind power capacity exceeded 1,000 GW in 2024, while the global energy demand continued to increase due to industrial electrification and renewable energy integration [1]. Offshore and onshore wind turbines are highly vulnerable to atmospheric electrical phenomena because of their tall tower structures, exposed rotating blades, and operation under complex meteorological conditions. Lightning strikes, electromagnetic interference, and transient overvoltage events represent major threats to turbine insulation systems, SCADA infrastructures, and electrical converters [2].

Modern wind farms therefore require intelligent centralized monitoring systems capable of continuously processing real-time sensor information, identifying abnormal transient phenomena, and forecasting lightning-related risks before catastrophic failures occur. Traditional threshold-based protection systems often experience difficulties in distinguishing real lightning impulses from electromagnetic background noise and transient corona discharge signals under harsh environmental conditions [3]. Recent studies demonstrate that artificial intelligence algorithms, multi-sensor fusion architectures, and deep learning models can substantially improve fault diagnosis accuracy and real-time operational reliability in wind power systems [4].

Furthermore, climate-related instability and increasing frequency of severe convective weather conditions have intensified the need for advanced lightning forecasting systems integrated with meteorological observations, satellite monitoring, LIDAR/RADAR technologies, and intelligent diagnostic platforms [5]. The integration of Bayesian inference, XGBoost prediction algorithms, and weighted data fusion methods provides new opportunities for constructing scalable and adaptive monitoring architectures suitable for large wind turbine installations [6].

In this study, a centralized AI-based monitoring and diagnostic framework for real-time lightning current analysis in wind power plants is developed and experimentally validated using multi-source sensor data, Rogowski coil measurements, and a laboratory-scale "plate–needle" experimental platform. The proposed architecture enables synchronization, normalization, weighted fusion, anomaly identification, and short-term lightning risk prediction under complex electromagnetic environments (Fig. 1).

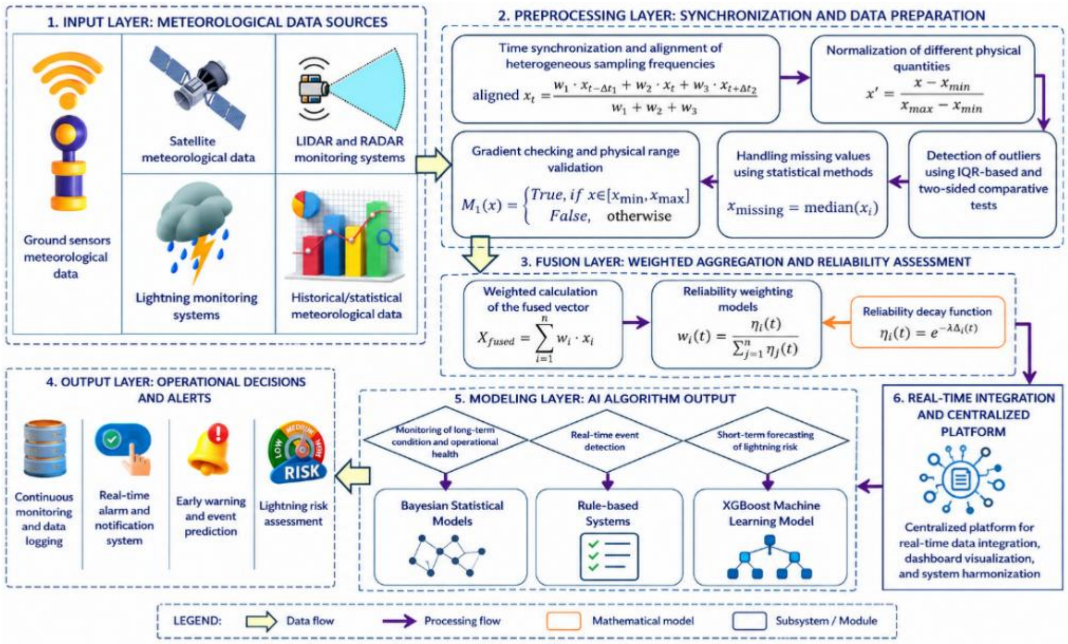

Fig. 1. Logical Framework of a Centralized Monitoring and Diagnostic System Using Artificial Intelligence-Based Forecasting Models for Real-Time Data Analysis

The proposed approach contributes to the development of intelligent wind farm protection systems capable of improving operational safety, minimizing false alarms, and supporting predictive maintenance strategies for next-generation renewable energy infrastructures [7, 8].

2. Materials and Methods

The proposed intelligent monitoring architecture was designed for real-time acquisition, processing, and classification of lightning-induced transient current signals in large-scale wind power plants. The framework integrates ground-based sensors, meteorological monitoring stations, LIDAR/RADAR systems, satellite observations, and lightning current measurement devices into a unified multi-source information fusion environment [9]. The input information vector for the monitoring system is represented as:

$$x_i(t) = \{I(t), v(t), T(t), H(t), E(t)\} \tag{1}$$

where $I(t)$denotes lightning current, $v(t)$wind speed, $T(t)$ambient temperature, $H(t)$humidity, and $E(t)$electric field intensity. The complete multi-source dataset is expressed as:

$$X(t) = \{x_1(t), x_2(t), \dots, x_n(t)\} \tag{2}$$

Because different sensor channels operate with varying sampling frequencies and transmission delays, time synchronization was performed using weighted interpolation:

$$x_c^{adapted} = \frac{w_1 x_{t-\Delta t_1} + w_2 x_t + w_3 x_{t+\Delta t_2}}{w_1 + w_2 + w_3} \tag{3}$$

where $w_i$are adaptive weighting coefficients associated with temporal confidence levels. Signal normalization was then applied to eliminate scaling differences between heterogeneous physical quantities:

$$x_i^{norm} = \frac{x_i - \mu_i}{\sigma_i} \tag{4}$$

where $\mu_i$is the mean value and $\sigma_i$is the standard deviation. The fused monitoring vector was calculated through weighted aggregation:

$$X_{total} = \sum_{i=1}^{n} w_i\,(t) x_i(t) \tag{5}$$

The confidence-based weighting function was defined as:

$$w_i(t) = \frac{\eta_i(t)}{\sum_{j=1}^{n} \eta_j(t)} \tag{6}$$

with exponential reliability decay:

$$\eta_i(t) = e^{-\lambda \Delta t_i} \tag{7}$$

The lightning probability estimation stage employed Bayesian inference:

$$P(L \mid X) = \frac{P(X|L)P(L)}{P(X)} \tag{8}$$

For short-term forecasting and classification tasks, the XGBoost model was implemented:

$$\hat{y} = \sum_{k=1}^{K} f_k\,(X) \tag{9}$$

where $f_k$represents decision tree functions and $\hat{y}$denotes predicted lightning risk.

The experimental platform consisted of a “plate–needle” discharge configuration integrated with a Rogowski coil and oscilloscope-based real-time data acquisition chain. The upper conductive plate received high-voltage excitation through a protective resistor, while the grounded lower plate incorporated a centrally positioned needle electrode to generate controlled corona discharge and transient impulse phenomena (Fig. 2).

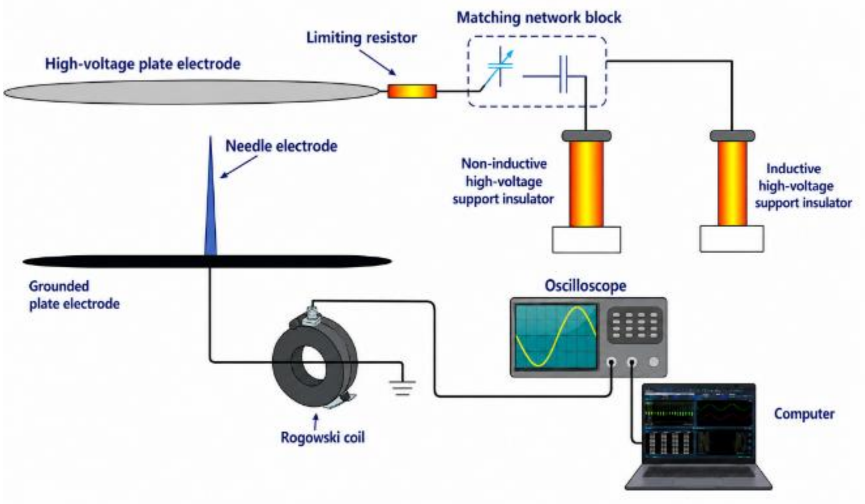

Fig. 2. Schematic Diagram of the Experimental Platform

The measurement system continuously recorded current signals under varying electromagnetic conditions [10]. Feature extraction included peak current, RMS current, transient energy, rise time, and statistical noise indicators:

$$F = \{I_{peak}, I_{rms}, E, \sigma, t_{rise}\} \tag{10}$$

These features were subsequently supplied to the AI-based classification layer for real-time decision-making. Table 1 presents representative experimental signal measurements obtained during laboratory validation.

The proposed methodology enables adaptive real-time monitoring under noisy and non-stationary electromagnetic environments while preserving high diagnostic sensitivity and operational scalability [11].

3. Result and discussion

Experimental validation demonstrated that the proposed centralized monitoring framework successfully distinguished between background noise, interference signals, probable discharge events, and genuine lightning transients under real-time operating conditions. The measured background current noise level reached a maximum value of 4,5 mA, which remained substantially lower than operational lightning discharge currents recorded during experimental tests. This result confirmed the feasibility of defining adaptive dynamic thresholds for reliable event identification (Fig. 3).

The real-time processing pipeline included signal preprocessing, adaptive thresholding, feature extraction, Bayesian probability estimation, and XG Boost-based classification. Dynamic trigger thresholds were determined using:

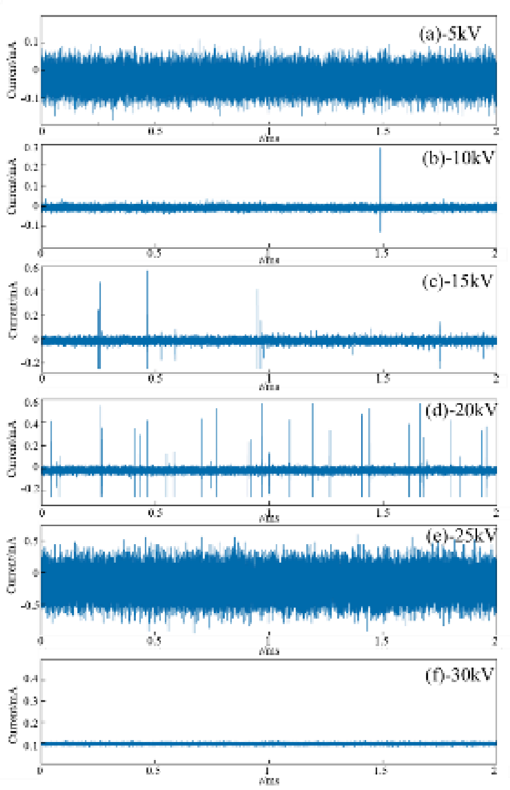

Fig. 3. Measurement Results

$$Th(t) = \mu + k\sigma \tag{11}$$

where $k \approx 3$. The AI model effectively identified high-energy transient events associated with lightning strikes. For example, at 1,127 ms, the system detected a transient event characterized by: $I_{peak} = 0{,}623$mA; $I_{rms} = 0{,}284$mA; $E = 0{,}164$mA^2·ms; $t_{rise} = 1{,}2$μs

Table 1. Experimental Lightning Signal Dataset for AI-Based Monitoring System Validation

№	Time, ms	Current, mA	RMS, mA	Energy, mA²·ms	Noise σ, mA	Peak, mA	Rise Time, μs	Normalized Value	Classification
1	0,102	0,045	0,021	0,0021	0,018	0,051	3,2	0,42	Noise
2	0,245	0,112	0,054	0,0084	0,022	0,134	2,8	0,73	Probable discharge
3	0,387	0,482	0,211	0,102	0,025	0,512	1,4	0,94	Lightning
4	0,511	0,038	0,019	0,0018	0,017	0,044	3,5	0,38	Noise
5	0,684	0,265	0,132	0,041	0,021	0,298	2,1	0,81	Lightning

Table 2. Real-Time AI-Based Classification Results for Lightning Monitoring

№	Time, ms	Peak Current, mA	Energy, mA²·ms	Normalized Value	AI Classification	Decision
1	0,102	0,051	0,0021	0,42	Noise	Reject
2	0,245	0,134	0,0084	0,73	Probable discharge	Store + Review
3	0,387	0,512	0,102	0,94	Lightning	Alert + Store
4	0,684	0,298	0,041	0,81	Lightning	Alert + Store
5	1,127	0,623	0,164	0,97	Lightning	Alert + Store

The normalized confidence value reached 0,97, leading to automatic classification as a lightning event. Similarly, at 0,387 ms, a transient pulse with energy 0,102 mA²·ms and normalized confidence 0,94 was also successfully identified as lightning discharge. Lower-energy events with moderate amplitudes were classified as probable discharge or electromagnetic interference, while low-amplitude transient disturbances were correctly rejected as background noise. The classification distribution for the experimental dataset included: 4 lightning events; 2 interference events; 3 noise events; 1 probable discharge event; These results indicate that the proposed AI-based framework can reliably operate even under severe electromagnetic interference conditions. Table 2 summarizes the real-time classification outcomes generated by the centralized monitoring architecture.

The integration of multi-source meteorological information, adaptive weighting functions, and intelligent fusion algorithms significantly improved system robustness and reduced false trigger probabilities. Continuous synchronization of heterogeneous data streams enabled stable operation during rapidly changing atmospheric conditions.

The proposed framework also supports scalability for large offshore wind farms involving multiple turbines and distributed sensor infrastructures. Through integration with SCADA systems and cloud-based monitoring platforms, the developed architecture can support predictive maintenance, early warning generation, and intelligent operational optimization.

Recent studies in AI-based wind turbine diagnostics confirm that hybrid monitoring architectures combining real-time sensor fusion, anomaly detection, and machine learning models provide superior operational reliability compared to conventional threshold-based methods [1]. Similarly, advanced lightning risk assessment techniques integrated with meteorological forecasting have demonstrated substantial improvements in protection efficiency for renewable energy infrastructures [9].

The experimental “plate–needle” platform additionally enabled controlled reproduction of transient discharge phenomena under laboratory conditions. This capability provided a repeatable environment for validating AI classification algorithms and optimizing feature extraction methods before deployment in full-scale wind farm installations.

The study presented in this article was performed within the scope of collaborative research programs established between Uzbekistan and China in the field of intelligent technologies for lightning protection, operational monitoring, fault prediction, and diagnostic systems for utility-scale wind farms. Financial and scientific support for the research was provided through the Uzbek project IL-8724053008 and the National Key Research and Development Program of China (Project No. 2025YFE0106900).

Conclusions. This study presented a centralized AI-based monitoring and diagnostic framework for real-time lightning current analysis and forecasting in large-scale wind power plants. The developed architecture integrates multi-source sensor data, meteorological observations, Rogowski coil measurements, Bayesian inference, and XGBoost prediction models into a unified intelligent monitoring environment. Experimental validation using a laboratory-scale “plate–needle” discharge platform confirmed that the proposed framework can reliably distinguish lightning impulses from background electromagnetic noise and interference signals under complex operating conditions. The adaptive synchronization, normalization, and weighted data fusion mechanisms improved information reliability and reduced false triggering probabilities. The proposed system demonstrated high effectiveness for real-time lightning risk estimation, transient signal classification, and automated warning generation. Furthermore, scalable architecture provides a strong engineering foundation for future multi-turbine monitoring systems, predictive maintenance platforms, and intelligent operational reliability management in modern wind farms.

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