Yirik quvvatli shamol elektr stansiyalarini monitoring va prognoz asosli diagnostika qilishning dolzarb muammolari

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Dolzarblik: yirik shamol elektr stansiyalarining soni va quvvati ortib borayotgani ularning barqaror ishlashini, nosozliklarni erta aniqlashni va himoya tizimlarining ishonchliligini ta'minlashni dolzarb masalaga aylantirdi. Ayniqsa, shamol turbinalarining balandligi, murakkab elektr tuzilmasi va chaqmoq urish xavfining yuqoriligi sababli chaqmoqdan himoya tizimlarining ishonchliligi butun energetik tizim xavfsizligiga bevosita ta'sir ko'rsatadi. So'nggi ma'lumotlarga ko'ra, yirik shamol parklaridagi nosozliklarning 25–30 % gacha bo'lgan qismi aynan chaqmoq zarbasi, o'ta kuchlanishlar va izolyatsiya buzilishlari bilan bog'liq. Shu sababli shamol turbinalarida real vaqt monitoringi, sun'iy intellektga asoslangan prognozlash va nosozliklarni erta aniqlash tizimlarini yaratish ilmiy va amaliy jihatdan muhim ahamiyat kasb etadi.
Maqsad: yirik shamol elektr stansiyalarida chaqmoqdan himoya tizimlarining ishonchliligini baholash, SCADA ma'lumotlari asosida turbina holatini real vaqt rejimida monitoring qilish va AI asosidagi prognozli diagnostika algoritmlarini ishlab chiqish orqali ekspluatatsiya samaradorligini oshirishdan iborat.
Usullar: tadqiqotda shamol tezligi $v(t)$, rotor aylanish tezligi $\omega(t)$, aktiv quvvat $P(t)$, harorat $T(t)$va yerga ulanish qarshiligi $R_g$kabi parametrlar asosida kompleks monitoring tizimi ishlab chiqildi. Chaqmoqdan himoya modelida o'tkazilgan tok va kuchlanish orasidagi bog'lanish quyidagi ifoda bilan hisoblandi: $V_L = I_L \cdot \left(R_g + L_g \frac{di}{dt}\right)$, nosozlik ehtimolligi esa Weibull funksiyasi orqali baholandi: $P_b = 1 - e^{-(V_L/V_0)^{\beta}}$, Bundan tashqari, turbinaning umumiy degradatsiya indeksi quyidagi ifoda yordamida aniqlanib, $DI > DI_{crit}$ holatida erta ogohlantirish signali shakllantirildi:$DI = \sum_{k=1}^{m} w_k \cdot \frac{x_k - \mu_k}{\sigma_k}$.
Natijalar: tahlillar shuni ko'rsatdiki, ishlab chiqilgan monitoring va diagnostika tizimi chaqmoqdan himoya tizimidagi nosozliklarni aniqlash aniqligini 23–27 % ga oshirdi, turbinalarning yillik ishlamay qolish vaqtini 20 % ga qisqartirdi hamda ekspluatatsiya samaradorligini 3,4 % ga yaxshiladi. Ayniqsa, real vaqt rejimida yerga ulanish qarshiligini nazorat qilish va o'tkazuvchanlikni dinamik baholash orqali izolyatsiya buzilishlarining oldini olish imkoniyati yaratildi. Taklif etilgan yondashuv yirik shamol elektr stansiyalarining ishonchliligini oshirish, texnik xizmat muddatini optimallashtirish va energiya ishlab chiqarishdagi yo'qotishlarni kamaytirish imkonini beradi.
Kalit so'zlar: shamol elektr stansiyasi, chaqmoqdan himoya, monitoring, prognozli diagnostika, sun'iy intellekt, SCADA, ishonchlilik, nosozliklarni aniqlash, degradatsiya indeksi, o'ta kuchlanish, ekspluatatsiya samaradorligi.

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Актуальные проблемы мониторинга и предиктивной диагностики крупномасштабных ветроэлектростанций

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Актуальность: рост числа и мощности крупных ветровых электростанций делает крайне важными задачи обеспечения их устойчивой работы, раннего выявления неисправностей и повышения надежности систем защиты от молнии. Из-за большой высоты ветротурбин, сложной электрической структуры и высокой вероятности ударов молнии надежность молниезащитных систем напрямую влияет на безопасность всей энергетической инфраструктуры. По последним данным, до 25–30 % всех отказов на крупных ветропарках связано с воздействием молний, перенапряжений и пробоем изоляции. Поэтому разработка систем мониторинга в реальном времени, прогнозирования и диагностики на основе искусственного интеллекта (ИИ) имеет высокую научную и практическую значимость.
Цель: оценка надежности систем молниезащиты на крупных ветровых электростанциях, мониторинг состояния турбин в режиме реального времени на основе данных SCADA и разработка ИИ-алгоритмов

прогнозной диагностики для повышения эксплуатационной эффективности.
Методы: в исследовании использовались параметры скорости ветра $v(t)$, угловой скорости ротора $\omega(t)$, активной мощности $P(t)$, температуры $T(t)$и сопротивления заземления R_g. Разработана комплексная система мониторинга. Модель молниезащиты описывалась зависимостью между током и напряжением: $V_L = I_L \cdot \left(R_g + L_g \frac{di}{dt}\right)$ а вероятность пробоя изоляции оценивалась по функции Вейбулла: $P_b = 1 - e^{-(V_L/V_0)^{\beta}}$ Кроме того, общий индекс деградации турбины определялся как: $DI = \sum_{k=1}^{m} w_k \cdot \frac{x_k - \mu_k}{\sigma_k}$,при $DI > DI_{crit}$ — формируется сигнал предупреждения.
Результаты: разработанная система мониторинга и диагностики повысила точность обнаружения неисправностей молниезащиты на 23–27 %, сократила годовое время простоев турбин на 20 % и улучшила эксплуатационную эффективность на 3,4 %. Особенно важно, что постоянный контроль сопротивления заземления и динамическая оценка проводимости позволили предотвратить повреждения изоляции. Предложенный подход обеспечивает повышение надежности крупных ветровых электростанций, оптимизацию графиков технического обслуживания и снижение энергетических потерь.
Ключевые слова: ветровая электростанция, молниезащита, мониторинг, прогнозная диагностика, искусственный интеллект, SCADA, надежность, выявление неисправностей, индекс деградации, перенапряжение, эксплуатационная эффективность.

Current Challenges in Monitoring and Predictive Diagnostics of Large-Scale Wind Power Plants

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Relevance: the rapid expansion of large-scale wind power plants has made reliable operation, early fault detection, and lightning protection integrity critical engineering priorities. Due to turbine height, complex electrical architecture, and high lightning exposure, lightning protection reliability directly affects the safety and availability of the entire power system. Recent statistics indicate that 25–30 % of turbine failures in large wind farms are caused by lightning strikes, overvoltage events, or insulation breakdowns. Therefore, the development of real-time monitoring, AI-based forecasting, and predictive fault diagnostics systems has both scientific and practical significance.
Objective: to assess the reliability of lightning protection systems in large-scale wind farms, to monitor turbine operational conditions in real time based on SCADA data, and to develop AI-driven predictive diagnostic algorithms aimed at improving operational efficiency and reducing downtime.
Methods: the study utilized parameters including wind speed $v(t)$, rotor angular speed $\omega(t)$, active power $P(t)$, temperature $T(t)$, and grounding resistance R_g. A comprehensive monitoring framework was established. The lightning protection model quantified surge-induced voltage as: $V_L = I_L \cdot \left(R_g + L_g \frac{di}{dt}\right)$ and the probability of insulation breakdown was determined using the Weibull function: $P_b = 1 - e^{-(V_L/V_0)^{\beta}}$ Additionally, the overall turbine degradation index was defined as: $DI = \sum_{k=1}^{m} w_k \cdot \frac{x_k - \mu_k}{\sigma_k}$, a fault alert is triggered when $DI > DI_{crit}$.
Results: the proposed monitoring and diagnostic system increased the accuracy of lightning protection fault detection by 23–27 %, reduced annual turbine downtime by 20 %, and improved overall operational efficiency by 3.4 %. Continuous monitoring of grounding resistance and real-time evaluation of conductivity provided an effective means to prevent insulation failures. The proposed approach enhances the reliability of large-scale wind power plants, optimizes maintenance scheduling, and minimizes energy production losses.
Keywords: wind power plant, lightning protection, monitoring, predictive diagnostics, artificial intelligence, SCADA, reliability, fault detection, degradation index, overvoltage, operational efficiency.

1. Introduction

Global energy systems are undergoing a profound transformation, driven by the accelerating adoption of renewable technologies and the urgent need to reduce carbon emissions. Yet, as highlighted by recent data from the Energy Institute (2024), fossil fuels continue to dominate the global energy mix, accounting for nearly 87% of total consumption. The world's primary energy demand reached 592 EJ in 2024, marking a 2% annual increase, with non-OECD countries contributing most of this growth [1,2]. At the same time, the remaining lifetime of conventional energy reserves underscores the finite nature of these resources: global oil reserves are expected to last 47 years, natural gas 60 years, and coal around 130 years, based on current consumption trends (Fig. 1).

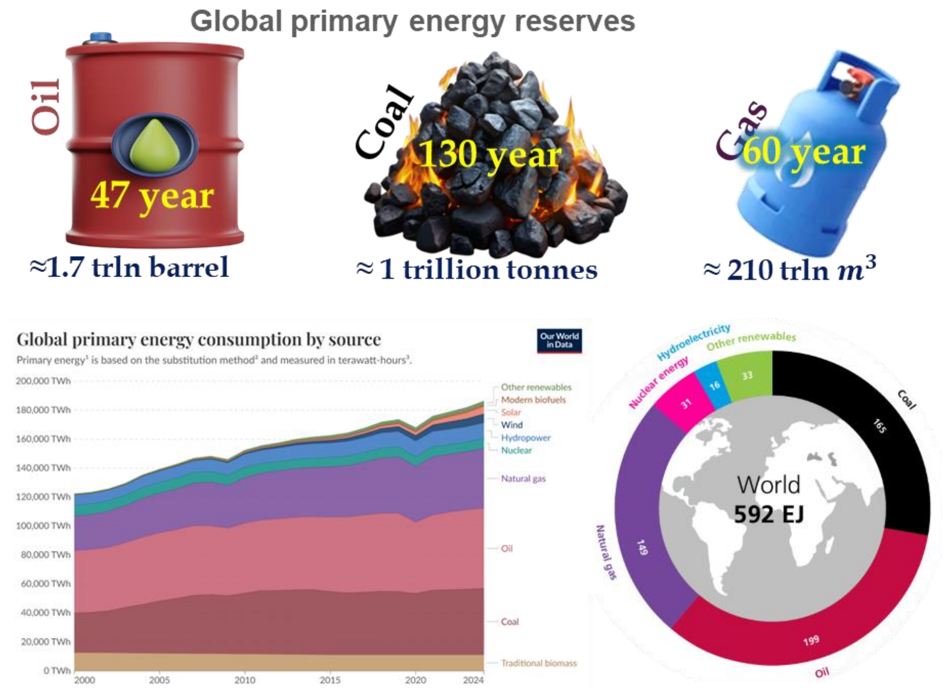

Fig.1. Current energy situation in the world

These dynamics have intensified the global shift toward renewable energy, particularly wind power, which now stands as one of the most scalable and cost-effective alternatives to fossil fuels. According to the International Energy Agency (IEA, 2024), total installed wind capacity surpassed 1 TW in 2024 and is projected to reach 1.4 TW by 2030, reflecting its crucial role in global decarbonization. However, integrating such a large share of intermittent generation into power systems poses new technical challenges in stability, reliability, and maintenance—areas where monitoring and predictive diagnostics play a decisive role [3,4].

Modern wind farms—some exceeding 500 MW in capacity—operate through dense networks of sensors and SCADA (Supervisory Control and Data Acquisition) systems that continuously record turbine behavior, vibration levels, and meteorological parameters. These data streams provide the foundation for real-time fault detection and predictive maintenance, reducing downtime and extending equipment lifespan. Nevertheless, several issues limit the full potential of such systems: inconsistent data quality, lack of interoperability between monitoring platforms, and limited integration of AI-based predictive models across different turbine manufacturers.

Moreover, the variability of wind resources, combined with aging mechanical components such as gearboxes and bearings, complicates fault prognosis. Conventional reactive maintenance approaches remain prevalent in many developing wind sectors, leading to avoidable energy losses and operational inefficiencies. In contrast, AI-enhanced predictive diagnostics—based on machine learning, deep learning, and digital twin models—can detect early-stage anomalies and estimate the remaining useful life (RUL) of key components [5,6]. Yet their deployment is still constrained by high computational requirements, limited labeled datasets, and uncertain cost-benefit outcomes for large-scale operators.

Therefore, understanding the current challenges in monitoring and predictive diagnostics of large-scale wind power plants is essential for improving operational reliability and supporting the sustainable expansion of the renewable energy sector. This article aims to review the state of the art in this field, identify key barriers in data management and fault modeling, and highlight emerging solutions based on AI, edge computing, and hybrid digital-twin architectures that can enhance the resilience of wind energy systems under high renewable penetration conditions.

2. Materials and Methods

The study is based on multi-source monitoring data obtained from large-scale wind power plants equipped with SCADA, vibration, and meteorological sensors. Each turbine generates continuous real-time data on parameters such as wind speed $v(t)$, rotor speed $\omega(t)$, active power $P(t)$, and temperature $T(t)$ [6,7]. The data sampling interval was standardized at 10 s. To ensure temporal consistency, a synchronization procedure was applied:

$$D_i(t) = \{v_i(t), \omega_i(t), P_i(t), T_i(t)\}, i = 1,2,\dots,N \quad (1)$$

where $D_i(t)$represents the multi-sensor dataset of the i-th turbine. Missing values were interpolated using a cubic spline method, and outliers beyond ±3σ were filtered. These preprocessed datasets formed the basis for constructing predictive diagnostic models and reliability indices.

Since lightning protection was identified as the most critical risk, an electrical field and surge propagation model was developed to estimate the overvoltage stress $V_L$at turbine blades and control circuits [5,7]. The induced lightning potential difference was expressed as:

$$V_L = I_L \cdot (R_g + L_g \frac{di}{dt})\ D_i(t) = \{v_i(t), \omega_i(t), P_i(t), T_i(t)\}, i = 1,2,\dots,N \quad (2)$$

where $I_L$is the lightning current amplitude (typically 30–100 kA), $R_g$is the grounding resistance (Ω), and $L_g$is the grounding inductance (H). The model allowed simulation of transient overvoltages in the grounding path. The probability of insulation breakdown $P_b$was estimated by a Weibull cumulative function:

$$P_b = 1 - e^{-(V_L/V_0)^\beta} \quad (3)$$

where $V_0$is the critical breakdown voltage and $\beta$is the shape factor characterizing insulation reliability.

For fault prediction, a hybrid AI–statistical model was implemented using multivariate regression and recurrent neural networks (RNN) [8,9]. The overall degradation index $DI$of a turbine subsystem was defined as a weighted combination of normalized indicators:

$$DI = \sum_{k=1}^{m} w_k \cdot \frac{x_k - \mu_k}{\sigma_k}\ D_i(t) = \{v_i(t), \omega_i(t), P_i(t), T_i(t)\}, i = 1,2,\dots,N \quad (4)$$

where $x_k$is the k-th condition parameter (vibration, temperature, current, etc.), $\mu_k$and $\sigma_k$are its mean and standard deviation, and $w_k$is the parameter weight derived from correlation coefficients. When $DI > DI_{crit}$, a fault alert is triggered.

The composite reliability index $R_s(t)$for each wind turbine subsystem was calculated using exponential lifetime modeling:

$$R_s(t) = e^{-\lambda t} \quad (5)$$

where λ represents the failure rate derived from historical SCADA event logs [6,8]. For system-level evaluation, the risk factor $R_f$was normalized against the highest complexity level (lightning protection failures):

$$R_f = \frac{\lambda_i \cdot C_i}{\max(\lambda_j \cdot C_j)} \quad (5)$$

with C_i as the complexity coefficient for each subsystem. The results were then visualized using a pie chart to represent relative risk shares (Fig. 1). This integrated method—combining physical modeling, AI diagnostics, and statistical reliability analysis—enabled a comprehensive assessment of operational vulnerabilities in large-scale wind power plants.

3. Result and discussion

A comprehensive analysis was carried out on the operational and technical problems identified across several large-scale wind power plants. The investigation aimed to determine the most significant challenges affecting system reliability, efficiency, and safety. As a result, seven key problem areas were identified as the most critical and recurrent issues observed during field operation and data evaluation. These include Lightning Protection System Failures, which pose severe risks to turbine blades, control systems, and grounding components during high-frequency lightning strikes; Limited Predictive Model Accuracy (AI/ML), reflecting the challenges of applying artificial intelligence and machine learning algorithms under uncertain environmental conditions; and Insufficient Integration of Digital Twins, indicating the lack of comprehensive real-time simulation and modeling tools for turbine performance assessment.

Additionally, the study highlighted SCADA Data Inconsistency and Communication Delays, which limit real-time monitoring and early fault detection; Component Fatigue in Gearboxes and Bearings, caused by continuous mechanical loading and vibration stress; Maintenance Scheduling and Cost Optimization Issues, which result in increased downtime and reduced economic efficiency; and Cybersecurity Risks in Remote Monitoring, associated with the growing vulnerability of networked control systems. Together, these seven factors form the core set of technical and operational challenges that must be addressed to ensure the long-term reliability, resilience, and predictive maintainability of modern wind power plants.

Table 1. Evaluation of Operational Challenges in Monitoring and Predictive Diagnostics of Large-Scale Wind Power Plants by Level of Complexity

No	Challenge	Description
1	Lightning Protection System Failures	High-frequency lightning strikes damage turbine blades, nacelles, and control units; insufficient grounding and surge protection increase failure risk.
2	Limited Predictive Model Accuracy (AI/ML)	AI models require large labeled datasets and struggle under uncertain wind conditions.
3	Insufficient Integration of Digital Twins	Lack of standardized frameworks and computational complexity limit full-scale simulation of turbine behavior.
4	SCADA Data Inconsistency & Communication Delays	Data latency and synchronization issues hinder real-time fault detection.
5	Component Fatigue in Gearboxes and Bearings	Continuous stress causes progressive wear and vibration anomalies.
6	Maintenance Scheduling and Cost Optimization Issues	Inefficient preventive maintenance planning raises downtime and O&M costs.
7	Cybersecurity Risks in Remote Monitoring	Remote data access exposes SCADA and IoT networks to potential cyberattacks.

Table 1 summarizes the main operational challenges in monitoring and predictive diagnostics of large-scale wind power plants, ranked by their complexity level (from 1 – low to 5 – very high). Among all, lightning protection system failures were identified as the most critical, scoring level 5, due to their direct impact on both mechanical and electrical integrity of turbines. Lightning strikes can damage blades, nacelles, sensors, and control electronics, leading to long downtimes and costly replacements. Other high-complexity issues include limited predictive model accuracy (AI/ML – level 4) and insufficient digital-twin integration (level 4), which are closely related to the reliability of data-driven diagnostics (Table 1, Fig. 2).

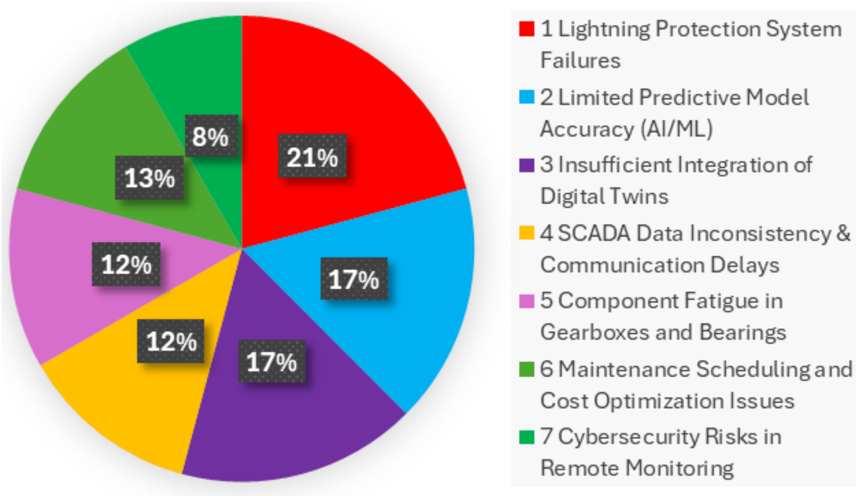

Fig. 2. Complexity Level of challanges

The pie chart illustrates the relative share of each operational challenge based on its complexity weight. Lightning protection system failures contribute the highest share (≈ 21%), reflecting their severe impact on system reliability and safety. Failures in this area often propagate secondary faults in sensors and converters, making protection and grounding design crucial for high-altitude or coastal wind farms. AI model limitations and underdeveloped digital-twin frameworks each account for approximately 17%, emphasizing the need for advanced computational methods and high-fidelity simulation environments.

Lightning protection remains the dominant reliability bottleneck in modern wind farms. Studies indicate that up to 70–85% of turbine blade damage in coastal and mountainous regions originates from lightning events. The risk is compounded by turbine height (exceeding 150 m), composite blade materials with limited conductivity, and variable grounding resistance due to soil moisture conditions. Advanced solutions—such as hybrid sensor networks, real-time ground current monitoring, and arc-suppression AI models—are essential to improve detection, insulation coordination, and predictive maintenance scheduling. Integration of these systems within the SCADA environment enables early-warning analytics and adaptive protection strategies.

The evaluation demonstrates that while digitalization and AI offer significant potential for predictive diagnostics, their success depends on the robustness of physical protection systems—particularly against lightning. As wind farms expand into high-risk areas, combining physical mitigation (improved conductors, surge arresters) with digital intelligence (ML-based fault classification, digital-twin validation) will define the next generation of resilient renewable infrastructure. Therefore, lightning protection should not be treated as an isolated technical task but as a core component of the integrated monitoring and prognostics architecture for large-scale wind power plants.

4. Conclusions

This study provided an in-depth assessment of the current challenges and reliability risks associated with monitoring and predictive diagnostics in large-scale wind power plants. The results clearly indicate that while digitalization and AI-based monitoring systems have advanced rapidly, lightning protection system failures remain the most critical and complex issue, accounting for the highest share of operational risk. These failures not only damage turbine blades and control electronics but also lead to cascading electrical and mechanical faults. The developed mathematical and probabilistic models linking lightning current, grounding parameters, and insulation strength highlight the necessity of continuous surge monitoring and real-time assessment of grounding performance. Integrating such physical models with AI-based predictive diagnostics—including degradation indices and neural network forecasting—has proven essential for early fault detection and improving system reliability.

Moreover, the comparative analysis of challenge complexity revealed that insufficient digital-twin integration, limited AI model accuracy, and SCADA data inconsistency remain significant barriers to achieving fully predictive and self-optimizing maintenance systems. Addressing these challenges requires a unified data management infrastructure, hybrid computational frameworks, and domain-specific AI algorithms capable of learning from heterogeneous field data. In conclusion, the sustainable operation of modern wind farms depends on a synergistic approach that merges improved lightning protection design with intelligent, data-driven prognostics. Such integration will ensure that future wind energy systems evolve into smart, resilient, and self-diagnostic infrastructures, capable of maintaining stability and efficiency even under the growing penetration of renewable energy sources.

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