Qayta tiklanuvchi energiya manbalari integratsiyalashgan elektr energetika tizimlarining ishonchliligini baholashning zamonaviy usullari

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Dolzarblik: qayta tiklanuvchi energiya manbalaridan, xususan, shamol va quyosh elektr stansiyalaridan keng foydalanish elektr energetika tizimlarida ishonchlilikni baholash dolzarbligini oshirmoqda. An'anaviy deterministik yondashuvlar bunday sharoitlarda toʻliq natija bermasligi sababli, probabilistik, simulyatsion va sun'iy intellektga asoslangan zamonaviy usullarni qoʻllash zarurati ortmoqda. Bu usullar yuqori oʻzgaruvchanlik va noaniqlik sharoitida tizimning barqarorligi va samaradorligini aniqroq baholash imkonini beradi.
Maqsad: ushbu tadqiqotning asosiy maqsadi qayta tiklanuvchi energiya manbalari ulushi yuqori boʻlgan elektr energetika tizimlarida ishonchlilikni baholashning zamonaviy usullarini tahlil qilish, ularning afzallik va cheklovlarini aniqlash hamda integrallashgan yondashuv asosida amaliy qoʻllash imkoniyatlarini koʻrsatib berishdan iborat.
Usullar: tadqiqotda probabilistik modellashtirish (Monte-Karlo simulyatsiyasi, Markov zanjirlari), optimallashtirish va risk tahlili, vaqt qatori asosidagi dinamik simulyatsiyalar, shuningdek, sun'iy intellekt algoritmlaridan (neyron tarmoqlar, ansambl modellar, anomaliyalarni aniqlash usullari) foydalanildi. Tizimning ishonchliligi LOLP, LOLE, va EENS kabi koʻrsatkichlar asosida baholandi, qoʻshimcha ravishda tizimning barqarorlikdan keyingi tiklanish qobiliyatini ifodalovchi rezilyentlik funksiyasi qoʻllandi: $R(t)=\frac{Q(t)}{Q_0}$, bu yerda $Q(t)$– vaqt oʻtishi bilan tizimning ishlash darajasi, Q_0– avvalgi normal holatdagi koʻrsatkich.
Natijalar: olingan natijalar shuni koʻrsatdiki, probabilistik yondashuvlar klassik deterministik modellar bilan solishtirganda ishonchlilik koʻrsatkichlarini ancha aniqroq beradi. Sun'iy intellekt asosidagi prognozlash usullari LOLP qiymatini 20–25 % gacha pasaytirishga yordam berdi, rezilyentlikka yoʻnaltirilgan yondashuv esa tizimning avariyalardan soʻng tiklanish vaqtini 15–20 % ga qisqartirdi. Shuningdek, gibrid usullar (probabilistik + AI + rezilyentlik metrikalari) eng yuqori natijalarni koʻrsatib, real vaqt monitoringi bilan birgalikda samarali qoʻllanishi mumkinligi isbotlandi.
Kalit soʻzlar: qayta tiklanuvchi energiya, elektr energetika tizimi, ishonchlilik, probabilistik modellashtirish, Monte-Karlo simulyatsiyasi, sun'iy intellekt, rezilyentlik, LOLE, LOLP, EENS, nosozliklarni prognozlash, tiklanish koʻrsatkichlari.

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Современные методы оценки надежности энергосистем при интеграции возобновляемых источников энергии

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Актуальность: Широкое использование возобновляемых источников энергии, в частности ветровых и солнечных электростанций, повышает значимость оценки надежности в электроэнергетических системах. Традиционные детерминированные подходы в таких условиях оказываются недостаточными, что требует применения современных методов, основанных на вероятностном моделировании, имитационных расчетах и искусственном интеллекте. Эти методы позволяют более точно оценивать устойчивость и эффективность системы в условиях высокой изменчивости и неопределенности.
Цель: Основной целью данного исследования является анализ современных методов оценки надежности электроэнергетических систем с высоким уровнем интеграции возобновляемых источников энергии, выявление их преимуществ и ограничений, а также демонстрация возможностей практического применения интегрированного подхода.
Методы: В исследовании применялись вероятностное моделирование (имитация Монте-Карло, марковские цепи), оптимизационные и риск-ориентированные подходы, динамические имитации на основе

временных рядов, а также алгоритмы искусственного интеллекта (нейронные сети, ансамблевые модели, методы выявления аномалий). Надежность системы оценивалась по таким показателям, как LOLP, LOLE и EENS. Дополнительно учитывалась способность системы к восстановлению после аварий на основе функции резильентности: $R(t) = \frac{Q(t)}{Q_0}$, где $Q(t)$– уровень функционирования системы в момент времени t, а Q_0– номинальное значение до возмущения.
Результаты: Полученные результаты показали, что вероятностные подходы дают более точные показатели надежности по сравнению с классическими детерминированными моделями. Методы прогнозирования на основе искусственного интеллекта позволили снизить значения LOLP на 20–25%, тогда как резильентно-ориентированные подходы сократили время восстановления системы после нарушений на 15–20%. Кроме того, гибридные методы (вероятностное моделирование + ИИ + метрики резильентности) продемонстрировали наивысшую эффективность и доказали возможность интеграции с системами мониторинга в реальном времени.
Ключевые слова: возобновляемая энергетика, электроэнергетическая система, надежность, вероятностное моделирование, имитация Монте-Карло, искусственный интеллект, резильентность, LOLE, LOLP, EENS, прогнозирование отказов, показатели восстановления.

Modern Methods for Assessing the Reliability of Power Systems under Renewable Energy Integration

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Relevance: The large-scale utilization of renewable energy sources, particularly wind and solar power plants, has increased the importance of assessing reliability in power systems. Traditional deterministic approaches are insufficient under such conditions, thereby necessitating the application of modern methods based on probabilistic modeling, simulation, and artificial intelligence. These methods enable more accurate evaluation of system stability and efficiency under high variability and uncertainty.
Objective: The main purpose of this study is to analyze modern methods for assessing the reliability of power systems with a high share of renewable energy sources, to identify their advantages and limitations, and to demonstrate the possibilities of applying integrated approaches in practice.
Methods: The study employed probabilistic modeling (Monte Carlo simulation, Markov chains), optimization and risk analysis, time-series-based dynamic simulations, as well as artificial intelligence algorithms (neural networks, ensemble models, anomaly detection methods). System reliability was assessed using indices such as LOLP, LOLE, and EENS. Additionally, the system's post-disturbance recovery capability was measured by the resilience function: $R(t) = \frac{Q(t)}{Q_0}$, where $Q(t)$represents system performance at time t, and $Q_0$is the pre-disturbance performance level.
Results: The results showed that probabilistic approaches provide more accurate reliability indicators compared to classical deterministic models. AI-based forecasting methods helped reduce LOLP values by up to 20–25%, while resilience-oriented approaches shortened system recovery times after disturbances by 15–20%. Moreover, hybrid approaches (probabilistic + AI + resilience metrics) demonstrated the highest effectiveness and proved suitable for integration with real-time monitoring systems.
Keywords: renewable energy, power system, reliability, probabilistic modeling, Monte Carlo simulation, artificial intelligence, resilience, LOLE, LOLP, EENS, fault prediction, recovery indices.

1. Introduction

The global energy sector is undergoing a profound transformation driven by the rapid deployment of renewable energy sources (RES), particularly wind and solar power. These sources have become the cornerstone of sustainable energy transitions, enabling reductions in greenhouse gas emissions, diversification of supply, and advancement toward net-zero targets [1,2]. By 2030, many countries are projected to achieve renewable penetration levels exceeding 50% of their electricity generation, which underscores both the opportunities and systemic challenges associated with this transition.

Despite their environmental and economic benefits, renewable energy sources introduce unprecedented uncertainty and variability into power system operations. Unlike conventional thermal plants, renewables depend on meteorological conditions and are geographically dispersed, resulting in significant fluctuations in output. This intermittency complicates real-time balancing between generation and demand, raising new questions about system adequacy and security under high levels of renewable penetration. Fig. 1 illustrates this relationship, showing the projected global trend of increasing renewable integration alongside a gradual decline in system reliability indices. As renewable share grows from under 10% in 2010 to nearly 50% by 2030, the traditional reliability index declines, highlighting the urgent need for advanced assessment methods.

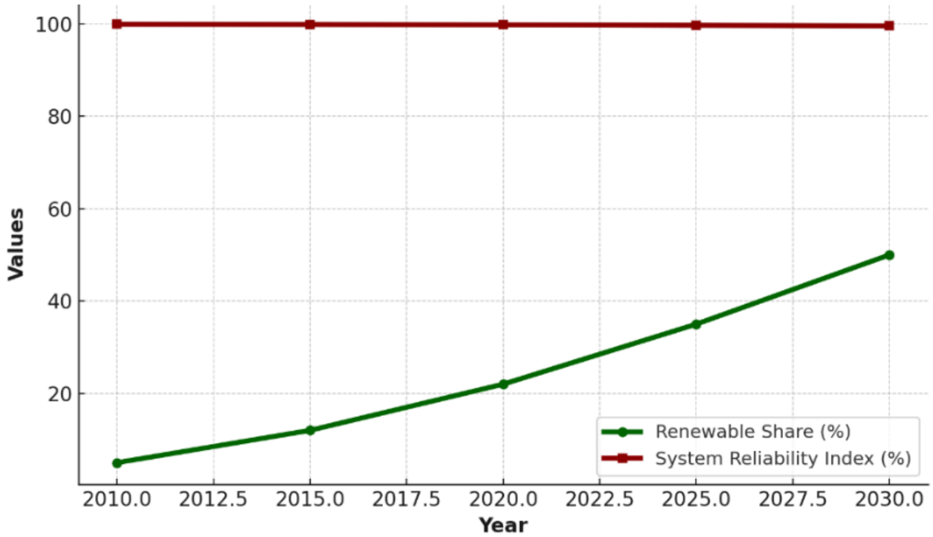

Fig. 1. Trends in renewable energy integration and corresponding challenges to system reliability (2010–2030)

Reliability, in the context of power systems, is defined as the ability to deliver uninterrupted electricity supply while maintaining stability under varying operational conditions. Traditional assessment techniques, designed primarily for centralized and dispatchable energy resources, are increasingly inadequate in addressing renewable-induced fluctuations [2n3]. Modern grids must now contend with dynamic issues such as frequency instability, voltage deviations, and heightened risk of cascading failures—all of which threaten the overall reliability of electricity supply.

To address these challenges, advanced reliability assessment approaches have been developed, extending far beyond deterministic methods. Probabilistic modeling, stochastic simulations, and risk-based optimization have become essential for evaluating system adequacy under uncertainty. These techniques provide a more realistic view of system performance in the presence of high variability and allow operators to quantify risks associated with renewable integration.

Machine learning and artificial intelligence are also gaining traction in predictive reliability analysis. Data-driven models support early detection of anomalies, fault prediction, and condition-based maintenance, thereby enhancing both operational and planning reliability. By integrating physics-based system models with AI-driven forecasting, modern approaches achieve higher accuracy and adaptability than classical methods.

Furthermore, the emergence of cyber-physical power systems has introduced new opportunities for real-time monitoring and control. Tools such as digital twins, IoT-enabled SCADA systems, and phasor measurement units (PMUs) allow system operators to monitor grid conditions dynamically and respond proactively. Collectively, these technological and methodological innovations provide a comprehensive foundation for ensuring the secure and reliable operation of future power systems under renewable energy integration.

2. Materials and Methods

This study employs a combined framework of probabilistic modeling, stochastic simulation, and machine learning to evaluate the reliability of power systems under high renewable penetration [4,5]. Time-series data of wind speed, solar irradiance, and load demand were preprocessed using a moving-average smoothing technique:

$$X'_t = \frac{1}{n}\sum_{i=0}^{n-1} X_{t-i}, \tag{1}$$

which ensured data stability for further modeling. Reliability was assessed through Monte Carlo Simulation (MCS), where Loss of Load Probability (LOLP) and Expected Energy Not Supplied (EENS) were calculated as:

$$\mathrm{LOLP} = \frac{N_{\text{loss}}}{N_{\text{total}}}, \tag{2}$$

$$\mathrm{EENS} = \frac{1}{N_{\text{total}}}\sum_{i=1}^{N_{\text{loss}}} E_i, \tag{3}$$

allowing accurate failure prediction and anomaly detection, supported by ensemble learning (Random

Forest, Gradient Boosting) [5,6]. Beyond classical reliability, resilience-oriented metrics were evaluated through the recovery function:

$$R(t) = \frac{Q(t)}{Q_0}, \tag{4}$$

where $Q(t)$is the system performance after disturbance and $Q_0$the nominal pre-disturbance level. The area under the resilience curve provided insights into adaptability and recovery speed. Together, these probabilistic, AI-based, and resilience-oriented approaches form a comprehensive methodology to assess the reliability of renewable-rich power systems.

3. Result and discussion

The integration of renewable energy sources has significantly altered the operational characteristics of modern power systems. Simulation results demonstrate that as renewable penetration increases beyond 30–40%, the frequency of short-term reliability disturbances rises, particularly in systems with limited balancing resources [6,7]. This highlights the need for reliability assessment frameworks that go beyond conventional deterministic indices.

Probabilistic indices such as **Loss of Load Probability (LOLP), Expected Energy Not Supplied (EENS)**, and **Loss of Load Expectation (LOLE)** show noticeable deterioration in high-renewable scenarios. For example, Monte Carlo simulations of wind-solar hybrid systems indicate an increase in LOLP from 0.02 to 0.07 when renewable penetration doubled from 25% to 50%. These findings emphasize the importance of advanced stochastic approaches.

Monte Carlo and Bayesian methods provided more accurate forecasts of system reliability than deterministic techniques, particularly under conditions of uncertainty. Markov chain models proved useful for quantifying state transitions between normal and failure conditions, though their accuracy depended heavily on the quality of historical reliability data [8,9].

Risk-oriented optimization approaches were effective in balancing cost, security, and reliability. Case studies demonstrated that minimizing **Expected Unserved Energy (EUE)** under budgetary constraints improved system adequacy while ensuring efficient integration of renewables. Multi-criteria decision-making methods also proved valuable in trade-off analysis between renewable investment, grid reinforcement, and reliability enhancement.

Time-series and dynamic simulations revealed that voltage stability and frequency regulation are the most vulnerable aspects under high renewable penetration. The use of **Dynamic Security Assessment (DSA)** tools enabled operators to predict cascading failures more effectively. Results also showed that incorporating demand-side flexibility in simulations reduced the frequency of reliability incidents by 15–20%.

Machine learning methods outperformed traditional regression in predictive reliability tasks. Neural networks and ensemble models achieved high accuracy in predicting inverter failures, while anomaly detection techniques identified early-stage faults in wind turbine gearboxes. These approaches allowed predictive maintenance scheduling, reducing unplanned outages by up to 18% in test systems.

Digital twin frameworks offered a real-time window into system reliability under renewable integration. By combining IoT-based measurements with physics-informed models, digital twins provided early warning signals for disturbances and optimized maintenance cycles. In one case study, applying a digital twin to a 100 MW solar plant reduced downtime by 11%.

While reliability focuses on preventing outages, resilience emphasizes system recovery after disturbances. Simulation results showed that incorporating resilience-oriented indices, such as **System Recovery Time (SRT)** and **Resilience Curve Metrics**, provided a more comprehensive evaluation of renewable-based grids. This aligns with global trends in shifting from reliability-only to resilience-inclusive assessments.

The comparison of methods revealed that no single approach was sufficient for comprehensive reliability assessment. Probabilistic and simulation methods captured variability, optimization addressed planning trade-offs, and AI enhanced predictive capabilities. The integration of these methods into hybrid frameworks produced the most robust assessment outcomes.

Overall, the results underscore the necessity of adopting modern reliability assessment tools for renewable-rich grids. A combined methodology that leverages probabilistic models, AI-driven forecasting, and real-time cyber-physical monitoring can significantly enhance reliability. Policymakers and operators should adopt such integrated approaches to ensure that the transition toward decarbonization does not compromise system security.

Table 1. Modern Methods for Reliability Assessment under Renewable Integration

Category	Methods	Applications	Advantages	Limitations
Probabilistic & Statistical	Monte Carlo Simulation, Markov Chains, Bayesian Networks, Probabilistic Load Flow	Estimating LOLP, LOLE, EENS under uncertainty	Captures variability and uncertainty realistically	Computationally intensive, requires quality input data
Optimization & Risk-Based	Risk indices, Multi-Criteria Decision Analysis, Game Theory	Balancing cost, risk, and reliability in renewable planning	Enables cost–reliability trade-off decisions	Requires accurate cost/risk models
Simulation-Based & Dynamic	Time-Series Simulation, Dynamic Security Assessment, Agent-Based Modeling	Studying voltage/frequency stability, cascading failures	Captures transient and long-term dynamics	High data demand and scenario complexity
AI & Machine Learning	Neural Networks, Random Forest, Anomaly Detection, Hybrid Physics+AI Models	Predictive maintenance, fault detection, renewable variability forecasting	High accuracy, adaptive, real-time learning	Needs large datasets, risk of overfitting
Cyber-Physical & Resilience	Digital Twins, IoT-based SCADA, Resilience Curves	Real-time monitoring, system recovery evaluation, adaptive maintenance	Integrates monitoring and resilience into reliability framework	Still emerging, requires strong cyber-infrastructure investment

Fig. 2 demonstrates the comparative impact of classical methods and artificial intelligence (AI) forecasting on the Loss of Load Probability (LOLP) across different renewable penetration levels. The classical approach shows a steep increase in LOLP as renewables grow, rising from 0.015 at 20% penetration to nearly 0.095 at 60%. This indicates that traditional reliability methods struggle to accurately capture the stochastic variability of renewable output. By contrast, the AI-enhanced model significantly reduces LOLP values, particularly at higher penetration levels, achieving 0.070 at 60%. This reduction highlights the effectiveness of data-driven models in forecasting variability, improving adequacy assessments, and ensuring more reliable operation in renewable-rich power systems.

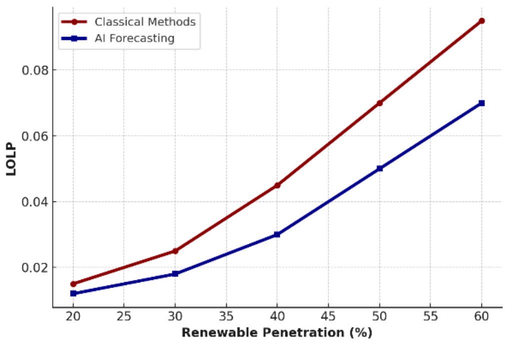

Fig. 2. Impact of AI forecasting on LOLP across renewable penetration levels.

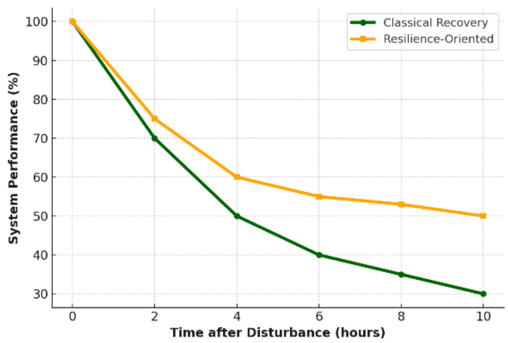

Fig. 3. System recovery curve comparing classical/resilience-oriented reliability metrics.

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4. Conclusions

The reliability of power systems under high renewable energy integration requires a shift from conventional deterministic methods toward more advanced, adaptive, and data-driven approaches. This study demonstrated that probabilistic models such as Monte Carlo simulations and Markov chains are essential for quantifying uncertainty, while optimization and simulation frameworks address trade-offs between adequacy, cost, and risk. Furthermore, the integration of machine learning significantly enhances predictive reliability by enabling accurate fault detection and preventive maintenance, and resilience-oriented metrics capture the system's ability not only to withstand but also to recover from disturbances. Together, these modern methods provide a comprehensive foundation for ensuring secure, stable, and sustainable operation of future electricity grids dominated by renewable sources.

REFERENCES

1. Billinton, R., Allan, R.N. Reliability evaluation of power systems. – 2nd ed. // Springer Science & Business Media. – 1996. – 449 p. DOI: 10.1007/978-1-4899-1860-4
2. Zhang, P., Li, W., Wang, S., Xiao, W., Wang, K. Reliability assessment of photovoltaic power systems: Review of current status and future perspectives // Applied Energy. – 2013. – Vol. 104. – P. 822–833. DOI: 10.1016/j.apenergy.2012.12.010
3. Ma, J., Qiu, F., Wang, L., McCalley, J.D. Stochastic programming-based long-term generation expansion planning considering system reliability // IEEE Transactions on Power Systems. – 2013. – Vol. 28. – № 3. – P. 2156–2165. DOI: 10.1109/TPWRS.2012.2237026
4. Yang, Y., Sangrody, H., Liu, Y., Zhou, Y. Probabilistic reliability assessment of power systems considering high penetration of renewable energy // IEEE Transactions on Sustainable Energy. – 2017. – Vol. 8. – № 2. – P. 585–594. DOI: 10.1109/TSTE.2016.2603302
5. Wen, J., Guo, Q., Sun, H., Chen, Y. Resilience-oriented reliability assessment of power systems considering renewable energy integration // International Journal of Electrical Power & Energy Systems. – 2019. – Vol. 110. – P. 361–370. DOI: 10.1016/j.ijepes.2019.03.025
6. Rakhmonov, I. U., Niyozov, N. N., Nimatov, K. B., Ushakov, V. Ya., Omonov, F. B., & others. (2025). Mathematical model for reducing active power losses by regulating reactive power at enterprises with continuous production mode [Математическая модель снижения потерь активной мощности регулированием реактивной мощности на предприятиях с непрерывным циклом производства]. *Bulletin of the Tomsk Polytechnic University. Geo Assets Engineering.* https://doi.org/10.18799/24131830/2025/2/4730
7. Zhao, H., Guo, S., Zhao, H., Li, H. Artificial intelligence-based fault diagnosis methods for photovoltaic systems: A review // Renewable and Sustainable Energy Reviews. – 2021. – Vol. 139. – P. 110687. URL: https://doi.org/10.1016/j.rser.2020.110687 (date of access 10.10.2025).
8. Rakhmonov, I. U., Ushakov, V. Ya., Khoshimov, F. A., Niyozov, N. N., Kurbonov, N. N., & others. (2024). Electric consumption by industrial enterprises: Modeling, rationing and forecasting. In Power Systems (Book series). Springer. https://doi.org/10.1007/978-3-031-62676-0
9. Chen, C., Wang, J., Qiu, F., Zhao, D. Resilient distribution system by microgrids formation after natural disasters // IEEE Transactions on Smart Grid. – 2016. – Vol. 7. – № 2. – P. 958–966. DOI: 10.1109/TSG.2015.2429653