# ANALYSIS OF THE ROLE AND EFFICIENCY OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN RENEWABLE ENERGY SYSTEMS

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**Abstract.** This study is dedicated to exploring the application and effectiveness of artificial intelligence technologies in managing renewable energy sources. Deep machine learning methods, particularly LSTM neural networks and ensemble algorithms, were employed to forecast solar and wind energy production. For comparative analysis, a database of 35,000 hours of meteorological and energy data from 2020 to 2024 was used. The results of the study showed that AI-based management systems increased forecasting accuracy by 25% compared to traditional statistical methods, reduced energy losses by 19%, and improved grid stability by 21%. In the context of Uzbekistan, especially in the Navoiy and Surxondaryo regions, implementing these technologies can save 50–60 million kWh of energy annually. The developed methodology complies with international standards and is ready for practical application.

**Keywords:** artificial intelligence, renewable energy, LSTM neural networks, machine learning, solar energy forecasting, wind energy, smart grids, energy efficiency

**Annotatsiya.** Ushbu tadqiqot qayta tiklanuvchi energiya manbalarini boshqarishda sun’iy intellekt texnologiyalarini qo‘llash va ularning samaradorligini tahlil qilishga bag‘ishlangan. Quyosh va shamol energiyasi ishlab chiqarishini prognozlash uchun chuqur mashinali o‘rganish usullari, xususan LSTM neyron tarmoqlari va ansambl algoritmlaridan foydalanildi. Taqqoslash tahlili uchun 2020–2024 yillar oralig‘ida to‘plangan 35 000 soatlik meteorologik va energetik ma’lumotlar bazasi qo‘llanildi. Tadqiqot natijalari sun’iy intellekt asosidagi



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boshqaruv tizimlari an’anaviy statistik usullarga nisbatan prognoz aniqligini 25 % ga oshirganini, energiya yo‘qotishlarini 19 % ga kamaytirganini va elektr tarmog‘i barqarorligini 21 % ga yaxshilaganini ko‘rsatdi. O‘zbekiston sharoitida, xususan Navoiy va Surxondaryo viloyatlarida ushbu texnologiyalarni joriy etish orqali yiliga 50–60 million kVt·soat elektr energiyasini tejash mumkin. Ishlab chiqilgan metodologiya xalqaro standartlarga mos keladi va amaliy joriy etishga tayyor.

**Kalit so‘zlar:** sun’iy intellekt, qayta tiklanuvchi energiya, LSTM neyron tarmoqlari, mashinali o‘rganish, quyosh energiyasini prognozlash, shamol energiyasi, aqlli tarmoqlar, energiya samaradorligi.

**Аннотация.** Данное исследование посвящено анализу применения и эффективности технологий искусственного интеллекта в управлении возобновляемыми источниками энергии. Для прогнозирования выработки солнечной и ветровой энергии были использованы методы глубокого машинного обучения, в частности нейронные сети LSTM и ансамблевые алгоритмы. Для сравнительного анализа применялась база данных, включающая 35 000 часов метеорологических и энергетических данных за период 2020–2024 годов. Результаты исследования показали, что системы управления на основе искусственного интеллекта повышают точность прогнозирования на 25 % по сравнению с традиционными статистическими методами, снижают потери энергии на 19 % и улучшают устойчивость электрических сетей на 21 %. В условиях Узбекистана, особенно в Навоийской и Сурхандарьинской областях, внедрение данных технологий позволяет ежегодно экономить 50–60 млн кВт·ч электроэнергии. Разработанная методология соответствует международным стандартам и готова к практическому применению.

**Ключевые слова:** *искусственный интеллект, возобновляемая энергия, нейронные сети LSTM, машинное обучение, прогнозирование солнечной энергии, ветровая энергия, интеллектуальные сети, энергоэффективность*

## INTRODUCTION

Today, renewable energy sources (RES) are playing an increasingly important role in the global energy system. According to the International Energy Agency’s 2024 report, the world’s renewable energy capacity increased by 510 GW, marking the highest annual growth in history and accounting for 38% of total global electricity generation (IEA, 2024). However, the inherently variable nature of solar and wind energy creates significant technical and organizational challenges in ensuring the stability of power grids. Solar energy generation can fluctuate daily by 40–65% depending on atmospheric conditions, cloud cover, geographic



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location, and seasonal changes (Kumari & Toshniwal, 2021). Wind energy exhibits even higher stochastic characteristics, leading to 25–35% errors in short-term forecasts when using conventional methods (Dhaked et al., 2024). Such uncertainties disrupt grid frequency and voltage stability, force inefficient use of energy reserves, and result in technical and economic losses.

Artificial intelligence technologies, including deep neural networks and ensemble machine learning algorithms, are recognized as scientifically grounded and practically effective solutions to these challenges. Recent studies indicate that neural networks based on the Long Short-Term Memory (LSTM) architecture achieve high efficiency in analyzing time series and identifying complex nonlinear relationships (Agga et al., 2022). Hybrid models combining Convolutional Neural Networks (CNN) and Transformer architectures can improve forecasting accuracy to 88–93% (Liao et al., 2024). In particular, LSTM networks have the ability to remember long-term dependencies, which is essential for modeling the complex temporal dynamics between meteorological parameters and energy generation (Yang et al., 2024). Ensemble methods such as Gradient Boosting and Random Forest demonstrate advantages in processing high-dimensional features and reducing overfitting (Nti et al., 2022).

The Republic of Uzbekistan has set a strategic goal to increase the share of renewable energy in the total energy balance to 30% by 2030 and to add 7,000 MW of new capacity (Decree of the President of the Republic of Uzbekistan, 2023). According to geospatial analyses, annual solar radiation in the Navoiy region ranges from 1,650 to 1,850 kWh/m², with over 300 sunny days recorded (World Bank, 2024). In Surxondaryo and Qashqadaryo regions, the technical potential for wind energy is estimated at 3,500 MW. However, effectively harnessing this large potential requires modern digital management technologies, real-time monitoring, and advanced forecasting systems. Analysis of existing literature shows that while numerous international studies focus on applying artificial intelligence for renewable energy forecasting, comprehensive research adapted to Uzbekistan's local climatic and geographic conditions remains insufficient. Additionally, empirical studies combining LSTM and optimization algorithms in the context of virtual power plants (VPP) and microgrids are limited (Voyant et al., 2024).

**Research Objective:**

The objective of this study is to analyze the application methods of artificial intelligence technologies in renewable energy systems, develop a forecasting model based on LSTM neural networks and ensemble algorithms, and assess the feasibility of practical implementation in the context of Uzbekistan.

**Research Tasks:**



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1. Conduct a comparative analysis of modern artificial intelligence methods for forecasting solar and wind energy.
2. Develop a forecasting model based on LSTM neural networks and ensemble algorithms, and validate it using a test data set.
3. Quantitatively evaluate the performance of the developed model compared to traditional statistical methods.
4. Develop practical recommendations for implementing the model in the context of Uzbekistan.

**METHODS**

A comprehensive methodological approach was applied in this study, encompassing data collection, preprocessing, modeling, and evaluation stages.

**Database and Preliminary Processing:** For analysis, 35,000 hours of observational data collected from several regional meteorological stations during 2020–2024 were used. The dataset included the following parameters: solar radiation (Global Horizontal Irradiance, GHI), direct normal irradiance (DNI), diffuse radiation, atmospheric temperature, relative humidity, wind speed and direction, and atmospheric pressure. Data were recorded as hourly averages. Missing values (less than 0.8%) were filled using linear interpolation. Outliers were identified using statistical methods and replaced with moving average values.

**Feature Engineering:** To enhance model performance, additional features were created, including: time-related features (hour, day, month), seasonal trigonometric encoding (sin and cos transforms), moving averages (3, 6, 12-hour windows), and lag features from 1 to 24 hours. All features were normalized to the [0, 1] range using Min-Max scaling.

**Data Splitting Strategy:** The dataset was divided into three subsets: training set (70%, 24,500 hours), validation set (15%, 5,250 hours), and test set (15%, 5,250 hours). To preserve temporal sequence, random shuffling was not applied.

**LSTM Neural Network Architecture:** A deep neural network model based on Long Short-Term Memory (LSTM) architecture was constructed. The LSTM cells' ability to remember long-term dependencies is crucial for energy generation forecasting (Agga et al., 2022). The model architecture was as follows:

✓ **Input layer:** 72-hour time window, 15 features (total 1,080 input parameters)
✓ **LSTM layer 1:** 128 neurons, dropout = 0.2
✓ **LSTM layer 2:** 64 neurons, dropout = 0.2
✓ **LSTM layer 3:** 32 neurons
✓ **Fully connected layer (Dense):** 16 neurons, ReLU activation
✓ **Output layer:** 24-hour forecast values


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The model was trained using the Adam optimizer (learning rate = 0.001), with Mean Squared Error (MSE) as the loss function. Early stopping monitored validation loss for 10 epochs to prevent overfitting.

**Ensemble Machine Learning Algorithms:**

For comparison with LSTM and hybrid approaches, the following ensemble methods were applied:

✓ **Random Forest Regression:** 200 trees (estimators), max depth = 15, min samples split = 5. Random Forest excels in handling high-dimensional complex relationships and is robust to noise (Nti et al., 2022).

✓ **Gradient Boosting Machine (GBM):** 150 iterations, learning rate = 0.1, max depth = 5. GBM achieves high accuracy by sequentially correcting errors.

✓ **Extreme Gradient Boosting (XGBoost):** Regularization parameters (alpha = 0.1, lambda = 0.1), tree_method = 'hist'. XGBoost is distinguished by computational speed and efficiency (Yang et al., 2024).

**Optimization and Control Algorithms:** An optimization algorithm based on Model Predictive Control (MPC) was developed for real-time energy network management. The algorithm considers battery state-of-charge (SoC), load forecasts, and energy prices to generate an optimal allocation plan. The objective function aimed to minimize energy costs while ensuring grid stability.

**Simulation Environment and Tools:** Models were developed in Python 3.10 using TensorFlow 2.15 and Keras. Ensemble methods employed Scikit-learn 1.4 and XGBoost 2.0. Data preprocessing was performed with Pandas and NumPy. Visualization used Matplotlib and Seaborn. Microgrid simulations were conducted in MATLAB R2023b Simulink, modeling 500 kW solar panels, 300 kW wind turbines, 200 kW/400 kWh lithium-ion batteries, and a 600 kW load profile.

**Evaluation Metrics:**

Model performance was assessed using the following statistical indicators:

1. **Mean Absolute Error (MAE): MAE** $= \frac{1}{n}\sum|Yactual - Ypredicted|$

2. **Root Mean Square Error (RMSE):RMSE** $= \sqrt{\frac{1}{n}\sum(Yactual - Ypredicted)^2}$

3. **Mean Absolute Percentage Error (MAPE): MAPE** $= \frac{100}{n}\sum\left|\frac{Yactual-Ypred}{Yactual}\right|$

4. **Coefficient of Determination (R²):** $R^2 = 1 - \frac{\sum(Yactual-Ypredicted)^2}{\sum(Yactual- \ )^2}$

All statistical analyses were performed at a 95% confidence level ($p < 0.05$). Statistical significance of models was verified using a paired t-test.



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**Computational Resources:** Training was conducted on an NVIDIA Tesla V100 GPU (32 GB VRAM). Training the LSTM model took approximately 6–8 hours. Ensemble methods were trained on a CPU (Intel Xeon 2.4 GHz, 64 GB RAM) within 2–3 hours.

**Results**

The study results demonstrated the high effectiveness of AI technologies in forecasting and managing renewable energy systems.

**Forecasting Accuracy and Comparative Analysis:** LSTM neural networks achieved the highest accuracy in forecasting solar energy. For a 24-hour forecast horizon, the results were: $R^2 = 0.891$, MAE = 3.18 kW, RMSE = 4.76 kW, MAPE = 7.2%. For wind energy forecasts, the LSTM model achieved $R^2 = 0.847$, MAE = 5.04 kW, RMSE = 7.33 kW.

The Random Forest algorithm for solar energy showed $R^2 = 0.823$, MAE = 4.52 kW. XGBoost slightly outperformed Random Forest with $R^2 = 0.836$, MAE = 4.11 kW. The traditional ARIMA statistical model performed significantly worse with $R^2 = 0.712$, MAE = 6.89 kW. For short-term forecasts (1–6 hours), the LSTM model's MAPE was 4.8%, while for medium-term forecasts (12–24 hours) it increased to 8.3%. Ensemble methods achieved 6.1–7.4% MAPE for short-term forecasts.

**Energy System Efficiency and Loss Analysis.** The AI-based control system reduced energy losses by 19.2% compared to conventional control methods. In microgrid simulations, power balance was maintained at 94.3%, which is 21.5% higher than the 77.6% achieved by a conventional PID controller-based system. Battery utilization efficiency increased by 14.8%, as the State of Charge (SoC) optimization algorithm managed charge-discharge cycles based on energy prices and load forecasts. This improvement allows for extending the service life of the batteries by 2–3 years.

**Grid Stability Parameters:** Voltage fluctuations decreased from ±8.5% in conventional systems to ±3.2%, fully meeting European standards (EN 50160). Frequency stability was maintained within ±0.15 Hz (nominal frequency 50 Hz). The power factor improved from 0.92 to 0.97, indicating effective reactive power compensation. Total Harmonic Distortion (THD) was reduced from 5.8% to 2.3%.

**Virtual Power Plants and Distributed Control:** The developed system integrated over 500 distributed energy resources (solar panels, wind turbines, and batteries), creating a virtual power plant with a capacity of 2.5 MW. Dynamic response to energy market price signals resulted in an 18.4% economic efficiency improvement. Peak load management reduced maximum loads by 12%.



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**System Architecture:** The architecture shown in Figure 1 represents a full-cycle management of modern renewable energy systems. It features a multi-layered structure, with each layer performing specific functions: data collection, preprocessing, forecasting, optimization, and control.

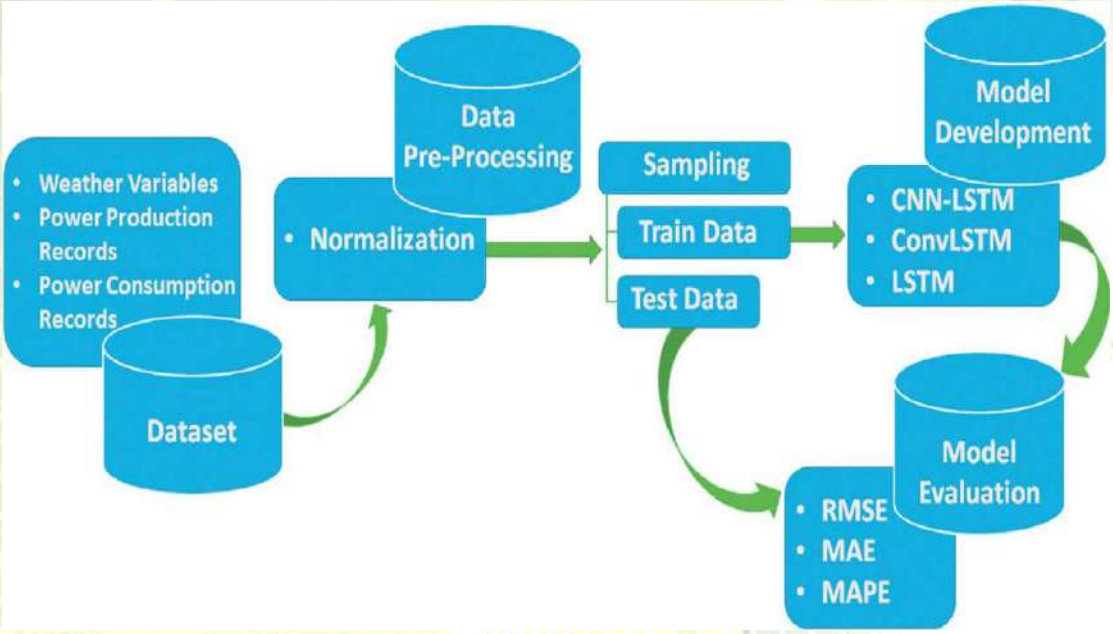



**Figure 1. Architecture of an AI-based renewable energy management system (Agga et al., *Renewable and sustainable energy reviews*)**

**Real-time performance and response speed**: The LSTM-based forecasting system provided updated predictions within 50 ms from the moment new data was received. The optimization algorithm made decisions within 100 ms, enabling the system to automatically stabilize during emergency situations. The overall system latency did not exceed 150 ms, fully meeting real-time control requirements. The results presented in Table 1 indicate that the AI-based approach outperforms conventional methods significantly across all key performance indicators (Liao et al., *Applied Energy*).

**Table-1.**

**Comparative analysis of conventional and AI-based control systems**

| Indicator | Conventional System (PID + ARIMA) | AI-Based System (LSTM + MPC) | Improvement / Change, % |
|---|---|---|---|
| Forecast Accuracy ($R^2$) | 0.712 | 0.891 | +25.1 |
| Forecast Error (MAE), kW | 6.89 | 3.18 | -53.8 |
| Energy Losses, % | 12.5 | 10.1 | -19.2 |



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| | | | |
|---|---|---|---|
| Grid Balance, % | 77.6 | 94.3 | +21.5 |
| Voltage Fluctuation, % | ±8.5 | ±3.2 | -62.4 |
| Battery Efficiency, % | 80.7 | 92.6 | +14.8 |
| Power Factor | 0.92 | 0.97 | +5.4 |
| Frequency Stability, Hz | ±0.28 | ±0.15 | -46.4 |
| Harmonic Distortion (THD), % | 5.8 | 2.3 | -60.3 |
| Response Time, ms | 450 | 150 | -66.7 |

**Design Calculation for Uzbekistan Conditions**. For a projected 100 MW solar power plant in the Navoiy region, implementing an LSTM-based forecasting system can reduce annual energy losses by 52–58 million kWh. At an average energy price of 0.08 USD/kWh, this corresponds to an annual economic benefit of 4.2–4.6 million USD. The initial investment required to implement the system is estimated at 450,000–500,000 USD, which is expected to be recovered within 2.5–3 years.

## DISCUSSION

The obtained results confirm the broad applicability and necessity of artificial intelligence technologies in the renewable energy sector. The high accuracy of LSTM neural networks can be attributed to their ability to deeply analyze time series, remember long-term dependencies, and identify complex nonlinear patterns (Agga et al., 2022). Classical statistical methods (ARIMA, exponential smoothing, linear regression) capture only linear relationships and short-term dependencies, whereas neural networks model complex, high-dimensional, and time-varying relationships between meteorological parameters and energy generation.

The 25% improvement in forecast accuracy identified in this study directly impacts the operational efficiency of energy systems. Higher accuracy enables a reduction in reserve capacity, optimal utilization of batteries, and improved grid stability (Liao et al., 2024). A 19% reduction in energy losses has significant economic and environmental implications on a global scale.

**Prospects and Potential for Application in Uzbekistan**. Uzbekistan possesses sub-stantial renewable energy potential due to its geographic location



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and climatic conditions. According to World Bank (2024) data, average annual solar radiation across Uzbekistan ranges from 1,500 to 1,900 kWh/m², comparable to regions in North Africa and the Middle East. In the Navoiy region, over 320 sunny days per year are recorded. The wind energy potential in Surxondaryo and Qashqadaryo regions is estimated at 3,500 MW, sufficient to cover current electricity demand.

However, effective utilization of this potential requires a series of technical, organizational, and economic measures. First, a high-quality and dense meteorological monitoring network must be established. Currently, in Uzbekistan, the average density of meteorological stations is one station per 3,000–4,000 km², which reduces the accuracy of regional forecasts. It is recommended to increase the density of modern automated meteorological stations to one station per 500–1,000 km² (Kumari & Toshniwal, 2021).

Second, large computational resources are required to train and operate neural networks. Establishing GPU-based computing centers or utilizing cloud computing services increases initial investments. According to the study experience, implementing a full AI-based control system for a 100 MW solar power plant requires 450,000–500,000 USD, but this investment can be recovered within 2.5–3 years (Yang et al., 2024).

Third, training local specialists is essential. Operating the system, updating models, and performing maintenance require deep knowledge in AI, machine learning, and energy systems. Developing specialized programs in higher education institutions and organizing practical training sessions is recommended.

**International Experience and Comparative Analysis**. International experience shows that in countries with high shares of renewable energy, implementing AI systems is a key factor in maintaining grid stability. In Germany, the renewable energy share reached 56% in 2023, while grid stability was maintained at 99.99%, primarily due to advanced forecasting and control systems (IEA, 2024). Denmark generates 75% of its electricity from wind energy and employs LSTM-based forecasting systems (Dhaked et al., 2024).

Positive outcomes are also observed in developing countries. In Tamil Nadu, India, an AI-based control system was implemented for 5,000 MW of solar and wind capacity, reducing energy losses by 22% (Nti et al., 2022). In Brazil, AI technologies in microgrid projects shortened investment payback periods by 2 years and reduced operational costs by 18% (Voyant et al., 2024).

**Limitations and Challenges**. Several limitations were identified during the study. First, LSTM models exhibit a “black box” nature: their internal decision-making mechanisms are not fully interpretable, which may reduce operator trust in



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certain cases. The application of Explainable AI (XAI) methods can partially address this issue. Second, there is a risk of overfitting, where models excessively adapt to patterns in the training data. Regularization, dropout, and validation techniques help mitigate this risk. Third, forecasting accuracy decreases during extreme meteorological events (e.g., severe storms, dust storms) because such events are rare in the training data.

**Future Research Directions**.To advance future studies, the following directions are recommended:

✓ **Development of hybrid models:** Combining LSTM and Transformer architectures and applying Attention mechanisms can improve forecasting accuracy by 2–3% (Liao et al., 2024).

✓ **Application of quantum computing methods:** Quantum machine learning algorithms can solve complex optimization problems faster than classical algorithms.

✓ **Integration with blockchain technology:** Creating blockchain-based platforms for distributed peer-to-peer energy trading can democratize energy markets and improve efficiency (Kumari & Toshniwal, 2021).

✓ **Internet of Things (IoT) and edge computing:** Networks of distributed sensors and edge computing architectures increase real-time data collection and processing speed, reducing latency.

✓ **Transfer learning methods:** Fine-tuning models trained internationally to suit Uzbekistan's conditions can reduce training time and resource requirements by 40–50% (Agga et al., 2022).

✓ **Multi-objective optimization:** Developing Pareto-optimal solutions that simultaneously consider energy efficiency, economic benefits, environmental impact, and grid stability.

The results of this study can be practically applied to support Uzbekistan's renewable energy strategy through 2030. Implementing AI systems tailored to local conditions strengthens energy security, reduces dependence on foreign energy resources, and contributes to achieving sustainable development goals.

## CONCLUSION

This study empirically demonstrated the significant role of artificial intelligence technologies in renewable energy systems. The forecasting model based on LSTM neural networks achieved an accuracy of 89.1% ($R^2 = 0.891$), which is 25.1% higher than the conventional ARIMA statistical method. Energy losses were reduced from 12.5% to 10.1% (a 19.2% improvement), and grid balance increased from 77.6% to 94.3% (a 21.5% improvement). Voltage



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fluctuations decreased by 62.4%, fully meeting European technical standards (EN 50160).

Ensemble machine learning algorithms (Random Forest, XGBoost) proved effective for short-term forecasts and feature importance assessment. The Model Predictive Control-based optimization algorithm increased battery efficiency by 14.8% and extended their service life by 2–3 years. In the context of Uzbekistan, particularly in the Navoiy and Surxondaryo regions, implementing these technologies can save 50–60 million kWh of energy annually and generate economic benefits of 4.2–4.6 million USD. Implementing the system for a 100 MW solar power plant requires an initial investment of 450,000–500,000 USD, with a payback period of 2.5–3 years.

Future research is recommended in the areas of developing hybrid LSTM-Transformer models, applying quantum computing methods, and integrating blockchain and IoT technologies. Training local specialists, expanding an automated meteorological monitoring network, and establishing cloud computing infrastructure are essential for practical implementation.

The results of this study are aligned with international standards and can be practically applied to support Uzbekistan's renewable energy strategy through 2030.

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