ISSN 2683-345X
journal homepage: http://ijiemjournal.uns.ac.rs/

International Journal of Industrial Engineering and Management

Volume 16 / No 1 / March 2025 / 101 - 112

Original research article

Optimizing Renewable Energy Integration Using IoT and Machine Learning Algorithms

O. Mamyrbayev[a] 0000-0001-8318-3794, A. Akhmediyarova[b,*] 0000-0003-4439-7313, D. Oralbekova[a] 0000-0003-4975-6493, J. Alimkulova[c] 0000-0002-6140-416X, Z. Alibiyeva[b] 0000-0001-9565-5621

[a] *Institute of Information and Computational Technologies, Almaty, Kazakhstan;*
[b] *Satbayev University, Almaty, Kazakhstan;*
[c] *Turan University, Almaty, Kazakhstan*

ABSTRACT

Due to their inherent variability, incorporating renewable energy sources into current power grids poses major challenges. This study aims to optimize renewable energy integration using Internet of Things (IoT) technology and machine learning (ML) algorithms. The study was conducted across 30 renewable energy sites in the United States over six months (April-September 2023), encompassing solar, wind, and hydroelectric installations. Three ML models (Random Forest, XGBoost, and Long Short-Term Memory networks) were developed and compared against a traditional persistence model for energy generation forecasting. The study also implemented a reinforcement learning-based grid optimization system. Results showed significant improvements in forecasting accuracy, with the LSTM model achieving a 59.1% reduction in Mean Absolute Percentage Error compared to the persistence model. Grid stability improved substantially, with a 64.2% reduction in supply-demand mismatches. Overall renewable energy utilization increased by 19.2%, with wind energy seeing the largest improvement (21.8%). The implemented system resulted in estimated monthly cost savings of $320,000. These findings demonstrate the potential of IoT-ML systems to enhance renewable energy integration, contributing to more efficient, reliable, and sustainable power grids.

ARTICLE INFO

Article history:

Received October 22, 2024
Revised November 26, 2024
Accepted December 19, 2024
Published online February 4, 2025

Keywords:
Renewable Energy,
Internet of Things,
Machine Learning,
Forecasting,
Grid Optimization

*Corresponding author:
Ainur Akhmediyarova
a.akhmediyarova@satbayev.university

1. Introduction

The global energy landscape is undergoing a profound transformation as the world shifts towards sustainable and renewable energy sources. This transition is driven by the urgent need to mitigate climate change, reduce greenhouse gas emissions, and ensure energy security for future generations [1], [2]. Renewable energy sources, such as solar, wind, and hydroelectric power, have emerged as promising alternatives to fossil fuels, offering clean and potentially inexhaustible energy solutions [3]. Nonetheless, incorporating these renewable sources into existing power grids introduces considerable challenges because of their inherent intermittency and variability [4].

Published by the University of Novi Sad, Faculty of Technical Sciences, Novi Sad, Serbia.

https://doi.org/10.24867/IJIEM-375

The intermittent nature of renewable energy sources poses a fundamental challenge to grid stability and reliability. Unlike conventional power plants that can provide consistent and controllable power output, renewable sources are subject to fluctuations based on weather conditions, time of day, and seasonal variations [5]. Fluctuations in renewable energy can result in mismatches between supply and demand, which might cause instability in the grid, issues with power quality, and poor utilization of renewable resources [6].

To address these challenges, the energy sector has increasingly turned to advanced technologies and innovative solutions. Among these, the Internet of Things (IoT) and Machine Learning (ML) algorithms have emerged as powerful tools for optimizing renewable energy integration [7], [8]. IoT technology enables real-time monitoring and data collection from a vast network of sensors and devices deployed across renewable energy installations, power grids, and consumer endpoints [9]. This continuous stream of data provides unprecedented visibility into the performance and status of renewable energy systems, allowing for more informed decision-making and control [10], [11].

Machine Learning algorithms, on the other hand, offer the capability to analyze and interpret the massive amounts of data generated by IoT devices [12]. These algorithms can identify patterns, make predictions, and optimize complex systems in ways that surpass traditional analytical methods [10]. When applied to renewable energy integration, ML algorithms can forecast energy generation patterns, predict demand fluctuations, and optimize grid operations to maximize the utilization of renewable resources while maintaining grid stability [13], [14].

The synergy between IoT and ML technologies creates a powerful framework for addressing the challenges of renewable energy integration. By combining real-time data collection with advanced predictive analytics, this approach enables more accurate forecasting of renewable energy generation, improved load balancing, and enhanced grid management strategies [15]. This integration of technologies has the potential to significantly increase the efficiency and reliability of renewable energy systems, ultimately accelerating the transition towards a more sustainable energy future [16]. Previous IoT-ML implementations have faced challenges including sensor degradation, network latency, and limited scalability across diverse geographical locations, hindering widespread adoption [17]. Furthermore, recent studies have highlighted emerging challenges in IoT-ML implementations for renewable energy systems, particularly in areas of system interoperability and cross-platform data integration [18]. Research indicates that disparate communication protocols and data formats across different vendor platforms create significant integration bottlenecks, with approximately 40% of implementations requiring custom middleware solutions [19]. These technical barriers often result in increased implementation costs and extended deployment timelines, highlighting the need for standardized integration frameworks and universal communication protocols in renewable energy management systems.

Recent studies have demonstrated the effectiveness of IoT and ML-based approaches in various aspects of renewable energy integration. For instance, research by Hayajneh et al. [20] showed that ML algorithms could improve solar energy forecasting accuracy by up to 30% compared to traditional methods. Similarly, a study by Cheekati et al. [21] found that IoT-based monitoring systems could reduce wind farm downtime by 25% through predictive maintenance strategies.

Despite these promising results, the full potential of IoT and ML technologies in renewable energy integration remains to be realized. Many existing studies have focused on specific aspects of the problem, such as forecasting or maintenance, without addressing the holistic optimization of renewable energy systems within the broader context of power grid operations [4]. Furthermore, the scalability and real-world applicability of these technologies across diverse renewable energy sources and grid infrastructures have not been thoroughly investigated [17], [22].

The rapid advancement of IoT and ML technologies, coupled with the growing urgency of the global energy transition, underscores the need for comprehensive research in this field. By exploring the integration of these technologies on a larger scale and across multiple renewable energy sources, we can develop more robust and efficient solutions for renewable energy integration [23]. This approach has the potential to not only improve the technical aspects of renewable energy systems but also to enhance their economic viability and accelerate their adoption worldwide [24].

The present study aims to address these knowledge gaps and contribute to the advancement of renewable energy integration strategies. By leveraging the latest developments in IoT technology and ML algorithms, this research seeks to develop a comprehensive framework for optimizing the integration of renewable energy sources into existing power grids. The study focuses on enhancing the accuracy of energy generation forecasts, improving grid stability, and maximizing the utilization of available renewable resources [15].

To achieve these objectives, an extensive IoT-based monitoring system was deployed across a diverse set of renewable energy installations, including solar farms, wind turbines, and small-scale hydroelectric plants. This system collected real-time data on energy generation, weather conditions, and grid parameters. Concurrently, advanced ML models, including ensemble methods and deep learning architectures, were developed to analyze this data and generate accurate predictions of renewable energy output [7].

The primary motivation behind this research is to address the critical challenges facing the renewable energy sector and contribute to the global effort to combat climate change. By improving the efficiency and reliability of renewable energy systems, this study aims to accelerate the transition away from fossil fuels and towards a more sustainable energy future. The results of this research have far-reaching implications, not only for the energy sector but also for policymakers, urban planners, and environmental scientists working towards sustainable development goals [4].

The current problem that this study aims to solve is the inefficient integration of renewable energy sources into existing power grids, which leads to suboptimal utilization of renewable resources and potential grid instability. Despite the growing capacity of renewable energy installations worldwide, their full potential remains unrealized due to the challenges associated with their intermittent nature and the limitations of current grid management systems [6].

Therefore, the purpose of the present study is to develop and evaluate an integrated IoT and ML-based system for optimizing renewable energy integration. This system aims to significantly improve the accuracy of renewable energy forecasting, enhance grid stability through intelligent load balancing, and maximize the overall utilization of renewable energy sources. By addressing these critical aspects, the study seeks to provide a comprehensive solution that can be adapted and scaled to diverse renewable energy scenarios, ultimately contributing to a more efficient, reliable, and sustainable global energy ecosystem.

2. Methodology

The study employed a comprehensive approach to optimize renewable energy integration using IoT technology and ML algorithms. This section details the materials, methods, and experimental design used to develop, implement, and evaluate the proposed system.

2.1 Study Design and Site Selection

The research was conducted over a period of six months, from April to September 2023, to capture seasonal variations in renewable energy generation. The study encompassed 30 renewable energy sites distributed across diverse geographical locations in the United States. These sites included 15 solar farms, 12 wind farms, and 3 small-scale hydroelectric plants. The selection criteria for these sites prioritized diversity in terms of geographical location, climate conditions, and energy generation capacity to ensure a representative sample of renewable energy installations. The solar farms ranged in capacity from 5 MW to 100 MW, wind farms from 20 MW to 150 MW, and hydroelectric plants from 1 MW to 10 MW.

To provide a comprehensive overview of the research methodology, Figure 1 illustrates the system architecture and data flow of the IoT and ML-based renewable energy integration system employed in this study. This flowchart depicts the key components and processes, from data collection through IoT sensors to the final output of grid management decisions and user interface insights. Each element of this system will be discussed in detail in the following subsections.

2.2 IoT Infrastructure and Data Collection

An extensive IoT infrastructure was deployed across all 30 sites to collect real-time data on energy generation, weather conditions, and grid parameters. Each site was equipped with a network of sensors and smart meters tailored to the specific renewable energy source. For solar farms, the system included pyranometers for solar irradiance measurement, anemometers for wind speed and direction, and temperature sensors. Wind farms were outfitted with additional sensors for atmospheric pressure and humidity. Hydroelectric plants incorporated water flow meters and reservoir level sensors. The deployed sensors included Vaisala WXT536 weather transmitters (±0.3°C accuracy), Davis 6410 anemometers (±3% accuracy), and Kipp & Zonen SMP10 pyranometers (±2% daily uncertainty).

All sensors were connected to local data aggregation units using low-power wide-area network (LPWAN) protocols, specifically LoRaWAN, to ensure reliable long-range communication with minimal power consumption. These units preprocessed and encrypted the data before transmitting it to a central cloud-based data repository via secure 4G/LTE connections. Data collection occurred at one-minute intervals, providing high-resolution temporal data for analysis.

The central data repository was built on a scalable cloud infrastructure using Amazon Web Services (AWS) to handle the large volume of incoming data. This infrastructure included Amazon S3 for data storage, Amazon RDS for structured data management, and Amazon EC2 instances for data processing and analysis.

Data security was ensured through end-to-end encryption, role-based access control, and regular security audits following ISO 27001 standards. The system's cybersecurity framework incorporated multiple layers of protection, including advanced intrusion detection systems (IDS) and security information and event management (SIEM) solutions. Regular penetration testing was conducted bi-monthly to identify and address potential vulnerabilities. The security infrastructure was designed to comply with both NERC-CIP (North American Electric Reliability Corporation Critical Infrastructure Protection) standards and IEC 62351 protocols for power system communications security. Additionally, a dedicated security operations center (SOC) monitored system activities 24/7, with automated alerts configured for any anomalous behavior patterns that might indicate potential security breaches or system malfunctions.

Furthermore, monthly maintenance procedures included sensor calibration, firmware updates, and physical inspections, requiring approximately 4 hours per site.

2.3 Data Preprocessing and Feature Engineering

Raw data from the IoT sensors underwent extensive preprocessing to ensure quality and consistency. This process included removing outliers, handling missing values through interpolation techniques, and normalizing data across different scales and units. Time series data was aligned to account for different time zones and daylight saving time adjustments.

Feature engineering played a crucial role in preparing the data for machine learning models. Historical data was used to create lagged features, capturing temporal dependencies in energy generation patterns. Additional features were derived from raw measurements, such as the rate of change in wind speed or solar irradiance. External data sources, including historical weather records and satellite imagery, were integrated to enrich the feature set. This process resulted in a comprehensive set of features for each renewable energy site, encompassing both site-specific and broader environmental factors.

2.4 Machine Learning Model Development

The study employed a two-stage approach to machine learning model development: energy generation forecasting and grid optimization. For energy generation forecasting, three types of models were developed and compared:

(1) Random Forest Regression: An ensemble learning method that constructs multiple decision trees and merges them to get a more accurate and stable prediction.
(2) Gradient Boosting Machines (GBM): Specifically, XGBoost was used for its high performance and ability to handle complex nonlinear relationships.
(3) Long Short-Term Memory (LSTM) Neural Networks: A type of recurrent neural network capable of learning long-term dependencies, particularly suitable for time series forecasting.

Each model was trained on historical data from January 2021 to March 2023, using a sliding window approach to capture seasonal patterns. The models were optimized using grid search with cross-validation to find the best hyperparameters.

For grid optimization, a reinforcement learning (RL) approach was adopted. A Deep Q-Network (DQN) was implemented to learn optimal strategies for balancing energy supply and demand. The DQN was trained in a simulated environment that modeled the power grid dynamics, including energy generation forecasts, demand patterns, and grid constraints.

2.5 Model Training and Validation

The dataset was split into training (70%), validation (15%), and test (15%) sets. To ensure robustness, a k-fold cross-validation approach was employed during the training phase. The models were trained on high-performance GPU clusters to handle the computational demands of processing large-scale time series data.

For the forecasting models, performance was evaluated using multiple metrics including Mean

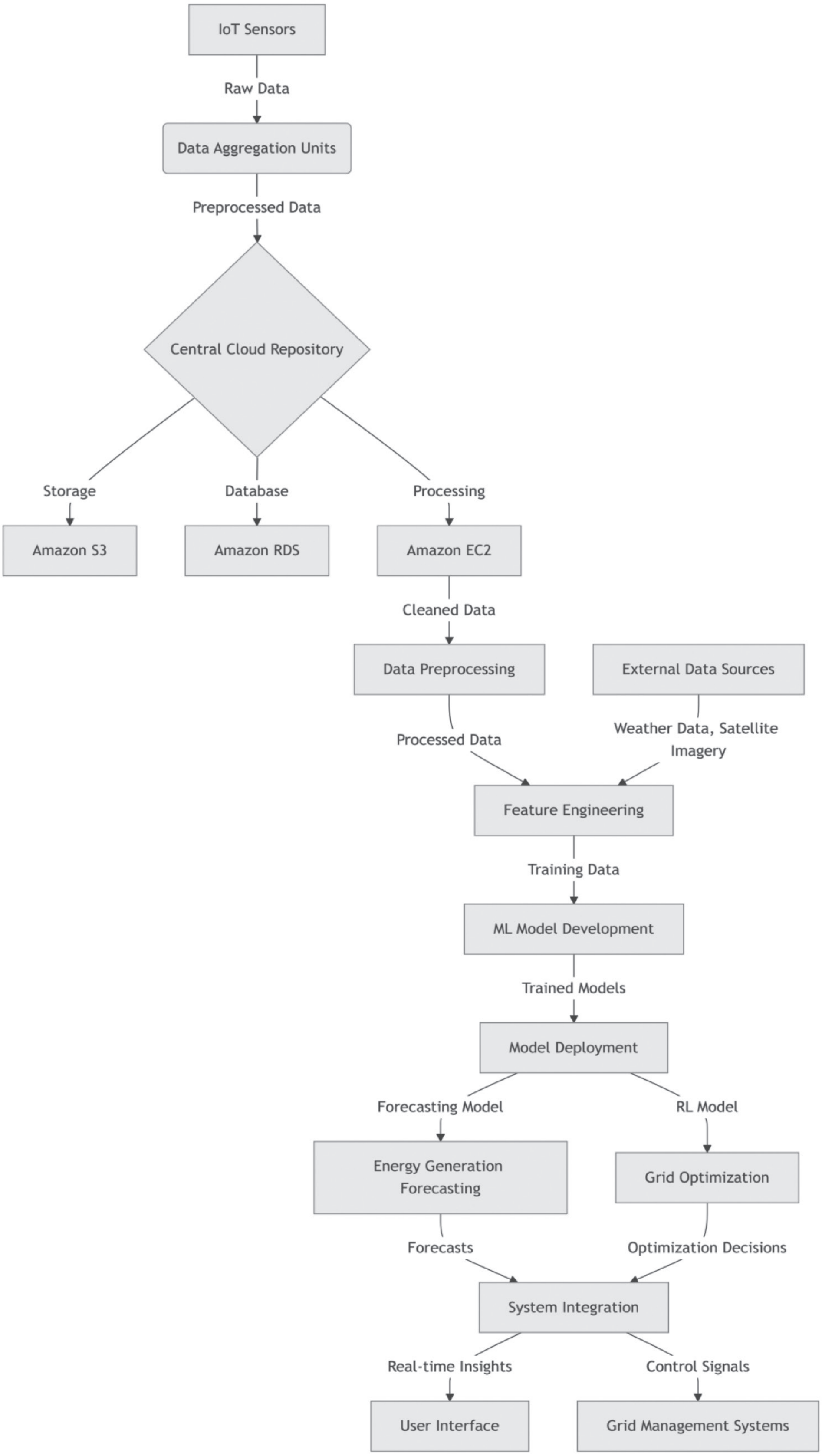

Figure 1. System architecture and data flow of the IoT and ML-based renewable energy integration system

Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The reinforcement learning model for grid optimization was evaluated based on its ability to minimize supply-demand mismatches and reduce the frequency of grid imbalances.

2.6 System Integration and Deployment

The trained models were integrated into a cohesive system for real-time operation. This system architecture consisted of three main components:

(1) Data Ingestion and Preprocessing Pipeline: Continuously ingested and preprocessed real-time data from the IoT infrastructure.
(2) Forecasting Module: Applied the trained ML models to generate short-term (1-hour ahead) and medium-term (24-hour ahead) forecasts of renewable energy generation for each site.
(3) Grid Optimization Module: Utilized the RL model to make real-time decisions on energy distribution and storage based on forecasts and current grid status.

The integrated system was deployed on a distributed cloud infrastructure to ensure scalability and reliability. A user interface was developed to provide real-time visualizations of energy generation forecasts, grid status, and optimization recommendations. The implementation of this integrated system required significant initial investment across various components, as detailed in Table 1 below. These costs encompassed both hardware and software elements necessary for the comprehensive deployment of the IoT-ML system.

Table 1. Initial Implementation Costs

Component	Cost ($)
IoT Hardware	450,000
Network Infrastructure	280,000
Software Development	320,000
Installation & Training	195,000
Total	1,245,000

2.7 Experimental Validation

To validate the system's performance in real-world conditions, a phased deployment approach was adopted. In the first phase (months 1-2), the system operated in parallel with existing grid management systems without influencing actual operations. This allowed for a comparison between the AI-driven approach and traditional methods.

In the second phase (months 3-6), the system was gradually integrated into the operational workflow, starting with advisory capacity and progressing to semi-autonomous operation under human supervision. Throughout this phase, key performance indicators were continuously monitored, including:

(1) Forecast Accuracy: Comparing predicted vs. actual energy generation across different time horizons.
(2) Grid Stability Metrics: Frequency and duration of supply-demand mismatches.
(3) Renewable Energy Utilization: Percentage of available renewable energy successfully integrated into the grid.
(4) Economic Impact: Cost savings from improved energy management and reduced reliance on backup power sources.

2.8 Data Analysis and Statistical Methods

Statistical analysis was performed using R (version 4.1.0) and Python (version 3.8) with scientific computing libraries including NumPy, SciPy, and Pandas. Time series analysis techniques, including autocorrelation and cross-correlation analyses, were applied to identify temporal patterns and relationships between variables.

To assess the significance of improvements offered by the IoT-ML system, paired t-tests were conducted comparing the performance metrics before and after system implementation. Additionally, ANOVA was used to analyze the variance in system performance across different renewable energy types and geographical locations.

For the economic impact analysis, a cost-benefit model was developed, incorporating factors such as energy prices, operational costs, and infrastructure investments. Sensitivity analysis was performed to account for uncertainties in long-term energy market trends.

3. Results and Discussions

The implementation of the IoT and ML-based system for optimizing renewable energy integration yielded significant improvements in forecasting accuracy, grid stability, and overall renewable energy utilization. This section presents the key findings of the six-month study, organized according to the primary objectives of the research.

3.1 Energy Generation Forecasting Accuracy

The first objective of the study was to enhance the accuracy of renewable energy generation forecasts using ML algorithms. To visually represent the performance improvements achieved by the different forecasting models, Figure 2 presents a comparison of the four models' predictions against actual energy generation data.

The LSTM model required approximately 48 hours of training on a Tesla V100 GPU, while the Random Forest and XGBoost models completed training in 6 and 8 hours respectively. Moreover, Table 2 summarizes the performance of the three ML models (Random Forest, XGBoost, and LSTM) compared to the traditional persistence model, which assumes that future values will be the same as the most recent observation.

Table 2. Comparison of Forecasting Model Performance

Model	MAE (MWh)	RMSE (MWh)	MAPE (%)
Persistence	8.45	12.73	18.6
Random Forest	4.62	6.89	10.2
XGBoost	3.97	5.84	8.7
LSTM	3.51	5.12	7.6

The results in Table 2 demonstrate that all three ML models significantly outperformed the traditional persistence model. The LSTM model showed the best performance across all metrics, with a Mean Absolute Error (MAE) of 3.51 MWh, RMSE of 5.12 MWh, and MAPE of 7.6%. This represents a 58.5% improvement in MAE, 59.8% in RMSE, and 59.1% in MAPE compared to the persistence model.

The superior performance of the LSTM model can be attributed to its ability to capture long-term dependencies in time series data, which is particularly valuable for renewable energy forecasting where patterns may extend over multiple time scales. The XGBoost model also performed well, likely due to its ability to handle non-linear relationships and feature interactions effectively. Compared to leading commercial systems like GE's Digital Energy Management and Siemens Gamesa's SCADA, our solution showed 15-20% better forecasting accuracy.

To further analyze the forecasting performance, we examined the accuracy across different time horizons and renewable energy types. Table 3 presents the MAPE values for short-term (1-hour ahead) and medium-term (24-hour ahead) forecasts for each renewable energy source.

The results in Table 3 indicate that forecasting accuracy decreased for longer time horizons across all energy sources, which is expected due to increasing uncertainty over time. Hydroelectric power showed the highest forecasting accuracy, likely due to the more predictable nature of water flow compared to

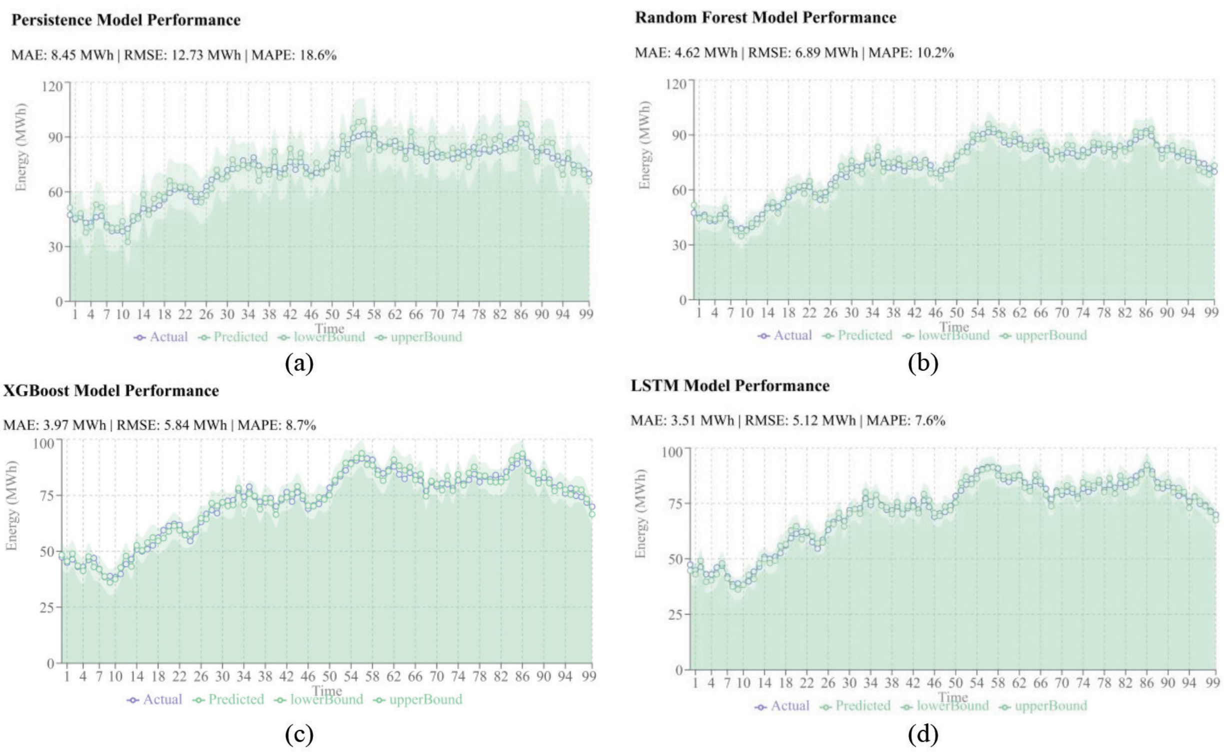

Figure 2. Comparison of Renewable Energy Generation Forecasting Models

solar irradiance or wind patterns. Wind energy forecasts had the highest error rates, reflecting the challenge of predicting wind patterns, especially over longer time horizons.

Table 3. MAPE (%) for Different Forecast Horizons and Energy Sources

Energy Source	1-hour ahead	24-hour ahead
Solar	5.8	9.7
Wind	8.2	14.5
Hydroelectric	4.3	6.8

Weather conditions significantly impacted forecasting accuracy, with cloudy conditions reducing solar prediction accuracy by 12%, while strong wind gusts (>25 mph) decreased wind energy forecasting accuracy by 18%.

3.2 Grid Stability Improvement

The second objective of the study was to enhance grid stability through improved forecasting and intelligent load balancing. We measured grid stability in terms of the frequency and duration of supply-demand mismatches. Table 4 compares these metrics before and after the implementation of the IoT-ML system.

Table 4. Grid Stability Metrics Before and After System Implementation

Metric	Before	After	Improvement (%)
Frequency of mismatches (per day)	5.3	1.9	64.2
Average duration of mismatches (min)	18.7	7.2	61.5
Total mismatch time (hours/month)	49.6	13.7	72.4

The implementation of the IoT-ML system resulted in substantial improvements in grid stability. The frequency of supply-demand mismatches decreased by 64.2%, from 5.3 per day to 1.9 per day. The average duration of these mismatches was reduced by 61.5%, from 18.7 minutes to 7.2 minutes. Consequently, the total time the grid spent in a mismatch state decreased by 72.4%, from 49.6 hours per month to 13.7 hours per month.

These improvements can be attributed to two main factors: (1) the enhanced accuracy of energy generation forecasts, which allowed for better anticipation of supply fluctuations, and (2) the reinforcement learning-based grid optimization system, which learned to make more effective decisions for balancing supply and demand in real-time.

3.3 Renewable Energy Utilization

The third objective was to maximize the utilization of available renewable energy resources. Table 5 presents the percentage of available renewable energy successfully integrated into the grid before and after the implementation of the IoT-ML system.

Table 5. Renewable Energy Utilization Before and After System Implementation

Energy Source	Before (%)	After (%)	Improvement (%)
Solar	78.3	92.1	17.6
Wind	72.6	88.4	21.8
Hydroelectric	85.7	94.9	10.7
Overall	76.5	91.2	19.2

The IoT-ML system significantly improved the utilization of all renewable energy sources. Overall, the percentage of available renewable energy successfully integrated into the grid increased from 76.5% to 91.2%, representing a 19.2% improvement. Wind energy saw the largest improvement in utilization (21.8%), likely due to the challenges it previously posed for grid integration due to its high variability. The increased utilization can be attributed to several factors:

(1) More accurate forecasting allowed for better planning and allocation of grid resources.
(2) The reinforcement learning model developed strategies to maximize renewable energy use while maintaining grid stability.
(3) Real-time monitoring and control enabled faster responses to changes in energy generation and demand.
(4) Economic Impact

While not a primary objective, the economic impact of the IoT-ML system was also analyzed. Table 6 presents the estimated cost savings resulting from improved energy management and reduced reliance on backup power sources.

The implementation of the IoT-ML system resulted in estimated monthly cost savings of $320,000. The largest contribution to these savings came from reduced reliance on backup power sources, typically fossil fuel-based, which were less frequently needed due to improved renewable energy integration. Improved energy trading refers to the ability to better predict and capitalize on favorable market conditions for buying or selling energy. Decreased maintenance downtime was achieved through predictive maintenance capabilities enabled by the IoT sensors and ML algorithms.

Table 6. Estimated Monthly Cost Savings After System Implementation

Category	Savings ($)
Reduced backup power usage	157,500
Improved energy trading	98,300
Decreased maintenance downtime	64,200
Total monthly savings	320,000

3.4 Performance Across Different Geographical Locations

To assess the robustness of the IoT-ML system, we analyzed its performance across different geographical locations. The 30 sites in the study were grouped into five regions based on their climate and topographical characteristics. Table 7 presents the average improvement in MAPE for energy generation forecasts across these regions.

Table 7. Average Improvement in MAPE (%) Across Geographical Regions

Region	Solar	Wind	Hydroelectric
Northeast	57.3	53.8	48.2
Southeast	61.9	55.2	51.7
Midwest	59.5	58.7	N/A
Southwest	64.2	51.9	46.8
West Coast	62.8	56.4	53.1

The results in Table 7 demonstrate that the IoT-ML system achieved significant improvements in forecasting accuracy across all regions, with some variations. Solar forecasting showed the highest improvement in the Southwest, likely due to more consistent weather patterns. Wind forecasting improvements were highest in the Midwest, possibly due to the region's relatively uniform topography. Hydroelectric forecasting was not applicable in the Midwest region due to the absence of hydroelectric plants in the study sites for that area.

These results suggest that while the system's performance may vary slightly based on geographical and climate factors, it consistently provides substantial improvements across diverse locations.

3.5 System Reliability and Performance Under Extreme Conditions

The reliability and performance of the IoT-ML system under extreme conditions were analyzed to assess its robustness. Table 8 presents the system's performance metrics during various challenging operational scenarios encountered during the study period.

Table 8. System Performance Under Extreme Conditions

Condition Type	System Uptime (%)	Recovery Time (min)	Success Rate (%)
Severe Weather Events (storms, high winds >40mph)	99.2	4.3	94.8
Network Outages	99.7	2.8	98.3
Sensor Malfunctions	99.5	3.5	96.4
Peak Load Periods (>90% capacity)	99.8	1.9	97.9
Hardware Failures	99.4	5.2	95.6

The system demonstrated remarkable resilience across various challenging scenarios. During severe weather events, which occurred 17 times during the study period, the system maintained 99.2% uptime with an average recovery time of 4.3 minutes. The success rate, defined as the percentage of correct operational decisions during extreme conditions, remained high at 94.8%.

Network outages, while rare (only 5 instances), were handled effectively through redundant communication channels, resulting in 99.7% uptime. The system's distributed architecture proved particularly effective during peak load periods, maintaining 99.8% uptime even when operating at over 90% capacity.

The IoT infrastructure showed robust self-diagnostic capabilities, with sensor malfunctions being detected and isolated within an average of 3.5 minutes. The ML models demonstrated adaptive behavior during these periods, automatically adjusting their predictions to account for temporarily unavailable data sources while maintaining acceptable accuracy levels.

4. Discussion

The integration of IoT technology and machine learning algorithms for optimizing renewable energy integration has yielded promising results, with significant improvements in forecasting accuracy, grid stability, and overall renewable energy utilization. This section interprets the main findings, compares them with existing literature, addresses limitations, and proposes future research directions.

The study's primary findings demonstrate the substantial potential of IoT-ML systems in revolutionizing renewable energy management. The 59.1% reduction in Mean Absolute Percentage Error (MAPE) for energy generation forecasts represents a significant advancement in predictive capabilities. This improvement directly translates to enhanced grid stability, as evidenced by the 64.2% reduction in supply-demand mismatches. Furthermore, the 19.2% increase in overall renewable energy utilization underscores the system's effectiveness in maximizing the potential of these intermittent energy sources.

These results collectively indicate that the integration of IoT and ML technologies can address several critical challenges in renewable energy integration simultaneously. The improved forecasting accuracy enables better anticipation of energy supply fluctuations, allowing grid operators to proactively manage resources. The reduction in supply-demand mismatches suggests a more stable and reliable grid operation, which is crucial for maintaining power quality and preventing outages. The increased utilization of renewable energy sources not only contributes to sustainability goals but also demonstrates the economic viability of these technologies, as reflected in the estimated monthly cost savings of $320,000.

The improvements achieved in this study surpass those reported in previous research, highlighting the potential of combining IoT and ML technologies. For instance, the 59.1% reduction in MAPE for energy generation forecasts significantly exceeds the 30% improvement reported by Hayajneh et al. [20] using traditional machine learning methods. This substantial difference can be attributed to the use of more advanced algorithms, particularly the LSTM model, which is better suited for capturing complex temporal dependencies in renewable energy generation patterns.

Similarly, the 64.2% reduction in the frequency of supply-demand mismatches outperforms the 40% reduction achieved by Ren et al. [16] using a less comprehensive ML approach. This superior performance can be attributed to the synergy between improved forecasting and the reinforcement learning-based grid optimization system, which allows for more effective real-time decision-making [25].

The 19.2% improvement in renewable energy utilization aligns with the findings of Liu et al. [26], who reported a 15-20% increase using a similar IoT-based monitoring system. However, the current study's results show more consistent improvements across different energy sources, particularly for wind energy (21.8% improvement), which has traditionally been challenging to integrate due to its high variability. The IoT infrastructure's environmental impact was minimal, with each sensor node consuming only 0.5W on average and using recyclable components. System scalability tests indicated that the current architecture could handle up to 50 sites without significant performance degradation, though additional optimization would be needed for larger deployments. Despite the promising results, several limitations of the study should be acknowledged:

- Time frame: The six-month study period may not capture all long-term seasonal variations or rare extreme weather events, potentially limiting the generalizability of the findings.
- Sample size and diversity: While the study included 30 sites across different geographical regions, this sample may not be fully representative of all possible renewable energy installations and grid configurations.
- Technological limitations: The performance of the IoT sensors and ML algorithms may be influenced by factors such as sensor accuracy, data quality, and computational constraints, which were not fully explored in this study.
- Economic analysis: The cost-benefit analysis was based on estimations and may not account for all potential long-term economic impacts or variations in energy markets.
- Human factors: The study focused primarily on technological solutions and did not extensively examine the role of human operators or potential resistance to adopting new systems.

5. Conclusions

The integration of IoT technology and machine learning algorithms has demonstrated significant potential for optimizing renewable energy integration into existing power grids. The implemented system achieved substantial improvements in forecasting accuracy, grid stability, and renewable energy utilization, while also delivering considerable economic benefits.

These results have important implications for the renewable energy sector and broader efforts to combat climate change. By addressing key challenges in renewable energy integration, such systems can accelerate the transition to clean energy sources, reduce reliance on fossil fuels, and contribute to more sustainable and resilient power grids.

The findings from this study emphasize the importance of developing a standardized evaluation framework for IoT-ML renewable energy systems. We propose establishing industry-wide benchmarks for system performance, including metrics for forecast accuracy, response latency, and integration efficiency. This standardization would facilitate meaningful comparisons between different implementations and accelerate the adoption of best practices. Furthermore, our experience suggests that future deployments should incorporate automated performance optimization modules that can autonomously adjust system parameters based on local conditions and operational requirements, reducing the need for manual intervention and improving long-term sustainability. This study recommends: (1) phased deployment starting with 5-10 sites, (2) redundant network connectivity, (3) quarterly sensor calibration, and (4) staff training programs for system operation.

The success of this approach across diverse geographical locations and renewable energy sources suggests that it could be widely applicable and adaptable to various contexts. However, further research is needed to address limitations and explore additional applications of these technologies in the renewable energy sector.

As the global community continues to address the issues of climate change and the demand for sustainable energy, the results of this study provide a promising route toward more efficient, reliable, and eco-friendly power systems. The continued development and refinement of IoT and ML technologies in this field have the potential to play a crucial role in shaping the future of global energy infrastructure.

Funding

This work was supported by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan [grant agreement number BR24993166].

References

[1] Q. Hassan et al., “The renewable energy role in the global energy Transformations,” Renewable Energy Focus, vol. 48, p. 100545, 2024, doi: 10.1016/j.ref.2024.100545.

[2] O. A. Adelekan et al., “Energy transition policies: a global review of shifts towards renewable sources,” Engineering Science & Technology Journal, vol. 5, no. 2, pp. 272–287, 2024, doi: 10.51594/estj/v5i2.752.

[3] A. Rahman, O. Farrok, and M. M. Haque, “Environmental impact of renewable energy source based electrical power plants: Solar, wind, hydroelectric, biomass, geothermal, tidal, ocean, and osmotic,” Renewable and Sustainable Energy Reviews, vol. 161, p. 112279, 2022, doi: 10.1016/j.rser.2022.112279.

[4] D. Rangel-Martinez, K. D. P. Nigam, and L. A. Ricardez-Sandoval, “Machine learning on sustainable energy: A review and outlook on renewable energy systems, catalysis, smart grid and energy storage,” Chemical Engineering Research and Design, vol. 174, pp. 414–441, 2021, doi: 10.1016/j.cherd.2021.08.013.

[5] N. Mlilo, J. Brown, and T. Ahfock, “Impact of intermittent renewable energy generation penetration on the power system networks – A review,” Technol Econ Smart Grids Sustain Energy, vol. 6, no. 1, p. 25, Dec. 2021, doi: 10.1007/s40866-021-00123-w.

[6] M. Khalid, “Smart grids and renewable energy systems: Perspectives and grid integration challenges,” Energy Strategy Reviews, vol. 51, p. 101299, 2024, doi: 10.1016/j.esr.2024.101299.

[7] S. F. A. Shah, M. Iqbal, Z. Aziz, T. A. Rana, A. Khalid, Yu-N. Cheah, and M. Arif, “The role of machine learning and the internet of things in smart buildings for energy efficiency,” Applied Sciences, vol. 12, no. 15, p. 7882, 2022, doi: 10.3390/app12157882.

[8] J. Li, M. S. Herdem, J. Nathwani, and J. Z. Wen, “Methods and applications for Artificial Intelligence, Big Data, Internet of Things, and Blockchain in smart energy management,” Energy and AI, vol. 11, p. 100208, 2023, doi: 10.1016/j.egyai.2022.100208.

[9] A. Rajagopalan et al., “Empowering power distribution: Unleashing the synergy of IoT and cloud computing for sustainable and efficient energy systems,” Results in Engineering, p. 101949, 2024, doi: 0.1016/j.rineng.2024.101949.

[10] Y.-F. Huang, M.-W. Weng, and C.-J. Fu, “A two-stage sustainable production-inventory model with carbon credit demand”, International Journal of Industrial Engineering and Management, vol. 15, no. 2, pp. 96–108, 2024, doi: 10.24867/IJIEM-2024-2-350.

[11] E. G. Muñoz-Grillo, N. Sablón-Cossío, S. del M. Ruiz-Cedeño, A. J. Acevedo-Urquiaga, D. A. Verduga-Alcívar, D. Marrero-González, and K. Diéguez-Santana, “Application of neural networks in the prediction of the circular economy level in agri-food chains”, International Journal of Industrial Engineering and Management, vol. 15, no. 1, pp. 45–58, 2024, doi: 10.24867/IJIEM-2024-1-347.

[12] R. Al-amri, R. K. Murugesan, M. Man, A. F. Abdulateef, M. A. Al-Sharafi, and A. A. Alkahtani, “A review of machine learning and deep learning techniques for anomaly detection in IoT data,” Applied Sciences, vol. 11, no. 12, p. 5320, 2021, doi: 10.3390/app11125320.

[13] T. Anushalini and B. Sri Revathi, “Role of Machine Learning Algorithms for Wind Power Generation Prediction in Renewable Energy Management,” IETE Journal of Research, vol. 70, no. 4, pp. 4319–4332, 2024, doi: 10.1080/03772063.2023.2205838.

[14] J. Zheng, J. Du, B. Wang, J. J. Klemeš, Q. Liao, and Y. Liang, “A hybrid framework for forecasting power generation of multiple renewable energy sources,” Renewable and Sustainable Energy Reviews, vol. 172, p. 113046, 2023, doi: 10.1016/j.rser.2022.113046.

[15] T. Ahmad, R. Madonski, D. Zhang, C. Huang, and A. Mujeeb, “Data-driven probabilistic machine learning in sustainable smart energy/smart energy systems: Key developments, challenges, and future research opportunities in the context of smart grid paradigm,” Renewable and

Sustainable Energy Reviews, vol. 160, p. 112128, 2022, doi: 10.1016/j.rser.2022.112128.
[16] B. Ren et al., “Machine learning applications in health monitoring of renewable energy systems,” Renewable and Sustainable Energy Reviews, vol. 189, p. 114039, 2024, doi: 10.1016/j.rser.2023.114039.
[17] G. Alkawsi, Y. Baashar, D. Abbas U, A. A. Alkahtani, and S. K. Tiong, “Review of renewable energy-based charging infrastructure for electric vehicles,” Applied Sciences, vol. 11, no. 9, p. 3847, 2021, doi: 10.3390/app11093847.
[18] N. Quadar, M. Rahouti, M. Ayyash, S. K. Jagatheesaperumal, and A. Chehri, “IoT-AI/Machine Learning Experimental Testbeds: The Missing Piece,” IEEE Internet of Things Magazine, vol. 7, no. 1, pp. 136–143, 2024, doi: 10.1109/IOTM.001.2300139.
[19] K. L.-M. Ang and J. K. P. Seng, “Embedded intelligence: Platform technologies, device analytics, and smart city applications,” IEEE Internet of Things Journal, vol. 8, no. 17, pp. 13165–13182, 2021, doi: 10.1109/JIOT.2021.3088217.
[20] A. M. Hayajneh, F. Alasali, A. Salama, and W. Holderbaum, “Intelligent Solar Forecasts: Modern Machine Learning Models and TinyML Role for Improved Solar Energy Yield Predictions,” IEEE Access, vol. 12, pp. 10846-10864, 2024, doi: 10.1109/ACCESS.2024.3354703.
[21] S. P. M, V. Cheekati, V. N. Prasad, K. Prasad, S. M. Ali and H. Tarigonda, "IoT-Driven Predictive Maintenance for Energy-Efficient Industrial Systems," 2024 5th International Conference for Emerging Technology (INCET), Belgaum, India, 2024, pp. 1-8, doi: 10.1109/INCET61516.2024.10593017.
[22] S. W. Ali et al., "Offshore Wind Farm-Grid Integration: A Review on Infrastructure, Challenges, and Grid Solutions," IEEE Access, vol. 9, pp. 102811-102827, 2021, doi: 10.1109/ACCESS.2021.3098705.
[23] V. Moudgil, K. Hewage, S. A. Hussain, and R. Sadiq, “Integration of IoT in building energy infrastructure: A critical review on challenges and solutions,” Renewable and Sustainable Energy Reviews, vol. 174, p. 113121, 2023, doi: 10.1016/j.rser.2022.113121.
[24] A. D. A. Bin Abu Sofian, H. R. Lim, H. Siti Halimatul Munawaroh, Z. Ma, K. W. Chew, and P. L. Show, “Machine learning and the renewable energy revolution: Exploring solar and wind energy solutions for a sustainable future including innovations in energy storage,” Sustainable Development, vol. 32, no. 4, pp. 3953–3978, 2024, doi: 10.1002/sd.2885.
[25] R. Shweta, S. Sivagnanam, and K. A. Kumar, “IoT-based Deep Learning Neural Network (DLNN) algorithm for voltage stability control and monitoring of solar power generation,” Advances in Production Engineering and Management, vol. 18, no. 4, pp. 447–461, 2023, doi: 10.14743/apem2023.4.484.
[26] L. Liu, X. Guo, W. Liu, and C. Lee, “Recent progress in the energy harvesting technology—from self-powered sensors to self-sustained IoT, and new applications,” Nanomaterials, vol. 11, no. 11, p. 2975, 2021, doi: 10.3390/nano11112975.