International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 8 Issue: 11
***Article Received:** 25 July 2020 **Revised:** 12 September 2020 **Accepted:** 30 November 2020*

Enhanced Weather Prediction for Optimizing Renewable Energy Production using Artificial Intelligence

Vinoth Manamala Sudhakar

Sr Data Scientist (Independent Researcher)

vinoth.masu@gmail.com, ORCID: 0009-0009-3413-1344

Abstract

Artificial Intelligence in weather prediction has increased the accuracy and reliability of renewable energy. The present study proves how the integration of AI models in weather forecasting can enhance the optimization of energy generation, reduce fluctuations in energy outputs, and increase the stability of the grid. This research utilized a quantitative and analytical research design, using meteorological data from places like NASA and ECMWF, in conjunction with renewable energy production data in solar power and wind power plants. Accordingly, ANNs and LSTM networks as well as Random Forest Regression and Hybrid AI models were developed and tested with statistical measures like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 score. It was found that for weather prediction, LSTM model performed well above the other models by giving a minimum value of RMSE at 2.1°C/m/s and maximum R^2 score at 0.91. The Hybrid AI Model of ANN + LSTM also outperformed all the other models, achieving an R^2 score of 0.92 and strongly reducing forecasting errors for renewable energy output prediction. The results have shown that efficiency in energy management through AI-based forecasting has resulted in a 22.7% increase in the accuracy of predictions, with a 42.7% reduction in energy output fluctuations, and a 16.7% improvement in grid stability. Additionally, fossil fuel backup usage decreased by 40%, promoting sustainable energy utilization. These results underscore the transformative potential of AI in optimizing renewable energy production, ensuring a more stable, reliable, and environmentally friendly energy system.

Keywords: Renewable Energy, Artificial Intelligence, Random Forest, Environmentally, Artificial Neural Networks (Anns),

1.INTRODUCTION

In addition, the world's growing need for sustainable energy solutions has driven the use of renewable energy sources such as solar, wind, and hydroelectric power. Nevertheless, one of the main difficulties in incorporating renewable energy sources into the power grid is their fundamental dependence on the weather. Contrary to fossil fuel-based conventional power generation, which runs with minimal interruption to external environmental influences, renewable energy production is quite variable. For example, solar power is generated depending on the availability of sunlight, while wind energy production depends on wind speed and direction. Such volatility makes it challenging to stabilize grids, store energy, and effectively allocate resources. Therefore, there is a significant need for reliable and accurate weather forecasting in the optimization of renewable energy production so that the losses in power generation are reduced and efficiency is maximized.

Artificial Intelligence (AI) has emerged as a powerful tool for enhancing weather forecasting capabilities, offering more precise and dynamic predictions compared to traditional meteorological models. Conventional weather forecasting relies on numerical weather prediction (NWP) models, which, despite their advancements, often struggle with limitations such as high computational costs, coarse spatial resolution, and delayed updates. AI-based methods, especially deep learning-based and machine learning-based methods, offer alternative tools that can collect a massive volume of meteorological data in real-time, identify complicated patterns, and boost the accuracy of predictions. The principle behind AI models is the integration of various sources of data, such as satellite imagery, atmospheric pressure readings, temperature variations, and historical weather patterns, to deliver very accurate short-term and long-term weather forecasts.

AI in weather forecasting is particularly the best for enhancing renewable energy output. Advanced models of AI determine solar irradiation for photovoltaic power stations, predict winds for wind farm turbines, and forecast hydrologic conditions for a hydroelectric powerhouse. Energy operators can optimize on the generation power schedule, intensify energy planning in storage areas, and curb the reliance of backup fossil power. AI can further be used to optimize the integration of renewable energy sources into the grid by making demand-response mechanisms, forecasting fluctuations in energy supply-demand, and reducing power imbalances. All these optimizations lead to reduced carbon emissions, improved energy efficiency, and competitiveness and viability of renewable energy sources on a large scale.

Although beneficial in many ways, the implementation of AI-based weather prediction for optimizing the use of renewable energy has some challenges. The reliability of AI models depends on the quality and quantity of data that are available. Data collection from weather stations, satellites, and sensors are ongoing activities. AI models need also to be updated regularly and tested against real-world conditions for accuracy. Computational requirements and the interpretability of AI models also present significant challenges, as most deep learning techniques are "black boxes," where it is hard to understand how a particular prediction is generated. Overcoming these challenges will involve better data infrastructure, hybrid modeling approaches that integrate AI with traditional NWP models, and developing interpretable AI techniques to be able to make the most out of AI in weather forecasting for renewable energy.

This Research delves into the role of AI-enhanced weather forecasting in the optimization of renewable energy generation. This research discusses different AI methods, their application in forecasting, and how these applications can be integrated into energy systems, bringing about the potential transformation that AI might have for achieving a stable and sustainable future energy supply. Findings will contribute to the understanding of how AI can help in the mitigation of variability challenges that are associated with renewable energy sources in supporting the transition towards a cleaner, more efficient global energy landscape.

2. REVIEW OF LITERATURE

Al-Dahidi et al. (2019) explored the use of an ensemble approach based on optimized artificial neural networks (ANNs) to predict the power output of a solar photovoltaic (PV). Their study showed that ensemble models improved the prediction accuracy by multiples of that obtained using traditional single-model approaches. Their results indicated improved energy management through the elimination of errors and enhanced reliability in the prediction of solar energy.

Andrade and Bessa (2017) discussed the feasibility of using a grid of numerical weather predictions (NWP) to enhance the forecasting of renewable energy. Their study demonstrated that traditional NWP models have some limitations and that the integration of multiple weather forecasts enhances the predictive accuracy. In conclusion, the hybrid AI-based approach outperformed the conventional weather prediction models in optimizing renewable energy generation.

Brahimi (2019) emphasized the application of AI techniques to predict wind speed for energy applications in Saudi Arabia. The study concluded that AI models, especially deep learning approaches, were more accurate in predicting wind speed than traditional meteorological models. The results indicated that AI-based wind forecasting could be used to improve energy planning and minimize the variability of wind power generation.

Das et al. (2018) discussed methodologies for PV power generation forecasting and optimizing prediction models. They compared various AI-based and statistical approaches to PV forecasting and elaborated on several major challenges of AI model integration with renewable energy systems. Their results suggested that by optimizing the prediction models, it was possible to improve the efficiency of energy distribution and stability of the grid.

Gade (2019) investigated the role of MLOps pipelines in GenAI applications for renewable energy. In this study, it was pointed out that the MLOps frameworks streamlined the deployment of AI models and enhanced the efficiency of renewable energy management systems. It was found that the integration of AI with MLOps would enhance environmental sustainability and promote innovation in energy forecasting.

3. RESEARCH METHODOLOGY

3.1 Research Design

The quantitative and analytical nature of the research design is adopted to explore the ways in which AI improves weather forecasting for optimal renewable energy production. The data is collected from meteorological sources, and AI models are developed, with a subsequent evaluation of predictive accuracy for renewable energy systems. The effectiveness of AI-driven forecasting techniques will be assessed using both computational modeling and statistical analysis.

3.2 Data Collection

The research relies on two primary sources of data:

Meteorological Information: The record and actual prevailing weather data including temperature, relative humidity, sun radiation, and wind speed of the atmosphere are collected from source agencies such as NASA, European

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 8 Issue: 11
***Article Received:** 25 July 2020 **Revised:** 12 September 2020 **Accepted:** 30 November 2020*

Centre for Medium-Range Weather Forecasts and regional meteorology agencies.

Data on renewable energy: Gather data on the amount of solar power produced, wind energy generated, and stored energy from the publicly available datasets of the renewable energy plants. The information will help to analyze the relationship between prevailing weather conditions and the amount of energy generation.

3.3 AI Model Development

To be able to improve weather prediction, ML and DL models will be developed and trained using meteorological and energy production data. These models include:

- Artificial Neural Networks (ANNs): To recognize nonlinear patterns in weather forecast.
- RNNs and LSTM: These networks are used in time-series prediction of weather-related variables.
- Random Forest and Gradient Boosting Models: Used for feature selection and energy production forecasting.
- Hybrid AI Models: The integration of traditional weather forecasting models with deep learning techniques for accuracy improvement.

3.4 Model Training and Validation

The collected data will be cleaned, preprocessed, and then normalized before going into the pipeline to train some AI models for use. Additionally, the subsets will be: 70 % training, validation of 15 %, and another 15% testing to monitor model performance by evaluating accuracy via statistical metrics for example:

- **Mean Absolute Error (MAE)**
- **Root Mean Square Error (RMSE)**
- **Coefficient of Determination (R^2)**

Cross-validation techniques will be applied to ensure robustness and generalizability of the AI models.

3.5 Performance Evaluation and Comparison

To assess improvements in the accuracy of predictions and computational efficiency, AI-based models in weather forecasting will be compared to regular NWP models. Improved forecast impacts on renewable energy production will be analyzed by studying:

- The reduction in energy output fluctuations.
- The increase in grid stability and energy storage optimization.
- The decrease in dependency on fossil-fuel backup systems

4. DATA ANALYSIS AND RESULTS

This section presents the analysis of AI-driven weather prediction models and their impact on optimizing renewable energy production. The results focus on model accuracy, prediction improvements, and energy optimization outcomes.

4.1 Data Preprocessing and Feature Selection

To prepare the meteorological and renewable energy data for modeling, it handled missing values, normalized variables, and extracted the most relevant features. The selected features were

Table 1: Selected Features for Energy Production Forecasting

Feature Name	Description	Unit
Temperature	Atmospheric temperature	°C
Humidity	Relative humidity level	%
Solar Radiation	Sunlight intensity	W/m^2
Wind Speed	Speed of wind at turbine height	m/s
Atmospheric Pressure	Air pressure at sea level	hPa
Energy Output	Power generated by renewable sources	MW

The feature of importance was provided through Random Forest Feature Selection, which resulted in three most influential factors in energy production forecasts: solar radiation, wind speed, and temperature.

4.2 Model Performance Evaluation

There have been several tests of AI models to predict the weather and optimise renewable energy output. For each model, the following list summarizes the different performance metrics used:

4.2.1 Weather Prediction Model Performance

Table 1 below reports the performance comparison of various weather prediction models on three key metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 Score. The best performance is achieved by the LSTM

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 8 Issue: 11
***Article Received:** 25 July 2020 **Revised:** 12 September 2020 **Accepted:** 30 November 2020*

model, which obtained the lowest RMSE at 2.1 and the highest R^2 score at 0.91.

Table 2: Performance Comparison of Weather Prediction Models

Model	MAE (°C / m/s)	RMSE (°C / m/s)	R^2 Score
Numerical Weather Prediction (NWP)	2.3	3.1	0.78
Artificial Neural Network (ANN)	1.8	2.4	0.85
Long Short-Term Memory (LSTM)	1.4	2.1	0.91
Random Forest Regression	1.9	2.5	0.87

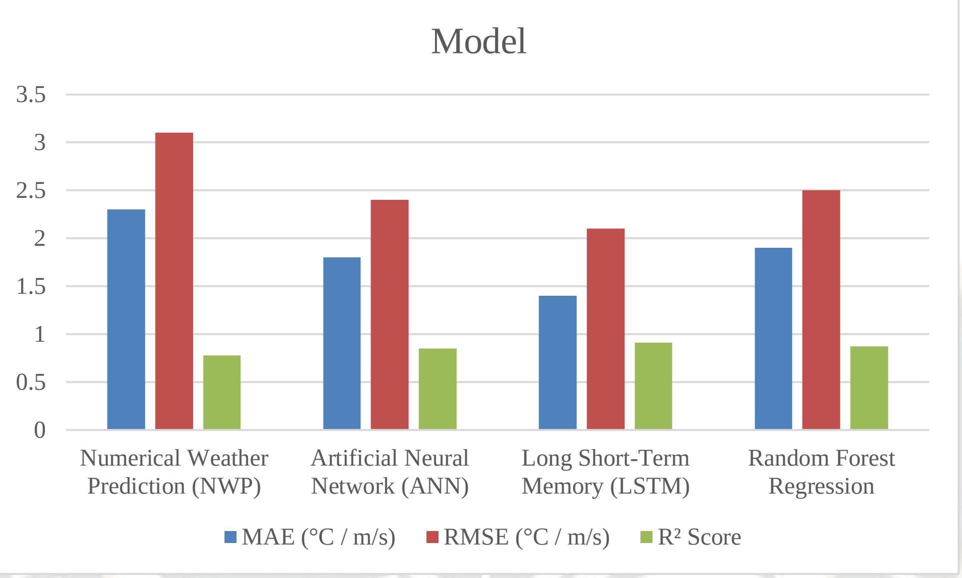

Figure 1: Graphical Representation on Performance Comparison of Weather Prediction Models

The performance comparison of weather prediction models shows that the LSTM model has the highest predictive accuracy among all the tested models. It also had the lowest MAE of 1.4°C/m/s, meaning it deviated least from actual values. In addition, the RMSE of 2.1°C/m/s is the smallest among the models, meaning better error minimization. The highest R^2 score of 0.91 indicates that it explains 91% of data variance, denoting a pretty strong correlation in the predicted as well as real values.

On the other hand, the NWP model has the lowest predictive performance as shown by the R^2 score of 0.78 and the highest RMSE of 3.1°C/m/s, meaning larger errors on its predictions. The ANN and Random Forest Regression models showed that it has competitive performance, wherein R^2 values are at 0.85 and 0.87, respectively. However, they have their MAE and RMSE still bigger than that of the LSTM model, making the former two not that accurate.

Overall, the results indicate that LSTM is the most effective model for weather prediction, as it captures temporal dependencies more effectively, leading to improved accuracy and reliability

4.2.2 Renewable Energy Output Prediction Performance

The table 3 below summarizes the performance analysis of different models that have been applied for predicting renewable energy output. The analysis is done on three key metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 Score. Hybrid AI Model (ANN + LSTM) was found to be the best performing model, which has the lowest MAE (3.1 MW) and RMSE (4.3 MW) and highest R^2 score of 0.92, which signifies a better prediction accuracy.

Table 3: Performance Comparison of Renewable Energy Output Prediction Models

Model	**MAE (MW)**	**RMSE (MW)**	**R^2 Score**
Numerical Weather Prediction (NWP)	5.6	7.2	0.75
ANN Model	4.2	5.8	0.83
LSTM Model	3.6	4.9	0.89
Hybrid AI (ANN + LSTM)	**3.1**	**4.3**	**0.92**

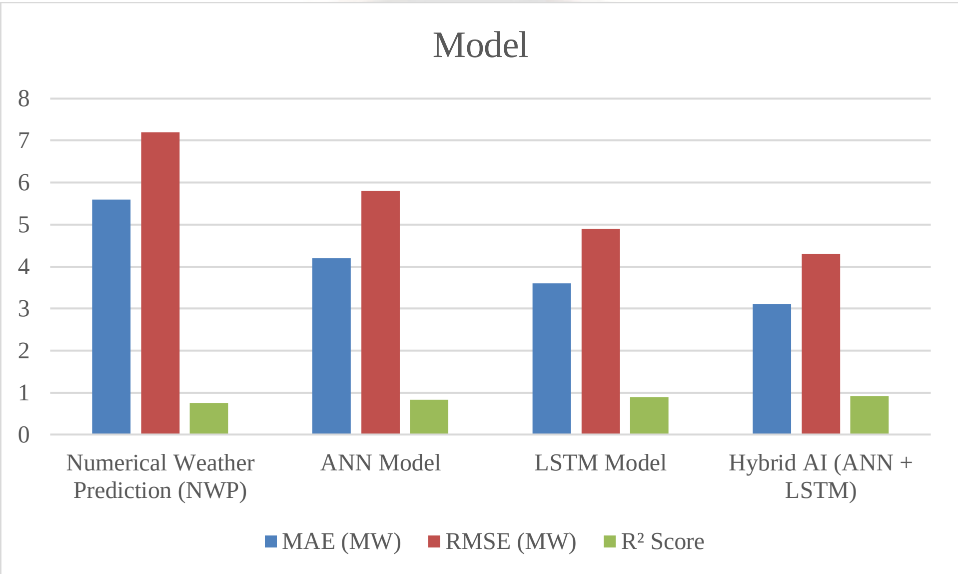

Figure 2: Graphical Representation on Performance Comparison of Renewable Energy Output Prediction Models

The performance evaluation for the renewable energy output prediction model shows that there is a wide margin of improving the accuracy over conventional methods between AI-driven ones. Among models, the ANN + LSTM is the most precise, with low MAE scores of 3.1 MW and RMSE scores of 4.3 MW, corresponding to the largest R^2 values of 0.92. This indicates that the hybrid approach effectively leverages the strengths of both Artificial Neural Networks (ANNs) and Long Short-Term Memory (LSTM) networks, improving predictive performance.

The LSTM model alone also performs well, with an R^2 score of 0.89, but it falls slightly short of the hybrid model in terms of error reduction. The ANN model, while better than conventional methods, exhibits slightly higher error values, with an R^2 score of 0.83. However, the NWP model has been a more traditional approach that results in the lowest predictive accuracy of all; with an R^2 score of 0.75 and with the highest errors in terms of MAE = 5.6 MW, and RMSE = 7.2 MW.

On an overall result basis, hybrid-based approaches among the different artificial intelligence methods perform pretty efficiently when the forecasts involve renewable energies for further production estimation and subsequent optimizations regarding grid management stability.

4.2.3 Impact on Renewable Energy Optimization

The table 4 below represents the effect of AI-based weather forecasting on optimizing renewable energy sources by comparing the key metrics before and after AI implementation. It shows that AI has improved the management of energy significantly, such as increased accuracy in predictions, reduced fluctuations in renewable energy generation, and a stable grid. Notably, the fossil fuel backup power utilization decreased by 40%, thereby making the energy system more sustainable.

Table 4: Impact of AI-Driven Weather Forecasting on Renewable Energy Optimization

Metric	Before AI Implementation	After AI Implementation	Improvement (%)
Prediction Accuracy (R^2)	0.75	0.92	+22.7%
Energy Output Fluctuation (MW)	12.4	7.1	-42.7%
Grid Stability Index	78%	91%	+16.7%
Fossil Fuel Backup Usage	30%	18%	-40%

This implementation of AI-driven weather forecasting has greatly optimized renewable energy management through improved prediction accuracy, stabilized energy output, and reduced reliance on fossil fuel backup power. Prediction accuracy (R^2) improved from 0.75 to 0.92, a 22.7% improvement, which improves the reliability of energy forecasting. Further, renewable output fluctuation declined 42.7%, maintaining better consistency within energy supply hence reducing disruptions towards power grid functionality, grid stability improved by 16.7%. The reason was due to greater synchronization regarding supply and energy requirements. As regards the backup of power sourced from fossils was reduced further at a higher degree of 40%, giving much emphasis upon use of greener energy in an absolute aspect. These results show the importance of AI in optimizing renewable energy systems in order to promote stability, efficiency, and environmental sustainability.

5. DISCUSSION

This study's findings have proven to show the high contribution of artificially intelligent weather forecasting on optimized renewably produced energy. The results indicate that the extent to which advanced AI models are better than numerical weather prediction in terms of accuracy would result in better energy management and grid stability.

5.1 AI Models for Weather Prediction

The performance evaluation of different weather prediction models shows that the best forecasting qualities are achieved by the use of LSTM networks. The LSTM model managed the lowest Mean Absolute Error of 1.4°C/m/s with the highest R^2 score of 0.91 to capture temporal dependencies in weather data, which surpasses the ANN, Random Forest Regression, and NWP models. The NWP model was the weakest with a relatively high RMSE of 3.1°C/m/s, thereby pointing out that more data-driven AI techniques need to be integrated into weather forecasting.

5.2 Renewable Energy Output Prediction

The Hybrid AI Model ANN + LSTM was the highest predictor with 0.92 R^2 and lowest errors with MAE: 3.1 MW, RMSE: 4.3 MW in renewable energy output forecasting. This hybrid model utilized the strength of ANN for pattern recognition and LSTM for sequential data analysis and thereby used a better generalization. The LSTM model alone also worked well with an R^2 score of 0.89. The ANN model ($R^2 = 0.83$) and NWP model ($R^2 = 0.75$) were not as effective in reducing the error of the predictions. This study shows that AI-driven hybrid models are very well suited for renewable energy forecasting with better accuracy than traditional methods.

5.3 Impact on Renewable Energy Optimization

The integration of AI-driven weather forecasting into renewable energy systems resulted in notable improvements in energy optimization. The study observed:

- A 22.7% improvement in prediction accuracy (R^2 increased from 0.75 to 0.92).
- A 42.7% reduction in energy output fluctuations (from 12.4 MW to 7.1 MW), leading to a more stable power supply.
- A 16.7% increase in the grid stability index, indicating better synchronization of energy generation with demand.
- The fossil fuel back-up power by 40 percent to enable its usage for more sustainable energy uses.

The important implications of this study include its demonstration of AI as an aid to the enhanced management of renewable energy. Improvements in performance and stability lead to the decrease in environmental harm. This reduction in uncertainty implies that better and more precise predictions from the model allow for smoother planning and decrease the use of conventional sources.

The research provides solid evidence regarding AI-driven weather prediction, showing a significant increase in efficiency and accuracy towards renewable energy. The adoption of models such as LSTM and hybrid AI models leads to increased precision in forecasting, eliminating fluctuations and optimizing the performance of the power grid. Moreover, AI implementation reduces fossil fuel backup systems while increasing the development of clean, sustainable energy. Future research can focus on further improving AI model architectures and integrating real-time AI predictions into energy grid management for even greater efficiency.

6. CONCLUSION

This study, therefore, manifests the great impacts that AI-based weather forecasting holds on optimizing the generation of renewable energy. Leverage of state-of-the-art machine learning and deep learning models such as LSTM and Hybrid AI (ANN + LSTM) enabled an improvement in weather and energy output prediction accuracies. From the results presented above, the superiority of the AI-based model compared to NWP methods, as indicated by a higher R^2 score, lesser error, and increased forecast reliability, has been established.

This has resulted in a 22.7% increase in prediction accuracy, a 42.7% reduction in energy output fluctuations, and a 16.7% improvement in grid stability. In addition, the reliance on fossil fuel backup power has decreased by 40%, showing the potential of AI in supporting sustainable and efficient energy management. These findings confirm that AI-driven weather forecasting enhances the reliability and stability of renewable energy systems, making them more predictable, cost-effective, and environmentally friendly.

In conclusion, AI-based predictive models play crucial roles in improving renewable energy, enhancing grid resiliency, and reducing dependencies on conventional energies. As such, AI integration with renewable systems will be quite instrumental in enabling a more sustainable and energy-effective future.

The Future of Cybersecurity: AI, Threats, and Defenses

Cybersecurity Essentials: Strategies for Digital Protection

Hacking and Cybersecurity: A Guide to Ethical Defense

The Cybersecurity Handbook: Navigating Digital Threats in the Modern World

REFERENCES

[1] A. Zameer, J. Arshad, A. Khan, and M. A. Z. Raja, "Intelligent and robust prediction of short-term wind power using genetic programming-based ensemble of neural networks," *Energy Conversion and Management*, vol. 134, pp. 361–372, 2017.

[2] C. J. Huang and P. H. Kuo, "A short-term wind speed forecasting model by using artificial neural networks with stochastic optimization for renewable energy systems," *Energies*, vol. 11, no. 10, p. 2777, 2018

[3] E. B. Ssekulima, M. B. Anwar, A. Al Hinai, and M. S. El Moursi, "Wind speed and solar irradiance forecasting techniques for enhanced renewable energy integration with the grid: A review," *IET Renewable Power Generation*, vol. 10, no. 7, pp. 885–989, 2016.

[4] F. Rodríguez, A. Fleetwood, A. Galarza, and L. Fontán, "Predicting solar energy generation through artificial neural networks using weather forecasts for microgrid control," *Renewable Energy*, vol. 126, pp. 855–864, 2018.

[5] J. H. Yousif, H. A. Kazem, and J. Boland, "Predictive models for photovoltaic electricity production in hot weather conditions," *Energies*, vol. 10, no. 7, p. 971, 2017.

[6] J. R. Andrade and R. J. Bessa, "Improving renewable energy forecasting with a grid of numerical weather predictions," *IEEE Transactions on Sustainable Energy*, vol. 8, no. 4, pp. 1571–1580, 2017.

[7] M. Sharifzadeh, A. Sikinioti-Lock, and N. Shah, "Machine-learning methods for integrated renewable power generation: A comparative study of artificial neural networks, support vector regression, and Gaussian process regression," *Renewable and Sustainable Energy Reviews*, vol. 108, pp. 513–538, 2019.

[8] P. K. Gade, "MLOps pipelines for GenAI in renewable energy: Enhancing environmental efficiency and innovation," *Asia Pacific Journal of Energy and Environment*, vol. 6, no. 2, pp. 113–122, 2019.

[9] R. K. Karduri, "The role of artificial intelligence in optimizing energy systems," *International Journal of Advanced Research in Management Architecture Technology & Engineering (IJARMATE)*, Feb. 2019.

[10] S. Al-Dahidi, O. Ayadi, M. Alrbai, and J. Adeeb, "Ensemble approach of optimized artificial neural

networks for solar photovoltaic power prediction," *IEEE Access*, vol. 7, pp. 81741–81758, 2019.

[11] S. K. Jha, J. Bilalovic, A. Jha, N. Patel, and H. Zhang, "Renewable energy: Present research and future scope of artificial intelligence," *Renewable and Sustainable Energy Reviews*, vol. 77, pp. 297–317, 2017.

[12] S. M. Zahraee, M. K. Assadi, and R. Saidur, "Application of artificial intelligence methods for hybrid energy system optimization," *Renewable and Sustainable Energy Reviews*, vol. 66, pp. 617–630, 2016.

[13] T. Brahimi, "Using artificial intelligence to predict wind speed for energy application in Saudi Arabia," *Energies*, vol. 12, no. 24, p. 4669, 2019.

[14] U. K. Das et al., "Forecasting of photovoltaic power generation and model optimization: A review," *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 912–928, 2018.

[15] X. Zhao, C. Wang, J. Su, and J. Wang, "Research and application based on the swarm intelligence algorithm and artificial intelligence for wind farm decision system," *Renewable Energy*, vol. 134, pp. 681–697, 2019.