Predicting Renewable Energy Production Based on Climate Conditions

LITERATURE REVIEW

Renewable energy integration into power systems and energy dependability establishment requires precise predictions of renewable energy outputs from weather-dependent factors. Lack of advance forecasting methods is necessary because renewable energy resources such as solar and wind create inherent prediction difficulties caused by atmospheric conditions.

The elements which affect solar radiation at Earth's surface include cloud cover aerosols and water vapor that collectively determine atmospheric conditions as a primary solar energy output factor. PV system output forecasting depends heavily on precise predictions of these characteristic variables. Scientists have proved that linking solar energy prediction algorithms with weather forecasting models enhances the accuracy level of solar power generation forecasts (Meenal, R., et al., (2022)).

Wind energy production depends on the direction and speed of wind among meteorological elements. Accurate forecasting models are essential because wind patterns remain difficult to predict therefore they produce unreliable power output expectations. Wind energy production connected to weather patterns has been studied using two machine learning methods known as deep neural networks (DNNs) as well as artificial neural networks (ANNs). The models identify historical patterns by analyzing previously collected data to generate precise forecasting outcomes (Gaamouche, R., et al., (2022).).

Machine learning allowed the forecasting of renewable energy to advance due to its power to examine large datasets and recognize complex relationships. Multiple machine learning techniques have merged into hybrid models for the purpose of improved prediction accuracy. Randomization-based machine learning methods achieve top ratings for renewable energy prediction models because they deliver both quick computational speed and advanced accuracy (Del Ser, J., et al., (2021)).

The generation of renewable energy demands probabilistic forecasting models so experts can deal with prediction uncertainties. Through Gaussian Process Regression (GPR) models probabilistic predictions of solar production become possible while meteorological variables enter the model as uncertain inputs. The probabilistic models evaluate uncertainty through a

predictive framework which enhances grid management decisions (Najibi, F., Apostolopoulou, D., & Alonso, E. (2020)).

Renewable energy output depends heavily on the seasonal changes of climate patterns. Research conducted by scientists confirmed that regional solar and wind production anomalies result from large-scale atmospheric circulation patterns that teleconnection indices can track. Experts confirm models that predict renewable energy generation based on seasonal variables show positive skills levels (Lledó, L.,et al., (2022)).

Energy management systems need advanced forecasting models to achieve the highest possible use of renewable resources. The reduction of fossil fuel usage alongside enhanced grid stability comes from better scheduling of energy delivery and storage which accurate forecasts make possible. Sustainable growth of renewable energy sectors depends on the development of adaptable forecasting models because weather patterns are changing because of climate change effects.

Knowledge of the complex interaction between weather conditions and power output remains vital for predicting renewable sources of energy generation according to environmental conditions. Power network integration of renewable energy sources became more successful because probabilistic modeling and machine learning technologies enabled significant improvements in forecasting accuracy. Active research and development work in this area helps tackle the problems that arise due to climate variations and supports long-lasting energy sustainability.

LITERATURE GAP

Meenal, R., Binu, D., Ramya, K. C., Michael, P. A., Vinoth Kumar, K., Rajasekaran, E., & Sangeetha, B. (2022). The article presents a comprehensive review of weather forecasting for renewable energy system applications. Archives of Computational Methods in Engineering. State of the Art Reviews, 29(5), 2875–2891. https://doi.org/10.1007/s11831-021-09695-3

The main emphasis of the reviewed work lies in AI applications toward energy efficiency though it fails to provide concrete methods to forecast renewable energy generation. The research demonstrates AI potential in climate solutions yet fails to deliver an actual framework to estimate solar and wind energy generation through climate factor analysis. The system does not present solutions for immediate model deployment within interactive decision-making platforms.

The project solves these challenges through energy forecast development using ML models and weather factor identification and time-series forecasting implementation alongside result visualization within a

user-friendly dashboard. Every aspect of the project involves measuring economic performance with environmental analysis tracking.

Lledó, L., Ramon, J., Soret, A., & Doblas-Reyes, F.-J. (2022). European renewable energy production can be predicted seasonally through the use of four teleconnection indices. In arXiv [physics.soc-ph]. http://arxiv.org/abs/2202.02258

Many European countries face an increasing reliance on wind power and solar power in their electricity systems so reliable operations demand accurate predictions of renewable energy output across various time frames. Seasonal supply and demand equilibrium in the region primarily depends on widespread atmospheric flows yet their future uncertainty results from both climate fluctuations and natural variations. Four teleconnection indices operate as remote atmospheric indicators that depict large-scale European atmospheric patterns across the seasonal timescale. Dynamical forecasts of teleconnection indices enable the prediction of renewable generation at country level with positive skill levels while demonstrating the relationship between teleconnections and wind and solar generation anomalies at the country and regional levels. The model demonstrates how the general circulation with teleconnection states drives the simultaneous behavior patterns of wind and solar generation across European countries.

Gaamouche, R., Chinnici, M., Lahby, M., Abakarim, Y., & Hasnaoui, A. E. (2022). Machine learning techniques for renewable energy forecasting: A comprehensive review. In Green Energy and Technology (pp. 3–39). Springer International Publishing.

The research paper organizes studies about machine learning for renewable energy projections but fails to show technical execution methods along with measurement criteria and measurements of practical effects. The study fails to determine climate variable impact strength and achieves minimal optimization for short-term predictive models. There are no plans mentioned for interactive visualization solutions that benefit stakeholders. The research fills important knowledge gaps by creating an exact model for solar and wind energy forecasting and examining major weather factors along with designing advanced time-series prediction tools and developing a real-time monitoring platform. An economic evaluation with environmental assessment provides essential practical information for renewable energy management decisions.

Del Ser, J., Casillas-Perez, D., Cornejo-Bueno, L., Prieto-Godino, L., Sanz-Justo, J., Casanova-Mateo, C., & Salcedo-Sanz, S. (2021). Randomization-based Machine Learning in renewable energy prediction problems: Critical literature review, new results and perspectives. In arXiv [cs.LG]. http://arxiv.org/abs/2103.14624

The examined research paper devotes its main focus to randomization-based machine learning tools for renewable energy prediction without extending coverage to all relevant project objectives. The paper fails to provide extensive knowledge on four fundamental aspects including climate variable analysis,

time-series prediction development, real-time monitoring technology integration and economic and environmental result evaluation. The research will combine SHAP and PCA as feature importance tools alongside LSTM and Transformer forecasting models as well as a real-time dashboard alongside case study assessments featuring cost savings and carbon reduction analysis.

Reference	Key Focus of the Study	Identified Gaps	How the Project Addresses
Meenal et al. (2022)	AI applications for energy efficiency in renewable systems.	 Lacks concrete methods for forecasting renewable energy generation. Does not analyze climate factors for energy prediction. No model deployment within interactive decision-making platforms. 	 the Gaps Develops ML-based energy forecasting models for solar and wind energy. Identifies key climate factors influencing renewable energy production. Implements an interactive dashboard for real-time decision-making.
Lledó et al. (2022)	Seasonal renewable energy prediction using teleconnection indices.	 Focuses on large-scale atmospheric patterns rather than specific climate variables. Does not provide short-term forecasting models. Lacks a real-time implementation approach. 	 Incorporates short-term forecasting models (LSTM, Transformer). Identifies key weather variables impacting renewable energy output. Develops real-time monitoring and forecasting dashboard.
Gaamouche et al. (2022)	Review of ML techniques for renewable energy forecasting.	 No technical implementation details for ML models. Fails to measure climate variable impact strength. No optimization for short-term forecasts. No interactive visualization for stakeholders. 	 Implements feature selection (SHAP, PCA) to analyze climate variable importance. Develops optimized short-term forecasting models (LSTM, Transformer). Designs an interactive dashboard for real-time monitoring.
Del Ser et al. (2021)	Randomization-based ML for renewable energy prediction.	 Does not cover climate variable analysis. Lacks time-series forecasting models. No real-time monitoring or interactive solutions. No economic or environmental impact assessment Uses SHAP and PCA for climate variable analysis. 	 Implements time-series forecasting models (LSTM, Transformer). Develops a real-time dashboard. Conducts economic and environmental impact assessments.

DataSet

The project adopts different methods from Teo Wai Hong's dataset through enhanced feature engineering with supplemental weather measurements while adding a real-time monitoring platform. MSE and MAE with Spearman correlation analysis as the main focus of Teo Wai Hong's study contrasts with our research that investigates various models starting from Transformers and performing comparative assessments. Our project focuses on hyperparameter optimization together with explainable SHAP analysis and assessments of economic along with environmental effects. The dataset was obtained from Kaggle and contains 196,776 rows of information that encompasses multiple weather elements and power characteristics. The practical application for decision support in renewable energy operations takes precedence in our approach through user-friendly visual interfaces despite following prior research.

References

Del Ser, J., Casillas-Perez, D., Cornejo-Bueno, L., Prieto-Godino, L., Sanz-Justo, J., Casanova-Mateo, C., & Salcedo-Sanz, S. (2021). Randomization-based Machine Learning in renewable energy prediction problems: Critical literature review, new results and perspectives. In *arXiv* [cs.LG]. http://arxiv.org/abs/2103.14624

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