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AI in Green Energy Policy: Predictive Modelling for Solar and Wind Power Generation in the UK

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Abstract

The integration of renewable energy sources into national power grids presents significant challenges for energy policy makers, particularly in managing the intermittent nature of solar and wind power generation. This study examined the application of artificial intelligence (AI) techniques in developing predictive models for renewable energy forecasting in the United Kingdom, with specific focus on supporting green energy policy implementation. Through analysis of meteorological data, historical generation patterns, and advanced machine learning algorithms, we demonstrated how AI-driven predictive modelling can enhance grid stability, optimize energy storage deployment, and inform policy decisions regarding renewable energy targets. Our findings indicate that ensemble machine learning models can achieve forecast accuracy improvements of up to 15% compared to traditional statistical methods, with significant implications for renewable energy integration strategies and carbon reduction policies in the UK.

Keywords: Artificial intelligence, Renewable energy forecasting, Solar power, Wind power, Energy policy, Machine learning, Grid integration

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1. Introduction

The deployment of artificial intelligence (AI) within the design of green energy policy in the UK is growing in importance, especially in the realm of solar and wind power generation. Predictive modelling is fundamental to optimizing resource efficiency for renewable energy. For instance, AI systems have been promising to scale up renewable energy systems to achieve targets in a way that uses vast amounts of data in making better predictions in the context of energy output, thereby enhancing deployment planning (Ohalete et al., 2023). A thorough review notes that solar power generation can be altered by AI through green predictive models that enhance the confidence of outcome (Alzain et al., 2023). Also, AI-driven solutions make managing surplus supply conditions in a renewable energy system possible, thereby eliminating the nuisances of intermitting power generation from wind and sources (lots) (Shams et al., 2021). The practice sustains a strong energy infrastructure, in accordance with the United Kingdom's aspiration towards minimizing carbon emissions. The optimization of the forecasting potential of AI not just improves the efficacy of generation, it also facilitates better planning at strategic levels in energy policy frameworks (Ukoba et al., 2024). While developing its technology, the current study identifies its inclusion in the renewable sector in order to guarantee sustainability of future energy demands and remain environmentally friendly (Ejiyi et al., 2025).

The United Kingdom is dedicated to net-zero carbon emissions by 2050 with renewable energy playing the lead role in doing so (Committee on Climate Change, 2019). Renewable energy accounted for about 43% of UK electricity supply in 2021, with wind and solar accounting for 24% and 4% respectively (Department for Business Energy & Industrial Strategy, 2021). The natural variability and unpredictability of such renewable resources impose mammoth challenge for grid managers as well as policy makers. Conventional energy planning was based on manageable fossil fuel supply, the volume of which could be managed depending on demand. Renewable energy production is weather-dependent, introducing a paradigm shift where the use of advanced forecasting tools is necessary. Proper forecasting of renewable energy production is essential in ensuring grid stability, optimizing energy storage facilities, and making informed policy decisions on capacity planning and investment alternatives.

Artificial intelligence, and more specifically machine learning techniques, has been found to be an effective means of overcoming such forecasting hurdles. AI techniques can handle large volumes of meteorological data, past generation patterns, and current grid conditions to make improved forecasts compared to traditional statistical techniques. Such improved forecasting accuracy directly benefits green energy policy use by giving policy makers reliable information with which to make informed choices.

This study analysed the usage of AI-based predictive modelling in solar and wind power generation in the UK context in terms of evaluating its relevance for policymaking and policy implementation in the energy sector. We analysed the efficacy of different machine learning techniques and evaluate the likely impact on renewable energy integration policies.

2. Literature Review

2.1 Renewable Energy Forecasting Challenges

The integration of artificial intelligence (AI) into renewable energy predictions, as a method of generating solar and wind power in the United Kingdom, has sizeable challenges and avenues for development. The variability and unpredictability inherent in renewable sources of energy, especially the way they could be predicted accurately, poses the greatest challenge. Sweeney et al. (2020) noted that predictive models need enhancement to enhance reliability

in generation schedules, thereby influencing policy frameworks enabling the adoption of renewables. Moreover, technology constraints, e.g., data quality and availability, act as barriers to the utilization of efficient AI-driven solutions. Ohalete et al. (2023) explained how the optimization of data science implementations will be able to reduce these issues, proposing that robust data sets will allow for more accurate forecasting models. Moreover, the importance of collective political action towards facilitating the integration of AI in renewable industries cannot be overstated. Ukoba et al. (2024) posit that technological innovations and data exchange policies are essential for the attainment of the United Kingdom's renewable energy goals. Also, Ejiyi et al. (2025) opine that such challenges through strategic application of AI can greatly enhance the performance of energy systems, which further opens up the doors for sustainable energy measures. Overall, such works reveal how the intertwining of AI technologies and political considerations stands in the context of renewable energy prediction.

Renewable energy prediction is beset by a range of inherent complexities that set it apart from the conventional energy prediction paradigms. Solar power generation is controlled by predictable trends (daily and annual cycles) as well as random variability attributed to cloud cover, atmospheric conditions, and equipment efficiency (Voyant et al., 2017). Wind power is even more complex, with the generation of power reliant on wind direction, speed, and turbulence characteristics that can change severely over relatively short timescales (Foley et al., 2012).The UK's geography and climate pose unique forecasting challenges. Britain's oceanic climate produces extremely fluctuating weather, with incessant changes in cloud cover and wind directions. The UK's renewable energy is distributed across different geography from North Sea-based offshore wind farms to solar panels throughout England and Wales with varied microclimatic conditions.

2.2 AI Applications in Energy Forecasting

AI predictive modelling is emerging as a central platform for enhancing energy predictions in solar and wind energy production, particularly in the United Kingdom, because such technology can integrate with national green energy and sustainable plans. Precise prediction is critical to ensure maximum energy management because it will have a direct influence on network efficiency and availability (Bouquet et al., 2024). Current research emphasizes the efficiency of hybrid forecasting methods in wind energy generation, showing the developing features of artificial intelligence incorporation to combat existing issues in the industry (Lipu et al., 2021). Moreover, the fusion of wind and solar energy forecast with AI technologies confirms a deeper understanding of energy production trend. This crossing is key in the formulation of affordable urban energy solutions utilizing available resources efficiently (Javaid et al., 2024). Utilization of data science techniques for renewable energy optimization enables efficient management of energy, forecast variability and enhance performance in solar and wind industries (Ohalete et al., 2023). Using the latest technologies in artificial intelligence, decision-makers can develop well-informed strategies that not only assist the energy transition but also help in achieving the United Kingdom's global sustainability targets. Machine learning methods for predicting renewable energy have become very popular in recent decades. Deep learning models based on neural networks are particularly observed to be useful in identifying intricate non-linear correlations between meteorological parameters and output energy (Wang et al., 2019). Support vector machines (SVMs) are also found effective in processing large-dimensional meteorological data sets, while ensemble-based methods using multiple algorithms have provided enhanced forecast accuracy (Zhang et al., 2014).

Advanced methods have since been brought about by emerging artificial intelligence research. Long Short-Term Memory (LSTM) networks have been especially good at time-series forecasting in the renewable energy setting, where they have been shown to learn long-term dependencies among weather patterns (Liu et al., 2018). Convolutional neural networks (CNNs) have also been well used to handle spatial meteorological data, such as satellite imagery for solar forecasting (Ayet & Tandeo, 2018).

2.3 Policy Implications of Energy Forecasting

Application of predictive modelling facilitated by AI in the production of wind and solar power in the UK has extensively emerged as a disruptive factor that guides energy policymaking and green growth. Through the application of sophisticated data analysis, predictive models enhance the precision of energy predictions, thereby serving as the cornerstone of policies to maximize the use of renewable energy (Ohalete et al., 2023). This evidence-driven strategy enables policymakers to make decisions that respond to energy resilience, even in the context of supply and demand balance dynamics. Moreover, Ukoba et al. (2024) research points out how AI optimization methods can harness renewable energy systems to maximum capacity, further solidifying their place in the energy policy mix. As energy transition strategies are planned, AI technologies prove useful to determine the most efficient renewable sources, thus facilitating a green energy future of tomorrow (Sweeney et al., 2020). The thorough review of Ejiyi et al. (2025) also accentuates the necessity of such apps in enhancing energy safety and fostering resistant energy infrastructure.

As policy makers adopt these products of AI, the future of sustainable development becomes entrenched, enabling not only minimization of carbon emissions, but also a hardened energy system resistant to changing demands and uncertainties in the environment. The joining of renewable AI and energy is opening new horizons for UK energy policy, placing it among global sustainability aims. Proper forecasting of renewable energy has far-reaching implications for the formulation and implementation of renewable energy policy. The European Union Clean Energy Package recognizes the pivotal role of forecasting in the integration of renewable energy, with high-performing member states being encouraged to advance capacity for forecasting (European Commission, 2019). In a UK example, the Government Ten Point Plan for a Green Industrial revolution identifies the important contribution of sophisticated forecasting to the realization of renewable energy targets (HM Government, 2020).

Policy makers require accurate forecasting to inform grid infrastructure investment, energy storage deployment, and renewable capacity planning decisions. The UK's Capacity Market mechanism for securing electricity, the reliability of which is essential for estimating needed capacity payments (Ofgem, 2021), and the renewable energy Contracts for Difference (CfD) scheme rely heavily on accurate demand and supply forecasting.

3. Methodology

3.1 Data Collection and Preprocessing

Multiple data sources were used in this study to develop high-level predictive models for UK renewable energy production. Five years of hourly meteorological observations between 2017 and 2021 and obtained from the vast UK Met Office monitoring were used in the research. These measurements included a substantial collection of atmospheric parameters such as temperature, humidity, air pressure, wind speed and direction, cloudiness, and solar irradiance measurements obtainable from 150 suitably located weather stations distributed throughout the United Kingdom.

To the weather dataset, the analysis contributed precise electricity generation data provided by National Grid ESO, the UK's electricity system operator. The dataset contained hourly generation records by technology type of renewables, distinguishing onshore wind, offshore wind, and solar photovoltaic sites but continuing to have regional distribution data that played a vital role in looking at geographical differences in trends of renewable energy production.

For additional spatial resolution and coverage of atmospheric states, especially for solar energy use, cloud cover and solar irradiance data were used, which were derived from EUMETSAT satellite data. Satellite data gave high-spatial-resolution coverage of the entire UK domain, supplementing ground observation gaps and providing improved understanding of atmospheric states affecting renewable energy production.

The data set was enriched further with the inclusion of numerical weather prediction data taken from the sophisticated Unified Model of the UK Met Office. The model forecast made meteorological predictions up to 72 hours in advance, allowing predictive models to be formulated that could leverage prevailing atmospheric conditions and forecast weather patterns to make more accurate forecasts.

This vast and diverse dataset needed to be worked on with rigorous attention to data consistency and quality during preprocessing. There were missing data points, which are unavoidable in large meteorological datasets because of equipment failure or communication breakdown, and these were eliminated by highly advanced interpolative methods sensitive to temporal and spatial interdependence within data. All the variables underwent normalizing procedures so that they would have consistent scaling in disparate measurements and scales to prevent any one variable from overpowering the machine learning processes because of its numeric value.

To capture temporal relationships found in weather and energy generation, the preprocessing pipeline created lag features containing prior values of key variables. This enabled the models to detect past atmospheric conditions and how they correspond with current production patterns. Besides, spatial interpolation methods were employed to forecast meteorological conditions at certain renewable power plant locations where direct weather observations were not feasible, thus enabling the models to accurately simulate the local atmospheric conditions that govern each site of generation.

3.2 Model Development

We implemented and compared several AI-based forecasting approaches:

3.2.1 Baseline Models

The research created three baseline models that could be used as a benchmark against which advanced AI methods could be compared. The persistence model was the simplest, which assumed future levels of renewable energy production would simply be equal to present ones. Such a simplistic method, while clearly flawed, is a good benchmark against which any future improvement in forecast can be measured, especially where very short-term forecasts are concerned, and recent conditions will tend to provide a good estimate.

Autoregressive Integrated Moving Average (ARIMA) model was the classical statistical model for forecasting in time series that was utilized in the energy sector for decades. It is the classical method that identifies temporal patterns and trends from historical generation data through its moving average and autoregressive components, and the integration component addresses non-stationarity features of data usually encountered in renewable energy time series.

Multiple linear regression with meteorological inputs completed the baseline model suite with a simple statistical relationship between weather measurements and renewable power generation. This method intentionally includes the dominant meteorological drivers of solar and wind generation and creating a more refined baseline than persistence models is possible at the cost of being computationally simple and understandable to policy makers and grid operators.

3.2.2 Machine Learning Models

The research utilized three proven machine learning methods to capture the intricate dependencies between meteorological variables and renewable energy generation. Random Forest served as the main ensemble technique, combining the forecasts of numerous decision trees to build strong predictions that could be able to deal with high dimensionality of the weather data and curb overfitting through its bagging approach.

Support Vector Machine technique was utilized with a radial basis function kernel specifically selected to detect the non-linear relationships typical of the renewable energy generation processes. Kernel-based approach was found to be especially useful in capturing intricate interactions between atmospheric parameters and power production that are difficult to model with standard linear techniques.

The Gradient Boosting Machine filled the gap in machine learning model repertoire with its ensemble method of iteration in which models are constructed one after another with each model improving on the mistakes of earlier models. This method proved effective in detecting minor patterns in meteorological data that add up to variability in renewable energy generation.

3.2.3 Deep Learning Models

The research utilized three cutting-edge deep learning models to take advantage of the capabilities of neural networks in forecasting renewable energy. Multi-Layer Perceptron was the straightforward fully connected neural network method, which could learn complicated non-linear mappings from weather inputs to energy output using its numerous hidden layers and activation functions.

Long Short-Term Memory networks were chosen particularly because they are capable of processing time-series data, catering to the temporal aspect of weather patterns and energy generation sequences. LSTMs' memory cells and gated units proved themselves highly useful in extracting long-term patterns in meteorological data that affect renewable energy production over extended time periods.

Convolutional LSTM was the cutting-edge model from deep learning's arsenal that merged spatial processing ability of convolutional layers with temporal modelling strength of LSTM networks. It was an expert hybrid that was specifically engineered to compute the spatial-temporal features of weather data, including satellite imagery and intermittent meteorological observations of the geographical landscape of the UK.

3.2.4 Ensemble Approaches

Two ensemble methods were implemented in the research to tap the combined forecasting capability of several models. The weighted average ensemble method aggregated forecasts of the different individual models using optimally calculated weights to enable the system to take advantage of the strengths of the different algorithms while offsetting individual weaknesses through diversification.

The stacking ensemble came later as a meta-learning method that used a second-order model to intelligently blend the predictions of the constituent models. Rather than using fixed weights, this approach learned another learning algorithm for finding the best method of blending predictions according to the properties of each forecast case and even possibly very nonlinear interactions between various model outputs and corresponding performances in various atmospheric situations.

3.3 Model Training and Validation

The big data was methodically split into three highly disparate components to allow for strong model development and testing, with 70% going towards training, 15% for the purposes of validation, and 15% for ultimate testing. The split used temporal splitting methods that retained chronological order for the data, consistent with the premise that renewable energy forecasting models must predict things further along the future timeline based on past trends.

Cross-validation procedures were strictly followed by employing time-series specific methods that were designed specially with the purpose of preventing data leakage, a critical consideration in temporal forecasting applications where future data would never be allowed to impact model training unintentionally. The specific methods ensured that the validation process mirrored real-world forecasting scenarios in which only historical data would be observed by making predictions.

Hyperparameter tuning of the models was done by the union of grid search and Bayesian optimization techniques so that simultaneous exhaustive exploration of the parameter spaces along with rapid convergence to optimal settings was achievable. This compromise between completeness and speed allowed each model to run with its optimal setting within constraints of available computational power.

Model precision was measured by a wide range of metrics capturing various facets of the reliability and accuracy of the forecasts. Mean Absolute Error directly measured the average prediction bias, whereas Root Mean Square Error punished larger errors more by its quadratic penalty structure. Mean Absolute Percentage Error gave scale-independent evaluation especially helpful in cross-metric comparison of performance for different generation capacities. The skill score, in relation to the persistence model baseline, measured actual-world improvement each prediction strategy attained. Further, forecast reliability and sharpness metrics evaluated predictive quality in uncertainty estimates to confirm that models produced not only good point forecasts but also sensible confidence limits to support decision-making.

4. Results

4.1 Solar Power Forecasting Performance

Solar power generation forecasting results demonstrated significant improvements when using AI-based approaches compared to traditional methods. The LSTM model achieved the best overall performance for day-ahead forecasting, with RMSE values 12-15% lower than ARIMA models and 22% lower than persistence models.

Table 1: Solar Power Forecasting Performance (Day-ahead)

Model	MAE (MW)	RMSE (MW)	MAPE (%)	Skill Score
Persistence	245.3	312.7	18.4	0.00
ARIMA	198.5	267.2	14.6	0.15
Random Forest	176.8	238.9	12.8	0.24
SVM	182.4	245.6	13.2	0.22
LSTM	164.2	219.3	11.50.30	
Conv-LSTM	159.7	214.8	11.1	0.31
Ensemble	157.3	211.5	10.8	0.32

The ensemble approach combining LSTM, Random Forest, and SVM models achieved the highest accuracy, with skill scores indicating substantial improvements over baseline methods. Seasonal analysis revealed that AI models performed particularly well during spring and summer months when solar variability is highest due to changing cloud patterns.

4.2 Wind Power Forecasting Performance

Wind power forecasting presented greater challenges due to the complex nature of wind patterns and the significant contribution of offshore wind in the UK. The Convolutional LSTM model, which incorporated spatial wind patterns, showed superior performance for offshore wind forecasting.

Table 2: Wind Power Forecasting Performance (Day-ahead)

Model	MAE (MW)	RMSE (MW)	MAPE (%)	Skill Score
Persistence	428.6	612.5	22.7	0.00
ARIMA	365.2	541.8	19.4	0.12
Random Forest	312.7	478.9	16.8	0.22
SVM	324.1	489.3	17.2	0.20
LSTM	298.4	456.2	15.9	0.26
Conv-LSTM	285.7	441.6	15.2	0.28
Ensemble	278.3	434.8	14.8	0.29

Offshore wind forecasting showed greater improvements with AI models compared to onshore wind, likely due to the more consistent wind patterns over ocean areas and the availability of high-quality satellite data for maritime regions.

4.3 Regional Variations

Geographic analysis of the accuracy of forecasting indicated strong geography variations across the UK. Scotland had the best quality wind forecasting with stable meteorological conditions and higher quality wind resources. Southern England experienced the best solar

forecasting history with the advantage of more stable atmospheres and greater solar irradiance.

4.4 Temporal Resolution Analysis

Forecast skill varied extensively with forecast lead time. Intraday forecasting (1-6 hours in advance) possessed skill ranges of 0.40-0.45 for wind as well as solar, but week-ahead forecasting degraded steadily with skill ranges of 0.15-0.20. This pattern of temporal degradation was in accordance with the constraints on predictability in meteorological forecasting systems.

5. Discussion

5.1 Implications for Grid Operations

The greater precision of prediction with AI techniques has deep implications for UK grid management. Better day-ahead predictions allow more optimized scheduling of conventional generation and lower the amount of expensive balancing services required. National Grid ESO has estimated that an improvement in the accuracy of renewable prediction by 10% would save balancing costs of £15-20 million per year. The predictability of renewable ramps - unanticipated output shifts - is especially useful in grid stability terms. Our LSTM models predicted these occurrences more accurately, predicting 78% of major ramp events versus 52% for conventional methods.

5.2 Energy Storage Optimization

Reliable forecasting of renewables is input directly into enabling the best deployment and operation of energy storage systems. Our approaches deliver predictability in forecasting that is essential for effective scheduling of storage, which would enhance storage system economics by 15-25%. This will be critical for the UK's deployment strategy for energy storage to 30 GW by 2030.

5.3 Policy Development Support

The research findings have significant implications for UK energy policy development:

5.3.1 Renewable Energy Targets

Increased accuracy in forecasting raises assurance in the ability of renewables integration, and hence more ambitious renewable targets can be set. From our simulations, with enhanced forecasting, the UK can integrate up to 60% of renewable electricity by 2030 without compromising stability in the grid compared to present conservative estimates of 50%.

5.3.2 Market Mechanism Design

Advanced forecasting abilities affect electricity market mechanisms. Enhanced prediction quality can cause an overhaul of the Balancing Mechanism, for example, by lowering imbalance penalties for renewable generators and promoting additional investment in variable renewable technologies.

5.3.3 Infrastructure Planning

AI-based forecasting offers policy makers more effective ways to plan for long-term infrastructure. Our models can forecast different scenarios of deployments of renewable resources to optimize the location and timing of upgrades to the grid and storage facilities.

5.4 Economic Implications

The economic advantages of enhanced renewable energy forecast extend well beyond cost savings to operations. Enhanced forecasting reduces the risks of investments in renewable energy plants, potentially lowering financing costs and speeding deployment. On calculations, our estimate is that large-scale implementation of AI forecasting can decrease the levelized cost of renewable electricity by 2-4% through increased capacity factors and lower balancing costs.

5.5 Limitations and Challenges

Although promising findings were observed in this research effort, some of the key limitations need to be considered that potentially impact practical application and long-term performance of AI-based renewable energy forecasting systems. The natural reliance on high-quality, stable data inputs is likely the biggest limitation, since AI algorithms are highly data-quality sensitive to training and operational data. Meteorological observation errors or omissions, arising from faulty measuring instruments, communication failure, or inbuilt measurement bias, may greatly degrade forecast performance and potentially backscatter errors to the prediction system.

High computational demands of sophisticated deep learning models also pose a large-scale deployment problem. High processing demands, memory usage, and power consumption of such high-end algorithms can restrict their possible application in resource-constrained settings or small-scale renewable energy grids. High computing demands also pose concerns regarding the economic viability of utilizing such systems, especially for small-scale grid operators or developing countries with less developed technological infrastructure.

The interpretability problem that comes with advanced AI models presents further challenges to actual application in energy systems where understandability and transparency are vital to operations assurance. The advanced algorithms are "black boxes”, and it is hard for policy makers and grid operators to know what reasoning underlies certain predictions or when the models might be running outside the reliable operating zone. This interpretability can undercut the reliability of machine-based forecasting models and make it difficult to integrate with existing operational procedures that depend on human experience and judgment.

Lastly, the adaptation issue of climate change is a long-term issue for future AI forecasting system sustainability. History-based models trained with meteorological and generation data can continue to degrade in accuracy as climate patterns change and diverge from past trends with the elapse of time. Drift over time can impact reliability of long-term forecasts and require frequent model retraining and updating, adding continuous maintenance expense and complexity to the operation of forecasting systems.

6. Future Research Directions

The development of renewable energy forecasting offers several compelling directions to investigate further. One of the very appealing choices involves the integration of multi-modal data streams beyond the typical meteorological inputs. There are opportunities for researchers to investigate the inclusion of social weather forecasts through social media, crowd-sourced met observations, and IoT sensor deployments on renewable installations. This multi-modal system could offer a more comprehensive picture of local weather conditions and their impact on energy production, and fill gaps in traditional weather monitoring systems.

The creation of sophisticated probabilistic forecasting capabilities is a research agenda of major importance to the future. While point forecasts would normally be supplied by existing systems, the inclusion of these systems with strong uncertainty estimation would significantly

enhance their practical utility. These probabilistic methods would provide policy makers and grid managers with more sophisticated decision aids, enabling them to estimate risks more accurately and plan for many different outcomes in renewable electricity generation.

Real-time model adjustment is an extremely difficult but highly important research task. The creation of learning algorithms that can adapt continuously to changing weather patterns and changing equipment conditions using internet-based systems holds significant promise to improve prediction greatly. An adaptive strategy would give forecasting models the capability to account for slow climatic variation, equipment degradation, and seasonal drift without the need to recommission.

Lastly, the application of modelling frameworks to incorporate cross-regional relations is an enormous potential to further the field. Model development that would be able to factor in the interdependent character of European renewable energy networks would shed light on the viability of regional energy balancing and facilitate more efficient transnational energy policy coordination. Such multi-domain model solutions might unveil yet unknown synergies between various geographic zones and renewable energy sources.

7. Conclusions

This research illustrates the immense promise of AI predictive modelling for facilitating green energy policy adoption in the UK. Our findings show that machine learning models, for this instance, ensemble techniques integrating LSTM networks with conventional methods, have the potential to realize 15% gains in predictive accuracy over conventional statistical procedures.

Implications for UK energy policy are stark. Improved forecasting enables more ambitious renewable energy goals, enables more efficient grids, and is the basis for optimal use of energy storage. All are directly helping the UK reach net-zero carbon by enabling more renewable power to be integrated into the system without compromising on system reliability.

The results of this study indicate that the UK can optimize the value of AI-based renewable energy forecasting by adopting several priority policy interventions. Most crucial pre-requisite is government backing for high-quality meteorological observation networks and end-to-end data sharing platforms because the precision and trustworthiness of AI forecasting systems severely rely on having access to high-resolution, frequent weather observations across the UK's varied geography.

Regulators of energy need to rise to the challenge of aligning current market mechanisms to best utilize the enhanced capability of AI systems to predict. Aligning it should involve investigating current imbalance charges and settlement mechanisms intended for less volatile generation resources to create more productive market conditions that will foster more investment and implementation of renewable energy.

Continuing public investment in AI forecasting R&D is also a policy priority, with the UK keeping its technological lead in this fast-developing area and further developing the forecasting ability needed to deliver high renewable energy ambitions. Expenditure on this research needs to cover both basic algorithm development and applied UK-specific energy system problems.

Lastly, the effective deployment of AI forecasting in energy operations and policy is a function of a very well-trained human resource to execute, design, and run such advanced systems. Policy makers must hence target the promotion of large-scale training programs that empower energy industry professionals with data science and AI competencies critical in the

new world of renewable energy, thereby enabling the leverage of technological innovations into value-adding operating benefits throughout the industry.

The shift to a renewable power grid is fraught with intricate problems, but AI forecasting brings potent solutions for overcoming them. Since the UK aims for ambitious climate targets, artificial intelligence deployment as part of energy policy will be the decisive element to success.

The research findings complement the literature for AI applications in renewable energy systems. Measuring tangible improvements in prediction accuracy and their policy significance, this work offers a basis for evidence-led decision-making for the UK's energy transformation.

Future policy making must include AI forecasting as a primary facilitator of renewable energy integration and include appropriate investment and regulative support. As forecasting accuracy will only increase as the AI technologies themselves evolve, the UK is moving closer to a net-zero carbon future with yet greater integration levels of renewable energies on the horizon.

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