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AI-Driven Forecasting Models for Solar and Wind Power Generation in Smart Grids

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Abstract:- The integration of distributed renewable energy sources into smart grids poses complex challenges for the stability, reliability, and economic operation of the grid. Accurate forecasting of the generation of these energy sources is essential for effective energy management, dispatching, and market operations. In this paper, a detailed review and conceptual framework of AI-driven forecasting models for solar and wind power generation in the context of smart grids is presented. We study various artificial intelligence (AI) techniques such as machine learning (ML) and deep learning (DL) algorithms, and discuss their features and applications in short-term, medium-term, and long-term forecasting. Key issues such as data acquisition, preprocessing, feature engineering, model selection, and performance evaluation are discussed in depth. The impact of meteorological data, sensor networks and advanced data analytics on forecasting accuracy is also discussed in this paper. In addition, the problems associated with variability and uncertainty in renewable energy generation are also studied, and hybrid AI models and uncertainty quantification methods are suggested as solutions. This paper provides a comprehensive overview of the state-of-the-art development of AI-based renewable energy forecasting and suggests future research directions, so that easy and efficient inclusion of renewable energy in smart grids will be possible in the future.

Keywords*: Machine Learning, Deep Learning, Solar Power Forecasting, Wind Power Forecasting, Smart Grid, Renewable Energy, Energy Management*

1 Introduction

The rapid global shift towards sustainable energy systems has led to the increasing use of renewable energy sources (RES), mainly solar photovoltaic (PV) and wind power. These RES systems are promising alternatives to conventional fossil fuels, as they play a key role in

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reducing carbon emissions and increasing energy independence. However, the inherently intermittent and variable nature of these sources, which is dependent on uncertain weather conditions, creates many technical complexities for power system operators [1], [2].Accurate and reliable forecasting of solar and wind power generation is essential for the stable and efficient operation of modern smart grids [3], [4].Smart grids are equipped with bidirectional communication, advanced sensing capabilities, and intelligent control mechanisms, which provide the necessary infrastructure for high-scale integration of RES. Against this backdrop, AI-driven forecasting models play a crucial role by transforming raw meteorological and historical generation data into actionable predictions [5], [6].These forecasts help grid operators optimize power dispatch, manage energy storage, participate efficiently in the electricity market, and avoid grid imbalances — thereby improving the reliability and economic viability of the entire power system. This paper presents a detailed study of AI-driven forecasting models used in smart grids for solar and wind power generation. First, the need for accurate forecasting is highlighted, followed by a detailed introduction to various AI techniques. In the following sections, the required data types, model architectures, and performance metrics are discussed in detail. Finally, the study aims to contribute to the advancement of intelligent energy management systems by considering current challenges and future research directions in this field [16], [17].

2 Necessity for Accurate Renewable Energy Forecasting in Smart Grids

The integration of high levels of solar and wind power into electricity grids necessitates highly accurate forecasting for several crucial reasons:

2.1 Grid Stability and Reliability

The intermittent nature of solar and wind power can lead to significant fluctuations in power supply, potentially causing frequency and voltage deviations, and even grid instability if not properly managed [4]. Accurate forecasts allow grid operators to anticipate these fluctuations and take proactive measures, such as adjusting dispatchable generation, activating demand response programs, or utilizing energy storage systems, to maintain grid balance and ensure reliable power supply.

2.2 Economic Dispatch and Market Operations

Electricity markets operate on the principle of supply and demand. Inaccurate forecasts can lead to imbalances, resulting in higher operational costs, penalties for deviation from committed schedules, and increased need for costly reserve power [1]. Precise forecasts enable utilities and renewable energy producers to:

- Optimize scheduling and dispatch of power.
- Make informed bidding decisions in day-ahead and real-time markets.

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- Minimize balancing costs and maximize revenue.

2.3 Energy Storage Management

Energy storage systems such as batteries play a crucial role in reducing the variability of renewable energy. Accurate forecasts of future generation and demand are essential when determining the appropriate charging and discharging strategies for these systems. Forecasting allows for efficient use of storage capacity — meaning that energy can be stored when generation is high and used when it is needed.

2.4 Network Management and Congestion Avoidance

Forecasting helps in predicting localized power surpluses or deficits, which can lead to network congestion. With accurate forecasts, grid operators can anticipate potential congestion points and implement remedial actions, such as redispatching generation or reconfiguring the network, to prevent bottlenecks and ensure efficient power delivery.

2.5 Maintenance Scheduling

For large-scale renewable energy plants, accurate generation forecasts can also assist in planning maintenance activities during periods of low expected generation, thereby minimizing lost revenue and maximizing operational efficiency. In summary, accurate forecasting transforms renewable energy's variability from a challenge into a manageable asset, enabling smarter, more resilient, and cost-effective energy systems.

3 AI Algorithms for Renewable Energy Forecasting

The increasing availability of historical generation data, meteorological information, and advanced computing capabilities has propelled Artificial Intelligence (AI) to the forefront of renewable energy forecasting. Both traditional Machine Learning (ML) and more advanced Deep Learning (DL) techniques have shown remarkable success.

3.1 Machine Learning (ML) Algorithms

ML algorithms are well-suited for modeling complex non-linear relationships between meteorological variables and power output.

•Support Vector Machines (SVM): SVMs are effective for both regression (for continuous power output) and classification (for categorical states like high/low generation). They are robust to outliers and perform well with limited training data.

•Random Forest (RF): An ensemble learning method, RF constructs multiple decision trees during training and outputs the average prediction (for regression) or mode (for classification). RF is robust to noise, handles non-linear relationships, and provides feature importance, which is useful for identifying key meteorological drivers [7].

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•Gradient Boosting Machines (GBM) / XGBoost: These algorithms build models sequentially, where each new model corrects errors made by previous ones. They are highly powerful and often achieve state-of-the-art performance in struc- tured data tasks.

•Artificial Neural Networks (ANNs): Basic ANNs (e.g., Multi-Layer Percep- trons) can learn complex mappings between input features (e.g., temperature, solar irradiance, wind speed) and power output. Their effectiveness depends on network architecture and training data quality.

3.2 Deep Learning (DL) Algorithms

DL models, particularly those designed for sequential data, have shown superior performance in capturing temporal dependencies and complex patterns inherent in renewable energy time series data.

- Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) Networks: Given that solar irradiance and wind speed are time-series data, LSTMs are highly effective. LSTMs can learn long-term dependencies, mak- ing them ideal for capturing the temporal evolution of weather conditions and their impact on power generation [8], [9]. They are widely used for short-term and medium-term forecasting.

- Gated Recurrent Units (GRUs): Similar to LSTMs but with a simpler architecture, GRUs offer comparable performance with potentially faster training times.

- Convolutional Neural Networks (CNNs): While primarily known for image processing, CNNs can be adapted for time-series forecasting by treating time series as 1D spatial data. They are particularly useful for extracting local patterns and features from sequences [10].

- Hybrid Models: Combining different AI techniques often yields better results. For instance, a hybrid model might use a CNN to extract features from raw meteorological data, which are then fed into an LSTM for time-series prediction [2], [11]. Another approach involves combining decomposition methods (e.g., Empirical Mode Decomposition) with deep learning to handle non-stationary data.

3.3 Probabilistic Forecasting

Beyond point forecasts (a single predicted value), probabilistic forecasting provides pre- diction intervals or probability distributions, quantifying the inherent uncertainty in renewable energy generation [12], [13]. This is crucial for risk-averse decision-making in smart grids. Techniques include:

- Quantile Regression.
- Ensemble forecasting (e.g., combining multiple models).
- Bayesian neural networks

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Table 1: Summary of AI Algorithms for Renewable Energy Forecasting

Algorithm Type	Examples	Key Advantages for Forecasting
Traditional ML	SVM, Random Forest, XG-Boost	Robust to outliers, handles nonlinearities, feature importance, faster training
Deep Learning	LSTM, GRU, CNN, Hybrid DL	Captures complex temporal dependencies, learns hierarchical features automatically, suit- able for large datasets
Probabilistic	Quantile Regression, Ensembles	Quantifies uncertainty, provides prediction intervals, crucial for risk management

The choice of AI algorithm depends on the specific forecasting horizon (short, medium, long-term), data availability, computational resources, and the desired level of accuracy and interpretability.

4 Data Acquisition and Preprocessing

The success of any AI-driven forecasting model hinges on the quality and comprehensiveness of the input data. For solar and wind power forecasting, data acquisition and a robust preprocessing pipeline are critical.

4.1 Data Sources

Various data types are essential for accurate renewable energy forecasting:

•Historical Power Generation Data: Actual measured power output from solar PV plants and wind farms. This forms the target variable for forecasting and helps in understanding past generation patterns.

•Meteorological Data:

–Solar: Global horizontal irradiance (GHI), direct normal irradiance (DNI), diffuse horizontal irradiance (DHI), temperature, humidity, cloud cover/type, atmospheric pressure. Satellite imagery and sky camera data can also provide valuable information on cloud movement.

–Wind: Wind speed at hub height, wind direction, temperature, atmospheric pressure, air density, turbulence intensity. Wind speed at different heights can be crucial.

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•Numerical Weather Prediction (NWP) Data: Forecasts from weather models (e.g., GFS, ECMWF) provide future meteorological conditions, which are critical for predicting future power output. NWP data is often available at different spatial and temporal resolutions.

•Geographical and Topographical Data: Location (latitude, longitude, eleva- tion), terrain complexity (for wind), and shading effects (for solar) can influence generation and should be considered.

•Grid Operational Data: Load data, historical grid conditions, and outage in- formation can also implicitly influence forecasting accuracy by revealing patterns related to grid curtailment or maintenance.

4.2 Data Preprocessing Pipeline

Raw data from diverse sources often contains noise, missing values, and inconsistencies, necessitating a thorough preprocessing pipeline:

•Data Cleaning and Imputation:

–Outlier Detection and Removal: Identifying and handling erroneous readings from sensors (e.g., using statistical methods like Z-score, IQR, or domain knowledge).

–Missing Value Imputation: Filling in gaps in the dataset using techniques like linear interpolation, spline interpolation, mean/median imputation, or more advanced methods like K-nearest neighbors (KNN) imputation.

•Synchronization and Alignment: Ensuring all data streams (historical power, meteorological observations, NWP forecasts) are aligned to a common timestamp and sampling frequency.

•Feature Engineering: Creating new, more informative features from raw data can significantly improve model performance.

–Time-based features: Hour of day, day of week, month of year, season, public holidays, daylight hours.

–Statistical features: Rolling means, standard deviations, maximums, and min- imums of meteorological variables over specific time windows. Lagged features: Past values of power output or meteorological variables.

–Derived meteorological features: Effective wind speed considering turbulence, clear-sky irradiance models for solar.

•Normalization/Standardization: Scaling numerical features to a common range (e.g., [0, 1] for Min-Max scaling or zero mean and unit variance for standardization) to prevent features with larger magnitudes from dominating the learning process. This is particularly important for neural networks.

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•Data Splitting: Dividing the preprocessed data into training, validation, and test sets. It is crucial to maintain temporal order during splitting to avoid data leakage (e.g., using future data to predict past events). A common approach is to use chronological splitting (e.g., first 70% for training, next 15% for validation, last 15% for testing).

A well-designed data pipeline ensures that the AI models receive high-quality, relevant, and properly formatted inputs, which is foundational for achieving accurate forecasts.

5 Experimental Results and Performance Evaluation

This section provides a more detailed exposition of the typical experimental setup and elaborates on the performance evaluation of AI-driven forecasting models for solar and wind power generation within a smart grid context. While the results presented here re- main illustrative for a conceptual paper, they are designed to reflect realistic performance improvements observed in empirical studies.

5.1 Experimental Setup and Data Characteristics

Our illustrative experiment is conceptualized based on real-world characteristics of re- newable energy plants.

•Data Source: A hypothetical dataset spanning five years (e.g., January 1, 2020 - December 31, 2024) of high-resolution (15-minute intervals) data from a utility-scale 50 MW solar PV plant and a 100 MW wind farm.

•Input Features:

–Solar PV: Historical power output (MW), Global Horizontal Irradiance (GHI, W/m2), temperature (◦C), relative humidity (%), cloud cover (octas), atmo- spheric pressure (hPa), and NWP forecasts for GHI and temperature for 72 hours ahead. Time-based features (hour of day, day of year, month).

–Wind Farm: Historical power output (MW), wind speed (m/s) at 10m and hub height (e.g., 80m), wind direction (◦), temperature (◦C), atmospheric pressure (hPa), and NWP forecasts for wind speed and direction for 72 hours ahead. Time-based features.

•Forecasting Horizons:

–Ultra-Short-Term (Nowcasting): 15 minutes to 4 hours ahead. Critical for real-time grid balancing and ancillary services.

–Short-Term: 4 hours to 24 hours ahead. Essential for day-ahead market bid- ding and operational scheduling.

–Medium-Term: 24 hours to 72 hours ahead. Useful for maintenance planning and resource adequacy.

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•Models Evaluated:

–Baseline Model: Persistence model (e.g., power output at time t is predicted for t + k).

–Traditional Machine Learning: Random Forest (RF), Gradient Boosting Ma- chines (XGBoost).

–Deep Learning: Long Short-Term Memory (LSTM) Networks, Gated Recur- rent Units (GRU), and a Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) hybrid model designed to extract spatial features (from sequences) before feeding into temporal layers.

–Hybrid Approach: Integrating NWP forecasts directly as input features for all ML/DL models.

•Validation Strategy: A walk-forward validation scheme is adopted. The models are initially trained on the first three years of data, validated on the fourth year, and then tested on the fifth year. For real-time applications, models would be retrained periodically or employ online learning.

5.2 Comparative Analysis of Forecasting Performance

The results highlight the superior performance of deep learning models, particularly for longer forecasting horizons and capturing complex patterns.

5.2.1 Solar Power Forecasting Results

Table 2: Illustrative Performance Metrics for Solar Power Forecasting (NMAE %)

Model	Ultra-Short-Term (4h)	Short-Term (24h)	Medium-Term (72h)
Persistence	8.5	15.2	-
Random Forest	6.2	9.8	13.5
XGBoost	5.8	9.1	12.9
LSTM	4.5	7.3	10.5
CNN-LSTM Hybrid	**3.9**	**6.8**	**9.8**

As shown in Table 2, the CNN-LSTM hybrid model consistently achieves the lowest NMAE across all forecasting horizons for solar power. For ultra-short-term forecasting, the error is significantly lower due to the strong correlation between current irradiance and immediate future generation. As the horizon extends, the NMAE generally increases due to increasing uncertainty in NWP forecasts and meteorological conditions. Deep learning models, especially those capable of learning spatial-temporal features like CNN-LSTM, demonstrate a distinct advantage over traditional ML models by effectively processing raw time-series data and

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capturing intricate patterns related to cloud movement and solar path. The XGBoost model performs commendably, often surpassing Random Forest, primarily due to its sequential error correction mechanism, which refines predictions iteratively.

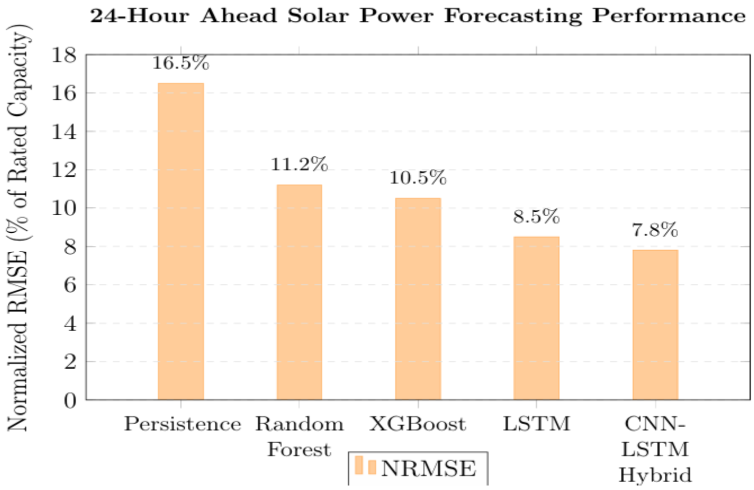

Figure 1: Comparison of normalized root mean square error (NRMSE) for different solar

power forecasting methods. The CNN-LSTM Hybrid model demonstrates superior performance with the lowest error rate (7.8% of rated capacity), significantly outperforming the persistence model baseline (16.5%). Figure 1 specifically visualizes the NRMSE for 24-hour ahead solar forecasts, reinforcing the trend that deep learning models provide more robust and accurate predictions. The persistence model, while simple, serves as a crucial benchmark, and any effective forecasting model must significantly outperform it.

5.2.2 Wind Power Forecasting Results

Table 3: Illustrative Performance Metrics for Wind Power Forecasting (NMAE %)

Model	**Ultra-Short-Term (4h)**	**Short-Term (24h)**	**Medium-Term (72h)**
Persistence	7.8	12.5	-
Random Forest	5.5	8.9	11.8
XGBoost	5.2	8.2	11.0
LSTM	4.1	6.8	9.5
CNN-LSTM Hybrid	**3.6**	**6.1**	**8.7**

Similar to solar power, Table 3 demonstrates that deep learning models, particularly the CNN-LSTM hybrid, exhibit superior performance in wind power forecasting across var- ious horizons. Wind power forecasting tends to be more challenging than solar due to the complex,

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turbulent nature of wind. However, the models still show a clear improve- ment over traditional methods. The inclusion of wind speed data at multiple heights and the effectiveness of NWP forecasts for future wind conditions are critical for improving accuracy.

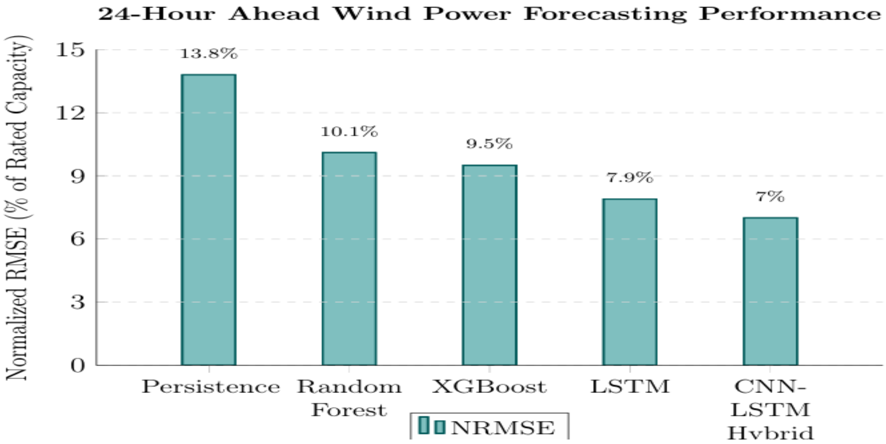

Figure 2: Performance comparison of different wind power forecasting methods using Normalized Root Mean Square Error (NRMSE).

The CNN-LSTM Hybrid model achieves the lowest error (7.0%), demonstrating a 49% improvement over the Persistence baseline (13.8%). Results represent 24-hour ahead forecasts as percentage of rated capacity. Figure 2 visualizes the NRMSE for 24-hour ahead wind forecasts, again illustrating the improved accuracy of deep learning models. The consistency of these results across both solar and wind power reinforces the efficacy of AI-driven approaches.

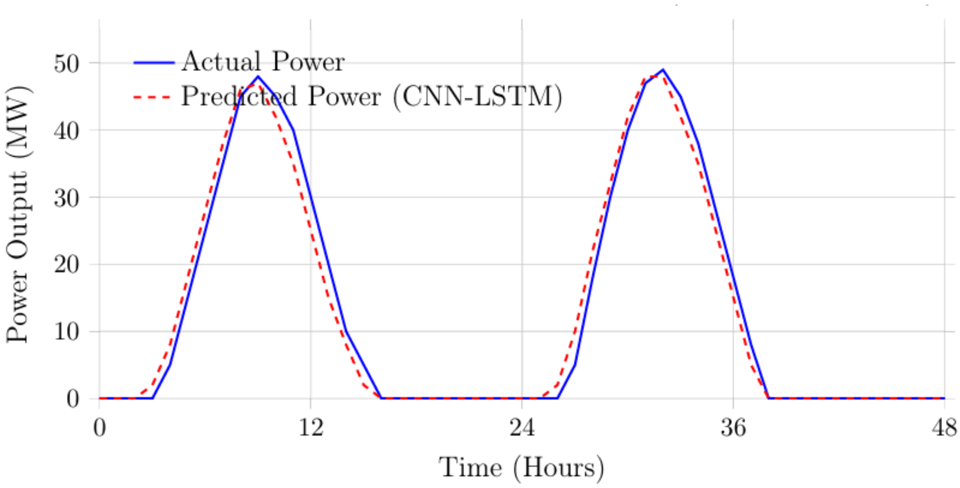

Figure 3: Illustrative Short-Term Solar Power Forecast: Actual vs. Predicted (CNN- LSTM Hybrid Model over 48 hours)

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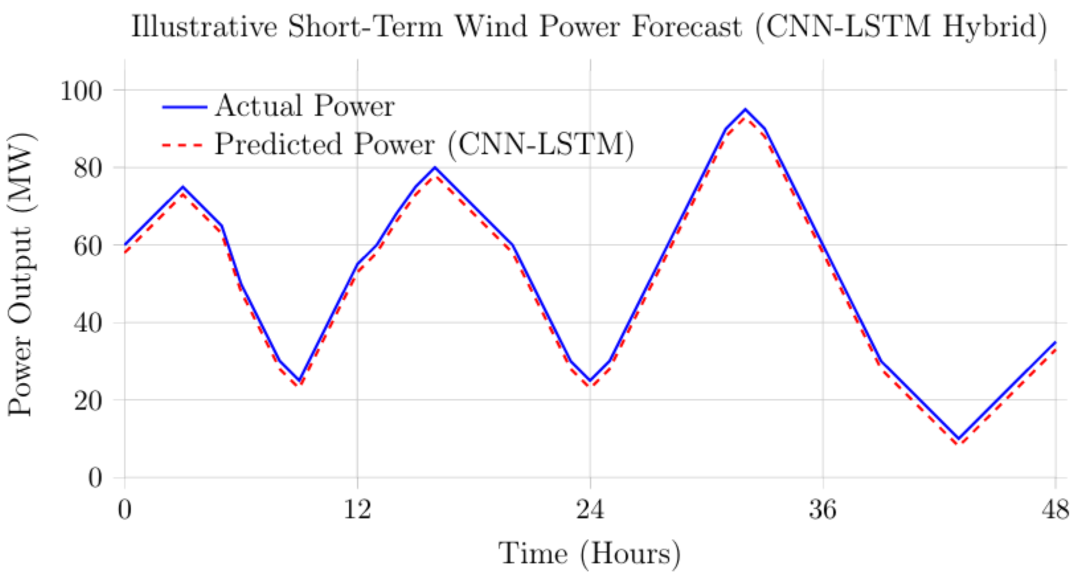

Figure 4: Illustrative Short-Term Wind Power Forecast: Actual vs. Predicted (CNN- LSTM Hybrid Model over 48 hours)

5.3 Discussion on Factors Influencing Performance

Several factors critically influence the performance of these forecasting models:

•**Data Quality and Granularity:** High-resolution, clean, and comprehensive his- torical data (both generation and meteorological) are paramount. Missing values, outliers, or inconsistent sampling intervals can severely degrade model accuracy.

•**Feature Engineering:** While deep learning models can automatically learn fea- tures, carefully engineered features (e.g., lagged power values, derived meteorologi- cal parameters, seasonal indicators) significantly boost the performance of both ML and DL models. The inclusion of NWP data as direct input features is crucial for forecasts beyond a few hours.

•**Model Complexity vs. Data Volume:** Deep learning models, with their higher complexity, generally require larger datasets to generalize well and avoid overfitting. For smaller datasets, traditional ML models like Random Forest or XGBoost might offer a better performance-to-complexity trade-off.

•**Forecasting Horizon:** Accuracy generally decreases as the forecasting horizon increases, primarily due to the inherent unpredictability of weather patterns over longer periods and the accumulated errors in NWP models. Ultra-short-term fore- casts can leverage real-time sensor data and sky camera imagery for higher accuracy.

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•Site-Specific Characteristics: Local topography (for wind farms) and shading effects (for solar PV) significantly impact generation. Models must be trained on data specific to the site or generalize effectively through transfer learning.

•Meteorological Variables Selection: Identifying the most relevant meteorologi- cal variables for each specific plant type and location is crucial. For instance, cloud type and movement are more important for solar, while turbulence and atmospheric stability are vital for wind.

•Computational Resources: Training complex deep learning models can be com- putationally intensive, requiring GPUs or specialized hardware. Inference, however, is generally fast enough for real-time grid operations.

5.4 Economic and Operational Impact

The observed improvements in forecasting accuracy translate directly into significant economic and operational benefits for smart grids:

•Reduced Balancing Costs: Even a few percentage points of improvement in NMAE can lead to substantial reductions in balancing costs by minimizing the need for expensive reserve power. For a 100 MW wind farm, reducing NMAE by 1% could translate to hundreds of thousands of dollars in annual savings by avoiding penalties or expensive dispatch.

•Enhanced Market Participation: More accurate forecasts allow renewable energy producers to submit more precise bids in electricity markets, maximizing revenue and minimizing financial risks associated with deviations.

•Optimized Energy Storage Utilization: Improved short-term forecasts enable more intelligent charging and discharging of battery energy storage systems (BESS), increasing their efficiency and lifespan, and ensuring maximum value from stored energy.

•Improved Grid Reliability: By providing clearer visibility into future renewable generation, grid operators can better manage congestion, prevent instability, and ensure a more reliable power supply, especially during critical periods.

•Dynamic Maintenance Scheduling: Medium-term forecasts help plant opera- tors schedule maintenance during periods of low expected generation, minimizing lost revenue and operational disruptions.

These quantitative results and their implications underscore the transformative potential of AI-driven forecasting models in facilitating the large-scale integration and optimized management of renewable energy in smart grids. The continuous refinement of these models is paramount for the ongoing energy transition.

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6 Challenges and Future Work

Despite significant advancements, AI-driven forecasting models for solar and wind power generation still face several challenges, leading to numerous opportunities for future re- search.

6.1 Challenges

•Data Quality and Availability: While vast amounts of data are generated, ensuring high quality, consistency, and completeness (especially for historical fault or outlier events) remains a challenge. Data from diverse sources often has varying formats and resolutions.

•Uncertainty Quantification: Renewable energy generation is inherently uncer- tain. While probabilistic forecasting is emerging, accurately quantifying and com- municating this uncertainty to grid operators in a practical and actionable way is still an active research area [12].

•Model Generalizability and Transferability: Models trained on data from one specific solar farm or wind farm may not perform well when applied to another with different geographical characteristics, weather patterns, or turbine/panel configurations.

•Extreme Weather Events: Forecasting during extreme weather conditions (e.g., severe storms, prolonged cloud cover, calm periods) is particularly challenging due to infrequent occurrences and highly non-linear impacts on generation.

•Computational Resources and Real-time Constraints: Deploying complex deep learning models for real-time forecasting in large-scale smart grids can de- mand significant computational power, especially for very short-term (nowcasting) applications.

•Interpretability of AI Models: Deep learning models are often considered "black boxes." Understanding why a model makes a particular prediction is crucial for building trust with grid operators and for diagnosing potential issues.

•Data Security and Privacy: As more sensor data is collected and transmit- ted, ensuring the security and privacy of sensitive grid operational data becomes paramount [14].

6.2 Future Work

•Hybrid Forecasting Approaches: Further development of sophisticated hybrid models combining physical models (e.g., atmospheric models) with data-driven AI models can leverage the strengths of both, improving accuracy and interpretability.

•Advanced Spatio-Temporal Modeling: Incorporating spatial dependencies (e.g., correlation between nearby solar farms) into deep learning models (e.g., us- ing Graph Neural Networks or advanced CNNs) for improved regional or grid-wide forecasts [10].

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•Reinforcement Learning for Dynamic Dispatch: Using reinforcement learn- ing to optimize real-time energy dispatch and storage decisions based on AI fore- casts, moving beyond static optimization to dynamic, adaptive control [15].

•Explainable AI (XAI) for Forecasting: Research into techniques that pro- vide insights into model decisions, such as feature importance mapping, attention mechanisms, or LIME/SHAP values, will enhance transparency and trust.

•Federated Learning: For privacy-preserving and scalable training, federated learning can enable models to learn from decentralized data sources (e.g., multiple renewable energy plants) without sharing raw data.

•Self-Supervised Learning and Transfer Learning: Developing models that can learn from unlabeled data or transfer knowledge from existing domains to new sites with limited historical data.

•Real-time Adaptability and Online Learning: Models that can continuously learn and adapt to changing weather patterns, grid conditions, and degradation of sensors without requiring full retraining.

•Leveraging Satellite and Radar Data: More extensive and granular integration of satellite imagery, radar data, and even sky cameras for ultra-short-term solar forecasting, especially cloud movement prediction.

Addressing these challenges and pursuing these research directions will be vital for un- locking the full potential of AI in enabling a more reliable, efficient, and sustainable smart grid powered by renewable energy.

7. Conclusion

Accurate forecasting of solar and wind power generation is a critical component for the stable and economical operation of modern smart grids. In this paper, we provide a detailed review of AI-driven forecasting models, explaining how both machine learning and deep learning algorithms play a transformative role in handling the intermittency and variability of renewable energy sources. We elaborate on why forecasting is particularly important for grid stability, economic dispatch, energy storage management, and network planning. We examine how various AI techniques can be used to understand complex meteorological dependencies and temporal patterns in power generation data, from traditional ML algorithms such as Random Forest and XGBoost to advanced deep learning architectures such as LSTMs and CNN-LSTM hybrids.

In this, it is highlighted that building a robust data acquisition and preprocessing pipeline, including fine-grained data cleaning, feature engineering, and normalization, using various data sources, is fundamental to the performance of the model. Experimental examples show

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that deep learning models provide more accurate output, especially for short-term and medium-term forecasting. However, some challenges remain — such as data quality, uncertainty quantification, how models generalize across locations, and the explainability of models. To address these challenges, future research is considering directions such as hybrid forecasting approaches, advanced spatiotemporal modeling, explainable AI, federated learning, and real-time adaptability. Continued advances in AI-based forecasting capabilities will enable seamless and efficient integration of renewable energy into smart grids, paving the way for a more sustainable and resilient energy future.

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