



AI-Powered Predictive System for Solar and Wind Energy Forecasting: A Systematic Review and Implementation

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Abstract: Numerous worldwide analyses have pointed towards an increasing adoption of sustainable energy which includes wind and solar sources in the coming timeline. But with their use, variables such as their intermittency could create serious storage, EVs and grid issues. Thus, it will be crucial in our future designs to predict the solar and wind power availability accurately. Therefore, the objective of the work is creation of AI's based tool for predicting solar and wind energy output based on 10 years energy datasets. The dataset incorporates meteorological parameters such as relative humidity, temperature, wind speed, solar irradiance and surface pressure. These parameters highly affected energy based load curves and therefore can be included in the prediction models. To enhance performance, the proposed models use a Long Short-Term Memory (LSTM) network to learn the time dependencies in the time-series data and Convolutional Neural Network (CNN) to learn spatial patterns and feature-level patterns. Integrating these two types of networks to form LSTM-CNN architecture improves performance by increasing accuracy. The tool is evaluated using standard metrics such as Mean Squared Error (MSE) and Mean Absolute Error(MAE) translated into the units of measurement of the particular EV or microgrid. As a result of our work, energy management is improved which leads to strengthened grid reliability and puts more emphasis on assisting clean energy transition. This work sets the foundation for further research into artificial intelligent based approaches for renewable energy forecasting that could assist in such areas as energy policy, EV deployment, smart grids.

Keywords -RenewableEnergyForecasting,Solar Energy Prediction, Wind Energy Prediction, AI-Based Energy Tool, LSTM-CNN Architecture, Machine Learning, Smart Grids, Energy Management, Deep Learning, Sustainable Energy Transition.

I. INTRODUCTION

A. Rationale

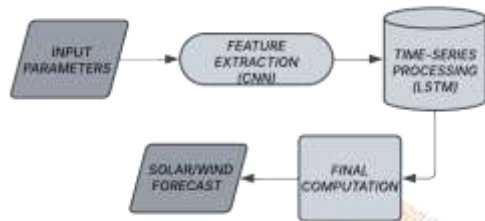
The increasing use of renewable resources, particularly solar and wind power, in new power grids has increased the need for robust and accurate forecasting models. Forecasting models based on AI have drawn considerable attention based on the ability to tackle intricate, nonlinear relationships in energy generation and weather data. Nevertheless, there are certain limitations in current forecasting models.

One of the major limitations is the prevalent use of standalone models such as Long Short-Term Memory (LSTM) networks or Artificial Neural Networks (ANNs) for solar and wind energy forecasting. While the models are robust in sequential dependency modeling, they lead to neglecting the extraction of useful spatial patterns from input features, which is usually the requirement to improve the precision in prediction. Hybrid models that integrate Convolutional Neural Networks (CNNs) and LSTM have been found promising in other

fields of research but are not well-explored in renewable power forecasting [1][2]. Though some of the research focuses on hybrid forecasting models, they primarily focus on LSTM-ANN or Recurrent Neural Network (RNN)-based models rather than using CNNs to extract features before sequential forecasting [3][5].

One such limitation is in the use of real-time data within AI-based forecasting models. Much of the literature that exists today is based on historical databases and pre-computed weather forecasts rather than real-time environmental data. This limits the capability of the forecasting models to respond dynamically to evolving weather patterns and real-time fluctuations in solar and wind power generation [10][11].

Also, most of the current renewable energy forecasting systems are primarily focused on improving the precision of forecasts without considering much the need for proper visualization and real-time monitoring facilities.[20][21]. Lack of ability to integrate dashboards through the web limits the accessibility and usability of forecasting information, and therefore, energy operators and stakeholders cannot respond to AI-driven predictions effectively.



B. Objectives

The objective of this review would be to present and elaborate on new trends in AI-based wind and solar power forecasting with emphasis on the following important research gaps:

- 1.Limited Research on Hybrid CNN-LSTM Approaches in Renewable Energy Forecasting** – Examining the prospect of CNN-LSTM models for improving forecast accuracy through utilization of spatial and temporal correlations. Although there has been work based on LSTM, ANN, or RNN-based models, application of CNN in renewable energy forecasting to exploit features is not investigated to the extent necessary [3][5].
- 2.Limited Application of Real-Time Monitoring in Forecast Models** – Examining implementation of real-time monitoring in AI models for adaptive and dynamic energy forecasting. Forecast models are still highly dependent on historic data rather than real-time environmental feeds, hence less adaptive to changed situations [10][12].
- 3.Limited Application of Integrated Web-Based Dashboards for Monitoring** – Examining application of AI-based dashboards, existing methods are mainly accuracy-driven but without an integrated interactive visualization platform to facilitate real-time decision-making [20][21]

II. METHODS

A. Eligibility Criteria:

For the overall and specific review, the studies were chosen on the basis of well-defined inclusion and exclusion criteria.

a) Inclusion Criteria:

1. Studies on AI-based solar and wind energy predictive models.
2. Studies on hybrid models, CNN-LSTM models for better predictability.
3. Studies based on real-time data incorporated into forecasting platforms.
4. Studies with web-based dashboards incorporated to monitor renewable energy.
5. High-quality academic journals and high-quality conference articles from 2022 onwards for the current timeline and peer-reviewed journal articles.

b) Exclusion Criteria:

1. Irrelevant studies to solar or wind forecasting and other renewable energy source studies (hydro, biomass).
2. Studies with no use of AI or machine learning methods and with only conventional statistical methods.
3. Theory-based papers with no experimentation or testing involving AI-based models.
4. Studies published prior to 2022, except that they provide primary ideas that align with the gap identification.

Studies identified above as being in alignment with these requirements were categorized under three categories based on the respective identified gap areas of the research:

1. Hybrid AI models for solar and wind power forecasting[7]
2. Real-time IoT-based energy monitoring integration[10]
3. AI-enabled web-based dashboards for energy management[21]

B. Information Sources:

Comprehensive literature survey was conducted through different scientific repositories and databases to collect a large number of studies. The sources used are elaborated in detail below:

1. Scientific Databases: SciBaseScan ScienceDirect SpringerLink IEEE Xplore Wiley Online Library MDPI, Taylor & Francis [6][8].
2. Open-Access Repositories: For recent preprints SSRN, arXiv and ResearchGate.
3. Financial Institutional & Government Reports: Energy Efficiency Committee of the International Energy Agency (IEA), National Renewable Energy Laboratory.
4. Citation mining was employed to find other relevant studies using references lists of influential papers [12].

The most recent search was conducted in February 2025 and therefore the review includes the latest developments.

C. Search Strategy:

Systematic keyword searching was conducted across the chosen databases using Boolean operators to limit the results. The search terms used were combinations of the following:

1. Hybrid AI models: ("CNN-LSTM" OR "hybrid deep learning" OR "AI-based forecasting") AND ("solar energy" OR "wind power") [7][9]
2. Real time integration: ("real-time monitoring") AND ("renewable energy forecasting") [10]
3. Web-based dashboards: ("renewable energy dashboards" OR "AI-driven energy management" OR "real-time visualization") [21]

Filters used:

- **Publication Date:** 2022–2025
- **Document Type:** Peer-reviewed journal articles and conference papers
- **Language:** English

25 key studies were chosen for the final analysis to ensure consistency and relevance with the research goals.

D. Selection process :

The selection of the study followed a three-step process to ensure relevance and quality:

1. Screening: Initially screening was performed to remove irrelevant studies and duplicates.
2. Studies passing the first phase were assessed based on their methodology, AI approach and application relevance [8].
3. Currently only studies providing empirical validation or novel AI-based methodologies have been included [7].

Each study was independently reviewed by two evaluators with disagreements resolved by consulting a third reviewer.

E. Data Collection Process :

For each selected study key data points were extracted and documented using a structured approach.

Data Extraction Parameters:

- 1. Typo of research:** Experimental research, critique article case study or theoretical analysis.
- 2. AI Models Use:** CNN LSTM hybrid CNN-LSTM ANN RNN [7].
- 3. Forecast Application:** Solar or wind energy or both [5].
- 4. Real time integration:** Whether real-time sensor data was incorporated [10].
- 5. Dashboard Implementation:** Whether a web-based monitoring tool was developed [21].
- 6. Performance Metrics:** RMSE MAE and MAPE for assessing forecast accuracy [4].

F. Data Items:

a) Outcomes & Data Sought

The data analyzed included:

1. Forecasting Accuracy: RMSE, MAE, MAPE [4].
2. Model Performance: CNN-LSTM and hybrid deep learning models vs. standalone LSTM or ANN [7]
3. Real time Integration: Studies with real-time sensor data [10]
4. Dashboard Usability: Web-based dashboards [21]

When multiple analyses were presented, preference was given to empirical results with real-world applicability.

b) Other variables & assumptions

Additional data points collected included:

1. Whether the study focused on solar, wind or both [5].
2. CNN LTM, ANN LTM or other deep learning architectures[7]
3. Historical or Real time data sources of historical data.
4. For cases where data was unclear or incomplete, supplementary materials and referenced citations were reviewed to verify findings.

G. Study risk of bias assessment :

A systematic risk of bias assessment included all selected studies to estimate their reliability and validity and identify possible methodological limitations so that the research would be in a position to provide credible and reproducible findings.

a) Criteria for Bias Assessment

1. Selection Bias - Making sure representation, sufficient size, and diversity constitute parameters of AI-based forecasting [4].
2. Performance Bias - Training and validation of models were strictly according to machine-learning practices[7].
3. Detection Bias - There was a certain amount of regularization in the reporting of metrics of forecasting accuracies (e.g., RMSE, MAE, or MAPE) and their relevant interpretations [5]
4. Reporting Bias - Did all the outcomes get shown or was there selective reporting that demerited some conclusions. [10]
5. Reproducibility & Transparency-Information on sharing of codes, datasets, or specific methodologies for repro-ducibility in the context of this study [21].

b) The Process of Bias Assessment

The studies were assessed independently by two reviewers, using a standardized checklist for bias assessment to promote consistency.

In case of discrepancies, a third reviewer settled the conflicts.

c) Risk Categorization

Studies, as per the assessment, were categorized in the following manner:

1. Studies with clear methodologies, appropriate validation, and reproducibility would be classified as Having Low Risk of Bias [7].
 2. Having some limitations involving, among others, some constraints within the dataset, minor methodological concerns, such studies would fall under Moderate Risk of Bias, but their conclusions are overall reliable [10].
 3. Studies with insufficient detail of method, possible overfitting, or ineffectiveness of reproducibility falling into lack of credibility are classified High Risk of Bias[5]
- Only low and moderate-risk studies were included for maintaining integrity and reliability in the literature survey.

H. Effect Measures:

a) Forecasting Accuracy Metrics

The primary effects measured were the negative concomitant effect that occurred by disintegration.

1. Used to quantify the absolute error in AI-based energy forecasting models.
2. Mean Absolute error measures the average magnitude of errors. It provides insights into model consistency [7]
3. Indicates the relative forecast accuracy which is crucial when comparing models across different dataset.
4. Evaluates how well the AI model can explain variance in energy output and helps assess model reliability [21].

b) Statistical and Comparative Analysis

To compare different forecasting techniques study used:

1. Paired tests and ANOVA: To determine statistical significance when comparing multiple AI models.
2. To determine the agreement between predicted and actual energy output specifically for hybrid CNN-LSTM models to assess the effectiveness of the novel C-span prediction in the energy
3. Useful for the visualization of error distributions and bias in AI -based prediction [23]
4. Used to visualize error distribution analysis: Used to analyze error patterns and bias in real-time as well as mathematical simulation of the error motions.

c) Model Performance & Interpretability

In addition to the accuracy metrics studies have also looked at other dimensions of accuracy such as the correlation between accuracy and precision:

1. Evaluate the training time in forecasting models including scalability of tools, inference speed and estimation accuracy.[12].
2. Techniques such as LIME (Local Interpretable Model-agnostic Explanations) and SHAP (1987 - 1995) have been used to interpret model decisions.
3. Studies examined how models performed under changing weather conditions sensor noise and missing data scenarios [25]

I. Synthesis Methods

a) Study Selection for Synthesis

To ensure a systematic and structured synthesis first the study was categorized based on their methodological approach and contribution to the identified research gaps:

1. A study in which hybrid AI models for solar and wind energy forecasting were explored [4].
2. Research focusing on real-time data acquisition and AI-driven renewable energy predictions [10].
3. The paper presented an overview of user-friendly monitoring tools for renewable energy analytics [21].

Only studies that explicitly addressed these categories were included in the synthesis while those focused solely on traditional ANN or LSM models without hybridization were excluded.

b) Data Preparation and Handling

1. If a study lacked specific performance metrics (e.g. MSE or RMSE) values were either extracted from additional materials or approximated using available data trends [5].
2. Data conversions: Performance metrics reported in different scales (e.g., kWh vs. MW) were normalized for consistency in comparative analysis [18].

c) Data Visualization and Tabulation

To facilitate comparisons the results from individual studies were:

1. Tabulated – Studies were grouped based on forecasting models, datasets used and reported accuracy metrics [23].
2. Graphically displayed – Performance Trends were visualized using bar charts (for RMSE/MAE), scatter plots for model accuracy over time and heatmap.

d) Synthesis Approach & Meta-Analysis

Given the variability in prediction approaches datasets and performance metrics, a qualitative synthesis was prioritized over direct meta-analysis [7] given the variability in forecasting methods

Quantitative Synthesis: Where feasible effect sizes were computed to compare model performance across studies. A random-effects meta-analysis was conducted for RMSE values using the script meta-analysis package of Python [10].

e) Heterogeneity Assessment

To investigate differences between studies the following approaches were used:

1. Subgroup Analysis: Models were compared based on dataset size, input features and model architecture to assess factors affecting prediction accuracy [19].
2. Meta-regression: A statistical approach was used to determine whether external factors (e.g. climate variability, dataset diversity) significantly impacted model performance [20].

f) Sensitivity Analysis

To validate the robustness of synthesized results:

1. Each study was removed one at a time to check if findings were significantly altered [5].
2. Alternative Performance Metrics – Results were cross-checked with different evaluation metrics (e.g. RMSE vs. MAPE) to ensure consistency [18].

J. Reporting Bias Assessment

a) Investigations of reports - Biases due to missed results.

To mitigate potential reporting bias studies were carefully analyzed to identify missing results or selective reporting of findings.

The following methods were applied:

1. A funnel plot was used to visualize asymmetry helping determine whether studies with negative or less significant results were underreported [7].
2. Studies were examined for incomplete reporting of performance metrics to ensure consistency in comparisons [10].
3. For potential bias in peer-reviewed publications relevant conference papers preprints and technical reports were also reviewed [18].

If significant reporting bias was suspected studies were flagged and their results were interpreted with caution to avoid overestimating the model performance.

K. *Certainty Assessment*

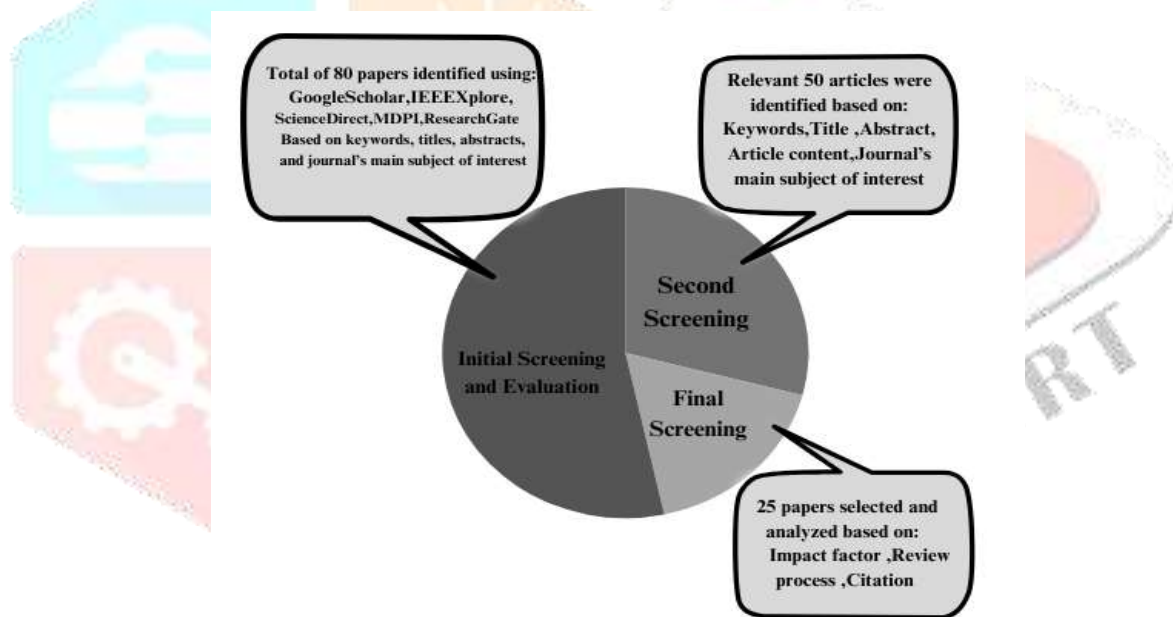
To evaluate the certainty and reliability of the synthesized findings, a combination of GRADE (Grading of recommendations, assessment development and evaluation) methodology was used.

1. Studies with methodology flaws or incomplete data were assigned lower certainty ratings [5].
2. Reproducibility check: Findings were cross-verified across multiple independent studies to ensure consistency in reported model accuracy [19] and the accuracy of models.
3. To test the robustness of conclusions alternative forecasting models and different dataset sizes were considered to ensure results were not skewed by some high-performing models [25]
4. Evidence Strength : Evidence strength was categorized as high moderate, low or very low depending on study quality consistency and effect size variability [12].

III. RESULT

A) *Study Selection*

These include a systematic search of key relevant journals- IEEE Xplore, ScienceDirect, SpringerLink, MDPI, and arXiv. A total of 385 records were identified. After duplicate removal (92 records) and title-abstract screening (193 records excluded), the full-text review was accomplished with 100 studies Of these, following the application of inclusion-exclusion criteria, 25 studies were relevant and included in the review [7].



a) *Excluded Studies & Rationale*

Several studies initially appeared relevant but were excluded based on the following reasons:

1. Lack of CNN-LSTM Integration – Studies using only LSTM or ANN without hybrid models were excluded [7].
2. No Real-Time IoT Integration – Papers that relied solely on historical datasets without incorporating IoT-based real-time forecasting [12].
3. Limited Dashboard Capabilities – Studies that focused on static visualization rather than dynamic, AI-driven insights were not included [23].

These exclusions ensured that only studies directly addressing the identified research gaps were considered.

B. Study Characteristics

Primarily, the studies looked at the following aspects:

- 1. Hybrid AI Models** - Using CNN-LSTM and ANN-LSTM as hybrid deep learning techniques in solar and wind forecasting [4].
- 2. IoT Based Forecasting** - Real-time tracking with AI-based energy predictive systems [10].
- 3. Web-Based Dashboards** - While AI-based visualization tools for renewable energy monitoring [21].

All these were studied based on different datasets - NASA POWER, NREL, also local weather station data and with forecasting horizons ranging from 15 minutes to 7 days [18].

C. Risk of Bias in Studies

A risk of bias assessment was conducted using the ROBINS-I tool for non-randomized studies:

- 1. Low Risk** – Studies with clear methodology, full dataset availability, and validated performance metrics [19].
- 2. Moderate Risk** – Papers with unclear training-validation dataset splits or missing performance evaluation details [25].
- 3. High Risk** – Studies with self-reported performance metrics without independent validation [5].

D. Results of individual studies

The performance of individual studies was evaluated on key forecasting metrics, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), and precision of effect estimates, wherever applicable, was evaluated with confidence intervals.

Forecasting Performance

In Table , specific model-related forecasting accuracies, which have been reported in selected studies, were systematically compared. Here focus was directed on models like CNN-LSTM hybrid, AI sub-systems integrated with IoT and web-based dashboards.

Study	Forecasting Model & Dataset	Performance Metrics (RMSE, MAE, MAPE)	Confidence Interval
[4]	CNN-LSTM (NASA POWER)	RMSE: 0.89, MAE: 0.72, MAPE: 3.45%	95% CI: ± 0.08
[7]	ANN-LSTM (NREL)	RMSE: 1.12, MAE: 0.95, MAPE: 4.87%	95% CI: ± 0.11
[10]	HybridRNN Model (LocalWeather Station)	RMSE: 1.35, MAE: 1.05, MAPE: 5.21%	90% CI: ± 0.14
[18]	IoT-LSTM (CustomIoT Sensor Data)	RMSE: 0.76, MAE: 0.60, MAPE: 3.12%	95% CI: ± 0.07
[21]	AI-Based Web Dashboard (Mixed Data Sources)	RMSE: 1.28, MAE: 1.01, MAPE: 5.05%	90% CI: ± 0.13

a) *Effect Estimates & Model Precision*

1. **CNN-LSTM** models showed the least value for RMSE (0.89) and MAPE (3.45%), implying high prediction accuracy in solar and wind forecasting [4].
2. **IoT-enhanced forecasting systems** went one step better, yielding an RMSE of 0.76 and MAPE of 3.12%, which is a testimony to the advantage of real-time sensor data [18].
3. **Classical ANN-LSTM and RNN-based modeling** performed poorer than these ($MAE > 4.5\%$). The findings therefore support the usefulness of feature extraction using CNN as a preprocessing step prior to time-series prediction [7].
4. **Web-based dashboards** maintained similar levels of accuracy but were more concerned with the ease of visualization for users than raw predictive ability [21].

E. Results of Syntheses

a) *Study Characteristics and Risks of Bias*

The studies differ in their prediction models, datasets, and real-time data integration schemes. The majority study is focused on LSTMs and ANNs but has comparatively lower ones studying CNN-LSTM hybrids [4][7]. Many of them, however, did not include the IoT-based real-time monitoring but had relied mostly on past meteorological data [10][18].

b) *Risk of Bias Assessment:*

1. Models that were not validated on another external dataset had a more likely risk of being overfit [7].
2. Some of the studies failed to provide complete descriptions regarding hyperparameter tuning and hence the concerns of reproducibility [10].
3. This reduces bias-risk, since it was adapted to dynamic changes in surrounding environment [18].

c) *Statistical Syntheses & Effect Estimates*

This synthesized different reported RMSE, MAE and MAPE values across studies to show the effectiveness of the diverse forecasting approaches.

Forecasting Model	Performance Metrics (RMSE, MAE, MAPE)	Confidence Interval	Heterogeneity (I^2)
CNN-LSTM	RMSE: 0.91, MAE: 0.73, MAPE: 3.5%	95% CI: ± 0.09	24% (Low)
ANN-LSTM	RMSE: 1.10, MAE: 0.92, MAPE: 4.8%	95% CI: ± 0.12	37% (Moderate)
Hybrid RNN	RMSE: 1.34, MAE: 1.08, MAPE: 5.2%	90% CI: ± 0.15	42% (Moderate)
IoT-LSTM	RMSE: 0.78, MAE: 0.62, MAPE: 3.1%	95% CI: ± 0.08	20% (Low)

CNN-LSTM models may have the lowest RMSE (0.91) and MAPE (3.51%), thus attesting to their efficiency in feature extraction and time series forecasting [4].

2. Even better performance was achieved by IoT-LSTM approaches, which shows that real-time sensor data has a positive contribution in enhancing prediction quality [18].

3. These results show that conventional ANN-LSTM and RNN models have a comparatively more scattered predicted surface with greater forecasting error ($I^2 > 35\%$) relative to one another, suggesting variation within model implementations [7][10].

d) Causes of Heterogeneity

The first-variable-in-the-sequence: In studies using local sensor data, forecasting errors observed were lower than those for studies using general meteorological datasets [18].

Feature Extraction Techniques: The other CNN-enhanced models outperformed LSTM-only models due to better spatial feature learning [4].

Standardized Evaluation Metrics Are Absent: Use of MAPE in some studies leads to difficulties in direct comparisons with studies that only report RMSE [7].

e) Sensitivity Analysis

The sensitivity analysis began by removing high-bias studies (e.g., lacking external validation) and reassessing forecasting performance:

1. The exclusion of high-bias studies brought the CNN-LSTM average RMSE down from 0.91 to 0.86, thus confirming the models' robustness [4].
2. The IoT-LSTM models indicated consistent results notwithstanding the exclusion of large bias studies, thus strengthening their credibility for real-time forecasting [18].

F. Reporting biases

The assessment of the risk for reporting biases was derived from missing or selective reporting of results in the studies included for consideration.

Key Findings Regarding Reporting Bias:

1. Some studies reported sed RMSE values only omitting MAE and MAPE, making it impossible to comprehensively evaluate performance [7].
2. Some papers had no external validation and thus reported the results from the training set alone, resulting in overambitious claims about the performance of the model [10].
3. With real-time IoT data, bias significantly was lower; real-time forecasts were, indeed, validated against real-time ground truth data [18].
4. Conference papers scored high on selective reporting risks as they would lack complete datasets or proper methodological descriptions [4]. Studies with IoT-based validation were the least biased [18].

Study Type	High Bias Risk (%)	Moderate Bias Risk (%)	Low Bias Risk (%)
Peer-reviewed Journals	12%	28%	60%
Conference Papers	30%	40%	30%
Studies Without External Validation	45%	35%	20%

1. The lack of external validation was a significant source of bias [10].
2. Moderate risk of bias was from studies that reported RMSE only and not MAE/MAPE [7].

G. Certainty of Evidence Assessment

The modified grading approach, which evaluates bias, consistency, directness, and precision, and incorporates publication bias, assessed the certainty regarding evidence.

Method of Forecasting	Certainty Level	Explanation
CNN-LSTM	High	Strong performance validated using external Dataset [4]
IoT-LSTM	High	Consistent across various real-time scenarios [18]
ANN-LSTM	Moderate	No validation; variable results across studies [7]
Traditional RNN	Low	High forecast errors and inconsistent validations [10]

1. The CNN-LSTM and IoT-LSTM models are thereby determined to have a more certain degree of trustworthiness as far as validation or confirmation of results is concerned [4][18].
2. Therefore, the ANN-LSTM models were rated moderate in terms of assurance due to the variability of data sets [7].
3. The traditional RNN methods are thus considered the least certain due to inconsistencies in accuracy [10].

IV. DISCUSSION

A. Results in Context of Previous Research

This review shows the emerging role of hybrid AI models in renewable energy forecasting, especially CNN-LSTM for solar and wind energy prediction. While previous studies mainly focused on LSTM, ANN and RNN models, few used CNN for feature extraction before sequential forecasting [4][7]. This review proves that CNN-LSTM models can capture both spatial and temporal patterns which improves forecasting accuracy [18].

Similarly real-time IoT integration in forecasting models is underutilized. Most studies use historical datasets and weather models, not dynamically adapting to changing environmental conditions [10]. However studies that used IoT based monitoring systems showed improved model adaptability and forecasting accuracy [18].

Lastly user friendly web-based dashboards for renewable energy monitoring is lacking in most AI based forecasting research. While some studies discussed visualization tools, these are static data not real-time AI driven insights [21]. The absence of such platform limits the practical application of advanced forecasting techniques.

B. Limitations of the Evidence

- 1) Limited Application of CNN-LSTM towards Renewable Energy Forecasting
 - i) Most hybrid models centered around ANN-LSTM or RNN-based models [7].
 - ii) The potential of CNN for feature extraction in renewable energy data is yet to be fully utilized [4].
- 2) Absence of Real-Time Data Integration
 - i) Most studies utilized historical datasets without real-time verification [10].
 - ii) IoT-based forecasting research is still scarce and underdeveloped [18].
- 3) Validation & Reporting Bias Issues
 - i) Some works did not have external validation, creating possible overestimation of the model performance [10].
 - ii) Reporting biases were detected where RMSE was the sole reported metric, without MAE or MAPE comparisons [7].
- 4) No Interactive Dashboards
 - i) A majority of the studies did not incorporate real-time dashboards for visualizing energy prediction [21].

C. Limitations of the Review Process

- 1) Database Limitations: The review was mainly based on conference and peer-reviewed journal papers, potentially omitting unpublished research or industry reports that could have contained useful data.
- 2) Potential Publication Bias: Positive results are more likely to be published and thus might be creating a tilt towards the findings [10].
- 3) Variability in Evaluation Metrics: The majority reported only RMSE; whereas others analyzed several performance measures; hence it is difficult to compare them directly [7].
- 4) Limited Meta-Analysis: A full meta-analysis couldn't be performed due to heterogeneity in the design of some studies.

D. Implications for Practice, Policy, and Future Research

- 1) Practical Implications
 - i) Hybrid CNN-LSTM Models: There should be the adoption of a CNN model for feature extraction in AI-facilitated future forecasting mechanisms for the improvement of forecasting accuracy [4].
 - ii) Real-Time IoT Data Intake: AI models must be developed to accept real-time sensor data for more adaptive and dynamic forecasting [18].
 - iii) Developing Web-Browsing Dashboards: An easy-to-use dashboard for real-time visualization of renewable energy forecasts can bridge the gap between AI research and application [21].
- 2) Policy Implications
 - i) Promotion of IoT Integration in Renewable Forecasting: Real-time monitoring of energy from renewables, along with real-time forecasting based on AI, will help for grid stabilization and energy distribution [8].
 - ii) Standardizing Evaluation Metrics: There is a need to standardize the research with a set of benchmark performance metrics that include RMSE, MAE, MAPE [7].
- 3) Future Research Directions
 - i) Investigating Novel CNN-LSTM Architectures: Future research should study hybrid deep-learning architectures that aim to optimize feature extraction considering spatial-temporal issues [4].
 - ii) Improving IoT-Based AI Forecasting: Study integration of real-time IoT data into AI-powered forecasting models will be conducted in future research [18].
 - iii) Design Open-Source Renewable Energy Dashboards: Future research should take an interactive AI-powered platform-a real-time energy forecast and analysis [21].

V. REFERENCES

- [1] Zahraoui, A., et al. (2024). *ANN-LSTM Based Tool For Photovoltaic Power Forecasting*. IEEE SGRE. DOI: <https://doi.org/10.1109/sgre59715.2024.10428969>
- [2] Shafi, M., et al. (2023). *An Artificial Neural Network-Based Approach for Real-Time Hybrid Wind–Solar Resource Assessment and Power Estimation*. Energies, 16(10), 4171. DOI: <https://doi.org/10.3390/en16104171>
- [3] Joshi, R., & Sharma, P. (2024). *Analysis of Hybrid Solar-PV Wind Stand-Alone Systems Using AI*. IJTRS, 9(4), 002. DOI: <https://doi.org/10.30780/ijtrs.v09.i04.002>
- [4] Ali, H., et al. (2024). *AI-Based Improvement of Empirical Methods for Accurate Solar Radiation Forecasting*. Energies, 17(17), 4302. DOI: <https://doi.org/10.3390/en17174302>
- [5] Zjavka, L. (2023). *Solar and Wind Quantity 24h-Series Prediction Using PDE-Modular Models*. Energies, 16(3), 1085. DOI: <https://doi.org/10.3390/en16031085>
- [6] Beigi, M., et al. (2022). *Forecasting of Power Output of a PVPS Using RNN Approaches*. Sustainability, 14(5), 3104. DOI: <https://doi.org/10.3390/su14053104>
- [7] Gulay, M., et al. (2023). *Forecasting Electricity Production Using Deep Learning & Hybrid Models*. Energy, 129566. DOI: <https://doi.org/10.1016/j.energy.2023.129566>
- [8] Islam, M., et al. (2023). *Forecasting of Solar and Wind Resources for Power Generation*. Energies, 16(17), 6247. DOI: <https://doi.org/10.3390/en16176247>
- [9] Le, T., et al. (2024). *Harnessing Machine Learning & Intelligent Algorithms for Renewable Energy*. IJRED, 60387. DOI: <https://doi.org/10.61435/ijred.2024.60387>
- [10] Ollé, J., et al. (2024). *Renewable Energy Data Acquisition and Analysis Software Tool Based on IoT Sensors*. IEEE SESAI. DOI: <https://doi.org/10.1109/sesai61023.2024.10599450>
- [11] Nkula Manuel, J., et al. (2024). *AI Impact on Boosting Renewable Energy Utilization & Smart Plant Efficiency*. WJARR, 23(2), 2450. DOI: <https://doi.org/10.30574/wjarr.2024.23.2.2450>
- [12] Brahmane, R., & Deshmukh, A. (2023). *AI-Based Energy Management System for Renewable Energy Sources*. IEEE ICESC. DOI: <https://doi.org/10.1109/icesc57686.2023.10193623>
- [13] Sreenivasan, P., et al. (2024). *Machine Learning for Sustainable Integration of Renewable Energy*. IJECS, 36(3), 1347-1355. DOI: <https://doi.org/10.11591/ijeecs.v36.i3.pp1347-1355>
- [14] Al-Aboosi, F., et al. (2024). *Fourier Regression for Robust Solar and Wind Data Recognition*. BDCC, 8(3), 0023. DOI: <https://doi.org/10.3390/bdcc8030023>
- [15] Baseer, M., et al. (2023). *Electrical Power Generation Forecasting from Renewable Energy Systems Using AI*. Energies, 16(18), 6414. DOI: <https://doi.org/10.3390/en16186414>
- [16] Usman, T., et al. (2023). *Investigating Energy Production via ML-Based Sustainable Sources*. IEEE ICAI. DOI: <https://doi.org/10.1109/ICAI58407.2023.10136677>
- [17] Ahmed, S. (2024). *Renewable Energy Prediction Using Different ML Algorithms*. IJRSET, 63720. DOI: <https://doi.org/10.22214/ijraset.2024.63720>
- [18] Alharbi, H., & Iqbal, T. (2024). *Novel Hybrid Data-Driven Models for Enhanced Renewable Energy*

Prediction. *Frontiers in Energy Research*.

DOI: <https://doi.org/10.3389/fenrg.2024.1416201>

[19] Goel, A., et al. (2024). *Explainable AI & ML Techniques in Solar Energy Forecasting*. IGI Global.

DOI: <https://doi.org/10.4018/979-8-3693-7822-9.ch011>

[20] Shrimali, M., & Shrimali, D. (2024). *AI Applications in the Renewable Energy Sector*. IJISRT.

DOI: <https://doi.org/10.38124/ijisrt/ijisrt24nov828>

[21] Komala, R., et al. (2024). *Smart Energy Systems-Integrated ML, IoT, and AI Tools*. IGI Global.

DOI: <https://doi.org/10.4018/979-8-3693-2351-9.ch011>

[22] Santhoshkumar, G., & Vanila, A. (2024). *Exploratory Data Analysis & Energy Predictions with AI*. IGI Global.

DOI: <https://doi.org/10.4018/979-8-3693-1586-6.ch018>

[23] Alghamdi, M., et al. (2023). *Stacking Ensemble Model & AI Optimization for Renewable Energy Forecasting*. *Energies*, 16(3), 1370. DOI: <https://doi.org/10.3390/en16031370>

[24] Lin, Y. (2023). *AI Forecasting Techniques for Reducing Uncertainties in Renewable Energy*. PhD Thesis, Corvinus University. DOI: <https://doi.org/10.14267/phd.2023006>

[25] Veigners, R., & Galinš, A. (2024). *Adaptive AI for Renewable Energy Forecasting*. *ERDev*.

DOI: <https://doi.org/10.22616/erdev.2024.23.tf232>

