Intelligent Systems for Renewable Energy Forecasting and Management

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Keywords: Renewable Energy Forecasting, Artificial Intelligence, Deep Learning, Hybrid Models, CNN-LSTM, Systematic Review.

Abstract: In the current study, a critical and analytical review of existing models of artificial intelligence for renewable energy utilization is provided, with specific reference to solar and wind energy forecasting. Unlike other studies that are directed toward developing new models of renewable energy forecasting and experimentally proving them, the current study is directed toward critically evaluating existing models of machine learning and deep learning that are applied for renewable energy forecasting. A range of models, including traditional statistical models, supervised learning models, and advanced models of deep learning like LSTM, CNN, hybrid models of CNN-LSTM, and Transformer models, are considered for review. By critically synthesizing existing literature, the study identifies the advantages and disadvantages of existing models of renewable energy forecasting with respect to forecasting accuracy, generalization, data dependency, computational complexity, and reproducibility. Additionally, it is shown how differences in data, forecasting horizons, and evaluation metrics impact the comparison of models of renewable energy forecasting. By summarizing recent developments in methodological approaches, the current review is directed toward providing structured insights that are helpful for future developments in intelligent renewable energy forecasting models.

1 INTRODUCTION

In the last decade or so, artificial intelligence has grown from a theory to one of the essential methods of programming and has found many applications as a tool of independent data analysis, prediction, and decision-making processes [1]. These include the proliferation and enhancement of computing technologies, extensive quantities of data, and the implementation of complex deep learning algorithms. While other statistical programming languages are unable to deal with nonlinear associations due to their lack of efficiency, artificial intelligence programming can easily detect complex nonlinear patterns existing in multivariate time series data, which cannot be easily executed using other means [2]. There are several recent works that imply that deep learning models can successfully process the complex spatiotemporal characteristics evident in renewable energy information. As such, deep learning was coupled with atmospheric information and wind observation for the determination of the accuracy of wind forecasts in three-dimensional forms within short-term lead times, and these works had promising results for various weather conditions [3]. Transformer models have been effective in processing multivariate time series, where intricate temporal relationships can be learned using deep learning models [1]. Classic forecasting methods, such as linear regression and ARIMA, develop under linear assumptions and linear temporal structures. Their capability is limited to give good predictions over long-term dynamics [4]. Systematic reviews are indicative of the fact that deep learning methods are considerably effective as compared to conventional methods. These conventional methods give small error values, such as RMSE and MAE for forecasting in the subject domain of wind energy [5]. From a broad perspective, the integration of deep learning into renewable energy forecasting cannot be underestimated since these greatly contribute to enhancing the accuracy of solar and wind energy predictions [6]. Furthermore, according to reports from the International Energy Agency-IEA and International Renewable Energy Agency-IRENA, solar and wind energy are one of the fast-increasing categories of renewable energy sources throughout the world, due to higher accessibility and reduced production costs [7], [8]. However, the major problem with the use of solar and wind energy sources lies in the fact that they show certain time dependency, and thus wind energy depends on changes in the speed and directions of winds, and solar energy depends on the amount of irradiance due to various changes in humidity, temperature, and cloudiness [9]. Moreover, it is difficult to model long-term dependencies and nonlinear effects of renewable energy with statistical measures, which might result in high prediction error [10]. Therefore, artificial intelligence techniques such as machine learning and deep learning have become imperative to improve the predictive accuracy and stability of models [11]. Among these models, LSTM networks have been able to efficiently solve long-term temporal patterns in a data series [12]. Further, hybrid models using a combination of CNNs and LSTMs have shown better performance compared to other models while solving complex multivariate time series problems [13].

The work described in this research tries to determine whether deep learning technologies, with a hybrid of CNN, LSTM, or Transformer models, have the potential to enhance the accuracy and reliability of renewable energy prediction technologies.

2 RENEWABLE ENERGY FORECASTING WITH EVOLVING ARTIFICIAL INTELLIGENCE TECHNOLOGIES

Recent breakthroughs in artificial intelligence have remarkably enhanced forecasting in solar and wind energy by replacing classical statistical methods with machine learning and deep learning methodologies that can model complex nonlinear energy patterns.

2.1 Traditional Forecasting Models

In past, various approaches for renewable energy forecasting employed classical statistical techniques, which are valid under the assumption of linear and relatively constant time series data, and include techniques such as linear regressions, autoregressive (AR), and autoregressive integrated moving average (ARIMA) models. Such statistical techniques were favorable for use in renewable energy forecasting as they were simple and easily understandable [4]. Renewable energy data, however, experiences a high impact from climate and seasonal variation and, as such, does not follow stationarity, making the data highly dynamic and nonlinear in nature. The accuracy of statistical modeling for renewable energy forecasting, under such conditions, experiences a considerable decline [4]. Moreover, the failure of ARIMA-based techniques in dealing with nonlinear phenomena in actual time series data for energy systems has led to the application of hybrid approaches for forecasting, which include intelligent techniques along with statistical modelling [14].

2.2 Machine Learning Models

It is observed that due to advances in accessible information regarding meteorology and energy production, machine learning algorithms have appeared as efficient substitutes for traditional statistical methodologies. These algorithms can learn and establish intricate nonlinear relationships between output variables and multiple inputs, such as temperature, wind speed, and solar irradiance [15]. Supervised learning methodologies, which involve artificial neural networks and support vector machines, show improvements in forecasting accuracy in comparison to conventional statistical methodologies while employing error metrics for evaluation purposes [15], [16]. However, there may exist limitations in the performance of machine learning algorithms that can limit the usage of such algorithms for sophisticated renewable energy forecasting, as they can become overly complicated in dealing with time-series inferences [6].

2.3 Deep Learning Models

Recent advancements made in the field of deep learning also aided in further developing renewable energy forecasting techniques, as many issues associated with traditional machine learning techniques were resolved. Deep learning techniques also proved to be effective in handling nonlinear variations of solar and wind energy data, as they can automatically learn features from raw data [6]. Deep learning techniques were also shown to possess good performance in handling both short-term and long-term dependencies of time-series data, thereby reducing the need to perform explicit feature learning during such tasks [17]. Effective forecasting strategies using intelligent techniques were also noted in recent comparative studies for renewable energy systems [18]. Figure 1 illustrates classification of artificial intelligence models used in renewable energy forecasting.

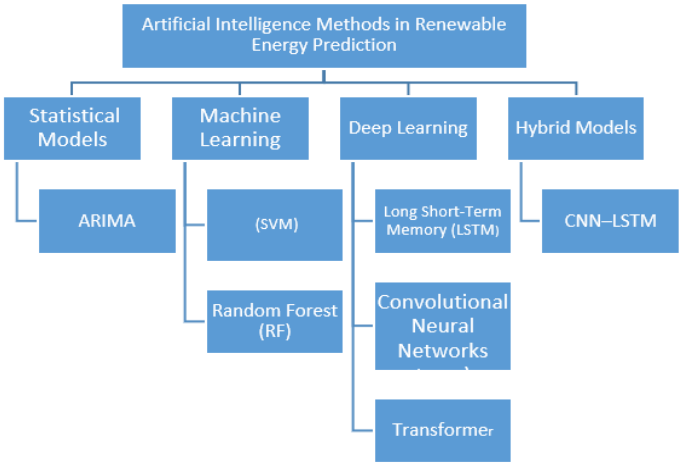

Figure 1: Classification of artificial intelligence models used in renewable energy forecasting.

3 RELATED WORK

3.1 Artificial Intelligence for Solar Energy Forecasting

Solar radiation forecasting with a plethora of machine learning and deep learning approaches has been in the limelight. Machine learning techniques can model intricate nonlinear relationships between the input features-temperature, irradiance, etc., of climatic parameters that exert higher accuracy than the traditional statistical methods [9], [15]. Deep learning models have further enhanced the reliability in forecasting by their greater capability in handling large-scale nonlinear data and extracting hierarchal features from the raw inputs. Hybrid models, especially those implemented by CNN and LSTM architecture, have shown better performance in the short-term prediction of solar radiation compared to the individual models [2], [19], [20].

3.2 Wind Energy Forecasting using AI

Applications of machine learning techniques have been quite successful in forecasting wind energy for the short term, providing a finer capture of nonlinearities present in wind speed series compared to traditional statistical approaches [12], [21]-[23]. In general, hybrid deep learning models, including LSTM and backpropagation neural networks, modeled the long-term temporal dependencies and presented results with higher accuracy. Advanced architectures like CNN-Transformer models increase the processing power of multimodal and multidimensional wind data for global-scale forecasting [24], [25].

3.3 General and Hybrid AI Models for Renewable Energy Forecasting

Comparative studies highlight that AI-based methods perform better when compared to classical statistical models for various renewable energy [19], [26]. Supervised learning can enhance energy management systems through the mitigation of renewable generation uncertainties, as well as in microgrid scenarios [27]. Advanced deep learning architectures, among which Transformer-based models perform very well, allow significant enhancements regarding the forecasting performance for high-dimensional and complex temporal data; thus, underlining the importance of hybrid and deep models in the modern field of renewable energy forecasting [1], [5]. A comprehensive summary of the reviewed studies, including data types, models used, advantages, and disadvantages, is shown in Table 1

4 REVIEW METHODOLOGY AND ANALYTICAL FRAMEWORK

The research design of this study follows a structured review approach to analyze AI-based methods of forecasting in the field of renewable energy. The general taxonomy presented earlier supports this classification.

4.1 Artificial Intelligence Models in Renewable Energy Forecasting

4.1.1 Machine Learning

Machine learning algorithms are prominent in the literature and are often compared to deep learning techniques in renewable energy forecasting.

4.1.2 Support Vector Machine (SVM)

The Support Vector Machine (SVM) algorithm is also very popular scheduled for its potential to create non-linear relationships between climatic factors and energy output using a kernel function. The algorithm shows good generalization ability, especially when dealing with small to medium-sized data sets [15].

4.1.3 Random Forest (RF)

Random Forest was chosen for its ensemble property, which reduces sensitivity to noise as well as overfitting, using complex interactions between features without making assumptions in the models [28].

4.1.4 Deep Learning

Deep learning models have attracted considerable attention in renewable energy forecasting due to their ability to handle complex non-linear relations and long-term temporal dependencies in time series. The Transformer-based models, including Temporal Fusion Transformer (TFT), utilize attention mechanisms to learn multivariate and multi-horizon forecasting patterns. The attention mechanism is particularly effective in time series data, as discussed in references [29]. Convolutional Neural Networks (CNNs) are commonly utilized in feature extraction from large-scale feature spaces. Recent studies demonstrate their potential in enhancing forecasting performance [19], [30].

4.1.4.1 Long Short-Term Memory (LSTM)

LSTM networks can be considered suitable for use in forecasting renewable energy due to their "gated" architecture that can efficiently handle long-term temporal dependencies. This can be considered especially useful while learning from sequential data under dynamic conditions that vary frequently with respect to the weather [24].

4.1.4.2 Hybrid CNN-LSTM

Hybrid CNN-LSTM models combine CNN layers for feature learning with LSTM layers for temporal sequence modelling in a unified model. This helps in modelling short-term changes as well as long-term trends in renewable energy time-series data. Research studies show that better performance in short-term forecasting can be achieved compared to CNN and LSTM models alone [19], [30].

4.1.4.3 Transformer-Based Models

Recently, the Transformer model and attention-based networks have been applied to the field of renewable energy forecasting to model long-range dependencies in multivariate time series data [29]. Such models can provide high accuracy in prediction tasks, but they often require large amounts of data and significant computational power.

4.2 Comparative Analysis between Machine Learning and Deep Learning Models

Traditional machine learning techniques, like SVMs and RFs, are popular due to their simplicity and computational ease. However, the predictive capability of these techniques heavily relies upon the selection of the best features, and their performance is not guaranteed when the generation of renewable energy sources experiences sudden changes [9], [20]. Deep learning techniques, like LSTM, have been found to perform better than other techniques in identifying the patterns of the variable weather conditions [24]. In addition, the hybrid model of CNN-LSTM has been found to perform better than other techniques in terms of short-term forecasting, as described in [19], [11].

5 RESEARCH GAP

Although some recent works have shown enhanced forecasting accuracy employing machine learning and deep learning methods [9], [20], there is a lack of comprehensive comparison among various datasets and forecasting intervals. The existing review papers have shown the variety of datasets, performance metrics, and settings in the literature of renewable energy forecasting research [5], [6]. Moreover, although some hybrid models like CNN-LSTM have shown improved short-term forecasting accuracy [19], [30], and some LSTM-based models are widely used for wind forecasting [24], the problem of generalization and standardized evaluation is not always considered.

Table 1: Research literature summary on renewable energy forecasting.

Reference	Data Type	Algorithm / Model	Objective	Main Strength	Main Weakness	Reported Comparison
Georgios Zerveas (2021) [1]	Multivariate time-series	Transformer	Time-series representation learning	Captures long-range temporal dependencies	High computational cost	Transformer > RNN
Philippe Voyant (2022)[2]	Solar radiation time-series	CNN, LSTM, DL hybrids	Solar radiation forecasting	Handles nonlinearity and temporal variability	Requires large datasets	DL > traditional ML
Shabbir (2022) [3]	Wind time-series data	Deep learning models (LSTM/RNN)	Short-term forecasting	High accuracy	Limited generalization	DL > traditional ML
George Box (2015) [4]	Time-series	AR, ARIMA	Classical forecasting	High interpretability	Poor performance with nonlinearity	Inferior to AI models
Carlos Manzano (2025) [5]	Wind energy studies	DL models (review)	Wind forecasting review	Identifies dominance of DL	No experimental validation	DL > traditional
Anitha Prema (2021) [6]	Wind & solar datasets	ML & DL (review)	Performance evaluation	Comprehensive comparison	Dependent on reported studies	DL > ML
IEA (2023) [7]	Global energy data	Policy analysis	Renewable outlook	Highlights solar & wind growth	No forecasting models	-
IRENA (2024) [8]	Global transition data	Energy outlook	Energy transition trends	Strong global perspective	No forecasting models	-
Ledmaoui (2023) [9]	Solar plant time-series	RF, SVR, ANN, XGBoost	Solar production forecasting	XGBoost achieved best accuracy	Single-site data	XGBoost > ANN, SVR
Imran Khan (2024) [10]	Weather + time features	CNN, LSTM, GRU, CNN-LSTM	Renewable forecasting	Captures spatial & temporal patterns	Higher model complexity	Hybrid > single DL
Ahmed Elmousalami (2025) [11]	Wind energy datasets	AI-based DL models	Sustainable wind forecasting	Improved accuracy and robustness	High data requirements	DL > traditional
Daniel Buturache (2021) [12]	Wind time-series	ML models	Wind energy prediction	Captures nonlinear patterns	Feature-dependent	ML > statistical
Wei Zhang (2023) [13]	Load time-series	Bayesian CNN-BiLSTM	Load forecasting	Low RMSE and high correlation	Computational cost	CNN-BiLSTM > LSTM
G. Peter Zhang (2003) [14]	Time-series	Hybrid ARIMA-NN	Nonlinear forecasting	Combines linear and nonlinear learning	Model tuning complexity	Hybrid > ARIMA
Demir Citakoglu (2023) [15]	Solar radiation data	SVM, ANN	Solar forecasting	Effective nonlinear modeling	Sensitive to feature quality	ML > statistical
Gutiérrez (2021) [16]	Solar power data	Supervised ML	Solar power prediction	Improved MAE and RMSE	Limited generalization	ML > baseline

Table 1 (continued): Research literature summary on renewable energy forecasting.

Reference	Data Type	Algorithm / Model	Objective	Main Strength	Main Weakness	Reported Comparison
Ahmed Mahmoud (2020) [17]	Time-series studies	DL models (survey)	DL forecasting review	Strong temporal modeling	No experiments	DL > ML
Shahiduzzaman (2021) [18]	Renewable datasets	Comparative ML	Energy forecasting	Reduced prediction error	Dataset-dependent	ML > classical
Marinho (2023) [19]	Solar irradiance data	CNN-1D, LSTM, CNN-LSTM	Short-term forecasting	CNN-LSTM best accuracy	Tuning required	CNN-LSTM > CNN
Nguyen (2025) [20]	Solar datasets	ML regressor	Solar prediction	High accuracy and stability	Feature engineering needed	ML > baseline
Metin Acikgoz (2020) [21]	Wind data (complex terrain)	ELM	Very short-term wind forecast	Fast training and low RMSE	Parameter sensitivity	ELM > ANN, SVR
Karim Bouabdallaoui (2023) [22]	Wind time-series	ANN, SVM, RF, KNN	Short-horizon wind forecast	SVM and ANN best	Scaling sensitivity	SVM/ANN > linear
Wei Lian (2022) [23]	Wind power data	Wavelet + optimized SVM	Wind forecasting	Noise reduction improves accuracy	Multi-stage complexity	Optimized SVM > classical
Fang Liu (2025) [24]	Wind time-series	Adaptive LSTM + BP NN	Wind forecasting	Better temporal learning	Higher complexity	Hybrid > LSTM
Li Qiao (2025) [25]	GNSS-R wind data	CNN-Transformer	Wind speed retrieval	Strong global representation	Large data requirement	Hybrid > CNN
Ramesh Kumbhar (2021) [26]	Power system studies	ML & DL (review)	Integrated power systems	Higher forecasting accuracy	Review-based	DL > ML
Elazab (2024) [27]	Solar microgrid data	NN, SVM, GPR	Uncertainty mitigation	NN achieved lowest error	Scenario-specific	NN > others
Huseyin Bilgili (2024) [28]	SCADA wind data	ML algorithms	Wind power forecasting	Accurate real-time prediction	Data noise	ML > conventional
Lim et al. (2021) [29]	Multivariate time-series	TFT	Multi-horizon forecasting	Interpretable predictions	Complex architecture	TFT > RNN
Punyam & Gebremedhin (2024) [30]	Solar microgrid data	Deep Learning	Solar forecasting	Improved accuracy	Data intensive	DL > ML

6 DISCUSSION OF FINDINGS IN REVIEWED STUDIES

In this section, we will discuss the major insights that can be derived from the literature reviewed above.

6.1 Reported Performance of Solar and Wind Energy Forecasting

It has been observed in some research that deep learning models tend to have lower MAE and RMSE values than traditional machine learning models and statistical models in the case of renewable energy forecasting tasks [5], [20].

In the case of solar energy forecasting, CNN-LSTM hybrid models are often found to perform better in terms of short-term forecasting than CNN models and LSTM models. This is because CNN models are capable of local feature extraction, and LSTM models are capable of modelling temporal sequences [19].

In the case of wind energy forecasting, LSTM models and hybrid models have been found to perform well in terms of modelling the fluctuating wind speed patterns and weather conditions [24].

6.2 Discussion

The results presented in the table indicate that the application of advanced deep learning and hybrid models is found to show better prediction capabilities than the traditional statistical models in the context of renewable energy forecasting. The literature reviewed in the paper points towards a gradual shift from the traditional linear-based models towards intelligent models suitable for modelling nonlinear and dynamic data. Even though models such as ARIMA are appropriate for modelling stationary and linear data processes [4], the renewable energy sources are greatly affected by meteorological conditions, which makes the data inherently nonlinear and non-stationary in nature [6].

The application of traditional machine learning models such as Support Vector Machines and Random Forest improves the prediction accuracy of the models but is highly dependent on the features and dataset characteristics [9], [15]. On the other hand, the application of deep learning models such as LSTM is found to show better capabilities in modelling the wind and solar data sequences [24]. Hybrid models such as CNN-LSTM improve the forecasting capability in the short-term horizon [19]. The application of Transformer models is also recently proposed in the context of modelling long-range dependencies in the context of multivariate forecasting models [29].

6.3 Relevance to Research Objective

The literature review indicates that there is evidence of the effectiveness of deep learning methods, specifically hybrid CNN-LSTM models, in achieving higher accuracy in forecasting through the efficient representation of temporal relationships and climatic variables [19], [24]. Compared to traditional methods, these models are more capable of handling the non-linear patterns of solar and wind energy production [19], [24].

The above points strengthen the research objective of assessing the effectiveness of advanced AI-based approaches for strengthening the precision of forecasting mechanisms in renewable energy systems [11].

7 CONCLUSIONS

In this paper, a structured and analytical review of artificial intelligence techniques for renewable energy forecasting with specific reference to solar and wind energy systems was presented. From the analysis of literature reviewed, it is evident that there is a shift from conventional statistical models to machine learning and deep learning models for forecasting nonlinear and time-dependent data. Although conventional models such as ARIMA are effective for stationary processes, their application is limited under dynamic conditions. Machine learning algorithms, including Support Vector Machine and Random Forest, have also been found to possess superior predictive properties compared to conventional statistical models. Nevertheless, their performance is subject to effective feature selection as well as data characteristics. In contrast, deep learning models, including LSTM as well as hybrid CNN-LSTM models, possess superior properties for learning temporal dependencies as well as hierarchical features from complex datasets, thus improving their performance in short-term forecasting. Despite these advancements, there exist some challenges like diversity in datasets and evaluation schemes. In conclusion, the increasing use of AI-based methods has proven their importance in developing renewable energy forecasting techniques.

8 FUTURE WORK

Future research directions in the field could be centred around the improved interpretability, scalability, and generalizability of deep learning techniques used in forecasting models of renewable energy systems. In addition, the transformer model and CNN-Transformer model, with the application of the attention mechanism, can be further researched because of their potential to address the complex temporal dependencies of multivariate data. Another way of improving the reliability of the forecasting model is through the application of probabilistic learning techniques, such as the Bayesian neural network. Lastly, the role of lightweight deep learning techniques is significant in the application of forecasting systems.

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