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Machine learning models in renewable energy forecasting: a systematic literature review

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ABSTRACT

During the past years, the convergence of machine learning (ML) technologies with renewable energy sectors has become a significant key area of innovation as a key area of innovation, enhancing the efficiency and predictability of sustainable energy sources. ML algorithms, adept at handling complex data, have become essential in forecasting energy outputs from variable sources like solar and wind. This integration has led to the development of smarter, more adaptive grid systems, capable of efficiently managing the variability of renewable energy sources. This review paper focuses on several key areas: firstly, it provides a summary of related work, specifically focusing on ML in the renewable energy field. Secondly, it delves into ML models and evaluation metrics used for solar and wind energy forecasting. Thirdly, it analyzes 21 studies published from 2019 to 2023, primarily centered on solar energy (60%) and wind energy (40%), with an emphasis on various forecasting horizons, highlighting the results of the ML algorithms used and the performance metrics to evaluate their effectiveness. Finally, it identifies gaps and opportunities in this field. The state-of-the-art review and its findings can offer a solid foundation for future research initiatives.

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1. INTRODUCTION

The evolution of electromobility, along with developments in agriculture and farming, telecommunications, and other domains, has led to an increased demand for electricity from renewable energy sources [1]. This growing need is a reflection of the global transformation towards cleaner, more sustainable energy forms. In recent years, renewable energy research and development has grown significantly due to the demand for sustainable energy solutions [2].

However, the adoption of renewable energy is very challenging, primarily due to the variability and unpredictability associated with weather conditions. Wind energy, for example, is highly dependent on weather patterns, which can be challenging to forecast with accuracy [3]. Also, the production of solar energy is affected by weather patterns such as seasonal changes in sunlight, cloud cover, and others [4]. These challenges present obstacles to integrating the power grid with renewable energy systems.

To meet the instability caused by weather patterns of renewable energy sources, it becomes essential for photovoltaic (PV) systems and wind farms to provide advanced electricity generation forecasts [5]. Traditional forecasting methods, which employed for decades, depend on statistical and physical approaches [6], often fail to handle the complex and nonlinear data of renewable energy characteristics [7]. In the last few years, machine learning (ML) has emerged as an effective solution in the renewable energy industry. ML models can handle and learn from vast quantities of data, including time series, meteorological, and geographical data. This makes ML a suitable solution for addressing the challenges in renewable energy data analysis, basically enhancing the efficiency and integration of renewable energy systems. Numerous studies have reviewed the literature on ML models in the renewable energy sector. Table 1 (in Appendix) [8]-[18] summarizes selected related works spanning from 2019 to 2023.

The novelty of this work lies in its focused review of recent advances in ML methods for forecasting solar and wind power, offering a perspective on the integration of artificial intelligence in enhancing the predictability and efficiency of RE systems. By extracting deep information from 21 carefully selected papers, this study provides an analysis of the performance, challenges, and opportunities of various ML models in the context of renewable energy forecasting. Additionally, the examination of forecasting horizons highlights the adaptability and effectiveness of these models across various temporal scales.

The structure of this paper is as follows: section 2 explores the materials and methods. In this section, we provide in-depth explanations of the ML algorithms, the metrics used to evaluate forecasting performance, and the different forecasting horizons employed in the reviewed studies. We also outline the methodology used for selecting relevant research articles for the literature review. In section 3 is dedicated to the discussion of the results.

2. MATERIALS AND METHODS

2.1. Machine learning

ML, a branch of artificial intelligence, involves the use of algorithms to uncover hidden patterns within data. It was first defined in 1959 by Arthur Samuel as the “field of study that enables computers to learn without explicit programming” [19]. ML algorithms are typically categorized into three main types: supervised learning, unsupervised learning, and semi-supervised learning. Figure 1 illustrates the different categories of ML algorithms.

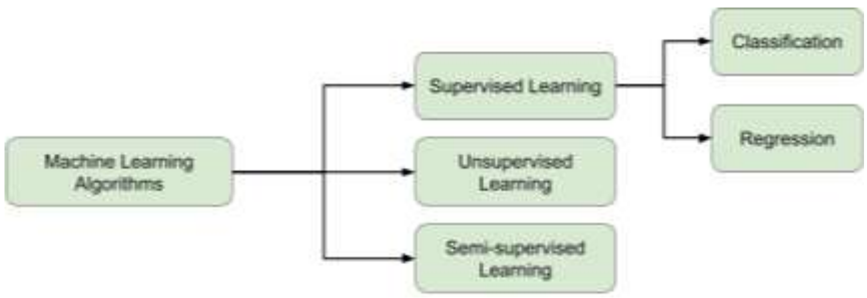

Figure 1. Categories of ML algorithms

In this review, we focus on supervised learning, specifically on regression problems, as shown in Table 2 (in Appendix) [21]-[37]. This focus is relevant in the context of renewable energy, such as solar and wind power, where ML models are used to forecast energy output. Regression models are applied to predict continuous values based on historical and environmental data, an essential step in optimizing the efficiency of renewable energy systems.

2.2. Machine learning algorithms used in solar and wind energy

Previously, we identified that predicting power output in renewable energy systems fundamentally constitutes a regression problem. Table 2 (in Appendix) presents common models used in selected studies.

2.3. Measurements of forecasting performance

Measurements of performance refers to a set of statistical tools and methods used to evaluate and quantify the effectiveness of a model in representing real-world phenomena [38]. As previously mentioned, forecasting solar and wind energy falls under the category of supervised learning, particularly focusing on regression problems. Therefore, our focus will be on evaluating performance metrics specific to supervised learning methods. Table 3 presents common performance metrics used in selected studies.

Table 3. Common performance metrics used in selected studies

Metric	Formula	Components
MAE	$\frac{1}{N}\sum_{i=1}^{N} \mid y_i - \hat{y}_i \mid$	N is the number of observations. y_i is the actual value. $\hat{y}_i$ is the predicted value. $\bar{y}_i$ is the mean of the actual values.
MSE	$\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$	
RMSE	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$	
Mean bias error (MBE)	$\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)$	
Mean absolute percentage error (MAPE)	$\frac{100}{N}\sum_{i=1}^{N}\left\|\frac{y_i - \hat{y}_i}{y_i}\right\|$	
R2-score (coefficient of determination)	$1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}$	
Normalized mean absolute error (nMAE)	$\frac{MAE}{\bar{y}}$	
Normalized root means square error (nRMSE)	$\frac{RMSE}{\bar{y}}$	
Normalized mean bias error (nMBE)	$\frac{MBE}{\bar{y}}$	
Normalized mean absolute percentage error (nMAPE)	$\frac{MAPE}{\bar{y}}$	

2.4. Forecasting horizons

Forecasting horizons refer to the time periods over which predictions are made, ranging from a few minutes to several months or even years. In the field of renewable energy, particularly for solar and wind power, the length of the forecasting horizon plays a crucial role in determining the accuracy and effectiveness of the predictions [17]. Forecasting horizons are typically classified into different categories based on the prediction duration, such as short-term, medium-term, and long-term forecasting. Table 4 provides an overview of forecasting horizons used in renewable energy prediction.

Table 4. Forecasting horizons in renewable energy forecasting [17]

Type	Description
Short-term	Few minutes or hours up to 72 hours ahead
Medium-term	From around 72 hours to a few weeks ahead
Long-term	From several weeks to several months or even years ahead

2.5. Method

The process followed to find pertinent research articles involves four stages: choosing keywords and selecting a database, setting criteria for filtering the search, selecting research articles, and conducting a manual screening. Figure 2 illustrates the proposed approach.

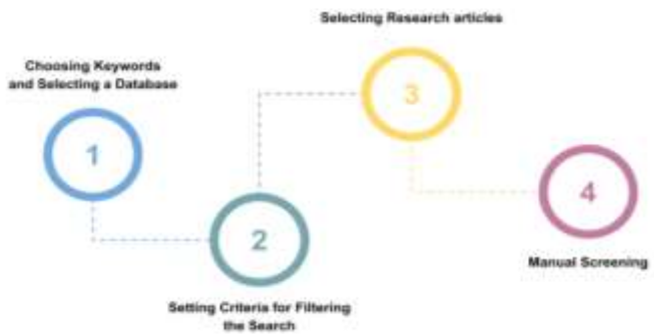

Figure 2. Methodology process

2.5.1. Choosing keywords and selecting a database

The selection of the Scopus database for sourcing articles was based on its reputation for delivering data of superior quality. Scopus provides a comprehensive collection of diverse publications, encompassing article and conference papers, books, and various websites across key disciplines [39]. Numerous query strings were employed to identify publications relevant to our topic, including terms like "machine learning", "forecasting", "prediction", and others related to renewable energy such as "renewable energy", "solar energy", "wind energy", "power prediction" and others. Using these targeted keywords, we collected a large number of papers.

2.5.2. Setting criteria for filtering the search

In the process of refining our search for relevant research articles, specific criteria were established to filter the results, ensuring both relevance and quality. Firstly, the document type was restricted to journal articles, a choice made to focus on peer-reviewed academic research. Regarding the publication year, we narrowed our scope to articles published between 2019 and 2023. This time frame was selected to capture the most recent developments and trends, ensuring that the analysis is based on up-to-date information and modern research findings. Lastly, language was a critical filter, we limited our search to articles written entirely in English. These criteria were essential in simplifying the search and obtaining the most relevant and high-quality papers.

2.5.3. Selecting research articles

For our analysis, we carefully chose articles that were specifically focused on solar and wind energy, with an additional emphasis on their relationship with ML. This precise criterion was crucial to ensure that our review remained focused on the intersection of RE and technological advancements in ML. Table 5 presents the articles selected for this study.

Table 5. Papers selected for review

Year	Ref	Sources of energy
2019	[40]-[44]	Solar
	[44], [45]	Wind
2020	[46], [47]	Solar
	[48], [49]	Wind
2021	[50], [51]	Solar
	[52], [53]	Wind
2022	[54], [55]	Solar
	[56], [57]	Wind
2023	[58], [59]	Solar
	[60]	Wind

2.5.4. Manual screening

Continuing with our research process, the upcoming section will display in-depth results from our manual screening. This part of our study is dedicated to closely examining the articles we initially chose, specifically concentrating on the results of their relevance to solar and wind energy and their connection with ML.

3. RESULTS AND DISCUSSION

In this section, we will detail the studies chosen from the earlier section. We start by describing the comparison criteria outlined in Tables 5 and 6 (in Appendix):

- Models: the forecasting models used in each study.
- Dataset: the data utilized for training, testing, and evaluating each model.
- Features: the input variables used in the model training process.
- Targets: the predicted outcomes from the models.
- Forecasting horizon: the time span the predictions cover.
- Metrics: the evaluation techniques employed to measure and improve the model's effectiveness.
- Best model: the model that achieved the highest performance in the test set.

V1: global horizontal irradiation, V2: temperature, V3: wind speed, V4: relative humidity, V5: atmospheric pressure, V6: diffuse horizontal irradiance, V7: timestamp, V8: precipitation, V9: wind direction, V10: PV surface temperature, V11: radiation, V12: beam normal irradiance, V13: clear-sky global horizontal, V14: solar power, V15: vapor pressure, V16: rainfall type, V17: sky type, V18: elevation, V19: weekly index, V20: dust accumulation, V21: cloud (and others related to cloud cover), V22: PV power output, V23: concentrated solar radiation, V24: non-concentrated solar radiation, V25: daily average wind speed, V26: daily average sunshine duration, V27: daily average temperature, V28: Azimuth, V29: declination angle, V30: maximum power of the cell, V31: Ultraviolet, V32: dew point temperature.

The results presented in Table 6 demonstrate the diversity of ML models used in these studies [40]-[44], [46], [47], [50], [51], [54], [55], [58], [59]. This diversity reflects the varied datasets employed in each study, indicating that no universal model is suitable for all cases. In the context of identifying the best model for each study, we found that decision tree (DT), particularly random forest (RF), demonstrated better accuracy, with 42.9%, followed by artificial neural network (ANN) and K-nearest neighbor (K-NN) with 14.3% each, and support vector regression (SVR), extreme learning machine (ELM), LightGBM, and Ridge with 7.1% each. These results suggest that RF, ANN, and K-NN are more suitable for handling complex data and uncovering hidden weather patterns in datasets. We conclude that future work should focus on combining these models into a hybrid model, which could be important for achieving better accuracy. Figure 3 presents the distribution of the top-performing models in selected studies.

In the realm of features used in each study, there is significant variation, but some are commonly selected. Global horizontal irradiation and temperature were used in 12.1% of the studies, wind speed and relative humidity in 7.6% each, and Atmospheric pressure in 6.1%. Diffuse horizontal irradiance, timestamp, and precipitation appeared in 4.5% of the studies each, while wind direction, PV surface temperature, and radiation were included in 3.0% each. The other features were used in 1.5% of the studies each. We conclude that future work should prioritize the refinement of features through the use of feature selection techniques. Figure 4 presents the distribution of the features in selected studies.

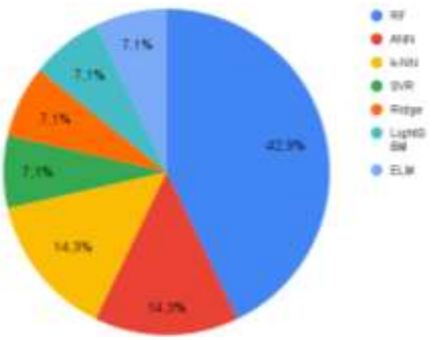

Figure 3. Distribution of the top-performing models in selected solar energy studies

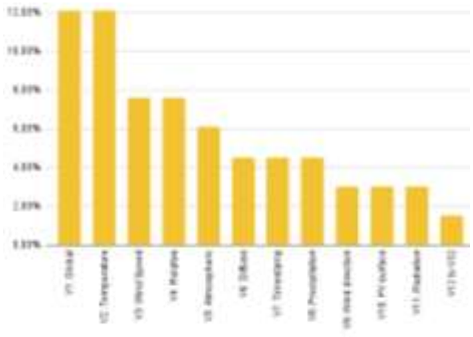

Figure 4. Distribution of features in selected solar energy studies

Identifying the forecasting horizon is an important step in renewable energy prediction. Studies [40]-[44], [46], [47], [51], [54], [55], [58], [59] focus on short-term prediction, while only study [50] addresses medium-term and long-term forecasting. These findings highlight a gap in medium-term and long-term forecasting, suggesting that future work should focus on these areas. Figure 5 presents the distribution of forecasting horizons in selected studies.

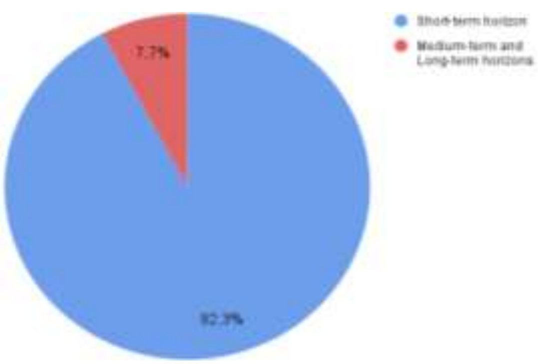

Figure 5. Distribution of forecasting horizons in selected solar energy studies

V1: wind speed, V2: wind direction, V3: timestamp, V4: wind power, V5: Atmospheric pressure, V6: temperature, V7: average of wind speed, V8: standard deviation of wind speed, V9: wind components, V10: wind norm, V11: longitude, V12: latitude, V13: height, V14: roll, V15: pitch, V16: yaw, V17: satellite count, V18: towing speed, V19: control line length, V20: maneuver type, V21: number of satellites, V22: theoretical power, V23: localization of wind turbines, V24: relative humidity, V25: Metmast weather measurements, V26: windfarm curtailment, V27: aggregate power, V28: number of turbines online, V29: turbine power, V30: turbine weather, V31: blade angle, V32: turbine curtailment.

The results presented in Table 7 in Appendix demonstrate the diversity of ML models used for wind energy forecasting in these studies [44], [45], [48], [49], [52], [53], [56], [57], [60]. Similarly, to solar energy forecasting studies, this diversity demonstrates that no universal model is suitable for all cases. The choice of the most appropriate model depends on the specific application and the data from the local climatic zone. Among the best models identified in each study, DT, including RF, GBM, and extreme gradient boosting (XGBoost), are the most frequently used, accounting for 66.7% of cases, followed by ANN, GBR, SVR, and voting regressor (VR), each at 8.3%. Figure 6 presents the distribution of the top-performing models in selected studies.

The diversity of datasets employed in each study highlights the variety of features used across the studies, although some are commonly selected in wind energy forecasting. Wind speed was employed in 12.5% of the studies, wind direction in 8.3%, wind power and timestamp in 6.3% each, and atmospheric pressure, temperature, average wind speed, and the standard deviation of wind speed each in 4.2%. The other features were used in 2.1% of the studies each. Figure 7 presents the distribution of features.

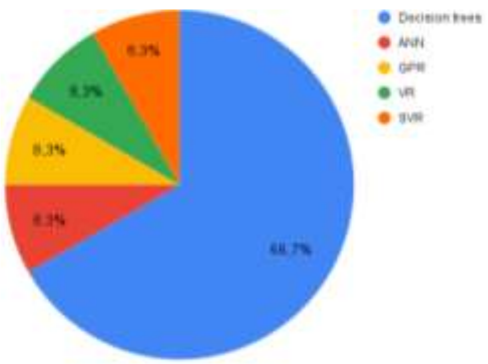

Figure 6. Distribution of the top-performing models in selected wind energy studies

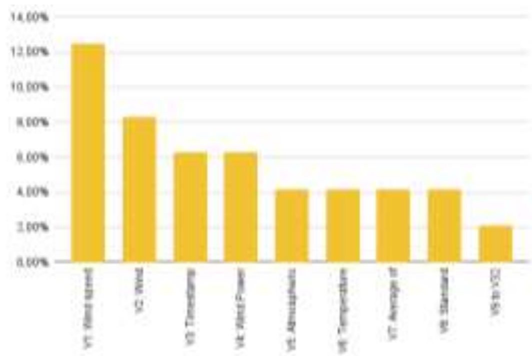

Figure 7. Distribution of features in selected wind energy studies

Similar to solar energy forecasting, determining forecasting horizons in wind energy is a crucial step. Studies [44], [49], [52], [53], [56], [57], [60] focus on short-term forecasting horizon, while only studies [44], [48] address long-term forecasting horizon. This also highlights a similar gap in wind energy forecasting for medium-term and long-term horizons, suggesting that future work should concentrate on these areas. Figure 8 presents the distribution of forecasting horizons in selected studies.

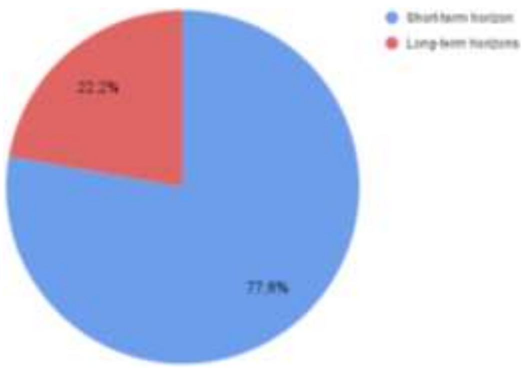

Figure 8. Distribution of forecasting horizons in selected wind energy studies

Both solar and wind energy forecasting studies employ a variety of evaluation metrics, including MAE, root mean squared error (RMSE), R2-score, MSE, MAPE, MBE, MRE, FS, t-stat, nRMSE, nMAE, and nMBE to assess model performance. This diversity in metrics underscores that no single evaluation metric is universally applicable to all models. However, some metrics are more commonly selected than others: MAE was employed in 26.6% of studies, followed by RMSE in 24.6%, R2-score in 18.5%, and MSE in 12.3%. Less frequently used metrics include nRMSE at 4.6%, MAPE and nMAE at 3.1% each, and MBE, MRE, nMBE, FS, and t-stat, each at 1.5%. Figure 9 presents the distribution of evaluation metrics in selected studies.

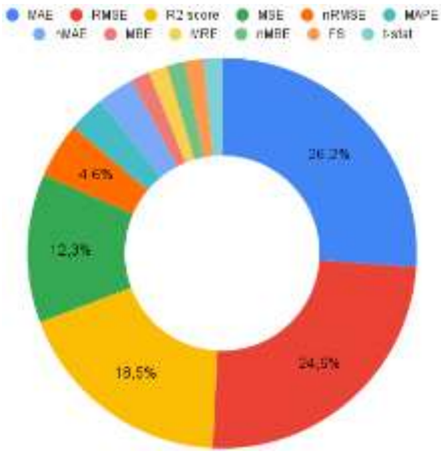

Figure 9. Distribution of evaluation metrics in selected solar and wind energy studies

4. CONLUSION

This paper presents a comprehensive systematic literature review on the use of ML models for forecasting renewable energy outputs, particularly focusing on solar and wind energy. An analysis of 21 studies published from 2019 to 2023 demonstrated that the models employed in these research efforts can manage the complexities and unpredictability characteristic of renewable energy resources. It's noted that DT were the most used method in forecasting renewable energy outputs. Additionally, for solar energy, the commonly used features are global horizontal irradiation, temperature, wind speed, relative humidity, atmospheric pressure, diffuse horizontal irradiance, timestamp, precipitation, wind direction, PV surface temperature, and radiation. For wind energy, the commonly used features include wind speed, wind direction, wind power, timestamp, atmospheric pressure, temperature, average wind speed, and the standard deviation of wind speed. Studies in both the solar and wind energy fields focus on short-term forecasting horizons. Finally, MAE, RMSE, R2-score, and MSE are the evaluation metrics most commonly used compared to other metrics.

Building on the findings of this literature review, future work should focus on the utilization of hybrid models that incorporate DT, aiming to leverage the strengths of various modeling techniques to enhance forecasting accuracy. Additionally, there is a critical need for the development and application of advanced feature selection techniques to identify the most adequate features for specific renewable energy forecasting contexts. As demonstrated in this study, no single model excels in all scenarios. Moreover, while short-term forecasting has been the primary focus, expanding research to include medium-term and long-term forecasting horizons could provide significant insights and benefits.

APPENDIX

Table 1. Literature reviews selected on ML models in renewable energy

Ref	Year	Description
[8]	2019	The paper presents a review of ML models applied in energy systems, focusing on studies conducted between 2015 and 2018. It classifies the models into 10 categories: DT, ensemble methods, support vector machine (SVM), hybrid models, ANN, deep learning (DL), ELM, multi-layer perceptron (MLP), adaptive neuro-fuzzy inference system (ANFIS), and wavelet neural network (WNN). The models are evaluated based on two key metrics: RMSE and correlation coefficient. The paper concludes that hybrid ML models offer the best performance.

Table 1. Literature reviews selected on ML models in renewable energy (*Continued*)

Ref	Year	Description
[9]	2019	The paper presents a literature review of short-term wind power forecasting, covering studies from 2017 to 2019. It finds that hybrid ML models, particularly those using ANN, are commonly employed. The evaluation of these models typically relies on MAE and root MSE. Frequently utilized climatic variables in these models include wind speed, ambient temperature, atmospheric pressure, and relative humidity.
[10]	2020	The paper presents a survey focused on the application of ML models in predicting renewable energy outputs, covering studies from 2017 to 2019. It concludes that there is an increase in the use of hybrid ML models in solar and wind energy forecasting. Additionally, the decomposition method is a commonly used data pre-processing technique in these models. Finally, SVM and ELM often employ metaheuristics for parameter selection.
[11]	2020	The paper presents a review of recent applications of ML and DL techniques for PV output power forecasting, covering studies from 2010 to 2019. It concludes that ML models are used more frequently than DL models. Additionally, most research focuses on forecasting power at a single location. Short-term and long-term forecasting horizons are the most investigated. Finally, hybrid models are considered the optimal choice for improving forecasting accuracy.
[12]	2021	The paper presents a state of art on ML in various fields of solar energy. These applications include forecasting solar irradiance, and power production, predicting electricity prices, forecasting energy demand and others, covering studies from 2018 to 2021. It concludes for PV production forecasting is the most researched area with a focus on short-term forecasts.
[13]	2021	The paper presents a review of the use of ML models for predicting global solar radiation by analyzing 232 studies focused on input parameters, feature selection, and model development. It concludes that data from surface observations provide the highest accuracy. Additionally, filter methods are computationally efficient but less accurate, while wrapper methods achieve optimal feature subsets with high computational costs, and embedded methods balance accuracy and computational efficiency. Also, ML models are classified into seven categories, including generalized, ensemble-based, cluster-based, decomposition-based, decomposition-cluster-based, transition-based, and post-processing-based models.
[14]	2021	The paper presents a systematic review of ML models used for wind and solar power forecasting, focusing on ANN, recurrent neural networks (RNN), SVM, and ELM, covering studies from 2012 to 2020. It concludes that statistical methods, like ARIMA, are favored for short to medium-term forecasts due to their simplicity and effectiveness. Additionally, ANN is effective for nonlinear systems, RNN excels at capturing information over time but can suffer from gradient vanishing problems, SVM offers reliable, generalized models with lower mathematical complexity, but still face overfitting and require careful kernel selection and parameter optimization, and ELM provides fast convergence but is only suitable for simple models. Finally, hybrid ML algorithms are the optimal choice to enhance forecasting accuracy.
[15]	2022	The paper presents a review of methods in wind power prediction, covering studies from 2016 to 2021. It concludes that wind power prediction methods can be categorized into three classes based on prediction horizons: ultra-short-term, short-term, and long-term. Additionally, time series methods are often less effective for predicting wind power due to their limitations in capturing the complexity and nonlinearity of meteorological patterns. In opposition, DL models demonstrate superior performance by effectively managing these complexities, extracting critical features, and achieving high accuracy. Finally, the growing trend of hybrid models, which have improved the accuracy of predictions.
[16]	2022	The paper presents a review of randomization-based ML models in renewable energy prediction. These models are recognized for their ability to balance predictive accuracy with computational efficiency. The review highlights the effective use of randomization-based ML algorithms across different renewable energy sources, such as solar, wind, and hydropower. Furthermore, these models consistently outperformed conventional ML methods in predictive accuracy. Lastly, multi-layered randomization-based models exhibited superior performance compared to single-layered models.
[17]	2023	The paper presents a review of current ML approaches for solar PV power forecasting, with a focus on short-term predictions, examining studies from 2010 to 2020. It concludes that solar PV power output is significantly affected by weather factors, particularly solar irradiance and ambient temperature. Solar PV power forecasting is further classified into different time horizons: very short-term, short-term, medium-term, and long-term. Among ML models with default settings, gradient boost achieved the best performance, while RF with optimized hyperparameters was identified as the top performer. Finally, ML models trained on historical PV power data combined with predicted weather variables outperformed baseline methods.
[18]	2023	The paper presents a review of ML and DL techniques for wind power forecasting, analyzing studies from 2010 to 2023. It explores various strategies for regional wind power prediction, including the accumulation method, upscaling method, and spatial resource matching method. The review concludes that the upscaling method is particularly effective in minimizing data requirements and reducing computational complexity. Furthermore, DL models often outperform traditional ML techniques. Finally, hybrid models, especially those combining AdaBoost with RF or ELM with particle swarm optimization (PSO), demonstrate superior accuracy compared to standalone models.

Table 2. Common models used in selected studies

Model	Short description
Linear regression (LR) [20]	A statistical method used to establish a linear relationship between a dependent variable and one independent variable. By employing a linear equation, this technique enables the prediction of the dependent variable's value based on the independent variable.
Multiple linear regression (MLR) [20]	Extends LR to include two or more independent variables.
Lasso regression (Lasso) [21]	A type of LR that includes regularization. The regularization term added helps in shrinkage and variable selection.

Table 2. Common models used in selected studies (*Continued*)

Model	Short description
Ridge regression (Ridge) [22]	Similar to LR but includes a regularization term that adds a penalty to the size of coefficients to reduce model complexity and prevent overfitting.
SVR [23]	A type of SVM [24] used for regression tasks. It predicts continuous values by determining the best hyperplane that has the height number of points within a predefined margin of tolerance, rather than classifying data into categories.
DT [25]	A method that splits data into branches at decision nodes, leading to possible outcomes or decisions.
RF [26], [27]	A method that builds multiple DTs and combines them to achieve a more accurate and stable prediction.
KNN [28]	A non-parametric technique employed for both classification and regression tasks, which predict the value of a point at the k nearest points.
Gradient boosting machine (GBM) [29]	An ensemble methods technique that sequentially constructs models, with each new one focusing on correcting errors from the previous ones. It merges several weak predictors to form a more powerful model.
Adaptive boosting (AdaBoost) [30]	An ensemble ML technique constructs a strong predictive model by iteratively combining multiple weak learners, specifically tuning the weights of instances based on their previous prediction errors.
XGBoost [31]	A scalable and accurate implementation of GBM, known for its performance and speed in ML competitions.
Category Boosting (CatBoost) [32]	An algorithm based on GBM over DTs. It's known for its effectiveness in handling categorical data directly, without the need for extensive pre-processing. give a minimal short description.
Gaussian process regression (GPR) [33]	A non-parametric kernel-based probabilistic model based on Gaussian Processes and is used for predicting continuous output variables.
Light gradient boosting machine (LightGBM) [34]	An implementation of the GBM framework, it's known for its speed and performance, especially with large datasets and on limited computing resources.
ANN [35]	A ML model composed of interconnected nodes or neurons, mimicking the human brain to model complex patterns and solve prediction problems.
Multilayer perceptron (MLP) [36]	A type of ANN commonly used in ML for both classification and regression tasks. It is composed of an input layer, one or more hidden layers, and an output layer. In an MLP, an activation function is applied to the weighted sum of the inputs, enabling the model to learn and make predictions.
ELM [37]	A type of ANN used in ML for classification, regression, and feature selection tasks. Similar to MLP, ELM assigns random input weights to the hidden layer, which are then kept fixed throughout the training process. This approach allows ELM to efficiently handle a variety of predictive tasks with faster training times compared to traditional neural networks.

Table 6. Results of ML models in solar energy forecasting

Ref	Forecasting horizon	Models	Dataset	Features	Targets	Metrics	Best model
[40]	Short-term	ANN, RF, scaled persistence	PROMES laboratory located in the south of France at Odeillo.	V1, V6, V12	Global horizontal irradiation, Beam normal irradiance, Diffuse horizontal irradiance	MAE, RMSE, nRMSE, nMAE	RF
[41]	Short-term	68 ML models (LR, SVR, LASSO, XGBoost, RF, and GBM)	National solar radiation database (NSRDB)	V1, V13	Global horizontal irradiation	nRMSE, nMBE, FS (Forecast Skill)	RF
[42]	Short-term	LR, SVR, ANN, DT, k-NN, AdaBoost, RF	Yeongam PV power plant in South Korea and Korea meteorological administration (KMA)	V2, V3, V4, V5, V7, V9, V11, V14, V15, V16, V17, V18, V19	Solar power	MSE, RMSE, R2-score	RF
[43]	Short-term	LR, GPR, ANN, M5P tree	PV system at Qatar University	V1, V2, V3, V4, V10, V20	PV power output	MAE, MSE, RMSE, R2-score	ANN
[44]	Short-term	RF, GBM, XGBoot	Global ensemble forecast system (GEFS), provided by the National Oceanic and Atmospheric Administration (NOAA)	V2, V4, V5, V8, V11, V21	Solar power	MAE	RF
[46]	Short-term	SVR, RF, LR, MLP	A 1.22 MW PV system installed at the University of Queensland (UQ), Brisbane, Australia	V7, V22	PV power output	MAE, MRE	RF

Table 6. Results of ML models in solar energy forecasting (*Continued*)

Ref	Forecasting horizon	Models	Dataset	Features	Targets	Metrics	Best model
[47]	Short-term	SVR, ANN, K-NN	Experimental rig by the authors	V7, V10, V23, V24	PV power output	MBE, RMSE, R2-score, t-statistics (t-stat)	SVR, k-NN
[50]	Medium-term, long-term	LR, DT, SVR, RF, MLP, polynomial regression	Historical weather data and actual PV power output from the desert knowledge Australia Centre	V1, V2, V4, V6, V8	PV power output	MAE, MSE, R2-score	RF
[51]	Short-term	ELM, ANN	Karaman province obtained from Turkey General Directorate of State	V25, V26, V27	Solar radiation	MSE, RMSE, R2-score	ELM
[54]	Short-term	24 ML models (LR, Lasso, Ridge, SVR, KNN, RF, GBM, XGBoost, LightGBM, and others)	Official measurements of 16 ground-mounted PV plants operated by MVM Green Generation Ltd in Hungary	V1, V2, V3, V28, V29	PV power output	RMSE	Ridge
[55]	Short-term	k-NN, MLR, DT	Meteorological data from King Abdullah City for Atomic and Renewable Energy (KACARE)	V1, V2, V3, V30	PV power output	RMSE, MAE, nRMSE, R2-score	k-NN
[58]	Short-term	XGBoost, LightGBM, CatBoost	Meteorological data from EDP Open Data, collected from a weather station in Faro, Portugal	V1, V2, V5, V6, V8, V9, V31	PV power output	MSE, RMSE, MAE, R2-score	LightGBM
[59]	Short-term	MLR, ANN	Experimental set-up of PV panels	V1, V2, V3, V4, V5, V32	PV Power output	MAE, MSE, RMSE, R2-score	ANN

Table 7. Results of ML models in wind energy forecasting

Ref	Forecasting Horizon	Models	Dataset	Features	Targets	Metrics	Best model
[44]	Short-term	RF, GBM, XGBoost	Numerical weather predictions (NWP), provided by European Centre for medium-range weather forecasts (ECMWF)	V5, V6, V9 (at surface level and 100 m), V10 (at surface level and 100 m)	Wind power	MAE	RF, XGBoost
[45]	Long-term	LASSO, KNN, XGBoost, RF, SVR	Five years of hourly wind speed observation values in Nigde, Cesme, Mamak, Bozcaada and Silivri in Turkey	V7, V8	Wind power	RMSE, MAE, R2-score	RF, SVR (using only daily wind speed)
[48]	Long-term	DT, RF, AdaBoost, XGBoost, GBM	Ghadamgah (36.104◦ north and 59.066◦ east longitude) and Khaf (34.567◦ north and 60.148◦ east longitude) wind farms, Iran	Case 1: V7, V8 (measured at a height of 40 meters, 10-min sampling time) Case 2: V1 (measured at a height of 40 meters, with 1-h, 12-h, and 24-h sampling times) Case 3: V1 (measured at heights of 30 meters and 10 meters, extrapolated to 40 meters)	Wind power	MAE, RMSE, R2-score	XGBoost
[49]	Short-term	VR, GBM, DT, linear, Ridge, Lasso, Elastic Net, AdaBoost	Experimentally-collected numerical and categorical data from multiple sensors on a kite system designed at Kyushu University	V3, V11, V12, V13, V14, V15, V16, V17, V18, V19, V20, V21	Tether force	MSE, R2-score	VR

Table 7. Results of ML models in wind energy forecasting (*Continued*)

Ref	Forecasting Horizon	Models	Dataset	Features	Targets	Metrics	Best model
[52]	Short-term	RF, K-NN, GBM, DTR, extra tree regression	Yalova wind farm in Turkey	V1, V2, V3, V4, V22	Wind power	MAE, MAPE, RMSE, MSE, R2-score	GBM
[53]	Short-term	RF, ANN, XGBoost	Polish transmission system and energy regulatory office	V1, V3, V4, V23	Wind power	MAPE, RMSE,	XGBoost (for hourly predictions) ANN (for daily prediction)
[56]	Short-term	GPR, SVR, RF, XGBoost	Senvion MM82 wind turbines in France, Wind turbine in Turkey, and Kaggle dataset	V1, V2, V4	Wind power	RMSE, MAE, R2-score	GPR, RF, XGBoost
[57]	Short-term	LR, SVR, LSTM, RF, GBM, XGBoost, Bayesian Ridge	Different wind farms and Darksky	V1, V2, V5, V6, V24, V25, V26, V27, V28, V29, V30, V31, V32	Wind power	MAE, RMSE	XGBoost
[60]	Short-term	GBM	Wind farm located on Jeju Island, South Korea	V1, V2, V3	Wind power	MAE, RMSE, nMAE	GBM

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