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Review

Machine Learning Approaches to Predict Electricity Production from Renewable Energy Sources

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Abstract: Bearing in mind European Green Deal assumptions regarding a significant reduction of green house emissions, electricity generation from Renewable Energy Sources (RES) is more and more important nowadays. Besides this, accurate and reliable electricity generation forecasts from RES are needed for capacity planning, scheduling, managing inertia and frequency response during contingency events. The recent three years have proved that Machine Learning (ML) models are a promising solution for forecasting electricity generation from RES. In this review, the 8-step methodology was used to find and analyze 262 relevant research articles from the Scopus database. Statistic analysis based on eight criteria (ML method used, renewable energy source involved, affiliation location, hybrid model proposed, short term prediction, author name, number of citations, and journal title) was shown. The results indicate that (1) Extreme Learning Machine and ensemble methods were the most popular methods used for electricity generation forecasting from RES in the last three years (2020–2022), (2) most of the research was carried out for wind systems, (3) the hybrid models accounted for about a third of the analyzed works, (4) most of the articles concerned short-term models, (5) the most researchers came from China, (6) and the journal which published the most papers in the analyzed field was Energies. Moreover, strengths, weaknesses, opportunities, and threats for the analyzed ML forecasting models were identified and presented in this paper.

Keywords: machine learning; deep learning; extreme learning machine; renewable energy sources; electricity production forecasting

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1. Introduction

Technological and urban development as well as population growth have resulted in increased energy demand. Much of the world's energy demand is covered by fossil fuels, but it has negative impact on the environment, severely polluting the atmosphere and increasing the carbon footprint. The European Union Policy, visible in The European Green Deal, announces the reduction of green house emissions by at least 55% by the year 2030, placing Europe as the first climate-neutral continent by 2050 [1]. Therefore, in addition to saving energy [2], it is necessary to produce energy from Renewable Energy Sources (RES) such as water, sun, and wind, which counteracts global warming. The energy production from RES is also driven by the threat of a global energy crisis and increasing world's energy demand [3,4]. Moreover, the development of environmentally friendly electromobility increases the need for electricity from RES [5]. All in all, the increasing demand for electrical energy, the care for the natural environment and the changes in legislation support the fast development of renewable energy.

Precise and reliable forecasts of electricity generation from renewable systems are needed for capacity planning, scheduling, managing inertia and frequency response during contingency events [6]. Imprecise predictions of electricity generation from renewables put into question smooth operation, balancing, and scheduling of renewable energy systems, threatening at the same time the security of the grid. Electricity generation from PV and wind systems can vary from 0 to 100%. It is affected by meteorological conditions and geographical characteristics. In order to overcome the negative effects on the grid associated with this volatility, hydropower plants, PV, and wind farms are required to give electricity generation forecasts in advance [7,8]. It is important to stress that improper balancing of electricity generation with a load demand results in fines for power producer [9], the amount of which varies from country to country which vary by country and is regulated by different patterns and policies [10]. If the actual amount of energy supplied to the grid exceeds the amount previously declared, negative pricing can take place in the electricity market. In the case of PV systems, it usually happens in the middle of the day, when the sun shines the most, and all PV generators supply energy [11]. Precise, reliable, and flexible electricity generation forecasts are solution to this phenomenon.

The forecasting of electricity generation from RES is a challenging task, because it is affected by multiple factors, such as meteorological and climatic conditions in the analyzed place. In the case of hydropower plants, electricity generation is dependent on, among others, reservoir or river inflows, temperature, electricity price, abrupt demands, seasonal demand, gross domestic product, as well as their correlations with human and meteorological phenomena [12]. In the case of hydropower, the fluctuations in the dam can occur, leading to fluctuations in hydro energy generation, causing instability of the system [13]. That is why making decisions for hydropower systems is difficult and requires having accurate forecasts [14]. In the case of wind power prediction, developing precise forecasts is very difficult, mainly due to intermittent nature of wind and dependencies on multiple weather, wind turbine, and rotor features [15].

Machine learning models have been successfully applied in many engineering applications, e.g., to predict risk value [16,17], for energy use forecasting [18], to predict ground settlements [19] or to evaluate safety risk [20].

The aim of this review is to present and analyze the existing research on machine learning approaches to predict electricity production from RES. The three most popular RES sources were taken into account: wind, sun, and water. This review provides a fresh look at the current trends in forecasting electricity generation from RES, taking into account the horizon of the last three years (2020–2022). The main contribution to the body of knowledge of this review is the presentation state-of-the art machine learning methods applied for forecasting and providing answers to the following research questions (RQs):

RQ1: What are the trends in the number of articles published in the analyzed field in the last 3 years in terms of the type of RES?
RQ2: What are the trends in terms of the ML methods used in the analyzed field in the last 3 years in terms of the type of RES?
RQ3: What are the global publication trends concerning location affiliation in the analyzed field in the whole dataset and in the subsets (photovoltaic, wind, hydro)?
RQ4: Was the application of hybrid ML methods or single ML dominant in the analyzed field in the last 3 years?
RQ5: Were short-term or long-term predictions ML models dominant in the last 3 years?
RQ6: Which authors published the most articles in the analyzed field in the last 3 years?
RQ7: What are the top 10 most cited articles in each analyzed year and what are the determinants of their success?
RQ8: What are the titles of the 10 journals in which researchers most frequently published articles from the analyzed area over the last 3 years?

This paper is organized as follows. Section 2 describes the eight-step methodology applied to retrieve and analyze relevant literature, Section 3 presents the obtained results, and Section 4 discusses the results. The paper ends with the conclusion.

2. Preliminaries of Artificial Intelligence

2.1. ML Models

Most of the ML models are inspired by the nature. The striking examples are neural networks. The increase in computer computing power has contributed to the development of more complex machine learning models that can be utilized in many areas. However, simple models can still prove to be highly useful. The overview of the ML models is presented in Figure 1.

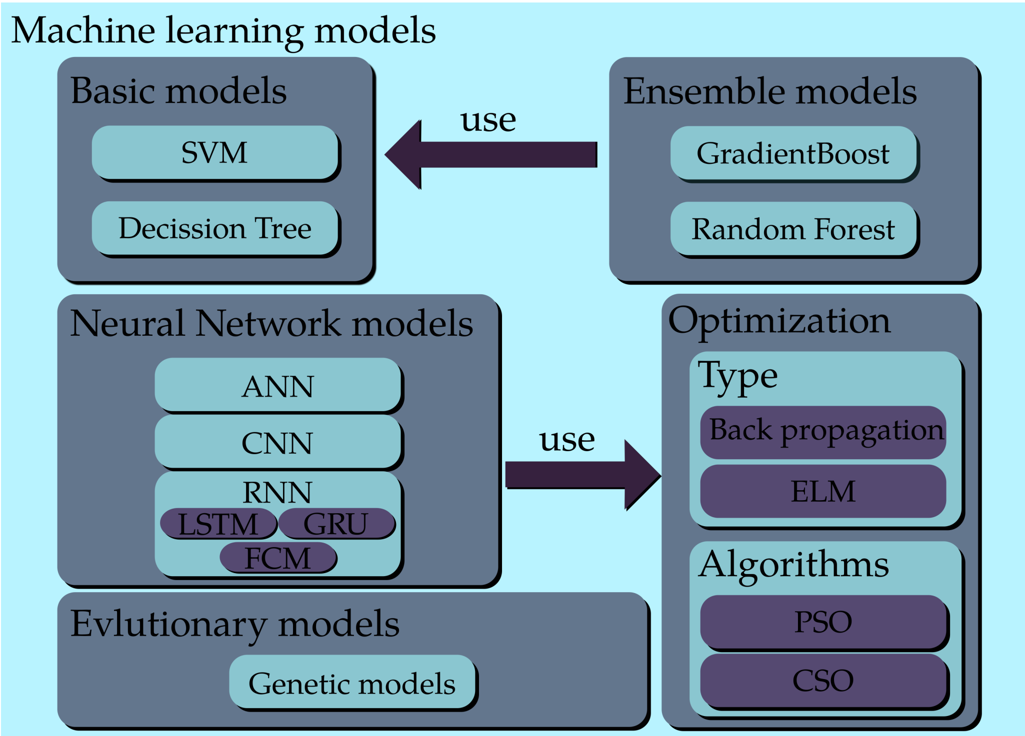

Figure 1. Machine learning models overview.

The main idea behind the simple ML models lies in finding the partitioning of the solution space into regions with similar characteristics. Decision Trees (DT) are one of the most recognizable examples of a such process [21]. In each step of developing DT, the best possible data partition is found in such a way that the data items inside a partition are most similar to each other. At the same time, the samples from different partitions are as different from each other as possible. To capture the optimal partition, even in the case of non linear problems, the so-called kernel can be utilized. It allows to transform the solution space in such a way that the given problem can be linearly separable. The Support Vector Machine (SVM) is one of the most recognizable examples of kernel-based techniques [22].

The availability of more computer power allows the utilization of more complex models. The Ensemble Learning models are a family of techniques that allow to utilize a group of basic models that can work in combination to achieve the better results than a single model; the Random Forest model is one of the most recognizable examples [23]. In this case, a group of DT models is created based on a random subset of the original data. This allows to avoid typical problems that may arise with classic DT models like decreasing the accuracy as the next levels of the tree are created. In the case of the Gradient Boosted Tree [24] technique, the subsequent trees are created in such a way that the next tree improves the prediction of the previous one. The ensemble methods allow to achieve good results even when the basic model does not present very good accuracy.

One of the most complicated machine learning models is based on neural networks. A typical Artificial Neural Network (ANN) is composed of many layers build with neurons.

They are classically trained using the Back Propagation (BP) algorithm, in which the weights of the neurons are adjusted sequentially from the last to the first layer.

In many areas of applications, like forecasting, the introduction of recurrent neural networks (RNN) is especially suitable. In such networks, the actual state is determined not only by the input values but also by its internal state. Because of that, recurrent neural networks are useful in time series forecasting. The internal state of the network needs to be stored in special cells, typically in the form of a Gated Recurrent Network (GRU) [25] or Long Short-Term Memory [26].

One type of a one-layer recurrent neural networks is a fuzzy cognitive map (FCM). It is a soft computing technique that enables knowledge representation in the form of important concepts and relationships between them. Fuzzy cognitive maps and their extensions can be successfully used for time series forecasting [18,27].

To capture some advanced patterns in the data, Convolution Neural Networks (CNN) are sometimes used [28]. They are usually used for image prediction, but by using different kernel and filter shapes, they can also be used in other application areas.

Many modern deep learning applications utilize large number of layers with a large number of neurons in them. Additionally, using CNN and RNN layers causes there to be a large number of parameters that need to be optimized during the learning procedure. Because of that, a large computational power is needed to prepare and use deep learning models, which seriously limits their real-world applications. To cope with this problem, an Extreme Learning approach (ELM) was developed. In ELM models, the learning process is extremely simplified because it only affect the last layer of the neural network [29].

Simplification of parameters tuning in the ELM models allows to use different optimization techniques in exchange for the typical BP algorithm. Particle Swarm Optimization (PSO) [30], and Chicken Swarm Optimization [31] methods are the most popular.

Apart from those, the most popular methods in some real-world applications use hybrid models which can integrate different approaches [32]. One of the most popular approaches in this area is the Evolutionary approach, mostly in the form of Genetic algorithms.

2.2. Evaluation Metrics

The analyzed models can be evaluated with the use of popular prediction metrics, such as the coefficient of regression R^2, Mean Square Error MSE, Root Mean Square Error $RMSE$, Normalized Root Mean Square Error $NRMSE$, Mean Absolute Error MAE, Normalized Mean Absolute Error $NMAE$, and Mean Absolute Percentage Error $MAPE$.

These metrics are describes as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{1}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{2}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{3}$$

$$NRMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}}{y_{max} - y_{min}} \tag{4}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i) \tag{5}$$

$$NMAE = \frac{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)}{y_{max} - y_{min}} \tag{6}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \mid \frac{y_i - \hat{y}_i}{y_i} \mid \tag{7}$$

where N is the number of samples, y_i is the true value of the i-th sample, $\hat{y}_i$ is the predicted value of the i-th sample, $\bar{Z}$ is the mean value of the true values, $\bar{y}$ is the mean value of the predicted values, and y_{max}, and y_{min} are the maximal and minimal values in N samples of the actual output set, respectively.

In the case of value y_i being equal to zero, MAPE can be also calculated as follows:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \frac{\mid y_i - \hat{y}_i \mid}{max(\epsilon, |y_i|)} \tag{8}$$

where ϵ is an arbitrarily small positive number in case of undefined results when y is zero.

In some cases, the proposed models do not predict the exact value of generated energy but instead predict moments when energy is not generated at all. Those situations occur, for example, in the case of detecting wind ramp events [33]. In these cases, it is possible to use metrics typical for classification problems such as accuracy, specificity, and selectivity [33].

3. Materials and Methods

The methodology applied to retrieve and analyze relevant literature consists of 8 steps: keywords, search scope, and database choice, defining search filtering criteria, searching, manual screening, defining classification criteria, division into subsets according to the defined classification criteria, statistical analysis, and drawing conclusions. Figure 2 illustrates the proposed approach.

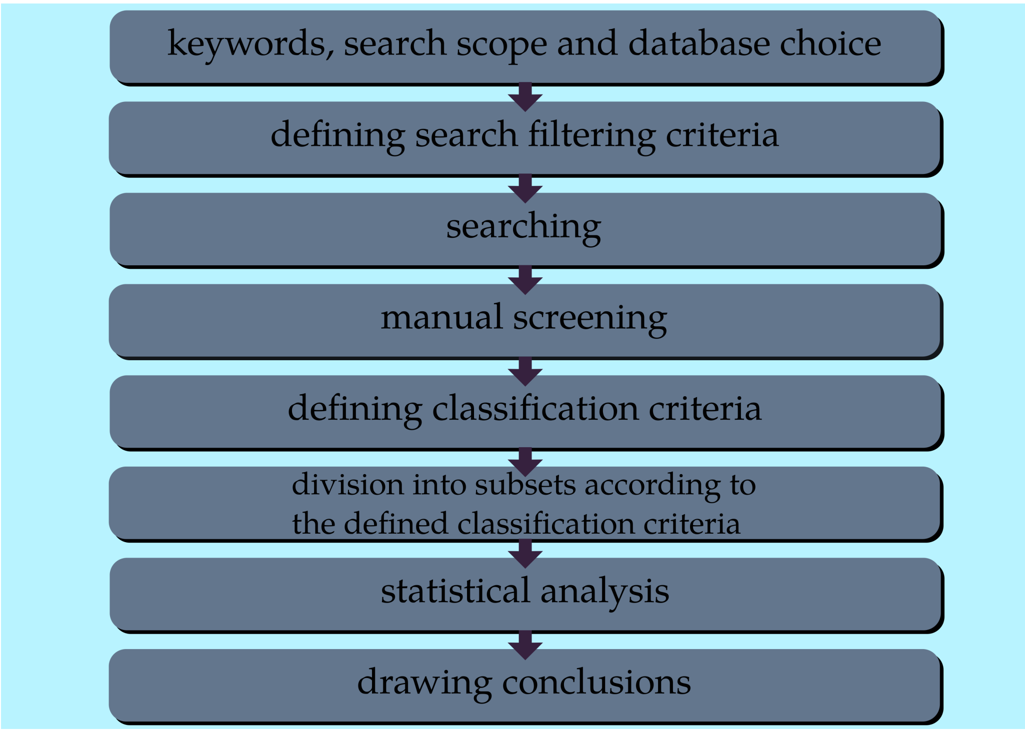

Figure 2. Proposed approach.

3.1. Keywords, Search Scope, Database Choice and Defining Search Filtering Criteria

It was decided to use the publicly available Scopus database, as it covers 7000 publishers that are reviewed and chosen by an independent Content Selection and Advisory Board [34] in order to be indexed, and it provides high quality data. Various unique combinations of keywords and search scopes were analyzed in order to ensure that all relevant research papers were captured. During trial tests in keyword search using the combination of keywords presented in Table 1, but searched by abstracts, keywords, and titles, over 600 articles were found, most of which did not concern directly the studied problem, but only referred to the given topic. Finally, the list of search keywords and search scopes as presented in Tables 1 and 2 was selected.

Table 1. List of search keywords and search scopes.

Searched Scope	Values
Title, abstract or keywords contains	”machine learning”
Title contains	• “photovoltaic power”, “pv power”, • “photovoltaic farm”, “pv farm”, • “wind power”, “wind farm”, • “hydro power”, “hydropower”, “hydro plant”
Title contains	• “predict”, “prediction”, • “forecast”, “forecasting”

Table 2 shows the list of criteria used for filtering.

Table 2. The list of criteria used for filtering.

Filtered Scope	Values
Document type	journal article
Title does not contain	”’review”
Publishing year	• 2020 • 2021 • 2022
Language	the whole paper written in English or at least abstract written in English

3.2. Searching and Manual Screening

In Step 3, the keyword search was carried out in Scopus and 276 articles were found. Second-stage filtering of articles (manual screening) was also used, as it was taken into account that the automatic selection of articles is devoid of human intelligence, which in this case may result in the need to remove mismatched articles. Therefore, manual screening was carried out to identify out-of-scope papers remaining in the dataset. As a result, 14 papers were deleted, and the dataset containing 262 articles was further analyzed.

3.3. Defining Classification Criteria

Eight classification criteria were defined and their choice was justified. This enabled further detailed analysis. The classification criteria included:

- Type of the RES (photovoltaic, wind, hydro)—Types of RES had to be separated so that, in addition to checking the trends in the entire data set (electricity generation from RES), it was possible to check the trends in each of these groups separately.
- Type of ML method applied—Various ML methods are used in the literature to perform electricity generation prediction from RES. The division of the entire dataset into a number of types of ML enabled to present a distribution of the methods used can show trends in the application of the various ML methods. It was analyzed in the whole dataset and in the subsets (photovoltaic, wind, hydro).
- Location affiliation (country of origin of corresponding author)—The insight into the location affiliation provides global overview, allowing to uncover the global publication trends in the analyzed fields in the whole dataset and in the subsets (photovoltaic, wind, hydro).

- Hybrid model proposed—The division of the whole dataset into Hybrid models and other allowed to identify the tendency in applying such models. In [35], it was found that applying hybrid models allowed to obtain better results than single ML models for forecasting electricity generation from sun and wind; it was shown in [36] for wind systems, and in [37] for PV systems. Therefore, it was necessary to check if there is a trend of developing hybrid models. It was analyzed in the whole dataset and in the subsets (photovoltaic, wind, hydro).
- Short term prediction—The division of the whole dataset into short-term models and others allowed to identify the tendency in applying such models. In [38] it was found that short-term models were crucial for RES-integrated energy management systems and very popular type of models. Therefore, it was necessary to check if there is still such a trend.
- Author name—It was needed to divide the entire dataset according to the number of presentations of each author. It allowed to identify top 10 authors publishing the most articles on the analyzed topic in the last three years. It was analyzed in the whole dataset and in the subsets (photovoltaic, wind, hydro).
- The number of citations—It was needed to divide the entire dataset according to the number of citations of the articles. This allowed to identify the group of ten most cited papers, which have the highest influence. Detailed analysis of these enabled to determine the reasons for high citations. It was analyzed in the whole dataset and in the subsets 2020, 2021, and 2022.
- Journal title—It was needed to divide the entire dataset according to journal. It allowed to identify the group of top 10 journals that published the most articles about application of ML in electricity generation forecasting from RES.

4. Results

4.1. The Summary of Studies on ML Models for Electricity Generation from RES

The intention of this review is to present and classify articles published in Scopus, which coped with Machine Learning (ML) models applied for forecasting electricity generation from RES. Tables A1–A3 in Appendix A present an overview of articles on Machine Learning (ML) models' applications for forecasting electricity generation from RES in the years 2020 (Table A1), 2021 (Table A2), and 2022 (Table A3). They present the article first author, article reference, type of RES, ML method applied, time horizon, and comments. The summary of results obtained in those studies is presented in Sections 4.1.1–4.1.3.

4.1.1. The Summary of Studies on ML Models for Electricity Generation Prediction from PV Systems

In [39], the authors carried out a comparison of several forecasting models an elastic net, support vector regression, random forest, and Bayesian regularized neural networks. It was found that Bayesian regularized neural networks outperforms other models with R^2 = 99.99%. Ref. [40] suggested a hybrid short-term forecasting model using an improved bird swarm algorithm and extreme learning machine algorithm. It received R^2 of 99.35% during a cloudy day, and R^2 of 99.59% during sunny day. In [41], the authors compared the performance of SVM, ANN, kernel, nearest-neighbor, and deep learning forecasting models. It was found that all models received R^2 higher than 0.96. The SVM model outperformed other models and generally presented better prediction results particularly with a satisfying R^2 = 0.9921. Ref. [42] developed a model for short-term PV power prediction using an improved hybrid sparrow search algorithm dedicated for an extreme learning machine neural network. It resulted in an R^2 of more than 99%. Ref. [6] developed and compared several ML forecasting models, including Linear Regression, Polynomial Regression, Decision Tree Regression, Support Vector Regression, Random Forest Regression, Long Short-Term Memory, and Multilayer Perceptron Regression. It was found that the Random Forest Regression model performed the best with NMAE = 0.0098 and R^2 = 0.9919. In [43], a deep machine learning model based on Variational AutoEncoder for short-term PV power prediction was proposed. The research has shown that it outperforms other models with R^2 = 0.997, RMSE = 420.029, and MAE = 193.157 for a 9 MW PV system, and R^2 = 0.921, RMSE = 23.134, MAE = 11.664 for a 243 kW PV system. In [44], 5 ML forecasting models were compared, including artificial neural network, random forest, decision tree, extreme gradient boosting, and long short-term memory. It was found that artificial neural network outperformed other models with the highest R^2 = 0.9988. In [45], efforts were made to develop a model combining random forest with feature selection and Principal component analysis. It resulted in obtaining R^2 = 0.9965, MAE = 47.39 kW, and RMSE = 104.67 kW for a 6 MWp PV station. Ref. [46] proposed a new hybrid model based on modal reconstruction forecasting for short-term PV power prediction. It allowed to receive R^2 higher than 98%. Ref. [47] compared the performance of support vector machine and Gaussian process regression forecasting models. It was found that the Matern 5/2 GPR outperforms other with R^2 = 0.98.

In [48], the authors developed a hybrid ensembled model based on Double-Input-Fuzzy-Modules (DIFM) and Extreme Learning Machine. It allowed to obtain an R^2 of 0.9423. In [49], the authors developed and compared the performance of seven ML models based on Lasso Regression, K-Nearest Neighbors Regression, Support Vector Regression, AdaBoosted Regression Tree, Gradient Boosted Regression Tree, Random Forest Regression, and Artificial Neural Network. It was found that the Random Forest Regression model outperforms the other with R^2 = 0.94, MAE = 15.12 kWh, RMSE = 34.59 kWh for a PV farm of 0.7 MW. In [50], the authors made an effort to develop a short-term forecasting model using Wavelet Transform and LSTM-dropout network. It resulted in obtaining R^2 = 0.93817 for one-month-ahead with night data, and R^2 = 0.91145 excluding night data. In [51], efforts were made to develop a hybrid model combining a deep feed forward network using the weather forecast data and a recurrent neural network using recent weather observations. It allowed to obtain an R^2 of 92.7% for a 24-hour-ahead prediction task. Ref. [52] proposed a physics-constrained LSTM for the hourly day-ahead forecasting of PV power generation. The proposed model outperforms standard LSTM, with NMAE of 2.62×10^{-2}, and R^2 of 0.876 for June. Ref. [53] developed and evaluated the performance of the support vector machine model based on gray-wolf optimization for PV power output prediction. It was found that it has a reasonable accuracy with R^2 = 0.908.

In [54], a model based on variational mode decomposition and a kernel extreme learning machine using the firefly algorithm intra-day-ahead PV Power output prediction was proposed. It reached NRMSE and NMAE below 10% in all weather conditions. Ref. [55] compared a proposed probabilistic ensemble method with the ensemble based on the mean value and found that the proposed method allowed to improve the NRMSE metric up to 4.79% in 2017 in the totally cloudy days in a day-ahead forecasting task. Ref. [56] proposed a new hybrid multicluster interval prediction method, which uses the sparse autoencoder, Bayesian regularized NARX network, density peak clustering improved by kernel Mahalanobis distance, and multivariate kernel density estimation for the PV power interval forecasting. It allowed to reach the average NRMSE = 4.45%, NMAE = 3.39%, and R^2 = 95.93% for the four periods for the PV installation located in Australia. In [57], a new ensemble method, called the evidential ELM algorithm, using the ELM and evidential regression, was proposed. It allowed to reach 15.45% lower NRMSE than the ELM method. In [58], a new hybrid model was proposed for a day-ahead prediction, which uses a cloud-based platform, consisting of a data quality block, a weather forecasting and ML power forecasting models, and an up-scaling aggregation step. In this model, a Bayesian regularized neural network allowed to obtain NRMSE = 10.29% and MAPE = 9.11% for PV power output prediction in Cyprus. In [59], the authors proposed a hybrid model based on Iterative Filtering and Extreme Learning Machine (ELM) for multi-step-ahead forecasting in a very short time-scale. The proposed model reached NRMSE less than 10% and R^2 less than 98% over all forecasting horizons.

In [60], the authors proposed a new model using similar days, seagull optimization algorithm, and a deep belief network for a short-term PV power output prediction. It allowed to obtain NMAPE of only 1.512% on a sunny day, 5.975% on a rainy day, 3.359% on a cloudy to sunny day, and 1.911% on a sunny to cloudy day. The short-term forecasting model proposed by [61] used an online sequential extreme learning machine with a forgetting mechanism. It allowed to obtain NRSME = 0.024 and MAPE = 9.708%. In [62], a new short-term prediction model using correlation coefficient method, the chicken swarm optimizer, and extreme learning machine thresholds was presented. It allowed to obtain average MAPE = 5.54% and RMSE = 3.08% under different weather conditions. Ref. [63] made efforts to develop a hybrid prediction model based on information entropy employing gray relation analysis and extreme learning machine. It allowed to obtain MAPE = 2.8425%, RMSE = 2.5675%, and the average R^2 = 98.66%. Ref. [64] used deep learning–based feed-forward neural network, LSTM and Gated Recurrent Unit recurrent neural network models for short-term PV power forecasting. The best results are MAPE for macro-level model ranging from 1.42% to 8.13% for all weather types and forecast horizons, provided 1–6 h ahead for a PV system of 75 MW. It was compared with other equivalent inverter-level forecasts, which provided MAPE values from 1.27% to 8.29%. Ref. [65] presented a novel discrete gray model with time-varying parameters for long-term PV power generation forecasting. The proposed solution was tested on data coning from America and China, and outperformed prevalent benchmarks, giving MAPE = 2.98%. Ref. [66] suggested using a hybrid model for a day-ahead PV power forecasting using Convolutional Self-Attention based LSTM. It allowed to improve the forecasting performance when comparing to other models, lowering MAPE by 7.7% in comparison with Deep Neural Network, by 6% in comparison with LSTM, and by 3.9% in comparison with LSTM with the canonical self-attention. In [67], the authors proposed a comprehensive hourly averaged day-ahead forecasting framework, in which artificial neural networks and K-means clustering were applied. It allowed to obtain MAPE for hot region of 4.7%, and for semi-arid region of 6.3%.

Ref. [68] compared various short-term forecasting models using Random Forest, SVR, CNN, LSTM, and a Hybrid of SVR and CNN with statistical models. It was found that Random Forest model obtained the best results with average RMSE = 11.77% , MAPE = 18.65% and R^2 = 0.94. Ref. [69] proposed a multivariable hybrid prediction framework using signal decomposition, artificial intelligence, deep learning, and a swarm intelligence optimization strategy. It resulted in obtaining low MAPE using three various datasets, from 2.129% to 3.654% in short-term prediction tasks. Ref. [70] made efforts to develop a hybrid method applying three independent MLP-type neural networks for a very short-term forecasting of PV power generation. It allowed to obtain RMSE of 122.558 W for the PV installation of 3.2 kW, and NMAPE of 1.474%. Ref. [71] developed and compared ANN and LSTM network short-term forecasting models. It was found that LSTM models have better accuracy than ANN. The LSTM model obtained MAPE of 19.5%. In [72], the authors proposed a hybrid model using an ANN with Wavelet Transform for 24-hour-ahead PV power forecasting. It received a MAPE of 6.75% and symmetric MAPE of 9.95%. Ref. [73] compared six ML forecasting models: multiple linear regression, ridge regression, decision tree, random forest, SVM, and K-nearest neighbor. The study revealed that random forest model outperforms the other methods with MAPE = 2.2790% and RMSE = 0.879%.

4.1.2. The Summary of Studies on ML Models for Electricity Generation Prediction from Wind Systems

Ref. [74] proposed a hybrid physical process with artificial neural networks for power prediction for wind turbines. The hybrid model that couples physical model and transfer learning approach obtained MAE = 94.70, RMSE = 140.11, R^2 = 0.91 and outperforms a pure physical model, a single artificial neural network, and two typical physical guided neural networks. In [75], artificial neural networks, multiple linear regression, and power regression techniques were used to predict wind power. Real data from a wind farm in Sri Lanka during the period of 2015–2020 were used to compare the analyzed models. The ANN model obtained the best performance with R^2 = 0.97, and RMSE = 109. In [76], the wind power data were utilized to form a graph neural network in order to compute the spatiotemporal correlation between the target turbine and adjacent turbines. Next, deep residual networks were applied for short-term wind power prediction. Real data collected from China were used to evaluate effectiveness of the proposed solution. The proposed solution obtained R^2 = 0.96 and RMSE = 70.19 kW. The results confirm the superiority of the approach based on deep residual networks. Short-term forecasting of wind power based on Three-level Decomposition, kernel extreme learning machine and Improved Grey Wolf Optimization was proposed in [77]. The proposed solution reached R^2 = 0.9922, NRMSE = 0.5071, NMAE = 0.3861 and outperformed models using different decomposition level and LSTM models. In [78], an ultra-short-term wind power prediction method based on swarm optimization–variational mode decomposition, enhanced slime mold algorithm for elite opposition-based learning strategy and deep extreme learning machine was proposed. It allowed to reach MAE = 0.9709, RMSE = 1.4188, R^2 = 0.9713. A day-ahead wind power generation forecasting based on a grid selection algorithm and feature selection models was analyzed in [79]. Results showed that the proposed model outperformed the other models with NRMSE = 7.6% and R^2 = 0.8989. In [80], a short-term wind power forecasting based on XGBoost Hyper-Parameters Optimization was analyzed. The proposed approach reached RMSE = 9.29 MW, MAE = 6.52 MW, R^2 = 0.64 and outperformed SVM, KELM, and LSTM.

An asexual-reproduction evolutionary neural network for short-term wind power prediction based on Wasserstein generative adversarial network, gradient penalty, and ensemble empirical mode decomposition was proposed in [81]. The asexual-reproduction evolutionary approach was applied to optimize the neural network. The proposed solution was compared with the neural networks with different loss functions and the SIA-based neural networks optimized by different swarm intelligence algorithms and outperformed them with MSE = 70.6169 kW, MAE = 42.2606 kW, R^2 = 0.9890. In [82], the transparent open-box machine learning method for wind-power data forecasting was analyzed. The method reached good forecasting performance with: RMSE = 791.4 MW and R^2 = 0.988. Two hybrid models of adaptive neurofuzzy inference system using genetic algorithm and particle swarm optimization each for a turbine were developed in [83] to forecast short-term wind power. The best prediction accuracy, RMSE = 0.180 and R^2 = 0.914, was obtained for a model based on particle swarm optimization. In [15], kernel-driven machine learning models (SVR and GPR) and ensemble learning models (Boosting, Bagging, XGBoost, and RF) were applied to forecast the future trends of wind power. The results showed that the optimized Gaussian process regression and ensemble models outperformed the other machine learning model with an average R^2 of about 0.95. Random forest, gradient boosting machine, k-nearest neighbor, decision-tree, and extra tree regression were used to improve the forecasting accuracy of short-term energy generation in the Turkish wind farms in [84]. The results showed the best forecasting performance: MAE = 0.0264, RMSE = 0.0634, R^2 = 0.9690 for gradient boosting machine regression.

In [85], deep neural networks were applied to forecast wind power of an offshore wind turbine based on high-frequency SCADA data. Pearson product–moment correlation coefficients were applied to select the most significant features.The results showed that the proposed approach can reduce the computational cost retaining good performance RMSE = 517.33, R^2 = 0.91, MAE = 374.41. Tree-based learning algorithms were used in [86] to forecast long-term wind power. The presented results demonstrated the effectiveness of the analyzed models against data uncertainties. XGBoost yield the best results with higher R^2 = 0.9997. In [87], support vector machine with improved dragonfly algorithm was used in short-term wind power forecasting. The proposed approach allowed to receive NRMSE = 3.25%, NMAE = 2.75%, MAPE = 10.58%, R^2 = 0.9791 in winter, and NRMSE = 5.24%, NMAE = 4.04% MAPE = 8.64% R^2 = 0.9544 in autumn. In [88], support vector regression was used to estimate the fatigue loads and power of wind turbines under yaw control. The SVR model outperformed the artificial neural networks with MAPE = 0.4, NRMSE = 0.0082 and R^2 > 0.99. In [89], wind power forecasting based on hourly wind speed data in South Korea was realized using ANN, KNN, RF and SVM. ANN models showed the best performance with R^2 above 0.99. Long-term forecasting electricity power generation of Pawan Danavi Sri Lanka wind farm was presented in [90]. The proposed approach based on gene expression programming obtained R^2 = 0.92 and RMSE = 259 kW. In [91], sparrow search algorithm optimization deep extreme learning machine was applied to ultra short-term wind power forecasting. The approach was compared with artificial neural network, random forest, extreme learning machine, and other deep extreme learning machine techniques. The proposed model obtained high prediction accuracy: R^2 = 0.927, MAE = 69.803, RMSE = 115.446.

Improved extreme learning machine based on autoencoder and particle swarm optimization was applied in [92] to predict short-term wind power. The PSO method was used to select hyperparameters of the analyzed model. The proposed approach was compared with back propagation, ELM, regularized ELM, and optimal regularized ELM. The results showed that the proposed solution achieved better accuracy: NMAE = 0.0211, NRMSE = 0.028 with a faster training time. In [93], a three-stage multi-ensemble short-term wind power prediction method based on variational mode decomposition, stacked denoising autoencoder, long short-term memory, bidirectional long short-term memory, and support vector machine was proposed. A multi-ensemble NRMSE decreased by 0.0343 compared with LSTM, decreased by 0.0336 compared with BLSTM, and decreased by 0.0323 compared with stacked denoising autoencoder. In [94], a combined model for wind power prediction based on feature extraction technique, extreme learning machine, and least squares support vector machine model was presented, improving cuckoo search. Real data collected from regional wind farms in China was used in the analysis. The results showed that the proposed solution achieved accuracy NMAE = 5.05%, NRMSE = 8.67% and outperformed other benchmark prediction models. In [95], extreme learning machine was used to predict wind power. The ELM model outperformed the artificial neural networks with NRMSE = 7.01, R = 0.95421 for two hours-ahead, NRMSE = 10.12, R = 0.91373 for three hours-ahead, NRMSE = 12.06, R = 0.87576 for four hours-ahead. In [96], single and combined models were analyzed in terms of use in wind power forecasting. The combined models: XGBoost, Linear SVR, Weighted Ensemble, and Stacking outperformed the single models XGBoost, Light Gradient Boosting Machine, SVM, Autoregressive Integrated Moving Average with Exogenous Variable and GAMAR. The ensemble Linear SVR obtained the best forecasting results with an average NRMSE of 11.59%.

In [97], a hybrid model based on Complementary Ensemble Empirical Mode Decomposition and Whale Optimization Algorithm–Kernel Extreme Learning Machine was used to predict short-term wind power. The proposed approach outperformed other benchmark models with MAE = 0.2911 mw/s, RMSE = 0.4305 mw/s, MAPE = 6.66%. Enhanced crow search algorithm optimization–extreme learning machine model was applied in [98] to forecast short-term wind power. The proposed approach obtained RMSE < 20%, MAPE < 4% and outperformed the state-of-the-art wind power prediction models, traditional machine learning models and ELM optimized by other techniques. An offshore wind power ramp prediction method was presented in [99]. It was based on Variational Modal Decomposition, Seagull Optimization Algorithm, Extreme Learning Machine, and Bayesian optimized Long Short Term Memory network. The approach was compared with BP, RNN, LSTM, and single model. The combined model obtained lower forecasting errors: RMSE of 71.10 kW, MAE of 50.26 kW and MAPE of 0.01%. In [100], various machine learning techniques were applied to predict day-ahead wind power at national level. The results showed that the Extreme Gradient Boosting obtained the best forecasting accuracy with MAPE = 26.7%, RMSE = 4.5%. In [101], wavelet decomposition-support vector machines-improved atomic search algorithm was proposed to predict wind power. SVM decreased of MAE = 1.14%, decrease of MAPE = 2.60% and decrease of RMSE = 1.52% in comparison to other models. A hybrid model based on convolutional layers, gated recurrent unit layers and a fully connected neural network was applied in [102] to predict wind power in Bodangora wind farm located in Australia. The analyzed approach improved MAE up to 1.59%, RMSE up to 3.73% and MAPE up to 8.13% in comparison to other methods.

In [103], a power system scheduling model based on wind power output forecasting errors was proposed. An Adaptive Mutation Fruit Fly Optimization Algorithm was used to optimize Extreme Learning Machine parameters. The proposed approach obtained MAE = 0.5483, RMSE = 0.0246, MAPE = 1.0712% and outperformed empirical formula and PSO-SVM model. In [104], robust regression models for forecasting the wind power generated through turbines based were compared. XGBoost regressor outperformed random forest regression model, k-nearest neighbors regression model, and gradient boosting regression model with RMSE = 0.1073, MAPE = 3.283% and MAE = 0.0524. An approach based on optimal weighting density peak clustering (DPC), principal component analysis and long short-term memory was applied in [105] to predict the potential of the wind energy. Compared with the traditional DPC-LSTM algorithm, the proposed approach obtained MAPE and RMSE value reduction of 0.014 and 0.068. A hybrid wind power prediction model based on extreme learning machine, improved teaching-learning-based optimization and recursive feature elimination was proposed in [106]. The hybrid approach outperformed the basic methods with RMSE = 3.64–6.16, MAE = 2.57–4.54 and MAPE = 5.59–9.76. An integrated machine learning and enhanced statistical approach for wind power interval forecasting was proposed in [107]. It was based on the nonlinearity and the time-changing distribution of wind speed, and six machine learning regression algorithms: linear regression, LSTM, lazy learning, regression tree, multilayer perceptron, and decision table. The results showed, that the long short-term memory network algorithm outperformed other methods with MAPE = 8.1. In [108], a long-short-term memory network two-stage attention mechanism for short-term wind power forecasting was presented. The proposed approach obtained MAPE = 2.66%, MAE = 131.11kW and outperformed the basic methods without attention mechanism.

4.1.3. The Summary of Studies on ML Models for Electricity Generation Prediction from Hydro Power Plants

In [109] the highest R^2 = 0.99992 was reached in the 1-day-ahead hydropower generation prediction task for Bayesian Linear Regression model. In second place was Boosted Decision Tree Regression model also with a very good R^2 of 0.998952. Ref. [110] proposed a hydropower capacity prediction model based on MLP, ELM, and SVR algorithms with various kernels. The research revealed that MLP outperformed other models with a RMSE = 0.2593, MAE = 0.2128 TWh and a correlation of 0.9735 for the hydropower plants in Northern Italy with the total installed capacity 12.40 TWh. Ref. [111] developed and evaluated the hydropower forecasting performance of the Gaussian process regression (GPR), support vector regression (SVR), multiple linear regression (MLR), and power regression (PR). It was found that GPR outperformed other models with a correlation coefficient of 0.92 and MAPE = 4.5%. In [112], the performance of various ensemble models based on the typical Random Forest was analyzed. It was found put that the best results (NMAE = 0.17, NRMSE = 0.2, R = 0.9) were obtained after introducing a finer spatial resolution for the inputs. In [113] the authors proposed a hybrid model consisting of signal decomposition and adaptive switching between ELM, backpropagation neural network (BP), and general regression neural network. The established hybrid model has shown to be superior on typical days and over the whole year, with MAPE of the whole year of 8.38%. In [14], the authors proposed proposed: ANN, AutoRegressive Integrated Moving Average (ARIMA), and SVM to predict hydropower generation. It was found that ANN outperformed SVM and ARIMA with correlation coefficient R = 0.94 for daily power generation prediction, R = 0.95 for monthly power generation prediction and R=0.96 for seasonal power generation prediction.

Ref. [114] developed an ANN model for future small hydropower potential prediction using a climate change scenario. It was found that the proposed model has sufficient efficiency measured with sufficient predictive performance with a coefficient of coefficient value of 0.77, percent bias of 16.8% and Nash–Sutcliffe efficiency of 0.6. In [115], a new hydropower generation capacity prediction model based on ELM with Monte Carlo algorithm was proposed. The performance evaluation of this model shown that proposed hybrid method outperforms traditional ELM. In [116], a Deep Feed Forward Neural Network was proposed to predict day-ahead energy generation in a small run-of-river hydropower plant in Western Greece. It was found that the ML model provides a better fitting to the observed flows than the simple regression model (84% vs. 63%). However, the conversion to energy was disappointing with the classical efficiency metric (measured by R^2 of only 50.7%), and the modified efficiency (modified version of R^2) being strongly negative.

In [117], a hybrid model using ELM and artificial bee colony (ABC) algorithm was suggested for prediction of small hydropower plant generations. It was found that the proposed model outperformed backpropagation-based artificial neural network, radial basis function-based ANN, and long short-term memory, with improvement percentages in comparison to traditional ELM for correlation coefficient of 6.20%, in RMSE of 29.80%, and in MAE of 26.29% for 14-days-ahead predictions. In [118], MLP, SVR, ELM or Gaussian processes were tested. These were applied for long- and short-term hydropower generation forecasting. The research revealed that SVR linear performed the best in spring with RMSE = 17.41 hm^3, MAE = 13.94 hm^3; ELM performed the best for summer with RMSE = 7.83, MAE = 5.73; GP in autumn with RMSE = 14.40 hm^3, MAE 1 1.01 hm^3; and SVR in winter with RMSE = 22.14 hm^3, MAE = 15.38 hm^3. In [119], a hybrid forecast tool aiming to support hydropower production decision making was developed. The prediction performance of SVR, Gaussian processes, LSTM, non-linear autoregressive neural networks with exogenous inputs, and a deep-learning neural networks model were compared. It was found that the ML models based on a complex or recurrent architecture better simulate the temporal dynamic behavior of the accumulated river discharge inflow.

4.2. RQ1: What Are the Trends in the Number of Articles Published in the Analyzed Field in the Last 3 Years in Terms of the Type of RES?

The intention of this review is to present and classify articles published in Scopus, which coped with Machine Learning (ML) models applied for forecasting electricity generation from RES. Tables A1–A3 present an overview and comparative analysis of articles on Machine Learning (ML) models applications for forecasting electricity generation from RES in the years 2020 (Table A1), 2021 (Table A2), and 2022 (Table A3). They present the article first author, article reference, type of RES, ML method applied and describe briefly the main results.

Figure 3 presents the number of published papers concerning machine learning applications in prediction of the electricity generation from RES in the years 2013–2022. Despite the fact that 2022 is not over yet (the research was conducted until 21 October 2022), it is easy to see a growing trend in the number of articles published in the years 2020–2022. This confirms that the topic of using machine learning to predict the amount of energy produced from RES is current. The increasing trend in the annual publications indicates that applications of machine learning in forecasting of electricity generation from RES is a developing field of study. This is likely due to the growing number of installations using RES to produce electricity and the growing amount of miscellaneous data collected by sensors within the RES installations themselves. In addition, the need to generate accurate and reliable forecasts of energy production for network operators requires the use of advanced tools, such as machine learning models, which will be able to meet the stringent requirements.

Figure 4 shows the number of published papers on ML applications in prediction of electricity generation with the division into various RES (wind, PV, and hydro). It can be seen that most articles (147) were published on the use of ML in predicting electricity generation from wind systems. Articles on electricity generation forecasting from PV installations also comprise a large group (106 papers). Moreover, four papers were found which concerned forecasting electricity generation from both PV and wind systems. Only 13 articles on forecasting electricity generation from hydropower plants using ML were published. It reflects a research gap in machine learning applications in forecasting electricity generation from hydropower plants.

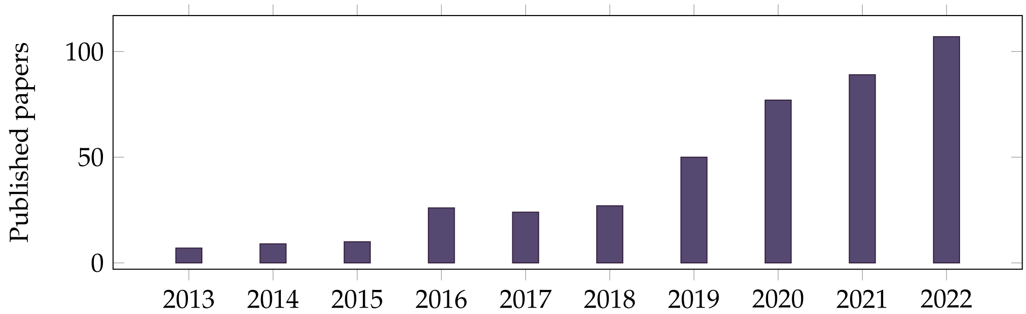

Figure 3. The number of published papers concerning machine learning applications in prediction of the electricity generation from RES.

It indicates that there is an open space for future works concerning ML applications for prediction of electricity generation from hydropower plants.

Looking at the detailed graphs of the number of articles published on individual RES (wind, PV, hydro) in individual years, it can be seen that the upward trend is particularly evident in the case of wind and PV systems. In 2022 in particular, there can be observed a large number of articles on both wind and solar PV systems. It indicates growing interest in ML applications in electricity generation forecasting from wind and solar systems.

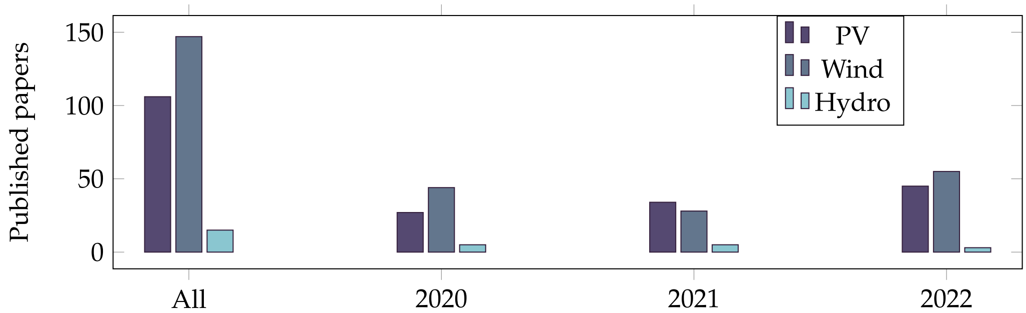

Figure 4. Annual distribution of published journal papers concerning machine learning applications in prediction of electricity generation from various RES (papers search last updated in October 2022).

4.3. RQ2: What Are the Trends in Terms of the ML Methods Used in the Analyzed Field in the Last 3 Years in Terms of the Type of RES?

All articles considered were analyzed according to the ML methods used. The overall results are presented in Figure 5. Extreme learning machines and ensemble methods were the most popular techniques. They were used in 64 and 62 papers, respectively. The popularity of ELM methods can be justified by the fact that they do not need a large amount of computational power.

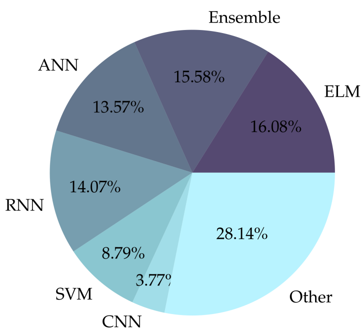

Figure 5. Top ML methods used in anayzed papers.

The annual distribution of the tools used is presented in Figure 6. The figure presents that the Ensemble methods, RNN, and CNN are gaining more and more popularity.

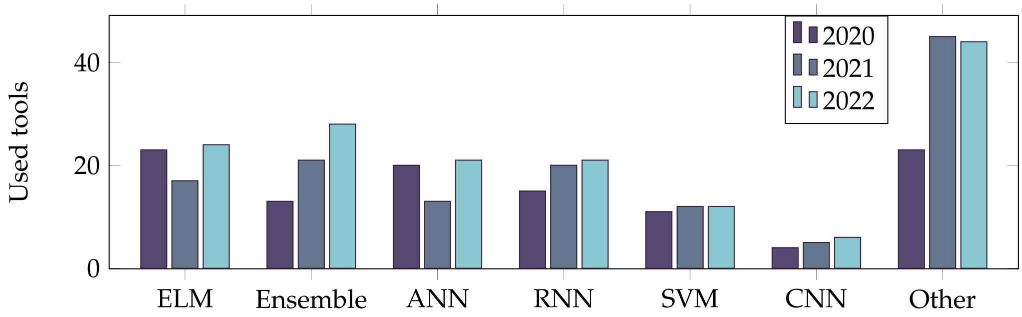

Figure 6. Top ML methods used in particular years.

The use of individual methods in relation to the installations used is presented in Figure 7. In the case of the wind systems, the ELM and Ensemble methods were the most popular (43 and 35 cases, respectively). In the case of PV installations, the Ensemble and RNN were most often used (27 and 18 cases, respectively). In the case of hydro-powered plants, the most popular were SVM and ANN (6 in both cases).

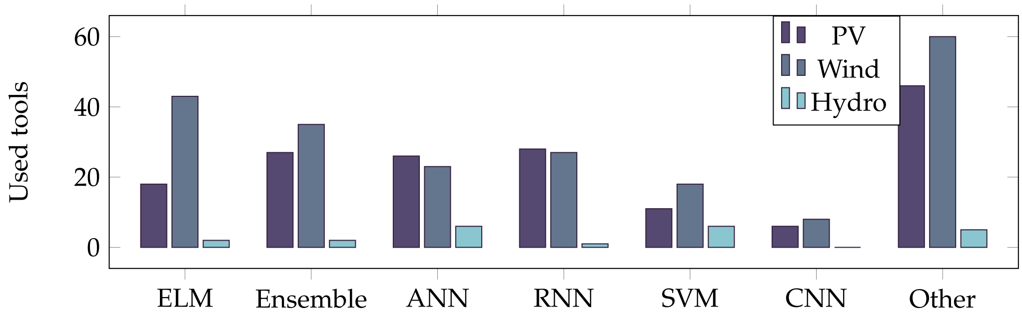

Figure 7. Top ML methods used in particular types of installations.

4.4. RQ3 and RQ4: Was the Application of Hybrid ML Methods or Single ML Dominant in the Analyzed Field in the Last 3 Years? Were Short Term or Long Term Predictions ML Models Dominant in the Last 3 Years?

The analysis of the works from Tables A1–A3 revealed that hybrid models were developed in 86 articles. It can be seen that these models account for 32.82% of all proposed models (34.91% for PV, 31.97% for wind, and 16.67% for hybrid power plants). It should be noted that not all articles from the tables in the Appendix A clearly indicated whether they concerned short-term, mid-term or long-term predictions. Among the articles that explicitly hinted at the time horizon, it can be observed that short-term forecasts are dominant, constituting 85% of the papers with clearly defined time horizon. The explicitly indicated time horizon of the forecast is shown in the Time horizon column in the table in the Appendix A.

4.5. RQ5: What Are the Global Publication Trends Concerning Location Affiliation in the Analyzed Field in the Whole Dataset and in the Subsets (Photovoltaic, Wind, Hydro)?

Figure 8 shows a Cholorpeth map with the number of papers on ML in electricity generation forecasting from RES published per country of the main author's affiliation. It can be seen that China has the highest number of published papers (124). It is followed by India with 14 contributions, South Korea with 11 contributions, Turkey with 8 contributions, Italy with 7, and the USA with 8 contributions. Poland, Pakistan, Saudi Arabia, Spain, and Australia contributed with 5 papers each. Most of the authors coping with ML prediction models for wind systems came from China (83), India (7), the USA (5), and Turkey (4). Most of the contributions concerning PV systems came from China (38), South Korea (8), and

India (7). Most authors proposing ML models for hydropower plants came from China, Italy, and Turkey.

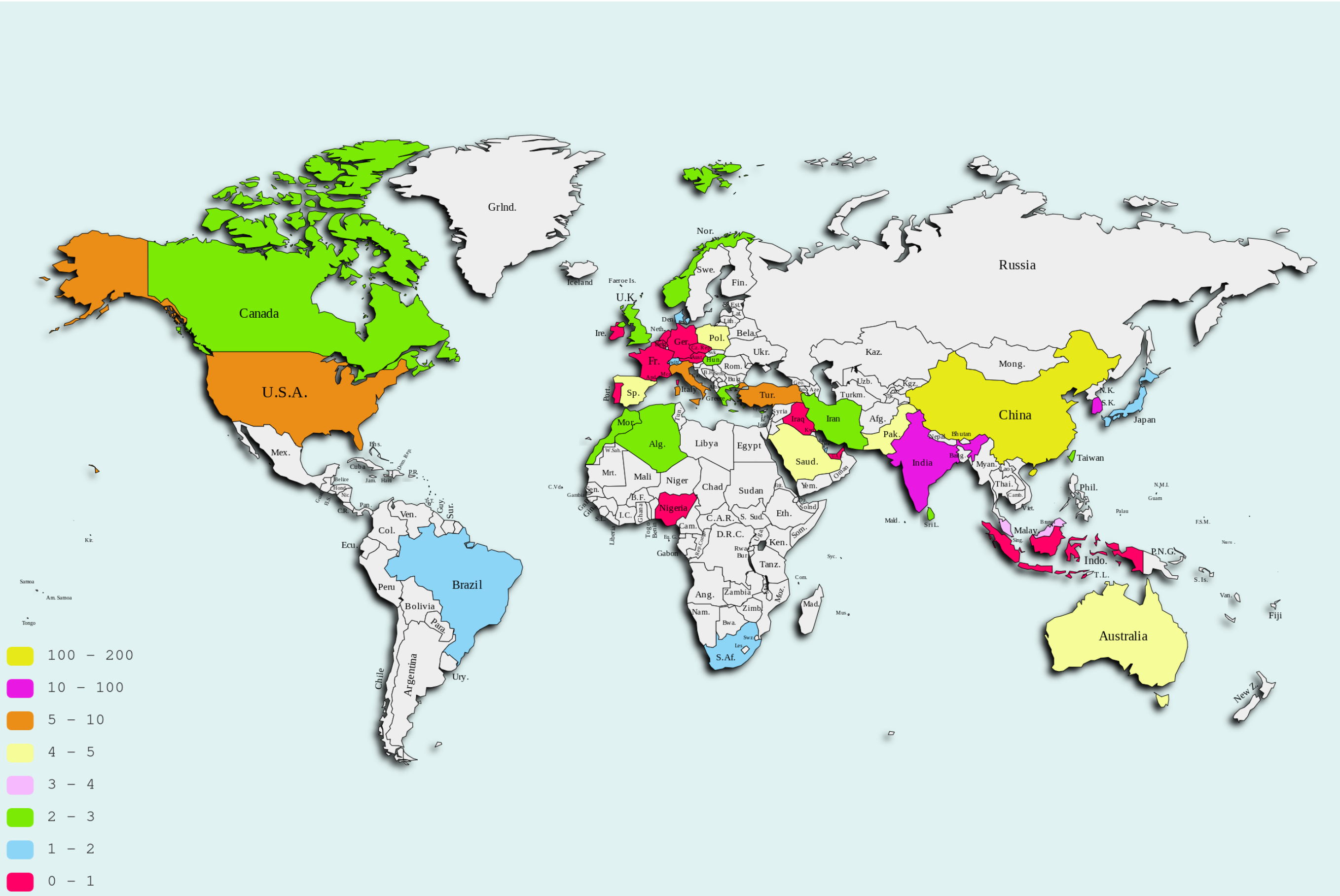

Figure 8. Global distribution of published journal papers concerning machine learning applications in prediction of the amount of energy produced from RES papers search last updated in October 2022).

4.6. RQ6: Which Authors Published the Most Articles in the Analyzed Field in the Last 3 Years?

It was also found which authors contributed with the most papers in the analyzed field in the last three years. Li L.-L., Tseng M.-L. and Zhang X. contributed with 5 papers each. Each of those authors contributed with papers both to PV and wind subsets. They are followed by Wan C., Ou Z., Li Z., Meng A., Song Y. and Yin H. with 4 papers each. After analysis of this issue in the subsets (PV, wind, and hydro), it can be concluded that the largest number of occurrences of the same author in the wind subset was 4 (authored by Yin H., Ou Z., Song Y., Li Z., and Meng A.). In the PV subset, a very large number of appearances of two articles by the same authorship was observed, and in the hydro subset the largest number of occurrences of the same author was 2.

4.7. RQ7: What Are the Top 10 Most Cited Articles in Each Analyzed Year and What Are the Determinants of Their Success?

In order to identify papers with the highest influence and find out the reasons for their success, the ten most cited papers were selected in each analyzed year. The list of these papers is presented in Table 3. It allowed to select top-cited papers fairly, avoiding the problem of multiple citations for articles that have been published previously. The research revealed that the top cited paper in 2020 is [87] with a record number of 169 citations. It is not an open access article. In this paper, a hybrid model for short-term wind power forecasting was proposed, which was a combination of SVM and improved dragonfly algorithm. It was proposed to improve the traditional dragonfly algorithm's performance using the adaptive learning factor and differential evolution strategy. This algorithm is applied to choose the optimal parameters of SVM. The proposed model was verified using a real datasets from a wind farm in France and received NRMSE = 3.25%, NMAE = 2.75%, MAPR = 10.58%, R^2 = 0.9791 for winter, and NRMSE = 5.24%, NMAE = 4.04%, MAPE = 8.64%, R^2 = 0.9544 for autumn. The proposed model outperforms back propagation neural network and Gaussian process regression models.

Table 3. Top cited papers.

Article	Type	Year	Cited by
Li L.-L. et al. [87]	Wind	2020	169
Zhou Y. et al. [120]	PV	2020	75
Liu W. et al. [121]	PV	2020	69
Lin Z. et al. [85]	Wind	2020	65
Shahid F. et al. [122]	Wind	2020	64
Hossain M.S. et al. [123]	PV	2020	64
Theocharides S. et al. [67]	PV	2020	46
Mishra M. et al. [50]	PV	2020	43
Li L.-L. et al. [87]	Wind	2020	41
Behera M.K. et al. [124]	PV	2020	41
Shahid F. et al. [125]	Wind	2021	84
Ding S. et al. [65]	PV	2021	61
Neshat M. et al. [126]	Wind	2021	51
Luo X. et al. [52]	PV	2021	44
Kabilan R. et al. [127]	PV	2021	32
Hossain M.A. et al. [102]	Wind	2021	30
Liu Z.-F. et al. [46]	PV	2021	24
Hu W. et al. [60]	Wind	2021	23
Mahmud K. et al. [6]	PV	2021	21
du Plessis A.A. et al. [64]	PV	2021	21
Li H. et al. [128]	Wind	2022	26
Ribeiro M.H.D.M. et al. [129]	Wind	2022	17
Markovics D. et al. [130]	PV	2022	16
Ding Y. et al. [97]	Wind	2022	15
Visser L. et al. [131]	PV	2022	13
Li Z. et al. [132]	Wind	2022	12
Zazoum B. [47]	PV	2022	10
Guo H. et al. [133]	Wind	2022	9
Sasser C. et al. [134]	Wind	2022	9
Huang X. et al. [135]	PV	2022	8

In 2021, the top cited paper is [125] with 84 citations. This is also not an open access paper. In this paper, authors proposed a new genetic LSTM approach to predict short-term wind power. Genetic algorithm was used to optimize window size and the number of neurons in LSTM layers. The proposed solution was evaluated on the basis of real datasets form seven wind farms in Europe. The genetic LSTM received MAE = 0.92%, MAE = 7.2% and outperformed the standard LSTM and SVR models. The Wilcoxon Signed-Rank test showed a significant difference between genetic LSTM and standard LSTM.

In 2022, the top cited paper is [76] with 26 citations. In contrast to the previous two works, this is an open access paper. In this paper, graph neural network was used to visualize a relationships between the target turbine power and power generated by adjacent turbines. The model showed the correlation between power output and a better power prediction result. The deep residual network was applied to the short-term wind power prediction. The real dataset from a wind farm named Kushui Wind Farm was used to evaluate the proposed solution. The proposed solution received the mean value of R^2 = 0.96 and outperformed ANN, SVR, and ELM.

In each analyzed year, the article on wind takes first place. Moreover, the real data from wind farms were used to evaluate the proposed methods in each of the most cited papers. All three papers concerned short-term forecasting, which is definitely the most frequently chosen one in the field of electricity production predcition. The most cited paper in each analyzed year presents an innovative and quite complex solution that gave better forecasting results compared to other popular models, such as ANN, SVR, and LSTM.

4.8. RQ8: What Are the Titles of the 10 Journals in Which Researchers Most Frequently Publish Articles from the Analyzed Area over the Past 3 Years?

In order to identify journals which contributed the most articles to the analyzed field, the entire dataset containing articles from 102 journals was divided according to the number of appearances of individual journals. It resulted in the identification of the top 10 journals which published the most papers: Energies (25 articles), Energy (22), IEEE Access (15), Energy Reports (13), Renewable Energy (11), Taiyangneng Xuebao/Acta Energiae Solaris Sinica (8), Applied Energy (8), IEEE Transactions on Sustainable Energy (7), Mathematical Problems in Engineering (7), and Energy Conversion and Management (7). In those journals, readers can find a lot of up-to-date papers in the analyzed field. A summary of this analysis can be found in Figure 9.

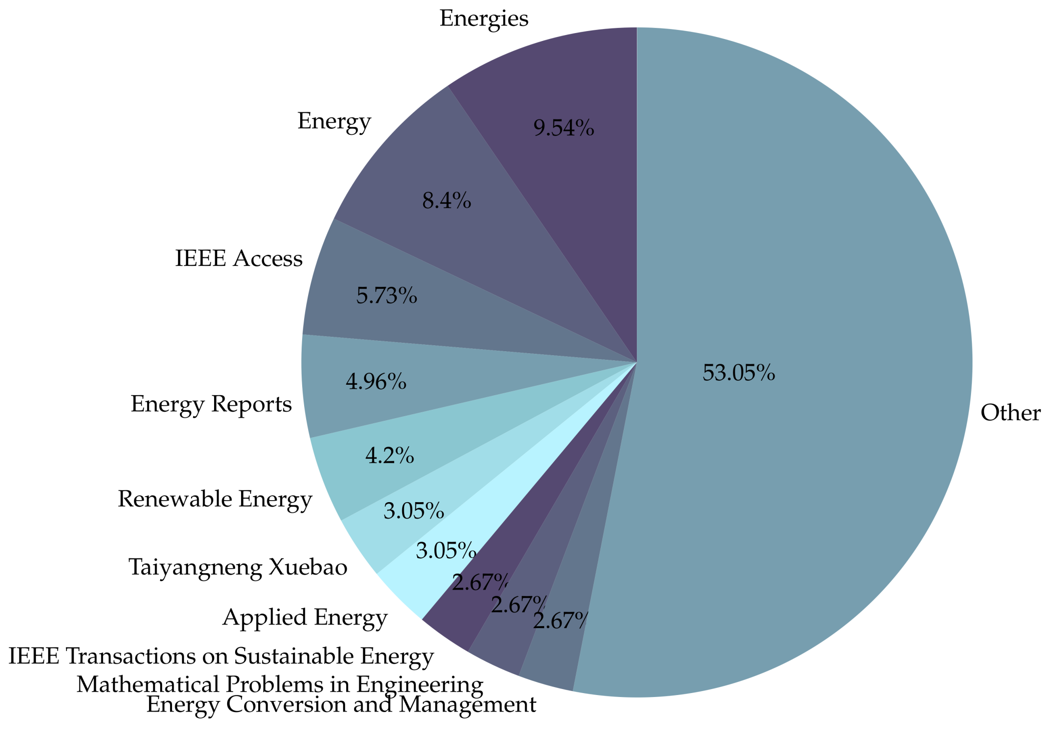

Figure 9. Top journals which contributed the most articles to the analyzed field.

5. Discussion of Results

Table 4 presents the results of the Strengths, Weaknesses, Opportunities and Threats (SWOT) analysis for papers concerning ML applications for prediction of electricity generation from RES. This table is a result of the analysis of the articles listed in Tables A1–A3, as well as related literature and contains conclusions drawn from this analysis. Those strengths, weaknesses, opportunities and threats were grouped into several topics and are discussed below.

5.1. Data Granularity

Data granularity influences the model performance. In the analyzed papers, various data granularities were found: 5-min (e.g., in [136,137]), 10-min (e.g., in [84,126]), 15-min (e.g., [45,64]), and hourly (e.g., in [103]). It can be observed that gathering data with a smaller time interval positively influences the prediction metrics.

Table 4. SWOT analysis for papers concerning ML applications for prediction of energy generation from RES.

STRENGTHS	WEAKNESSES
1. ML models are able to provide better performance than traditional forecasting models 2. Simple ML models with low computational cost are able to give sufficient results 3. ML models enable both short-term and long-term forecasting 4. Possibility of adjusting the ML model to changing climatic condition 5. Enabling adequate planning of the operation of coal and gas-fired power plants 6. Enabling a RES installation owner getting a higher price for the volume introduced to the power grid	1. Too short time horizon of the data taken into account 2. Too small dataset 3. Improper matrices chosen 4. Weather data from another location 5. Unjustifable choice of features 6. Difficult access to historical data needed for training the model 7. Dedication to a specific place
OPPORTUNITIES	**THREATS**
1. Introducing data preprocessing 2. Introducing data normalization 3. Using data with a small time interval 4. Carrying out analysis of the relationship between renewable energy sources power output and meteorological parameters for a certain location 5. Uncertainty quantification	1. Lack of comparability of the results due to filtering zero values (e.g., in the case of PV systems during night time 2. Lack of comparability of the results due to various time horizons taken into account 3. Lack of comparability of the results from the same region due to various scales of studies 4. Lack of cross-validation in works, which do not cope with time series forecasting 5. High computational costs and complexity of DL models 6. Difficulties with comparability of the results coming from various regions

5.2. Representativeness of the Data

The quality of the prediction model depends on the representativeness of the data. It also depends on the type of data used. Various types of data are used for training the ML models, e.g., real-time data, benchmark data, and simulation data. Moreover, the dataset size defined by total time duration and the dataset recording step is important.

In the case of using meteorological data that will be later selected as features, ideally they should be collected from the same location as the renewable energy installation in question or possibly close to it. In the absence of data from the analyzed region, taking data from other regions may cause an additional error in the analysis. It is also import ant to consider the impact of air pollution on renewable energy generation, especially in the case of PV systems. The ground receives less solar radiation during a polluted day due to attenuating the solar radiation received by the panel, which affects the performance of the prediction model. Moreover, dust from air pollution settles on the panel, decreasing the power production [11,138].

The main challenges connected with applying ML models for prediction of electricity generation from wind systems are the variations in the dataset. The main reasons for variations of the wind data are climate change, weather anomalies, storms, seasons, showing intermittency and the stochastic nature of wind. They lead to inconsistency in a regular electricity generation that can severely affect the power system operation. In the case of training a model on such inconsistent data, there is a risk of getting a false system image.

Such a problem may also occur when too short time horizon of the data is taken into consideration. It may result in obtaining a model which is suitable e.g., only for several days in the year or one month in the year.

It should be noted that gathering historical data from sensors needed for development of the ML model can be problematic for a researcher. Many renewable energy installation owners and utility companies treat these data as confidential because of privacy concerns and security restrictions. Most of the data were gathered using sensors, which influences its quality due to possible mislabeling, duplication or temporary loss.

5.3. False Readings and Data Preprocessing

It is important to note that PV installation is not active during night time, so if there are readings in the data that show different values, they are erroneous and may be due to a system breakdown. Even in the case of just after or before the sunrise/sunset, it advised to remove the reading from the dataset to avoid the problem of false reading due to cosine instrumentation error [11,139]. In the case of prediction of PV installation output, some researchers (e.g., [49,140,141]) decide to filter non-zero values during the night time, which improves the forecasting performance. It is also advised to filter out the values created during the failure or renovation of the installation.

5.4. Enhancement of Results

PV installation is not active during night time; therefore, its energy generation during night time is always 0, which is easy to predict. Some researchers evaluate the performance of the proposed models based on both day and night, which can improve the final results, making them difficult to compare with those obtained only from the night data.

5.5. Dedication to a Specific Place

It can be noticed that most of the research papers concerning renewable energy generation forecasting are based on the data gathered from a single PV or wind farm, proposing a machine learning model dedicated for a specific place and specific conditions. However, utility companies prefer to receive a tool enabling forecasting electricity generation from renewable energy for a whole city [142]. Spatiotemporal forecasting dedicated for smart microgrids may be the answer to the needs of utility companies, rather than a single location technique [143].

5.6. Uncertainty Quantification

There are several uncertainties that could be involved in forecasts developed by ML models. The development of machine learning prediction model starts with the gathering an appropriate datasets, choice of the machine learning models to be considered, training the models, and optimizing various learning parameters. These uncertainties are e.g., selection of training data set, and completeness and accuracy of the model [144].

5.7. Normalization

Some authors decide to normalize the training data. The most typical method for standardizing data is to use mean and standard deviation value [145]. In [6], it was found that it resulted in slightly better performance compared to data without normalization. On the other hand, in [49] the normalization did not allow to obtain better results. It should be noted that the normalization, apart from the improvement in the quality of the model occurring in some cases, allows for easier comparison of the analysis results from installations of different sizes.

5.8. Lack of Cross Validation

Another issue worth mentioning is a lack of cross validation carried out in works, which does not cope with time series forecasting. Carrying out cross validation makes it so that the results can be most reliably assessed, because the sets for validation are selected randomly and there are several of them (usually k = 5), and this reduces the possibility of obtaining high model parameters at the end of the day, and the possibility of overfitting the model is reduced. In some analyzed works e.g., in [49,141,146,147], a cross validation was carried out.

5.9. Choice of the Proper Metrics and Units

Some researchers [49,148], when developing machine learning models for PV or wind farms, reported that the mean absolute percentage error and root mean squared percentage error are not recommended as reliable error indicators. They tend to be very high even if the forecasting results are very close to the real values. Because in many situations, generated power can equal zero, the percentage value cannot be calculated based on the classical equation (4) and needs to be calculated using (7). The introduction of ϵ in the denominator can seriously increase the output value. Moreover, in some of the analyzed papers, it was found that in the case of non-standardized MAE and RMSE metrics, units and maximum energy production are not given as a reference point, which makes these results incomparable with the studies of other researchers.

5.10. Installation Scales

When comparing the ML performance, attention should also be paid to the different forecasting scales of energy generation from renewable energy sources. It is possible to forecast energy production at the level of a single installation, region or country, and at the same time for one renewable energy source and many renewable energy sources. It is difficult to compare the prediction model performance for a single PV farm to that developed for a national scale. It was noticed that the electricity generation process from PV installations on the regional level is associated with less fluctuation and better stability [149].

5.11. The Forecasting Performance for Various Regions

The studies concerning various types of RES systems performance (with different technologies applied) under different climatic conditions are much desired [150,151]. In the case of developing a prediction model for a single renewable energy installation, its performance is strongly affected by its climatic characteristics and geographical environment. Model performance may differ even if both analyzed installations are located in the same region [149]. Therefore, it is difficult to compare ML models performance for various regions, and it is necessary to consider various spatial characteristics when trying to compare it.

5.12. The Forecasting Performance for Various Time Horizons

The best solution is to show the possibility of forecasting, taking into consideration difficulties associated with the seasonality and specificity of individual seasons. That is why the results covering a wider time horizon are especially interesting, as they allow a more consistent comparison. It can be seen that, in the papers presented in Tables A1–A3, short-term models are dominant.

5.13. The Importance of Carrying out Analysis of the Relationship between Renewable Energy Sources Power Output and Meteorological Parameters for a Certain Location

Carrying out analysis of the relationship between renewable energy sources power output and meteorological parameters for a certain location can be very beneficial, improving the ML model's performance. For example, In the case of a warm temperate transitional climate, characterized by high fluctuations in temperature and solar radiation, the dependence between solar radiation and PV panel output can be much less remarkable than in a tropical and isothermal climate or continental climate, providing some challenges for the forecasting. Therefore, it may be needed to add several other features to improve the performance of the ML model. The proper choice and number of analyzed features determines the final performance of the forecasting model. In some cases, the greater number of the analyzed features gives the result with smaller forecast error, while in other cases it does not improve the performance of the model [49].

5.14. Dealing with High Computational Cost

Deep learning approaches application is associated with high computational cost and complexity [152]. Therefore, in the case of applying deep learning models, a lot of data storage devices and considerable processing power devices are needed to carry out a forecasting task. From the literature review presented in Tables A1–A3, it can be seen that Extreme learning approaches are becoming more and more popular nowadays, making it possible to deal with the problems encountered in deep learning by reducing the computational cost and complexity of the model.

5.15. Strengths

The analysis of the results obtained in the research articles listed in the Appendix A indicates that ML models are able to provide better performance than traditional forecasting models. It can be concluded that simple ML models with low computational cost are able to give sufficient results (e.g., ELM, ensemble, SVM), so the application of computationally expensive and more complex ML models such as ANN, RNN, CNN models is, in many cases, not needed. ML models enable both short-term and long-term electricity generation forecasting. Bearing in mind the fact that climate changes, it is important to note that it is possible to adjust the ML model to changing climatic condition thanks to relearning the model on changing data. In the analyzed works many reliable and accurate ML models were developed, which enable delivering precise and reliable ML forecasts of electricity generation from RES. Such forecasts are indispensable for adequate planning of the operation of coal and gas-fired power plants at individual hours in the national energy system. Besides this, precise and reliable ML forecasts of electricity generation from RES enable a RES installation owner getting a higher price for the volume introduced to the power grid at the specified time.

6. Conclusions

This review identifies the growing interest in the subject of ML applications in electricity generation prediction from RES in the last 10 years. A particularly large number of articles were written in the years 2020–2022. The increased interest in RES due to Green Deal requirements and associated growth of the number of RES installations, drives the need to develop many various ML models taking into account the specificity of location's spatial characteristics. In this review, 262 articles from Scopus from the years 2020 to 2022 were analyzed. Statistic analysis based on eight criteria (ML method used, renewable energy source involved, affiliation location, hybrid model proposed, short-term prediction, author name, the number of citations, and journal title) was shown. The main contribution to the body of knowledge of this review is uncovering answers to the research questions stated, which are as follows:

RQ1: A growing trend in the number of articles published in the years 2020–2022 was identified, which confirms that the topic of using machine learning to predict the amount of energy produced from RES is current, being a developing field of study. It was found that 56.11% of articles concerned ML applications in predicting electricity generation from wind systems, 40.46% from PV systems and only 4.96% from hydropower plants. It reflects a research gap in machine learning applications in forecasting electricity generation from hydropower plants, and indicates that further research is needed in this field.
RQ2: It was found that Extreme learning machines and ensemble methods were the most popular ML techniques in the analyzed papers in the last three years. In the case of the wind systems, the ELM and Ensemble methods were the most popular; in the case of PV installations, the Ensemble and RNN were most often used; and in the case of hydropowered plants, the most popular were SVM and ANN. The growing popularity of ELM methods can be justified by the fact that they do not need a large amount of computational

power. Simple ML models with low computational cost are able to give sufficient results (e.g., ELM, ensemble, SVM), so the application of computationally expensive and more complex ML models such as ANN, RNN, CNN models is, in many cases, not needed.
RQ3: Was the application of hybrid ML methods or single ML dominant in the analyzed field in the last 3 years? The hybrid models constituted 32.82% of all analyzed works, so they are not dominant in the analyzed field in the last 3 years.
RQ4: It was found that short-term forecasts are dominant among the articles that explicitly hinted at the time horizon.
RQ5:The global publication trends concerning location affiliation in the analyzed field were uncovered. China revealed to have the highest number of published papers (125) in the analyzed field in the last three years. It is followed by India with 14 contributions, South Korea with 11 contributions, Turkey with 8 contributions, Italy with 7, and the USA with 8 contributions.
RQ6: The study revealed that Li L.-L., Tseng M.-L. and Zhang X. contributed with the most papers (5 each) in the analyzed field in the last three years.
RQ7: The most cited articles in each analyzed year and the determinants of their success were presented in Section 4.
RQ8: The study revealed the top 10 journals which published the most papers in the analyzed field in the last three years: Energies, Energy, IEEE Access, Energy Reports, Renewable Energy, Taiyangneng Xuebao/Acta Energiae Solaris Sinica, Applied Energy, IEEE Transactions on Sustainable Energy, Mathematical Problems in Engineering, and Energy Conversion and Management.

Moreover, strengths, weaknesses, opportunities and threats for the analyzed ML forecasting models were identified and presented in Table 4. Despite identifying some weaknesses related to the use of a too short time horizon or problems with data, the results presented in the analyzed papers confirm that the machine learning approaches can be effectively used to forecast electricity production in modern renewable energy systems.

This review is a response to the needs of engineers and PV, water, and hydro-power plants and RES installations' owners who are willing to develop reliable and accurate electricity generation forecasts. The information provided in this review, together with critical discussion and future research directions included, also gives a helping hand to researchers involved in forecasting electricity generation from RES in finding a proper ML model that could best meet the specificity of their needs. The development of methods for forecasting electricity production from RES also contributes to the reduction of harmful carbon dioxide emissions, as the utility owners become aware of the fact that they can find reliable tools for precise electricity generation forecasts are more willing to start RES power plants.

The main limitation of this study is the fact that it covered only whole papers or at least abstracts written in English. Therefore, it is possible that some valuable research articles having abstracts in other languages, which concerned the analyzed topic, were not covered by this work. Besides this, this study was limited to the Scopus database to ensure high quality data, as this database covers publishers that are reviewed and chosen by an independent Content Selection and Advisory Board. However, it cannot be ruled out that other valuable, high-quality papers were created in the analyzed period and published in journals outside Scopus. Another limitation of this study is the fact that, in some analyzed research papers, the units of unnormalized metrics or a reference value in terms of the largest observed reading were not provided. This made it impossible to compare the results with the work of other researchers.

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Abbreviations

The following abbreviations are used in this manuscript:

AdaBoost	Adaptive boosting
AE-SCN	Stochastic configuration networks
ALO	Ant Lion Optimizer
ANN	Artificial Neural Networks
BP	BackPropagation
BTR	Boosted Regression Tree
CEEDMAN	complete ensemble empirical mode decomposition with adaptive noise
CSO	Chicken Swarm Optimization
CNN	Convolutional Neural Network
CVOA-LSTM	Long short-term memory with the coronavirus optimization algorithm
DA-ELM	Deep auto-encoded extreme learning machine
DAFT-E	Dynamic Adaptive Feature-based Temporal Ensemble
DBN	Deep Belief Network
DL	Deep Learning
DT	Decision Tree
EDNQR	Ensemble deep learning based non-crossing quantile regression
ELM	Extreme Learning Machine
EELM	Evidential extreme learning machine
ET	Extra trees
FCM	Fuzzy Cognitive Maps
FTSVM	Fuzzy-Twin Support Vector Machine
GAM	Generalized additive model
GAN	Generative Adversarial Network
GB	Gradient Boosting
GCLSTM	Graph-convolutional long short term memory
GCTrafo	Graph-convolutional transformer
GEP	Gene expression programming
GPR	Gaussian stochastic-based machine learning process model
GRU	Gated Recurrent Unit
HFCM	High-order Fuzzy Cognitive Maps
IFOA-BP	Fly optimization algorithm and back propagation neural network
IVOA	improved whale optimization algorithm
IVMDHFCM	Improved Variational Mode Decomposition HFCM
KNN	K-Nearest Neighbors
LSTM	Long Short-Term Memory
LR	Linear regression
M2TNet	Multi-modal multi-task transformer network
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MSE	Mean Square Error
MVEW-DNN	Multi-view ensemble width-depth neural network
NARX	Nonlinear autoregressive exogenous neural network model
NMAE	Normalized Mean Absolute Error
NN	Neural Networks

NRMSE	Normalized Root Mean Square Error
PLSR	Partial least squares regression
PSO	Particle Swarm Optimization
PV	Photovoltaic
R^2	Coefficient of regression
RES	Renewable Energy Sources
RFR	Random forest regressor
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RVFLN	Random vector functional-link network
RVM	Relevance vector machine
SD	Signal decomposition
SI	Swarm intelligence
SSA	Sparrow search algorithm
SSA-DELM	Deep extreme learning machine optimized by the SSA
SVM	Support Vector Machine
SVR	Support Vector Regression
TCN	Temporal convolu-tional network
TGML	Theory-guided machine learning
TL	Transfer learning
TSVR	Wavelet-Twin support vector regression
VMD	Variational Mode Decomposition
VMD-ALODLFTSVM	VMD combined FTSVM using ALO and DL
XGB	Extreme gradient boosting

Appendix A

Table A1. An overview and comparative analysis of articles from 2020.

Article	Type	Used Tools	Time Horizon	Comment
Chang G.W. et al. [153]	PV	DBN	day-ahead	hybrid
Behera M.K. et al. [124]	PV	ELM	short-term	
Lawan S.M. et al. [154]	Wind	ANN		
Li L.-L. et al. [87]	Wind	SVM	short-term	hybrid
Liu Z.-F. et al. [62]	PV	ELM, CSO	short-term	
Nielson J. et al. [155]	Wind	ANN		
Rana M. et al. [156]	PV	ANN, Ensemble, SVM	multiple step ahead	
Dorado-Moreno M. et al. [33]	Wind	ANN		hybrid
Zhao C. et al. [157]	Wind	ELM		
Shahid F. et al. [122]	Wind	Ensemble		
Wang H. et al. [158]	Wind	ELM, SVM		
Ding J. et al. [159]	Wind	ELM, GWO	short-term	
Li P. et al. [108]	Wind	Attention network	short-term	hybrid
Tian B. et al. [160]	Wind	Other	short-term	hybrid
Yin H. et al. [161]	Wind	CNN, GRU	short-term	
Maitanova N. et al. [162]	PV	LSTM		
Kosovic B. et al. [163]	Wind	Fuzzy		
Tan L. et al. [164]	Wind	ELM	short-term	
Lu H. et al. [148]	Wind	GWO		hybrid
Theocharides S. et al. [67]	PV	ANN, Clustering	hourly-averaged day-ahead	
Acikgoz H. et al. [95]	Wind	ANN	short-term	
Spiliotis E. et al. [165]	Wind	Ensamble		
Lin Z. et al. [85]	Wind	ANN		
Han Y. et al. [77]	Wind	ELM, GWO	short-term	
Alessandrini S. et al. [166]	PV, Wind	Ensemble		hybrid

Table A1. *Cont.*

Article	Type	Used Tools	Time Horizon	Comment
Li N. et al. [167]	Wind	ELM, Evolution		
Li J. et al. [168]	PV	ELM	short-term	
Shahid F. et al. [169]	Wind	LSTM		hybrid
Yi J. et al. [170]	Wind	ELM		
Zhang J.-Y. et al. [171]	PV	ANN	short-term	hybrid
Rushdi M.A. et al. [172]	Wind	ANN		
Zhou Y. et al. [120]	PV	Genetic, ELM		hybrid
Chang X. et al. [173]	PV	Ensemble	short-term	hybrid
Carrera B. et al. [51]	PV	ANN, RNN		hybrid
Li L.-L. et al. [101]	Wind	SVM		hybrid
Huang Q. et al. [174]	PV	CNN	day-ahead	
Ağbulut Ü. et al. [41]	PV	ANN, SVM, Other		
Castillo-Botón C. et al. [118]	Hydro	SVM	long and short-term	
Chen J. et al. [175]	Wind	Autoencoder	short-term	
Yu M. et al. [176]	Wind	ANN		
Wang Y. et al. [115]	Hydro	ELM, Monte Carlo		
Hashemi B. et al. [177]	PV	Ensemble, ANN, RNN		
Yongsheng D. et al. [178]	PV	ELM, LSTM	short-term	
Mishra M. et al. [50]	PV	LSTM	short-term	hybrid
Wood D.A. [82]	Wind	Other		
Sapitang M. et al. [109]	Hydro	ANN, Ensemble	1-day-ahead	
Yu D. et al. [66]	PV	CNN, Attention, LSTM	day-ahead	hybrid
Wan C. et al. [179]	Wind	ELM		
Wu X. et al. [54]	PV	ELM		
Aly H.H.H. [147]	Wind	ANN		hybrid
Ahmadi A. et al. [86]	Wind	DT, Ensamble	long term	
Choi S.-H. et al. [180]	PV	Ensamble, LSTM		
Yao F. et al. [107]	Wind	LSTM		hybrid
Tahmasebifar R. et al. [181]	Wind	ELM	1h-ahead and day-ahead	hybrid
Wang H. et al. [182]	Wind	ELM	short-term	hybrid
De Caro F. et al. [183]	Wind	Ensemble	short-term	
Wei M. et al. [184]	PV	ELM		
Buhan S. et al. [185]	Hydro	ANN, SVM, PSO		hybrid
Xue W. et al. [106]	Wind	ELM, TLBO		hybrid
Chen Y. et al. [186]	Wind	DT		
Wang Q. et al. [187]	PV	ELM		
Dairi A. et al. [43]	PV	CNN, LSTM	short-term	
Zhang H. et al. [188]	Wind	ELM	short-term	
Hu W. et al. [189]	Wind	ANN, SVM	short-term	hybrid
Yang X. et al. [190]	Wind	ELM		
Hossain M.S. et al. [123]	PV	LSTM	short-term	
Liu W. et al. [121]	PV	Ensemble		hybrid
Huang Y. et al. [105]	Wind	Clustering, ANN	short-term	
Gómez J.L. et al. [191]	PV	ANN		hybrid
Essenfelder A.H. et al. [119]	Hydro	SVM, LSTM, ANN		hybrid
Ananthanatarajan V. et al. [192]	Wind	LSTM		
Yan H. et al. [193]	Wind	ELM	short-term	hybrid
Daneshvar Dehnavi S. et al. [194]	Wind	Fuzzy, SVM, FPA		
Guo X. et al. [195]	PV	Ensemble	short-term	

Table A2. An overview and comparative analysis of articles from 2021.

Article	Type	Used Tools	Time Horizon	Comment
Marinšek A. et al. [196]	Wind	Ensemble, SVM, LSTM	short-term	hybrid
Adedeji P.A. et al. [83]	Wind	PSO		hybrid
Yildiz C. et al. [197]	PV	ELM	short-term	
Ding S. et al. [65]	PV	GWO, Genetic	long	
Özen C. et al. [198]	Wind	Ensemble		hybrid
Lee D. et al. [199]	PV	LSTM		
Hu W. et al. [60]	PV	DBN	short-term	
Khan M. et al. [145]	Wind	DT		hybrid
du Plessis A.A. et al. [64]	PV	ANN, LSTM, GRU	short-term	
Pathak R. et al. [104]	Wind	Ensemble, KNN		
Yildiz C. et al. [117]	Hydro	ELM		hybrid
Meka R. et al. [200]	Wind	CNN	short-term	
Phan Q.T. et al. [201]	Wind	Ensemble	short-term	hybrid
Li Y. et al. [202]	PV	LSTM	short-term	hybrid
Zhao C. et al. [203]	Wind	ELM		
Konstantinou M. et al. [146]	PV	LSTM	short-term and long-term PV	
Shahid F. et al. [125]	Wind	LSTM, Genetic		
Zhao W. et al. [204]	PV	Genetic	day-ahead	hybrid
Li Q. et al. [205]	PV	ELM		
Cheng L. et al. [206]	PV	Graph Modeling	short-term	
Sun K. et al. [103]	Wind	ELM		
Hu S. et al. [207]	Wind	Evolutionary	short-term	hybrid
Liu Z.-F. et al. [46]	PV	GWO	short-term	hybrid
Hossain M.A. et al. [102]	Wind	GRU	very short-term	hybrid
Luo X. et al. [52]	PV	LSTM		hybrid
Fan H. et al. [208]	Wind	Clustering	short-term	
Mahmud K. et al. [6]	PV	Ensemble, ANN, LSTM	short-term and long-term PV	
Ti Z. et al. [209]	Wind	ANN		
Condemi C. et al. [110]	Hydro	ANN, SVM		
Ziane A. et al. [45]	PV	Ensemble		
Rodríguez F. et al. [210]	PV	Ensemble	short-term	
Chen H. et al. [211]	Wind	SVM, ANN, Ensemble, LSTM	short-term	
Neshat M. et al. [126]	Wind	Deep belief network		hybrid
Kabilan R. et al. [127]	PV	ANN	short-term	
Miao C. et al. [212]	Wind	CNN, LSTM	short-term	hybrid
Bochenek B. et al. [100]	Wind	Ensemble	day-ahead	
Niu H. et al. [213]	Wind	ELM, PSO		
Ahmad T. et al. [214]	PV, Wind	GPR	short-term, medium-term	
Lee D. et al. [215]	PV	EM	short-term	
Ekanayake P. et al. [75]	Wind	ANN		
Lv J. et al. [216]	Wind	Other	short-term	
Yin H. et al. [217]	Wind	CNN, LSTM, CCO		
Jung J. et al. [114]	Hydro	ANN		
Putz D. et al. [218]	Wind	N-BEATS	multi-horizon	hybrid
Dhiman H.S. et al. [219]	Wind	TSVM	short-term	hybrid
Massaoudi M. et al. [136]	PV	Ensemble, KNN	short-term	
Li L.-L. et al. [98]	Wind	ELM	short-term	
Zhang H. et al. [220]	Wind	Attention network		
Gupta D. et al. [221]	Wind	CNN, LSTM	short-term	
Guermoui M. et al. [59]	PV	Hybrid	multi-step ahead forecasting in a very short time-scale (up to 60 min)	

Table A2. *Cont.*

Article	Type	Used Tools	Time Horizon	Comment
Bezerra E.C. et al. [222]	Wind	Self-Adaptive Multikernel Machine	short term	
Li W. et al. [223]	Wind	CSO, ELM		
An G. et al. [224]	Wind	Ensemble, PSO, ELM	short term	hybrid
Ekanayake P. et al. [111]	Hydro	SVM		
Li Q. et al. [225]	Wind	ELM, ECBO, VMD	ultra short term	hybrid
Lu P. et al. [94]	Wind	SVM, ELM		hybrid
Ahmad T. et al. [226]	PV, Wind	KNN, Ensemble		hybrid
An Y.-J. et al. [227]	PV	LSTM		
Singh U. et al. [84]	Wind	Ensemble, KNN	short term	
Chahboun S. et al. [39]	PV	Ensemble, SVM, ANN		
Wu D. et al. [40]	PV	ELM, SVM	short term	hybrid
Yin H. et al. [81]	Wind	GAN, Evolutionary		
Xiang W. et al. [228]	Wind	DT		
An G. et al. [91]	Wind	ELM, SSA	ultra short-term	
Verma A. et al. [73]	PV	MLP, Ridge regression, DT, Ensemble, SVM, KNN		
Shams M.H. et al. [229]	PV, Wind	Ensemble, ANN, LSTM, SVM		
Matsumoto T. et al. [230]	PV	GAM		
Zhang Q. et al. [231]	Wind	LSTM	short term	
Lin W.-H. et al. [232]	Wind	LSTM, GRU, CNN	long-term	
Zhang C.-Y. et al. [233]	Wind	SVM, PSO		
Qin J. et al. [234]	Wind	ANN, SVM	short term	
Massaoudi M. et al. [235]	PV	ELM, Ensemble, KNN	short term	
Chen H. et al. [236]	Wind	ANN, LR, Ensemble	ultra-short-term	
Micha G.O. et al. [237]	PV	Ensemble		hybrid
Xu H. et al. [238]	Wind	ELM		
Chen H. et al. [239]	PV	LSTM		
Li J. et al. [240]	Wind	SVM	short term	hybrid
Salman D. et al. [241]	Wind	RNN, SVM, Hybrid	short-term	hybrid
Mohana M. et al. [242]	PV	ANN, Ensemble		
Zeng L. et al. [243]	Wind	ELM	short term	
Ramkumar G. et al. [61]	PV	ELM	short term	
Baran S. et al. [244]	Wind	Ensemble		
Dimitropoulos N. et al. [137]	PV	Autoencoder	short term	
Pu S. et al. [63]	PV	Hybrid		hybrid
Sessa V. et al. [112]	Hydro	Ensemble		

Table A3. An overview and comparative analysis of articles from 2022.

Article	Type	Used Tools	Time Horizon	Comment
Theocharides S. et al. [58]	PV	Hybrid	day-ahead	hybrid
Rodríguez F. et al. [245]	PV	ANN	intra hour term	
El Bourakadi D. et al. [92]	Wind	Autoencoder, ELM	short term	
Ribeiro M.H.D.M. et al. [129]	Wind	Ensemble	very short-term and short-term	
Keynia F. et al. [246]	Wind	LSTM	the next 24 h prediction	hybrid
Guo H. et al. [133]	Wind	ELM		hybrid
Simeunovic J. et al. [247]	PV	LSTM, CNN	short-term	
Visser L. et al. [131]	PV	Regression, SVM, Ensemble, Physical based techniques	day-ahead	
Sasser C. et al. [134]	Wind	Other		
Akhter M.N. et al. [248]	PV	Hybrid	an hour ahead	hybrid
Zazoum B. [47]	PV	SVM		
De Caro F. et al. [249]	Wind	Ensemble	multi-step ahead	

Table A3. *Cont.*

Article	Type	Used Tools	Time Horizon	Comment
Abubakar Mas'ud A. [250]	PV	KNN, DT		
He B. et al. [251]	Wind	CNN, LSTM	short term	hybrid
Luo X. et al. [252]	PV	TL, LSTM		hybrid
Zhang M. et al. [253]	Wind	ANN, LSTM, NARX, Persistence	short-term	
Pretto S. et al. [55]	PV	Ensemble	day-ahead	
Huang H. et al. [254]	Wind	Echo state networks	short-term	
Drakaki K.-K. et al. [116]	Hydro	Other	day-ahead	
Shi J. et al. [255]	PV	ELM, Autoencoders		
Huang X. et al. [135]	PV	Hybrid	short-term	hybrid
Piotrowski P. et al. [256]	Wind	Ensemble, Hybrid	one-day-ahead	hybrid
Özen C. et al. [79]	Wind	Ensemble	day-ahead	
Li H. et al. [128]	Wind	ELM	short term	
Li Z. et al. [132]	Wind	SVM		
Wood D.A. [257]	Wind	CNN, Ensemble		
Liu Y. et al. [258]	Wind	ELM		
Chen X. et al. [259]	PV	ELM, PSO	short term	
Ding Y. et al. [97]	Wind	ELM	short term	hybrid
Zhang S. et al. [113]	Hydro	Hybrid		hybrid
Tovilović D.M. et al. [260]	PV	Ensemble		
Zhang H. et al. [48]	PV	ELM, Fuzzy		hybrid
Li C. et al. [93]	Wind	Ensemble	short term	
Nespoli A. et al. [261]	PV	Ensemble, ANN	short-term	hybrid
Xiao B. et al. [53]	PV	SVM		
Markovics D. et al. [130]	PV	ANN		
Yadav H.K. et al. [72]	PV	ANN, Hybrid	24-h-ahead	hybrid
Akhter M.N. et al. [262]	PV	LSTM	short-term, an hour-ahead	hybrid
Alkesaiberi A. et al. [15]	Wind	SVM, Ensemble		
Yin S. et al. [263]	Wind	Other		
Chen W.-H. et al. [56]	PV	Hybrid		hybrid
Wentz V.H. et al. [71]	PV	LSTM, ANN	short-term	
Wang Q. et al. [264]	PV	RVM	short-term	hybrid
Ye J. et al. [265]	Wind	ELM, Ensemble	short term	hybrid
Shin W.-G. et al. [266]	PV	ANN		
Piotrowski P. et al. [70]	PV	Hybrid	very-short-term	hybrid
Li J. et al. [267]	Wind	ELM, SVM	short term	
Suárez-Cetrulo A.L. et al. [268]	Wind	Ensemble	Short -term	
Bai M. et al. [269]	PV	CNN, LSTM		
Tian W. et al. [270]	Wind	ANN, IFOA		hybrid
Li H. [76]	Wind	DBN	short term	
Pombo D.V. et al. [68]	PV	CNN, Ensemble, LSTM, SVM, Hybrid, Persistence	short term	hybrid
Zheng X. et al. [99]	Wind	ELM, LSTM		hybrid
Xiong X. et al. [80]	Wind	Ensemble	short term	
Wan J. et al. [271]	Wind	Ensemble, ANN	short-term	
Wang M. et al. [57]	PV	ELM	short-term	
Galphade M. et al. [272]	Wind	Ensemble		
Herath D. et al. [90]	Wind	Genetic	long-term	
Chen H. et al. [273]	Wind	Ensemble	day-ahead	
Krechowicz M. et al. [49]	PV	SVM, Ensemble, ANN		
Sun Y. et al. [274]	Wind	Attention network, LSTM		
Wang L. et al. [275]	Wind	M2TNet	short-term	
Gunadin I.C. et al. [276]	Wind	ELM		
Zhong W. et al. [277]	Wind	ELM	short term	hybrid
An G. et al. [78]	Wind	ELM, PSO	short term	
Ghenai C. et al. [278]	PV	ANN		
Zhou Y. et al. [69]	PV	Hybrid	short-term	hybrid

Table A3. *Cont.*

Article	Type	Used Tools	Time Horizon	Comment
Peng X. et al. [279]	Wind	ELM	short term	
Xu T. et al. [280]	Wind	ELM		
Amato F. et al. [281]	Wind	ELM		
Mayer M.J. [282]	PV	hybrid method based on the most physically-calculated predictors, ANN		hybrid
Kuzlu M. et al. [283]	PV	ANN		
Yadav O. et al. [284]	PV	ANN		
Wang L. et al. [285]	Wind	Attention network	short term	
Abdelmoula I.A. et al. [286]	PV	Ensemble		
Guo X. et al. [287]	PV	Ensemble	short-term	
Huang Y. et al. [288]	Wind	Hybrid	ultra-short-term	hybrid
Rosa J. et al. [96]	Wind	RNN, Ensemble	short-term, medium-term	hybrid
Sattar Hanoon M. et al. [14]	Hydro	ANN, SVM		
Meng A. et al. [289]	Wind	ELM		hybrid
Ma W. et al. [290]	PV	SSA, RVM	ultra-short-term (4 h ahead)	hybrid
Zhou X. et al. [291]	Wind	LSTM		
Zhou H. et al. [74]	Wind	ANN		hybrid
Wang N. et al. [292]	Wind	Enemble	short-term	
Mishra S.P. et al. [293]	Wind	ELM	short term	hybrid
Zjavka L. [294]	PV	ANN	intra day ahead, day ahead	hybrid
Hu D. et al. [295]	PV	ELM		hybrid
Yu R. et al. [296]	Wind	LSTM		
Abdellatif A. et al. [297]	PV	Ensemble	Short-term	
Zhou Q. et al. [298]	Wind	ELM	short term	
Cui W. et al. [299]	Wind	Ensemble		
Qiao B. et al. [27]	Wind	HFCM, IVMDHFCM		
Yang S. et al. [300]	Wind	LSTM, ELM, IWOA	ultra short-term	hybrid
Pang C. et al. [301]	Wind	Ensemble	short term	
Balraj G. et al. [302]	PV	VMD-ALODLFTSVM		hybrid
Guo N.-Z. et al. [303]	Wind	ANN	short term	
Yan M. et al. [42]	PV	ELM	short term	hybrid
Liu Y. [304]	PV	GRU, Clustering	short-term	
He R. et al. [88]	Wind	SVM, ANN		
Zhang W. et al. [305]	PV	CNN,LSTM	short-term	
Essam Y. et al. [44]	PV	ANN, Ensemble, LSTM, DT, LSTM		
Polo A. [306]	PV	SVM	short-term, long-term	
Kim J. et al. [89]	Wind	ANN, KNN, Ensemble, SVM	1 h	

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