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Review

Advancing Renewable Energy Forecasting: A Comprehensive Review of Renewable Energy Forecasting Methods

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Abstract: Socioeconomic growth and population increase are driving a constant global demand for energy. Renewable energy is emerging as a leading solution to minimise the use of fossil fuels. However, renewable resources are characterised by significant intermittency and unpredictability, which impact their energy production and integration into the power grid. Forecasting models are increasingly being developed to address these challenges and have become crucial as renewable energy sources are integrated in energy systems. In this paper, a comparative analysis of forecasting methods for renewable energy production is developed, focusing on photovoltaic and wind power. A review of state-of-the-art techniques is conducted to synthesise and categorise different forecasting models, taking into account climatic variables, optimisation algorithms, pre-processing techniques, and various forecasting horizons. By integrating diverse techniques such as optimisation algorithms and pre-processing methods and carefully selecting the forecast horizon, it is possible to highlight the accuracy and stability of forecasts. Overall, the ongoing development and refinement of forecasting methods are crucial to achieve a sustainable and reliable energy future.

Keywords: forecasting; meteorological variables; renewable energy; machine learning; algorithms; pre-processing

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1. Introduction

The constant economic challenges, technological development, and population growth lead to the permanent demand for energy. In fact, the energy sector is a parameter that can help determine a country's economic, social, and political development [1]. According to the authors of [2,3], energy consumption is increasing by 2% per year, and energy production remains heavily reliant on fossil fuels.

To decrease fossil dependency, greenhouse gas emissions, and carbon emissions, measures and policies are needed to mitigate these problems including energy management through renewable and sustainable energy systems [1,2,4–7].

Between 2021 and 2030, carbon emissions from the energy sector are projected to decrease by a third, with the power sector contributing to over half of this reduction according to the International Energy Agency (IEA) [8]. By 2050, electricity generation will grow by around 3.3% per year, with renewable installed capacity increases by four times, from 290 GW in 2021 to around 1200 GW in 2030, with photovoltaic and wind generation accounting for around 690 GW and 400 GW, respectively.

In this context, renewable energy is a solution to replace fossil fuel fonts in energy systems, making energy transition essential. According to Cantarero [9], energy transition involves energy efficiency, accessibility, affordability, and energy independence. In developed nations, shifting from fossil fuels to renewable energy sources is essential for economic growth, social equity, and environmental well-being.

Therefore, there are many applications for renewable energy in the context of energy transition, such as microgrids or hybrid systems. According to Rodríguez et al. [10], a microgrid is a distributed energy system that combines loads, power generators, and storage technologies along with control components to connect to the main network, with the benefits of reducing losses and costs and helping to mitigate reliability issues. In turn, a hybrid energy system (HES) has as its main objective to meet the electricity demand of consumers by generating electricity from two or more energy sources to ensure a more stable and efficient supply [11].

However, renewable energies still have limitations due to the intermittency and unpredictability of the resources or even problems related to the electrical grid, such as load balancing or the integration of renewable sources [12]. In this way, forecasting models emerge as a solution to overcome these problems and have become increasingly important as renewable energy sources grow.

Nowadays, accurate forecasts can help grid operators better manage the integration of renewable energy into the grid, minimising carbon emissions, decreasing operation costs, minimising the difference between electricity demand and supply, and reducing the use of electricity reserves through improved scheduling of production [13].

In recent years, there have been significant advances in renewable energy forecasting such as improved weather forecasting, as renewable energy is very dependent on weather conditions; machine learning and artificial intelligence algorithms have been making more accurate renewable energy forecasts, because these algorithms are able to learn from historical data, taking into account factors such as weather conditions, time of day, or energy demand; the integration of data sources, which can improve the forecast accuracy and the advances in data analysis, have made it easier to process and analyse large volumes of data; the growing use of distributed energy resources has made renewable energy forecasting more challenging, but advances in forecasting technology have made it possible to better predict energy production, improving the overall accuracy of renewable energy forecasts; cloud computing has made it easier to process and analyse large volumes of data and can be used to save and analyse information from different sources, improving the accuracy and timeliness of forecasts.

1.1. Classification of Forecasting Methods

There are two major types of machine learning algorithms that allow for predictive models to learn and analyse data: supervised and unsupervised. In supervised learning [14], algorithms learn from labelled data and provide corresponding values to the machine. Once the algorithm comprehends the data, it labels new data, resulting in predictions. In turn, in unsupervised methods, the entire dataset is unidentified, and the learning machine can identify patterns by classifying the data by itself.

In the current literature, there are also four main types of forecasting models that take into account various factors such as forecasting errors, the technology applied, and/or the conditions under study, which may affect the performance of the models, leading to economic problems or problems related to the proper functioning of the energy system, for example.

According to [15–17], physical models consider data such as temperature, solar radiation, or wind speed based on numerical weather prediction (NWP). However, they cannot deal with short-term forecasts and require high computational costs. On the other hand, statistical models are more appropriate for short-term forecasts. Statistical models rely on past data to forecast and use the gaps between the observed and predicted values to adjust the model parameters. However, they are not capable of making forecasts with data that have high noise, irregular and non-linear fluctuations, and patterns [15–17]. To overcome these problems, artificial intelligence models have been widely used given their capacity to predict non-linear data. However, the main disadvantages of these types of methods are the ease in which the method starts right away at an optimal solution, over-fitting, and low convergence. Finally, as individual models do not take into consideration the pre-processment of data, these methods do not always achieve high accuracy in model performance. Thus, combined or hybrid models use the main advantages of individual approaches to achieve higher forecast accuracy. Their efficiency and performance strongly depend on the historical dataset, so data pre-processing is required.

Table 1 shows distinct types of methods considered in the literature, as well as their main characteristics, advantages and disadvantages, and the forecast horizon to which they are applied. The advantages and disadvantages are also categorised according to calculation efficiency (E) and model structure (S).

Table 1. Types of forecast methods.

Characteristics	Advantages	Disadvantages
Type: Physical, Forecast horizon: Long-term Works: [14–29]		
• Based on meteorological parameters; • Historical relation between the input data and physical information is kept in the future; • NWP combines physical information and equations from physical models.	• Simple method; (S) • No need to be trained; (S) • High accuracy; (E) • Always perform well in long-term forecasting. (E)	• Difficult application (high number of meteorological parameters); (S) • High computational cost; (E) • Need additional information; (S) • Require considerable amounts of observable data in a limited scale of observation; (S) • NWP model is not updated; (S) • Deficient performance in short-term forecasts. (E)
Type: Statistical, Forecast horizon: Short-term Works: [14–29]		
• Uses historical measured data and does not consider physical parameters; • Based on existing statistical equations; • Establishes the mapping between input vectors and their corresponding outputs.	• They are simpler and more economical; (S) • Minimise training error; (E) • Faster calculation speed. (E)	• Forecast result affected by the quality of historical data; (E) • Linear structure is not applicable to depict the random and nonlinear characteristics of time series; (S) • Rely heavily on extensive historical data; (S) • Need data pre-processing; (S) • Cannot solve spatial and linear problems. (S)
Type: Machine learning, Forecast horizon: Short-term Works: [15–17,20,22,25,27,28]		

Table 1. *Cont.*

Characteristics	Advantages	Disadvantages
• Can mitigate the effects of randomness and non-stationarity in temporal and weather data; • Capable of learning a valuable representation of features from data to achieve their objectives; • Trained using historical data and can non-linearly map the given random input to the target without assuming any fixed relationship.	• Effective at capturing the non-linear characteristics of time series data; (S) • Capable of achieving higher prediction accuracy; (E) • Excellent self-learning and self-organizing capabilities. (S)	• Due to inherent properties, they can easily fall into a locally optimal solution; (S) • Over-fitting; (E) • Low convergence rates; (E) • Require larger computational resources and time. (E)
Type: Hybrid, Forecast horizon: Short-term Works: [16,17,19,22,25,26,28]		
• Considered advanced models; • Use the advantages and strengths of individual methods; • Learna valuable representation of features from data.	• Higher levels of accuracy. (E)	• The efficiency and performance is dependent on the historical data quality; (E) • Need data pre-processment. (S)

In several literature works, three additional types of forecasting methods are discussed: persistence, probabilistic, and spatial correlation. According to Ahmed et al. [29], persistence methods are very commonly used for very short- and short-term forecasting horizons. This technique is based on the concept that today is expected to be similar to tomorrow, assuming that conditions of the one day ahead will be similar to those of the previous day. Persistence methods have lower computational and time costs, as well as acceptable accuracy. On the other hand, spatial relation methods describe the relationship between different observed locations and the correlation among the locations for a specific region [15]. These methods use the inherent relationship between the properties of meteorological variables and their geographic location, as mentioned in [30]. However, the application of these models is challenging due to measurement errors and time lags, and while they can achieve higher accuracy under certain conditions, they have substantial information requirements [15,20]. Also, in [30], probabilistic models are also presented for wind speed prediction, where it is represented as a probabilistic density forecast (PDF), with parameters determined using different approaches.

There are important concepts to be addressed to better analyse and compare different forecasting methods, as well as the methods themselves, as discussed in the subsections below.

1.1.1. Artificial Neural Networks

Machine learning (ML) has widespread applications across various domains, offering a distinct advantage in tackling complex problems that are difficult to articulate using explicit models [31]. ML methods analyse the relationships between outputs and inputs, which allows the application of these methods in several problems such as classification problems, pattern recognition, or forecast problems. According to [32,33], the main objective of a ML forecast is reaching higher precision, and with the increasing amount of data, ML methods can highlight the explanatory and prediction capabilities of regressions. Among ML techniques, artificial neural network (ANN) models are frequently used for forecasting.

According to Gonzalez and Botto [34], ANN consists of a computational system that takes inspiration from the animal brain, with the primary purpose of recognising patterns in a certain set of data. It comprises multiple layers of artificial neurons, with each generally linked to all the neurons in adjacent layers. The strength of the connections is characterised with a specific weight or parameter. In fact, this concept provides the fundamental idea of long-term memory in neural networks. The modulation of an ANN depends on the number of layers of neurons, as well as the quantity and distribution of neurons in them. The results in [34] show that the method has a relative error lower than 3% for the long-term forecast for electricity demand and final energy in Portugal, making it twice as effective as the linear regression method.

ANNs are advantageous in their capacity to modulate complex non-linear relationships between the data. However, they are prone to over-fitting and easily falling into the minimum optimal location, as mentioned in [19].

There are four main steps when using ANNs for forecasting. The first is data preparation, where the historical data are collected and pre-processed, and then the data are normalised to improve the training process. Finally, they are split into training, validation, and test sets. The second step is the choice of model design considering the number of layers and neurons that characterise the network, as well as the activation function. The third step consists of training, evaluation, and testing the model's performance. Finally, the trained ANN is used to forecast future values.

Over the years, several works have been developed for renewable energy production forecasting using ANNs. Some are described below.

Brodny et al. [1] developed a study for renewable energy production in Poland. For this purpose, a modern forecasting model involving ANNs was considered to perform production mapping. Considering the analysis of renewable energy production (in total and individually), the total amount of renewable production, up to 2025, was predicted. Overall, it was observed that the mapping of the total renewable and electricity production was quite accurate.

Albogamy et al. [35] considered consumers and electricity producers in a microgrid. An ANN forecasting combined with enhanced differential evolution (ANN-mEDE) was performed to forecast electricity generation for effective management of renewable energy. In the prediction process, an ANN utilises the training datasets to predict solar radiance and wind speed for a day. The results are evaluated against the actual values using the MAPE metric and subsequently refined to further minimise errors.

In [36], a photovoltaic (PV) prediction model utilising dendritic neuron network (NBDM) was introduced to enhance computational efficiency and forecast precision. This model was subsequently integrated with a wavelet transform (WT) to more effectively capture features of varying frequencies from the input data.

Hassan et al. [37] introduced an innovative method that uses a genetically optimised non-linear auto-regressive recurrent neural network (NARX) system for ultra-short-term PV production prediction. Their method achieved significant improvements, with performance gains of up to 58.41%.

In [38], PV short-term forecasting was used for real-time balance operation of the electricity market, benefiting both power marketers and consumers. Since PV intermittence leads to inconsistencies in forecasting, a new seasonal auto-regressive integrated moving average-random vector functional link neural network assisted maximum overlap discrete wavelet transform (SARIMA-RVFL-MODWT) hybrid time-adaptive model was proposed [38].

Similarly, accurate wind speed forecasting plays a crucial role in optimising wind energy utilisation [18]. While numerous studies have concentrated on creating robust wind speed prediction models that can handle the inherent instability, irregularity, and noise in wind speed data, some of these works overlook the significance of properly modelling the samples, potentially leading to subpar forecasting performance. To perform the final forecasts, a wavelet neural network (WNN) model was considered, established by selecting a sample with distinctive similarity traits, allowing the generation of short-term wind speed predictions.

Zhang et al. [19] proposed a combined forecasting model aiming to improve wind speed accuracy for short-term horizons. Through a deep belief network (DBN), the fluctuation component of the original wind power data series was predicted. In [39], an accurate model for wind speed and power forecasts was proposed. Considering data aggregation segments, ANN and WNN are fed to forecast different segments, improving the accuracy of the predicted data by reducing the error.

In conclusion, ANNs offer significant benefits for short-term solar radiance prediction, including high speed, accuracy, and overall performance. Due to their inherent non-linearity, ANNs can effectively handle various temporal structures and network layers, making them adaptable to datasets of varying sizes related to climate and energy consumption for forecasting analysis [31]. Moreover, ANNs are widely recognised as the most effective and popular approach for predicting PV power production, leveraging the non-linear characteristics of meteorological data [40].

1.1.2. Support Vector Machine

According to Li et al. [5], support vector machine (SVM) is a supervised learning algorithm that is based on statistics combined with the theory of structural risk minimisation. It is useful for predictive pattern recognition and regression to solve different sample sizes and non-linear problems. Because of the influence of external factors, the PV power output exhibits significant randomness. In the present study, an SVM optimised by the hybrid improved multi-verse optimiser algorithm (HIMVO) was employed to predict PV production. The results showed improved accuracy and stability in the predictions, highlighting the effectiveness of this approach.

The basic SVM defines a hyperplane, i.e., a boundary that separates two classes in the data space. This hyperplane position and orientation are determined by the support vectors, corresponding to the data points more closely [41,42]. For classification tasks, SVMs find the best solution that separates two classes with the same margin on both sides of the hyperplane. To achieve this, first, it is necessary to prepare the dataset and divide it into train, validation, and test datasets. Then, the hyperplane equations are determined, and the new data classification is based on the hyperplane side where the new data fall.

In advanced SVM, some kernel functions are used to map the data points into new spaces that are then divided by a hyperplane.

In turn, in [40], SVM was extended to regression problems through support vector regression (SVR), which is a non-linear algorithm where the input data are mapped into a higher-dimensional feature space.

In [43], the use of storage systems increased the reliability of renewable system integration. Thus, an SVR model was proposed for the efficient prediction of energy storage. The proposed method uses kernels to establish a non-linear relation between the input and output, and the results show that energy operators can rely on the proposed model for monitoring storage systems as the method is able to predict their efficiency.

In [19], the least squares support vector machine (LSSVM) model was used to forecast the tendency on the original wind series. This method uses equality instead of inequality constraints, transforming SVM into a solving system of linear equations, reducing its complexity.

Eseye et al. [23] combined WT, SVM, and particle swarm optimisation (PSO) for daily power production prediction in a microgrid with PV integration. The results show that the proposed approach performs considerably effectively.

1.1.3. Deep Learning Methods

Deep learning (DL) is one of the most common and interesting field of ML [44], and DL techniques automatically learn valuable features from data rather than relying on traditional feature selection methods.

Deep learning models are highly effective for complex tasks like image recognition and time series forecasting. This is because they can automatically learn features from data, uncovering increasingly complex patterns layer by layer. A typical DL network has an input layer that receives the data, followed by some hidden layers that progressively transform the data, such as fully connected, convolutional, pooling, and recurrent layers, among others. Finally, in the output layer, the model's predictions are made.

In [44], two long short-term memory (LSTM) model are employed for temperature and power forecasting, respectively. The predictions are then smoothed and combined using a fully connected layer to improve the accuracy of the forecasting process.

In [2], DL models are used with the empirical mode decomposition (EMD) for energy forecasting to overcome the weakness of statistical models. Gated recurrent unit (GRU) and LSTM networks consider the characteristic time series of the data. The findings indicate that the GRU prediction model outperforms other deep learning (DL) and statistical models in terms of the mean absolute scaled error (MASE). Additionally, it effectively captures and predicts rapidly fluctuating time-series data.

The deep learning neural network (DLNN) is an improvement over neural networks and consists of adding hidden layers, for instance, multiple processing layers, to learn data representations. Through a comparison of LSTM-based forecasts and two classical time series forecasting methods, it was found that the long-term results of LSTM are better, and it was possible to demonstrate that a simple DLNN architecture can provide very good forecasting [45].

Xia et al. [46] emphasise the importance of accurate forecasts for renewable energy production and electricity consumption in smart grids. However, due to the intermittent nature of resources and the diverse behaviour of consumers, forecasting remains a challenging task. To address this, the authors propose an innovative hybrid improved stacked method for predicting wind energy production and electricity consumption. Notably, the use of GRU reduces model complexity by employing fewer parameters, minimising computational costs, and requiring less training data [46].

As per Khan et al. [3], the recent literature focuses on improving forecast accuracy without considering the temporal complexity of their methodologies. They develop a lightweight echo state network (ESN)-convolutional neural network (CNN) model for accurate solar power forecasting. The obtained results show a significant reduction in the error rate with lower complexity computation. In turn, in [47], an LSTM-CNN model is proposed and applied to PV prediction.

Jahangir et al. [48] introduce an accurate prediction model based on deep learning (DL) with micro-clustering (MC). Their results demonstrate that the proposed MCB-LSTM is a viable tool for various time series forecasting tasks, particularly when dealing with data exhibiting high stochastic behaviour and abrupt variations, such as wind speed or load requirements.

In [49], an analysis comparing CNN-L, MICNN-L, and MICNN-L focuses on the trade-off between model complexity and performance for solar irradiance forecasting as time series-based, image-based, and hybrid models. The results indicate that MICNN-L outperforms other models, particularly under cloudy sky conditions.

Finally, in Sharma et al. [50], a hybrid MODWT-LSTM is presented that can capture the data in a manner suitable to predict the values with higher accuracy for longer intervals.

1.1.4. Statistical Methods

Statistical methods can be defined as some of the main types of forecasting methods. At present, there is a vast number of state-of-the-art approaches concerning this type of methods.

Forecasting using statistical methods involves several key steps, namely data collection and preprocessing, selection of the appropriate statistical model based on data characteristics, parameter estimation, and model validation. Once the model is validated, it is used to forecast future values.

The regression method shows the relationship between dependent and independent variables. Considering the auto-regressive integrated moving average (ARIMA), the relation between the input and output data as well as the pre-processing of the input data were discussed [40]. The results obtained show that the accuracy is higher when the inputs have a strong relation with the output, and the result can be improved by the pre-processing of the input data.

Aasim et al. [51] mention that statistical methods are used for short-term wind speed forecasting. The novelty of this work is the use of the forecast error due to different decomposed time series in the resulting error forecast. WT is used to obtain the low- and high-frequency characteristics of different time series. The time series are modelled as an ARIMA model. Thus, the repeated WT-ARIMA (RWT-ARIMA) is able to model the variation of the high-frequency band of the wind speed more accurately than with WT-ARIMA, resulting in a lower root mean squared error (RMSE) in the wind speed forecast.

In [2], a seven-day-ahead forecasting model for electricity demand and renewable energy production is developed. Multiple linear regression (MLR) predicts a dependent variable considering two or more independent variables by adjusting linear equations, while SARIMA enhances forecasting accuracy by accounting for seasonal variation trends through the differences.

For Wang et al. [52], the MLR generates a linear function between the variables and the response. Although effectively representing the linear relationship, it cannot represent any non-linearity relationship. Therefore, a hybrid adaptive learning model (ALHM) is proposed for accurate short- to long-term solar intensity accuracy. A time-varying multiple linear model (TMLM) combined with ALHM is developed to capture the linear and dynamic features of data.

In turn, Alsharif et al. [53] consider a time series implemented through an SARIMA method for predicting daily and monthly solar radiation, considering the accuracy, suitability, quality, and timeliness of the collected data. The results demonstrate that the proposed model accurately predicts daily and monthly solar energy. This accuracy is attributed to its convenience, low data input requirements, and efficient computational process. Agoua et al. [54] refer to the importance of forecasting PV power due to the significant variability that characterises it. In this regard, a statistical model based on auto-regressive (AR) is proposed to deal with stationarity data and for short-term PV power forecasting. The results show that the computational requirements are low and that the model reduces, by about 28%, the average performance, and the normalised RMSE (nRMSE) can reach an improvement of 20%.

Pearre and Swan [55] analyse the effect of the predicted wind speed on the power of a wind energy converter (WEC). Wind speed and direction are corrected by considering two new forecasting techniques. The first technique consists of a statistical correction to improve wind speed prediction. Through this correction technique, the errors of wind speed prediction are reduced by about 20–25% in a 24 h range. The second consists of interpolating correction topographies and instantaneous forecast errors, and a similar error reduction is achieved at distances of 10 km from known locations.

1.1.5. Grey Model

Generally, research methods predominantly employ statistical regression or intelligent models to investigate factors related to energy consumption [56]. However, considering the multitude of factors involved, collecting variable data can be time-consuming, potentially impacting the system's credibility. To address this, a non-homogeneous grey model (GM) was introduced for predicting renewable energy consumption in Europe. This model emphasises the weight relationship between the most recent value and historical data, following the principle of adjacent accumulation.

According to [56–59], the GM emphasises the study of modelling uncertain systems with limited samples and sparse information, thereby mitigating error accumulation resulting from excessive data perturbation.

In fact, GM builds mathematical models to generate predictions based on incomplete information, and compared with other methods, requires less historical data it has a more straightforward modelling process and is more accurate [59]. Thus, the forecast performance of an GM largely depends on how effectively the information can be measured from data [57].

In [60], a fractional-order full-order time power seasonal discrete GM deals with non-linear and periodically long-term renewable production data sequences. The empirical results demonstrate that the model generally outperforms the GM as it can capture the non-linear and seasonal characteristics.

Qian and Sui [61] propose a new structural adaptive discrete grey model (SADGM) which aims to solve the problem of the structural prediction error of the traditional GM method. Thus, the proposed model is a forecasting model with time-varying parameters. It enhances adaptability for forecasting features with non-linear trends and periodic fluctuations in time series. The results demonstrate that the model benefits from its adaptive structure, producing reliable forecasts. Ding et al. [59] emphasise the importance of long-term PV power forecasts for grid balancing in systems with high PV resource integration. While ANNs are commonly used for short-term PV power forecasting, they tend to suffer from over-fitting and generate large forecast deviations over long time intervals. To address this, a new discrete grey model (DGM) with time-varying parameters is developed. The DGM effectively handles power data time series with non-linearity, periodicity, and volatility. The results demonstrate that the DGM outperforms other reference models due to its flexible structure, which adapts well to the non-linearity, volatility, and periodicity of the datasets.

1.1.6. Ensemble Methods

According to Bhardwaj et al. [62], ensemble methods employ a divide-and-conquer approach to enhance performance. The main principle is that a group of weak learners can reduce variance and improve model performance. Ahmad et al. [31] categorise ensemble models into cooperative and competitive models. Cooperative models distribute prediction assignments across selected predictors and appropriate sub-tasks. In contrast, competitive models train multiple features separately, using various types of datasets or similar datasets with numerous variables.

In Wang et al. [21], a hybrid wind power forecasting model is constructed with Bayesian averaging and ensemble learning model. According to the results, the method increases the reliability of the predictions and has a low overall error.

To effectively improve the accuracy and stability of PV power forecasting, an ensemble forecasting model based on singular spectrum analysis (SSA) and MOGWO was developed [63]. The results indicate that the proposed model outperforms the comparative hybrid models in terms of accuracy and stability. Additionally, the ensemble strategy successfully enhances short-term PV power prediction performance.

Elephant herding optimisation (EHO) based on LSSVM is used to ensemble the sample results to obtain the final prediction value [64]. The conclusion reached is that the method is considerably effective and highly reliable for predicting wind power data.

Random forest (RF) is a non-parametric and randomised ensemble ML method used for regression and classification tasks, composed of less robust algorithms or weak learners [65]. For predicting renewable production density, a quantile regression forest (QRF) model is considered as a valid non-parametric model capable of achieving adequate performance in terms of reliability and overall predictive ability. The results indicate that the RF algorithm exhibits superior overall performance across all classes, achieving 98% accuracy in data classification.

Ahmad et al. [66] note that ensemble-based techniques outperform individual learners by overcoming their limitations. RF and extra trees (ET) are particularly well-suited for output prediction of stochastic PV models, as they reduce variance and bias by combining various ML techniques, thereby enhancing stability.

Liu et al. [24] propose a new ensemble model, combining four new hybrid models as baseline predictors MOGWO, wavelet packet decomposition (WPD), AdaBoost.MRT, and outlier-robust extreme learning machine (ORELM) to obtain high prediction accuracy of multi-stage wind speed. The results demonstrate that the proposed ensemble model performs effectively in terms of convergence and prediction accuracy.

1.1.7. Probabilistic Methods

Probabilistic forecasting provides intervals or probability distributions as outcomes, offering power system operators more comprehensive information and tools for managing the power system [67,68]. In [67], various methods were applied to probabilistic forecasting in PV energy production. This study considered three different probabilistic methods: the first was based on Gaussian distribution (GD), which relied on point forecasting and assumed a specific distribution for the forecast error; the second was a quantile regression (QR) model, commonly used for PV forecasting; and the third method, quantile regression averaging (QRA), combined several point forecasts to generate a probabilistic distribution for the forecast error. The forecasts were compared using various evaluation metrics for probabilistic forecasts to determine the best-performing method in terms of accuracy and reliability, with results indicating that the GD assumption performed best.

For example, Xie et al. [69] noted that probabilistic forecasting methods can determine the upper and lower boundaries of wind energy and/or wind speed within a probability density or interval, providing additional information about wind fluctuations.

For Pretto et al. [27], grid operators face the challenge of maintaining the stability and reliability of the power grid due to the significant variability of the PV resource. This paper proposed a probabilistic ensemble method (PEM) to enhance the quality of ensemble predictions on cloudy days, where the sample distribution is often non-normal and requires more precise statistical analysis. The PEM leverages the probability distribution of the trials to provide a more reliable indicator for planning solar energy production for the next day. The results obtained show that the proposed method outperformed the reference methods in almost all metrics.

1.2. Data Pre-Processing

One factor that affects forecasting models is the data. In fact, as seen in [14,70], the historical and real-time data required during the development of a forecast model must be as complete and accurate as possible. However, in forecasting processes, numerous inputs often contain a high number of missing values and noise, among other issues. Consequently, the quality of the input data directly impacts the performance and accuracy of the forecast model and can cause defects in the acquisition, transmission, and processing of data.

Thus, data pre-processing is an important step in forecasting methods to guarantee the quality of data and, therefore, improve forecasting performance. Data processing techniques include data synchronization, identifying and processing abnormal data, or replacing missing data. There are several methods for data acquisition pre-processing: normalization [5,10,44,71], WT [23,29,38], and self-organizing mapping (SOM) [70].

1.3. Forecast Horizon

One of the key concepts in forecasting methods is the forecast horizon. In [40], the forecast horizon is defined as the time interval in the future for which the variable under study is to be forecasted. The purpose and accuracy of the forecasting model depend significantly on the forecast horizon. Generally, forecasting models used in most research can be defined as shown in Figure 1. Some literature also considers ultra-short-term forecasting, which, in this study, refers to the time interval between one minute and one hour. The forecast horizon impacts both the objective and the accuracy of a forecast, as accuracy varies with changing forecast horizons, even when using the same model and identical parameters.

According to [29,38], the forecast accuracy depends of the time interval, and the error values and variance increase when the forecast horizon increases. An ultra-short-term forecast, on the other hand, suffers more due to the intermittence of climate variables.

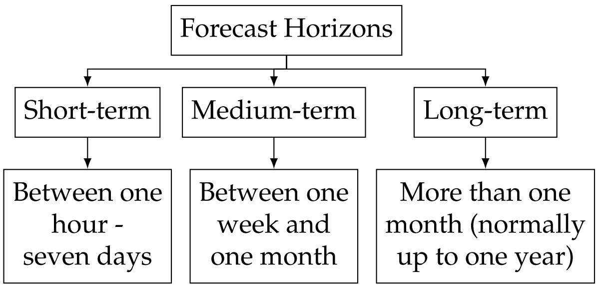

Figure 1. Classification of forecast horizon.

1.4. Optimisation Algorithms

Optimisation algorithms are crucial in accurately forecasting renewable energy generation, enabling efficient integration of renewable energy sources into power grids. Several optimisation models and algorithms improve the accuracy and reliability of renewable energy predictions throughout the work mentioned in state-of-the-art approaches. These models aim to optimise specific goals such as minimising forecast errors, maximising the utilisation of renewable energy resources, or optimising energy generation and consumption scheduling.

Liu et al. [56] explored the multi-objective grasshopper optimisation algorithm (MOGOA) as an effective parameter optimisation technique capable of determining the optimal coefficients for each sub-model. MOGOA utilises an archive to estimate approximate values of the Pareto optimal front, enhancing prediction accuracy and stability. Additionally, it helps address complex optimisation problems.

Jiang et al. [15] employed a modified multi-objective dragonfly algorithm (MMODA) to determine the weight coefficients of combined models, aiming to enhance the prediction accuracy and stability of the forecasting system. In [5], the HIMVO algorithm was used to optimise the SVM model parameters. The results demonstrated that the HIMVO algorithm possesses superior optimisation capabilities and can effectively avoid local optima.

The genetic algorithm (GA) is a popular algorithm for search and optimisation based on the evolution and adaptation of the fittest beings. In particular, it is inspired by the selection, crossover, and mutation operations. In prediction methods, GA is used to optimise parameters and other features.

In [37], GA was employed for gradient-free training of NARX models. The coupling of NARX with GA enhances optimisation of weights and biases, particularly beneficial when using a reduced number of indicators. In turn, in [25], GA optimised both the window size and the number of neurons within the layers of the LSTM model.

In the adaptive time-varying discrete grey model, the two coefficients not only impact estimation accuracy, but also decisively influence the temporal variation trend of estimated values. To optimise these coefficients which minimise the mean absolute percentage error

(MAPE) between predicted and actual values, the GA algorithm, known for its exceptional performance, is employed [59].

1.5. Performance Evaluation Metrics

Evaluation metrics are employed to gauge the precision and dependability of forecast models and to contrast various forecasting methods. In the context of renewable energy production, evaluation metrics are used to measure the accuracy of forecasts for energy production from renewable sources. The selection of an evaluation metric hinges on the particular forecasting problem and the nature of the data employed. Different metrics may be suitable for varying types of forecasts, and utilising a combination of metrics can provide a more thorough evaluation of forecast accuracy.

In [17,20], it is noted that while there exist numerous performance metrics to evaluate the forecasting effectiveness of various models, there is a lack of a universal standard for assessing forecasting model errors. Therefore, the selection of performance evaluation criteria should aim to highlight the disparities between actual observations and estimated values [59]. Generally, the lower the criteria values, the closer the predicted values are to the actual values. The quality of the input data is another crucial factor influencing the performance of a forecasting model [14].

Thus, some of the most commonly used metrics for assessing the performance of forecasting models are mean absolute error (MAE), which calculates the mean absolute difference between predicted and observed values and is a commonly used metric to verify the accuracy of time series in forecasting models; RMSE, which takes into account the squared difference between predicted and actual values, makes larger error penalties compared to MAE, and is used to compare the performance of different forecasting models; coefficient of determination, R^2, which measures the proportion of the variation in actual values that is explained by the predicted values; MAPE, which calculates the percentage difference between predicted and actual values and is commonly used to assess the accuracy of energy demand forecasts.

There is a vast number of state-of-the-art works where these and other metrics are highlighted, which allow different forecasting models to be assessed and compared. For example, in [66], the RMSE, MAE, and R^2 were determined to evaluate the performance of the developed models in predicting PV power. De Guia et al. [72] also introduced the explained variance score (EVS), which quantifies the dispersion within specific datasets, the maximum residual error (MRE) that captures discrepancies between predicted and actual values, and the mean squared error (MSE) that calculates the average squared difference between predicted and actual values. According to He et al. [18], the MSE penalizes larger errors more severely than multiple smaller errors.

1.6. Forecast Variables

In general, forecast variables refer to the specific parameters considered to generate forecasts about future events or outcomes. For renewable energy production, forecast variables can include parameters that can have a significant impact on the renewable energy produced, like weather variables (solar radiance or wind speed, for example), as well as factors like energy demand and storage capacity.

Accuracy and reliability are two of the most important criteria to take into consideration when analysing a forecast model. They are critical to effective energy management and the integration of renewable sources in power systems.

According to [73], the performance of wind power forecasts is impacted by historical wind power values and NWP variables. The paper also notes that while additional input features theoretically provide more information, an excess of information can actually diminish forecast accuracy. Therefore, it is crucial to carefully select the appropriate input variables.

1.7. Objectives of the Work

This paper aims to develop a comparative analysis of forecasting methods for renewable energy production, particularly PV and wind power. To this end, a review of state-of-the-art research was developed to synthesise and frame different forecast models, taking into consideration climatic variables, optimisation algorithms, pre-processing techniques, and different forecast horizons. Compared with other works, the main contributions of this research are (1) a systematic review of the applications of forecasting methods in a renewable context; (2) due to the variety of climatic variables and the intermittent behaviour that characterises them, an analysis of different techniques that allow minimising these effects on the forecast, permitting the increase in the efficiency and accuracy of the forecasts; (3) analysis of the different methods proposed over the last years in order to determine the best forecasting methods for renewable energy in a short- to medium-term forecast.

The rest of the paper is organised as follows: Section 2 shows the research methodology considered for the selection of different manuscripts that are relevant to this paper; Section 3 presents one of the main forecasting support tools developed; and Section 4 contains the results and their discussion, considering the relevant points of previous research in order to analyse the efficiency and relevance of the predictions. Finally, in Section 5, the main conclusions and future considerations are drawn.

2. Methodology

The literature on forecasting methods and renewable energy is extremely extensive [74]. Therefore, the review method used in this research consists of a structured selection using the academic search engine Google Scholar, which already indexes the main journals in the field. The selected manuscripts are written in English and include publications in well-known journals, papers presented at conferences, and theses. The papers are related to "forecasting" or "renewable energy" topics and published from 2018. Figure 2 illustrates the manuscript selection criteria.

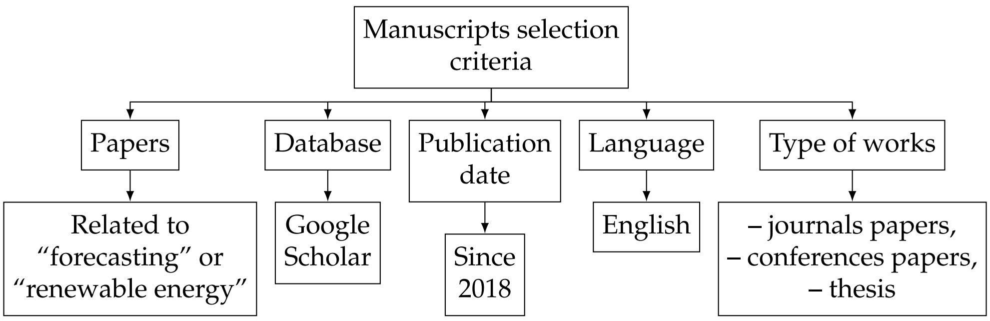

Figure 2. Methodology applied in the selection of papers.

Figure 3 shows the percentage distribution of the manuscripts considered in this paper. The total number of considered manuscripts is 101, classified into five categories: journal paper, conference paper, thesis, review, and research paper.

As can be seen, articles published in well-known newspapers have the highest percentage of articles collected (73%), followed by reviews with 13%, and conference and research papers, with 10% and 3%, respectively. Only a small percentage (1%) is related to thesis developed.

Figure 4 shows the number of selected manuscripts by publication year from 2018 to 2023, reflecting the interest in the topic. The number of publications is quite similar for all years except 2023. This is because the date of this work is mid-2023.

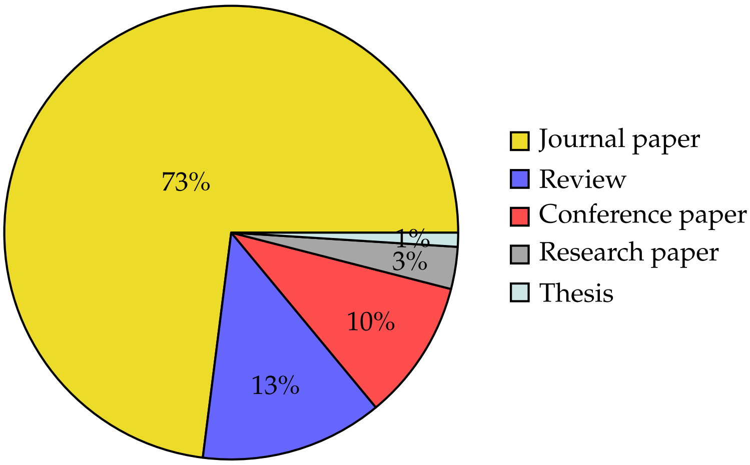

Figure 3. Type of work distribution.

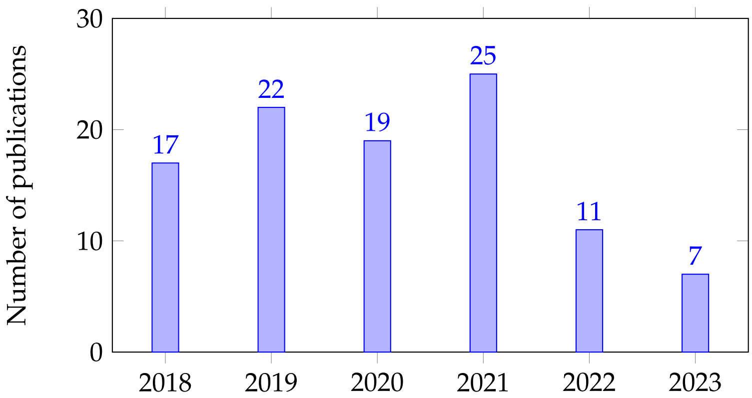

Figure 4. Selected manuscripts, by year, from 2018 to 2023.

3. Forecasting Support Tools

Forecasting softwares are specialised tools designed to help businesses and organisations predict future trends, patterns, and outcomes based on historical data and statistical analysis. These tools use advanced algorithms and statistical models to generate accurate forecasts that can help businesses make informed decisions, optimise resource allocation, manage inventory, and improve overall operational efficiency.

Waikato Environment for Knowledge Analysis (Weka) [75] is a popular and widely used open-source data mining and machine learning software tool. It offers an extensive array of algorithms and tools for data pre-processing, classification, regression, clustering, association rules, feature selection, and visualisation. It can be utilised for renewable energy production forecasting by applying its machine learning and data mining capabilities to relevant datasets. It allows for the collection of historical data related to renewable energy production, the cleaning of the data, the handling of missing values, and normalisation or scaling of the variables as required. It can also identify the most relevant features that affect renewable energy production, select appropriate forecasting models, split the historical data into training and validation sets, and evaluate the model performance.

In short, by utilising forecast software, businesses can benefit from more accurate predictions, improved planning, reduced costs, and better alignment between demand and supply. These tools offer organisations a competitive edge by enabling them to anticipate market trends, adapt to changing customer demands, optimise inventory levels, and make data-driven decisions for sustainable growth.

4. Results and Discussion

To analyse and compare the works developed, this section presents the main points and the main characteristics considered, such as forecasting variables. The forecasting horizon and the evaluation metrics, among others, are also analysed in order to evaluate the performance of the methods and compare their efficiency and accuracy. Finally, the results obtained are discussed in order to find the best forecasting methods for renewable energy production.

Table 2 shows the main highlights for the considered manuscripts and their key characteristics of the forecast. The first column, "Ref.," indicates the manuscript. The next column, "Method," enumerates the used methods. Column 3, "Opt.," indicates the associated optimisation techniques used in the method to find its best parameters, and Columns 4 and 5 show the forecast variable and horizon. Column "Pre-processing" lists the input data pre-processing technique, and the last column presents the best metric. The main objective proposed is comparison of the different forecasting methods and analysis of these characteristics taking into consideration the lowest metric and their efficiency. The main contributions of each manuscript are also highlighted in the table.

Table 2. Description of forecast methods.

Ref.	Method	Opt.	Forecast Variable	Forecast Horizon	Pre-Processing	Lowest Metric
[1]	ANN	–	Renewable energy and biofuel production	Long term	–	MAE−0.47
Research novelties/Contributions: ANN models the complex relationships between input and output data; analyses the structure and amount of renewable energy produced.						
[2]	DNN, LSTM, GRU	–	Wind and PV power	7 days ahead	EMD	MASE-0.19
Research novelties/Contributions: Development of a forecasting model based on deep learning in order to surpass the performance limitations of conventional forecasting models and enhance model effectiveness.						
[3]	ESN-CNN	–	Energy production	Long term	–	MBE-1.2%
Research novelties/Contributions: Selects the optimal model for renewable energy prediction with the primary objective of analysing the performance of various techniques.						
[4]	LSTM-EFG	Clustering	Wind power	30 min	–	MSE-5.5451
Research novelties/Contributions: Improved LSTM network that enhances the effect of forget-gate, optimises convergence speed, and increases accuracy of wind power forecast in 18.3%.						
[5]	HIMVO-SVM	HIMVO	PV power	Short term	Normalisation	MSE-0.0025
Research novelties/Contributions: The model exhibits superior convergence speed and accuracy, which helps enhance the quality of PV grid connections and reduce PV output volatility.						
[6]	Seasonal ARMA	MILP	Wind speed and day-ahead price	Long term, Short term	–	profit increase-12%
Research novelties/Contributions: Integrates CVPP optimisation and uncertainty modelling with multiple scenario analyses for various renewable plants, considering separation distances for both aggregated plants and individual operations.						
[7]	ANN, SVR, GPR	GA	Wind and Solar Power, Electricity Demand	Long term, Short term	Normalisation	MSE-0.00079575
Research novelties/Contributions: Establishes datasets and develops data-driven models using ML techniques, aiming to calculate uncertainties within the grid and analyse the predictability of actions.						
[10]	ANN	–	Radiation	10 min	Normalisation	RMSE-5.16
Research novelties/Contributions: ANN predicts solar energy with a high standard accuracy for short-term horizons and increases the capabilities of computers by replicating the human biological information processing system.						
[12]	Tucker-Clus	–	PV and Wind power	24 h	–	MAE-0.0529
Research novelties/Contributions: Tucker tensor extracts a new feature space for the learning task, minimising the running time, and allows for capturing spatial auto-correlation.						
[13]	HSA-ANN	HSA	Solar radiation, Wind speed	Short term	Standard scalar	MSE-0.04754; 0.30944
Research novelties/Contributions: Development of an HSA-optimised ANN model for reliable and accurate prediction of solar and wind energy, utilising HSA to assign optimised weights to the edges of the ANN. This enables the proposed forecasting algorithm to achieve high precision, faster convergence speed, and reduced complexity.						

Table 2. *Cont.*

Ref.	Method	Opt.	Forecast Variable	Forecast Horizon	Pre-Processing	Lowest Metric
[70]	ARIMA, ANN, SVR, RT	–	Solar radiation	Ultra short term	Normalization, WT, SOM	–
Research novelties/Contributions: Review of different types of methods.						
[14]	–	–	Solar power	–	–	–
Research novelties/Contributions: Review of different types of methods.						
[15]	ARIMA, BPNN, GRNN, DBN, ELM, ENN, LSTM	MMODA	Wind speed	Short-term	SSA	MAE-0.1260
Research novelties/Contributions: The developed combined system combining PF and IP to provide accurate point and interval forecasting performance.						
[16]	MWDO-CEEMD-BP	MWDO	Wind speed	10, 30 min	CEEMD	MAE-0.2856
Research novelties/Contributions: CEEMD de-noises and plays an important role in removing noise from raw data. When the convergence criterion is increased, MWDO improves optimisation speed and optimisation accuracy, and it has good non-linear forecasting ability.						
[17]	BP, ENN, WNN, GRNN	GWO	Wind speed	Short term	ICEEMDAN	MAE-0.1931
Research novelties/Contributions: Using a decomposition and ensemble strategy, a data preprocessing technique is applied to remove the adverse effects of high-frequency noise and to extract the primary characteristics of the data, enhancing the accuracy of short-term wind speed forecasts.						
[18]	WNN	–	Wind speed	Short-term	EEMD	MAPE-1.24%
Research novelties/Contributions: EEMD decomposes wind speed series and removes high frequency signals to obtain a smoother series; KFCM extracts data characteristics with similarities before the training, and the data clustering module obtains samples with highly similar fluctuation patterns.						
[19]	LSSVM-DBN-SSA-LSH	LSSVM	Wind power	Short term	SSA	nMAE-1.64%
Research novelties/Contributions: SSA-based models choose the suitable method for the trend component and the fluctuation; the LSSVM evaluates their own performance; the LSH search algorithm optimally selects training samples modelled by LSSVM.						
[20]	MOGWO-ENN	MOGWO	Wind speed	Short-term	VMD	MAPE-14.4656%
Research novelties/Contributions: An optimised ANN combines the original time series prediction with the error sequence prediction non-linearity to obtain higher accuracy; VMD captures and integrates the characteristics of data; MOGWO optimises the parameters of the ANN to improve the accuracy and stability of the prediction, resulting in the average reduction in MAPE in 14.4656%.						
[65]	Conv-LSTM1D	XGBoost	PV power	15, 30 min, 1 h	EDA	MAE-0.0125
Research novelties/Contributions: A $ConvLSTM1_D$ model captures both seasonality trends and high variability during sudden power production changes.						
[76]	Auto-LSTM	–	Solar power	Day ahead	–	RMSE-2.566087
Research novelties/Contributions: Auto-LSTM can optimise the accuracy of time series prediction, and it improves short-term solar power forecast using more frequent updated of meteorological parameter prediction.						
[71]	CLSTM	–	PV power	–	Normalization	MRE-0.38%
Research novelties/Contributions: DL has good results in the prediction of PV power, guaranteeing that the stability and robustness of the model are high.						
[77]	DL techniques	–	PV power	–	–	–
Research novelties/Contributions: Review of deep leaning methods.						
[78]	Conv-LSTM	Bayesian	PV power	30 min, day, month	–	nRMSE-0.03
Research novelties/Contributions: Conv-LSTM networks have the best performance when predicting region-level PV generation regarding the time horizons.						
[79]	–	–	Wind energy	–	–	–
Research novelties/Contributions: A review regarding the use of big data and AI in wind energy forecasting research, analysing the data characteristics and analysis techniques.						

Table 2. *Cont.*

Ref.	Method	Opt.	Forecast Variable	Forecast Horizon	Pre-Processing	Lowest Metric
[80]	24 ML models	Analysis of optimisation methods	PV power	Day ahead	–	RMSE-13.1%
Research novelties/Contributions: By incorporating angles derived from the sun's position, along with time-shifted and averaged versions of the global horizontal radiance, the RMSE is reduced by 13.1% compared to NWP outputs alone.						
[81]	ARIMA	ACF and PACF plots	Solar energy	Daily	Filling up the missing data	MAPE-17.70%
Research novelties/Contributions: ARIMA forecasts daily solar energy production and transforms the seasonal and non-stationary time series into stationary.						
[82]	LSTM-NN	–	PV power	Hourly, daily	Min–max normalisation	MAE-0.69
Research novelties/Contributions: A synthetic weather forecast is employed to select PV plant locations, integrating statistical insights from historical solar radiance data with publicly available sky forecast data.						
[83]	DSE-XGB	Grid search	Solar energy	15 min, 1 h, day ahead	Linear interpolation	R^2-0.96
Research novelties/Contributions: A deep ensemble stacking model forecasts solar PV energy on different locations and time steps.						
[84]	CNN-LSTM	Adam	Solar radiation	1 day up to 8 months	–	APB-1.233%
Research novelties/Contributions: A hybrid model with CNN accurately predicts global solar radiation and energy availability to be regularly monitored when linked to an LSTM.						
[21]	BMA-EL	–	Wind power	Short term	GF and Normalisation	MAPE-10.0848%
Research novelties/Contributions: SOM clustering and k-fold cross-validation increases the diversity of base learner's input samples, and they have more different outputs. BMA combines the forecasting results of different base learners, resulting in higher precision and stability for wind power prediction.						
[44]	ALSTM	RMSProp	PV power	7.5, 15, 30, 60 min	Normalisation	MAE-0.80
Research novelties/Contributions: The ensemble deep framework with an attention mechanism allows the two LSTM neural networks to focus on significant input features.						
[85]	ECMWF-HRES	–	Solar radiance	Short term	Normalisation	–
Research novelties/Contributions: This work primarily aims to acquire predictability maps for CONUS, which offer fresh perspectives on solar forecast verification.						
[22]	LSTMDE-HELM	DE	Wind speed	10 min, 1 h	–	MAE-0.47054
Research novelties/Contributions: ELM considers the fact that the output depends not only on its input but also on derivative information, and it prevemts the neuron from becoming struck in the local minima by switching between two segments.						
[23]	WT-PSO-SVM	PSO	PV-solar power	1 day ahead	WT	SDE-0.7072
Research novelties/Contributions: Implementation of WT-PSO-SVM for short-term solar power prediction.						
[24]	MOGWO -WPD-AdaBoost. MRT-ORLEM	MOGWO	Wind speed	–	WPD	MAE-0.1691
Research novelties/Contributions: The base predictors guarantee the tuning and optimisation of mother wavelets in the wind speed forecasting performance in order to find the optimal mother wavelet.						
[25]	GLSTM	GA	Wind power	Short term	16-dimensional wind features	MSE-0.00924
Research novelties/Contributions: An LSTM is employed due to its capability of automatically learning features from sequential data. An GA adjusts the size of the window and neurons in the LSTM layers.						
[26]	MCEEMD -MOSCA -WNN	MOSCA	Wind speed	10, 30 min	MCEEMD	MAE-0.099039
Research novelties/Contributions: A hybrid WNN based on MOSCA obtains high accuracy and strong stability simultaneously; the model effectively captures the strengths of each component, making it a robust technique for enhancing wind speed forecasting with high accuracy and stability.						
[27]	PEM	–	PV power	day-ahead	MCD	SS-0.540

Table 2. *Cont.*

Ref.	Method	Opt.	Forecast Variable	Forecast Horizon	Pre-Processing	Lowest Metric
Research novelties/Contributions: A novel ensemble method, PEM, based on probabilistic distributions of trials, is introduced to enhance forecasting performance specifically on cloudy days.						
[28]	CEEMD-MOGWO-ELM	MOGWO	Wind speed	Short term	CEEMD	AE-0.0064
Research novelties/Contributions: CEEMD decomposes the original wind speed sequence into a series of intrinsic mode functions, followed by optimisation using ELM enhanced by MOGWO, resulting in excellent forecasting performance.						
[29]	Review of forecast methods	GA, PSO	PV-solar power	–	Normalisation and WT	–
Research novelties/Contributions: Ensemble ANNs forecast short-term PV power and online sequential extreme learning machine superb for adaptive networks, while the Bootstrap technique is optimal for estimating uncertainty.						
[30]	FN	Whale Algorithm	Wind speed	Short term	BE	MAE-1.05
Research novelties/Contributions: FN's foundation lies in generating problem-specific network topologies and optimal neural networks with diverse structures, leading to optimal models for precise forecasting of wind speed and power.						
[34]	RNN	Gradient descent algorithm	Electricity and energy needs	Long term	Normalisation	ER < 3%
Research novelties/Contributions: Uncovering of the untapped potential of modern AI techniques for long-term forecasting of electricity and final energy needs in Portugal through the development of a dynamic model based on low-error ANN methods.						
[35]	ANN-mEDE	ACO	WT and PV energy	Day ahead	-	nRMSE < 0.09%
Research novelties/Contributions: An ANN-mEDE model forecasts the generation profile of microgrid using weather information and mathematical models of WT and PV, and ACO is used to efficiently manage energy, the scheduling of load, and EV charging/discharging needs to be adjusted.						
[36]	WT-NBDM	Mallat algorithm	PV power	15 days	WT	MAPE-9.2%
Research novelties/Contributions: The dendritic neural network is used to directly design the PV power forecasting model, avoiding the need for empirical adjustments in the size of traditional neural network models. Additionally, WT assists in PV forecasting design by decomposing input data into high and low frequency components.						
[67]	GD, QR, QRA	–	Solar power	24 h	–	CRPS-0.2636
Research novelties/Contributions: Review of solar power forecasting literature.						
[46]	GRU-RNN	AdaGrad	Renewable energy and electricity load	Long-term	Normalisation	MAE-0.0393
Research novelties/Contributions: The stacked GRU-RNN achieves precise energy prediction using time-series data and monitoring parameters. The enhanced GRU-RNN reduces model complexity, resulting in lower computational costs and requiring less training data.						
[37]	NARX-GA	GA	PV power	5, 15, 30, 60 min	Normalisation	MPE-0.012%
Research novelties/Contributions: Ultra-short-term forecasting of PV power is made with an NARX model. This extends the high prediction accuracy of static multi-layered perceptron neural networks to dynamic models with a more stable learning process. The proposed NARX-GA demonstrates superior performance as the forecasting horizon narrows, achieving improvements of up to 58.4%.						
[38]	SARIMA-RVFL	–	Solar-PV power	Very short term	MODWT	MASE-0.589
Research novelties/Contributions: Combination of forecast models for solar PV power that has positive effects of wavelet decomposition which helps achieve better forecasts.						
[39]	12 hybrid models	–	Wind speed and power	Hourly	FS	nRMSE-0.04446
Research novelties/Contributions: Clustered segments and DL hybrid models improve the aggregated system performance, and it is validated by using a different unseen dataset with the proposed models as well as using k-fold cross-validation.						
[31]	ML, ANN and Ensemble methods	–	Renewable energy and electricity needs	Intra-hour, intra-day, day ahead	–	–
Research novelties/Contributions: Review of machine learning, ANN, and ensemble-based approaches applied in energy planning and management.						
[43]	SVR	–	Energy storage systems	–	–	MSE-0.0002

Table 2. *Cont.*

Ref.	Method	Opt.	Forecast Variable	Forecast Horizon	Pre-Processing	Lowest Metric
Research novelties/Contributions: Evaluation of the performance of different kernels for SVR for predicting the storage efficiency of energy; SVR can minimise the generation error of a prediction problem.						
[51]	RWT-ARIMA	–	Wind speed	1, 3, 5, 7, 10 min	MODWT	MAE-0.2268
Research novelties/Contributions: RWT-ARIMA decomposes the high-frequency time series into further subsequent detailed coefficients, reducing forecasting errors.						
[52]	ALHM	GA	Solar intensity	Long term	–	MAPE-13.68%
Research novelties/Contributions: ALHM predicts solar intensity based on meteorological data. TMLM identifies linear relationships and time-varying features, while GABP efficiently learns non-linear relationships in the data with accelerated training and searching capabilities.						
[53]	SARIMA	–	Solar radiation	Daily, monthly	–	RMSE-33.18
Research novelties/Contributions: An implementation of SARIMA time series forecasts daily and monthly solar radiation, taking into account the precision, appropriateness, sufficiency, and promptness of the gathered data.						
[54]	Spatio-temporal model	–	PV power	Few min–6 h	Normalisation	RMSE-4.5
Research novelties/Contributions: A new stationarisation process aims to suppress weaknesses of the clear sky-based normalisation considering local meteorological conditions and proposes a model that integrates an automatic selection of the appropriate input variables.						
[55]	Statistical	–	Wind speed	24 h	–	–
Research novelties/Contributions: A statistical-based correction method is employed to enhance wind speed forecasting, involving the development of a "correction topography" that is valuable for wind field operators and utilities focused on integrating wind energy, and also interpolates correction topographies and instantaneous forecast errors.						
[56]	ANDGM	PSO	Renewable energy consumption	Long term	–	MAPE-3.21%
Research novelties/Contributions: ANDGM is introduced to achieve accurate predictions of annual renewable energy consumption, utilising an accumulation parameter to flexibly adjust the weighting between historical and new information.						
[60]	FOTP-DGM	PSO	Hydropower consumption	Annual	–	MAPE-2.43%
Research novelties/Contributions: FOTP-DGM uses periodic aggregation generation operators to unify short-term and long-term system development, fully leveraging the long-term trends in seasonal sequences.						
[57]	PGM	PSO	Electricity consumption	Annual	Bernoulli distribution	MAPEVE-0.18%
Research novelties/Contributions: PGM based on P-AGO eliminates invalid information, mines grey information, and maximises grey information.						
[58]	FTDP-DGM	GA	Energy generation	Long term	R-function cumulative sequence	MAPE-2.45%
Research novelties/Contributions: FTDP-DGM models and forecasts the problem of small-sample time series containing time-delay, non-linearity, and uncertainty characteristics. GA finds the optimal value of the non-linear parameter.						
[59]	ATDGM	GA	PV power	Long term	–	GRC-0.94
Research novelties/Contributions: ATDGM is modelled to grasp non-linear, fluctuant, and periodic patterns, and GA obtains the best solutions to deal with complex optimisation problems.						
[61]	SADGM	PSO	Renewable energy generation	Mid to long term	1-order accumulation	MAPE-1.99%
Research novelties/Contributions: SADGM enhances prediction performance and improves the DGM model's ability to capture the periodicity of complex data sequences by introducing non-linear and periodic terms.						
[69]	–	Single and multi-objective algorithms	Wind speed and power	Short term	Data decomposition, dimensional deduction, and data de-noising	–
Research novelties/Contributions: Systematic review of deterministic and probabilistic methods for wind forecasting.						
[66]	ET and RF	–	PV power	Hourly	–	$R^2 - 0.7293$
Research novelties/Contributions: Tree-based ensemble methods analyse the variable importance of each input characteristic, improving the prediction and stability of the method.						

Table 2. *Cont.*

Ref.	Method	Opt.	Forecast Variable	Forecast Horizon	Pre-Processing	Lowest Metric
[72]	Bagging ensemble learning	PCA	Solar irradiance	Annual	Z-score normalisation	EVS-0.92
Research novelties/Contributions: Bagging-based ensemble learning system forecasts solar radiation based on weather patterns.						
[86]	ELM	–	Wind power	Next hour	–	MSE-0.0716
Research novelties/Contributions:The objective of utilising ELM is to retrieve the quantity of wind energy produced while avoiding complex mathematical calculations to address uncertainties in the system.						
[63]	SSA-MOGWO-EF	MOGOA	PV power	Short term	SSA	MAPE < 2%
Research novelties/Contributions: The proposed forecasting method considers the advantages of multiple algorithms and validly depicts the linear and non-linear characteristic of PV time series to obtain precise and reliable predictions.						
[64]	EHO-LSSVM	EHO	Wind power	Ultra short term	EEMD	nRMSE-0.282
Research novelties/Contributions: Wind power is decomposed into a series of signal sets by EEMD. An optimised LSSVM by EHO is used to predict each component signal, and then the EHO-LSSVM is used to ensemble the sample results into the final prediction value.						
[87]	EEMD-LSSVR-K-LSSVR	GSA	Solar radiation	1, 3, 6 steps ahead	EEMD	MAPE-2.83%
Research novelties/Contributions: A novel DCE with EEMD, K-means, and LSSVR improves the performance of solar radiation forecasting and compares its predictive capabilities rivaling those of popular existing forecasting models.						
[88]	Bi-GRUNN	–	Wind power	Short term	–	RMSE-2.40%
Research novelties/Contributions: Bidirectional GRUNN is used to correct NWP wind speed considering statistical and time series characteristics.						
[89]	SVM	Sine cosine algorithm	Load	Short term	FD, FFT	MASE-0.197
Research novelties/Contributions: Adaptive Fourier decomposition obtains the fluctuation characteristics, and an optimised sine cosine algorithm obtains the penalty and kernel parameters of an SVM.						
[90]	Different models	GA, PSO	Wind energy	–	WD, WPD, EMD, EEMD, CEEMD, CEEMDAN	–
Research novelties/Contributions: Review and comparison of different decomposition-based models.						
[50]	MODWT-LSTM	–	PV power	Day ahead	MODWT	MBE-0.0262
Research novelties/Contributions: Historical solar power and environmental factors are used with MODWT to decompose the time series into components, while LSTM extracts the non-linearities and deep features.						
[45]	DLNNs	Adam	PV power	1, 5, 30, 60 min	Normalisation	MAE-0.05
Research novelties/Contributions: Various DLNN algorithms predict PV power for both single-step and multi-step forecasting across different time periods.						
[48]	B-LSTM	Adam	Wind speed, load demand, electricity price	daily	MC	MAPE-0.91%
Research novelties/Contributions: The MC task clusters the input data sequence, categorising each hour's data into distinct groups. Each group is assigned a dedicated forecasting unit. B-LSTM is then applied for multitask forecasting, handling the dataset profile for each cluster hourly.						
[91]	FNDGM	GWO	Hidropower, renewable energy	1 year	–	TIC-0.0129
Research novelties/Contributions: To effectively capture the non-linear relations among system variables and the evolving non-linear behaviour of each variable, the proposed FNDGM incorporates the GWO algorithm and hold-out cross-validation method. This approach significantly improves generalisation ability and mitigates over-fitting issues.						
[92]	RF, DT, KNN	GA	Load and supply dispatch	Hourly	Normalisation	Precision-1
Research novelties/Contributions: Comparison of the outcomes of ML techniques, namely RF, DT, and KNN.						
[47]	LSTM-CNN	–	PV power	Short term	Normalisation	MAPE-0.042
Research novelties/Contributions: PV temporal data features are extracted by an LSTM and spatial features by a CNN.						
[93]	GA-BiLSTM	GA	PV power	Ultra short term	Normalisation	MSE-0.191

Table 2. *Cont.*

Ref.	Method	Opt.	Forecast Variable	Forecast Horizon	Pre-Processing	Lowest Metric
Research novelties/Contributions: BiLSTM predicts the output of the target PV station with its bi-directional learning characteristics. GA optimises the structure and the parameters of the Bi-LSTM in order to attain the best performance.						
[94]	BILSTM-AE-ORELM	PSO	PV power	1 day	–	MAPE-0.0134
Research novelties/Contributions: BiLSTM forecasts each input weather piece of data that affects PV power, and an improved ELM predicts the future PV power based on the anticipated weather data.						
[95]	QRF	Chance-constrained stochastic optimisation	Renewable Energy	Day ahead	Normalisation, logit transform	nCRPS-0.012
Research novelties/Contributions: The proposed approach involves generating scenarios of the combined production with probabilistic forecasts. Additionally, the method incorporates correlations using a multivariate Gaussian copula.						
[96]	HFEGM	–	Renewable energy	1 year	–	sMAPE-12.10%
Research novelties/Contributions: Integration of EGM and heuristic FTS to obtain precise forecasts for renewable energy in Taiwan.						
[97]	CNN-LSTM, Conv LSTM	–	PV power	1 day to 1 week ahead	Normalization	MAE-5.05
Research novelties/Contributions: CNN-LSTM and ConvLSTM are proposed for time-series predictions.						
[98]	GA, RNN, KNN	–	Solar power	Shortcterm	–	rMAE-4.49
Research novelties/Contributions: The application of forecasting high-frequency solar radiation data using GA, RNN, and KNN models is discussed.						
[99]	EWT-GWO-RELM-IEWT	GWO	Wind speed	10 min	EWT	MAE-0.0273
Research novelties/Contributions: EWT decomposes the raw series into several wind speed subseries; an optimised RELM with GWO forecasts each subseries, and to avoid unexpected forecasting values, IEWT is employed for reconstructing the projected results.						
[100]	ANN, RF, Persistence	–	Solar radiation	1 h up to 6 h	Cleaning and filtering	nMAE-12.63%
Research novelties/Contributions: The forecast of the components of solar radiation are compared through smart persistence, ANN, RF.						
[32]	BORT	Bayesian	Solar irradiance	1 year	Normalisation	$R^2 - 0.98$
Research novelties/Contributions: Bayesian optimisation adjusts the hyperparameter of the regression tree algorithm, and BORT forecasts the global radiation.						
[101]	Spatio-temporal Probabilistic	–	Wind power	24 h ahead	Normalisation	CRPS < 0.15
Research novelties/Contributions: Non-linear and non-stationary patterns exhibited by the data are effectively handled using non-linear transformations and sinusoidal basis functions. These methods can accurately capture high-frequency observations and provide estimation efficiently.						
[102]	CEEMD-AWDO-MSA-ENN	AWDO-MSA	Wind speed	Ultra short term	CEEMD	MAE-0.2696
Research novelties/Contributions: An improved optimisation algorithm which combines AWDO and MSA is proposed to optimise the initial weights and thresholds of ENN, improving the global and local search ability.						
[73]	AGRU	–	Wind power	5 min up to 2 h	Normalisation	MAPE-4.25%
Research novelties/Contributions: AGRU improves the accuracy of forecasting processes, a hidden activation of GRU blocks correlates different forecasting steps, and an attention mechanism selects the most significant input variables.						
[103]	EWT-LSTM-ENN	–	Wind speed	–	EWT	MAE-0.51
Research novelties/Contributions: EWT decomposes the raw wind speed data, LSTM predicts low-frequency, and ENN forecasts high-frequency wind speed sub-layers.						
[104]	GRU-CSNN-GWO	GWO	Wind speed	Short and long term	EWT	MAPE-1.40%
Research novelties/Contributions: The original wind speed series are decomposed into multiple sub-series, each containing distinct oscillatory characteristics. GRU models are employed initially to forecast each sub-series. Subsequently, CSNN corrects these forecasts, extracting previously unexplored temporal information. The GWO algorithm is then utilised to optimise weights for a linear combination of the forecasting results, improving overall accuracy.						

Table 2. *Cont.*

Ref.	Method	Opt.	Forecast Variable	Forecast Horizon	Pre-Processing	Lowest Metric
[105]	IMODA-ELM	IMODA	Wind speed	Short term	VMD	nMSE-0.0062
Research novelties/Contributions: A two-stage wind speed forecasting model combines the advantages of the VMD technique, IMODA, error correction, and the non-linear ensemble method.						
[49]	CNN-L; MICNN-L	Adam	Solar irradiance	10 min	–	r-0.94
Research novelties/Contributions: Infrared sky images and past values of GHI are predicted, considering CNN for spatial features extraction and LSTM for temporal feature extraction.						

The state-of-the-art research presented in Table 2 illustrates the feasibility of forecasting in managing and integrating renewable energy sources into the electricity grid.

To predict renewable energy production, the forecast variables considered can be the renewable energy production itself, such as wind and PV energy, or the meteorological variables that directly affect renewable energy production, such as solar radiation, temperature, and wind speed.

According to the state-of-the-art research that we analysed, in this paper, four main types of methods were considered. The physical methods comprised physical characteristics (temperature, solar radiation, wind speed). However, they are not able to deal with short-term forecasts and require high computational costs. Statistical methods are more appropriate for short-term forecasts and consider historical data for the forecast. However, they cannot deal with irregular and non-linear data. In this regard, ML methods were considered, since they are capable of dealing with non-linear data. Despite the advantages of each of these methods, the individual methods do not consider the pre-processing of the input data, which decreases their efficiency. Thus, combined or hybrid methods emerge as a solution to this problem, as they combine the main advantages of the individual methods, allowing for a significant improvement in forecast accuracy.

The forecast horizon is also another factor to take into consideration when choosing a forecasting method. In this review, three main types of horizons were considered: short, medium, and long. According to some literature, a very short forecast horizon was also considered. In general, analysing state-of-the-art research, regardless of the forecasting method and the forecast variable, research was carried out for short-term forecast intervals.

Methods based on ML, in particular ANN and ensemble-based approaches, play a crucial role in renewable prediction, appearing to be the most considered methods in this context and with better prediction results [31]. ANNs enhance forecasting efficiency by establishing non-linear mappings between input and output data. However, they are prone to over-fitting and easily converge to local optima. ML approaches offer solutions for addressing complex issues that are challenging to model explicitly, and they can perceive relationships between outputs and inputs. ML methods have higher accuracy and improve the accuracy of regression models witha greater amount of data. On the other hand, ensemble-based approaches are based on the concept of divide and conquer and can improve the performance of forecasts.

A common technique used in state-of-the-art research to evaluate forecasting methods is the comparison of referenced and proposed methods [29]. In general, the reference methods considered are persistence methods, statistical methods, or methods that consider physical and meteorological characteristics. The main evaluation metrics considered were RMSE, MAE, MAPE, and MSE, among others.

The conjugation of the forecasting methods with optimisation techniques and/or data pre-processing techniques also improves the performance of the proposed methods.

4.1. Real Grid Operation

Grid operators rely on forecasting methods such as statistical, artificial intelligence, or hybrid methodologies to manage electricity supply and demand [106]. To address the increasing complexity of the power grid and the need for more precise forecasts, Ahmad et al. [31] suggests the use of ML algorithms, ensemble-based approaches, and ANN. These methods deal with large amounts of data and provide accurate forecasting analysis. Furthermore, Wazirali et al. [107] emphasise the significance of ANN, ML, and DL techniques in predicting energy flows in microgrids, providing a systematic analysis of their applications.

According to the results in Table 2, traditional methods like time series and regression models are commonly used by grid operators due to their simplicity and interpretability. In turn, there is a growing trend towards implementing ML methods, like ANNs, in real grid operations. Hybrid methods are also being explored, with some grid operators starting to implement them for their improved accuracy and robustness.

Overall, grid operators use a combination of statistical and ML methods for forecasting loads and renewable energy production. While traditional methods still hold significant ground due to their simplicity and reliability, ML approaches are rapidly being considered. Our research shows a strong focus on practical applicability, with a considerable share of studies detailing methodologies that are implemented or validated in real operations. As computational resources and data availability continue to improve, the adoption of advanced machine learning techniques is expected to rise.

4.2. Literature Gaps and Future Work

The comprehensive review presented in this paper highlights significant advancements in renewable energy forecasting methods. However, there are still several gaps in the literature that future research should address for improvement of accuracy, efficiency, and applicability of these models. Some of these gaps are presented below.

- While current models incorporate various climatic and historical data, there is a need for more sophisticated integration of multivariate data sources. Future research should focus on developing models that can effectively integrate diverse data types, such as satellite imagery, real-time sensor data, and socioeconomic factors, to improve forecast accuracy.
- Short-term models often fail to maintain accuracy over extended periods, while long-term models may not capture short-term fluctuations adequately. Research should aim to develop hybrid models that can seamlessly transition between short-term and long-term forecasting, maintaining high accuracy across different time horizons.
- Many advanced forecasting models, particularly those involving ML and artificial intelligence, require substantial computational resources. This limitation can hinder their scalability and practical application in real-time scenarios. Future research should focus on improving the computational efficiency of these models and developing scalable algorithms that can be deployed in large-scale energy systems.
- As smart grids become more prevalent, integrating forecasting models with these technologies can provide real-time adjustments and enhance grid stability. There is a need for research that explores how forecasting models can be embedded into smart grid systems to enable dynamic and responsive energy management.

Transfer learning is a type of ML that has emerged as a powerful technique enabling the application of knowledge gained from one domain to improve performance in another. For renewable energy forecasting, transfer learning methods hold significant promise. These methods allow pre-trained models, developed for related tasks such as weather prediction or energy consumption forecasting, to be adapted for renewable energy contexts. By leveraging existing models, transfer learning can mitigate the challenges posed by limited data availability and high computational costs, facilitating accurate and efficient forecasting models. This approach not only enhances predictive capabilities but also accelerates the deployment of sophisticated forecasting tools in regions with sparse historical data, thereby supporting the broader integration of renewable energy into the power grid [108,109].

Future work should also analyse and consider innovative synthetic data generation techniques in order to fill the gaps in the availability of historical data; forecasting models should also predict rare events like tornadoes or periods of severe drought in order to minimise the effects of climate change; and theoretical and practical data obtained with forecasting models should also be compared in order to check that the models are reliable.

5. Conclusions

With the growing integration of renewable energy sources in the electricity system, new technologies were developed. However, renewable energy still has some limitations due to the intermittency and unpredictability of resources. In this regard, forecasting methods appear as a solution, allowing, for example, a more efficient management of renewable sources in the grid, or minimising the difference between electricity demand and its supply.

A systematic review of forecasting methods in a renewable context was performed. According to the current literature, there are several factors that affect the results of forecasting methods, in particular the type of method, the data pre-processing, the forecast horizon, optimisation algorithms, the forecast variables, and the efficiency evaluation metrics.

In conclusion, forecasting methods for renewable energy play a crucial role in shaping the sustainability of our energy landscape. Accurate predictions not only enhance the reliability of renewable energy but also drive innovation in energy storage and grid management, accelerating the global shift into a cleaner and resilient energy ecosystem.

For regions with highly variable weather conditions, such as coastal areas or mountainous regions, advanced forecasting models using ML techniques such as neural networks and SVM coupled with detailed meteorological data are recommended. These models can effectively anticipate fluctuations in renewable energy generation due to dynamic weather patterns and seasonal variations, ensuring a more reliable integration of renewable sources into the grid.

In urban areas with high energy demand, short-term forecasting methods that leverage real-time data and optimisation algorithms, such as ARIMA models and hybrid models combining statistical and ML approaches, are more suitable. These methods can minimise the discrepancy between electricity demand and supply, enhancing grid stability and efficiency. For rural or remote regions where grid infrastructure may be less robust, long-term forecasting techniques that incorporate historical data and trend analysis, such as time series analysis and regression models, are recommended. These techniques can support better planning and investment in renewable energy infrastructure, ensuring a stable and sustainable energy supply over time.

Finally, in regions where multiple renewable resources are available, such as areas with both wind and solar potential, hybrid forecasting methods that integrate data from various sources and use ensemble techniques can provide more accurate and comprehensive forecasts. These methods combine the strengths of individual forecasting models to handle the complexity of multiple energy sources.

Overall, the selection of an appropriate forecasting method and evaluation metric depends on the specific forecasting problem and the type of data being used. Continued development and refinement of these methods is essential for achieving a sustainable and reliable energy future.

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Abbreviations

The following abbreviations are used in this manuscript:

ATDGM	adaptive time-varying discrete grey model
ANN	artificial neural network
ARIMA	auto-regressive integrated moving average
BMA	Bayesian averaging model
CNN	convolutional neural network
DBN	deep belief network
DL	deep learning
DLNN	deep learning neural network
DGM	discrete grey model
ESN	echo state network
EHO	elephant herding optimisation
ENN	Elman neural network
EMD	empirical mode decomposition
EDE	enhanced differential evolution
EL	ensemble learning
EVS	explained variance score
ET	extra trees
FOTP-SDGM	fractional-order full-order time power seasonal discrete grey model
GRU	gated recurrent unit
GD	Gaussian distribution
GA	genetic algorithm
GM	grey model
MOGWO	multi-objective grey wolf optimisation
ALHM	hybrid adaptive learning model
HIMVO	hybrid improved multi-verse optimiser
LSSVM	least squares support vector machine
LSTM	long short-term memory
MAE	mean absolute error
MAPE	mean absolute percentage error
MASE	mean absolute scaled error
ML	machine learning
MRE	maximum residual error
MSE	mean squared error
MODWT	maximum overlap discrete wavelet transform
MC	micro-clustering
NBDM	model based on dendritic neuron network
MMODA	modified multi-objective dragonfly algorithm
MOGOA	multi-objective grasshopper optimisation algorithm
MLR	multiple linear regression
NARX	non-linear auto-regressive recurrent network
nRMSE	normalized root mean squared error
NWP	numerical weather prediction
ORELM	outlier-robust extreme learning machine
PSO	particle swarm optimisation
PV	photovoltaic
PEM	probabilistic ensemble method
QR	quantile regression
QRA	quantile regression averaging
QRF	quantile regression forest
RF	random forest

RVFL	random vector functional link neural network
RNN	recurrent neural network
RMSE	root mean squared error
SARIMA	seasonal auto-regressive integrated moving average
SOM	self-organizing mapping
SSA	singular spectrum analysis
SADGM	structural adaptive discrete grey model
SVM	support vector machine
SVR	support vector regression
TMLM	time-varying multiple linear model
WNN	wavelet neural network
WPD	wavelet packet decomposition
WT	wavelet transform

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