Heliyon 10 (2024) e26088

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Renewable energy sources integration via machine learning modelling: A systematic literature review

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ARTICLE INFO

Keywords:
Renewable energy sources (RESs)
Machine learning
RES power output forecasting

ABSTRACT

The use of renewable energy sources (RESs) at the distribution level has become increasingly appealing in terms of costs and technology, expecting a massive diffusion in the near future and placing several challenges to the power grid. Since RESs depend on stochastic energy sources —solar radiation, temperature and wind speed, among others— they introduce a high level of uncertainty to the grid, leading to power imbalance and deteriorating the network stability. In this scenario, managing and forecasting RES uncertainty is vital to successfully integrate them into the power grids. Traditionally, physical- and statistical-based models have been used to predict RES power outputs. Nevertheless, the former are computationally expensive since they rely on solving complex mathematical models of the atmospheric dynamics, whereas the latter usually consider linear models, preventing them from addressing challenging forecasting scenarios. In recent years, the advances in machine learning techniques, which can learn from historical data, allowing the analysis of large-scale datasets either under non-uniform characteristics or noisy data, have provided researchers with powerful data-driven tools that can outperform traditional methods. In this paper, a systematic literature review is conducted to identify the most widely used machine learning-based approaches to forecast RES power outputs. The results show that deep artificial neural networks, especially long-short term memory networks, which can accurately model the autoregressive nature of RES power output, and ensemble strategies, which allow successfully handling large amounts of highly fluctuating data, are the best suited ones. In addition, the most promising results of integrating the forecasted output into decision-making problems, such as unit commitment, to address economic, operational and managerial grid challenges are discussed, and solid directions for future research are provided.

1. Introduction

In recent years, the increasing need for decarbonising power systems has favoured the penetration of renewable energy sources (RESs), especially solar and wind energies, in the distribution grids. According to Ref. [1], over the last decade, the penetration of RESs in the power sector has remarkably increased in European countries, raising from 27 % to 57 % in Denmark, from 10 % to 26 % in Germany, from 15 % to 40 % in Spain and from 16 % to 44 % in Italy. Nevertheless, the transition to a higher penetration of RESs leads to several challenges in the power system [2–5]. In particular, since RESs depend on stochastic energy sources, they introduce a high

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https://doi.org/10.1016/j.heliyon.2024.e26088
Received 30 April 2022; Received in revised form 25 January 2024; Accepted 7 February 2024
Available online 14 February 2024

level of uncertainty to the grid, leading to power imbalance and deteriorating its stability. In this scenario, managing RES uncertainty is vital to successfully integrate them to the grid.

Although different technologies, such as the ones based on energy storage, can be used to support the integration of RESs, they usually demand a huge investment. To avoid the installation of expensive devices in the network, RES uncertainty can be managed by a more proactive distribution system operator (DSO) that is capable of taking advantage of RES flexible resources for the provision of ancillary services (ASs). This approach requires efficient coordination between transmission systems operators (TSOs) and DSOs [2,3]. On the one hand, TSOs should support voltage in the transmission network, maintaining the overall system security via frequency control and congestion management across borders and on the TSO level. On the other hand, DSOs should manage voltage stability and congestion on the distribution grid, being responsible for providing data about consumers and distributed generation behaviour to the TSOs.

To enable DSOs use ASs, an accurate RES power output prediction should be included into the unit commitment (UC) problem. Different strategies have been proposed in the literature to predict the RES behaviour [6–8]. Traditionally, physical-based models, such as the weather research and forecasting (WRF) models, and statistical models, such as the autoregressive moving average (ARIMA) model, the Bayesian approach, the Kalman filter and the Markov chain model, have been used [6,7]. On the one hand, physical methods are computationally expensive since they rely on solving complex mathematical models of the atmospheric dynamics. In addition, they are not able to handle unexpected errors, making them not suitable for short-term horizon applications [7,8]. On the other hand, statistical methods are focused on modelling the mathematical relationship between the online time series associated with RESs. Unfortunately, although they outperform physical methods in terms of high spatio-temporal resolution forecasting [6], they usually consider linear models, which prevents them from addressing challenging prediction time horizons, such as long-term ones [7].

In recent years, the continuous development of artificial intelligence (AI) techniques has provided researchers with powerful data-driven tools that can outperform physical and statistical methods. Among them, machine learning (ML)-based techniques, which are non-linear, non-parametric models that can learn from historical data, allowing the analysis of large-scale datasets, even under non-uniform characteristics or noisy data, deserve especial attention [8]. According to Ref. [9], ML-based methods are suitable for RES behaviour forecasting applications since they can adapt themselves to changing trends inside datasets. In Refs. [7,10–15], recent state-of-the-art reviews of ML-based RES behaviour forecasting approaches can be found. They agree that artificial neural networks (ANNs), support vector machines (SVMs), deep learning (DL) and ensembles significantly outperform traditionally used statistical methods in terms of accuracy, robustness, precision and generalisation capability.

According to Ref. [16], where different ML-based models were used to predict the behaviour of different types of RESs – wind, solar and geothermal energies –, ML-based methods can achieve results relevant to policy and planning objectives. In this same line, authors in Ref. [17] highlight that the predicted RES power output can be used as the input of several decision-making grid problems, including UC and Economic Dispatch (ED), the design of optimal trading and maintenance strategies, and the electricity market-clearing, among others. In this scenario, accurately predicting RES behaviour could not only improve power balancing and grid stability but also provide valuable data to the system operators —DSOs and TSOs—, enabling them to perform control actions, optimally dispatch various distributed RES generator types, manage voltage control devices, relieve the pressure of peak and regulate frequency.

In this paper, a systematic literature review (SLR) is conducted to identify the most widely used ML-based approaches for RES power output forecasting. In particular, they are evaluated in terms of the ML technique, the predicted time horizon, the data collection, the model parameters and the obtained results. In addition, the main implementation steps of the ML-based model – data pre-processing, feature extraction and selection, hyper-parameter optimisation and validation – are studied in detail. The SLR results provide valuable insights into the best ML-based RES power output forecasting strategies to facilitate their integration into the grid, giving stakeholders useful tools to design – and implement – them according to their needs. In addition, the feasibility of actually using the prediction within the context of different decision-making problems, enabling an efficient TSO-DSO coordination capable of managing RESs – and their ASs –, to address economic, operational and managerial grid challenges, is discussed.

The rest of the paper is organised as follows. The review methodology is described in Section 2. Section 3 addresses generic aspects of the SLR articles. The main aspects of the SLR results are analysed in Section 4. The current trends in ML-based RES power output forecasting and their applications in decision-making grid problems to address economic, operational and managerial challenges are discussed in Section 5. Section 6.1 and Section 6.2 introduce the main research findings and gaps identified from the SLR, respectively. Finally, the limitations of the conducted SLR are introduced in Section 7, whereas Section 8 provides the concluding remarks.

2. Review methodology

2.1. Research questions

The first step in a SLR process is to define the research questions (RQs). In this paper, the following RQs were defined.

- **RQ1**: Which are the most widely used ML-based techniques to forecast RES power outputs?
- **RQ2**: Which are the main operational, economic and managerial grid challenges addressed by forecasting RES power outputs?

2.2. Literature search

The literature was searched based on the database search methodology [18,19]. Since the use of different databases allows covering as many evidence as possible, generic sources, such as Science Direct and Google Scholar, as well as a specialised source, such as the IEEE Xplore, were used [18–20]. Science Direct, which has more than 15 million records, was used as the principal search database, whereas Google Scholar, which allows retrieving a large amount of free-access articles, was used as the complementary one [20,21]. Finally, the IEEE Xplore database, which provides access to a great amount of high quality engineering articles, was used as the specialised search database [20].

Using the digital libraries described above, the literature was searched for relevant contributions to the SLR subject based on the following search strings.

- ML-based techniques to forecast RES power outputs.
- Economic, operational and managerial grid challenges addressed by forecasting RES power outputs.

2.3. Inclusion/exclusion criteria

In this paper, not only books, international journals and the proceedings of international conferences were considered for inclusion in the SLR but also articles from the grey literature, such as PhD theses and reports from the main associations in the field of power systems, like CIGRE[1] and ENTSO-E,[2] were considered. On the other hand, articles without a peer-reviewed process, such as on-line presentations, were not included. Finally, in order to focus on the current trends in the ML-based forecasting of the RES power output as well as on its future horizons, only articles published from 2013 were taken into account. The described inclusion and exclusion criteria is summarised in Table 1.

2.4. Literature search results

Fig. 1 shows the literature search overview. A total of 463 articles were retrieved: 383 corresponded to RQ1 and 80 corresponded to RQ2, as shown Table 2. First, a preliminary relevance analysis, where the titles were evaluated to decide whether the articles discussed the ML-based forecasting of the RES power output, was conducted. The corresponding full references of those that did, including the abstracts, were retrieved. Then, the duplicates were removed, obtaining 425 articles. Subsequently, all the abstracts were read to determine to which extent the articles were relevant to the SLR subject. Finally, 127 full-text articles were carefully read and their quality and eligibility were assessed to select the 82 articles included in the SLR. The selected articles not only make valuable contributions to ML-based RES power output forecasting in power grid applications but also provide a reliable theoretical framework, presenting a clearly explained methodology and obtaining significant results. Their full reference is provided in ble A1 of Appendix A, whereas they are listed as follows: [6–11],[13,14,16,17],[22–93].

3. General aspects of the SLR

Fig. 2 shows the amount of selected articles published between 2014 and 2023. The 54.21 % of them have been published between 2020 and the first semester of 2023, demonstrating that ML-based forecasting of RES power outputs is a hot research topic.

Table 3 shows the number of SLR articles published in different types of publications. In particular, 84.14 % of them were published in international journals, 8.53 % in PhD theses, 4.87 % in international conferences proceedings or technical reports, and 2.44 % in books.

The relevant information extracted from the 82 articles included in the SLR is synthesised in Table A2 of Appendix A. In particular, the following categories are considered.

- Article proposal
- ML-based technique
- Type of RES
- Used Parameters
- Estimated output
- Time horizon prediction
- Data
- Feature selection algorithm
- Hyper-parameter optimisation technique
- Accuracy measurements

4. SLR results

In recent years, the use of RESs, including geothermal, biomass, hydro, tidal, wind and solar ones, has gained great popularity since they are more sustainable than fossil fuels [22]. In particular, wind turbines and photovoltaic (PV) cells have been installed worldwide, making it crucial to efficiently integrate them into the distribution grid [23,22]. In this scenario, the SLR conducted in this paper focuses on ML-based forecasting of solar and wind energy systems' power output.

[1] https://www.cigre.org/.
[2] https://www.entsoe.eu/.

Table 1
Inclusion/exclusion criteria.

Inclusion Criteria	Exclusion Criteria
English language **Books, book chapters, peer-reviewed journals, peer-reviewed conference proceedings, PhD theses, high-quality reports with well-cited references** **Publication date between 2013 and 2023** **Content answering the RQs:** • ML-based techniques to forecast the RES power output. • Economic, operational and managerial grid challenges addressed by forecasting the RES power output.	Non-English language Dissertation/on-line presentations (lack of peer-review process) Publication date before 2013 Content out of the scope of the RQs: • General RES behaviour modelling. • Only solar irradiance or wind speed forecasting. • Power load and price forecasting.

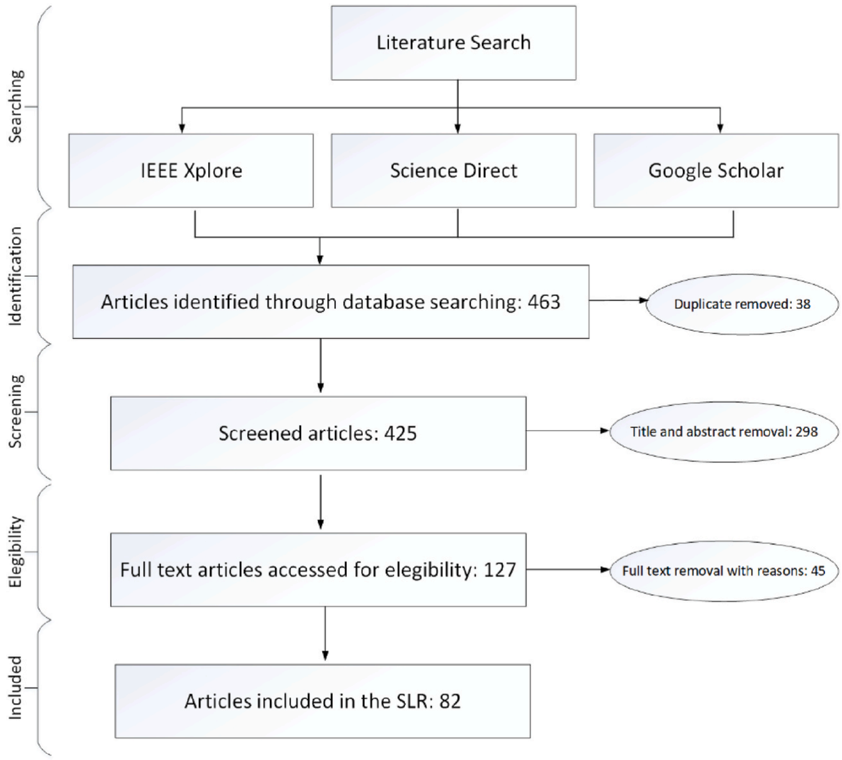

Fig. 1. Literature search overview.

Table 2
Retrieved articles for each of the defined search strings.

Search String	Number of retrieved articles
ML-based techniques to forecast the RES power output	383
Economic, operational and managerial grid challenges addressed by forecasting the RES power output	80

Due to the uncertain nature of the wind direction and speed, researchers agree that predicting wind turbine power is more complex than predicting PV power. In this line, literature addressing the former is not as vast as the one devoted to the latter. The SLR results confirm this, surpassing the articles devoted to PV power forecasting by 35.71 % the ones addressing wind turbine power prediction, as shown in Table 4. In addition, only 26.82 % of the articles focus their work on both technologies.

4.1. Design of the ML-based RES power output forecasting

In this section, the results of the SLR regarding the use of ML-based techniques to forecast PV and wind turbine power output are discussed. The approaches proposed in the literature are evaluated in terms of the ML model and its parameters, the prediction time

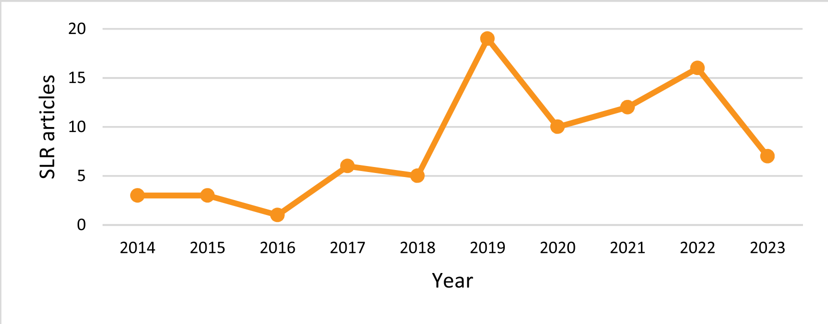

Fig. 2. Number of SLR articles per publication year. *Note.* SLR: systematic literature review.

Table 3
Types of publications in the SLR.

Publication type	Number of articles
Journals	69
PhD theses	7
Conference proceedings, reports	4
Books	2

Table 4
SLR coverage of the different types of RESs.

Type of RES	Number of articles
Solar	57
Wind	42
Solar and wind	22
Solar, wind, hydrogen, hydropower, ocean, geothermal	2

Note. RES: renewable energy source.

horizon and the data collection method. In addition, the main implementation steps in the modelling process – data pre-processing, feature extraction and selection, hyper-parameter optimisation and performance evaluation – are studied in detail.

4.1.1. ML-based model

Recent reviews have shown that ML-based methods are capable of automating the intricate mathematical calculations required for predicting the RES power output, outperforming traditional statistical methods [16,24,25,26]. Nevertheless, the discussion regarding which ML-based technique is better suited for this application is still open. Several works in the literature have compared the performance of different ML algorithms. In Ref. [27], a comparison between ANNs, SVMs, multiple linear regression (MLR) and random forest (RF) for PV power output prediction was conducted. Results of [27] showed that RF achieved better performance for 5-min to 3-h-ahead predictions. In Ref. [28], a comparison between ANNs, support vector regression (SVR) and Gaussian progressive regression (GPR) to predict PV power output, wind power output and electricity demand was proposed. The best results for wind and PV power outputs were obtained with SVR, whereas the best results in terms of electricity demand were the ones corresponding to the ANN-based model.

Table 5 shows the most widely used ML-based methods in the SLR articles. ANN-based methods are the most popular ones, being used in 65.85 % of the cases. They are followed by SVM and SVR (21.95 %), RF (10.97 %) and boosting techniques (10.97 %).

4.1.1.1. ANNs. ANNs are one of the most popular AI methods worldwide, being used in a wide variety of applications. They are based on a number of processing units – called neurons – which store knowledge to make it available as and when needed. Patterns are presented to the ANNs through the input layer, transferred to hidden layers, where actions are taken based on a system of weighted connections, and received by the output layer [95]. ANNs are easy to use and allow handling large amounts of data to solve non-linear problems. In this sense, they are well suited for RES power output forecasting, as the preference of researchers in the field demonstrate.

There exist different types of ANN architectures. In Ref. [50], a comparison between the performance of different ANN architectures for PV power output forecasting can be found. Fig. 3 shows the most widely covered in the SLR. The results demonstrates the popularity of deep neural networks (deep NNs) to forecast RES behaviour. Similarly to extreme learning machine (ELM) —a special kind of Single Hidden Layer Feedforward (SHLF) ANN—, deep NNs can overcome some of the practical issues that arise when traditional ANNs are applied to a complex problem like the RES power output forecasting [7]. Among them, the following ones should be highlighted.

Table 5
Most popular ML techniques used in the SLR articles.

Art.	ANN	LR	GPR	MLP	SVM/SVR	RF	KNN	CNN	RNN	LSTM	GRU	Boosting	ELM	DT	Others
[6]	X				X	X						X			
[7]	X								X						X
[8]															
[9]					X	X						X			X
[10]															
[11]	X							X	X						X
[13]	X														
[14]	X														
[16]															
[17]															
[24]															
[25]															
[29]	X														
[26]	X		X	X	X								X	X	X
[30]	X								X						
[31]	X														
[32]	X														
[33]	X	X	X											X	X
[34]															
[28]	X		X		X										
[35]	X												X		
[23]					X										
[36]	X														
[37]						X									
[38]	X							X							
[39]	X														
[40]	X														
[41]					X										
[42]															X
[27]	X	X			X	X									
[43]					X										
[44]		X			X	X	X					X		X	
[45]	X							X							
[46]	X								X	X	X				
[47]	X								X	X					
[48]					X										
[49]	X														
[50]															
[51]						X									
[52]					X		X								
[53]	X												X		
[54]	X												X		
[55]	X								X	X					
[56]	X				X				X						
[57]	X								X	X					
[58]					X									X	
[59]					X										
[60]	X														
[61]												X			X
[62]	X								X	X					
[63]	X			X				X	X	X					
[64]	X														
[65]	X														
[66]												X		X	
[67]	X								X	X		X			
[68]	X							X	X	X					
[69]	X				X										
[70]															
[71]	X							X							
[72]	X	X	X		X	X	X								
[73]	X								X	X					
[74]	X								X	X					
[75]	X								X	X	X				
[76]	X								X	X					X
[77]	X														
[78]	X							X	X		X				
[79]	X							X	X	X					
[80]	X														

(continued on next page)

Table 5 (*continued*)

Art.	ANN	LR	GPR	MLP	SVM/SVR	RF	KNN	CNN	RNN	LSTM	GRU	Boosting	ELM	DT	Others
[81]	X					X	X		X	X		X			X
[82]			X		X										
[83]	X								X	X	X				X
[84]												X		X	X
[85]															
[86]	X							X							
[87]	X									X					X
[88]	X									X					
[89]	X							X	X	X					
[90]	X								X	X					
[91]															
[92]	X			X	X	X	X					X		X	
[93]															
[94]	X								X	X					

Note. Art.: Article; ANN: artificial neural network; CNN: convolutional neural network; DT: decision tree DT; ELM: extreme machine learning; GPR: Gaussian process regression; GRU: gate recurrent unit; k-NN: k-nearest neighbours; LR: linear regression; LSTM: long-short term memory; MLP: multiple layer perceptron; SVM: support vector machine; SVR: support vector regression; RF: random forest; RNN: recurrent neural network.

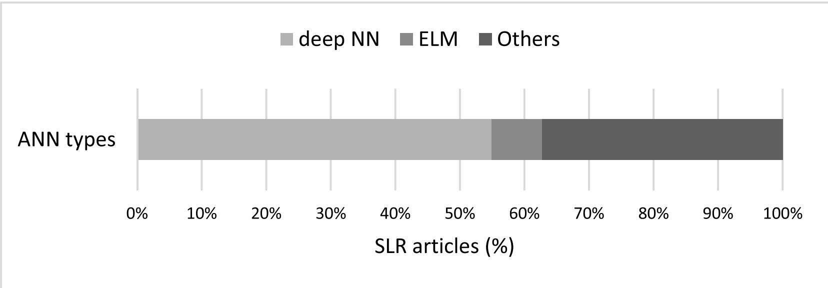

Fig. 3. Most used types of artificial neural networks. *Note*: ANN: artificial neural network; deep NN: deep neural network; ELM: extreme learning machine; SLR: systematic literature review.

- Hand-engineered feature selection: ANN feature selection not only requires significant personal experience, but also prevents traditional ANNs from dealing with inherently non-linear features, as in the case of RESs.
- Time-consuming training phase.
- Limited generalisation capability: Traditional ANNs fail to learn complex patterns from intermittent, stochastic and highly-varying data, such as weather data.
- Sample complexity: ANNs will suffer from network instability and parameters non-convergence if, due to the increasing availability of environmental meters, huge amounts of training data related to RESs are available.

ELM methods overcome the slow training speed and overfitting problems of traditional ANNs. They are based on the empirical risk minimisation theory, where none of the parameters of hidden nodes need to be tuned. In this way, the learning process needs only a single iteration, being thousands of times faster than traditional ANNs [96]. In addition, ELM has demonstrated to outperform them in terms of generalisation capability, robustness and controllability [97].

Unlike traditional ANNs, deep NNs use an unbounded number of heterogeneous layers increasing the flexibility of the model as well

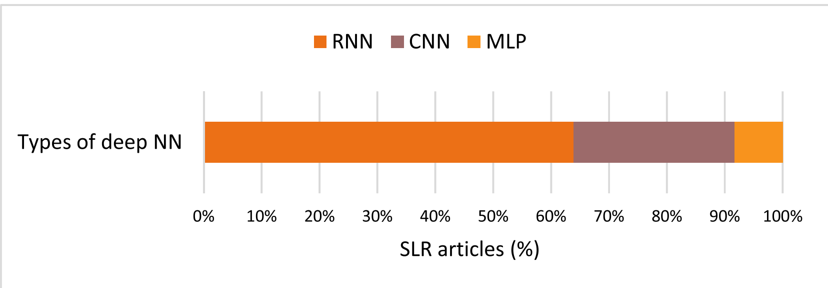

Fig. 4. Most popular architectures used for deep NNs. *Note*. Deep NN: deep neural network; CNN: convolutional neural network; MLP: multiple layer perceptron; RNN: recurrent neural network; SLR: systematic literature review.

as improving its efficiency, trainability and understandability [7]. In particular, they allow unsupervised feature learning, where features are automatically deduced and optimally tuned, avoiding time consuming feature extractions. In addition, the robustness to natural variations in the data is automatically learned, ensuring strong generalisation capability and enabling big-data training.

Fig. 4 shows the deep NN coverage in the SLR. Results suggest that recurrent neural networks (RNNs) are the most popular ones. They are based on loops that allow passing information from one step of the ANN to another, making information to persist. In this way, using previous sequence samples can help to better understand the present one. A well-known example of RNNs are LSTM architectures, which are based on memory blocks connected through successive layers. An advantage of LSTMs is that they can learn short- and long-term dependencies, avoiding the long-term dependency problem of RNNs [54].

4.1.1.2. SVMs and SVRs. Although there is a clear trend for using deep NNs, their complex implementation makes other learning strategies, such as SVM/SVR, RF and boosting techniques, also attractive to researchers, as seen from Table 5. SVMs and SVRs, first introduced in Ref. [98], are non-linear, non-parametric methods that have demonstrated to be well suited for many complex non-linear applications. They aim to minimise the margin between a separation hyperplane and the training data previously mapped by a non-linear mapping function. Provided their internal parameters are properly adjusted, SVMs and SVRs can achieve a good out-of-sample generalisation, making them robust even in the presence of biased data. In addition, SVMs and SVRs deliver a unique solution since the optimality problem is convex. This constitutes an advantage compared to ANNs, which can have multiple solutions associated with local minima. Finally, they have an excellent learning ability in processing small sample data and are less prone to overfitting in comparison with other ML-based methods [23].

4.1.1.3. Ensemble methods. Together with the increasing trend for using deep NNs discussed in Section 4.1.1.1, ensemble methods have also been identified as one of the most popular ML-based techniques among the SLR articles. Whereas 37.8 % of them are devoted to the former, 19.51 % proposed the latter. Ensemble methods use multiple learning algorithms – called base learners – to improve the predictive performance corresponding to the use of individual learning algorithms. RF is an ensemble of decision trees (DTs), focused on increasing the diversity among the trees to enhance its prediction performance. In addition to its very good discriminative capability, RF can manage large databases, handle a great number of input variables without performing variable selection, deal with missing data and outlier removal and avoid overfitting. Boosting techniques, including Gradient Boosting (GB) and Extreme Gradient Boosting (XGBoost), are also ensembles of DTs. In GB, additive regression models are built by fitting them according to the residuals' least square minimisation [99]. One of the main advantages of GB algorithms is their flexibility; they allow to optimise different loss functions and provide several options for hyper-parameter tuning. The XGBoost algorithm extends the GB one by providing customisable optimisation objectives and evaluation criteria, as well as allowing regularisation, which helps to reduce overfitting [100].

In addition to RF and boosting techniques, several articles propose ensembles of different base learners. Using different ML-based models as base learners allows obtaining a higher output diversity compared to the case of using the same method, such as in RF or XGBoost, improving the ensemble performance [39]. In RES power output prediction applications, where data strongly depends on atmospheric conditions, the output of the individual base learners can vary significantly [39]. In this context, increasing the diversity of the ensemble is crucial to make it more robust to the changing weather conditions and improve the overall forecasting performance [42].

4.1.2. Time horizon

The different needs of decision-making activities in the smart grids require different prediction horizons. Each of them is described as follows [8,54].

- Very short-term forecasting (from a few seconds to minutes): This kind of forecasting is useful for RES power storage control and electricity marketing. Nowadays, very short-term forecasting of solar and wind power has become crucial.
- Short-term forecasting (up to 2–3 days ahead): This forecasting horizon is essential for different decision-making activities involved in the electricity market and power system operation, including economic load dispatch, UC, etc.
- Medium-term forecasting (up to 7 days ahead): Medium-term forecasting is useful for scheduling maintenance of wind and solar power generating stations, conventional generating stations, transformers and transmission lines.

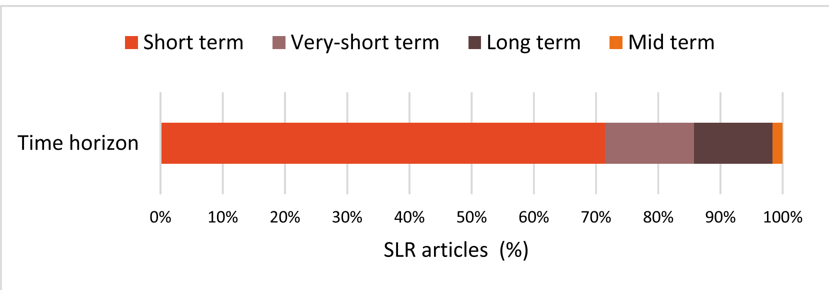

Fig. 5. Number of articles performing the different time horizon predictions. *Note.* SLR: systematic literature review.

- Long-term forecasting (from 1 month to years): Long-term estimation can be applied for long-term wind and solar energy measurement and planning of the power plant.

Forecasting RES power output at different time horizons implies different challenges. Fig. 5 shows the time horizon predictions addressed in the selected articles. Most of them are devoted to short-term forecasting. This agrees with previous observations from Ref. [54]. Within the context of energy management applications, short-term forecasting is essential for different activities, such as operation of wind and solar energy generating stations, real-time UC, storage control and electricity marketing. The high practical applicability of short-term horizons can explain the number of articles devoted to it. In addition, short-term forecasting models are simpler than the ones corresponding to other forecasting horizons, being usually more accurate [9].

The SLR results show a lack of very short-term, medium- and long-term horizon predictions [9,30]. The former has already been highlighted in Ref. [30]. Very short-term forecasting is particularly challenging since it cannot rely neither on historical power output nor on weather forecasting data recorded on an hourly basis. Instead, it needs real-time or nearly real-time measured data to perform the prediction, which makes the model technically and economically expensive. In Ref. [30], a very short-term (5- and 15-min ahead) PV power generation forecasting algorithm based on RNNs was proposed. On-site weather Internet of Things (IoT) dataset and power data were collected in real-time. In order to build a model using low-cost and low-computational power, only IoT sensors without image data, including solar radiation, module and ambient temperature, wind speed and humidity, were used. Using three RNN layers, authors of [30] achieved an accuracy of 99.01 %, in terms of the normalised Mean Average Error (nMAE), and of 98.02 %, in terms of the normalised Root Mean Squared Error (nRMSE), for the 5-min-ahead PV power output forecasting. In the case of the 15-min-ahead prediction, the accuracy was 98.16 % (nMAE) and 96.58 % (nRMSE). In Ref. [67], an improved stacked ensemble algorithm (SEA) combining ANNs and LSTM was proposed to forecast PV power output from 15-min ahead to 1-h ahead. Results of [67] demonstrated an improvement in the R2 score value of 10 %–12 % in comparison to other models.

The lack of long-term forecasting has been discussed in Ref. [9]. There, daily wind power values of past years were used to forecast year-ahead wind power since the unstable and unpredictable nature of wind speed makes it not suitable for long-term forecasting scenarios. In order to properly forecast the wind power based on the continuous wind power values, different regression algorithms, including Least Absolute Shrinkage Selector Operator (LASSO), k-nearest neighbours (k-NN), XGBoost, RF and SVR were used. Results of [9] showed that ML-based algorithms could be successfully applied to long-term wind power forecasting problems, being the accuracy obtained by SVR particularly remarkable. In addition, they also showed that, by using a pilot region for the training set and generating a base model with it, the base model could be used for other locations, even if they have different wind characteristics.

4.1.3. Data collection

Fig. 6 shows the different types of data used in the SLR articles. Most of the works are based on historical data collected on site. This suggests that researchers in the field prefer to collect historical weather and power output data from real power systems than using data from benchmark databases or weather forecast providers. There are many reasons for using on-site measured data. On the one hand, although weather data provided by weather forecaster agencies can be easily found on the Internet, they are usually released at intervals of at least 1 h. In this sense, they are not suitable for very short-term predictions. On the other hand, since the published meteorological data are measured based on meteorological observations, they may differ from the on-site weather conditions of the power system being studied.

Despite the benefits of using on-site measured data, researchers still resort to benchmark databases since technical and economic barriers often prevent them from acquiring real power system data. In addition, using benchmark datasets allows fair results comparisons. In this line, it is important to highlight the vital importance of the availability of public benchmark data since it gives researchers a low-cost resource to train, tune and validate their approaches, while guarantying benchmark results.

Finally, as the lack of very-short term predictions suggests, only a few articles have access to real-time data to develop their forecasting models. This is in line with the observations of [30], where the technical and economic challenges of installing sensors have been identified as the main barriers for addressing very short-term horizons.

4.1.4. Parameters

RES power outputs highly depend on weather conditions [33,23,37,44,45,54]. For instance, different parameters, including solar

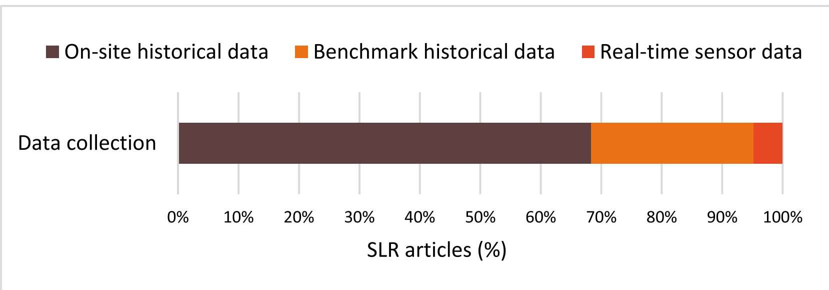

Fig. 6. Number of articles using different types of data. *Note.* SLR: systematic literature review.

elevation angle, haze effect and cloud cover, can make the power output from PV panels drop to near zero over the scale of minutes [33,23,44,45]. In this context, the weather features used to train the ML-based model will highly influence the forecasting accuracy, being crucial to select them carefully to obtain a good performance, even in adverse weather conditions. As discussed in Section 4.1.3, weather parameters can be obtained by on-site measurements or using the regularly published data of weather information providers. According to Ref. [45], although the former are usually helpful, there are cases in which they do not improve the forecast performance.

In addition to weather variables, satellite and sky images can also be considered when forecasting solar energy. The former are usually used for longer prediction horizons and coarser resolution. In this case, cloud motion vector methods are used to extract cloud movement from satellite images and predict future cloud map and irradiance [45]. The latter allow capturing the sun position, cloud distribution, cloud movement and haze in the area of the PV system. Finally, the historical or real-time power output from neighbouring RES plants, modules or locations can also be used.

Fig. 7 (a) and Fig. 7 (b) classify the different features used to model the wind and PV power outputs, respectively, into weather-, module-, price-, electricity- and power-related ones. In both cases, weather features are the most frequently considered, whereas historical power data are also utilised. On the other hand, module features, such as module temperature or turbine capacity, are not among the most useful ones. Finally, neither the electricity price nor network data, like load or transmission data, are regularly taken into account.

Figs. 8 and 9 provide more detail about the features included in the forecasting models for the wind and PV power outputs, respectively. Fig. 8 shows that, in the case of wind power output forecasting, researchers prefer to use weather parameters directly related to the wind, including wind speed, direction and temperature. In addition, there is a clear trend for using historical wind power outputs. According to Fig. 9, weather parameters are also widely considered for PV power output forecasting, being the ambient temperature, solar radiation, wind speed and humidity the most popular ones. Nevertheless, in this case, historical PV power data ranks first.

Finally, as mentioned above, parameters related to the electricity network are not widely used neither to forecast wind power output nor PV power output. This is probably due to the fact that most of the found articles in the literature are only focused in the development of the RES power output forecasting model, lacking a further application of the obtained data as input of a UC problem. It would be reasonable to expect that parameters which are directly related to the power network, such as energy demand, load and price, could help the forecasting approach to provide more useful and accurate data to be used as the input of different UC problems to deal with the main economic, operational and managerial issues of the grids. In this line, further research needs to be conducted to determine, which are the best network-related parameters to predict the RES power outputs.

4.1.5. ML-based model implementation

In general, the implementation of a ML-based model involves the following steps.

- Data pre-processing
- Feature extraction
- Feature selection
- Optimisation of ML-based model hyper-parameters
- Model training
- Model validation
- Performance evaluation

In the following sections, how the SLR articles implements each phase is studied.

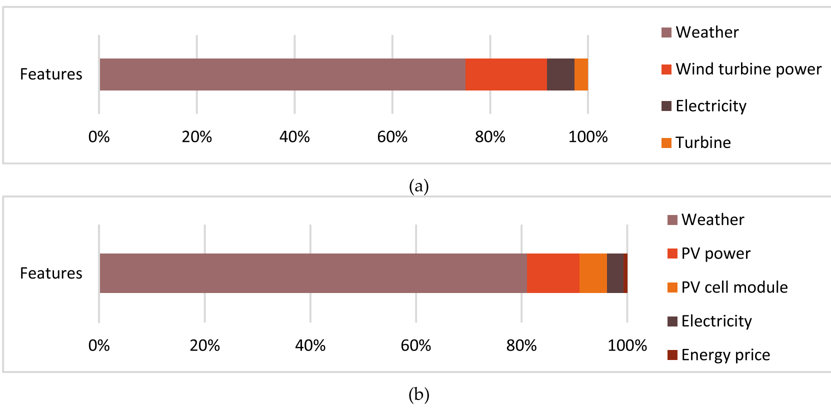

Fig. 7. Type of features used in the selected articles for forecasting (a) the wind power output; (b) the PV power output. *Note.* PV: photovoltaic; SLR: systematic literature review.

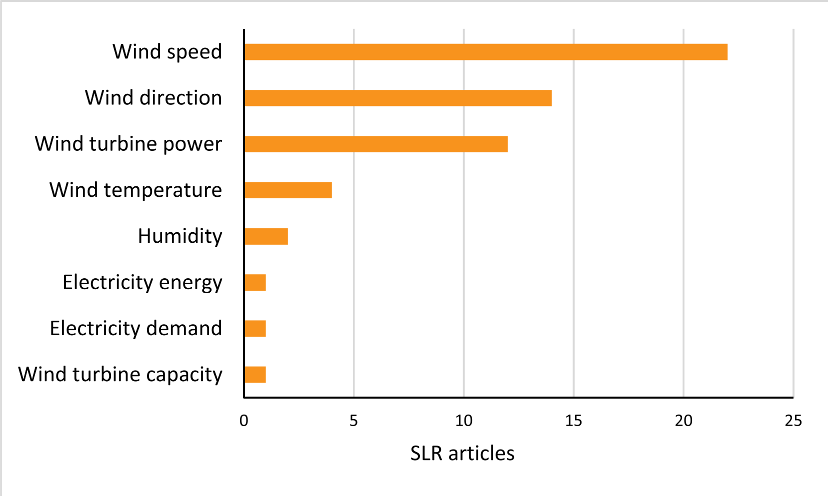

Fig. 8. Most used features to train the machine learning-based wind power forecasting model. *Note.* SLR: systematic literature review.

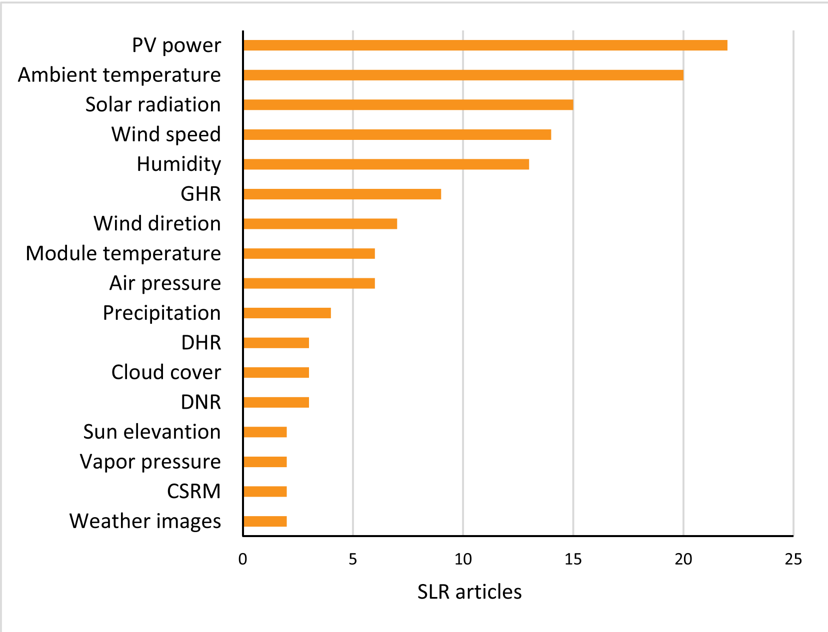

Fig. 9. Most used features to train the machine learning-based photovoltaic power forecasting model. *Note.* CSRM: clear sky radiation model; DHR: Diffuse Horizontal Radiation DNR: Diffuse Normal Radiation; GHR: Global Horizontal Radiation; PV: photovoltaic; SLR: systematic literature review.

4.1.5.1. Pre-processing. Depending on the data acquisition method, the different features used to train the ML-based models, such as the ones shown in Figs. 8 and 9, can be saved in different formats and scales. In addition, these parameters are usually time series, resulting in large amounts of high dimensional data, which can have missing values or outliers. In this context, pre-processing techniques should be applied to convert data to a suitable format, put them into a normalised scale, remove missing values and outliers, and reduce dimensionality if needed. According to a recent review conducted in Ref. [16], where the ML-based models were evaluated in terms of their pre-processing techniques, parameter selection algorithms and prediction performance measurements, data decomposition and normalisation are the most popular pre-processing strategies used in the literature. The former improves the forecast accuracy by decomposing the original dataset into different lower-dimensional datasets, whereas the latter is crucial to eliminate the influence caused by the distinction of different magnitudes [16].

Despite the importance of data pre-processing, only a few of the SLR articles mention it in their works [7,16,44,101]. This observation is in line with previous ones found in Ref. [22], where it was highlighted that further research should be conducted regarding data pre-processing methods within the context of ML-based RES power output forecasting. Finally, the selected articles where the pre-processing technique has indeed been mentioned resort to data decomposition and normalisation, which reinforces the observations of [16].

4.1.5.2. Feature extraction and selection. After data pre-processing, feature extraction is performed to model the time functions corresponding to each of the chosen parameters. Then, a feature selection is conducted to ensure the ML-based model is trained based on the most representative ones. This allows reducing the time and resource consumption as well as avoiding overfitting in contexts where datasets have thousands or hundreds of thousands of variables. In addition, by removing features that can negatively impact the model, feature selection can also improve the forecasting performance. According to the SLR results, the most popular feature selection strategies are the principal component analysis (PCA) and the gini importance.

4.1.5.3. Hyper-parameter optimisation. To accurately forecast the RES power output, the hyper-parameters of the ML-based model need to be properly optimised. To avoid overfitting, this should be done in a separate and independent set of data, which should not be used neither to train nor to validate the model. In this regard, the availability of reliable data is crucial. Fig. 10 shows the most widely used hyper-parameter optimisation algorithms, being the grid search and the particle swarm optimisation (PSO) the most popular ones. In addition, the Adam optimiser is widely used to optimise the parameters of the ANNs.

4.1.5.4. Performance measurement. After designing, developing, training and optimising the ML-based model, the validation phase takes place. In this stage, it is crucial to use standard error measurements since they allow researchers to compare their results with similar ones in the state of the art. A good forecasting error metric should have a good trade-off between bias and precision. Fig. 11 shows the most widely used error measurements in the SLR articles. The root mean squared error (RMSE) and the mean average error (MAE) resulted to be the most popular ones. The former represents the root of the mean squared distances between the actual and predicted values. The lower the RMSE value, the better the model. Although it has the advantage of keeping the output unit, making the interpretation of the result easier, it is not robust to outliers. The MAE is a common measure within the context of time series forecasting applications, which evaluates the mean of the absolute difference between actual and predicted values. As in the case of the RMSE, it keeps the output unit, and the smaller the MAE value, the better the model. In addition it has the advantage of being more robust to outliers than the RMSE.

5. Current trends in ML-based approaches to forecast the power output of RESs

According to the SLR results presented in Section 4, deep NNs, SVR/SVM and ensembles are the most popular ML-based methods to forecast wind and PV power outputs. Section 5.1.1, Section 5.1.2 and Section 5.1.3 discuss the most relevant works in the SLR using each one of them, respectively. In addition, Section 5.1.4 summarises their main pros and cons, and suggests suitable scenarios for their implementation. Finally, Section 5.2 introduces some real-life applications of the proposed ML-based RES power output forecasting approaches within the context of different UC problems.

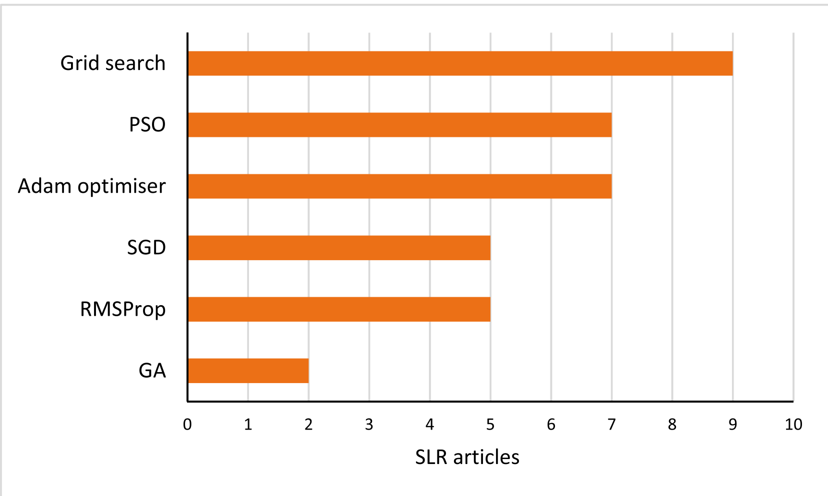

Fig. 10. Number of articles using different hyper-parameter optimisation algorithms. *Note*. GA: genetic algorithm; PSO: particle swarm optimisation; RMSProp: root mean squared propagation; SGD: stochastic gradient descent; SLR: systematic literature review.

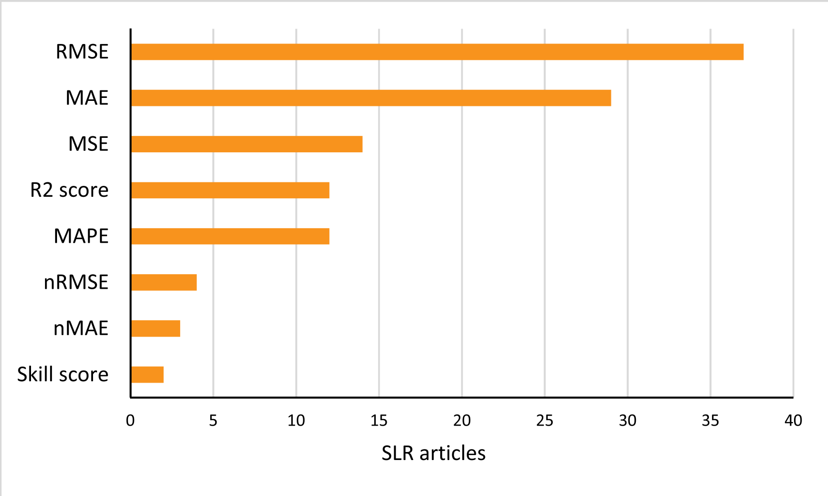

Fig. 11. Number of articles using different error measurements to evaluate the performance of the ML-based approach. *Note*. MAE: mean absolute error; MAPE: mean absolute percentage error; MSE: mean squared error; nMAE: normalised MAE; nRMSE: normalised RMSE; RMSE: root mean squared error; SLR: systematic literature review.

5.1.

5.1.1. Deep NN-based RES power output forecasting

As discussed in Section 4.1.1.1, there is a clear trend for using deep NNs instead of traditional ANNs since they provide a stronger generalisation capability, which allows big-data training to avoid the laborious feature extraction and selection, reducing computational costs and times. This observation is in line with the ones of [7,50], where the benefits of using deep NNs for RES power output forecasting have been highlighted. In Ref. [7], a comprehensive review of different deep NN approaches, including deep belief networks (DBNs), stack auto-encoder (SAE) and RNNs, to forecast PV and wind power output was presented. In particular, different pre- and post-processing data techniques were studied to evaluate their impact in the whole forecasting performance. The experimental results confirmed the potential of deep NN-based approaches for RES power output forecasting.

Among deep NNs, RNNs —specifically LSTM— have gained great popularity. This is mainly due to the LSTM capability to capture the dynamic behaviour of RES non-linear time series data with their autoregressive dependency. In Ref. [67], an ANN was used to extract regression rules from the weather data, whereas the autoregressive nature of LSTM was used to retain past information and model the time series. Then, the prediction from each model was aggregated via XGBoost, which allowed to quantify the individual model miscalculation and data noise uncertainty, leading to higher prediction accuracy. In Ref. [62], the periodicity, nonlinearity and volatility of monthly RES data, including solar, wind, hydropower and geothermal, was modelled by the seasonal-trend decomposition procedure based on Loess (STL). The resulting trend, seasonal and remainder subseries were predicted by LSTM, and the projections were integrated to compose the ultimate forecasted results, which outperformed baseline autoregressive and ML-based approaches. Similarly to Ref. [62], in Ref. [47], an LSTM-based hour-ahead PV output power forecasting was proposed, outperforming different regression approaches, including MLR, bagged regression trees (BRT) and traditional ANNs. According to the authors of [47], the recurrent nature of LSTM and its memory units allowed to accurately model the temporal changes inherent to atmospheric data.

While RNNs —especially LSTM— are well suited to model temporal data, convolutional neural networks (CNNs) are suitable to model spatial data, being widely used for image recognition and processing. Although sky images can be used to forecast PV power output, Fig. 9 reveals that it is not the most common practice. Therefore, CNNs are much less used than RNNs in RES power output prediction applications, as Fig. 4 suggests. In Ref. [45], a CNN, consisting in two convolution blocks and two fully-connected layers, was proposed to perform 15-min-ahead PV power output forecasting. A sensitive analysis was conducted to select sky images and lagged PV power output features. Results of [45] showed that the proposed CNN-based approach was capable of comprehending cloud movement and accurately forecasting very short-term PV power output when using both sky images and PV power data. In Ref. [38], CNNs were used to forecast the wind power output. The wind feature extraction was performed resorting to a wavelet transform (WT). Results of [38] showed that the uncertainties in wind power data can be accurately modelled by a WT-based feature extraction and learned by an CNN model, obtaining results comparable with similar ones in the state of the art.

Hybrid methods, combining the temporal capabilities of RNNs and the spatial capabilities of CNNs, have also been proposed in the literature. In Ref. [78], a gate recurrent unit (GRU)-CNN network was used to learn temporal features, based on a multilayered GRU sequential deep model, and spatial features, based on CNNs. The proposed model prioritised temporal features to efficiently capture the long-range complex non-linear PV power patterns for an hour-ahead forecasting. The results obtained in Ref. [78], outperformed several state-of-the-art ones. In Ref. [89], a CNN model was used to discover the non-linear features and invariant structures exhibited in historical PV power output data, whereas the LSTM was utilised to model the temporal changes in the latest PV data, to predict the

PV power of the next time step. The proposed combination provided a competitive prediction performance for real data from a PV power plant in Limberg, Belgium.

Finally, as discussed in Section 4.1.1.1, in addition to deep NNs, ELM has also gained popularity in the field of RES power output forecasting. In Ref. [54], a ELM-based approach was proposed for the PV power output forecasting of a real-time model. To train the single layer feed-forward neural network (SLFN), the weights of the ELM algorithm were optimised by different PSO techniques. Results of [54] showed that the proposed combination of PSO and ELM of SLFNs effectively improved the accuracy in PV power output prediction, outperforming classical backpropagation ANN-based models. In addition, authors of [54] highlighted that the proposed model efficiently solved the invalidity issues of forecasting changing time intervals by maintaining the consistency of the daily forecasting accuracy within a certain limit that fulfils the necessity of scheduling and economic operations of the power grid. In the same line, an improved PSO-ELM model was used in Ref. [53] to estimate PV power output using an empirical PV model based on estimated solar radiation data. Results of [53] revealed that the proposed approach outperformed not only typical ML-based algorithms, such as SVMs and DTs, but also traditional ELMs, especially in areas where on-site measurements are unavailable.

5.1.2. SVM and SVR for RES power output forecasting

Despite the strong trend for using deep NNs, other simpler but still powerful learners are also widely used in the literature. In contrast to deep NNs that need a huge amount of data to obtain accurate prediction results, SVM and SVR have the advantage of obtaining a good generalisation performance even when the training dataset is small. This is a key aspect in applications where there is not much historical data available, such as the new RES systems. In Ref. [23], a review of the state of the art regarding the use of SVM models to forecast PV and wind power outputs can be found. Results of [23] show that, in general, SVM can model wind and PV power systems in an effective and precise way, especially for short-term forecasting, outperforming other ML-based methods. In addition, they are easy to compute, simple to use and reduce computational time and costs, which makes them an attractive option. Nevertheless, they are highly sensitive to their hyper-parameter optimisation.

Different SLR articles studied SVM or SVR hyper-parameter optimisation problems within the context of RES power output forecasting. In Ref. [48], the selection of suitable hyper-parameters for the SVM model was performed by an improved version of the moth-flame optimisation (MFO) algorithm. In particular, different meteorological conditions affecting the PV power generation were discussed, and the experimental input data was optimised by a grey relational analysis (GRA), improving the PV power output forecasting. In Ref. [41], the SVM hyper-parameter selection was performed using an improved dragonfly algorithm (IDA), based on an adaptive learning factor and a differential evolution strategy, to improve the search ability of the traditional dragonfly algorithm (DA). Results of [41] showed that the short-term IDA-SVM-based wind power output forecasting not only outperformed the classical DA but also other optimisation strategies, such as genetic algorithms (GAs) and the exhaustive grid search. Finally, authors of [41] highlighted that SVM models are ideal for the prediction of short-term wind power output since they have an excellent learning ability in processing small sample data. In this same line, the influence of different training data scales on the SVM-based PV power output forecasting was evaluated in Ref. [52]. After training SVM and k-NN models with different sample data scales, the former resulted to be more robust, achieving higher prediction accuracy on small datasets. This is a great advantage of SVM models to forecast wind and PV power outputs since, as highlighted in Ref. [41], handling small sample datasets makes them well suited for forecasting applications in newly built PV and wind plants that lack great amounts of historical data.

5.1.3. Ensemble of ML-based methods for RES power output forecasting

As introduced in Section 4.1.1.3, together with the remarkable trend for using deep NNs, a strong trend for using ensembles of the same or different base learners has also been identified. In the former case, RF and XGBoost are the most popular. RF can handle large databases without the need for feature selection and tuning their hyper-parameters. Compared with SVMs, which are highly sensitive to hyper-parameter optimisation, this constitutes a great advantage. In addition, although being simple, they can achieve high generalisation capability. In Ref. [37], a RF-based hour-ahead wind power output predictor was proposed using correlation and importance metrics to select the best-suited weather features. Experimental results of [37] not also highlighted the immunity of RF to irrelevant inputs but also showed the proposed RF-based approach outperformed ANNs trained on the same dataset. In Ref. [51], the potential of introducing smart persistence (SP) predictions, solar irradiance and past production data to a RF model to predict short-term PV power output was evaluated, showing that the forecasting performance highly depends on the analysed PV modules. In addition, authors of [51] highlighted that using only measured data is usually not enough to accurately predict the future PV production for farther horizons.

In RES power output forecasting problems, ensembles of different ML-based models are used to overcome the sensitivity of base learners to the atmospheric conditions. In Ref. [39], a genetic programming based semi-stochastic combination of feed forward back propagation neural networks (FFBPNNs), radial basis function neural networks (RBFNNs), back propagation neural networks (BPNNs) and Broyden Fletcher Gold-Farb Shano neural networks (BFGSNNs) was proposed to forecast the wind power output. Results of [39] showed the effectiveness of the approach to mitigate the influence of the inherent instability in wind power generation due to atmospheric as well as meteorological variables. In particular, authors of [39] highlighted the advantages of generating a collective decision space to avoid large errors due to the inaccurate decisions of some of the base learners, making the forecaster robust against sudden changes in the input and enhancing its performance. In Ref. [42], BPNNs, RBFNNs and SVMs were combined based on a Bayesian model averaging (BMA) strategy to forecast wind power output. In addition of the diversity provided by the different ML-based models, more diversity was introduced by using self organising map (SOP) clustering, combined with k-fold cross-validation, to divide the meteorological data training set into three training subsets which feed each base learner. Results of [42] showed that the proposed SOP-based strategy could accurately and reliably forecast the wind power output under different meteorological conditions, outperforming similar approaches in the state of the art.

Finally, the two trends identified in the SLR can be combined by proposing an ensemble of deep NNs. In Ref. [46], LSTM, GRU, auto-encoder LSTM (auto-LSTM) and a novel approach called auto-encoder GRU (auto-GRU), which is similar to the auto-LSTM but using GRU cells, were used for PV power output forecasting. The deep NNs used as base learners were combined based on four different methods: simple averaging, weighted averaging using linear and non-linear approaches, and a combination through variance using inverse approach. In Ref. [67], an SEA combined different ANNs and a LSTM for 15-min and 1-h-ahead PV power output prediction. The promising results obtained in Refs. [46,67] show the predictive potential of combining the ensemble strategy with deep NNs. In this line, they can be used as a starting point to develop further research in this direction towards achieving the next performance level of RES power output forecasting.

5.1.4. *Advantages and disadvantages of the most popular ML-based approaches to forecast RES power ouputs*

The main difficulty of RES power output prediction is to simultaneously model the autoregressive nature of the power (temporal features) as well as its dependence on the uncertain, non-linear and complex atmospheric spatial features. Each of the ML-based methods analysed in the SLR proposes different strategies to address these challenges. Since all of them have their advantages and disadvantages, there is no one-for-all approach. Using one or another will depend on the application as well as the data and resource

Table 6
Advantages and disadvantages of the most popular ML techniques to forecast PV and wind power.

Approach	Advantages	Disadvantages	Application
Traditional ML-based models			
ANN	• Can learn non-linear relationships.	• Hand-engineered feature selection. • Fail to learn complex patterns from intermittent, stochastic and highly-varying data. • Sample complexity: Network instability and parameters non-convergence when dealing with huge amounts of training data. • Time-consuming training phase.	RES power output forecasting within stationary frameworks.
SVM/SVR	• Well-suited for complex non-linear applications. • Robust to noisy and biased data. • Less prone to overfitting than others ML-based methods. • Good generalisation capability for small datasets.	• Highly sensitive to hyper-parameter tuning.	Newly built PV or wind plants, which lack large amounts of historical data.
Deep NNs			
LSTM	• Automatic feature selection. • Can handle time series data. • Can handle long-term time dependencies. • Can capture complex patterns in sequential data. • More robust than simple RNN to noisy and missing data.	• Prone to overfitting. • Sensitive to hyper-parameter tuning. • Computationally expensive.	RES power output forecasting considering autoregressive features (time series).
CNN	• Automatic feature selection. • Accurate modelling of spatial features.	• Requires large amounts of data to lean. • Computationally expensive.	• PV power output forecasting based on sky or satellite images. • Spatial feature modelling for weather-related data.
Ensembles			
RF	• Robust to missing data and outliers. • No need for variable selection. • Can handle large datasets. • Can handle high-dimensional data. • Easy hyper-parameter tuning. • Less prone to overfitting than others ML-based methods.	• Not suitable for low-dimensional data. • Not suitable for small datasets.	RES power output forecasting within the context of high-dimensional, large datasets.
Different base learners	• Reduce overfitting. • Robust to base learners' errors. • Robust to inconsistencies on the changing weather data. • Better performance than traditional ensembles. • Improve of individual ML-based models.	• Computationally expensive. • Depend on the combination strategy.	RES power output forecasting within highly complex scenarios.

Note. ANN: artificial neural network; CNN: convolutional neural network; deep NN: deep neural network; LSTM: long-short term memory; ML: machine learning; PV: photovoltaic; RES: renewable energy source; RF: random forest; SVM: support vector machine; SVR: support vector regression.

availability. Table 6 summarises the main pros and cons of the most widely used ML-based approaches for PV and wind power forecasting, and suggests the most suitable application for each of them.

5.2. ML-based RES power output forecasting in real-life grid applications

Several SLR articles highlight that the predicted ML-based RES power outputs can significantly impact the whole grid performance. In particular, they can be used as the input of several decision-making grid problems, including UC and ED, design of optimal trading and maintenance strategies, and electricity market-clearing, among others. This would help DSOs and TSOs to perform control actions, optimally dispatch various distributed RES generator types, manage voltage control devices, relieve the pressure of peak and regulate frequency [16,17,29,35,47,55,56]. Nevertheless, only a few of the SLR articles integrate their ML-based approach to real-life economic, operational or managerial grid problems [29,55,56].

In [29], an ensemble of ANNs was used to predict the day-ahead PV power output to reduce the grid power imbalance. The proposed ensemble of ANNs was fed by the sun azimuth and elevation, the clear sky irradiance (CSI) and the ground temperature predicted by the WRF model, as well as the PCA pre-processing of the relative humidity of 20 vertical atmospheric levels forecasted by the Numerical Weather Prediction (NWP) model. The predicted PV power output was then used within the framework of a power transmission scheduling approach, reducing 7 % the grid imbalance. In Ref. [55], the forecast of future wind load and power was integrated into a classical UC optimisation problem. In particular, a LSTM model was used to predict wind load and power. Then, the predicted data was used within the framework of a rolling horizon UC problem. Results of [55] showed that the proposed approach achieved a maximal cost saving ratio of 22.91 %. Nevertheless, authors of [55] highlighted that there was a need for improving power forecasting approaches in terms of accuracy and speed. In the same line, authors of [56] proposed forecasting the day-ahead performance of the wind power via RNNs and SVMs, and used the outputs for day-ahead planning by using UC optimisation techniques. Experimental results of [56] showed that RNNs outperformed SVMs in short-term wind power forecasting. The RNN-based forecasted data was then used as the input of the UC problem optimised by a GA, achieving an accurate day-ahead operation planning. The results in Refs. [29,55,56] are promising and provide baseline examples to integrate ML-based forecasted RES power outputs to real-life grid problems. Nevertheless, further research is needed in this direction.

6. Main research findings and gaps

The SLR results allow to identify the most relevant trends in ML-based approaches to forecast RES power outputs from the model design, including selection of the ML technique, data collection, time horizon definition and selection of the model parameters, to the model implementation, including data pre-processing, feature extraction and selection, hyper-parameter optimisation and performance evaluation. In addition, the main applications proposed in the literature to integrate them into different real-life grid scenarios to address economic, managerial and operational problems have also been discussed. As a result, the research findings listed in Section 6.1 and the research gaps listed in Section 6.2 can be highlighted.

6.1. Main research findings

6.1.1. Feasibility of using ML-based techniques for forecasting the power output of RESs

ML-based techniques have shown to be well suited to forecast RES power outputs. In particular, the following findings can be mentioned.

- Relying only on historical data, ML-based models have the advantage of being able to forecast the RES power output without the need of a strong domain of knowledge of the power systems, as it would be the case of using a physical-based model [60].
- ML-based approaches have demonstrated to improve the accuracy, robustness, precision and generalisation ability of the traditionally used data-driven methods in RES power output forecasting applications, such as statistical models [17].
- ML-based models are potentially more flexible than physical and statistical forecasting models regarding the forecasting time horizons [60].
- In the case of solar energy, ML-based methods have the advantage of being able to directly forecast the PV power output, without the need for forecasting the solar irradiance, as is the usual case in physical-based models [60].

6.1.2. ML-based model implementation

Regarding the implementation of the ML-based models to forecast RES power outputs, the following findings can be highlighted.

- ML-based strategy:
  - Together with the increasing availability of weather data provided by weather agencies as well as the increasing feasibility of acquiring on-site data, the RES power output forecasting can be treated as a big-data problem. As such, there is a clear trend for using deep NNs to solve it, being RNNs – especially LSTM – the most popular ones.
  - LSTM networks are the best suited to model the autoregressive nature of the RES power output.
  - Providing a good generalisation capability even when the sample data is small, SVMs are well suited for RES power output forecasting applications where there is not too much historical data available [41]. In this way, they can predict the power output of newly installed PV or wind plants.

  - Wind and solar power generation are highly influenced by atmospheric and meteorological properties, making them inherently instable. In this line, ensembles of different ML-based methods are one of the most promising strategies to mitigate this impact since they generate a collective decision space avoiding large errors due to the inaccurate decisions of some of the base learners, making the forecasting model robust against sudden changes in the input [39].
- Data collection and ML-based model parameters:
  - Although weather parameters provided by weather agencies are useful to train ML-based models to forecast RES power outputs, researchers agree that including on-site measurements can improve the forecasting performance [39]. This shows that the ML-based RES power output forecasting performance strongly depends on location.

6.1.3. Applications

In general, the ML-based models proposed in the literature to forecast RES power outputs are focused on their design, development, optimisation and accuracy assessment rather than on implementing them within the framework of real-life grid problems. In particular, the following observations can be done.

- Numerous researchers highlight that the predicted RES power output can be used as the input of several decision-making problems, such as UC and ED, design of optimal trading and maintenance strategies and electricity market-clearing, among others, enabling DSOs and TSOs to perform control actions, optimally dispatch various distributed RES generator types, manage voltage control devices, relieve the pressure of peak and regulate frequency [16,17,35,47,53].
- Only a few of the retrieved articles actually use the ML-based predicted RES power output to address economic, managerial or operational real-life grid problems [29,55,56]. In general, they solve a UC problem.

6.2. Main research gaps

6.2.1. Feasibility of using ML-based techniques for forecasting the power output of RESs

The main research gaps encountered in the literature are related to the flexibility and robustness of the proposed ML-based approaches since they highly depend on external factors, such as weather conditions and locations. In addition, several practical issues related to the data collection have been identified since data nature and quality significantly impact the performance of the forecasting models. The most concerning research gaps are listed as follows.

- ML-based model flexibility and robustness:
  - There is a lack of a ML-based PV and wind power output forecasting approach that fits diverse weather conditions [39].
  - Although some researchers suggest their developed ML-based RES power output forecasting model could be adapted for implementation in different locations, such as the ones in Ref. [39], the strong dependence of these type of models to the local parameters calls for further research towards developing standard forecasting methods capable of being practically implemented in different locations. In Ref. [45], authors suggest that joint training on heterogeneous location data could yield a more generalisable and accurate ML-based RES power output forecasting model.
- Data collection and processing:
  - The quality of the training data used to build the ML-based model is a key aspect to obtain an accurate RES power output forecast. In this line, further research needs to be conducted to improve data acquisition methods and data pre-processing techniques.
  - Further research needs to be conducted regarding which are the best parameters to train ML-based models to improve PV and wind power output forecasting. In particular, further works evaluating the performance of demand, load and price features to forecast RES power outputs are required.
  - Although ML-based models have the potential to forecast RES power output within a flexible range of time horizons, only a few articles devoted to medium- and long-term horizons have been found in the literature. In this line, further efforts need to be done in this research direction. Similarly, since most of the ML-based RES power output forecasting models are developed using training data from weather forecasters (usually released at an hourly basis), there is a lack of very short-term forecasting approaches [30]. In general, economic and technical barriers have prevented researchers from developing such predictors since they require on-site data acquired by expensive sensors. Although the use of IoT sensors could be a low-cost alternative, as suggested in Ref. [30], further research needs to be conducted in this direction.

6.2.2. Applications

The integration of ML-based models to forecast RES power outputs into real-life power systems is still pending. In particular, although the researchers suggest that the RES power output predicted based on ML can be used as the input of several decision-making problems, only a few of them actually use it to address economic, managerial or operational grid challenges [29,55,56]. In general, they solve a UC problem based on the forecasted RES power output. There is a need for further research in this direction to enable the DSO to manage the ASs provided by the RESs, facilitating the coordination between the DSO and the TSO.

7. Research limitations

Within the framework of grid applications, it would be desirable to forecast not only the RES power output but also the energy demand, load and price. The SLR conducted in this paper only focuses on the former, whereas the latter is out of its scope. In addition, due to the lack of articles actually implementing the ML-based forecasted RES power output in real-life grid scenarios, this aspect could not be analysed thoroughly. Finally, although it would be preferable to analyse more articles, only 82 were left —and included in the SLR— after the application of the literature search methodology described in Section 2.

8. Conclusions

The increasing penetration of large-scale RESs – especially solar and wind energies – in the distribution grid has risen several operational, managerial and economic challenges to the power grid. In this paper, a SLR has been conducted to evaluate the feasibility of using ML-based methods to forecast the RES power output to facilitate their integration. The most widely used ML-based methods in the literature to forecast RES power outputs have been evaluated in terms of the ML technique, the time horizon predicted, the data collection, the considered ML-based model parameters and the obtained results. In addition, the main implementation steps of the ML-based model – data pre-processing, feature extraction and selection, hyper-parameter optimisation and performance evaluation – have been studied in detail. Finally, the feasibility of actually using the ML-based prediction of the RES power output as the input of different decision-making problems, enabling TSOs and DSOs to efficiently manage RESs – and their ASs – to address economic, operational and managerial grid challenges within the context of a high penetration of RESs, has been discussed.

The SLR results have shown that different ML-based approaches, including ANNs, SVM/SVR, RF, XGBoost, DTs, LR, and k-NN, have been successfully implemented to predict PV and wind power outputs. A remarkable trend for using deep NNs – especially RNNs –, which allow unsupervised feature learning, avoiding tedious and time consuming feature extractions, and can automatically learn the natural variations in the data, mitigating the negative effect of the fluctuations in the atmospheric conditions and meteorological properties, has been identified. Among them, LSTM networks, which are well suited for time series data modelling, allowing to accurately capture the autoregressive nature of PV and wind power outputs, are the most popular ones. In addition, ensemble methods of different ML-based learners are also widely used to improve the forecasting robustness against the high varying weather conditions. Finally, it is important to highlight that the computational complexity of deep NNs and ensemble methods can favour the use of simpler ML-based methods, such as SVMs and RF, which have also demonstrated to be well suited for RES power output forecasting applications. In particular, SVMs can provide a good generalisation capability even when the sample data is small, constituting a great advantage for applications where data is scarce, such as newly installed PV or wind plants.

Although researchers in the field recognise that the ML-based predicted RES power outputs can be integrated into different grid decision-making problems, such as UC and ED, the design of optimal trading and maintenance strategies and the electricity market-clearing, among others, their actual implementation within the framework of real-life power systems is still pending. In this line, further research needs to be conducted in this direction. The promising balance and economic results obtained by solving UC optimisation problems based on the outputs of some RNN-based RES power prediction models can be used as a solid starting point.

As future work, the authors intend to design and implement a ML-based approach to provide accurate RES power output forecasting to the DSO and help it to manage the ASs provided by the RESs, facilitating the coordination between the DSO and the TSO.

CRediT authorship contribution statement

Talal Alazemi: Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Mohamed Darwish:** Investigation, Supervision, Validation, Project administration. **Mohammed Radi:** Investigation, Supervision, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A 1
Articles included in the SLR.

Art.	Year	Publication	Title
[6]	2020	UNIVERSITY OF TEXAS AT DALLAS	MACHINE LEARNING-BASED RENEWABLE AND LOAD FORECASTING IN POWER AND ENERGY SYSTEMS
[7]	2019	Energy Conversion and Management	A review of deep learning for renewable energy forecasting
[8]	2017	Optimisation in Renewable Energy Systems: Recent Perspectives	Impacts of Accurate Renewable Power Forecasting on Optimum Operation of Power System
[9]	2019	Energy Convers. Manag.	Wind power forecasting based on daily wind speed data using machine learning algorithms
[10]	2022	Comput. Intell. Techniq. For Green Smart Cities	Machine Learning Techniques for Renewable Energy Forecasting: A Comprehensive Review

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Table A 1 (*continued*)

Art.	Year	Publication	Title
[11]	2023	J. Clean. Prod.	Deep learning for renewable energy forecasting: A taxonomy, and systematic literature review
[13]	2023	Sustainability	Forecasting Renewable Energy Generation with Machine Learning and Deep Learning: Current Advances and Future Prospects
[14]	2021	Renew. Sustain. Energy Rev.	A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids
[16]	2020	Appl. Sci.	A Survey of Machine Learning Models in Renewable Energy Predictions
[17]	2019	Wiley Interdiscip. Rev. Energy Environ.	The future of forecasting for renewable energy
[24]	2020	J. Stat. Manag. Syst.	Machine learning models for renewable energy forecasting
[25]	2019	Energies	State of the Art of Machine Learning Models in Energy Systems, a Systematic Review
[29]	2018	Sol. Energy	Photovoltaic generation forecast for power transmission scheduling: A real case study
[26]	2019	Energies	Energy Consumption Prediction Using Machine Learning; A Review.
[30]	2021	Energies	Deep RNN-Based Photovoltaic Power Short-Term Forecast Using Power IoT Sensors
[31]	2018	Applied Sciences	Comparison of Training Approaches for Photovoltaic Forecasts by Means of Machine Learning
[32]	2014	2014 Int. Joint Conf. On Neural Networks	Wind power forecasting — An application of machine learning in renewable energy
[33]	2019	Energies	Machine Learning Based Photovoltaics (PV) Power Prediction Using Different Environmental Parameters of Qatar
[34]	2014	Data Analytics for Renewable Energy Integration	Machine Learning Techniques for Supporting Renewable Energy Generation and Integration: A Survey
[28]	2019	Renew. Sustain. Energy Rev.	Machine-learning methods for integrated renewable power generation: A comparative study of artificial neural networks, support vector regression, and Gaussian Process Regression
[35]	2014	IEEE Trans. Power Syst.	Probabilistic Forecasting of Wind Power Generation Using Extreme Learning Machine
[23]	2018	Journal of Cleaner Production	Application of support vector machine models for forecasting solar and wind energy resources: A review,
[36]	2020	Applied Sciences	Advanced Methods for Photovoltaic Output Power Forecasting: A Review
[37]	2017	Renew. Energy	Hour-ahead wind power forecast based on random forests.
[38]	2016	Applied Energy	learning based ensemble approach for probabilistic wind power forecasting
[39]	2017	Energy Convers. Manag.	Intelligent and robust prediction of short term wind power using genetic programming based ensemble of neural networks
[40]	2019	Future Generation Computer Systems	LSTM-EFG for wind power forecasting based on sequential correlation features
[41]	2019	International Journal of Smart Grid and Clean Energy	Short-term wind power forecasting based on support vector machine with improved dragonfly algorithm
[42]	2020	Renewable Energy	A hybrid wind power forecasting approach based on Bayesian model averaging and ensemble learning
[27]	2020	Sustain. Energy Grids Network	Multiple steps ahead solar photovoltaic power forecasting based on univariate machine learning models and data re-sampling
[43]	2019	Proceedings of the 3rd International Conference on Smart Grid and Smart Cities	A Hybrid Approach of Solar Power Forecasting Using Machine Learning
[44]	2019	Sustainability	A Two-Step Approach to Solar Power Generation Prediction Based on Weather Data Using Machine Learning
[45]	2019	Solar Energy	Short-term solar power forecast with deep learning: Exploring optimal input and output configuration.
[46]	2019	Applied Computer Information	Solar power generation forecasting using ensemble approach based on deep learning and statistical methods
[47]	2017	Neural Comput. & Applic.	Accurate photovoltaic power forecasting models using deep LSTM-RNN
[48]	2020	Renewable and Sustainable Energy Reviews	An improved moth-flame optimisation algorithm for support vector machine prediction of photovoltaic power generation
[49]	2019	Chapter: Advances in Intelligent Systems and Computing	Deep Learning for Big Data Time Series Forecasting Applied to Solar Power.
[50]	2019	Case Studies in Thermal Engineering	A comparison study based on artificial neural network for assessing PV/T solar energy production
[51]	2018	Energies	Using Smart Persistence and Random Forests to Predict Photovoltaic Energy Production
[52]	2017	Applied Sciences	Comparative Study on KNN and SVM Based Weather Classification Models for Day Ahead Short Term Solar PV Power Forecasting
[53]	2020	Renew. Sustain. Energy Rev.	Machine learning models to quantify and map daily global solar radiation and photovoltaic power.
[54]	2018	Engineering Science and Technology	Solar photovoltaic power forecasting using optimised modified extreme learning machine technique
[55]	2019	Energy	Deep learning-based rolling horizon unit commitment under hybrid uncertainties
[56]	2021	Sustainability	Short-Term Unit Commitment by Using Machine Learning to Cover the Uncertainty of Wind Power Forecasting
[57]	2019	University of Sussex	WIND FARM POWER OUTPUT PREDICTION BASED ON MACHINE LEARNING RECURRENT NEURAL NETWORKS
[58]	2016	Oldenburg University	Wind Power Prediction with Machine Learning Ensembles
[59]	2019	Oldenburg University	Support Vector Regression for Solar Power Prediction
[60]	2019	University of Sydney	SOLAR POWER FORECASTING

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Table A 1 (*continued*)

Art.	Year	Publication	Title
[61]	2021	University of Stavanger	Predictive Analytics for Maintaining Power System Stability in Smart Energy Communities.
[62]	2022	Expert Syst. Appl.	Integrating data decomposition and machine learning methods: An empirical proposition and analysis for renewable energy generation forecasting
[63]	2021	Sustainability	Prospective Methodologies in Hybrid Renewable Energy Systems for Energy Prediction Using Artificial Neural Networks
[64]	2021	Energies	Numerical Weather Prediction and Artificial Neural Network Coupling for Wind Energy Forecast
[65]	2017	Energy Procedia	Short-range wind speed predictions for complex terrain using an interval-artificial neural network
[66]	2021		Renewable Energy and Demand Forecasting in an Integrated Smart Grid
[67]	2022	Energies	Improved solar photovoltaic energy generation forecast using deep learning-based ensemble stacking approach
[68]	2022	Electr. Power Syst. Res.	CNN-LSTM: An efficient hybrid deep learning architecture for predicting short-term photovoltaic power production
[69]	2022	Comput. Intell. Neurosci.	Photovoltaic Power Generation Forecasting Using a Novel Hybrid Intelligent Model in Smart Grid
[70]	2015	CSEE J. Power Energy Syst.	Photovoltaic and solar power forecasting for smart grid energy management
[71]	2022	J. King Saud Univ. - Sci.	Boosting energy harvesting via deep learning-based renewable power generation prediction
[72]	2022	Sustainability	Performance Analysis of Machine Learning Algorithms for Energy Demand & Supply Prediction in Smart Grids
[73]	2023	Sustainability	An Artificial-Intelligence-Based Renewable Energy Prediction Program for Demand-Side Management in Smart Grids
[74]	2023	Neural Comput. Appl.	AI-based solar energy forecasting for smart grid integration
[75]	2021	2021 20th IEEE Int. Conf. On Mach. Learning and Applicat. (ICMLA)	Deep Learning Applied on Renewable Energy Forecasting Towards Supply-Demand Matching
[76]	2016	2016 IEEE Int. Conf. On Systems, Man, and Cybern. (SMC)	Deep Learning for solar power forecasting — An approach using Auto-Encoder and LSTM Neural Networks
[77]	2020	Renew. Sustain. Energy Rev.	A deep learning-based forecasting model for renewable energy scenarios to guide sustainable energy policy: A case study of Korea
[78]	2022	Complexity	A Hybrid Deep Learning-Based Network for Photovoltaic Power Forecasting
[79]	2021	Frontiers in Energy Research	Deep Learning-Based Prediction of Wind Power for Multi-turbines in a Wind Farm
[80]	2021	Appl. Energy	A review of wind speed and wind power forecasting with deep neural networks
[81]	2023	Comput. Mater. Contin.	Wind Power Prediction Based on Machine Learning and Deep Learning Models
[82]	2022	Energies	Efficient Wind Power Prediction Using Machine Learning Methods: A Comparative Study
[83]	2021	Applied Sciences	Wind Power Forecasting with Deep Learning Networks: Time-Series Forecasting
[84]	2022	Energy Explor. Exploit	Use machine learning algorithms to predict turbine power generation to replace renewable energy with fossil fuels
[85]	2022	Vaasa University	Machine Learning based Wind Power Forecasting for Operational Decision Support
[86]	2022	Frontiers in Energy Research	A hybrid deep learning model with error correction for photovoltaic power forecasting
[87]	2020	NCE J. Sci. Eng.	Solar Power Forecasting for Smart Grid System by Using Deep Learning Techniques
[88]	2022	IEEE Access	Solar Power Forecasting Using Deep Learning Techniques
[89]	2020	IEEE Access	Photovoltaic Power Forecasting With a Hybrid Deep Learning Approach
[90]	2023	Forecasting	A Day-Ahead Photovoltaic Power Prediction via Transfer Learning and Deep Neural Networks
[91]	2023	Energy Reports	Trends and gaps in photovoltaic power forecasting with machine learning
[92]	2022	R. Sehgal, N. Gupta, A. Tomar, M. D. Sharma, and V. B. T.-S. E. and M. S. Kumaran, Eds. Academic Press	Chapter Six - Renewable energy sources forecasting and integration using machine learning
[93]	2022	Int. J. Photoenergy	Forecasting Solar Energy Production Using Machine Learning
[94]	2021	Mathemathics	AB-Net: A Novel Deep Learning Assisted Framework for Renewable Energy Generation Forecasting
[22]	2020	Energies	The Challenges and Opportunities of Renewable Energy Source (RES) Penetration in Indonesia: Case Study of Java-Bali Power System

V is computationally expensive and not adaptive for other comfort related factors [12,25], researchers have been investigating data driving approaches from a machine learning perspective. Quite a few literature suggests the application of Artificial Neural Network for comfort learning and estimation [26,31,32], while other supervised learning methods have also been explored, such as Support Vector Machine (SVM) with radius basis kernel. [4,7] and locally weighted non-linear reg.

Table A 2
Relevant information extracted from the selected articles.

Art.	Proposal	ML	RES	Parameters	Output	Time Horizon	Data	Feature selection	Hyper-parameter optimisation	Accuracy metric
[6]	Ensemble of ANN, SVM, GB, RF for wind power forecasting	Ensemble of ANN, SVM, GB and RF	Solar, wind	Humidity, wind speed, wind direction, pressure, air temperature, historical GHI, clear sky GHI, CSI, sky imaging features, DNI, DHI	PV and wind turbine power	Shor term, very-short term	Wind Integration National Dataset (WIND) Toolkit, National Renewable Energy Laboratory (NREL) data	PCA, GCT, AA, PAA, RFE	SGD, Adam optimiser, AdaDelta	MAE, MAPE, RMSE
[7]	Review	DL: DBN, SAE, deep RNN	Solar, wind							
[8]	Conceptual study		Solar, wind							
[9]	Case studies implementation of different ML algorithms	XGBoost regression, SVR, RF, LASSO regression, kNN regression	Wind	4-year hourly wind speed data	Wind turbine power	Long term	5 years of hourly wind speed observation values of Nigde, Turkey	Weibull distribution		R2 score, RMSE, MAE
[10]	Review									
[11]	Review	SAE, DBN, CNN, GAN, RNN	Solar, wind, ocean, hydrogen							
[13]	Review	ML, DL	Solar, wind							
[14]	Review									
[16]	Survey		Solar, wind							
[17]	Conceptual study		Solar, wind							
[24]	Review		Solar							
[25]	Review		Solar, wind							
[29]	Evaluate the impact of using PV forecast for power transmission scheduling	ANN	Solar	PV power, load and transmission data, weather data (sun azimuth and elevation, the clear sky irradiance and the ground temperature), energy price data	PV power	Day ahead	Data from a South Tyrol Region located in Northern Italy	PCA	MOP	
[26]	Review	ANFIS, ANN, DT, ELM, MLP, SVM/SVR, ensemble, hybrid, DL	Solar, wind	Review						
[30]	Deep RNN-based PV power short-term forecast	Deep RNN	Solar	Solar radiation, ambient temperature, module temperature, humidity, wind speed and power data	DC current, voltage and PV power	Real-time short term	Real-time PIoT sensors data	PCC	DLR, SGD	nRMSE, nMAE
[31]	Comparison of different training methods in ANNs for PV power forecasting	ANN	Solar	Ambient temperature, solar irradiance, wind speed, wind direction, pressure, precipitation, cloud type, cloud cover, CSRM	PV power	Day ahead	Data from the Laboratory SolarTechLab		Sensitivity analysis	Enveloped Weighted MAE

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Table A 2 (*continued*)

Art.	Proposal	ML	RES	Parameters	Output	Time Horizon	Data	Feature selection	Hyper-parameter optimisation	Accuracy metric
[32]	Novel neuro evolutionary technique based on CGP to evolve ANN for modelling wind power forecasters	ANN	Wind	Hourly-spaced wind power production	Wind turbine power	Short term, long term	Historical data of hourly produced wind power plant situated in Galicia		CGP	MAPE, nRMSE
[33]	Study of the effects of the relevant environmental parameters on the output power of the PV panel	LR, DT, GPR, ANNs	Solar	Temperature, relative humidity, PV surface temperature, solar irradiance, dust accumulation, wind speed	PV power	hourly	Two years' deployment period of PV system	CFS	Exhaustive search	MAE
[34]	Survey		Solar, wind							
[28]	Review	ANN, SVR, GPR	Solar, wind							
[35]	ELM-based probabilistic forecasting method for wind power generation	Bootstrap-based SLFN-based ELM	Wind	Wind power, speed and direction	Wind turbine power	Short term	Wind farm in Australia		Cross-validation	MAE, RMSE
[23]	Review	SVM	Solar, wind							
[36]	Review	DL and hybrid methods	Solar							
[37]	Choose the appropriate weather factors to forecast wind power	RF	Wind	Wind power, speed and direction	Wind turbine power	Day ahead	Wind farm in Tunisia			MAE, MASE, RMSE, nMAE, MXE, MAPE
[38]	Advanced point forecasting method based on Wavelet transform and CNN	CNN	Wind	Wind turbine parameters: wind speed, capacity, capacity factor, used area	Wind turbine power	Shor term, long term	Large-scale real data from a wind farm in China	PCA		MAE
[39]	Ensemble regression comprising ANN and Genetic Programming to forecast wind power	ANN	Wind	Wind speed and direction	Wind turbine power	Shor term	Five different wind farms located in Europe	Information-theoretic method	Genetic programming	RMSE, MAE
[40]	Improved LSTM-EFG to forecast wind power	LSTM-EFG	Wind	Wind speed and power	Wind turbine power	Shor term, long term	Data from the National Renewable Energy Laboratory	Time series correlation		MSE
[41]	Improved LSTM-EFG to forecast wind power	LSTM-EFG	Wind	Wind speed and power	Wind turbine power	Shor term, long term	Data from the National Renewable Energy Laboratory	Time series correlation		MSE
[42]	Hybrid wind power forecasting approach based on BMA-EL	BMA-EL	Wind	Wind speed and direction, temperature	Wind turbine power	Shor term	SCADA data of a wind farm in Inner Mongolia Autonomous region, China	SOM clustering		MAPE, RMSE
[27]	Univariate approach to predict solar PV power output multiple steps ahead	ANN, RF, LR, SVR	Solar	PV power	PV power	Shor term	2 years of data from a 1.22 MW PV system in Australia		Exhaustive grid search	MAE, MRE, RMSE
[43]	Analyse multiple ML models and different weather parameters for PV forecasting	SVM	Solar	Wind temperature at 2 m height, wind speed at 30 m height, wind direction at 30 m height, precipitation, solar radiation, air pressure at sea level, relative humidity at 2 m above ground, snowfall amount, total cloud cover	PV power	Day ahead	Historical weather data from the weather station managed by Meteorology department of Ludwig Maximilian University	Sensitivity analysis	Grid search	RMSE, R2 score

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Table A 2 (*continued*)

Art.	Proposal	ML	RES	Parameters	Output	Time Horizon	Data	Feature selection	Hyper-parameter optimisation	Accuracy metric
[44]	Predict amounts of PV power generation using weather information provided by weather agencies	LR, SVR, CART, kNN, AdaBoost, RF	Solar	Weather forecast: rainfall type, sky type, wind direction, wind speed, humidity, temperature, solar elevation; weather observation: radiation, vapor pressure, surface temperature, atmospheric pressure	PV power	Day ahead	Publicly available dataset from the Yeongam PV Power Plant in South Korea.	Gini importance		RMSE, R2 score
[45]	Specialised CNN to predict 15-min ahead minutely-averaged PV output	CNN	Solar	Weather images, PV power	PV power	15 min ahead	Sky images and PV generation collected over a year	Sensitivity analysis	Adam optimiser	RMSE
[46]	Hybrid model combining ML with Theta statistical methods for future PV power generation prediction	LSTM, GRU, AE- LSTM, AE-GRU	Solar	GHI, Global GTI, solar irradiance, air temperature, panel temperature, wind speed, wind direction, precipitations, humidity	PV power	Day ahead	Two real-time series datasets		RMSProp	nMAE, nMSE
[47]	LSTM-RNN to forecast PV power output	LSTM-RNN	Solar	PV power	PV power	Hour ahead	PV datasets from Aswan and Cairo, Egypt			RMSE
[48]	Improved MFO for SVM prediction of PV power generation	SVM	Solar	Radiation intensity, atmospheric temperature, relative humidity, wind speed	PV power	Short term	Real data of PV power station in Australia	GRA	MFO, IMFO	RMSE, MAPE, R2 score
[49]	DL for PV power forecasting for the next day	PSF based on similarity of patterns and ANN	Solar	Big PV power data (time series)	PV power	Day ahead	Australian solar PV data for two years		Grid search method	RMSE, MAE
[50]	Review		Solar							
[51]	RF for forecasting PV power generation based on smart persistence, irradiance, and past production data	RF	Solar	PV production, GHI, DNI, mean clear sky index, standard deviation clear sky index, PV smart persistence, mean PV Smart Persistence and SD PV Smart Persistence	PV power	Short term	Three years of data from six solar PV modules at Faro, Portugal		BF search	Skill score, nRMSE
[52]	Evaluate the correlation between classification accuracy and sample dataset scale	kNN, SVM	Solar	Extraterrestrial and surface solar irradiance	PV power	Day ahead	Grid-connected PV plant situated in Hohhot, Inner Mongolia, China			R2 score, RMSE
[53]	Hybrid PSO-ELM to accurately predict daily solar radiation and PV power.	PSO-ELM	Solar	Sunshine duration, PV power, extra-terrestrial solar radiation, relative humidity, global solar radiation, average air temperature, maximum air temperature, minimum air temperature, vapor pressure deficit	PV power	Day ahead	Daily meteorological variables measured during 1961–2016 in China's Loess Plateau		PSO	MAE, RMSE
[54]	ELM for PV power forecasting of a real time model	ELM	Solar	Temperature, solar irradiance, PV power	PV power	Short term	Real time PV power data		PSO, CRPSO, APSO	RMSE, MAE, MAPE

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Table A 2 (*continued*)

Art.	Proposal	ML	RES	Parameters	Output	Time Horizon	Data	Feature selection	Hyper-parameter optimisation	Accuracy metric
[55]	DL-based rolling horizon UC	LSTM	Wind	Historical wind load and power, real-time weather	Wind turbine load and power	Rolling horizon	3 Irish wind farms		GA	
[56]	RNN and SVM wind power forecasting for planning the day-ahead performance of the generation system by using UC optimisation techniques	RNN, SVM	Wind	Wind power	Wind turbine power	Day ahead				
[57]	LSTM for wind power forecasting	LSTM	Wind	Wind speed and direction	Wind turbine power	Short term	Real 14-turbine wind farm		RMSProp, SGD	RMSE, MSE, MAPE
[58]	Heterogeneous machine learning ensemble combining SVR and DT ensembles for wind power forecasting	Ensemble of SVR and DT ensemble	Wind	Wind speed and power	Wind turbine power	Short term	Australian public datasets		EMOA	MSE
[59]	SVR for PV power forecasting	SVR	Solar	PV power, solar irradiance, air temperature	Wind turbine power	15 min ahead	Publicly available weather forecast	RF importance, k-means clustering	Grid search	RMSE
[60]	Direct and pair patterns clustering using ANN and SVR as well as ANN ensembles for PV power forecasting	Direct and pair patterns clustering (using ANN and SVR), ANN ensemble	Solar	Solar irradiance, temperature, wind speed, humidity, PV power	PV power	Short term	Australian PV and weather data	RF Selection	Grid search	MAE, RMSE
[61]	PV power forecasting using an ensemble of GBR with tree algorithms and several SSLSTM networks	Ensemble with GBR and LST	Solar	Cloud opacity, DHI, DNI, GHI, solar zenith angle, air temperature, wind speed, wind direction, PV power	PV power and demand	Short term	Australian public dataset	PCC, RFE		MAE, RMSE
[62]	STL data decomposition and LSTM RESs' power output prediction.	STL-LSTM	Solar, wind, hydropower, geothermal			Mid-term				
[63]	Review	MLP, CNN, RNN, LSTM								
[64]	NWP and ANN coupling for wind energy forecast	ANN	Wind	Wind power	Wind turbine power	>6 h ahead	Historical weather data from 2019 to 2020		Standard heuristic approach	MAE, RMSE, MedAE, ME
[65]	Interval-based NN for short-term wind power prediction	interval-based NN	Wind	Temperature, wind speed and wind direction, relative humidity, pressure		intra days to days ahead term	Benchmark NWP datasets		Adam optimiser	MSE
[66]	Medium DT and sequential boost ensemble technique to forecast wind and solar power generation	medium DTs, sequential boost ensemble	Solar, wind	Solar irradiance, wind speed		Short-term	Benchmark datasets		Standard heuristic approach	

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Table A 2 (*continued*)

Art.	Proposal	ML	RES	Parameters	Output	Time Horizon	Data	Feature selection	Hyper-parameter optimisation	Accuracy metric
[67]	DL-based ensemble stacking approach for solar PV energy generation forecast	Ensemble GB, ANN, LSTM	Solar	GHI, temperature, relative humidity	PV power	15 min and 1 h ahead	Solar farms on commercial buildings in Bunnik, Netherlands and benchmark weather data	Literature search	Stacked generalization framework	R2, RMSE, MAE
[68]	Merge two DL architectures: LSTM and CNN to predict PV power output	LSTM and CNN	Solar	PV power	PV power	Short-term	Real-world dataset from Rabat, Morocco			MAE, MAPE, RMSE
[69]	Hybrid method based on SVM, ANNs and PSO	SVM, ANNs	Solar	Solar irradiance, temperature, humidity, wind speed	PV power	Long term	Real data of consumption and climate factors of Douala, Cameroon		PSO	MSE, RMSE, MAPE, MAE, R2
[70]	Review		Solar		PV power					
[71]	Hybrid DL model for power generation	CNNESN	Solar, wind	Wind speed, temperature, humidity, GHR, DHR, wind direction, rainfall, RGT, RDT	PV and wind turbine power	short-term	Historical data			RMSE, MSE, nRMSE, MAE
[72]	Performance analysis of ML algorithms for energy demand–supply prediction in smart grids	ANN, Gaussian regression, KNN, LR, RF, SVR	Solar, wind	PV and wind power	PV and wind turbines power	hourly	Eskom benchmark database		Grid search	CC, RAE, MAE, RRSE, RMSE
[73]	RESs' power output prediction program for demand-side management in smart grids	LSTM	Solar, wind	Solar irradiance, local sky imaging	PV and wind turbines power		Benchmark datasets			
[74]	Hybrid method based on the combination of an LSTM and AE	LSTM	Solar	PV power	PV power		Benchmark datasets			RMSE
[75]	Demand-supply matching approach based on an accurate renewable energy forecasting and demand forecasting	RNN, LSTM, GRU	Solar, wind		PV and wind turbines power		Real historical data			
[76]	Combine DL and ANN, including DBN, AE and LSTM, to forecast renewable energy power	DBN, LSTM, Auto-LSTM	Solar	PV power, weather data	PV power	Day ahead	Historical NWP data from 21 photovoltaic facilities in Germany		RMSprop optimiser	RMSE, MAE
[77]	Korean policy case study based on RESs' power output forecasting	DL	Solar, wind		PV and wind turbines power		Korean energy policy			
[78]	End-to-end hybrid deep network for automatic PV power forecasting	GRU-CNN	Solar		PV power		Publicly available real-world PV power datasets gathered in Alice Springs, Australia			MSE, MAE, RMSE, MBE

(*continued on next page*)

Table A 2 (*continued*)

Art.	Proposal	ML	RES	Parameters	Output	Time Horizon	Data	Feature selection	Hyper-parameter optimisation	Accuracy metric
[79]	Two-stage modelling strategy, in which a DNN combines spatiotemporal correlation to simultaneously predict the power of multiple wind turbines	LSTM, CNN	Wind	Wind power	Multi-turbines wind power		Wind historical power data from an offshore wind farm in China		Adam optimiser	RMSE, MAE, MSE
[80]	Review	DL	Wind		Wind speed and wind turbine power					
[81]	Wind power prediction based on DNN, KNN, LSTM, RF, bagging regression and GBR	DNN, KNN, LSTM, averaging model, RF bagging regression, GBR	Wind	Wind speed, direction and power	Wind turbine power	Hourly to two days horizon			SFS-PSO, Adam optimiser	MAE, NSE, MSE, R2, RMSE
[82]	Forecast univariate wind power time-series data	GPR, SVR, ensemble learning: Boosted trees and Bagged trees	Wind	Wind speed, direction and power	Wind turbine power	Days ahead	French and Turkish wind farms		BO	R2, RMSE, MAE
[83]	24–72-h ahead prediction of wind power using the TCN	TCN, LSTM, RNN, GRU	Wind	Wind speed and wind direction	Wind turbine power	24–72 h ahead	Historical dataset from SCADA wind farm in Turkey	PCA	Gradient descent algorithms, Adam optimiser, SGD, RMSprop	MAPE
[84]	Evaluate different ML methods for wind power forecasting	ET, LGB, GBR, DT, Ada Boost, ridge algorithms	Wind	Wind power	Wind turbine power	Day ahead	Benchmark datasets			R2
[85]	Conceptual study		Wind		Wind turbine power					
[86]	DL-based hybrid technologies for ultra-short-term PV power forecasting consisting of a feature engineering module, a DL-based point prediction module and an error correction module	NPCNN	Solar	PV power	PV power	15 min ahead	PV data from Limburg, Belgium	IF		MAE, RMSE, MAPE
[87]	PV power modelling using polynomial regression and DL-ANNs	MNN, LSTM	Solar	PV power	PV power		35.58 kWp solar PV system installed inside the K3 substation of Singhdarbar, Kathmandu Nepal			RMSE

(*continued on next page*)

Table A 2 (*continued*)

Art.	Proposal	ML	RES	Parameters	Output	Time Horizon	Data	Feature selection	Hyper-parameter optimisation	Accuracy metric
[88]	PV power forecasting using LSTM	LSTM	Solar	PV power	PV power	Short term	One-year data (2017) from Halifax, located in Nova Scotia, Canada			MAE, MAPE, RMSE, R2
[89]	Hybrid CNN-LSTM DL approach	CNN, LSTM	Solar	PV power	PV power	15 min ahead to 180-min ahead	Real PV power data from Limberg, Belgium		BPTT	MAE, RMSE, R2
[90]	Transfer learning method to use reliable trained DL models of old PV plants in newly installed PV plants in the same neighborhoods.	LSTM	Solar	PV power, ambient temperature, humidity.	PV power	hourly day-ahead	Limited historical data		Adam optimiser	MSE, wMAPE
[91]	Review		Solar		PV power					
[92]	Review	DT, RF, ANN, SVM, MLP, GB, KNN								
[93]	Hybrid model combining ML with statistical methods for future PV power generation prediction	ensemble	Solar	Solar radiation	PV power		Polycrystalline solar panels and thin-film solar cells	PCC		RMSE
[94]	One-step forecast of RES generation for short-term horizons by incorporating an AE BiLSTM	BiLSTM	Solar, wind	Solar inclined irradiance, surrounding temperature, surface temperature, wind direction, air temperature, wind speed, air density, surface air pressure	PV and wind turbine power	Short-term	Benchmark datasets		Adam optimiser	RMSE, MSE

Note. AA: autocorrelation analysis; AE: auto-encoder; ANFIS: adaptive neuro fuzzy inference system; ANN: artificial neural network; APSO: accelerated PSO; BiLSTM: bidirectional LSTM; BF: brute force; BMA: Bayesian model averaging; BO: Bayesian optimisation; BPTT: back propagation through time; CC: correlation coefficient; CFS: correlation feature selection; CGP: cartesian genetic programming; CNN: convolutional neural network; CRPSO: craziness PSO; CSI: clear sky index, CSRM: clear sky radiation model; DBN: deep Bayesian network; DHI: direct horizontal irradiance; DHR: diffuse horizontal radiation; DL: deep learning; DLR: decayed learning rate; DNI: direct normal irradiance, DNN: deep neural network; DT: decision tree; EFG: enhanced forget-gate; EL: ensemble learning; ELM: extreme learning machine; EMOA: evolutionary multi-objective optimisation algorithm; ESN: echo state network; ET: extra tree; GA: genetic algorithm; GAN: generative adversarial networks; GB: gradient boosting; GBR: gradient boosting regression; GCT: Granger causality tes; GHI: global horizontal irradiance, GHR: global horizontal radiation; GPR: Gaussian progressive regression; GRA: grey relational analysis; GRU: gated recurrence unit; GTI: global tilt irradiance; IDA: improved dragonfly algorithm; IF: isolation forest; IMFO: improved MFO; KNN: k-nearest neighbours; LASSO: least absolute shrinkage and selection operator; LGB: light gradient boosting; LR: linear regression; LSTM: long-short term memory; MAE: mean absolute error; MAPE: mean absolute percentage error; MASE: mean absolute squared error; MBE: mean bias error; ME: maximum error; MedAE: median absolute error; MFO: moth-flame optimisation; ML: machine learning; MLP: multiple layer perceptron; MNN: multilayer neural network; MOP: master optimisation procedure; MSE: mean squared error; MXE: maximum absolute error; nMAE: normalised MAE; nMSE: normalised MSE; NNCNN: non-pooling CNN; nRMSE: normalised RMSE; NSE: Nash Sutcliffe efficiency; NWP: numerical weather prediction; PAA: partial autocorrelation analysis; PCA: principal component analysis; PCC: Pearson correlation coefficient; PSF: point spread function; PSO: particle swarm optimisation; PV: photovoltaic; RAE: root absolute error; RES: renewable energy source; RDT: radiation diffuse tilted; RF: random forest; RFE: recursive feature elimination; RGT: radiation global tilted; RMSE: root mean squared error; RMSProp: Root Mean Square Propagation; RNN: recurrent neural network; RRSE: root relative squared error; SAE: stacked auto-encoder; SCADA: supervisory control and data acquisition; SD: standard deviation; SFS: stochastic fractal search; SGD: stochastic gradient descent; SLFN: single layer feed-forward neural network; SOM: self organising map; SSLSTM: sequence-to-sequence LSTM; STL: seasonal-trend decomposition based on Loess; SVM: support vector machine; SVR: support vector regression; TCN: temporal convolutional network; UC: unit commitment; wMAPE: weighted MAPE; XGBoost: extreme gradient boosting.

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