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Review article

Unveiling the backbone of the renewable energy forecasting process: Exploring direct and indirect methods and their applications

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ABSTRACT

A myriad of techniques regarding renewable energy forecasting have been proposed in recent literature, commonly classified as physical, statistical, machine learning based or a hybrid form thereof. The renewable energy forecasting process is however elaborate and consists of multiple stages, where different approaches from these four categories apply variably, complicating a holistic classification of the process. This paper resolves this by utilizing the fundamental difference between direct and indirect forecasting in terms of model complexity, data availability, spatial and time horizons as the backbone to structure this intricate forecasting process. As such, a significant step towards a generalized framework for renewable energy forecasting is presented. Additionally, a most promising recommendation emerges: leveraging physics-based knowledge from indirect models to enhance training of direct methods.

1. Introduction

1.1. Relevance and background

The gradual replacement of fossil fuels by their renewable counterparts is an essential strategy to pursue when aiming at mitigating the detrimental consequences of human-induced climate change (Moriarty and Honnery, 2012). Renewable energy will undoubtedly play a major role in the transition towards a carbon neutral society. Wind and solar power are at the centre of this shift, accounting for almost 90% of the worldwide growth in renewable electricity generation in 2021 (IEA, 2022). Contrary to fossil fuels, however, renewable energy brings volatility and uncertainty due to its direct dependence on the condition of the weather (Wang et al., 2019a). Accurate forecasts of the weather and by extent the available Renewable Energy Sources (RES) are therefore vital and are only gaining in importance. These forecasts are already being used in all segments of the energy and power industry (Feng, 2020). Reliable renewable energy forecasts are essential for transmission grid operators in order to ensure appropriate electricity grid management (Elia, 2019). As such, they are crucial for guaranteeing stable electricity provision, i.e. balancing supply and demand Goodarzi et al. (2019). Inaccuracies in renewable energy forecasting can result in significant disruptions and economic losses (Ziel, 2017). In Belgium, for example, wind power forecast errors lead to balancing costs of which the lower bounds vary between 4.3 and 6.7 Euros per MWh (Bruninx et al., 2014). Next, the uncertainty associated with wind power forecasts brings an imbalance which sometimes requires adjustments from fossil powered sources. Consequently, this source of renewable energy does not always deliver the reduction in carbon emissions expected from the installed power capacity (Forbes and Zampelli, 2020, 2019). Next to reducing balancing costs, minimizing forecast errors therefore also leads to significant decreases in carbon emissions. As such, realizing high-performing RES forecasting models is motivated by both economic and environmental incentives.

1.2. Literature review

The literature on solar and wind energy forecasting is extensive and a myriad of various different methods to go through (parts of) the RES forecasting process have already been proposed. Similarly, various comprehensive review papers approaching renewable energy forecasting from different angles have been published recently. A review discussing the most influential papers along with recent research trends and data sources can be found in Hong et al. (2020). The future of RES forecasting is addressed by Sweeney et al. (2019) based on the distinction between physical and statistical forecasting methods. In Tawn and Browell (2022), on the other hand, the focus of the review lies on very short timescales. Next, the applications of Artificial Intelligence (AI) in RES forecasting are presented in a bibliometric analysis

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by Zhang et al. (2022b). Similarly, in Lai et al. (2020), Machine Learning (ML) methods are discussed together with preprocessing steps and performance metrics. Literature statistics concerning Deep Learning (DL) approaches in RES forecasting are presented in a literature review by Ying et al. (2023). Analogously, while distinguishing between probabilistic and deterministic forecasting, Wang et al. (2019a) published a comprehensive survey paper on DL forecasting methods. An overview of the taxonomy concerning the RES forecasting process as a whole is presented in a survey paper by Alkhayat and Mehmood (2021). In this work, the difference between direct forecasting based on historical power data and its indirect counterpart employing weather forecasts is briefly emphasized. Although essential, the distinction between direct and indirect forecasting is seldom comprehensively discussed in the literature. Both approaches are considered and compared in the research papers of Yakoub et al. (2023) and Dione and Matzner-Løber (2019) concerning wind power forecasting, where the latter prefers the direct approach while the former is inconclusive. The direct approach is favored by Shi et al. (2011) in their work on wind power forecasting based on statistical methods. The systematic literature review on solar power forecasting by Başaran et al. (2020) is among the few to recognize the fundamental difference between direct and indirect power forecasting as a criterion to categorize existing methods. The focus of the work lies on type of solar panels, data sets and ML based forecasting methods. Despite sporadic mentions in research and survey papers, a significant gap remains when it comes to studying the differences between direct and indirect renewable energy forecasting methods. They are yet to be thoroughly compared based on variations in model complexity, from a temporal and spatial perspective or from a data point of view. Moreover, the distinction between the direct and indirect pathways has never served as the foundation for dissecting the RES forecasting process, although leveraging these differences could lead to useful results.

Beyond the necessity of discussing the distinctions and applications of direct and indirect forecasting methods, it is crucial to meticulously examine each stage of the renewable energy forecasting process. However, these stages have seldom been considered collectively. Therefore, there is need for a structured and accessible review which probes the various steps in a chronological manner. Additionally, given the diversity in RES forecasting methods, a clear and unambiguous classification framework is necessary. Review papers until now have mainly focused on the division between physics-based, statistical, ML based and hybrid methods. This distinction lacks absoluteness and does not distinctly apply for models describing the whole forecasting chain. Similarly, methods are often categorized based on the timescale of the forecast. This is, however, not a fundamental property inherent to a forecasting model, and as such not an appropriate discriminator. A last common practice is distinguishing between deterministic and probabilistic methods, arguably one of the most important characteristics of a forecast. This attribute is however alterable by the choice of postprocessing step (Yang and van der Meer, 2021) and as such does not represent a property inherent to the model. Given the shortcomings of current classification methods and scarcity of complete step-by-step descriptions of the RES forecasting process, there is a critical imperative to establish a simple but fundamental framework to address these issues.

1.3. Contribution of this work

This work aims at providing a general overview of the different stages which accumulate to RES forecasting, while focusing on wind and solar energy, listing the various approaches to tackle at each step and mentioning the state-of-the-art best performing methods, without going into detail. Where needed, concepts are defined and provided with the appropriate context. As such, a clear and holistic framework for the complete renewable energy forecasting process emerges, as depicted schematically in Fig. 1. Outlining the intricate RES forecasting process step-by-step, while providing definitions for widely used concepts, brings clarity in a process which is too often presented as a confusing sequence of algorithms. Additionally, breaking a model down to parts allows others to straightforwardly optimize and apply each element.

The core distinction between direct and indirect forecasting is used as a foundation to carefully analyze the complete process, as shown in Fig. 1. Studying the differences between these two pathways in terms of data, spatial and temporal scopes and model complexity can help in identifying ideal approaches for future forecasting tasks. This approach allows for a comprehensive understanding of forecasting models that goes beyond the mere comparison of evaluation metrics between different methods. A more complete understanding of the differences between direct and indirect methods could lead to a generalized framework presenting tailored renewable energy forecasting models suitable to the particular forecasting task at hand. In order to maintain a bird's eye view, the RES forecasting model is envisioned here as consisting of several (chronological) steps, at each of which a certain approach should be taken (e.g. statistical, physical, ML or hybrid). The term *hybrid model* is, despite being frequently used, rarely defined in the literature. Here, it is envisioned to mean the following:

A ***hybrid RES model*** *is a model for forecasting renewable energy sources where at least two methods with different natures are used at a different or equal chronological point in the forecasting proces.*

In essence, a RES forecasting model takes meteorological observations (e.g. wind speed) as input in order to provide an educated guess regarding the matching power output (e.g. wind power). Fig. 2 depicts all steps of the RES process, together with the most important classes of possible techniques to carry out the task at hand. This diagram essentially entails the structure of this paper. The following section lists the various types of possible input data for the RES forecasting process, while Section 3 discusses the most widely employed preprocessing techniques. Section 4 discusses the core of the RES forecasting process, namely the actual power forecasting, where the distinction between direct and indirect forecasting is made. The latter is represented by the bottom pathway in Fig. 1, while the former corresponds to the upper path. Next, a discussion of possible postprocessing techniques follows in Section 5. Finally, the most significant evaluation methods are assessed in Section 6 before ending with a discussion, concluding remarks and possible future prospects in Section 7.

2. Data for RES forecasting

The data supplied as input to a model directly impacts its performance and consequently is of vital importance (Yoosefdoost et al., 2022). Careless input selection can lead to forecast errors and jeopardizes the model's overall performance (Ahmed et al., 2020). To avoid any confusion regarding the operation of the model, it is imperative to clarify not only the different types of input used but also to state their origin. In the context of RES forecasting, various kinds of input are commonly used. They can roughly be divided into four categories: observations, modeled data, geographical info and energy infrastructure. A non-exhaustive list of features belonging to these categories as input for a RES model is given in Table 1. The first and most obvious kind are observations of meteorological variables and related parameters. To forecast future wind and solar power, time series of past wind power and photovoltaic (PV) power output, typically originating from renewable power plants, are often used as input (Hu et al., 2018; Zhang et al., 2020; Akhter et al., 2022; Rafati et al., 2021; Ahmad et al., 2018). These historical power series form the basis for direct forecasting methods, while they can serve as supplementary input for their indirect counterparts. Next, a whole range of meteorological variables directly influence renewable energy output such as solar irradiance, temperature and humidity for PV output (Lateko et al., 2022) or wind speed, sea level pressure and dew point for wind power

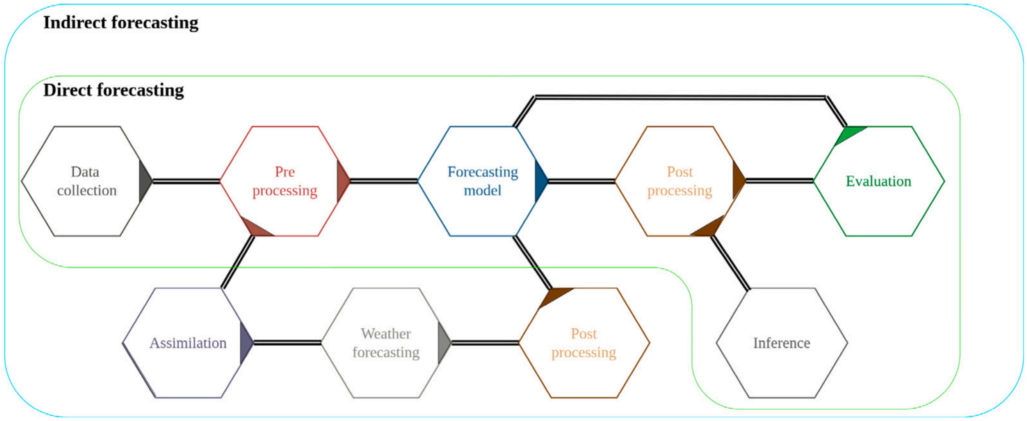


Fig. 1. A complete overview of the RES forecasting scheme, including all potential stages of a forecasting model, presented chronologically from left to right. Two distinct approaches are evident: direct forecasting is represented by the uppermost pathway, while indirect forecasting is illustrated by the lower counterpart. Colored arrows indicate the direction of the RES forecasting process.

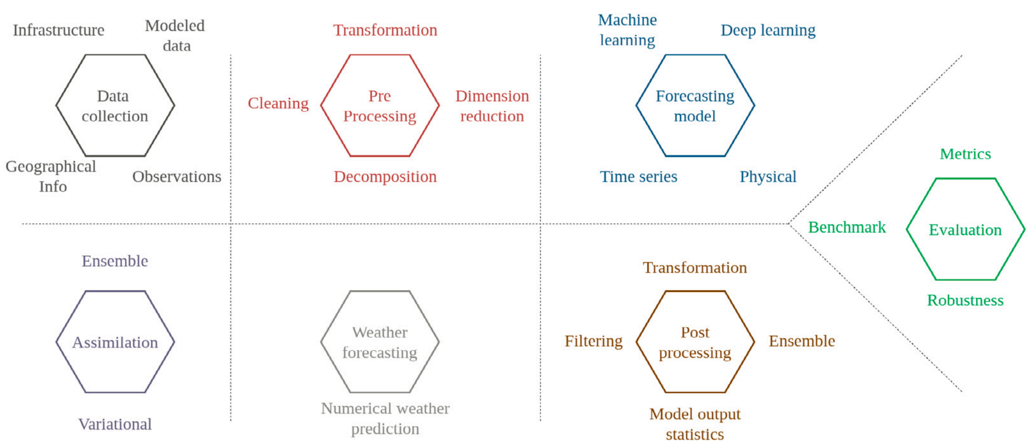


Fig. 2. A complete, schematic depiction of the RES forecasting process. The same elements of the process as in Fig. 1 are presented where additionally categories of approaches for the various stages in the RES forecasting scheme are provided.

Table 1
Various types of input that can be supplied to a RES model. Possible examples of each type are presented.

Observations	Modeled data	Geographical info	Infrastructure
Temperature, humidity, pressure, irradiance, wind speed, measured wind and solar power, …	Past or future NWP output: wind speed, solar irradiation, air temperature, humidity,..	Topographic terrain features, altitude, longitude, …	Type of PV cell, hub height, PV cell inclination, …

output (Ouyang et al., 2017; Vladislavleva et al., 2013). Observations of these variables from difference sources such as weather stations, satellites, radiosondes are commonly used to predict renewable energy power (Lateko et al., 2022; Ahmad et al., 2018; Zjavka, 2020; Ouyang et al., 2017; Vladislavleva et al., 2013). Observations are, however, not always readily available for certain locations at certain times, and they can be costly or incomplete. To overcome these shortcomings, the output of Numerical Weather Prediction (NWP) models, such as the worldwide renowned integrated forecasting system (IFS) developed by the European Centre for Medium-range Weather Forecasts (ECMWF) (ECMWF, 2021), can be used as input for RES models (Böök and Lindfors, 2020; Al-Yahyai et al., 2010). NWP modeled values, both for the past and future, for solar irradiance and temperature can for example be employed to forecast PV power (Böök and Lindfors, 2020; Bacher et al., 2009), while correspondingly modeled values for wind speed and temperature offer the means to predict wind power (Zhang et al., 2020; Mujeeb et al., 2019a; Xu et al., 2015; Vaccaro et al., 2011). As explained in Section 4.2.2, these NWP models form the backbone of indirect forecasting but are absent in direct methods. Next to meteorological variables, geographical properties of the location where the wind turbines and PV cells are installed have an effect on energy output. Complex terrain properties of wind or solar farms can be taken into account when predicting renewable energy production (Qian and Ishihara, 2022; Lurwan et al., 2014). Lastly, the properties of the PV cells and wind turbines producing the energy in question must be considered. The type or orientation of a PV cell plays a role in the amount of energy it produces (Mubarak et al., 2023; Hossain et al., 2017; Böök and Lindfors, 2020), whereas the rotor swept area and hub height influence the ultimate energy output of a wind turbine (Ge et al., 2020).

3. Preprocessing

As the input data is selected, the individual datasets need to be modified prior to the actual forecasting. This process is called data preprocessing and it encompasses a wide range of techniques, ranging from trivial feature selection to rather complex data transformations. The following broad definition for preprocessing inspired by Mishra et al. (2020) and Rabier (2011) is provided:

Data Preprocessing *refers to the modification of raw data in order to simplify the data, complete it or remove unwanted variability and irregularities with the goal of preparing the data for assimilation or forecasting.*

The first crucial preprocessing step in the RES forecasting process involves data cleaning, of which the removal of outliers from the input data is a first important example. This can be achieved by various techniques like e.g. Gaussian fitting (Wang et al., 2020a). Outliers may occur due to different reasons, turbine failure can, for instance, lead to outliers in wind power data. In contrast to removing faulty or misleading data, there is the process of data completion, which involves adding essential but missing data. The absence of data can be explained by equipment failure or temporal site closure, among other reasons (Ghimire et al., 2019). Examples of techniques applied in the literature to tackle the issue of missing data are linear interpolation (Peng et al., 2020), particular functions in statistical software (Atique et al., 2019) or filling data gaps with the mean values of previous data points (Ghimire et al., 2019).

Next, data transformation encompasses another wide range of important preprocessing techniques. First, normalization of the data is imperative to ensure a similar scale for all input features, given that the RES forecasting process often relies on different meteorological variables as input which often have dissimilar scales (Alkhayat and Mehmood, 2021). This step is necessary to avoid computationally ill-conditioned calculations, particularly if machine learning techniques are employed later in the process (Sharifzadeh et al., 2019). A myriad of normalization methods exists, where the most prominent examples are min–max normalization (Mujeeb et al., 2019b) and z-standardization (Manero et al., 2019). Sometimes more advanced data transformations can be applied in order to ensure the input data has the desired properties, such as a certain degree of symmetry, variance stability or normality which is a precondition for particular statistical forecasting methods (Alghamdi et al., 2019). A Box–Cox transformation can, for example, be applied to obtain Gaussianity (Voyant et al., 2020) while a logarithmic transformation can reduce skewness (Incremona and De Nicolao, 2022). Changing the temporal or spatial resolution is a last important subclass of data transformation (Rabier, 2011). This is particularly relevant for indirect RES forecasting processes involving NWP, since these models operate on a grid of certain spatial resolution, where observations used often need to be spatially averaged to comply with the grid. Similarly, to match with the fixed time step of the model, data might need to be averaged in the time domain Rabier (2011). Next to averaging, interpolation or downscaling of data might be necessary to acquire the desired resolution.

Dimensionality reduction covers another important class of data preprocessing techniques for the RES forecasting process. These methods are most relevant since the values of numerous meteorological variables over a long period of time can be of interest when forecasting solar and wind power, resulting in tremendous amounts of data. In order to minimize necessary computational resources and avoid loss of generality, dimensionality reduction is necessary, which can be done both by feature reduction or feature extraction (García-Cuesta et al., 2023). Additionally, Since the correlation between power output and all sorts of meteorological variables is case-specific, i.e. depends on the location and local climate, researchers should carefully perform feature selection methods (Alkhayat and Mehmood, 2021). Commonly used methods to perform dimensionality reduction can mainly be found in the domain of machine learning, where some important algorithms are the Auto-Encoder (AE) (Zhang et al., 2019), Principal Component Analysis (PCA) (Wang and Chen, 2020) and the K-means clustering algorithm (Ayodele et al., 2019).

Lastly, decomposition techniques are by far the most employed preprocessing methods for RES forecasting (Wang et al., 2019a; Lai et al., 2020). The general idea is to decompose a complex, noisy time series into various, more understandable frequencies using an iterative process. These signal processing techniques serve to extract meaningful features from complex data. In the context of RES forecasting, popular decomposition techniques are Discrete Wavelet Transform (DWT), Empirical Mode Decomposition (EMD) or Wavelet Packet Transform (WPT). The latter has proven to be the most accurate (Mujeeb et al., 2019a). This iterative process decomposes the signal in a high and low frequency component at each iteration. The decomposition into wavelets provides useful information in both the time and frequency domain for non-stationary signals such as wind speed and power time series (Yang et al., 2017). Wavelet decomposition is indispensable when it comes to enhancing the prediction accuracy of wind speed and power time series (Meng et al., 2016). Wavelet packet transform is often used in combination with a deep learning technique, where often a variation of deep neural networks is chosen to forecast RES later in the process (Mujeeb et al., 2019a; Meng et al., 2016; Wang et al., 2018c; Azimi et al., 2016; Nguyen Trong et al., 2023).

4. Forecasting power

Once input data is gathered and preprocessed, one arrives at the core of the process, i.e. the actual power forecasting. The first essential feature concerns the prediction horizon, i.e. at what point in the future does the power value need to be calculated? As many different interpretations of short and long time horizons exist in the literature, it is advisable to explicitly define the intended meaning of these terms. In the remainder of this paper five different prediction horizons are distinguished: now (0–5 min), very short (5–30 min), short (30 min to 6 h), medium (6 h to 1 day) and long (more than one day) (Hossain et al., 2017). Table 2 lists this classification together with their individual applications (Alkhayat and Mehmood, 2021; Hossain et al., 2017; Ahmadi et al., 2020) .

Next, the appropriate algorithm should be selected to forecast the power output. The common division between hybrid, physics-, statistics- and ML-based RES models often employed in the literature and mentioned in Section 1 is usually based on the choice of technique in the actual forecasting step of the RES process. A vast amount of forecasting methods exist in each of these classes, where the usefulness of each method highly depends on time horizon, location and feature selection, among others (Alkhayat and Mehmood, 2021; Gupta and Singh, 2021). It is therefore not particularly insightful to study power forecasting by attempting to list every possible forecasting technique, given their abundance and sporadic effectiveness. A more fundamental characteristic of a particular RES forecasting process is whether the solar and wind power data is estimated *directly* from input data or rather *indirectly*, by first forecasting solar radiation and wind speed.

4.1. Direct forecasting

Before delving into the methods used for direct forecasting in more detail, it is advisable to explicitly define the concept (Gupta and Singh, 2021; Başaran et al., 2020; Yakoub et al., 2023):

Direct forecasting *of renewable energy sources refers to the forecasting of renewable power production directly from available historical data, without first forecasting other meteorological variables.*

In recent years, direct forecasting has been applied more widely in solar and wind power forecasting as compared to the indirect method (Başaran et al., 2020; Piotrowski et al., 2022b), due to the increased adoption of renewable energy sources and the growing availability of power data measurements. Most of the papers concerning direct RES forecasting supply historical power data with additional meteorological input such as temperature, humidity, wind direction among other, with the goal of improving the forecasting accuracy. The correlation between various input variables and the eventual forecast accuracy is however location dependent (Alkhayat and Mehmood,

Table 2
Different prediction horizons together with their possible applications.

Prediction horizon	Time ahead	Applications
Now	0 to 5 min	Managing ramp rates and smart grids, ensuring grid stability
Very short	5 to 30 min	Electricity pricing, control strategies
Short	30 min to 6 h	Economic load dispatching, power scheduling
Medium	6 h to 1 day	Unit commitment, energy storage dispatching
Long	More than one day	Maintenance planning, long-term feasibility

2021) and inclusion of additional features does not always guarantee improved performance (Jebli et al., 2021) and can even lead to decreased accuracy (He et al., 2022). As direct forecasting exploits the relationship of the power variable to be forecasted with its past values, it tends to be more accurate on rather short prediction horizons (Son and Jung, 2020). As such, most direct wind and solar power forecasting research is concerned with short or medium forecasting horizons, where long-term predictions are rarely investigated (Ahmed et al., 2020; Ahmadi et al., 2020; Piotrowski et al., 2022b).

4.1.1. Direct forecasting techniques

The lionshare of direct RES forecasting techniques are data-driven. Among these methods, linear statistical time series techniques are commonly used in direct power forecasting. These models typically require less data than deep learning models and outperform physical methods on very-short to short timescales (Ahmed et al., 2020; Zhou et al., 2020). Another clear advantage of time series models is their simplicity, given that they are relatively easy to understand and implement. As time series models typically extrapolate historical time series to points in the near future, as depicted in Fig. 3(a), one only needs observations of the variable in question (Khashei and Bijari, 2011). One widely applied example of such methods is the AutoRegressive-Moving-Average (ARMA), which combines two polynomials: one for the AutoRegression (AR) and one for the Moving Average (MA). ARMA exhibits high accuracy for power forecasting on very short time scales but experiences a decline in performance as the prediction horizon increases (Wang et al., 2018). The AMRA model, however, lacks the capability to deal with non-stationary time series (Sharadga et al., 2020), a characteristic frequently observed in both wind and solar power time series (Tian, 2023; Cheng et al., 2023). Non-stationarity, due to e.g. seasonality (Sangwan and Herrmann, 2020), can be removed from a time series by applying the AutoRegressive Integrated Moving Average (ARIMA) model. Consequently, ARIMA has been commonly employed to directly forecast power production based on non-stationary historical power time series, see e.g. Atique et al. (2019).

Nevertheless, when a certain degree of randomness and uncertainty is present in the time series, which is often the case for weather-related variables, the linear models discussed above fail to achieve the required accuracy. When it comes to time series predictions that involve non-linearity, ML algorithms outperform the traditional, linear statistical models (Chen et al., 2022). The significance of artificial intelligence, and ML in particular, grows in every sector (Aggarwal et al., 2022), so to do these ML-methods nowadays outperform other direct forecasting methods on short-term forecasting horizons (Wang et al., 2019a). Interest in the RES forecasting literature shifts away from more classic shallow machine learning algorithms, meaning algorithms with one or no hidden layer(s), towards DL methods, given their promising potential regarding unraveling non-linear features and high-level invariant structures in data (Wang et al., 2019a; Alkhayat and Mehmood, 2021). Classical ML algorithms have, however, been widely applied in the RES forecasting literature in recent years, either as sole forecasting technique or combined with other ML or DL algorithms in a hybrid format. Artificial Neural Networks (ANNs), Support Vector Machine (SVM) and Random Forest (RF) are three frequently applied ML algorithms in the context of renewable energy forecasting. They are readily employed, do not require vast computational resources and can be highly interpretable (Xu et al., 2021). As such, these models are often used for direct PV and wind power forecasting on the short to medium-term, where historical power data is almost always supplemented with additional meteorological data (Khandakar et al., 2019; Li et al., 2020a; Pan et al., 2020; Lahouar and Ben Hadj Slama, 2017; Huertas Tato and Centeno Brito, 2018; Ledmaoui et al., 2023).

In recent years, research into DL applications for renewable energy forecasting has flourished, as various novel methods recently have been proposed (Alkhayat and Mehmood, 2021; Ying et al., 2023). As compared to the more classic ML models discussed above, DL networks can readily learn from large, possible imbalanced and heterogeneous datasets and unravel complex non-linear relationships between the predictors and the power output (Ying et al., 2023; Verma et al., 2023; Pramono et al., 2019). As such, these methods tend to outperform other data-driven methods on solar and wind power forecasting (Gupta and Singh, 2021; Hossain et al., 2021). In both solar and wind power forecasting, convolutional neural networks (CNNs) and long short-term memory networks (LSTMs) are the two most prominent deep learning algorithms in the current literature (Ying et al., 2023) and are often employed in combination. CNNs are capable of extracting the most relevant features of meteorological data due to their convolutional layers, while a pooling layer reduces data quantity by removing redundant characteristics. This way, CNNs achieve high accuracy in weather pattern classification and can learn complex relations between the input features and the power output (He et al., 2022; Li et al., 2022). This last capability results in a high accuracy for wind and solar power forecasting on short to medium prediction horizons, outperforming classical ML algorithms such as SVM and RF (Yu et al., 2019; Huang and Kuo, 2019). LSTMs, on the other hand, are capable of detecting long-term dependencies in a time series in addition to discovering hidden, non-linear relationships between variables, resulting in more accurate forecasts as compared to classical ML algorithms (Li et al., 2020b; Tarek et al., 2023). Their capacity to memorize the relationships between input and output makes them more accurate than CNNs on the medium prediction horizon (He et al., 2022). Both LSTMs and CNNs are frequently used for RES forecasting on the very short to medium prediction horizons, where historical power output is usually supplied with additional meteorological input variables (Li et al., 2020b; Tarek et al., 2023). Lastly, deep belief networks (DBN), which are generative probabilistic models which learn the distribution of the input data in order to realize more accurate output, are commonly used in the RES forecasting literature (Chang and Lu, 2020). The main advantage of this algorithm is its capability to handle strongly irregular data and computational efficiency (Ying et al., 2023; Chang and Lu, 2020).

To take the advantage of multiple methods, recent research often combines two (or more) complementary forecasting models. This approach often proves useful given that power output series can be decomposed in different frequencies, contain residuals and possibly exhibit various characteristics, such as seasonality or trend. Particular algorithms can be more fit to tackle the direct forecasting of high frequency components while others can be used for lower frequencies (Han et al., 2022). This approach requires the application of a decomposition technique in the preprocessing step, as discussed in Section 3. Similarly, different algorithms can be applied for the forecasting of seasonality and residuals (Zhang et al., 2022a), or for extracting temporal as opposed to spatial characteristics from the data (Zhao et al., 2023). Hybrid models in general outperform classical, single ML or DL models in terms of accuracy and speed and as such represent a promising path towards effective renewable energy forecasting (Mosavi et al., 2019).

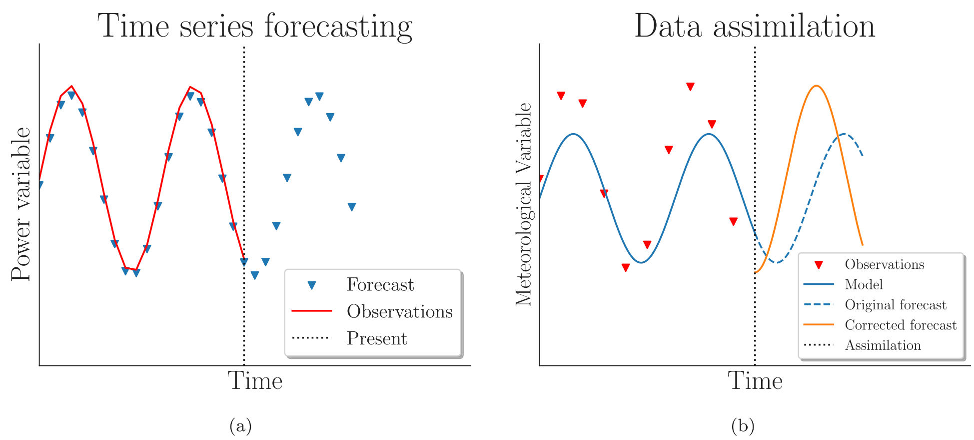


Fig. 3. (a) General graph depicting time series forecasting. (b) Assimilation of observations and forecasts in the context of forecasting a meteorological variable. Figure inspired by an article on data assimilation by the ECMWF (ECMWF, 2017).

4.2. Indirect forecasting

In contrast to direct RES forecasting, the indirect forecasting route involves a preceding step of weather forecasting, primarily focusing on variables such as wind speed and solar radiation for the prediction of wind power and solar energy, respectively. As such, indirect forecasting is defined as follows:

Indirect forecasting *of renewable energy sources entails all methods in which meteorological variables rather than power data are forecasted prior to and in function of the power forecast.*

Indirect forecasting, and therefore weather forecasting, becomes necessary in cases when historical meteorological data is unavailable, e.g. when assessing the viability of a location for a new wind farm or PV plant, and when making forecasts on medium and long-term horizons (Gupta and Singh, 2021; Piotrowski et al., 2022b; Bouche et al., 2023; Jimenez et al., 2016). Weather forecasting constitutes an autonomous field on its own, which will only be broadly discussed here. Numerical weather prediction models, which are physics-based modeling techniques, are the operational tools for weather forecasting in meteorological services worldwide, although progress is also being made on the machine learning front concerning weather forecasting (Schultz et al., 2021). When applying NWP models, data assimilation precedes weather forecasting. The latter is discussed in Section 4.2.2, while the former is the subject of the next subsection.

4.2.1. Data assimilation

NWP models are essentially mathematical tools serving to solve initial value problems, where the initial condition of the atmosphere serves as starting condition from where the time-dependent physical equations describing the evolution of the atmosphere can be solved (Ghil et al., 1981). The initial values for meteorological variables supplied to the NWP model will contain a certain degree of error, which will quickly enlarge in time due to the chaotic nature of the atmosphere (Reichle, 2008). Consequently, the accuracy of NWP models diminishes as the error enlarges as it propagates through time due to the imperfectness of both the model and the initial conditions. This can be overcome by repeatedly generating new initial conditions, the main origin of NWP model errors, using observations, through the process known as data assimilation. In this process, the model is initiated using the available initial conditions, and as it runs, observations are continuously collected (Fig. 3(b)). These observations and the current model are then assimilated to generate new initial conditions used to run a new, adjusted model (ECMWF, 2017). Data assimilation is regarded as the techniques used to combine mathematical models with observations (Kalnay, 2003) and called *the art of combining model and observations* (Rabier, 2011). Therefore, data assimilation in the context of RES forecasting is defined as follows:

Data assimilation *encompasses the mathematical techniques used to combine datasets of observations with the output of theoretical models in order to improve RES forecasting.*

Operational data assimilation techniques can be divided into two main categories, being ensemble methods and variational methods, together with hybrid forms thereof Gustafsson et al. (2018). Variational methods fall within the category of optimization problems, since the goal is to minimize a cost function in order to fit the model in question to the observations and find a single optimal state (Bannister, 2017). Ensemble methods, on the other hand, generate an ensemble of forecasts and as such estimate the true state of e.g. the atmosphere with a probability distribution (Mandel et al., 2011). In the class of ensemble methods, the Ensemble Kalman Filter (EnKF) (Evensen, 1994) is one of the most commonly used methods which exists in a myriad of different forms (Houtekamer and Zhang, 2016). The original Kalman filter (KF) is a linear, recursive filtering algorithm aimed at optimal fusion between a model's estimates and measurements (Kalman, 1960). It aimes at forecasting uncertainty reduction by making a weighted correction to the model's estimate using measurements, where the weight is based on both the model's and measurement's errors which are assumed to be Gaussian (Bishop et al., 2001). Contrary to KF, a general EnKF can handle non-normal error distributions and non-linearity between consequent states. After generating an ensemble of possible plausible states obtained by perturbing a best-guess estimate, the numerical model is applied to this ensemble of states (Evensen, 2003). Next, the measurements are assimilated to the ensemble, i.e. the true state is approximated by correcting the estimates using weights based on the measurements. The EnKF is widely applied, e.g. for the forecasting of wind speed (Wei and Weimin, 2010), wind power (Chainok et al., 2020) or solar insolation (Ray et al., 2022).

Variational methods are the second class among the most widely used data assimilation methods. As opposed to the ensemble of states generated when using the EnKF, variational methods aim at estimating a single optimal evolving state by minimizing the cost function representing the mismatch between model and observations (Bannister, 2017). The most widely used variational method is the four-dimensional variational data assimilation method (4D-Var) developed by the ECMWF (Courtier et al., 1994), which added a time dimension to the already existing 3D-Var method (ECMWF, 2017). Among many other things, 4D-var can be used in the process of solar irradiance forecasting (Huva et al., 2020) or estimating wind energy potential (Nino-Ruiz et al., 2020).

4.2.2. Weather forecasting

Once observations are assimilated with the initial conditions, within NWP models, the differential equations can be solved to provide forecasts of meteorological variables, of which, with regards to RES, wind speed and solar irradiation are the most important variables. As generating these dynamical forecasts requires extensive atmospherical knowledge and considerable computational resources, the task is usually carried out by (inter)national weather agencies, after which the output can be used by researchers to perform RES forecasting (Wang et al., 2022a). Examples of widely used, state-of-the-art global NWP models are the IFS of the ECMWF (ECMWF, 2023), the Global Forecast System (GFS) developed by the National Oceanic and Atmospheric Administration (NCEP) (NCEP, 2023) and the Unified Model (UM) maintained by the Met Office (Met Office, 2023). The Weather Research & Forecasting Model (WRF) developed by the National Center for Atmospheric Research (NCAR), on the other hand, is a state-of-the-art mesocale NWP model (NCAR, 2023). In addition to the dynamic equations incorporated in NWP models, Computational Fluid Dynamics (CFD) can be incorporated in NWP models in order to improve accuracy (Wang et al., 2018a).

4.2.3. Indirect forecasting techniques

After forecasting meteorological variables, the actual power conversion can be carried out in a similar fashion as for direct forecasting. A myriad of various forecasting techniques exist for indirect forecasting, which take predictions of weather variables as input in order to calculate the estimated power output. Physics-based forecasting is frequently considered to be identical to indirect forecasting in the literature (Alkhayat and Mehmood, 2021; Markovics and Mayer, 2022), as in the latter NWPs are often employed for the forecasting of meteorological variables. However, if one dissects the RES forecasting process as depicted in Fig. 1, indirect forecasting can be carried out by utilizing NWP output as input for a data-driven algorithm which calculates the power forecast (Wang et al., 2018b), resulting in a hybrid method rather than one that is purely physics-based.

When it comes to physics-based models for power forecasting, fewer methods exists as compared to the wide variety available in the data-driven catalogue, which are discussed later in this section. One example can be the power curve, which, in the most broad sense, relates input variables, e.g. wind speed and solar irradiance, to power output. For wind power, the power curve quantifies the relationship between wind speed at hub height and power output (Yan et al., 2019), while a similar definition exists for irradiance and solar power (Yang et al., 2023). Many examples of physics-based, deterministic mathematical relationships between wind speed and the capacity factor for power generation; given by e.g. a polynomial (Diaf et al., 2007) or a logistic function (Villanueva and Feijóo, 2018) can be found in the literature. Similarly, deterministic polynomial models (Samy et al., 2021) or logaritmic relations (Nyenah et al., 2022) exist for solar power output. Recently, more advanced physical model chain approaches have been proposed, which combine a series of models each performing a task in the power conversion process, taking both meteorological input and physical properties of the power conversion tool into account (Wang et al., 2022a; Yang et al., 2023).

In addition to physics-based models, data-driven models are frequently combined with forecasted meteorological variables to estimate power output. Next to the usage of a single NWP model, such as the IFS of the ECMWF, multiple NWP models can be combined in order to improve forecasting accuracy (Jimenez et al., 2016). Generally, the prediction horizon typically ranges from medium to long, with forecasting horizons of less than 6 h being the exception rather than the rule (Jimenez et al., 2016; Wang et al., 2018b; Cervone et al., 2017; Eseye et al., 2017). Although classical ML algorithms such as ANNs and regression trees have been widely applied for indirect forecasting (Jimenez et al., 2016; Cervone et al., 2017; Eseye et al., 2017), the literature on indirect forecasting is shifting towards DL algorithms such as LSTMs and DBNs (Wang et al., 2018b, 2022b; Peng et al., 2021) given their improved accuracy (Hossain et al., 2017).

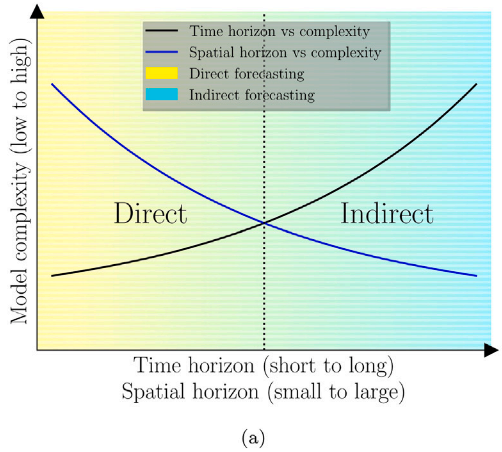
4.3. Comparing direct and indirect forecasting

Although rarely thoroughly explored in the literature, there are some significant differences in the application fields of direct and indirect forecasting. The largest differences are related to required prediction time horizon, data availability and the granularity of the location for which the forecasts are calculated. These factors play a central role in choosing between indirect and direct methods and subsequently in selecting the appropriate forecasting technique.

First, the prediction horizon is an important discriminating factor between direct and indirect forecasting, and has already been touched upon in Section 4.1.1, where a possible categorization of time horizons was presented in Table 2. In general, direct forecasting is more applicable for shorter time horizons while indirect forecasting performs better on longer horizons, where the boundary is situated between a few hours and a day ahead (Bouche et al., 2023; Jimenez et al., 2016; Wang et al., 2022b; Simeunović et al., 2022). NWP models typically used in indirect forecasting methods are not suited on shorter timescales given the time necessary for computation and data assimilation (Tawn and Browell, 2022). Direct data-driven methods, on the other hand, are more appropriate for shorter forecasting horizons. On scales from nowcasting to very-short-term forecasting, linear statistical time series methods have the advantage of simplicity and yet achieving a high accuracy, although errors accumulate as the time horizon grows (Piotrowski et al., 2022b; Son and Jung, 2020; Wang et al., 2018; Jimenez et al., 2016). On the short-term, direct ML, and especially DL, techniques can outperform indirect methods (Simeunović et al., 2022). These techniques are suitable to model complex systems and unravel non-trivial relationship between the input meteorological variables and power output (Piotrowski et al., 2022b), especially on a timescale of a few hours. For medium and long-term forecasting, indirect forecasting, and NWP models more specifically, become the indispensable backbone of RES forecasting (Piotrowski et al., 2022a). One reason for this is that purely data-driven direct methods are incapable of extrapolating non-linear features this far into the future (Wang et al., 2022a), consequently accurate weather forecasting becomes vital on longer time horizons. Forecasts on horizons much longer than a day are rare, given the difficulty to obtain NWP models for these timescales and the associated loss of quality which increases in conjunction with growing prediction horizon (Piotrowski et al., 2022b). Accordingly, the bulk of the literature is concerned with now, very-short and short-term forecasting, while a very limited number of papers investigate long-term RES forecasting (Ahmadi et al., 2020). The black curve in Fig. 4(a) shows the increasing complexity of forecasting models with increasing time horizon.

Next, spatial granularity, i.e. the spatial resolution, is an important discriminator between direct and indirect forecasting. When highly localized predictions are necessary, for example a single PV panel or a few wind turbines (Pan et al., 2020; Han et al., 2022), direct forecasting has advantages over its indirect counterpart. Using a direct data-driven method based on historical data of that specific site allows for local characteristics to be taken into account (Poolla and Ishihara, 2018). Weather variables forecasted by means of NWP, on the other hand, often have a limited resolution and are therefore less fit to serve for the estimation of local energy processes (Bouche et al., 2023). However, combining these forecasted variables with local data, if available, could be a solution to this problem for site-specific modeling (Kay, 2016). As the spatial scale increases, so does the need for broadly spaced weather forecasts (Ye et al., 2022), given that capturing large scale phenomena requires more global weather data (Poolla and Ishihara, 2018). A larger spatial resolution results in more complex models, as the blue curve in Fig. 4(a) indicates. This figure also indicate that for small spatial and time horizons, direct forecasting is advised while the indirect method is suited for longer prediction horizons.

Lastly, given the inherently data-driven nature of direct forecasting, its dependence on qualitative, historical data is obvious. In the absence



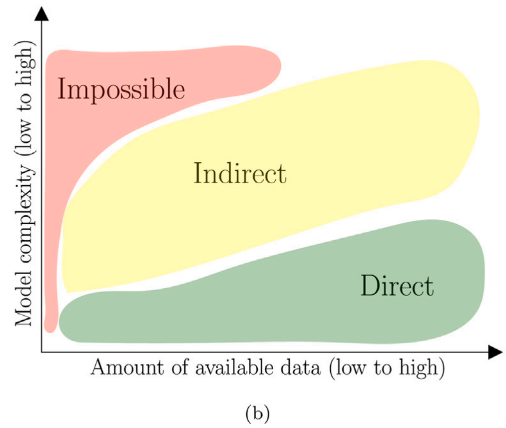


Fig. 4. (a) Model complexity increases for growing time horizon, while the opposite relation holds for the spatial horizon. The shaded regions depict when direct and indirect forecasting are advised, as a function of temporal and spatial granularity. The color gradient illustrates the lack of absolute boundary between the two forecasting methods. (b) Possible complexity of RES forecasting models related to the amount of available data.

of historical data, which can occur when assessing new power plant locations, in case of sensor malfunctioning or when forecasting in remote areas, one is reliant on indirect forecasting (Yang et al., 2023) or transfer learning. The former does not require abundant historical data and can therefore be conducted in the case of data scarcity. However, accurate forecasting of weather variables also relies on substantial amounts of data in the form of initial and boundary conditions (Son and Jung, 2020). Transfer learning, on the other hand, can be employed to transfer knowledge from a model trained priorly on adequate data, which performed a similar RES forecasting task, to the current model experiencing data unavailability. As such, direct forecasting can be employed without vast amounts of historical data and without weather forecasting being necessary, although much further research is required (Sarmas et al., 2022). In the case historical data is present, direct forecasting can be applied. Most studies applying a direct method supply historical power data with additional meteorological data such as temperature or humidity (Alkhayat and Mehmood, 2021). Direct data-driven methods require a rich supply of historical data (Ying et al., 2023) and to be able to catch seasonal patterns, RES forecasting models need at least one calendar year of training data (Piotrowski et al., 2022b; Sarmas et al., 2022). Therefore, sufficient data is indispensable in order to train sophisticated models and accurately regress the complex relationships between input variables and power output. When historical data is scarce, simple, linear statistical time series models can be a solution to directly forecast on (very) short time horizons since only observations of the variable in question are necessary (Khashei and Bijari, 2011). Fig. 4(b) indicates in a schematic way the amount of data needed in order to construct a forecasting model of a certain complexity. With a small amount of data simple direct forecasting models can be realized. While large amounts of data, on the other hand, allow for a more complex RES forecasting model. Indirect RES forecasting models are more complex as compared to their direct counterparts based on the same amount of data due to the weather forecasting component. Building complex models based on very limited data is virtually impossible, as indicated by the red zone in Fig. 4(b).

5. Postprocessing

As the name suggest, postprocessing takes place after the forecasting of the variable in question and aims at maximizing forecasting accuracy. A multitude of postprocessing methods exists, ranging from basic techniques like adjusting for measurement device bias by subtracting a term to more complex approaches involving ML or statistics, such as the member-by-member approach (Van Schaeybroeck and Vannitsem, 2015). Postprocessing should not be confused with model evaluation, which is the subject of the next section, where the goal is to simply measure the skill of the model, not improve it. Additionally, postprocessing is vital both for weather forecasts and the eventual power forecasts. The methods discussed below can be applied to postprocess both the power forecasts themselves or the weather variable forecasts in an earlier stage of the RES forecasting scheme. The following definition is adopted here (Yang and van der Meer, 2021):

Postprocessing *refers to all techniques applied to initial weather or RES forecasts in order to improve the goodness of fit of the forecast.*

A first, straightforward category of postprocessing techniques is that of the data transformations. In many cases, it reverses a transformation done before the forecasting, i.e. during the preprocessing step (see Section 3). Typical transformations are denormalization (Zhang et al., 2022a), inverse wavelet transforms (Almaghrabi et al., 2022) or resolution changes. The latter might be necessary when the forecast does not attain the required temporal (or spatial) resolution. Downscaling (requiring a lower resolution) can be done by aggregating data before the forecast, while upscaling (requiring a higher resolution) is performed on the initial low-resolution forecast (Yang and van der Meer, 2021). The latter can be done, for example, by replacing the forecast with similar historical data of higher resolution (Yang et al., 2019). Next, filtering is a popular, sequential postprocessing category which aims at finding the true state of the predictand by stabilizing and denoising the forecasted time series based on recent observations (Yang and van der Meer, 2021; Pereira et al., 2019). The most prominent example is the Kalman Filter (Zhang et al., 2022c), as discussed in Section 4.2.1.

Weather forecasts are often accompanied by systematic modelled biases and are therefore in strong need of effective postprocessing techniques (Yang, 2019). The most popular class of techniques for postprocessing weather forecasts, and NWP models in particular, is model output statistics (MOS) (Zhang et al., 2022d). The MOS techniques essentially involves representing the bias in NWP model output as a regression formula that is a function of relevant parameters (e.g. zenith angle) (Yang and van der Meer, 2021). The function fitted can then be used to calculate the expected bias of a new forecast (Yang, 2019). This can essentially be done using any regression form and as such an endless number of techniques exist (Yang and van der Meer, 2021). Possible examples are a simple linear regression model (Lazić et al., 2014; Theocharides et al., 2020), fourth grade polynomials (Lorenz et al., 2009d) and neural networks (Pereira et al., 2019). MOS techniques specifically developed for the postprocessing of ensemble weather forecasts are called ensemble MOS (EMOS) (Baran and Lerch, 2016). Various other ensemble postprocessing methods exist, similar to the methods discussed for ensemble forecasts in Section 4.2.1 regarding data assimilation, which are capable of correcting for biases while producing probabilistic information regarding the forecast uncertainty (Vannitsem et al., 2020). These techniques are called ensemble methods, which produce various outcomes for the same forecasts using different data or models, by for example perturbing the initial conditions or by combining the results of different models (Yang and van der Meer, 2021). As such, postprocessing forecasts with an ensemble method does not result in one deterministic forecast value, but rather in an ensemble of forecasts. An important subcategory in these ensemble methods is the Analog Ensemble (AnEn), which is inspired by the frequent repetition of weather patterns (Yang and van der Meer, 2021). This method matches the forecast with historical, near-identical forecasts and uses the corresponding historical observations to create an ensemble of forecasts. This essentially provides a probability distribution, from which the mean or median can be calculated to obtain a deterministic forecast (Davò et al., 2016). For example, solar power ensembles can be generated by combining past power production observations, where this power data is linked to historical NWP forecasts similar to the current weather forecast (Alessandrini et al., 2015). Another statistical technique, the member-by-member approach, is developed specifically to postprocess ensemble weather forecasts (Van Schaeybroeck and Vannitsem, 2015) and is used to process ECMWF forecast by the Belgian met service (Demaeyer et al., 2021). This approach corrects each member of the ensemble individually by means of a linear map, retaining correlations present in the data (Van Schaeybroeck and Vannitsem, 2015). Lastly, very recently, a promising new ensemble method was proposed making use of hierarchical transformers, a natural language processing technique based on neural networks, and applied in order to improve ECMWF forecasts (Ben-Bouallegue et al., 2023).

6. Model evaluation

The last and crucial step in the process, before the model can be used for inference, comes down to the evaluation of the RES forecasting model. In the end, after going through all steps depicted in Fig. 1 passing data through various algorithms, what matters most is the quality of the final forecast. To assess this quality, answers to the following three questions should be formulated: (1) How well do the forecasts compare to actual observations, (2) How well does the model perform compared to other models and (3) How user-friendly is the model? Answering the first question essentially involves evaluating the model's accuracy, which can be quantified by using metrics such as the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and the coefficient of determination R^2 (Aslam et al., 2021). Many other metrics exist (Alkhayat and Mehmood, 2021) and given that these metrics each have certain limitations, as for example described in Willmott and Matsuura (2005) for the RMSE, the use of various different metrics is advised (Ding et al., 2022; Qi et al., 2023). Alternatively, the use of performance metrics that integrate multiple measures, such as the Kling-Gupta Efficiency (KGE), commonly used in hydrology, can provide a more balanced evaluation by combining three metrics: correlation, bias, and the ratio of variances or coefficients of variation (Gupta et al., 2009).

A new model can perform excellent with regards to the accuracy metrics described above, but if the lionshare of similar models in the literature perform better, the model is not that much of an innovation. As such, it is necessary to benchmark the models performance against the state-of-the art, or at least verify that the model performs better than the persistence model (Abedinia et al., 2020). The persistence model is a trivial method often applied in the literature, which assumes the state of a variable (e.g. solar power) at time $t+1$ is the same as at time t. It is imperative to know if a new proposed model performs at least better then this trivial method (Yahyaoui, 2018).

Next, the characteristics of the model are an important evaluation factor. A trade-off between computational complexity and model accuracy can be made by using the training and running time as evaluation indices for a forecasting model (Alkhayat and Mehmood, 2021). The former is one of the most important indicators for the evaluation of PV power forecasting models (Jailani et al., 2023), especially as short-term RES forecasting is becoming increasingly important (Woo et al., 2020).

Another important characteristic of a RES forecasting model concerns its robustness, which refers to the consistency of a models performance under varying or unusual conditions. In the context of RES time series forecasting, such conditions could take the form of outliers, data gaps, seasonality, unusual weather patterns or perturbations in the time domain Alkhayat and Mehmood (2021), Yoon et al. (2022). Testing a proposed forecasting method on multiple or all of these factors is imperative, as robust models are more reliable in applications, and it is vital to understand the circumstances under which the model may fall short. Lastly, extreme weather events are often lacking from training datasets, resulting in models not being able to accurately predict the occurrence of these events. This problem can be overcome by using generative ML algorithms to augment the dataset with artificially generated extreme events (Wang et al., 2019b).

7. Concluding remarks

7.1. Discussion

As solar and wind power become evermore present in the global energy landscape, our dependence on these renewable energy sources grows and the energy sector consequently exhibits a pressing need for accurate RES forecasts. Inaccurate forecasts have, furthermore, grave environmental and economical consequences, as they lead to imbalances and consequently an increase in carbon emissions due to the utilization of fossil reserves (Bruninx et al., 2014; Forbes and Zampelli, 2020, 2019). Accurate RES forecasts as such become vital for the operational management of our power grids (Elia, 2019), but remain a challenging endeavor due to the intermittent nature of solar and wind power. Realizing these accurate forecasts requires traversing several important stages, of which some have already been thoroughly reviewed in the literature. This paper, however, provided a clear description of all stages, studied in chronological order. As such, the complete process was presented in a comprehensive way, facilitating the study and optimization of each individual stage. Every step was concisely described while the state-of-the-art methods were presented. It is common practice in the literature to classify RES forecasting models into physical, statistical, machine learning-based or hybrid methods solely based on their use of algorithm in the forecasting step (Wang et al., 2019a, 2020b; Jiang et al., 2019; Meenal et al., 2022; Hodge et al., 2018; Hu et al., 2018). This approach is, however, too limited, since this work has made clear that at every point in the process, several possible techniques can be employed, belonging to the realm of either physics-based or data-driven methods. Instead, a holistic view on the RES forecasting process was presented, proposing a generalized framework based on the fundamental difference between direct and indirect forecasting, a characteristic inherent to the model as a whole. Moving beyond merely classifying methods based on their forecasting algorithm or performance regarding simple evaluation metrics, this paper sought to unravel why direct or indirect methods might be more suitable in particular applications. Each of these methods is expected to excel within dissimilar spatial and temporal scales, the reasons for which lie in their inherent differences in model complexity and data requirements. The latter issue of data requirement, and more specifically data availability, is a most relevant matter, rarely touched upon in the literature, given that the performance of a model is directly linked to the knowledge contained in the data it is trained on Jain et al. (2020), Gupta et al. (2021). Consequently, this work distinguished between direct and indirect forecasting from a data perspective, next to the more common discussion regarding the temporal and spatial application field of forecasting methods. Considering these factors when assessing the performance of RES forecasting models contributes to a more comprehensive understanding of the subject. Given the complete overview of the RES forecasting process and building on the distinctions between direct and indirect forecasting, a significant step towards a generalized framework is realized. This is, however, merely a rough first indication and considerable research still needs to be carried out to bring further clarity on the differences between direct and indirect forecasting.

7.2. Recommendations for future research directions

In depth research into the difference in application fields of direct and indirect forecasting constitutes a promising avenue for future work. Conducting profound research that compares indirect and direct forecasting could reveal more clear differences between these methods in terms of spatial, temporal and data aspects, beyond the indicative results presented here in Fig. 4. This could be realized, for example, by carrying out several studies employing various indirect and direct forecasting models on one or several widely used, benchmarked renewable energy datasets, such as the recently published dataset for statistical postprocessing (Demaeyer et al., 2023). This would allow for fair, quantitative comparisons between methods instead of isolated studies which differ too much for reliable comparison (Dueben et al., 2022). Systematic research conducted in this way could lead to the development of a generalized framework for renewable energy forecasting, offering tailored RES models for various application domains based on available data, required prediction horizon and spatial granularity .

Currently, direct forecasting models need vast amounts of data and are impractical in data-scarce environments. Investigating the feasibility of training models using physics-based knowledge, thus adopting an indirect approach, and subsequently applying these trained models directly warrants further investigation. Incorporating physics-based knowledge as we know it form indirect models into direct models will enhance performance on longer time horizons while reducing the need for data. An interesting approach could be to study the so-called black box of deep learning algorithms of well-performing, direct forecasting models to unravel the useful relations they contain regarding input data and power output, as all the mathematical relations contained in these models are known and can be studied (Maier et al., 2023). Similarly, transfer learning might constitute a potential means of circumventing the need for large amounts of data. Traditional DL models rely on extensive amounts of data to be build from scratch, whereas knowledge regarding parameter weight initialization and feature extracting can be transferred from already well performing forecasting models (Sarmas et al., 2022; Schreiber, 2019). Consequently, both the amount of required training data and time would be greatly reduced. Although promising results have been reported in this regard (Sarmas et al., 2022), further exploration in the literature remains necessary.

Lastly, given that the forecasting accuracy of both direct and indirect RES forecasting approaches depends on the performance of each individual stage as depicted in Fig. 1, their impact on the overall process requires more extensive research. While the importance of studying the impact of data availability has already been highlighted, and several studies regarding the accuracy of various forecasting techniques exist, it is equally important to pay similar attention to the other stages of the forecasting process. Preprocessing, for example, is a crucial aspect of the RES forecasting scheme that can have a substantial impact on prediction performance but has not yet been extensively explored (Lai et al., 2020).

CRediT authorship contribution statement

Aaron Van Poecke: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Hossein Tabari:** Conceptualization, Methodology, Supervision, Writing – review & editing, Visualization. **Peter Hellinckx:** Conceptualization, Funding acquisition, Methodology, Supervision, Visualization, Resources, Writing – review & editing.

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.

Data availability

No data was used for the research described in the article.

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