

Very Short-Term Wind Power Forecasting: State-of-the-Art

Decision and Information Sciences Division

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Very Short-Term Wind Power Forecasting: State-of-the-Art

by

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List of Abbreviations

AI	Artificial Intelligence
ANFIS	Adaptive Neural Fuzzy Inference System
ANN	Artificial Neural Network
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
ARPS	Advanced Regional Prediction System
AWPPS	Armines Wind Power Prediction System
bias	an estimate of the systematic error
BP	Back-propagation
CAPS	Center for Analysis and Prediction of Storms (USA)
CFD	Computational Fluid Dynamics
DA	Data Assimilation
DEM	Digital Elevation Model
DHT	Discrete Hilbert Transform
DMI	Danish Meteorological Institute
DWD	Deutscher Wetterdienst (German's Weather Service)
DWM	Diagnostic Wind Model
ECMWF	European Center for Medium-Range Weather Forecasts (UK)
EMD	Empirical Mode Decomposition
EWEC	European Wind Energy Conference
FAA	Federal Aviation Administration (USA)
f-ARIMA	Modified ARIMA
FIS	Fuzzy Inference System
FSL	Forecast Systems Laboratory (USA)
GFS	Global Forecast System
GMDH	Group Method of Data Handling
HIRLAM	High-Resolution Limited Area Model
HIRPOM	HIRlam POver prediction Model
IEA	International Energy Agency
IFS	Integrated Forecast System
IGCM	Intermediate Circulation Model (UK)
IMF	Intrinsic Mode Function

ITSM	Improved Time Series Method
KA	Kernel Adaline
KF	Kalman Filter
KH	Kernel Hebbian
KLMS	Kernel Least Mean Squares
LF-DFNN	Locally Feedback Dynamic Fuzzy Neural Network
LM	Levenberg Marquardt
LRC	Long-Range Correlation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MKL	Multiple Kernel Learning
MLP	Multilayer Perceptron
MM5	Fifth-generation mesoscale model
MOS	Model Output Statistics
MRI	Meteo-Risk Index
MSAR	Markov-Switching AutoRegressive
MSE	Mean Square Error
NAM	North American Mesoscale Model
NCAR	National Center for Atmospheric Research (USA)
NCEP	National Center for Environmental Prediction (USA)
NMAE	Normalized Mean Absolute Error
NOAA	National Oceanic and Atmospheric Association
NOGAPS	Navy Operational Atmospheric Prediction System
NPRI	Normalized Prediction Risk Index
NRMSE	Normalized Root Mean Square Error
NRL	Naval Research Laboratory (U.S. Air Force)
NWP	Numerical Weather Prediction
PSO	Particle Swarm Optimization
RAMS	Regional Atmospheric Modeling System
RBF	Radial Basis Function
REE	Red Eléctrica de España (Spanish Distribution Energy Company)
RKHS	Reproducing Kernel Hilbert Spaces
RLS	Recursive Least Squares
RMSE	Root Mean Square Error
RUC	Rapid Update Cycle
SCADA	Supervisory Control and Data Acquisition
SCP	Spatial Correlation Predictor

SDE	Standard Deviation of the Errors
SETAR	Self-Exciting Threshold Autoregressive
SP	Single Perceptron
STAR	Smooth Transition Autoregressive
SVM	Support Vector Machine
UM	Unified Model
VA	Viterby Algorithm
WASP	Wind Atlas Analysis and Application Program
WEFS	Wind Energy Forecasting System
WPF	Wind Power Forecasting
WPPT	Wind Power Prediction Tool
WRF	Weather Research and Forecasting Model
WTG	Wind Turbine Generator

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Abstract

Because of the high variability of the wind resource and the nonlinear relation between wind speed and power, wind power forecasting on the very short-term horizon is a complex task that is subject to the stochastic nature of the wind speed. At the same time, accurate forecasts are important for wind plant management and power system operations.

This report presents a comprehensive state-of-the-art review of very short-term wind power forecasting with a focus on forecasting horizons up to 6 hours ahead. The report describes both (1) numerical weather prediction (NWP)/physical, and (2) statistical/artificial intelligence (AI) forecasting techniques and models. We find that hybrid methods have shown to deliver better wind power predictions than persistence and most individual methods at the very short-term timescale. In fact, the hybrid approaches benefit both from the high level of accuracy in the physical models and of the computational learning capabilities of statistical/AI models. Therefore, the combination of both into a hybrid model is often the best approach. At the same time, the best forecasting methodology will also depend on the characteristics of the specific location as well as the intended use of the forecast.

The development of NWP/physical models with higher accuracy and resolution, as well as new and more sophisticated statistical/artificial intelligence methods, can both contribute to improve the quality of very short-term forecasts. In addition, at these timescales, particular attention should also be addressed to improve wind power and wind speed ramp forecasting algorithms.

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1. Introduction

The variability inherent in the wind resource implies that wind power is a fluctuating source of energy. Therefore, as the penetration of wind power into power systems increases, the development of accurate forecasting tools to predict the wind power becomes more crucial for all electricity market participants who seek to reduce the economic and technical risks associated with the uncertainty in wind power production. Wind power forecasting enables better power system operations terms of scheduling, unit commitment, and dispatch decisions, and also provide improved market trading for wind power producers [1][2]. Because these activities have different timescales, their forecasting time period dictates the prediction system. Thus, wind power forecasting (WPF) techniques focus on three distinct timescales: very short-term, short-term, and medium-term [1]:

- **Very short-term** forecasting systems are suitable to predict the wind power production of sudden events, such as ramps (e.g., due to wind gusts), and to support the management of corresponding risks, as they occur in periods from a few seconds or minutes up to a few hours.
- **Short-term** forecasting is used for predictions with look-ahead periods ranging from the very short-term upper limit up to 2–3 days ahead. It is useful in unit commitment, dispatch, and electricity market trading.
- **Medium-term** forecasting systems predict the production of wind power from the short-term upper limit up to 7 days ahead. Such forecasts are typically used in power systems' operational planning for maintenance planning and longer-term scheduling.

In addition, the choice of a prediction model includes the selection of the forecast parameters and the degree of aggregation. It is possible to forecast wind parameters, such as wind speed, and then, by using a wind turbine model or an appropriate power curve, convert it into wind power; on the other hand, wind power output can be directly predicted. The level of aggregation in WPF can range from a forecast for a single turbine, the aggregated output of a selection of wind turbines, predictions for the production of an entire wind park, or forecasts of the aggregated power output of a certain region. Therefore, the prediction horizon, the forecast parameters, and the type of aggregation define the forecasting technique to adopt.

The forecasting error of a certain model is defined as the difference between the measured and the predicted value. Point forecasting models are assessed by a variety of metrics. Models can be compared using mean error (bias), mean absolute error (MAE), mean square error (MSE), root MSE (RMSE), mean absolute percentage error (MAPE), standard deviation of the errors (SDE), and the normalized MAE (NMAE) and RMSE (NRMSE). On the other hand, uncertainty analysis measures the degree of 'error' of the model, addressing probabilistic forecasts, risk indices, or scenario generation. In probabilistic forecasting, the uncertainty is estimated as a probabilistic measure [1]. Probabilistic measures include quantiles, interval forecasts, and

probability density functions (pdfs), as well as probability mass functions, for each time step of the prediction horizon. Risk indices include the meteo-risk index (MRI) and the normalized prediction risk index (NPRI). These indices are not related to the prediction method and provide a priori information on the expected level of forecast error. Scenarios can be generated by a Monte Carlo sampling procedure.

WPF models can be divided into two main categories: numerical weather prediction (NWP) or physical models, and statistical or artificial intelligence (AI) methods. The first group is based on the physical laws that govern the atmosphere. It uses forecasted values (e.g., of wind speed and direction) from an NWP model, which are applied as inputs to predict the wind power generation of a wind farm. NWP and physical-based tools are well established to predict wind conditions in the short-term horizon. These techniques can be adapted for shorter timescales, although they have proven to be generally less suitable for the very short-term.

The second group is based on statistical and learning approaches. It employs a set of historical time series data of the wind to predict the future values of wind speed and direction, or to directly forecast the wind power production. These methods provide good results in the very short-term horizon, whereas physical methods perform better in longer-term (daily, monthly) forecasts [3]. The learning techniques include classical linear statistical models, such as autoregressive and the Box-Jenkins approach. In addition, there are nonlinear approaches used to perform very short-term wind power predictions, namely, AI models, such as artificial neural networks, fuzzy logic, and support vector machine (SVM) models. Persistence also fits in the statistical group, equating the forecast variable to its current value, and it can be used to benchmark different methods.

Because wind speed (and hence wind power) is a stochastic data source, wind power prediction on a very short-term horizon has been posing several challenges to the research community. Still, many of the methods developed so far have delivered promising prediction results. In particular, nonlinear techniques can better represent the non-stationary and nonlinearity of the wind resource in shorter time scales, hence enabling improvements of wind power forecasts on the time horizon of a few seconds to a few hours [1]–[6].

In a previous report from this project, we described the state-of-the-art in WPF models and their application to power system operations, including with regard to benchmarking results, approaches to uncertainty estimation, and on how to include WPF in the unit commitment problems [7]. We have also reviewed prediction of wind ramp events in [8], including the various ramp definitions and state-of-the-art ramp forecasting techniques, as well as the metrics for ramp detection and forecast accuracy, probabilistic ramp forecasts, and the economic value of ramp predictions.

The goal of this report is to review the current state-of-the-art in *very short-term* WPF models in greater detail, expanding on the content of the two above-mentioned reports. This document is organized as follows. In Chapter 2, we present the forecasting techniques using NWP or physical methods. Statistical and AI prediction methods for the very short-term are described in Chapter 3. Chapter 4 presents a synthesis of the state-of-the art techniques and benchmarking models. Chapter 5 reports the concluding remarks of the state-of-the art review.

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2. NWP and Physical Methods

Because of the high variability of the wind resource and thus of wind power, a growing share of wind power in competitive electricity markets demands shorter forecasting timescales and more sophisticated methods, particularly with regard to the technical and economic risks associated with wind power variability. This chapter describes the methods used to forecast the wind speed and the wind power using numerical weather prediction models or physical approaches, focusing on the very short-term timescale.

2.1. Persistence

Persistence, also known as the naïve predictor, is the simplest wind (power) prediction model and provides a benchmark method (i.e., a comparison of the performance against a forecasting model). Persistence was developed by meteorologists as a comparison tool to supplement NWP models [2][9]. Although it is not a physical prediction method per se, the persistence technique represents the wind (power) as a time series, taken at discrete time intervals, assuming that the wind (power) in the immediate future will be the same as in the present time period [4]. This assumption means that the forecasts for all time steps ahead are set to its current observed value and that the current error is always null [10]. Not surprisingly, this approach has proved to be more effective on the very-short horizon.

2.2. Architecture and Specifications

NWP models were developed by meteorologists to simulate the Earth's atmosphere, land surface, and oceans, thereby providing weather forecasts. Although these models are suitable for short-term or medium-range predictions, their accuracy can be compromised for shorter horizons [4].

Atmospheric processes occur on a wide range of spatial scales, from the small wind gust to large weather systems such as cyclones. Therefore, NWP models comprise the physical state of the atmosphere: fluid dynamic and thermodynamic equations are used to represent the synoptic scale (i.e., from a few hours to seven days), and micro-physical processes are represented by equations and parameterizations of processes such as turbulence, condensation, evaporation, and precipitation. Because the atmosphere is a chaotic system, NWP models consist of initial value problems, and their sensitivity to the initial conditions (previous model forecast and/or observations) demands an accurate specification of the current atmospheric information as inputs. A data assimilation (DA) scheme generates the initial conditions (analysis) that can accurately describe the observed reality by combining the previous model forecast (background) with atmospheric observations. DA schemes vary in computational cost, optimality, and speed, being divided into two groups. Sequential algorithms, such as Optimal Interpolation (OI) [11] or the Kalman filter (KF) [12] use optimal estimation equations to compute the analysis explicitly. Variational algorithms, such as 3D-Var

(three-dimensional variational data assimilation) [13] or 4D-Var (four-dimensional variational data assimilation) [14], compute the analysis by minimizing a cost function as a least squares problem; in the former, observations are distributed in space only, being valid for a single time period, whereas in the latter, the observations are distributed in time as well as in space.

The first few hours of the forecast can be compared with real observations. Hence, the raw output of a weather model is often modified before the actual forecast is issued. This step can be performed using techniques based on statistics, the minimization of biases, or errors. Model output statistics (MOS) is a technique that consists of determining a statistical relationship between the initial and forecasted variables. MOS enables the interpretation of the model output, provides probability estimates of the relevant fields, and avoids systematic prediction errors by correcting the output for systematic errors. The relevant forecasted weather data (e.g., wind speed and direction) are then used to predict the wind power production.

The power curve of the wind turbine generators (WTGs) establishes a power law relation between wind speed and wind power, delivering power production forecasts. In this step, the use of the manufacturer's power curve is the straightforward approach, although there are advantages in estimating the power curve from dynamic information [15]. Alternatively, power can be obtained with a computational fluid dynamics (CFD) method, which adjusts to the local conditions of the terrain [16].

Given that wind patterns may differ between sites, wind forecasts are site specific. In spite of that, there are ways to improve the portability and hence to decrease forecasting errors. Downscaling aims at interpolating NWP wind speed and direction forecasts (usually delivered at 10 m above ground level) to the level of the wind farm (i.e., at the turbine hub height, typically around 80 m). For the very short-term [2], examples include nonhydrostatic features, such as land/sea breezes and the *venturi* effect (mountain winds), which can be considered by the NWP model by using a digital elevation model (DEM). The better the DEM represents the features of the terrain, the better the space resolution and the finer the monitoring grid are and thus, the more accurate the forecasts become. Yet, DEM is limited to the variability of the area over which the winds flow (e.g., forests and urban areas), which may result in a need to remodel the environment. Another way to decrease NWP systematic prediction errors due to imperfect representations of sub-grid phenomena is by employing post-processing approaches based on statistical methods. Kalman filtering is an example of the latter, consisting of a set of mathematical equations that provides a solution of the least square method with minor computational cost, being adaptive to variations in the observations. In particular, current forecasting systems are mostly developed for the onshore environment. On the other hand, there are several issues related to offshore wind (power) prediction, namely, the scarcity of meteorological data and of models properly adapted to the extension of the oceans, their flat and smooth terrain (although with highly variable roughness), and to sudden weather changes (e.g., the quick passage of weather fronts and wind gusts), which lead to the amplification of thermal, wake, and coast-land effects [1].

Because generating wind power forecasts for many individual wind farms might be time consuming, an upscaling technique can be used to aggregate different park outputs to form the basis of a set of reference data, thus reducing the forecast error (as it is averaged over the whole region) [17]. In contrast, downscaling involves the extraction of more detailed spatial information from coarse NWP outputs using physical and/or statistical methods. The latter is similar to NWP, although with higher resolution over a smaller area, whereas the former uses the wind speed/power of a specific wind farm and NWP models to generate a transfer function in order to forecast the wind power from other wind farms within the region of interest [18].

The design of NWP models also differs according to the customer's requirements. The differences concern the domain, resolution, accuracy, and the hierarchical importance of the physical processes. Given these assumptions, the equations are solved. The output of an NWP model delivers the state of the atmosphere at a given time, predicting the values of the variables (e.g., wind speed and direction, temperature, atmospheric pressure, humidity) at each grid point of the geographical domain. Because of the large amount of data needed and the complex calculations involved, the construction of a weather model is a compromise between cost, computing power, and available time.

When building a physical-based wind power prediction model, the selection of the NWP model is a critical step that determines the accuracy of the results. Depending on the user, limiting criteria may include the data variability, the spatial and temporal resolution, geographical area, orography/topography/roughness, and the time horizon, particularly considering boundary layer flows (i.e., in the lower atmospheric layer). The output of a weather model usually becomes available 2 to 4 hours after initialization. Therefore, this computation time compromises the usefulness of NWP models for online applications in power systems [2][4].

NWPs are the most accurate method for short-term and long-term wind forecasts, particularly for time horizons greater than 4 hours ahead [1][2][10]. Hence, because of the high variability of the wind, NWP models are usually less effective on the very short-term forecasting timescale. In contrast, "nowcasting" is the prediction of weather for 0 to 7 hours ahead, and this approach is useful for the prediction of severe weather events, such as wind gusts. Nowcast outputs aim to be available shortly after the time of the observations, within a compromise between computation time (data assimilation and NWP systems) and transmission/pre-processing of observations (e.g., surface and upper-air observations, wind profiler, reflectivity and refractivity data). The British Joint Centre of Mesoscale Meteorology (JCMM) is developing a 1.5-km resolution, NWP-based hourly nowcasting system to forecast high-impact weather [19].

An operational NWP model delivers weather outputs with a fixed frequency. Such models typically cover large areas (about several thousands of kilometers), have grid sizes ranging between 5 km and 25 km, and typically run every 6 or 12 hours. The set of inputs to predict wind power includes dynamic and static information. The former comprises the relevant NWP output variables and measurements of the wind power production (either of each individual turbine, or the wind farm total), which can be online (for models based on autoregression) or

offline (for models to update parameters); the latter includes wind farm and terrain characteristics, such as the layout of the wind farm (to account for wake effects) [20].

The physical approach uses micro- or mesoscale (i.e., regional) weather models, depending on the resolution of local flow patterns and the domain size. Therefore, additional information on the terrain (orography, topography, roughness) may be required. In these models, lateral boundary conditions are provided by the global model and solutions are damped near the boundaries (considered to be far from the area of interest) in order to prevent waves from reflecting back into the domain. Examples of such models currently used today include these:

- High-Resolution Limited Area Model (HIRLAM) is the Danish Meteorological Institute (DMI) regional model, which was developed with seven other partners [21];
- ALADIN is the French Meteorological Institute (Météo France) model and was developed by a consortium of sixteen European members [22];
- The Météo France research model MesoNH [23];
- The Weather Research and Forecast (WRF) model, originating from the United States, is freeware and used worldwide. It was developed through a collaboration among the National Center for Atmospheric Research (NCAR), the National Oceanic and Atmospheric Administration (NOAA) (including the National Center for Environmental Prediction [NCEP] and the Forecast Systems Laboratory [FSL]), the U.S. Air Force Naval Research Laboratory (NRL), the University of Oklahoma, and the Federal Aviation Administration (FAA) [24];
- The Fifth-Generation Mesoscale Model (MM5) was developed by the Pennsylvania State University and is used by NCAR [25];
- The Regional Atmospheric Modeling System (RAMS) model, which was developed by the Colorado State University [26];
- The U.S. Navy's model, Coupled Ocean Atmosphere Mesoscale Prediction System (COAMPS) [27];
- Rapid Update Cycle (RUC), an analysis/forecast data assimilation system developed by the FSL of NOAA's Environmental Research Laboratories [28];
- The High Resolution Rapid Refresh (HRRR), also developed by NOAA [29];
- Advanced Regional Prediction System (ARPS) is a nonhydrostatic model developed at the Center for Analysis and Prediction of Storms (CAPS) at the University of Oklahoma [30];

- The North American Mesoscale (NAM) forecast system, implemented at NCEP [31].

The limit for meaningful deterministic predictions is around 14 days, although imperfections in the model scheme and/or data observations might lower it to 7–10 days at most. Weather forecasts for more than 5 days ahead need to use the global domain. One of the main advantages of using it is the elimination of edges and boundaries, although problems may arise near the poles as the grid boxes become smaller and the winds become stronger, causing numerical instability. The main focus of global NWP models has been to provide accurate weather forecasts for onshore and near-shore areas, instead of offshore [1]. Some of the global models currently used are the following:

- The Global Forecast System (GFS), developed by NOAA in the United States;
- The Integrated Forecast Model (IFS), developed by the European Centre for Medium-Range Weather Forecasts (ECMWF).
- The German Global Meteorological Model (GME), developed by the German Weather Service Deutscher Wetterdienst (DWD);
- The Unified Model (UM), developed by the UK Met Office;
- The Navy Operational Atmospheric Prediction System (NOGAPS), developed by the U.S. Navy;
- The Global Environmental Multiscale Model (GEM), developed by the consortium between the Recherche en Prévision Numérique, the Meteorological Branch, and the Canadian Meteorological Centre;
- The Intermediate Circulation Model (IGCM), developed at the Department of Meteorology of the University of Reading (England);

An NWP model provides deterministic or point forecasts of the atmospheric variables, which limits its usefulness for stochastic optimization and probabilistic risk assessment. However, the unpredictable nature of the atmosphere and the sensitivity of forecasts to the specification of the initial conditions can be overcome by ensembles [32]. Ensemble prediction techniques may involve different runs of the same NWP model (with different initial conditions, model parameters, or schemes) in order to forecast various weather outcomes. The complete set of individual forecasts (i.e., members) forms the ensemble. Assessment follows by examining the distribution of the ensemble members. Another approach employs the evolution of different NWP models (the multi-NWP method) to produce an ensemble. Ensemble forecasts provide probabilistic results within the range of possible outcomes. This range, in turn, indicates the reliability of the prediction by determining the uncertainty inherent in the difference between ensemble members: the more (less) they differ, the larger (lower) the uncertainty [33].

Although ensembles may not make forecasts more accurate, they enable risk assessment and therefore timely decision making upon the occurrence of certain (extreme) weather events. Hence, the economic value of an ensemble forecast overcomes that of a point forecast [34]. Ensemble forecasting research therefore provides a range of products aimed at increasing the value of weather forecasts to the general public and commercial customers.

2.3. Applications

NWP forecasts are used in a variety of fields, and prediction of wind energy is only one of many applications. In the following sections, we provide a chronological overview of the most relevant physical methods used to predict wind (power) production, particularly on the very short-term time horizon.

2.3.1. The First Models

The energy industry first realized the advantages of wind power predictions by the end of the 1970s, when scientists of the U.S. Pacific Northwest Laboratory concluded that weekly, daily, and hourly forecasts of the wind power were useful for maintenance scheduling, load scheduling, and dispatch decisions, respectively [34][35]. The first relevant works regarding wind power predictions were published during the 1980s. In 1983, Notis et al. applied the MOS technique to the output of an NWP model in order to predict hourly values of the wind speed 24 h ahead, which was intended to be used in load scheduling [36]. This method was later improved by Wegley and Formica [37]. In 1985, Kaminsky's and Bossanyi's works stood out. Kaminsky concluded that different synoptic weather classes demanded distinct regression methods [38]. Bossanyi, on the other hand, predicted the wind speed applying Kalman filters over a data set of a thousand hours and obtained the best improvement over persistence for time steps of 1 minute, although persistence performed better for hourly forecasts; in addition, the smallest prediction errors were for 5-minute time steps [39]. During the 1985–1987 period, McCarthy developed a prediction model for the Central California Wind Resource Area. He used observational data (meteorological and local upper air) to forecast daily averaged wind speeds (up to 24 h ahead), obtaining results that outperformed persistence and climatology [40][41]. One of the earliest reviews in short-term prediction was published in 1987 by Bailey and Stewart, where they stressed the need to improve forecasting models, particularly in what concerns the quality of the information of the features of the terrain, as well as meteorological observation and NWP output databases [42].

Because of the wind's variability, the increase of wind energy capacity worldwide during the 1990s impelled the improvement of power prediction models as helpful tools for the integration of wind power into the electrical grid. In 1990, Risø National Laboratory in Denmark developed a physical short-term prediction model named Prediktor [43][44]. It applies MOS to the weather predictions from HIRLAM [45] (to correct biases and scaling errors) and uses the WAsP [46] and PARK [47] models to, respectively, convert the wind to the local conditions and to take into account wake effects in the wind park (attributable to the layout of the turbines

and other obstacles, orography, or roughness of the terrain). A similar approach was developed at the University of Oldenburg in Germany, where the German weather service (DWD) NWP model, LokalModell [48], was used to build the forecasting model Previento [49].

Based on [44], Watson et al. employed, in 1992, an NWP model with MOS to forecast hourly values of wind speed and direction up to 18 h ahead [50]. They concluded that fossil fuel costs (from spinning reserve and wind power's variability) can be decreased when using this model, comparing with persistence's prediction results. Landberg et al. improved the latter work, obtaining better results [51]. Among others, they presented two physical-based models at the 1994 EWEC conference. The one belonging to Landberg [52] reported results from the application of the Prediktor model in 17 wind farms in Denmark. Jensen et al., on the other hand, presented the Wind Power Prediction Tool (WPPT), which uses wind speed to predict half-hourly values of wind power for a 36-hour time horizon by applying an autoregressive method that directly predicts the wind power, comparing it to wind speed forecasts converted to wind power through a power curve model [53]. The authors concluded that for horizons up to 12 h ahead, the former method performed better, whereas for longer periods the latter presented advantageous results over a direct wind power prediction. That same year, Landberg and Watson developed eight different models, including NWP and neural network methods, comparing them with a persistence model. They concluded that all models outperformed persistence, except in the very short-term (i.e., for the 3–6-h prediction horizon) [54].

Akylas et al. tested three different physical-based methods, using NWP forecasts and meteorological observation data to predict hourly values of the wind speed up to 24 h ahead. Wind power forecasts were obtained by converting the speed with measured power curves of the WTGs. They concluded that a multivariable regression over the observational data slightly overcame persistence, and that the latter was considerably overcome by a regression method of NWP forecasts over the observation time series, but particularly by corrections of NWP predictions for microscale effects [55]. In 1999, Landberg issued a paper describing a physical model based on [44] (using HIRLAM, WAsP, and MOS), for 36 h ahead, to predict the wind power production of wind farms located on the Zealand and Bornholm islands in Denmark. With the intent of introducing this model into the dispatching system, he concluded that it outperforms persistence after the first four hours, meaning that it is not suitable for very short-term forecasts and thereby suggesting that statistical methods should deliver better results for such timescales [3].

Another model resembling Prediktor was built by the company AWS TruePower (formerly AWS TrueWind) and named eWind [56]. It tailors a mesoscale model, such as ForeWind [57], NCEP's ETA model [58], MM5 or WRF, to the local conditions, eliminating systematic errors by adaptive statistics, linear regression, or Bayesian neural networks; besides, MOS was employed for online operation. In addition, wind was converted into power production according to either statistical or physical methods. eWind and Prediktor have been used in California both for the very-short and short time horizons [59]. Beyer et al. developed a method analogous to [44], using DWD's LM as the weather model to predict wind speed every 6 hours up to 48 h ahead, then using the manufacturer's power curve to convert into wind power. They tested six

different sites in northern Germany and obtained good forecasting results, concluding that the spatial correlation decreased with an increasing distance and that, owing to increasing systematic errors for longer times, deviations for longer forecast horizons were more correlated than for shorter ones [60]. Nielsen et al. proved that persistence was not suitable as a benchmark for forecast horizons longer than a few hours. They have also suggested that a weighting between persistence and the mean wind power is a more adequate reference model for all forecast lengths [61].

2.3.2. Recent Developments

Over the past decade, attention has been drawn to the development of tools for online operation and uncertainty forecast assessment. Since 2000, new versions of WPPT have been developed, with self-calibration and being auto-adaptive to changes (e.g., different NWP models, variability of real data). Nielsen and his collaborators built the fourth version of WPPT, which easily adapts to changes [62][63]. At the First International Energy Agency (IEA) Joint Action Symposium on Wind Forecasting Techniques, held in Sweden in 2002, three models based on WPPT were presented, which adaptively optimize the MM5 predictions (including wind direction) and use time series and the power curve to forecast the wind power. Sipreólico was developed by teams from Universidad Carlos III de Madrid and the Spanish system operator Red Eléctrica de España (REE), delivering hourly wind power forecasts up to 36 h ahead. The best output was obtained by using an ensemble of nine mathematical/statistical models, then performing a linear combination of the three predictors presenting the lowest exponentially weighted mean-squared prediction error [64]. The other two were LocalPred [65], which consists of an improvement to the model reported for the CENER-CIEMAT Foundation at the 2001 EWEC conference [66], and RegioPred, which additionally delivers regional forecasts [67]. Another contribution to this symposium was the Wind Power Management System (WPMS), which is being widely operated in Germany to predict the wind power by introducing NWP outputs into an artificial neural network. Berge presented a model there as well that combines MM5 and CFD to predict the wind speed and then the wind power production [68]. Westrick presented his work on the very short-term prediction of the wind power in the U.S. Pacific Northwest using NWP and statistical techniques [69].

At the 2001 EWEC conference, Giebel et al. reported the launching of a 3-year project funded by the Danish Ministry of Energy with the intent to develop a method that combines Prediktor and WPPT, giving optimal forecast for all horizons. The new model was named Zephyr; it is based on online data using an autoregressive algorithm as well as on offline data using a statistical estimated power curve model with an upscaling module [70][71]. In particular, WPPT delivers better predictions on the very short-term, that is, for horizons of up to 6 h, and it is able to extend the NWP forecast horizon as well as handle changes in the input. Prediktor, on the other hand, predicts better for horizons ranging from 6 h to the maximum horizon of the NWP model, enabling forecasts even when measurements are not available. Furthermore, the tool is flexible, stable, and independent of both the platform and operational system used. Lange and Waldl also presented at that conference on the uncertainties of Previento forecasts, concluding that the uncertainty of wind speed forecast is independent of the magnitude of the

predicted wind speed, although it presents some dependence on the relevant weather, and also that the uncertainty of the power forecast is a function of both the power curve and the mean error of the related wind speed forecast [72]. Giebel et al. presented promising preliminary results of the online version of Prediktor, i.e. Zephyr, although they claimed that the model was still not tuned for specific sites [73]. Martí et al. studied the refinement of wind power predictions from the HIRLAM model for a Spanish wind farm in semicomplex terrain. They used two spatial resolutions of the NWP model (0.2° and 0.5°) to develop three different models. The wind speed model was tested for three different approaches, namely, the interpolation of the grid points using a weight factor, the wind speed corrected to the air density, and downscaling based on principal components and multiple regression. The power curve and the power prediction models considered wind direction and were based on adaptive local polynomial regression. They concluded that downscaling based on principal components outperformed interpolation and density correction-based methods for both spatial resolutions, although HIRLAM 0.2° outperformed HIRLAM 0.5° for horizons up to 24 h [74]. Hatzigiorgiou et al. presented the Armines Wind Power Prediction System (AWPPS), developed in the frame of the MORE-CARE Project [75].

In 2002, at the Global Windpower Conference and Exhibition, Jørgensen et al. also presented a new approach to HIRLAM, which, coupled with the wave model WAM, forecasts real-time (i.e., few-minute time step), on- and offshore values of wind power, including density changes, stability effects, and direction dependency. It is called the HIRlam POver prediction Model (HIRPOM) [76]. In 2003, Landberg and Giebel issued an overview of wind (power) short-term forecasting [20], and Giebel et al. also published a review on the state-of-the-art of short-term prediction tools [77].

At the 2003 EWEC conference, Martí et al. presented an enhancement of the Sipleóico model, that combines the LocalPred and Sipleóico tools, improving the results for a wind farm in complex terrain [78]. Gallardo et al. informed the conference about the launch of the CASANDRA Project, a collaboration between three Spanish institutions, whose aim was to develop a model that delivers hourly forecasts of the wind power up to 24 h ahead. Based on a mesoscale model and the NCEP global model, it uses MOS and a power curve model (based on a multivariate regression over the wind farm data) and provides risk confidence levels. The authors suggested that the performance of the model can be improved by ensemble techniques [79]. At the same conference, Kariniotakis et al. also informed attendees about launching the ANEMOS Project (a consortium of institutions from seven countries under the Fifth Framework Programme of the European Commission), whose aim was to develop a prediction system for the large-scale integration of on- and offshore wind farms. Although the main forecast horizon was 48 h, the project also considered longer timescales (up to seven days) for maintenance scheduling purposes. Among others, this project tested the Prediktor model, WPPT, Zephyr, Sipleóico, Previento, and LocalPred under different weather conditions and for various types of terrain (onshore and offshore), including assessments of online operation [80].

In 2004 at the EWEC conference held in London, Kariniotakis et al. presented preliminary results from the ANEMOS Project, concluding that in complex terrain the spatial resolution of the NWP model plays a crucial role, the model error becomes more dispersed and the models are less accurate, as well as that any of the tested models prevailed for all time steps of the horizon, suggesting hybrid models should reduce the prediction error [81]. Jiménez studied the sensitivity of hourly WRF wind forecasts for a 72-h horizon to the domain size, spatial resolution, boundary layer schemes, and the frequency supply of boundary conditions. They concluded that the wind predictions were more sensitive to the boundary layer scheme than to the domain size and frequency of the boundary conditions' supply; they also inferred that the wind predictions were slightly influenced by the propagation error on the boundaries and that forecasting results were improved for higher horizontal resolutions [82]. Another contribution to this conference was the method presented by Pinson and Kariniotakis to perform an online evaluation of the risk associated with the wind power forecasts by using the meteorological risk index (which translates the probability of occurrence of high prediction errors) to adjust the confidence bands [83].

At the second Joint Action Symposium on Wind Forecasting Techniques held in Denmark in 2004, Kariniotakis reported the status of tasks of the (by then) ongoing development of the ANEMOS Project [84]. With the intent to unify all of the data to and from a wind farm, Giebel described the progress of the standard IEC 61400-25, which claimed to ease data acquisitions, although not being particularly directed to short-term predictions [41][85]. Nielsen presented new methods that transform global meteorological wind ensembles into wind power ensembles, establishing a correct set of quantiles. He also used ECMWF and NCEP ensembles as inputs to statistical models in order to assess the availability of the forecasts up to seven days [86].

At the Global Windpower Conference and Exhibition held in Chicago in 2004, Madsen et al. presented their work on the standardization of performance assessment of short-term forecasting models, claiming that the use of persistence as a reference model is rather misleading (overly optimistic) about the performance of the model in question. They applied the proposed protocol on the ANEMOS's database, emphasizing the need to improve uncertainty evaluation methods [87]. The same authors later proposed guidelines to assess the performance of prediction models. They suggested that the minimum set of error measures to be considered for each step ahead comprise the normalized bias, normalized MAE, and normalized RMSE, while also remarking that the most appropriate performance metric depends on the application of the model [88].

The 3TIER Environmental Forecast Group in cooperation with the University of Washington developed a WPF system named PowerSight for the hour-ahead, as well as the day- and week-ahead, time horizon [89]. Wind speed is predicted by a combination of NWP models and uses MOS to correct the prediction bias, with conversion into wind power accomplished through a power curve. For the very short-term, Larson and Westrick proved that the performance of the PowerSight forecasts can be improved if off-site (geographically dispersed) meteorological observations are used as inputs to the mesoscale NWP models [90]. Moreover, Grit and

Potter find that, when using this prediction system, both the day- and hour-ahead ramp forecasting, as well as intra-hour wind power forecasting, benefit from lower prediction errors than are found using other models [91].

In 2006, Ceña published the conclusions of the work introduced by Moliner in [92] for various prediction tools and different types of onshore and offshore terrains. His main conclusions were that: (1) the accuracy of the predictions is influenced by the level of wind speed, (2) the different terrains did not seem to have any influence on the quality of the forecasts, (3) the prediction error can be reduced by an aggregation of wind farms, and (4) persistence performs best for the very short-term horizon [93]. Nielsen et al. used meteorological forecasts from HIRLAM and the wind power predictions from WPPT as regression variables in order to develop a model of the quantiles of the prediction error (based on [94]), as well as to evaluate the influence of risk indices (as introduced in [83]). They concluded that the most relevant variable was the forecasted power and that the risk index did not have any influence over the quantiles [95].

At the 2006 EWEC held in Athens, Greece, several works were presented on the results of the ANEMOS Project. Kariniotakis and his collaborators gave a final overview of the project and issued guidelines for the use of wind (power) prediction systems particularly on online operations both on- and offshore [96]. Martí et al. combined the forecasts and selected the one with the best performance, studying the influence of the distribution of forecasting errors on wind power prediction and accounting for the first four moments of the distribution (i.e., bias, standard deviation, skewness, and kurtosis) [97]. Short-term forecasting using physical methods and offshore short-term prediction of wind power were also reported at the conference in, respectively, [98] and [99]. Costa et al. presented physical models that apply stability and microscale orographic corrections to decrease the prediction error, intending to expand these by downscaling through mesoscale models [100]. El-Fouly et al. explained the basis of physical models for the 48-h horizon, which consider, among others, weather data, orography, roughness, and speed up or down effects [101].

In 2007, Negnevitsky et al. reported the need to apply DEMs and MOS corrections on NWP outputs for short-term prediction, although these did not improve the very short-term performance [102]. Rodrigues et al. developed a wind power forecasting tool within the EPREV project, which consisted of a self-financed consortium of Portuguese universities and research institutes [103]. The EPREV system uses the output of global and mesoscale NWP models, tailored with CFD, and supervisory control and data acquisition (SCADA) data to forecast wind speed and power output up to 72 h ahead. They also employed three types of statistical models: a power curve model, an autoregressive model, and a neural network model, obtaining promising prediction results on the very short-term. In 2008, Costa et al. published a review of the past 30 years of short-term wind power forecasting, during which enhancements to the physical and statistical methods, as well as hybrid approaches [104], have occurred. Louka et al. issued a study on the application of Kalman filters on wind speed prediction data from different NWP models, concluding that this method clearly improves the models' forecasting skills, as it leads to the elimination of any systematic error within a shorter computational run-time [105].

A detailed report on the state-of-the-art of wind power forecasting, describing the existing models for all time horizons (very short-term, short-term, and regional forecasting), as well as the NWP/physical, statistical, and combined methods, was issued from this project by INESC Porto and Argonne National Laboratory in 2009 [7]. The authors also explained the uncertainty in WPF and the application of prediction models in power system operations, focusing on unit commitment in U.S. electricity markets. Another review of wind speed and wind power forecasting models was released by Lei et al. [6]. Cutler and his collaborators developed a method to display wind forecast information (e.g., surface roughness and terrain orography) from various grid points and at hub height around the wind farm location in order to avoid erroneous NWP outputs. This method works as a decision support tool in wind power forecasting by enabling the user to assess the possibilities of large, rapid changes in wind power (i.e., ramps), the evaluation of deterministic forecast uncertainty, and the improvement of downscaling results [106]. Ramp events have also been studied by Greaves et al., where they focused on developing methodologies for generating temporal forecast uncertainty for rapid changes in wind farm production. They used multiple NWP inputs, statistical processing, and adaptive algorithms, concluding that the determination of temporal forecast uncertainty indicates the likely timing and amplitude of wind energy ramp events [107].

The company Precision Wind developed a physical WPF system named Precise Stream, which provides point and regional wind power forecasts [108]. The method applies micro- and mesoscale NWP models using CFD techniques to improve the performance of wind speed predictions in very complex terrains. The manufacturer's power curves are then used to determine the wind power production, followed by an adjustment of observed power data, in order to reduce systematic errors due to loss factors. Time horizons of this forecasting system can range from within-hour, 1 h to one day (24 h) ahead, and up to days (48–72 h) ahead. Forecasting errors in terms of NMAE are reported for 6 h ahead forecasts between 2.5% and 5.5%, 6% to 9.5% for 12 h ahead, and between 10% and 17% for one-day-ahead predictions. In 2009, Kusiak et al. used a combination of NWPs from the Rapid Update Cycle (RUC) model and the NAM model in order to forecast the wind power for the very short-term horizons (1 to 12 hours ahead) and short-/medium-term horizons (3 h–84 h ahead), respectively [109]. WindLogics developed Visionpoint, a prediction system of ensembles using NWP from RUC, NAM, and the GFS. Wind speed is converted into power through an SVM, providing 10-minute wind power output predictions that are updated on an hourly basis for the first 3 h, as well as hourly predictions up to 84 h ahead that are updated every six hours. At the 2010 EWEC conference, Zack et al. presented an innovative ramp-event short-term forecasting system to estimate the probability of occurrence and characteristics for large wind ramps for 6-h look-ahead periods. The system employs NWP models (with fast update), a statistical combination method between NWP model outputs and recent measured data, and ramp-type specific prediction algorithms [110]. Davy et al. used NCEP's downscaled reanalysis fields, developing stochastic empirical models to predict the wind variability. The fields were decomposed using empirical orthogonal function (EOF) techniques and the downscaling method applied to two seasonal cycles (winter-spring and summer). The identification of meteorological patterns related with the flow variability in coastal regions provided useful information to electricity operators of large wind farms [111].

In 2011, the results of the ANEMOS follow-up project were published as ANEMOS.plus [112]. This report provides the best integration of ANEMOS results, delivering an overview of short-term wind power forecasting for single WTGs, wind farms, or regions from a few minutes up to a few hours ahead. Since issuance of the first edition of the ANEMOS report, the wind power forecasting field has expanded widely, as has the increasing penetration around the world of wind power, which has directly affected energy operators and power traders. Tastu et al. studied the spatiotemporal correlation between point forecasting errors, as well as the effects of prevailing wind speed and direction on autocorrelation and cross-correlation patterns, for a flat region in western Denmark. They observed a significant correlation between various areas for time delays up to 5 h, concluding that the wind direction has a fundamental role, whereas the speed effect is more complex. The authors also proposed forecasting models which capture the interdependent structure of prediction errors, concluding that the one with best performance captured more than half the variations of the errors observed for individual forecasts [113]. Myers and Linden developed an overall power forecasting system, named DICAST, which optimizes the forecast by decreasing the hub height wind speed error, hence reducing the prediction error [114]. This method benefits both the power system operators and wind power producers.

In 2012, Foley et al. published a review of the methods used and advances in wind power prediction regarding NWP/physical point and ensemble forecasting, upscaling, and downscaling, as well as statistical/machine learning approaches, the benchmarking techniques, and uncertainty analysis [1]. They found that hybrid methods deliver better results, thus reducing the financial and technical risk of wind power uncertainty for all energy market participants. Efforts were also under way in the United States in the so-called Wind Forecast Improvement Project to improve NWP through higher resolution models with more rapid updates while using a wider network of hub-height weather measurements as inputs [115]. This project focuses particularly on the very-short term time horizon and the prediction of ramping events.

Overall, it is clear that a good representation of the atmosphere over the area of interest by a suitable NWP or physical model delivers better wind speed forecasts. As the performance of NWP/physical-based wind power prediction models depend highly on the quality of the wind forecast, better wind speed results also lead to reduced wind power prediction errors. Although the NWP/physical models do not usually perform as well on the very short-term timescale, their products are often used as inputs to statistical-based methods, which, along with hybrid models, are oftentimes considered as preferred tools for the very-short horizon. NWP/physical models are good at predicting large-scale area wind speed and power, usually achieving better results than persistence for short-term prediction horizons, particularly from 6 h ahead and onwards. Nevertheless, most studies have shown that the terrain influences the quality of the production forecasts. In fact, for the very short-term in complex terrain, atmospheric models with finer spatial resolutions (e.g., micro- or mesoscale NWPs using CFD techniques, Kalman filters and/or geographically dispersed observations) yield enhanced wind results and thus better wind power predictions. The forecast error can also be improved by wind farm aggregation or by combining several NWP forecasts.

The next chapter describes the statistical and artificial intelligence methods to predict the wind speed and the wind power.

3. Statistical and Artificial Intelligence Methods

This chapter describes the prediction models based on statistical or artificial intelligence methods, namely autoregressive, fuzzy logic, and artificial neural networks (ANNs) or combinations of these.

3.1. Architecture and Specifications

Very short-term prediction tools based on statistical methods are classified as univariate or multivariate, depending on the input (explanatory) variables. Univariate models only consider past values of the variable to be predicted and they can be expressed as:

$$\hat{y}_{t+k|t} = f(y_t, y_{t-1}, \dots, y_{t-n}) + e_t \quad (3-1)$$

where $\hat{y}_{t+k|t}$ is the variable to be forecasted (e.g., wind speed, wind power) for the following time step $t+k$, y_t represents the measured values of the (only) explanatory variable at the present instant t , e_t is white noise, and f is a generic function that can either be linear or nonlinear. Univariate methods are based on past data only and can outperform persistence for very short-term forecasts, with the maximum improvement over this reference model in the range of 15% to 20% [77]. Multivariate models, on the other hand, use past values of the variable to be predicted, as well as past and forecasted values of other (external) variables, such as NWP outputs (e.g., wind speed and direction) and measurements from the wind farm's SCADA system¹ (e.g., on-site meteorological data, active generation). The multivariate model can be represented by:

$$\hat{y}_{t+k|t} = f(y_t, y_{t-1}, \dots, y_{t-n}, \hat{x}_{t+k}, \dots, \hat{x}_{t+1}, x_t, x_{t-1}, \dots, x_{t-n}) + e_t \quad (3-2)$$

where x_t, \dots, x_{t-n} is the set of measured (past) external variables and $\hat{x}_{t+k}, \dots, \hat{x}_{t+1}$ the corresponding prediction set. Very short-term forecasts may benefit from a multivariate model formulation whenever there is available information with sufficient temporal and spatial resolutions.

Based on equations 3-1 and 3-2, there are two possible forecasting schemes that can be used to predict a complete time horizon. One approach consists in training a model for each look-ahead time step ($t+k$), in order to deliver a single (point) prediction for corresponding instant. The other scheme relies on training a single model iteratively, such that the first look-ahead time step is used to replace the input lagged value, in order to determine the next look-ahead forecast (i.e., the $t+1$ prediction of the explanatory variable is fed into the $t+2$ forecast); this

¹ SCADA is the supervisory control and data acquisition systems that monitor and archive the meteorological and production parameters associated with an individual WTG and/or the entire wind farm.

process is repeated until the completion of the time horizon. Although this last solution only needs to train a single model, errors are propagated and thus accumulated throughout the forecast horizon.

A very short-term prediction system based on statistical methods consists of associating the explanatory time series to a certain prediction algorithm. The choice of the external variables depends on the use of the forecasting model. As mentioned before, NWP or physical methods use physical meteorology information (e.g., orography, roughness), whereas statistical models use historical data (e.g., wind speed, wind power). Moreover, NWP/physical model outputs can be taken as an initial analysis for the statistical methods, enhancing their performance in shorter horizons. It is still worth noting that the accuracy of the gathered data as well as the accuracy of the NWP model determine the quality of the forecasting results. In fact, there is a very strong interdependence between the accuracies of WPF and NWP models [1].

The choice of forecasting approach depends on the application of the forecast; therefore, a trade-off between NWP costs and the utility of the forecasting model should be assessed. For instance, if wind power forecasts are inputs to an energy scheduling or market tool for time horizons ranging from 10 minutes to 1 h ahead only, the use of very short-term statistical predictions should be sufficient, and it is not necessary to incur additional costs with NWPs.

Statistical-based models can predict the wind speed and then, by applying a power curve model, determine the wind power for all time-steps of the horizons, or can directly predict the wind power. Examples of such models include Box-Jenkins models, artificial neural networks and fuzzy logic models. The following section describes various models to predict wind speed and wind power, namely, conventional statistical and AI methods.

3.2. Applications

The choice of a model that can predict wind (power) for the very short-term horizon mainly depends on the forecast parameter data set. For these timescales, the variability of the wind resource (and hence of the power production) can only be modeled if, along with past values of the wind speed and power, its present state is included as inputs [2]. Statistical and AI models use a large amount of data (from both the past and present), and meteorological processes are not explicitly represented; thus, they are capable of capturing the nonstationary nature of and nonlinearity inherent to the wind resource. These models are therefore in general more suitable for performing forecasts at this timescale than are NWP or physical-based models. Besides, unlike physical methods, statistical approaches can directly predict the wind power by finding a relationship between the NWP (and possibly other) data and the wind power output [1].

The following subsections describe prediction methods with the potential to outperform persistence for these time scales, that is, classical linear statistical (e.g., Kalman filters and autoregressive methods), nonlinear (e.g., ANNs, fuzzy logic), and hybrid or combined methods

(e.g., adaptive neuro-fuzzy inference systems [FISs]). We describe both wind speed forecasting, which is often converted to power through an empirical or manufacturer’s power curve, as well as (direct) wind power forecasting.

3.2.1. Linear Statistical Methods

Beyond the traditional meteorological use, Kalman filters can be applied in wind speed prediction, providing improved inputs to a WPF model [105]. This technique was introduced by Kalman in 1960 [116]. As mentioned in the previous chapter, the first wind forecasting model, specifically used in wind generation forecasting, was published by Bossanyi in 1985 [39]. He applied a Kalman filter that uses the last six measured values as inputs to forecast wind speed for the following minutes. The results were good (10% in RMSE) when compared with the persistence for time horizons below 10 minutes of averaged data. The improvement decreased for longer averages and was null for 1-h averages. In 1999, a similar approach was used by Wilhelmshaven to reduce the flicker on the wind speed prediction [117]. In addition, Vihriälä et al. applied a Kalman filter to control a variable speed wind turbine [118].

Over the past decade, other prediction methods using Kalman filters have been published. Costa et al. applied Kalman filters to predict wind speed and compared the performance with persistence, concluding that the latter performed better for hourly data and the prediction model did best for 5-minute time steps [104]. In 2008, Louka et al. presented improved results of wind speed forecasts for wind power prediction using Kalman filters. They suggest that higher-resolution applications may be improved by the combination of NWP models with moderate resolution and by using statistical techniques, such as Kalman filters, to ameliorate the wind data. This approach provides similar or even more accurate predictions at the wind farm scale. Such improvements in prediction models can benefit wind power integration into the grid by facilitating better power system operations such as unit commitment, economic dispatch, and market bidding strategies, as well as maintenance scheduling [105].

Conventional statistical methods resemble direct random time series models. In fact, based on a number of historical data, pattern identification, parameter estimation, and model assessment are used to elaborate a mathematical approach to the problem. When applied to wind (power) forecasting, such approaches usually consider the difference between the predicted and the actual values to retune the model parameters.

These models can be divided into the autoregressive (AR) model; moving average (MA) models, such as autoregressive moving average (ARMA) model; and autoregressive integrated moving average (ARIMA) models [6]. The random time series can be described as follows:

$$x_t = \sum_{i=1}^n \varphi_i x_{t-i} + \alpha_t - \sum_{j=1}^m \theta_j \alpha_{t-j} \tag{3-3}$$

where x_t is the value of the wind (power) at time t , φ_i is the autoregressive parameter, α_t is the normal white noise, and θ_j is the moving average parameter [119]. Equation 3-3 represents a typical ARMA model and, for $m=0$, it represents an AR model. In particular, persistence is the simplest ARMA model, considering the present value as the value of any time step ahead. When applying a differential transformation, an ARIMA model is obtained.

The use of an AR model in WPF was analyzed by Contaxis and Kabouris in 1991 [120]. They employed a third-order AR model to forecast the wind speed for time horizons ranging between 30 minutes and 5 hours ahead using the values to control an isolated hybrid diesel/wind system and for short-term operation scheduling. In 2003, Poggi et al. used an autoregressive model for each month in order to forecast the wind speed for the following 3 hours [121]. Duran et al. performed several tests to select the AR order, stating that the order does not depend on the training period but rather on the characteristics of the area (e.g., wind farm terrain complexity) and the time horizon of the forecast [122]. Their best model was an AR of order 11; however, this finding may not be true for applications in other wind parks, where lower AR orders are usually found [7]. The improvement over persistence in three wind farms ranged between 3% and 17%, and the standard deviation of the error was also lower in the AR model when compared with persistence. Results for the independent and aggregated wind farms showed that the aggregation reduces uncertainty and forecast error, namely improving the forecasts by 23.1% for a 6-h horizon.

In 1984, Geerts developed two ARMA models of orders 1 and 2 that were oriented to the integration of wind energy into the grid [123]. He applied a Kalman filter and predicted hourly values of the wind speed until 24 h ahead, comparing the results against persistence. Both models overcame persistence in a forecast horizon of up to 16 h, claiming that, in addition to wind speed, other variables could be employed in order to improve the accuracy (e.g., wind direction, atmospheric pressure, and temperature). One year later, Bossanyi used ARMA models (of orders 1 and 5) to predict the wind speed up to 10 h ahead, with time steps of 2 seconds and 1 minute. He obtained better performance results over persistence, with slight improvements when determining the k -step ahead predictor recursively. The author also presented applications of the forecasts for wind turbine furling operations and switch-on/switch-off operations of diesel generators in autonomous wind/diesel systems [124][125]. In 1992, Tantareanu found that ARMA models can perform up to 30% better than persistence for 3 to 10 steps ahead in 4-second averages of 2.5-Hz sampled data [126]. More than a decade later, Milligan et al. carried on the research introduced by Tantareanu to understand to what extent time series analysis can improve simple persistence forecasts, as well as their usefulness in hour-ahead markets [127]. The ARMA models for both wind speed and wind power output were tested with different parameters, concluding that the capacity of ARMA forecasting models differed when applied to different time periods. The authors suggest the possibility of using an ensemble of models instead of a single model. Torres et al. used five ARMA models to predict the hourly averaged wind speed for a time horizon of 10 hours [128]. The application of this model was over a nine-year data set of five locations with distinct topographic characteristics. They presented an off-line approach to transform and standardize the time series in order to make the distribution approximately Gaussian and to avoid seasonality.

Adjusting one model for each one of the 12 months of the year, they achieved significant improvements over persistence on the RMSE basis (20% reduction), observing that the MSE presented a certain dependence on the wind speed values.

In 1976, Box et al. presented a methodology where the general ARIMA approach was first employed to time series [129]. Fellows and Hill performed 10-minute wind speed forecasts until 2 h ahead. They optimized iterative Box-Jenkins forecasts from de-trended data and then applied central moving average smoothing. They obtained a 57.6% reduction on RMSE over persistence [130]. Kamal and Jafri used an ARIMA model to forecast the wind speed and estimate confidence intervals [131]. Schlink and Tetzlaff employed these models to forecast the wind speed for the following 10 minutes in an airport [132].

The California Independent System Operator (CAISO) prototype forecasting algorithm for short-term forecasting is described in [133]. A modified ARIMA model is used to forecast the wind power growth/decline factor for 2.5 hours ahead [134]. The model coefficients were adapted online, and a bias self-compensation scheme was used by incorporating an additional term into the modified ARIMA model. The model presents good results in the first two hours, where the MAPE is below 3% and 8%, respectively, of the maximum observed generation. The authors stressed the need to incorporate NWP and unit status information into the model. Following the results presented in [134], Kavasseri and Seetharaman suggested a modified ARIMA model (f-ARIMA) to deal with long-range correlations (LRCs), which are characterized by a slow decay of the autocorrelation function [135]. They predicted the wind speed until one and two days ahead and then converted it into wind power by using a manufacturer's power curve. This model allows parameter differentiation to assume fractionally continuous values in the interval $[-0.5, 0.5]$, hence representing distinct LRCs for each parameter.

Researchers have studied other statistical prediction methods. For instance, Bayesian methods (see [136]) have also been employed in wind speed prediction. Miranda and Dunn developed an AR model based on a Bayesian approach to obtain 1-h ahead forecasts of the wind speed [137]. In 2008, Riahy and Abedi proposed a new method to perform very short-term wind speed predictions [138]. It is based on linear forecasting approaches and filtering methods to discard undesired frequency components of the wind speed waveform. Compared with real wind speed data, this model proved to be efficient in delivering wind speed forecasts, although its performance could be improved by increasing the model order (but decrease the stability of the system).

Comparisons between conventional statistical models have also been published. Makarov et al. presented prototype algorithms at the CAISO for short-term wind power forecasting based on retrospective data methods such as persistence [133]. The models tested included random walk, moving average, exponential smoothing, Kalman filtering, auto regression, and Box-Jenkins, the latter being the model with the best performance.

The Sipleóico tool uses HIRLAM forecasts and SCADA data, from 80% of all Spanish wind turbines, as inputs [64]. These data, together with different power curves, predict the wind

power by applying nine nonparametric mathematical/statistical models: one model does not use NWP predictions, three include increasing order terms of forecasting wind speeds, yet another three also take forecasted wind direction as input, and two are linear combinations of the previous models, plus a nonparametric prediction of the diurnal cycle. These nine models are recursively estimated with both a recursive least squares (RLS) algorithm and a Kalman Filter, delivering hourly wind power forecasts up to 36 h ahead. The error is given by an exponentially weighted mean-squared prediction error with a forgetting factor of 24-h memory. The model performs well when driven by measured wind speeds instead of predicted ones. The best output was for an ensemble of all models, for which the lowest error was obtained.

Bracale and his collaborators presented a very short-term (1 h to a few hours ahead) steady-state analysis of an electrical distribution system with wind farms [139]. They used various deterministic (e.g., persistence and generalized) and probabilistic (e.g., Bayesian and Markov) wind prediction methods to perform load-flow analyses. They concluded that, apart from the generalized persistence method, all models provided similar predictions with acceptable results for voltage profile and losses. In addition, probabilistic approaches were more suitable to incorporate the variability of the wind resource and of the loads in the steady state.

A Markov chain is a process where, given the present state, the probability of future states is independent of past states; that is to say, state transitions only depend on the transition probabilities associated with the current state. In 2011, Kani et al. developed a new hybrid model, combining a linear method with a Markov chain, to predict the wind speed on the very short-term [140]. Results showed improvements in the uncertainty forecast, providing a reduction in forecasting error and the decrease of CPU time.

Liu et al. proposed a hybrid statistical model to predict wind speed and power based on the wavelet method and the improved time series method (ITSM) [141]. Compared with traditional time series analysis methods, the proposed algorithm significantly improves the accuracy of forecasting without increasing the computational cost in modeling. Unlike ANNs, this method can attain forecasting results readily after modeling.

3.2.2. Nonlinear and Hybrid Methods

During the past decade, attention has also been drawn to nonlinear statistical methods that perform very short-term wind power prediction. Examples include machine learning (or artificial intelligence) approaches and kernel methods [7]. In fact, continuing innovations in statistical and machine learning prediction techniques have been showing considerable improvements on the very short-term forecasting timescale. In addition, hybrid or combined methods are delivering prediction accuracy benefits not only to NWP and physical methods but also to statistical and machine learning techniques, particularly in terms of better time and space resolution scales.

Artificial intelligence methods use historical time series to learn the relationship between the input data and the output. These include artificial neural networks and fuzzy logic systems. ANNs have the ability to learn and train, performing well for raw input data; however, their accuracy decreases rapidly with an increasing prediction horizon. Fuzzy methods, on the other hand, have a poor learning and adjustment ability, although they can outperform other models for reasoning problems [6].

An ANN consists of an input layer, an output layer, and one or more hidden layers. Each layer has neurons connected to all neurons of the previous layer, whereas the neurons among the same layer are independent. Each connection has its own weight, and each neuron is related to a transfer function in the hidden layer (usually a sigmoid function for wind power prediction). The training process is the procedure to adjust the weights of each connection, such that the outputs become closer to the expected value, thereby minimizing the prediction error. Back-propagation (BP), Levenberg Marquardt (LM), MSE, and entropy criteria are some of the training algorithms and criteria that have been developed so far.

At the 1993 European Community Wind Energy Conference, Tande and Landberg presented an application of an ANN model to predict the wind power for a single turbine, using 1-s wind speed data [142]. They generated point forecasts for 10 seconds ahead, obtaining a slight improvement over persistence, while claiming the need for further investigations about the capabilities of the model. The following year, Beyer et al. contributed with the use of various neural network models (single perceptron [SP], multilayer perceptron [MLP], and radial basis function [RBF]) to predict wind speed and wind power for a single WTG with time steps of 1 and 10 minutes [143]. They obtained approximately the same improvement over persistence for both time steps when forecasting the wind speed and the power output (determined by using the power curve of the turbine). However, wind speed and wind power predictions both proved that the improvement for the SP model was smaller. The authors also compared these results with previous publications, concluding that, because of the insufficient information in the time series at these timescales, it was not expected that these results could be enhanced further. Moreover, they claimed that simple network architectures give comparable results to more complex approaches at these timescales. Lin et al. employed different architectures of neural networks (different neuron layers, activation functions, learning algorithms, and training set) to predict wind speed and direction with a time step of 1 second [144]. The results showed a considerable improvement over an AR model and also showed an improvement of 32% over persistence in the forecast error for a 1-h time horizon. The same method was employed by Alexiadis et al. for a different location in Greece, and the improvement over persistence was of 27% for a 2-h horizon [145]. Mohandes et al. developed an ANN model to predict the wind speed [146]. Results were compared to an AR model, concluding that the ANN outperformed the AR in terms of lower RMSE. Li et al. used an ANN to forecast wind turbine generation for horizons as low as 10 minutes ahead [147].

In 2002, Sfetsos presented a novel approach based on ANNs and time series to predict the mean hourly wind speed. He obtained an RMSE four times lower than other models merely based on historical data [148]. Bustamante et al. used AR models and ANNs, as well as

dynamical and statistical downscaling methods to predict hourly wind speeds for the very short-term horizon [149]. The statistical downscaling was based on the ERA40 reanalysis project [150] (e.g., combination of atmospheric fields, removing redundant information in the data), whereas the dynamical downscaling was used on the mesoscale model MM5. The authors concluded that the former applied over the latter leads to improved prediction results. Maqsood et al. used four different types of ANNs to forecast three meteorological variables (including wind speed) for a 24-h ahead interval: MLP, the recurrent neural network of Elman, RBF, and the Hopfield neural networks. An ANN of each type was trained for each season of the year. The best result was the one obtained with the RBF neural network, although the accuracy increases when all models are combined into an ensemble of models [151]. A number of studies apply the most commonly used neural models, which are the recurrent version of ANNs [152] or the standard MLP network method [153].

In 2007, Cadenas and Rivera compared an ARIMA and an ANN for wind speed forecasting in the south coast of the state of Oaxaca, Mexico, using a data set of 7 years' worth of measurements [154]. They concluded that, for this case in particular, seasonal ARIMA models present a better sensitivity to the adjustment and prediction of the wind speed. Later, the same authors tested four ANN configurations to forecast hourly wind speed [155]. The model with best performance was the simplest one, an ANN with two layers and three neurons. Moreover, Sørensen et al. address the problem of wind power forecasting for offshore wind farms, stressing that the wind production located offshore may suffer more significant fluctuations than does onshore production [156]. Kani et al. developed a novel model for very short-term wind speed prediction [157][158]. The ANN is used to predict primary values, and then a Markov chain is applied to determine the transition probability matrix for predicted values; afterwards, a linear regression applied to the ANN estimated values and Markov chain-calculated probabilities delivers the final prediction results. This model proved the effectiveness of the proposed integration, presenting a slight reduction in forecasting error compared with a simple ANN. Jursa and Rohrig presented a model that combined an ANN and the nearest-neighbor method [159]. Results presented an improvement of 10.75% in normalized RMSE over persistence.

In 2009, Ramirez-Rosado et al. presented novel very short-term wind power forecasting systems based on a combination of power curve models and dynamic methods [5]. The difference between the two forecasting systems relied on the presentation of the power curve. The dynamic models were a forecast system, which used an MLP ANN, and a SGP system, which used a combination of a Kalman filter and statistical models, which were input to a first-order Takagi–Sugeno–Kang fuzzy inference system, providing the forecasted value of wind power as a nonlinear combination of the selected models. Within a total of 11 forecasting models, each specific to a certain horizon of from 0.5 to 4.5 h ahead (one ARMA (1,1) model, a new-reference model, and nine ANN models), the selection of the best combination of models was based on the one with lowest forecasting error. Results have shown that these systems combining different methods significantly improve the prediction results when compared to a persistence model. Abdel-Aal et al. applied abductive networks based on the group method of data handling (GMDH) [160] to predict mean hourly wind speeds [161]. The authors demonstrated that the main advantage of this method over the ANN is the fast convergence during training

and automatic selection of both input variables and model structure. This model was also used to forecast the wind speed for 6 and 24 h ahead, achieving an improvement over persistence of 14.6% and 13.7%, respectively. On the other hand, Baile et al. presented an AR seasonal model employing continuous random cascades [162]. They forecasted hourly surface layer wind speeds between 1 and 12 h ahead, obtaining systematically improved results over three reference models. The system proposed by the authors minimized the RMSE and MAE and yielded results that were more accurate than persistence, as well as a merging model of persistence and global average and an ANN. That same year, Kani and Ardehali developed a new prediction model combining an ANN with a Markov chain [163]. They performed very short-term wind speed forecasts, showing a decrease in prediction errors (MAPE and MAE) and forecasting uncertainty. In addition, the reduction of calculation time is also useful for running online applications for wind turbine control.

Another nonlinear statistical method is the fuzzy logic, which uses membership values in the interval (0,1) and fuzzy variables, particularly to model complex systems [6]. Damousis and Dokopoulos developed a Takagi and Sugeno FIS [164] based on wind measures of the target location and on the wind speed forecasts of neighboring locations for a time horizon between 30 and 240 minutes [165]. A genetic algorithm is used in order to optimize the FIS parameters. The improvement over persistence ranges between 9.5% and 28.4%, depending on the time horizon (increases with horizon).

Fuzzy systems and neural networks are complementary tools in building intelligent systems. Therefore, their integration into a neuro-fuzzy system offers a promising approach for very short-term prediction. In fact, ANNs are low-level computational structures that perform well when dealing with raw data, whereas fuzzy logic deals with reasoning on a higher level while lacking the ability to learn and auto-adjust [2]. For instance, an adaptive neuro-fuzzy inference system (ANFIS), as proposed by Jang in 1993, is a six-layer, feed-forward neural network that uses a hybrid learning algorithm that combines the least-squares estimator and the gradient descent method [166]. The ANFIS model increases the prediction accuracy and enables an easy system installation at a variety of different sites. In addition, its design is flexible and capable of handling sudden fluctuating data patterns, thus covering the very short-term wind prediction criterion. Another fuzzy method was developed by Sideratos and Hatziargyriou, who combined the fuzzy model with ANNs and obtained satisfactory results [167]. Frías et al. developed an ANFIS model with the intention of participating in the Spanish intra-daily energy markets [168]. The model used online generation data of wind farms as well as forecasts for the daily market, focusing on prediction horizons up to 10 h ahead. A heuristic method combining quantity and type of membership functions of the input variables was used to optimize the operative time through a selection of training samples. Barbounis and Theocharis presented a locally feedback dynamic fuzzy neural network (LF-DFNN) for wind speed forecasting using a spatial correlation predictor (SCP), proving that the proposed model outperformed other network models [169]. Pinson and Kariniotakis developed a prediction system that integrates models based on adaptive fuzzy neural networks, either for 1–10 h or 1–48 h ahead, to predict the power generation in Irish wind parks [170]. The authors evaluated one year's worth of, using as inputs on-line SCADA measurements, as well as HIRLAM's NWP outputs. The authors also developed a

method for the online estimation of confidence intervals of the forecasts, together with an online assessment index that represents the risk due to the inaccuracy of the numerical weather predictions. Results showed a considerable improvement over persistence. In 2006, Potter and Negnevitsky presented an ANFIS to forecast the wind vector (rather than wind speed or power output) for a 2.5-minute time horizon for a site in Tasmania, Australia [2]. The input data were the measured wind speeds, which are then adjusted through splines that considerably lower the forecast error relative to persistence (additional expert input is not required on the condition that the data provided are reliable and have an even time step). Results were less than 4% of the MAE of persistence. In 2007, Negnevitsky et al. also employed an ANFIS to perform short-term wind power forecasts, stating that these models are particularly useful for when the problem formulation is characterized by some indefinite and vague elements [102]. Hong et al. presented a new model that employs a multilayer feed forward ANN with fuzzy inputs using a simultaneous perturbation stochastic approximation (SPSA) algorithm to train the neural network [171]. It performs hourly wind speed and power forecasts for horizons ranging from a few minutes to up to an hour and delivering better results than persistence. The main advantages of this training algorithm consist in the control of the complexity of the networks and the estimation of the uncertainty of the prediction. In 2011, Blonbou proposed a very short-term wind power forecasting model employing an ANN as predictor along with adaptive Bayesian learning and Gaussian process approximation [172]. Results for three prediction horizons (10, 20, and 30 minutes) showed that this method performed better than the persistence model. Moreover, the Bayesian framework also enables forecast of the probability interval within which the generated power should be observed.

In 1998, Alexiadis et al. proposed an SCP to forecast the wind speed for the Syros island (in Greece) using historical wind data from the island and from other neighboring islands as input variables [173]. This novel approach delivered good prediction results. The reduction of the prediction error by using a spatial correlation model was studied by Focken et al., who analyzed the aggregation of wind power forecasts for wind farms over 30 different regions in Germany within 48-h horizons [17]. They observed a decrease in the prediction error for flatter terrains, the magnitude of the error being more sensitive to the size of the region than to the number of sites. The authors found that the error of the SCP was less than that of a single site because of the spatial smoothing effect, the error reduction mainly being influenced by the size of the region and the number of sites it contained. A saturation level was also found, meaning that only a few sites were needed for determining the improvement of the power production forecast. In 2004, Damousis et al. proposed a fuzzy model based on a spatial correlation method to predict the wind speed and the wind power [174]. The model was trained using a genetic-based learning algorithm, providing good performance over flat terrain—better than its performance in complex terrain. The drawbacks of this model are the large numbers of fuzzy rules and the subsequent large amount of computational time required. Another spatial correlation-based neural network was further developed in 2007 [152]. Although better than other static neural and neuro-fuzzy models, its performance did not surpass the LF-DFNN model mentioned previously, because the former LF-DFNN model employed wind direction whereas the latter did not. Another model based on the ANN method and spatial correlation was developed by Bilgili et al. [175]. The authors concluded that this model could predict the wind

speed of target stations without any topographic details or other meteorological data. Cellura et al. provided an overview of some of the neural, geostatistical, and hybrid models used for space-temporal wind forecasting in 2008 [176].

In 2003, McCarthy et al. presented the Wind Energy Forecasting System (WEFS), a hybrid model consisting of physical mesoscale and statistical algorithms [177]. In order to improve the forecasts of very short-term horizons, the authors have used on-site wind measurements as inputs to the NWP models (MM5 and WRF), coupled with a Diagnostic Wind Model (DWM) that takes into account the local topography and microscale effects. A study for a wind farm in Texas showed that, for a 48-h time horizon, the WEFS was the best model, with an improvement over persistence of 26.1% for wind speed and 28.3% for wind generation [178].

Kariniotakis et al. tested various forecasting methods, obtaining improved wind power prediction results over persistence for ANNs and fuzzy logic-based models within a time horizon of 2 hours and a 10-minute time step [179]; the worst performance was achieved by the naïve and AR models. Sfetsos compared several forecasting methods of the wind speed, namely linear models, such as persistence, an AR model, and Box-Jenkins, as well as nonlinear feed-forward ANNs, RBF networks, an Elman recurrent network, ANFIS models, and a neuro-logic model. All nonlinear models exhibited comparable RMS errors, which were better than any of the linear methods. The best model for hourly time steps was a neural network with a 20–40% average improvement over persistence [119]. Later, the author used two models based on ANN to forecast the wind speed for a time horizon of one hour [148]. The first model used the last known values of the hourly wind speed as inputs, and the results were only 3% better than those for persistence. The second model used the wind speed time series with 10-minute intervals as inputs, in addition to the ANN output used iteratively to forecast the subsequent 60 minutes. An improvement of 10% was seen with the second model over persistence. Ramírez-Rosado and Fernández-Jiménez employed 23 Takagi-Sugeno FISs to forecast the coefficients of the Fourier transform of the past 24 values of mean wind speed, using these to predict the mean wind speed for the following hour [180]. In fact, fuzzy time series were coupled with fuzzy linguistic information about wind, such as “strong wind” (e.g., given by an expert), which allowed the forecasting method to register an improvement of 14.3% over persistence. The same authors later presented a model based on grouping historical data by using a subtractive clustering method [181]. For each group, a linear regression model was used to forecast wind generation. The improvement over persistence for a 6-h horizon was around 14%. Costa et al. tested a purely and fuzzy autoregressive model, as well as an MLP ANN, in order to forecast for 10 steps ahead with 10-minute time steps [182]. The only inputs were measured time series. The models were tested in three wind farms located in Spain. The neural network reached the best overall performance.

Kernel methods, such as SVMs [183], regularization networks [184], and kernel Principal Component Analysis (PCA) [185] are prediction approaches that can overcome some of the disadvantages of other models (e.g., the over-learning of ANNs), particularly in the very short-term. These can be derived either in the batch or online modes. The former requires operations

along with storage to perform the inversion or the singular value decomposition of the Gram matrices, whereas the latter are easily adaptive to varying signals.

The least-mean square (LMS) is the simplest online learning algorithm [186]. A kernel-based extension of LMS was exploited by Liu et al., who named it kernel LMS or KLMS [187], as it adapts filter parameters using a stochastic gradient approximation in reproducing kernel Hilbert spaces (RKHSs) [188]. Other kernel-based online learning algorithms include the kernel online learning [183], the kernel Hebbian (KH) [189], kernel Adaline (KA) [190], or the kernel RLS [191]. KLMS diverges from these models in what concerns the creation of a growing radial basis function, or RBF, network. RBF has a learning strategy similar to Platt's resource allocating networks (RANs) [192], which employ heuristic techniques to adapt the network parameters. Foresti et al. presented the multiple kernel learning (MKL) regression model. MKL is an extension of support vector regression that uses dedicated kernels to separate tasks and treat them independently [193]. This model provides better interpretability to nonlinear robust kernel regression, as it is able to compute the features of complex terrain well by avoiding the use of topographic indices as variables of the statistical models. In addition, the authors also addressed three types of feature selection, namely, filter methods ranking the features according to predefined relevance criteria; wrapper methods involving the predictor as a part of the selection process by scoring the predictive power of features; and embedded methods that perform feature selection as a part of the training process.

In 2004, Mohandes et al. introduced the application of SVMs for wind speed prediction [194]. They compared the forecasting results with those from an MLP neural network, proving that the SVM model had a lower RMSE. Further improvements were explored by Ji et al., who used a support vector classifier to estimate the prediction error, obtaining a lower MSE and MAE compared to the SVM method [195]. The SVM model presented a lower RMSE, thereby outperforming MLP for system orders from 1 to 11. Larson and Westrick compared ANNs, conditional ANNs, and support vector classifiers with linear regression algorithms [90]. The authors concluded that besides obtaining lower MSEs and MAEs than found using a traditional SVM model, conditional ANNs provided better forecasts than linear regression or ANNs for the very short-term, with an NRMSE error improvement over persistence of between 5% and 25%.

A new approach to model wind vector fields was introduced by Goh et al. [196] and further developed by Mandic et al. [197], where the wind vector is represented as a complex-valued quantity; thus, wind speed and direction are modeled simultaneously. Juban et al. studied five data-mining models to predict wind speed and wind power, including SVM, MLP ANN, regression trees, and random forests [198]. Results indicated that the MLP ANN outperformed the other four models in the very short, short-, and medium-term horizons. The direct approach of feeding the wind ensembles' NWP directly into the model also outperformed the integrated approach for both very-short, short-, and long-term models. Kusiak et al. tested five different data-mining algorithms to forecast the wind power: SVM, MLP ANN, the M5P tree algorithm, the Reduced Error Pruning tree, and the bagging tree [199]. The SVM and MLP ANN performed particularly well. The SVM provided accurate forecasts from 10 minutes up to 1 hour ahead, whereas the MLP ANN was accurate for forecasts of up to 4 hours.

Reikard presented regime-switching models to study the temperature dependence of the wind speeds, then added state transition models to achieve a performance of up to 10% better than persistence [200]. Because other tested models (Generalized Auto-Regressive Conditional Heteroskedasticity [GARCH], Exponential Generalized Auto-Regressive Conditional Heteroskedasticity [EGARCH], ANNs, and Kalman filters) did not perform better on the eight time series of hourly wind speeds, conclusions followed that the variability in wind speed leads to difficulties in its prediction, increasing the forecasting error. In a later paper, regime-switching models achieved a similarly good performance with multivariate regressions using selected causal factors or state transition models [201]. However, two regime-switching models (a high regime where persistence was used, and a low regime using regressions) were closer to the measured values than the other methods. Reikard claimed that if states were perfectly predicted, then the regime-switching model would improve the forecast accuracy by 2.5% to 3%. Pinson et al. tested regime-switching approaches based on observable (i.e., based on recent production) or nonobservable (i.e., Markov method) regime sequences for time steps of 1, 5, and 10 minutes [202]. They presented three types of models: the self-exciting threshold autoregressive (SETAR), the smooth transition autoregressive (STAR), and the Markov-switching autoregressive (MSAR). The performance of the models was compared with the ARMA linear model. In all test cases, the MSAR models significantly outperformed the other models. Although not significant, there was also a gain in applying the SETAR and STAR models instead of ARMA. The authors concluded that the MSAR captured the influence of some complex meteorological variables on the power fluctuations. They demonstrated that the regime sequence-leading successive periods with different behaviors is very complex and cannot be considered as a simple function of the wind generation level. The authors also observed that wind power, particularly its variability from large offshore wind, occurs in certain regimes, concluding that the methods studied significantly outperformed models based only upon observable regime sequences. The reduction in RMSE ranged from 19% to 32%, depending on the wind farm and time resolution considered. Pinson and Madsen later improved the previously described MSAR model [203]. A time-variant estimation of the model coefficients was described, as well as a regularization term that enabled the reduction of the variability of the model coefficients' estimates. In addition, predictive densities were provided by a combination of conditional densities in each regime. Their quantiles can then be computed by numerical integration methods. In 2011, Gallego et al. used a benchmarking effort between regime-switching and conditional parametric models to predict wind power on a very short-term basis for offshore wind farms in Denmark [204]. Results have shown that conditional parametric models achieve a better performance than the regime-switching approach.

Wegley et al. predicted wind speed for three different time steps [205]. They tested persistence, autoregressive models, and a generalized equivalent Markov model [206], concluding that the former and the latter performed best for the shortest and longest time steps, respectively. Use of Grey predictors is another approach that has been widely applied in different fields [207]–[210]. El-Fouly et al. [211] presented a new technique to forecast wind speed for the upcoming hour based on the Grey predictor model. The wind speed was then converted to wind power by a manufacturer's power curve. The improvement over persistence

was 12% for the wind power forecast. Studies of the use of discrete Hilbert transforms (DHTs) to predict the wind speed were published by Zhua and Yang [212] and by Alpay et al. [213]. In 2012, Vaccaro et al. compared physical models (white-box) with learning approaches (black-box), integrating the latter techniques with physical methods into grey-box predictors [214]. They forecasted the wind speed both for short- (hourly, until 24 h ahead) and medium-term (monthly, until 18 months ahead) horizons. Results for a south location in Italy showed that the proposed grey models outperformed the other methods, particularly in the short-term. In addition, the authors have concluded that the wisest prediction approach consists in not limiting the family of models to use but rather in adopting combinations of statistical, learning, and physical methods.

In 2011, Huang and collaborators performed ultra-short wind power forecasts based on the Multiple Models Extreme Learning Machine (MMELM), where the final output is given by the weighted sum of all the model outputs, and they succeeded in obtaining accurate results [215]. Mori and Umezawa used decision tree techniques in data mining, concluding that the wind power is strongly related to the atmospheric pressure in summer and to the air relative humidity during winter [216]. Damousis and Dokopoulos applied a genetic algorithm (GA) to optimize a FIS model and predict wind speed and power production, obtaining improvement between 9.5% and 28.4% over persistence depending on the time horizon [165]. Jafarzadeh et al. developed a new stochastic method to predict very short-term (1-h ahead) wind power [217]. They used Hidden Markov Models (HMMs) and the Viterby Algorithms (VAs), adopting three different strategies to find the best estimate of the wind power for the next hour. The authors first used a Prediction Transition Probability (PTP) method to estimate the wind power, yielding the results with highest prediction error; the second strategy used transition probabilities and VA, with a shorter time step than the horizon and without observations to estimate the most likely state, although the poor improvements over the latter approach do not justify the additional computational effort; the third strategy, on the other hand, used pseudo-measurements, that is, predicted values of wind speed or power as observations, applying the VA to provide the best estimates of wind power generation. In 2012, An et al. presented a grey model combining Empirical Mode Decomposition (EMD) and chaotic theory to predict the wind speed on the very short-term [218]. EMD is used to decompose the wind power into different Intrinsic Mode Functions (IMFs) and a residual component. If the IMF terms are chaotic time series, then a largest Lyapunov exponent method is applied as a predictor; if not, the grey predictor is used. Prediction results of IMFs and the residual component are aggregated into a unique wind power output. The proposed model reduces the nonstationarity of wind power time series and improves the forecasting accuracy compared to a prediction method that uses the power data directly.

Safavieh et al. proposed a new integrated method applying a Particle Swarm Optimization (PSO) algorithm to train wavelet networks in order to forecast the wind speed for a very short-term horizon [219]. The proposed approach is compared to MLP ANNs with the BP training algorithm. Results show that the new approach improved MAPE and the maximum prediction error. Jursa performed short-term wind power forecasts, comparing classical MLP ANNs, a mixture of experts, SVM, and nearest neighbor with PSO [220]. He concluded that the

combination of several models for day-ahead forecasts delivers better results. In 2011, Salcedo-Sanz et al. presented an application of two evolutionary computation techniques to handle the hyper-parameters estimation problem in SVM for regression [221]. Namely, the authors used an evolutionary programming algorithm and a PSO approach to deliver short-term wind speed forecasts for wind farms in Spain. The system showed good forecasting performance, outperforming an MLP.

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4. Synthesis of State-of-the-Art Methods

This section presents a synthesis of the most relevant state-of-the-art methods for very-short term forecasting. Apart from persistence, Tables 4-1 and 4-2 summarize the main techniques currently used to predict wind speed and power using physical and statistical-based techniques, respectively.

Table 4-1 Very short-term physical and hybrid forecasting techniques.

Techniques/Models	Description and Performance
Prediktor [43], [44], [50]–[52]; [80]	Prediktor applies MOS to HIRLAM and uses WAsP and PARK for local refinement. Wind speed is converted into power through the manufacturer’s power curve. Fossil fuel costs are lower compared with persistence predictions.
Previento [49], [80]	Approach employed is similar to that of Prediktor but uses the LokalModell instead for NWP. Regional forecasts and uncertainty estimations can also be determined with better performance than persistence.
WPPT [53], [62], [63], [68], [69], [80]	The WPPT is a hybrid system that combines an NWP model to predict the wind speed, such as MM5, with power curves to statistically estimate the power output. It can also include CFD techniques to adapt to local features and uses a time-adaptive process to deal with nonstationarities. This system is more advantageous for the short term than a direct wind power prediction.
eWind [56]	eWind runs an ensemble of NWP models (e.g., ForeWind, ETA, MM5, WRF), applying MOS to forecast the wind speed. Ensemble results are used either as inputs to power curves or to train ANNs to deliver power outputs. Spatial correlation results have been shown to decrease with increasing distance, and deviations for longer forecast horizons are more correlated than for shorter ones.
Sipreólico [64], [78], [80]	This hybrid system applies an ensemble of NWP models to predict the wind speed and uses various adaptive statistical models to forecast the wind power. This method presented the lowest prediction error in some studies when compared to other models and persistence.
LocalPred [65], [80]	LocalPred combines microscale NWPs with autoregressive models to predict the wind speed and power for the very short-term, delivering better results than persistence.
Zephyr [70], [71]	Zephyr combines Prediktor with WPPT. For horizons longer than 6 h ahead, the former has lower forecast error, whereas the latter performs better for the very short-term.

Table 4-2 (Cont.)

Techniques/Models	Description and Performance
AWPPS [75]	The AWPPS consists of a weighted combination of NWP and fuzzy ANNs. It delivers improved very short-term forecasting results.
HIRPOM [76]	A power prediction module (wave model) is coupled with HIRLAM, enhancing its physical properties and improving the accuracy of wind speed predictions. WTG data series as inputs to the NWP model lower the prediction error.
PowerSight [89]	PowerSight forecasts the wind speed using the best weather forecast ensemble with MOS. Power generation is predicted by quantile regression or a power curve model. The performance of this forecasting system can be improved by using off-site meteorological observations. It delivers lower prediction errors for day-/hour-ahead ramp, as well as intra-hour wind power forecasting.
Precise Stream [108]	In this physical model, CFD methods are applied to micro- and mesoscale NWP tools. Wind speed predictions are improved, particularly in complex terrain. The manufacturer's power curves are used to determine the wind power. NMAE for 6 h ahead ranges between 2.5% and 5.5%, 6% to 9.5% for 12 h ahead, and 10% to 17% for daily predictions.
Visionpoint [109]	Visionpoint combines mesoscale NWP, RUC, and NAM with the GFS. A support vector machine is used to convert wind speed into power. For very short-term generation, outputs are provided every 10 minutes, being updated on an hourly basis for the following 3 hours; NMAE is typically between 5% and 12%.

Table 4-3 Very short-term statistical and hybrid forecasting techniques.

Techniques/Models	Description and Performance
<p>Kalman Filter (KF) [104], [105], [116]–[118]</p>	<p>A KF consists of a set of mathematical equations that provide a solution of the least square method with minor computational cost. Adaptive to variations in the observations. Improves the quality of time series, delivering better wind forecasting results with fewer systematic errors.</p>
<p>Linear Prediction Methods [138]–[140]</p>	<p>Based on time series techniques, these methods elaborate a mathematical approach to the problem, considering the difference between the predicted and the actual wind speed values to retune the forecasting parameters. Shown to establish a high correlation between predicted and real wind speeds.</p>
<p>AR [120]–[122], [137]</p>	<p>AR methods are based on a number of historical data, pattern identification, and parameter estimation. The differences between the predicted and the actual values are used to retune the model parameters. Can deliver better wind speed forecasting results than persistence.</p>
<p>ARMA [123], [127]; Combined ARMA [128]</p>	<p>If the time series has a varying average, the autoregressive model is given by equation (3-3), obtaining an AR moving average, or ARMA. These models reduce the wind speed prediction error, compared with persistence, and, when combined, the forecasting results can be improved.</p>
<p>ARIMA [129], [132]; f-ARIMA [133], [135]</p>	<p>When a differential transformation is applied to ARMA, an autoregressive integrated moving average (ARIMA) is obtained. A modified version of ARIMA is named f-ARIMA. Both models can have a better wind speed forecast performance than persistence.</p>
<p>Regime-Switching AR [200], [203]–[204] (SETAR, STAR, MSAR)</p>	<p>For addressing potential nonlinearities in the time series represented by an AR model, this approach can assume subsamples (or regimes) with different behaviors. Regime-switching AR models can capture the (causes of) power fluctuations, in some cases delivering better results than persistence. In particular, the Markov-switching autoregressive (MSAR) model outperforms the self-exciting threshold autoregressive (SETAR) and the smooth transition autoregressive (STAR) methods.</p>
<p>Grey Predictor [200]–[210], [214], [215]</p>	<p>Grey theory has the ability to deal with systems characterized by poor or nonexistent information. When applied to wind forecast, grey predictors deliver improved wind speed prediction results over persistence, particularly for low-rated time series.</p>

Table 4-4 (Cont.)

Techniques/Models	Description and Performance
<p>Combined Linear Statistical Methods [64]</p>	<p>The combination of various linear statistical methods yields better wind speed prediction results and power forecasting accuracy when compared with (individual) traditional time series methods.</p>
<p>SCP [152], [173], [174]</p>	<p>A spatial correlation predictor uses spatial (terrain) information to reduce the prediction error compared with persistence, particularly for complex terrain.</p>
<p>ANN (SP, MLP, RBF, Elman, Hopfield) [153]–[155], [157], [158], [172], [173]; Combined ANNs [151]</p>	<p>ANNs may present various architectures/structures (e.g., single, multilayer perceptron [SP, MLP]) or radial basis function (RBF) and different training algorithms (e.g., back-propagation, Bayesian techniques). ANNs can perform better than physical and linear statistical models in the very-short term. Combined ANNs’ performance can surpass persistence. These models can directly forecast either wind speed or wind power, also enabling probabilistic forecasts, with lower forecast errors than simple ANNs.</p>
<p>Takagi-Sugeno [164] Fuzzy Logic [165] FIS [181]</p>	<p>Takagi-Sugeno (T-S), fuzzy logic, and FIS use fuzzy variables to model the wind speed and power. In some case studies, they have shown to deliver better performance than persistence, increasing the accuracy with the forecasting horizon.</p>
<p>ANFIS [102], [166], [167], [170]; LF-DFNN + SCP [168]; Multi-Layer FF ANN + Fuzzy [171]</p>	<p>The combination of ANNs and fuzzy systems—such as adaptive neuro-fuzzy inference systems (ANFIS), locally feedback dynamic fuzzy neural network (LF-DFNN), and multi-layer feed-forward ANN with fuzzy inputs—can control the complexity of networks, having a flexible design capable of handling sudden fluctuating data patterns, thus increasing the wind power prediction accuracy on the very short-term when compared to other network models.</p>
<p>Kernel Methods (KLMS, RKHS, KH, KA, Kernel RLS, MKL) [187]–[191], [193]</p>	<p>Kernel prediction methods are nonlinear statistical methods. They can overcome some of the disadvantages of other nonlinear prediction models, particularly on the very short-term, enabling high-dimensional feature spaces and avoiding over-fitting. Examples of such methods include kernel least mean squares (KLMSs), reproducing kernel Hilbert spaces (RKHSs), kernel Hebbian (KH), kernel Adaline (KA), kernel recursive least squares, and multiple kernel learning (MKL).</p>
<p>SVM [183], [195]</p>	<p>Support vector machines (SVMs) are kernel-based models that can deliver lower forecasting errors than ANNs.</p>

Table 4-5 (Cont.)

Techniques/Models	Description and Performance
<p>Abductive Networks (GMDH) [160], [161]</p>	<p>Abductive networks based on the group method of data handling (GMDH) are simplified and more automated methods that can automatically select the influential inputs, allowing comparisons between statistical and empirical models. These models have faster training convergence than an ANN and have achieved proven improvements over persistence in the very short-term.</p>
<p>WEFS [177], [178]</p>	<p>Wind Energy Forecasting System (WEFS) is a hybrid model composed by physical mesoscale (MM5, WRF) and statistical algorithms. Very short-term wind speed prediction is improved over persistence, when using on-site wind measurements as inputs to the NWP coupled with a DWM.</p>
<p>Quaternions [196], [197]</p>	<p>Representing the wind vector as a complex variable (quaternions), wind speed and direction are modeled simultaneously. These methods have delivered good prediction results.</p>
<p>DHT [212], [213]</p>	<p>Discrete Hilbert transforms (DHT) is a family of waveform transformations, which allow regular analytic samples of a signal to be calculated from its real sampling. These models have been used to predict the wind speed, in some cases yielding better forecasting results than persistence.</p>
<p>PSO [217]</p>	<p>Particle swarm optimization (PSO) methods consist of the optimization of nonlinear functions using a particle swarm methodology, which can be used to train wavelet networks. Wind speed forecasting results have shown lower prediction error than ANNs.</p>
<p>Hybrid Methods [5], [90], [141], [163], [175], [176], [217], [218], [220], [221] (e.g., WT + ITSM); ANN + Kalman filter + AR methods + nearest neighbor + SCP + MC); MC + VA EMD + chaotic theory; EPSO + SVM</p>	<p>Hybrid models, combining different methods, have shown to deliver better wind speed and power forecasting results, with lower prediction errors than other individual statistical methods. In particular, hybrid methods can yield accuracy improvements over persistence.</p>

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5. Concluding Remarks

The stochastic nature of the wind resource brings variability to wind power production, which adds complexity to the very short-term forecasting horizon, and consequently affects wind farm management and power system operations. As a continuation of our previous state-of-the-art review [7], this report includes an overview of WPF methodologies with a focus on the very short-term forecasting horizon (of up to 6 hours).

WPF models are classified into NWP/physical or statistical/AI methods. The former use the physical laws of the atmosphere to predict the relevant meteorological variables (e.g., wind speed) through an NWP model or ensemble. The NWP outputs are then used as inputs to power curve or statistical models to predict the wind power. As the performance of NWP/physical-based wind power prediction models depends highly on the quality of the wind forecast, results show that models that better characterize the atmospheric and terrain features of the area under study (e.g., by finer spatial resolution using micro- or mesoscale NWPs with CFD techniques and/or geographically dispersed observations) deliver enhanced wind predictions, thus leading to improved wind power forecasts.

Statistical or learning approaches employ wind (power) time series to predict the wind speed or to directly forecast the wind power generation. Examples of these approaches include classical linear statistical models, such as persistence, autoregressive, and Box-Jenkins methods; or nonlinear techniques, such as ANNs, fuzzy logic, and kernel-based methods. Nonlinear statistical methods are able to capture the nonstationary nature and nonlinearity of the wind resource, hence delivering results with lower prediction errors, particularly for horizons until 6 h ahead.

The main drawback of forecasting the wind speed first, and then the power, relies on the inability of power curves to fully represent the turbine dynamics. However, this method is valid for different systems regardless of the wind farm specifications. Besides, wind speed data are measured directly and thus do not suffer from external influences. On the other hand, a direct wind power prediction model is specific to a certain generator, park, or region and is invalid for others with different characteristics (e.g., terrain orography/roughness, machine design, and layout). In addition, a wind power data set is more difficult to collect and might be influenced by external factors that cannot be predicted.

Hybrid methods have been shown to deliver better wind power predictions than persistence and most individual methods at the very short-term timescale. In fact, the hybrid approaches benefit both from the high level of accuracy in the physical models and of the computational learning capabilities of statistical/AI models. Therefore, when answering the question of whether it is preferable to forecast the wind speed and then the power, or to directly predict the wind power, the answer tends to be that the combination of both into a hybrid model is the best approach. At the same time, the best forecasting approach will also depend on the characteristics of the specific location as well as the intended use of the forecast.

On the basis of the findings presented in this report, although the persistence model has been assumed to be the benchmark technique for the very short-term, wind power prediction still lacks a default forecasting system (or set of models) that is widely accepted by the wind energy community. In the continuation of this analysis, the best hybrid methods are promising starting points for further improvements in the WPF for the 0–6-h ahead horizon. Toward this end, the development of physical/NWP models with higher accuracy and resolution, as well as new and more sophisticated statistical/artificial intelligence methods, can both contribute to improve the quality of very short-term forecasts. In addition, at these timescales, particular attention should also be addressed to improve wind (power) ramp forecasting algorithms.

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