The Future of Forecasting for Renewable Energy

Conor Sweeney[*][†], Ricardo J. Bessa[‡], Jethro Browell[§], Pierre Pinson[¶]

Abstract

Forecasting for wind and solar renewable energy is becoming more important as the amount of energy generated from these sources increases. Forecast skill is improving, but so too is the way forecasts are being used. In this paper, we present a brief overview of the state-of-the-art of forecasting wind and solar energy. We describe approaches in statistical and physical modelling for time scales from minutes to days ahead, for both deterministic and probabilistic forecasting. Our focus changes then to consider the future of forecasting for renewable energy. We discuss recent advances which show potential for great improvement in forecast skill. Beyond the forecast itself, we consider new products which will be required to aid decision making subject to risk constraints. Future forecast products will need to include probabilistic information, but deliver it in a way tailored to the end user and their specific decision making problems. Businesses operating in this sector may see a change in business models as more people compete in this space, with different combinations of skills, data and modelling being required for different products. The transaction of data itself may change with the adoption of blockchain technology, which could allow providers and end users to interact in a trusted, yet decentralised way. Finally, we discuss new industry requirements and challenges for scenarios with high amounts of renewable energy. New forecasting products have the potential to model the impact of renewables on the power system, and aid dispatch tools in guaranteeing system security.

[*]School of Mathematics and Statistics, UCD, Dublin, Ireland
[†]UCD Energy Institute, UCD, Dublin, Ireland
[‡]INESC Technology and Science (INESC TEC), 4200-465 Porto, Portugal
[§]Department of Electronic and Electrical Engineering, University of Strathclyde, Glasgow G1 1XQ, UK
[¶]DTU Informatics, Technical University of Denmark, Lyngby, Denmark

1 INTRODUCTION

Forecasting for renewable energy is under substantial focus as the penetration of renewable energy from wind and solar increases, with an overwhelming consensus on its importance for the economic and reliable integration of their energy production into existing power networks. While other forms of renewable energy sources may also involve some forecasting tasks and challenges, most emphasis was placed on wind and solar energy over the last decade or two, owing to their variability and limited predictability, and instantaneous response to weather phenomena. In contrast, hydropower generation depends on the hydrology of extensive catchment areas and the operation of storage capacity in addition to local weather. For a recent coverage of a broad range of topics of interest in renewable energy forecasting, the reader is referred to Jung and Broadwater (2014) (wind speed and power forecasting), Gallego-Castillo, Cuerva-Tejero, and Lopez-Garcia (2015) (wind power ramp forecasting), Antonanzas et al. (2016) (photovoltaic power forecasting) and Bessa et al. (2017) (uncertainty forecasts in the electric power industry).

Of course, the value of any forecast is only realised when it results in better decision-making. Broadly speaking, users of renewable energy forecasts fall into two groups: energy market participants, and power system operators. The former is concerned with the buying and selling of energy, while the latter's priority is maintaining a reliable energy supply, but both require timely and accurate forecast of renewable power generation. Liberalised energy markets, such as those in Europe and the US, vary considerably in structure but the timescales involved are common: long-term trading (and hedging) takes place weeks to years ahead, day-ahead markets establish a preliminary schedule for power plants, and intra-day markets enable further adjustment, right up until delivery begins in some cases. Accurate forecasting on all of these horizons is therefore an economic imperative for market participants, and understanding forecast uncertainty is necessary to manage risk. System operators similarly depend on renewable energy forecasts to prepare for whatever generation mix the market (and weather) delivers. This may include holding reserve power to manage ramps in renewable production, or procuring 'ancillary services' to manage technical constraints.

Advances in research and connection of forecasting to decision-making in operations and markets are happening in multiple areas. Looking at the forecasting process itself, both physical and statistical modelling approaches are commonly involved today. On the one hand, the physical modelling part is concerned with solving the governing equations of the atmosphere and generating forecasts for those atmospheric variables relevant for renewable energy, often being very computationally expensive to run. Statistical modelling approaches bridge the gap between the information from those meteorological forecasts and observations (being meteorological or power). Further than those physical and statistical approaches, we are today at a cornerstone in the development and applications of forecasting approaches, as enabled by the wealth of data being collected, rapid increase in computational capabilities and the need to rethink business models related to renewable energy forecasting.

Consequently, the main objective of this review is to start with a brief overview of the state of the art in renewable energy forecasting, and to highlight some of the promising paths for future development in forecasting research and application in the energy industry.

2 Forecasting Renewable Energy Today

Even though statistical and physical modelling approaches are often blended today in renewable energy forecasting, we will consider them separately here, so as to cover the components of physical and statistical modelling which are used in practice.

2.1 Physical Modelling

2.1.1 Numerical Weather Prediction

Advances in Numerical Weather Prediction (NWP) have been described as a quiet revolution (Bauer, Thorpe, & Brunet, 2015), in that great advances have been made, but this has been done by a succession of steady advances, such as improved numerical schemes to solve the governing equations, parameterizations schemes for sub-grid scales, access to more observation data including satellites, and increases in computing power, rather than any fundamental breakthrough.

NWP models, which use computers to solve the governing equations of the atmosphere, are being run at higher horizontal and vertical resolutions as available computing power increases. Along with changes in resolution, there have been advances made in how the model approximates, or parameterizes, the sub-grid scale processes which are not resolved by the model, such as turbulence and cloud physics. NWP skill continues to improve, albeit at a slower rate than previously (Hoffman et al., 2018), and current NWP forecasting of mid-latitude weather can remain skillful out to 10 days when comparing 500-hPa geopotential height between the forecasts and observations (F. Zhang et al., 2019). An indication of the improvement of NWP skill is shown in Figure 1, which shows the improvement in 48-hour wind speed forecast skill between 2007 and 2018 for two widely used NWP models: the deterministic Integrated Forecasting System (IFS) model produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), and the deterministic Global Forecast System (GFS) model produced by the National Centers for Environmental Prediction (NCEP). All forecast centres attempt to produce the best forecast posssible, but there is no single best way to do this. Differences in how NWP models assimilate observation data, solve the governing equations, and the computational power available to run these models mean that different models may have different skills.

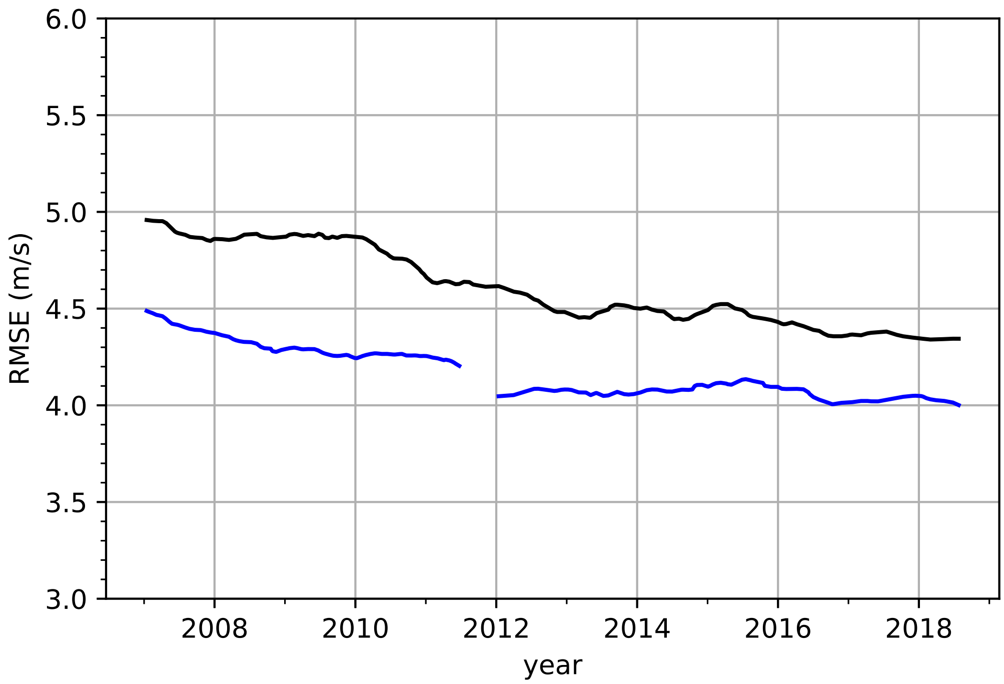


Figure 1: 12-month rolling average of the 48-hour ahead root mean square error (RMSE) forecast skill for wind speed on the 850 hPa pressure level in the Northern Hemisphere. Blue lines: old/new ECMWF IFS. Black line: NCEP GFS

NWP models are first run with a grid covering all of the Earth (a global model), and the data from these forecasts are then used to drive higher-resolution NWP models which cover a more limited area of interest (local models). As an indication of the resolution currently being used for these models, Table 1 shows the horizontal resolution for a selection of NWP models operationally used to a forecast horizon of 48 hours or more. Forecast centres listed are: ECMWF, NCEP, United Kingdom Met Office (UKMO), the German Meteorological Service Deutscher Wetterdienst (DWD) and Japan Meteorological Agency (JMA).

Forecast centre	Domain	Model Name	Horizontal resolution
ECMWF	Global	IFS HRES	9 km
NCEP	Global	GFS	28 km
NCEP	Local	NAM	3 km
UKMO	Global	UM	10 km
UKMO	Local	UKV	1.5 km
DWD	Global	ICON	13 km
DWD	Local	COSMO-DE	2.8 km
JMA	Global	GSM	20 km
JMA	Local	MSM	5 km

Table 1: Horizontal resolution of a selection of NWP models

As the atmosphere is chaotic, with sensitive dependence on initial conditions, a single (deterministic) forecast is widely seen as providing too limited information. Uncertainties in the initial state of the atmosphere, combined with approximations in the NWP model, result in forecasts which can diverge widely from each other.

Uncertainty in the initial conditions is generally handled by different data assimilation approaches. The area of data assimilation is concerned with producing initial conditions in balance with the NWP model which are as close to reality as possible. As there are many times more model grid points than observations this is a difficult task, and also one with a large computational expense. Different data assimilation approaches are used in different operational NWP centres, such as variational approaches (3D-VAR, 4D-VAR), which iteratively solves a cost function to optimise the fit between observational data and the model initial conditions, and the ensemble Kalman filter (EnKF) (Bannister, 2017), which uses a Monte Carlo approach to estimate both the mean and the covariance of the error between the model and observations. Advances in data assimilation, such as improving the way error covariance is estimated in a hybrid of ensemble Kalman and 4-dimensional variation, can lead to improved NWP forecasts, and new methods are still being tested and applied to operational NWP (Lorenc & Jardak, 2018).

Improving NWP models requires good, relevant observation data, and projects such as the Wind Forecast Improvement Project (WFIP) (Wilczak et al., 2015) combine field campaigns which target a range of relevant observations with assessment of NWP models specifically for wind energy, resulting in larger reductions of RMSE for wind power. Improvements in NWP have also targeted solar energy, as in the WRF-Solar NWP model (Jimenez et al., 2016), which showed improved skill by better representing atmospheric aerosols and their interactions with clouds and radiation.

Uncertainty in the NWP models themselves can be quantified by running a collection, or ensemble, of NWP forecasts. Ensembles can be generated by using different NWP models, and different parameterizations within those models. This ensemble of forecasts can be used to produce probabilistic forecasts, for example counting the percentage of ensemble members which forecast a parameter above some threshold. Probabilistic forecasting has been shown to outperform deterministic forecasts, e.g. (Siuta & Stull, 2018) show improvements in both forecast accuracy and correlation for wind speeds at wind turbine heights when using an ensemble instead of a deterministic forecast. Probabilistic forecasts also allow a quantification of uncertainty in the forecast values. As probabilistic forecasting becomes more widely used, its ability to quantify this uncertainty is becoming more important, and there is active research into improving how NWP captures uncertainty (Leutbecher et al., 2017). Forecasting large changes in wind power, called wind ramp events, is becoming more important as wind penetration increases. There are a variety of methods used in forecasting wind ramps (Gallego-Castillo et al., 2015), with probabilistic approaches offering a clear advantage here. Some examples are: (Bossavy, Girard, & Kariniotakis, 2013) that used a filtering approach applied to each member of the forecast power ensembles for detecting and producing probabilistic forecasts of ramps by combining a NadaryaWatson estimator and logistic regression; (Taylor, 2017) uses autoregressive logit models fitted to the change in wind power to perform probabilistic forecasts of ramp events for different thresholds and multiple wind power plants (with multinomial logit structure); in (Chu, Pedro, Li, & F.M.Coimbra, 2015) and for solar energy, information from sky-camera images is used as exogenous input to neural networks in order to produce minute averaged values of global and direct irradiance ramp forecasts.

It should be noted that the improvements in detecting possible ramps from ensemble forecasting arises from the analysis of the multiple individual forecasts. The simpler approach of averaging all forecasts and using the mean should not be used here (or, arguably, anywhere), as this would smooth any individual forecast ramps.

2.1.2 Hydrological Models

The majority of water resources available to hydropower generators come from precipitation and snow melt that has been channelled into rivers and reservoirs from large catchment areas. These additional hydrological processes often require explicit modelling, which represents a significant additional stage of the forecasting process for hydropower that is not required in wind and solar forecasting. These processed are typically modelled using water budget or *bathtub* models that calculate the volumes of water in different elements in the hydrological system such as soil moisture, ground water, reservoir storage, snow pack, and so on, in addition to transfers in/out of the system and between elements (Bergstrm & Lindstrm, 2015; Gragne, Sharma, Mehrotra, & Alfredsen, 2015). Hydrological models may be driven by observations and NWP, for example temperature forecasts can drive predictions of snow melt and resulting inflow to rivers and reservoirs. Similarly, precipitation forecasts drive soil moisture and rainfall runoff. Beyond power production, hydropower operators often have additional responsibilities associated with ecological and floor risk management requiring specialist hydrological forecasts, which are beyond the scope of this article.

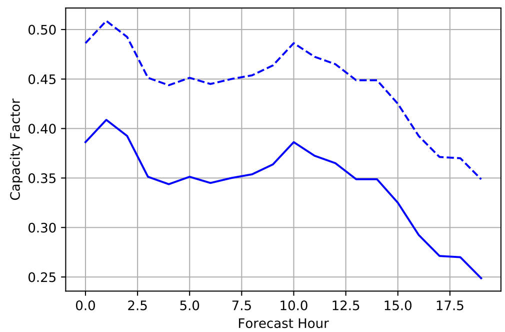
2.2 Statistical Modelling

Statistical modelling plays a number of roles in renewable energy forecasting and has been the focus of research since the first attempts to produce wind and solar power forecasts and characterise predictability in the late 1970s and 1980s. For instance, in (Wendell, Wegley, & Verholek, 1978) it was mentioned, for the first time, the use of an analog approach to construct a forecast probability distribution of wind speed; (Brown, Katz, & Murphy, 1984) proposed a time series model to directly forecast wind power up to several hours ahead; in (Bossanyi, 1985), Kalman filter was applied to forecast short-term wind speed and outperformed persistence in 10 minutes resolution; statistical post-processing with Model Output Statistics (MOS) was applied to forecast daily solar radiation for two days ahead (Jensenius & Cotton, 1981); an ARIMA model was applied to model cloud cover time series to forecast global solar irradiance (Chowdhury & Rahman, 1987). Since this time there has been a clear distinction between methods for 1) post-processing NWP in order to produce power production forecasts, favoured for lead-times of a few hours to days ahead, and 2) predicting the next values(s) of power production time-series, favoured for lead-times of less than a few hours. We examine both here and note that there is a third class of statistical modelling which concerns the 'blending' of predictions from both types of models to produce a smooth transition from one approach to the other across forecast lead-times.

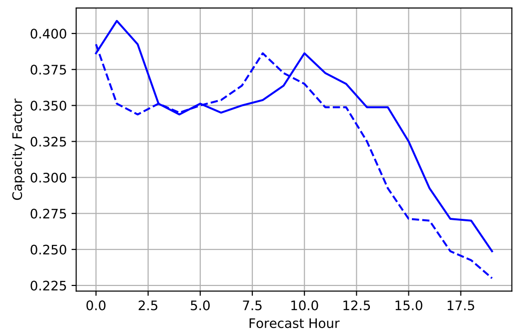
2.2.1 Post-processing Numerical Weather Predictions

Due to finite observations and computational power, all NWP models are limited in their resolution, and use approximations when solving the governing equations of the atmosphere. These limitations mean that there may be systematic biases in the model forecast, for example where the model topography does not exactly match that of the real world, or other biases which depend on the state of the atmosphere. The purpose of post-processing weather forecasts in renewable energy forecasting is threefold: first to model the power conversion process for the site of interest, second to correct systematic bias in the NWP forecast data, and third to quantify forecast uncertainty.

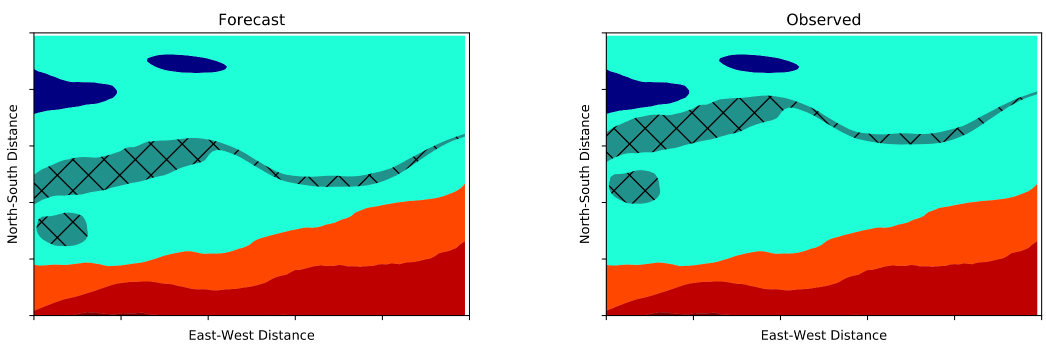
The physics of the weather-to-power process for wind turbines and solar technologies is well understood and modelled, but the input to such models rarely corresponds to those available for forecasting. For example, the hub height wind speed used to characterise a manufacturer's wind turbine power curve is not directly comparable with the wind speed forecast produced by NWP which is produced for a cell which may contain multiple wind turbines with wake and local terrain effects becoming important. Therefore, statistical methods are employed to model the relationship between available NWP variables and renewable energy production. Forecasts based on power curve models are necessary where no data are available to estimate a statistical model, such as when a wind or solar farm is first commissioned, but generally produce poorer quality forecasts than statistical post-processing. Similar principals may be applied to run-of-river hydro (Camal, Teng, Michiorri, Kariniotakis, & Badesa, 2019), but for dispatchable hydro, water infolw to storage reservoirs would be the forecast variable (Maier & Dandy, 2000).



(a) Forecast: Dashed line. Observed: Solid line.



(b) Forecast: Dashed line. Observed: Solid line.



(c) Forecast: Left plot. Observed: Right plot. Spatial difference highlighted as hatched area.

Figure 2: Illustration of different types of errors: (a) Level Error, (b) Phase Error, (c) Spatial Error.

When comparing NWP to a single measurement location, such as a meteorological station or renewable power plant, it is typical to observe some systematic bias that results from local effects, such as terrain, which are not fully captured by the NWP. Statistical models are able to learn these biases from historic data and then correct for them in subsequent forecasts. These biases may manifest in different ways, illustrated in Figure 2; as 'level errors', simply over- or under-predicting the value of a variable; 'phase errors', predicting events earlier or later than they are observed; or 'spatial errors', predicting events at the wrong location. Level errors are automatically dealt with when modelling power production as a function of NWP variables for the same target time. Phase errors may be addressed by modelling power production as a function of NWP targeting the same and neighbouring time periods, as in (Landry, Erlinger, Patschke, & Varrichio, 2016), and similarly location errors may be addressed by modelling power as a function of a grid of NWP encompassing the target location (Andrade & Bessa, 2017).

Quantifying uncertainty is critical for risk management and optimal decision-making. While the statistics of deterministic forecast errors provide some information on uncertainty the majority of use-cases for renewable energy forecasts benefit from the more detailed information provided by probabilistic forecasts. As mentioned earlier, an ensemble of NWP model forecasts can be used to produce a probabilistic forecast. The probabilistic forecast itself may have systematic errors, which can be removed by statistical post-processing, or by an approach like the Analog Ensemble approach, which builds an ensemble by using a set of past observations that correspond to the best analogs of NWP forecasts. This approach has been used to improve the skill of both deterministic and probabilistic forecasting for both wind and solar power (Yang, Astitha, Delle Monache, & Alessandrini, 2018). Recent developments in renewable energy forecasting have focused on probabilistic forecasts and can be divided into two groups: univariate and multivariate probabilistic forecasting.

A reliable probabilistic forecast is one for which the forecast probability corresponds well with observations: an event which is forecast with 80% probability should be observed to occur 80% of the time. A sharp probabilistic forecast is one for which the spread is small. Ideally, probabilistic forecasts should be as sharp as possible, while still being reliable. Univariate probabilistic forecasts aim to produce a sharp and reliable density forecast for a particular variable, such as solar power production from a single power plant at a particular time. This can be achieved by forecasting the parameters of a suitable probability distribution (e.g. mean and standard deviation for a normal distribution), or by constructing a density forecast from multiple quantile forecasts. The latter has emerged as the leading approach as the shape of the predictive distribution is not constrained and therefore better able to model complex densities; however, parametric models are still preferred for modelling the tails of predictive distributions where quantile regression suffers from high model variance.

Multivariate probabilistic forecasts aim to forecast the joint density for multiple values, such as multiple locations, multiple time periods, or even multiple resources (Camal et al., 2019). This information is important in decision-making problems with temporal or spatial constraints, such as energy storage management (including hydro reservoirs (Stedinger, Sule, & Loucks, 1984)) or probabilistic power flow analysis. Such forecasts may take the form of the full joint distribution function, or a set of scenarios or trajectories. Statistical methods to produce multivariate forecasts using deterministic NWP typically involve producing univariate forecasts for each variable and a copula to model the dependency structure (Tastu, Pinson, & Madsen, 2015). Methods have also been proposed to post-process ensemble NWP in order to produce a calibrated set of power production ensemble members.

2.2.2 Very Short-term Forecasting

The most relevant information to use when predicting weather dependent power production on timescales of minutes to a few hours ahead is near real-time measurement data. The requirement for NWP to assimilate large volumes of data and then run computationally expensive physical models means that by the time a new forecast is issued the most recent observation it is based on is already out-of-date. When forecasting on timescales of minutes, models which resolve the necessary physical processes are prohibitively expensive to run operationally. Instead, statistical models based on recent observations are used in very short-term forecasting, and it is this distinction that defines *very short-term* here.

On very short time scales *persistence* (where a forecast is equal to the most recent observation) is a competitive benchmark. For solar forecasts, it is now standard to apply a "smart persistence" baseline that accounts for changes in the solar angle. Time series methods based on classical statistics such as auto-regressive models have been well studied and perform well, especially when extended to consider multiple spatial locations simultaneously. However, one must consider how well the characteristic size and time scales of the weather match the forecast lead-time. In the simplest case forecasts are largely based on power production observations only. Typical methods include time-series models (auto-regression, and variants to incorporate spatial dependence) as well as machine learning approaches such as SVM and neural networks. Recent research in this area has focused on scaling-up these methodologies to be able to incorporate many spatial locations (Cavalcante, Bessa, Reis, & Browell, 2016; Messner & Pinson, 2018), and conditioning statistical model on large scale weather regimes for wind energy applications (Browell, Drew, & Philippopoulos, 2018) or cloud regimes for solar (McCandless, Haupt, & Young, 2016). Augmenting power production data with remote sensing is a well established strategy for improving solar power forecast performance via incorporation of satellite imagery (Blanc, Remund, & Vallance, 2017) for hours-ahead forecasting and sky cameras (Chow et al., 2011; Kazantzidis et al., 2017) for intra-hour forecasting. Similar methods are beginning to emerge in wind power forecasting with the use of LIDAR and RADAR technology to observe and advect changes in wind speed as they approach a wind farm (Trombe, Pinson, Vincent, et al., 2014; Valldecabres, Peña, Courtney, von Bremen, & Kühn, 2018; Valldecabres, Nygaard, Vera-Tudela, von Bremen, & Kühn, 2018; Würth et al., 2019).

The previous sections have separated forecasts based on physical or statistical approaches, and considered different time scales. Ideally, all of these approaches would be used together, as appropriate for the end-user. A good example of this is the system developed by NCAR and Xcel Energy (Mahoney et al., 2012) which combines real-time four-dimensional data assimilation, a high-resolution ensemble and adaptive statistical postprocessing technologies.

3 The Future of Forecasting Renewable Energy

Looking towards the future, we place emphasis here on some of the research problems at hand involving physical and statistical modelling while also considering current game changers related to data aspects, novel business models and industry requirements.

3.1 Advances in Very Short-term Forecasting

There is significant scope for innovation in very short-term forecasting, largely with regard to leveraging a greater volume and range of near real-time data from both SCADA systems and remote sensing. Even though solar and wind power applications are different in their details, most of the areas with high potential for further developments revolve around the same concepts, which include (i) availability of large quantities of data, (ii) availability of new types of data, e.g. from remote sensing, and (iii) novel approaches proposed in statistical and machine learning.

Looking at the wind power case, high temporal resolution ($\mathcal{O}$(seconds)) wind speed and power observations can today be obtained at the level of individual turbines and are available in principle for use in forecasting to learn more accurate statistical models (though often not actually utilized in practice) (Gilbert, Browell, & McMillan, 2019). For example, propagating wind speed or power changes from the upwind row of turbines to those further downstream could significantly improve minute-scale forecasts, especially at large offshore wind farms. Similarly, derived features such as ramp rates could further improve forecasts of 5- and 10-minute resolution power forecasts if combined with appropriate statistical modelling. These time scales are important, for example, in electricity markets which allow trading close to real-time, or for operators with co-located storage. The same goes for solar power generation, for which measurements can be made available at very high sampling rates and then used to improve forecasts at various spatial and temporal resolutions. In all cases, this calls for new methodological developments which could take advantage of such high-resolution information, ideally both in space and in time. An example relates to the use of stochastic (partial) differential equations for the high-resolution modelling and forecasting and solar power generation (Iversen et al., 2017). In parallel, considering novel remote sensing inputs to renewable energy forecasting, such as from sky imagers and radars, these require a wealth of methodological developments inspired by, for example, image analysis in order to define, extract and use relevant features from those images. Some may be directly informed by expert knowledge, but the most likely data-driven approaches are those which will be able to readily obtain the required features directly from analysis of the input images, as for the example of weather systems in the vicinity of offshore wind farms (Trombe, Pinson, & Madsen, 2014).

3.2 Advances in Physical Modelling

The continuing increase in the availability of affordable computing power is making more of this computing power available to NWP models. This allows NWP models to be run at higher resolutions, with some currently being run in the 100 m to 1 km range. However, running NWP models at higher resolutions requires new parameterization schemes for the sub-grid scale physics in the model, such as for turbulence. The grey zone of turbulence refers to resolutions at which turbulent eddies in the atmospheric boundary layer are partially resolved and partially parameterized, a regime that is now emerging in the highest resolution mesoscale models. Turbulent eddies are important due to the mixing and dissipation effect they have between different layers of the atmosphere. Incorrectly representing them in a model could, for example, result in systematic errors in wind speed or cloud cover, amongst other things. Careful perturbations of turbulence need to be introduced into the model to allow proper treatment of turbulence (Kealy, Efstathiou, & Beare, 2019). Radar data can be used to derive turbulence statistics for evaluating better parameterization of turbulence in NWP models (Feist et al., 2019).

Different types of models which have traditionally been used for small-scale modelling in aerodynamics and fluid dynamics, such as the LES model, are now being used alongside NWP models. This approach allows research to bridge the gap between mesoscale and microscale, and the two models have been coupled together to model a wind farm (Sanz Rodrigo et al., 2017; Gilbert, Messner, et al., 2019). LES models can also be used to further understand cloud processes and evolution (McMichael et al., 2019) and to compare LES output to NWP output (Angevine et al., 2018).

Recently, the effect of the wind farms themselves, including the turbulent wake behind wind turbines, and reduced energy in wind which has passed through a wind farm, is being included as a wind farm parameterization within NWP (Fitch et al., 2012; Redfern, Olson, Lundquist, & Clack, 2019). Such parameterizations generally consider two turbine impacts: elevated drag in the region of the wind turbine rotor disk and increased turbulent kinetic energy production. Results in terms of skill score improvements are mixed at the moment, but further advances in this area would make these schemes a valuable addition for wind energy forecasting, as they would potentially reduce systematic errors in the location of the wind farm itself.

Alongside increases in computing power, there has been a large increase in the amount of atmospheric data available over the past decade. Some of this increase is associated with higher sampling of data in time and space, and some of the increase is due to the availablility of new sources of data. It is the job of data assimilation to make these data available to the NWP models. A survey of data assimilation approaches for high-resolution NWP has shown improvements in skill of variables such as wind, temperature, cloud cover and precipitation by assimilating data at a higher resolution, with good potential for further improvements in convective-scale data assimilation of data from satellites, aircraft and radar (Gustafsson et al., 2018).

Satellites are the most important source of data for NWP, yet much of the data from satellites is not being used. Existing satellite products which are not being used by NWP have the potential to improve forecast skill (Fang et al., 2018), and new schemes are still being developed to make more satellite data available to NWP data assimilation, such as for cloud-affected infrared radiances (Aulign, 2014). Newer satellites will provide data with high spatio-temporal resolution information on the surface boundary which could lead to improvements in NWP forecasts (Parodi et al., 2018) as well as providing data from new satellite-mounted instruments (Carminati, Candy, Bell, & Atkinson, 2018). Satellite data can also be used to improve the climatology fields which are used by NWP models, such as aerosol climatology (Choi, Park, & Lee, 2019).

Wind data from instruments carried on aircraft are currently used in some operational NWP models (de Haan, 2011). Although there are uncertainties in data from aircraft during ascent and descent (Stone, 2018), further advances here would be important for renewable energy, as it would provide additional data at heights relevant for wind energy. Similarly, valuable information on hub-height wind speed could be gained by assimilating data available from wind farms. Assimilating data from nacelle anemometers has been shown to improve forecast skill (Cheng, Liu, Bourgeois, Wu, & Haupt, 2017; Cutler, Outhred, & MacGill, 2012), and reverse-calculating wind from delivered power using power curves presents another opportunity. However, data sensitivity concerns from wind plant owners may create barriers to sharing some wind farm data.

New sources of observation data such as LIDAR and floating LIDAR have the potential to provide wind data at multiple heights for less cost than traditional met masts (Gottschall, Gribben, Stein, & Würth, 2017), while data assimilation of radar reflectivities has been shown to improve the representation of clouds and precipitation in NWP (Ivanov, Michaelides, & Ruban, 2018).

Even our phones may help improve forecasting renewable energy in the future. Data from pressure sensors on modern smartphones can be used as inputs for data assimilation. If proper quality control and bias correction is applied, this data can improve the skill of operational NWP models (McNicholas & Mass, 2018).

The field of quantum computing is one of active research and much investment. While there is no commercially feasible quantum computer available today, NWP is a good application for quantum computing (Frolov, 2017), and advances in this area could result in a large increase in NWP model resolution and ensembles size.

Finally, the lowering price of cloud computing, open access to observation data, and the availability of operational quality NWP code such as WRF may result in more widespread generation of weather forecasts by the end-users themselves (Chui et al., 2019). Having more people active in the area would, one hopes, drive further advances and increase forecast skill.

3.3 Advances in Uncertainty Forecasting Products

Presently, it is widely recognised by both academia and industry that point forecasting is not enough to aid decision-making when subject to risk constraints. Therefore, uncertainty estimation in forecasting has been a focus of research and definition of industry requirements during the last years (Bessa et al., 2017). Nevertheless, a survey conducted in the framework of International Energy Agency (IEA) Task 36 on Forecasting for Wind Energy[1] showed that there is very little knowledge of the tools and applications available to deal with uncertainty and awareness of renewable energy inherent uncertainty and variability is not strong enough to start including uncertainty information in operational practices (Möhrlen, Bessa, Barthod, Goretti, & Siefert, 2016). Besides this connection between probabilistic forecasts and their actual adoption by industry, general challenges remain related to appropriate verification frameworks that are theoretically sound and of pragmatic relevance to practitioners.

During the last years, research work produced the following set of uncertainty forecasting

[1] IEA Wind Task 36 website: www.ieawindforecasting.dk

products for renewable energy:

- Non-parametric predictive marginal distributions that can take different representations, such as conditional quantiles, conditional probability density functions, skewness, kurtosis, etc. This uncertainty product is only adequate for decision-aid problems without temporal dependency across intervals, e.g. setting balancing reserve requirements for the next hours/days (operational planning) that are required to handle system imbalances due to renewable energy and load forecast errors (M. A. Matos & Bessa, 2011), define optimal (i.e., maximize revenue) renewable energy bids for each interval of the day-ahead, intraday and ancillary services market sessions (Botterud et al., 2012).

- Power ensembles produced either from NWP ensembles converted into power by using statistical models and post-processing (Pinson & Madsen, 2009) or generated with pure statistical approaches such as copula modelling (Pinson, Madsen, Nielsen, Papaefthymiou, & Klöckl, 2009). This product is suitable for multi-period decision-making problems such as: stochastic unit commitment (J. Wang et al., 2011) that consists in scheduling the generation units for minimizing the cost of supplying the forecasted load with a set of constraints related with power system security and operation; optimization of storage operation to maximize market revenues (Haessig, Multon, Ahmed, Lascaud, & Bondon, 2015). Moreover, ensembles with spatial dependency structure are suitable for power flow calculations where the objective can be to predict the future states (e.g., voltages, power flow) of the electrical grid and/or identify flexibility needs to solve grid technical problems (e.g., voltage, congestion) (Soares, Bessa, Pinson, & Morais, 2018).

- Ramp forecasts characterised by magnitude, duration, ramp intensity, timing and direction (Gallego-Castillo et al., 2015). This information has been used primarily for situational awareness (e.g., probabilistic ramp alarms) of human operators in control rooms (Orwig et al., 2015).

Many argued that trajectories (also referred to as scenarios) were the most relevant and advanced forecast product since they include information of all uncertainties (marginals) and space-time dependencies (Pinson, 2013). For instance, those may be used as input to network-constrained stochastic unit commitment and economic dispatch problems (Papavasiliou & Oren, 2013), with significant reduction of operational costs by appropriately accommodating both uncertainties and space-time dependencies. When dimension increases and decision processes become more complex, using such scenarios may not be practical, owing to the difficulty in solving the resulting optimization problems, and may not be possible at all at reasonable computational costs. This motivated various developments in stochastic optimization and control that, instead of relying on a large number of trajectories, prefer to solve problems based on multivariate forecast regions, possibly taking the form of ellipsoids (Golestaneh, Pinson, Azizipanah-Abarghooee, & Gooi, 2018) or polyhedra (Golestaneh, Pinson, & Gooi, 2019). Today, there is a general need to rethink forecasting products that are of most relevance to various forecast users and their decision problems. Possibly, and more efficiently, it is the process of streamlining the definition, generation and verification of new forecast products that should be rethought, as it is likely that with the massive use of renewable energy forecasts, most practitioners will come with their own views and requirements on forecast products, which should then be accommodated in the most efficient manner.

Finally, to facilitate prosumers and flexibility providers with selling their flexibility in the electricity market, a new forecasting product could be created which consists of a multi-period flexibility forecast combining renewable energy sources (RES) uncertainty with flexibility from distributed energy resources (e.g., storage, controllable loads) (Pinto, Bessa, & Matos, 2017). This product is represented by a set of technically feasible net-load trajectories, which represent alternative paths to the expected (baseline) net-load profile (trajectory). In other words, these trajectories are samples taken from the multi-dimensional space forming the feasible flexibility set.

3.4 New Business Models for Forecasting

A range of business models have emerged in the energy forecasting sector since the first commercial offerings appeared in the early 2000s. Today both large (national weather services, multi-national corporations) and small (SME forecast and software vendors, start-ups) organisations offer full or partial power forecasting services. However, over the past 5–10 years a number of small specialised energy forecasting companies have been acquired by large organisations. Today, services may range from site-specific weather variables to detailed power forecasts and a highly functional user interface. Choice of service will depend on the needs, capabilities and budgets of the forecast user. Examples of different arrangements are illustrated in Figure 3 characterising four user groups with different supply chains.

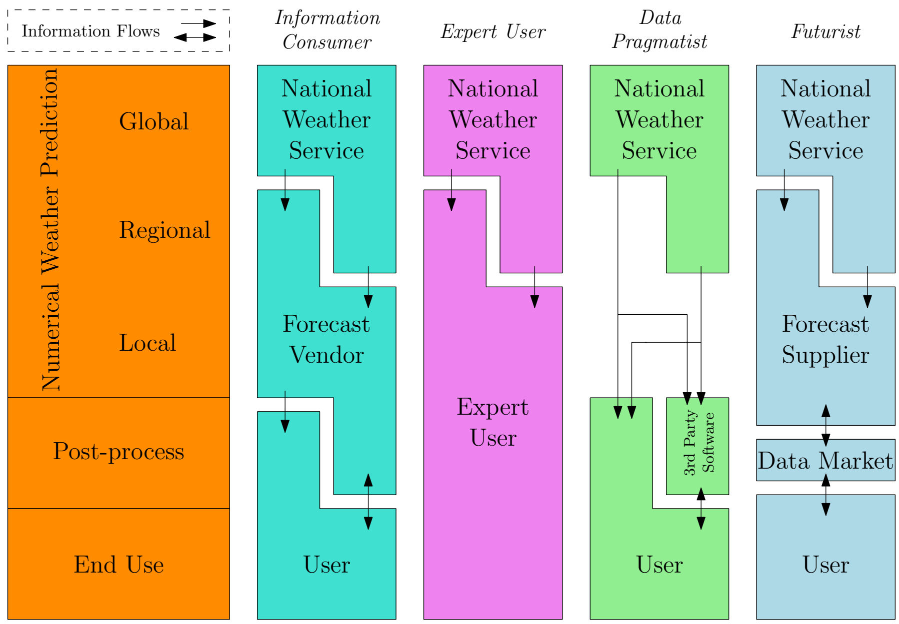


Figure 3: Graphical representation of different business models in renewable energy forecasting.

Some users want to purchase a forecast that will be used directly by decision-makers. These *information consumers* perform little post-processing perhaps beyond blending and visualising renewable production forecasts. Many forecast vendors offer services to these users based on producing power forecasts from global NWP models and other data, often including live data from their customers' wind farms, while some will also run in-house NWP. A typical *information consumer* would be an energy trading company (who may procure forecasts from multiple vendors) or network operator. *Expert users* on the other hand will perform post-processing and perform NWP down-scaling in house, and will employ meteorologists and analysts to maintain an operational forecasting capability. The typical *expert user* is an international utility with a large fleet of renewable generation assets or with special requirements.

The *data pragmatist* adopts a lean approach based on extracting maximum value from free or low-cost NWP via statistical post-processing, perhaps enabled by specialized software. Such users include utilities and network operators as well as flexibility providers and energy start-ups. In the future, market places for forecasts may facilitate new forms of forecast information exchanges as discussed next. One possible business model for a *futurist* forecast consumer is illustrated in Figure 3. In addition to cost and skill, users may also consider customer service, cyber security and uptime guarantees or forecast delivery reliability when deciding on a forecasting solution. Some of these issues can be key driving factors for forecasting users, often trumping cost and skill in decision making.

Trends in energy forecasting include a growth in the number of *'expert users'* procuring large volumes of NWP data as input to advance statistical methods; vendors re-selling global NWP from (multiple) national weather services/models via convenient APIs or cloud computing facilities, and increasing sources of open data, including NWP; and new software solutions for forecast visualisation and integration with other business functions. The number of expert users running their own local NWP models is however in decline, as global and regional models from national weather services and large weather forecast providers are at such a high resolution that, when coupled with advanced statistical methods for post-processing, there is less value added from downscaling than in the past. A rise in demand for probabilistic forecasting, however, may reverse this trend, as uncertainties derived from NWP models are different from those produced by statistical models.

One of the most innovative business models for RES forecasting can be an intersection of forecasting methods (e.g., statistical learning, machine learning or artificial intelligence (AI) techniques), blockchain and cryptocurrencies. The basic idea is a company that hosts a platform that enables different users to submit and buy RES forecasts in a completely decentralised way. This business model contributes to "democratize" the forecasting business since it provides the mechanisms for any supplier (data scientist, PhD student, etc.) to submit forecasts and obtain profit via cryptocurrency tokens indexed to the forecasting skill. For a forecast end-user, this provides access to a plethora of RES forecasts, with different accuracy and price, which can be combined to create a single and more accurate forecast.

Some fundamental requirements are necessary to materialise this model:

- Statistical or machine model fitting without the need to disclose data. This requires seamless approaches for maintaining a certain level of privacy or confidentiality and perform numerical computations using this data at the same time. This requirement can be ensured by cryptography solutions, such as: (i) homomorphic encryption that encrypts the original values in such a way that the application of arithmetic operations does not compromise the encryption, ensuring that after the decryption step, the resulting values correspond to the ones obtained by operating on the original data (Gentry, 2010); (ii) differential privacy, which is usually achieved by adding properly calibrated noise to an algorithm or to the data, and requires computations to be insensitive to changes in any particular record or intermediate computations (Dwork, 2006). However, in differential privacy there is a trade-off between accuracy and privacy, which can be critical for forecasting problems. Recent advances in deep learning, like generative adversarial network (GAN) which is an unsupervised learning technique composed of a system of two competing neural network models (generator and a discriminator) which are able to analyze, capture and copy the variations within a dataset (Goodfellow et al., 2014), can provide a data-driven approach for optimizing privacy-preserving data (Tripathy, Wang, & Ishwar, 2019).

- Forecast output transparently available to all parties without the need of trusting in a centralised entity. Blockchain and smart contracts technology can be used to build a trustworthy distributed peer-to-peer network with automated transactions (Christidis & Devetsikiotis, 2016). For instance, with a smart contract, which is a computer transaction protocol, it is possible to create "autonomous agents" with a set of computational instructions (e.g., partially or fully self-executing, self-enforcing) that manage agreements between users and forecast providers without third parties and with high security.

- Adequate economic model where third parties are incentivised to share knowledge/data and improve forecasting skill, e.g. through cryptocurrencies (altcoins, tokens) protocols (ElBahrawy, Alessandretti, Kandler, Pastor-Satorras, & Baronchelli, 2017) or data marketplace mechanisms (Agarwal, Dahleh, & Sarkar, 2019).

In non-energy domains, this business model is already being explored by several companies and open-source initiatives. OpenMined[2] combines federated machine learning, blockchain, multi-party computation, and homomorphic encryption. In this model, deep learning algorithms fitted in distributed data blocks are traded through smart contracts. The Ocean protocol[3] uses blockchain and provides a tokenized service layer connecting data providers and consumers, which was designed so that data owners control each dataset. Numerai[4] developed Erasure, a decentralized prediction marketplace for financial forecasting, where data scientists can upload forecasts based on available data, stake them using crypto tokens and earn rewards based on the forecasting performance. SingularityNET is a distributed computing architecture that supports new types of smart contracts templates to facilitate token-based market interactions with AI and machine learning tools (Goertzel, Giacomelli, Hanson, Pennachin, & Argentieri, 2017). Finally, Algorithmia DanKu developed a protocol for a marketplace where machine learning models are exchanged in an automated and anonymous manner and cryptocurrency can be used for payment (Kurtulmus & Daniel, 2018).

3.5 New Industry Requirements and Challenges

Future scenarios with near-100% RES integration in electric power systems will define new use cases for RES uncertainty forecasting and require new forecasting products. Two important challenges, amongst many, for power system operations are: (i) decline of power-frequency control reserves and system inertia due to high shares of non-synchronous technologies; (ii) decentralised small-scale RES that create local technical problems in electrical grids (mainly in MV and LV levels), such as voltage and congestion problems in specific areas of the electrical grid.

For the first challenge, renewable power plants can provide frequency containment reserve, including fast frequency reserve (Morren, de Haan, Kling, & Ferreira, 2006), such as frequency containment reserve and synthetic inertia. Regarding system inertia, the state-of-

[2] https://www.openmined.org/ (accessed on March 2019).
[3] https://oceanprotocol.com/ (accessed on March 2019).
[4] https://numer.ai/homepage (accessed on March 2019).

the-art is developing new modelling approaches for: (i) inertia monitoring and forecasting from synchronous generation using a network model-driven approach (Du & Matevosyan, 2018); (ii) dispatching synchronous inertia in order to satisfy the minimum required synchronous inertia for frequency-control purposes in face of the loss of the largest online synchronous generator (Gu, Yan, & Saha, 2018). This induces forecasting requirements, which may consist of high temporal resolution weather and power forecasts that can be used to estimate how much fast frequency response power renewable power plants can deliver in the next minutes or hours. These may then be accommodated by dispatch tools with additional security constraints to guarantee minimum inertia or frequency containment reserves aiming to securely operate power systems with near-100% RES integration.

An interesting idea in (Zhou et al., 2014) is to explore data assimilation that has been widely studied and used in weather forecasting (see section 2.1) to construct a real-time dynamic state estimator of a power grid. The fundamental goal of data assimilation is to fuse phasor measurement unit (PMU) data with power system dynamic models and estimate the dynamic states of synchronous generators. This establishes a synergy between research conducted in weather and power systems domain, and can provide new tools for look-ahead dynamic simulation and contingency analysis in systems with high integration levels of renewable energy.

The second challenge is being covered at the academic level with stochastic optimal power flow methods, which in general result in high computational times, require a full modelling of the network equations and do not include domain knowledge from human operators. As mentioned in section 3.3, this requires new representations for forecast uncertainty, such as multivariate (i.e., modelling temporal/spatial or multivariable correlations) ellipsoids or polyhedra for robust, chance-constrained and interval optimization problems where the required uncertainty representation takes the form of prediction regions rather than scenarios (or ensembles) (Golestaneh et al., 2019).

Moreover, this also creates some pressure in improving forecasting skill at the individual installation level and the development of local (or distributed) control algorithms with RES forecasts as input and relying on robust optimisation (Ma, Wang, Gupta, & Chen, 2018). This is particularly challenging for "behind-the-meter" solar power forecasting due to the lack of individual solar power data and in some cases there is a mismatch between licensed and true PV rated power. In order to solve the monitoring problem, in (Kara, Tabone, Roberts, Kiliccote, & Stewart, 2016) a contextually supervised source separation problem is proposed to disaggregate PV generation at individual households from historical metering data; (X. Zhang, , & Grijalva, 2016) uses a change-point detection algorithm to detect abnormal energy consumption points and unauthorized PV installations (confirmed with permutation test with Spearmans rank coefficient), and the cloud cover index is combined with smart meter data to estimate the rated power of the PV system. These methods provide visibility about PV location in the electrical grid, rated power and generation profile. Recently, data-driven algorithms for forecasting net-load in cases with "behind-the-meter" PV were proposed. The authors in (Y. Wang et al., 2018) propose a probabilistic net-load forecasting method that: (i) applies grid search to estimate equivalent PV parameters (rated power, tilt angle, azimuth) that are used to decompose the net-load time series into PV output, actual load profile and residual; (ii) forecasts the three components separately with gradient boosting regression trees; (iii) analyze their distributions and the dependencies of the forecasting errors and generate with copula modeling a joint probability distribution. Gaussian process with different combinations of covariance functions are used in (van der Meer, Shepero, Svensson, J.Widén, & Munkhammar, 2018) to compare two different net-load forecasting strategies: (i) direct forecasting of net-load; (ii) separated forecasting of electricity consumption and PV generation and subtracting both afterwards. The direct strategy resulted in sharper forecast intervals, but lower performance in terms of calibration (or reliability).

In the planning domain (e.g., from months to years ahead), both market players and transmission/distribution system operators face economic and technical (e.g., reliability) risks and the increasing integration of RES maximises the uncertainty associated with the decision-making process. Traditionally, chronological Monte Carlo simulation from historical time series was used for assessing power system reliability (e.g., loss of load expectation) with renewable energy and for future power system scenarios (M. Matos et al., 2009). However, an emerging requirement is seasonal forecasts of energy-related weather variables. For instance, the *Added Value of Seasonal Climate Forecasting for Integrated Risk Assessment* (SECLI-

FIRM) Horizon 2020 project (2018–2021)[5] is covering nine use cases to improve seasonal climate forecasts. One use case is titled "winter weather and energy system balancing" and the main objective is to study the benefits of using seasonal forecast information (i.e., wind speed, temperature, mean sea level pressure) to better predict the UK winter mean electricity demand and wind power, and seek a reduction of balancing costs over the winter period. For electricity markets, the use case titled "high/low winds in Spain and energy generation" is driven to demonstrate the use of wind speed seasonal forecast information for long-term management of a portfolio with conventional and renewable power plants. The sub-seasonal to seasonal time frame is also being investigated in projects such as the Horizon 2020 S2S4E (Sub-seasonal to Seasonal climate forecasting for Energy)[6], which is developing new renewable energy forecasting products for time horizons of weeks and months and a decision-aid tool that integrates sub-seasonal to seasonal weather forecasts with renewable energy generation and electricity demand.

4 CONCLUSIONS

Forecasting for wind and solar energy is already well-established and an important part of efficiently integrating renewable energy into existing power networks. Forecast skill is continuing to improve, driven by advances in both physical modelling (NWP), statistical modelling and and AI. Recent focus has shifted to probabilistic forecasting, which tends to outperform deterministic forecasts whilst also providing a quantification of uncertainty. We have reviewed current activities in both of these areas, and noted recent advances.

In physical modelling, the continuing increase in computing power available for forecasting is allowing NWP models to be run at higher resolutions, and for more models to be run to create ensembles for probabilistic forecasting. There has also been an increase in the amount and types of atmospheric data available. It is the job of data assimilation to make these data available to the NWP models, and higher-resolution data assimilation, as well as including new sources of data, continues to help improve the skill of NWP forecasts.

[5] www.secli-firm.eu

[6] S2S4E website: www.s2s4e.eu

Statistical modelling and AI is widely used for wind and solar energy forecasting. Very short-term forecasting, from minutes to hours ahead, uses data from the renewable energy plant itself to forecast future values. Skill here can be improved by including other sources of data, such as cloud imagery, radar, or weather typing. Longer-term forecasting, from hours to days ahead, includes NWP forecast data as inputs. Statistical methods are used to remove systematic biases, convert to power, and quantify uncertainty. Phase errors and spatial errors, which become more noticeable as model resolution increases, can be addressed by considering neighbouring time and grid points.

Our discussion then shifted to the future of forecasting for renewable energy. With the availability of large data sets, and new sources of data being included, there is great potential to broaden the types and amount of data used in both statistical and physical modelling. Larger datasets can be used to drive novel approaches in statistical and machine learning, while making new sources of data available to NWP through new data assimilation processes will improve forecast skill.

NWP models are now being run at resolutions where sub-grid scale processes like turbulence and cloud processes are partially resolved, but still partially parameterized. When the scale of the energy- and flux-containing turbulence approaches the scales resolved by NWP models the model is said to be operating in "terra incognita" (Wyngaard, 2004) and care needs to be taken in how turbulence is parameterized by the model. Work coupling NWP with higher-resolution physical LES models, informed by new sources of data, will allow forecast skill to be further improved at these high resolutions.

With the shift towards high-resolution probabilistic forecasting comes a need for new forecasting products. End-user requirements vary across different industries, and there is a need for forecasting products to translate the large amount of forecast data available into a format which can be readily understood by industry, and inform their decision-making processes. This may involve delivering forecast data in different formats, or integrating forecast variables into end-user models to optimise their overall operation. This integration of forecast data into different modelling processes may change business models in the area of renewable forecasting. Some businesses may shift towards increasing their in-house modelling skills to include forecasting, while other businesses may act as expert users for a range of clients.

The way forecast and energy data are exchanged may in itself change with the adoption of blockchain technologies. Coupled with encryption methods which preserve confidentiality, these could allow people to exchange forecast and energy data in a decentralized yet trusted manner.

As electric power systems move towards integration of ever higher amounts of renewable energy, renewable energy forecasting will have an important role to play in preserving system stability. The decline of power frequency control and system inertia from synchronous generation technologies should be managed with predictive dispatch tools with additional security constraints to guarantee minimum fast frequency response (including the participation from RES power plants), which will require forecasts with higher temporal resolution. Managing power systems with large amounts of decentralised renewable energy generation will also require advanced forecasting skills for these energy sources, considering "behind-the-meter" forecasting, and new representations for forecast uncertainty.

Finally, on planning timescales from months to years ahead, advanced forecasting techniques from seasonal to climate modelling scales will allow better predictions of future power system scenarios and the critical underlying weather-driven uncertainties for systems with high levels of renewable energy generation.

Funding Information

Conor Sweeney is a member of the UCD Energy Systems Integration Partnership Programme, which includes the financial support of Science Foundation Ireland under the SFI Strategic Partnership Programme Grant Number SFI/15/SPP/E3125. The opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the Science Foundation Ireland. Jethro Browell is supported by an EPSRC Innovation Fellowship (EP/R023484/1). Data statement: No new data were created during the study. Ricardo Bessa acknowledges finance by the National Funds through the Portuguese funding agency, FCT - Fundao para a Cincia e a Tecnologia within project: UID/EEA/50014/2019.

References

Agarwal, A., Dahleh, M., & Sarkar, T. (2019). A marketplace for data: An algorithmic solution. arXiv:1805.08125, 1–26.

Andrade, J. R., & Bessa, R. J. (2017, oct). Improving renewable energy forecasting with a grid of numerical weather predictions. IEEE Transactions on Sustainable Energy, 8(4), 1571–1580. doi: 10.1109/tste.2017.2694340

Angevine, W. M., Olson, J., Kenyon, J., Gustafson, W. I., Endo, S., Suselj, K., & Turner, D. D. (2018). Shallow cumulus in wrf parameterizations evaluated against lasso large-eddy simulations. Monthly Weather Review, 146(12), 4303-4322. Retrieved from https://doi.org/10.1175/MWR-D-18-0115.1 doi: 10.1175/MWR-D-18-0115.1

Antonanzas, J., Osorio, N., Escobar, R., Urraca, R., de Pison, F. M., & Antonanzas-Torres, F. (2016). Review of photovoltaic power forecasting. Solar Energy, 136, 78 - 111. Retrieved from http://www.sciencedirect.com/science/article/pii/S0038092X1630250X doi: https://doi.org/10.1016/j.solener.2016.06.069

Aulign, T. (2014). Multivariate minimum residual method for cloud retrieval. part ii: Real observations experiments. Monthly Weather Review, 142(12), 4399-4415. Retrieved from https://doi.org/10.1175/MWR-D-13-00173.1 doi: 10.1175/MWR-D-13-00173.1

Bannister, R. N. (2017). A review of operational methods of variational and ensemble-variational data assimilation. Quarterly Journal of the Royal Meteorological Society, 143(703), 607-633. Retrieved from https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/qj.2982 doi: 10.1002/qj.2982

Bauer, P., Thorpe, A., & Brunet, G. (2015). The quiet revolution of numerical weather prediction. Nature, 525(7567), 47.

Bergstrm, S., & Lindstrm, G. (2015, may). Interpretation of runoff processes in hydrological modelling-experience from the HBV approach. Hydrological Processes, 29(16), 3535–3545. doi: 10.1002/hyp.10510

Bessa, R., Möhrlen, C., Fundel, V., Siefert, M., Browell, J., Gaidi, S. E., ... Kariniotakis, G. (2017). Towards improved understanding of the applicability of uncertainty forecasts in the electric power industry. Energies, 10(9), 1402.

Blanc, P., Remund, J., & Vallance, L. (2017). Short-term solar power forecasting based on satellite images. In Renewable energy forecasting (pp. 179–198). Elsevier. doi: 10.1016/b978-0-08-100504-0.00006-8

Bossanyi, E. (1985). Short-term wind prediction using Kalman filters. Wind Engineering, 9(1), 1–8.

Bossavy, A., Girard, R., & Kariniotakis, G. (2013, January). Forecasting ramps of wind power production with numerical weather prediction ensembles. Wind Energy, 16(1), 51–63.

Botterud, A., Wang, J., Zhou, Z., Bessa, R., Keko, H., Akilimali, J., & Miranda, V. (2012, May). Wind power trading under uncertainty in LMP markets. IEEE Transactions on Power Systems, 27(2), 894-903.

Browell, J., Drew, D. R., & Philippopoulos, K. (2018, may). Improved very short-term spatio-temporal wind forecasting using atmospheric regimes. Wind Energy, 21(11), 968–979. doi: 10.1002/we.2207

Brown, B. G., Katz, R. W., & Murphy, A. H. (1984). Time series models to simulate and forecast wind speed and wind power. Journal of Climate and Applied Meteorology, 23(8), 1184-1195. doi: 10.1175/1520-0450(1984)023⟨1184:TSMTSA⟩2.0.CO;2

Camal, S., Teng, F., Michiorri, A., Kariniotakis, G., & Badesa, L. (2019, may). Scenario generation of aggregated wind, photovoltaics and small hydro production for power systems applications. Applied Energy, 242, 1396–1406. doi: 10.1016/j.apenergy.2019.03.112

Carminati, F., Candy, B., Bell, W., & Atkinson, N. (2018). Assessment and assimilation of fy-3 humidity sounders and imager in the uk met office global model. Advances in Atmospheric Sciences, 35(8), 942–954.

Cavalcante, L., Bessa, R. J., Reis, M., & Browell, J. (2016). Lasso vector autoregression structures for very short-term wind power forecasting. Wind Energy, 20, 657–675. Retrieved from http://dx.doi.org/10.1002/we.2029 doi: 10.1002/we.2029

Cheng, W. Y., Liu, Y., Bourgeois, A. J., Wu, Y., & Haupt, S. E. (2017). Short-term wind forecast of a data assimilation/weather forecasting system with wind turbine anemometer measurement assimilation. Renewable Energy, 107, 340 - 351. Retrieved from http://www.sciencedirect.com/science/article/pii/S0960148117300927 doi: https://doi.org/10.1016/j.renene.2017.02.014

Choi, I.-J., Park, R.-S., & Lee, J. (2019). Impacts of a newly-developed aerosol climatology on numerical weather prediction using a global atmospheric forecasting model. Atmospheric Environment, 197, 77 - 91. Retrieved from http://www.sciencedirect.com/science/article/pii/S135223101830709X doi: https://doi.org/10.1016/j.atmosenv.2018.10.019

Chow, C. W., Urquhart, B., Lave, M., Kleissl, A. D. J., Shields, J., & Washom, B. (2011). Intra-hour forecasting with a total sky imager at the uc san diego solar energy testbed. Solar Energy, 85(11), 2881–2893.

Chowdhury, B. H., & Rahman, S. (1987). Forecasting sub-hourly solar irradiance for prediction of photovoltaic output. In 19th ieee photovoltaic specialists conference (pp. 171–176).

Christidis, K., & Devetsikiotis, M. (2016, May). Blockchains and smart contracts for the internet of things. IEEE Access, 4, 2292–2303.

Chu, Y., Pedro, H., Li, M., & F.M.Coimbra, C. (2015, April). Real-time forecasting of solar irradiance ramps with smart image processing. Solar Energy, 114, 91–104.

Chui, T. C. Y., Siuta, D., West, G., Modzelewski, H., Schigas, R., & Stull, R. (2019). On producing reliable and affordable numerical weather forecasts on public cloud-computing infrastructure. Journal of Atmospheric and Oceanic Technology, 36(3), 491-509. Retrieved from https://doi.org/10.1175/JTECH-D-18-0142.1 doi: 10.1175/JTECH-D-18-0142.1

Cutler, N. J., Outhred, H. R., & MacGill, I. F. (2012). Using nacelle-based wind speed observations to improve power curve modeling for wind power forecasting. Wind Energy, 15(2), 245-258. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1002/we.465 doi: 10.1002/we.465

de Haan, S. (2011). High-resolution wind and temperature observations from aircraft tracked by mode-s air traffic control radar. Journal of Geophysical Research: Atmospheres, 116(D10). Retrieved from https://agupubs.onlinelibrary.wiley.com/doi/abs/

10.1029/2010JD015264 doi: 10.1029/2010JD015264

Du, P., & Matevosyan, J. (2018, March). Forecast system inertia condition and its impact to integrate more renewables. IEEE Transactions on Smart Grid, 9(2), 1531-1533.

Dwork, C. (2006). Differential privacy. In Icalp 2006: Automata, languages and programming (pp. 1–12).

ElBahrawy, A., Alessandretti, L., Kandler, A., Pastor-Satorras, R., & Baronchelli, A. (2017). Evolutionary dynamics of the cryptocurrency market. Royal Society open science, 4(11), 170623.

Fang, L., Zhan, X., Hain, C., Yin, J., Liu, J., & Schull, M. (2018). An assessment of the impact of land thermal infrared observation on regional weather forecasts using two different data assimilation approaches. Remote Sensing, 10(4), 625.

Feist, M. M., Westbrook, C. D., Clark, P. A., Stein, T. H., Lean, H. W., & Stirling, A. J. (2019). Statistics of convective cloud turbulence from a comprehensive turbulence retrieval method for radar observations. Quarterly Journal of the Royal Meteorological Society, 145(719), 727-744. Retrieved from https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/qj.3462 doi: 10.1002/qj.3462

Fitch, A. C., Olson, J. B., Lundquist, J. K., Dudhia, J., Gupta, A. K., Michalakes, J., & Barstad, I. (2012). Local and mesoscale impacts of wind farms as parameterized in a mesoscale nwp model. Monthly Weather Review, 140(9), 3017-3038. Retrieved from https://doi.org/10.1175/MWR-D-11-00352.1 doi: 10.1175/MWR-D-11-00352.1

Frolov, A. V. (2017, Sep 01). Can a quantum computer be applied for numerical weather prediction? Russian Meteorology and Hydrology, 42(9), 545–553. Retrieved from https://doi.org/10.3103/S1068373917090011 doi: 10.3103/S1068373917090011

Gallego-Castillo, C., Cuerva-Tejero, A., & Lopez-Garcia, O. (2015). A review on the recent history of wind power ramp forecasting. Renewable and Sustainable Energy Reviews, 52, 1148 - 1157. Retrieved from http://www.sciencedirect.com/science/article/pii/S1364032115008011 doi: https://doi.org/10.1016/j.rser.2015.07.154

Gentry, C. (2010, March). Computing arbitrary functions of encrypted data. Communications of the ACM, 53(3), 97–105.

Gilbert, C., Browell, J., & McMillan, D. (2019). Leveraging turbine-level data for improved probabilistic wind power forecasting. *submitted*.

Gilbert, C., Messner, J. W., Pinson, P., Trombe, P.-J., Verzijlbergh, R., van Dorp, P., & Jonker, H. (2019). Statistical post-processing of turbulence-resolving weather forecasts for offshore wind power forecasting.
(Submitted)

Goertzel, B., Giacomelli, S., Hanson, D., Pennachin, C., & Argentieri, M. (2017). SingularityNET: A decentralized, open market and inter-network for AIs. Retrieved from https://public.singularitynet.io/whitepaper.pdf (The SingularityNET whitepaper)

Golestaneh, F., Pinson, P., Azizipanah-Abarghooee, R., & Gooi, H. B. (2018). Ellipsoidal prediction regions for multivariate uncertainty characterization. IEEE Transactions on Power Systems, 33(4), 4519–4530.

Golestaneh, F., Pinson, P., & Gooi, H. B. (2019). Polyhedral predictive regions for power system applications. IEEE Transactions on Power Systems, 34(1), 693–704.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... Bengio, Y. (2014). Generative adversarial nets. In Advances in neural information processing systems 27 (nips 2014) (p. 2672-2680).

Gottschall, J., Gribben, B., Stein, D., & Würth, I. (2017). Floating lidar as an advanced offshore wind speed measurement technique: current technology status and gap analysis in regard to full maturity. Wiley Interdisciplinary Reviews: Energy and Environment, 6(5), e250. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1002/wene.250 doi: 10.1002/wene.250

Gragne, A. S., Sharma, A., Mehrotra, R., & Alfredsen, K. (2015, aug). Improving real-time inflow forecasting into hydropower reservoirs through a complementary modelling framework. Hydrology and Earth System Sciences, 19(8), 3695–3714. doi: 10.5194/hess-19-3695-2015

Gu, H., Yan, R., & Saha, T. K. (2018, March). Minimum synchronous inertia requirement of renewable power systems. IEEE Transactions on Power Systems, 33(2), 1533-1543.

Gustafsson, N., Janji, T., Schraff, C., Leuenberger, D., Weissmann, M., Reich, H., ... Fujita, T. (2018). Survey of data assimilation methods for convective-scale numerical weather prediction at operational centres. Quarterly Journal of the Royal Meteorological Society, 144(713), 1218-1256. Retrieved from https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/qj.3179 doi: 10.1002/qj.3179

Haessig, P., Multon, B., Ahmed, H. B., Lascaud, S., & Bondon, P. (2015). Energy storage sizing for wind power: Impact of the autocorrelation of day-ahead forecast errors. Wind Energy, 18(1), 43-57.

Hoffman, R. N., Kumar, V. K., Boukabara, S.-A., Ide, K., Yang, F., & Atlas, R. (2018). Progress in forecast skill at three leading global operational nwp centers during 2015-17 as seen in summary assessment metrics (sams). Weather and Forecasting, 33(6), 1661-1679. Retrieved from https://doi.org/10.1175/WAF-D-18-0117.1 doi: 10.1175/WAF-D-18-0117.1

Ivanov, S., Michaelides, S., & Ruban, I. (2018). Mesoscale resolution radar data assimilation experiments with the harmonie model. Remote sensing, 10(9), 1453.

Iversen, E. B., Juhl, R., Møller, J. K., Kleissl, J., Madsen, H., & Morales, J. M. (2017). Spatio-temporal forecasting by coupled stochastic differential equations: Applications to solar power. (Arxiv preprint: arXiv:1706.04394v1)

Jensenius, J., & Cotton, G. (1981). The development and testing of automated solar energy forecasts based on the model output statistics (MOS) technique. In 1st workshop on terrestrial solar resource forecasting and on use of satellites for terrestrial solar resource assessment.

Jimenez, P. A., Hacker, J. P., Dudhia, J., Haupt, S. E., Ruiz-Arias, J. A., Gueymard, C. A., ... Deng, A. (2016). Wrf-solar: Description and clear-sky assessment of an augmented nwp model for solar power prediction. Bulletin of the American Meteorological Society, 97(7), 1249-1264. Retrieved from https://doi.org/10.1175/BAMS-D-14-00279.1 doi: 10.1175/BAMS-D-14-00279.1

Jung, J., & Broadwater, R. P. (2014). Current status and future advances for wind speed and power forecasting. Renewable and Sustainable Energy Reviews, 31, 762 - 777. Retrieved from http://www.sciencedirect.com/science/article/pii/S1364032114000094 doi: https://doi.org/10.1016/j.rser.2013.12.054

Kara, E. C., Tabone, M., Roberts, C., Kiliccote, S., & Stewart, E. M. (2016). Estimating behind-the-meter solar generation with existing measurement infrastructure. In Buildsys '16 proceedings of the 3rd ACM international conference on systems for energy-efficient built environments. Palo Alto, CA, USA.

Kazantzidis, A., Tzoumanikas, P., Blanc, P., Massip, P., Wilbert, S., & Ramirez-Santigosa, L. (2017). Short-term forecasting based on all-sky cameras. In Renewable energy forecasting (pp. 153–178). Elsevier. doi: 10.1016/b978-0-08-100504-0.00005-6

Kealy, J. C., Efstathiou, G. A., & Beare, R. J. (2019, Apr 01). The onset of resolved boundary-layer turbulence at grey-zone resolutions. Boundary-Layer Meteorology, 171(1), 31–52. Retrieved from https://doi.org/10.1007/s10546-018-0420-0 doi: 10.1007/s10546-018-0420-0

Kurtulmus, A., & Daniel, K. (2018). Trustless machine learning contracts; evaluating and exchanging machine learning models on the ethereum blockchain. arXiv:1802.10185.

Landry, M., Erlinger, T. P., Patschke, D., & Varrichio, C. (2016). Probabilistic gradient boosting machines for GEFCom2014 wind forecasting. International Journal of Forecasting, 32(3), 1061–1066. doi: http://dx.doi.org/10.1016/j.ijforecast.2016.02.002

Leutbecher, M., Lock, S.-J., Ollinaho, P., Lang, S. T. K., Balsamo, G., Bechtold, P., ... Weisheimer, A. (2017). Stochastic representations of model uncertainties at ecmwf: state of the art and future vision. Quarterly Journal of the Royal Meteorological Society, 143(707), 2315-2339. Retrieved from https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/qj.3094 doi: 10.1002/qj.3094

Lorenc, A. C., & Jardak, M. (2018). A comparison of hybrid variational data assimilation methods for global nwp. Quarterly Journal of the Royal Meteorological Society, 144(717), 2748-2760. Retrieved from https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/qj.3401 doi: 10.1002/qj.3401

Ma, W.-J., Wang, J., Gupta, V., & Chen, C. (2018, March). Distributed energy management for networked microgrids using online ADMM with regret. IEEE Transactions on Smart Grid, 9(2), 847-856.

Mahoney, W. P., Parks, K., Wiener, G., Liu, Y., Myers, W. L., Sun, J., ... Haupt, S. E. (2012, Oct). A wind power forecasting system to optimize grid integration. IEEE Transactions on Sustainable Energy, 3(4), 670-682. doi: 10.1109/TSTE.2012.2201758

Maier, H. R., & Dandy, G. C. (2000, jan). Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. Environmental Modelling & Software, 15(1), 101–124. doi: 10.1016/s1364-8152(99)00007-9

Matos, M., Lopes, J. P., Rosa, M., Ferreira, R., da Silva, A. L., Sales, W., ... López, R. (2009, October). Probabilistic evaluation of reserve requirements of generating systems with renewable power sources: The portuguese and spanish cases. International Journal of Electrical Power & Energy Systems, 31(9), 562-569.

Matos, M. A., & Bessa, R. (2011, May). Setting the operating reserve using probabilistic wind power forecasts. IEEE Transactions on Power Systems, 26(2), 594-603.

McCandless, T., Haupt, S., & Young, G. (2016). A regime-dependent artificial neural network technique for short-range solar irradiance forecasting. Renewable Energy, 89, 351–359. Retrieved from http://www.sciencedirect.com/science/article/pii/S0960148115305346 doi: https://doi.org/10.1016/j.renene.2015.12.030

McMichael, L. A., Mechem, D. B., Wang, S., Wang, Q., Kogan, Y. L., & Teixeira, J. (2019). Assessing the mechanisms governing the daytime evolution of marine stratocumulus using large-eddy simulation. Quarterly Journal of the Royal Meteorological Society, 145(719), 845-866. Retrieved from https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/qj.3469 doi: 10.1002/qj.3469

McNicholas, C., & Mass, C. F. (2018). Impacts of assimilating smartphone pressure observations on forecast skill during two case studies in the pacific northwest. Weather and Forecasting, 33(5), 1375-1396. Retrieved from https://doi.org/10.1175/WAF-D-18-0085.1 doi: 10.1175/WAF-D-18-0085.1

Messner, J. W., & Pinson, P. (2018, apr). Online adaptive lasso estimation in vector autoregressive models for high dimensional wind power forecasting. International Journal of Forecasting. doi: 10.1016/j.ijforecast.2018.02.001

Möhrlen, C., Bessa, R., Barthod, M., Goretti, G., & Siefert, M. (2016). Use of forecast uncertainties in the power sector: State-of-the-art of business practices. In Proceedings of the 15th international workshop on large-scale integration of wind power into power systems as well as on transmission networks for offshore wind power plants. Vienna, Austria.

Morren, J., de Haan, S., Kling, W., & Ferreira, J. (2006, February). Wind turbines emulating inertia and supporting primary frequency control. IEEE Transactions on Power Systems, 21(1), 433–434.

Orwig, K. D., Ahlstrom, M. L., Banunarayanan, V., Sharp, J., Wilczak, J. M., Freedman, J., ... Marquis, M. (2015, July). Recent trends in variable generation forecasting and its value to the power system. IEEE Transactions on Sustainable Energy, 6(3), 924-933.

Papavasiliou, A., & Oren, S. (2013). Multiarea stochastic unit commitment for high wind penetration in a transmission constrained network. Operations Research, 61(3), 578–592.

Parodi, A., Pulvirenti, L., Lagasio, M., Pierdicca, N., Marzano, F. S., Riva, C., ... Rommen, B. (2018, July). Ingestion of sentinel-derived remote sensing products in numerical weather prediction models: First results of the esa steam project. In Igarss 2018 - 2018 ieee international geoscience and remote sensing symposium (p. 3901-3904). doi: 10.1109/IGARSS.2018.8518830

Pinson, P. (2013). Wind energy: Forecasting challenges for its operational management. Statistical Science, 28(4), 564–585.

Pinson, P., & Madsen, H. (2009, March). Ensemble-based probabilistic forecasting at Horns Rev. Wind Energy, 12(2), 137-155.

Pinson, P., Madsen, H., Nielsen, H. A., Papaefthymiou, G., & Klöckl, B. (2009). From probabilistic forecasts to statistical scenarios of short-term wind power production. Wind Energy, 12(1), 51-62.

Pinto, R., Bessa, R., & Matos, M. (2017, December). Multi-period flexibility forecast for low voltage prosumers. Energy, 141, 2251-2263.

Redfern, S., Olson, J. B., Lundquist, J. K., & Clack, C. T. M. (2019). Incorporation of the rotor-equivalent wind speed into the weather research and forecasting models wind farm parameterization. Monthly Weather Review, 147(3), 1029-1046. Retrieved from https://doi.org/10.1175/MWR-D-18-0194.1 doi: 10.1175/MWR-D-18-0194.1

Sanz Rodrigo, J., Chvez Arroyo, R. A., Moriarty, P., Churchfield, M., Kosovi, B., Rthor, P.-E., ... Rife, D. (2017). Mesoscale to microscale wind farm flow modeling and evaluation. Wiley Interdisciplinary Reviews: Energy and Environment, 6(2), e214. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1002/wene.214 doi: 10.1002/wene.214

Siuta, D. M., & Stull, R. B. (2018). Benefits of a multimodel ensemble for hub-height wind prediction in mountainous terrain. Wind Energy, 21(9), 783–800.

Soares, T., Bessa, R., Pinson, P., & Morais, H. (2018, November). Active distribution grid management based on robust AC optimal power flow. EEE Transactions on Smart Grid, 9(6), 6229–6241.

Stedinger, J. R., Sule, B. F., & Loucks, D. P. (1984, nov). Stochastic dynamic programming models for reservoir operation optimization. Water Resources Research, 20(11), 1499–1505. doi: 10.1029/wr020i011p01499

Stone, E. K. (2018). A comparison of mode-s enhanced surveillance observations with other in situ aircraft observations. Quarterly Journal of the Royal Meteorological Society, 144(712), 695-700. Retrieved from https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/qj.3238 doi: 10.1002/qj.3238

Tastu, J., Pinson, P., & Madsen, H. (2015). Space-time trajectories of wind power generation: Parametrized precision matrices under a gaussian copula approach. In A. Antoniadis, J.-M. Poggi, & X. Brossat (Eds.), Modeling and stochastic learning for forecasting in high dimensions (pp. 267–296). Cham: Springer International Publishing.

Taylor, J. W. (2017). Probabilistic forecasting of wind power ramp events using autoregressive logit models. European Journal of Operational Research, 259(2), 703–712.

Tripathy, A., Wang, Y., & Ishwar, P. (2019, January). Privacy-preserving adversarial networks. arXiv:1712.07008, 1–15.

Trombe, P., Pinson, P., & Madsen, H. (2014). Automatic classification of offshore wind regimes with weather radar observations. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 7(1), 116–125.

Trombe, P., Pinson, P., Vincent, C., Bøvith, T., Cutululis, N. A., Draxl, C., ... Sommer, A. (2014). Weather radars-the new eyes for offshore wind farms? Wind Energy, 17(11), 1767–1787.

Valldecabres, L., Nygaard, N., Vera-Tudela, L., von Bremen, L., & Kühn, M. (2018, oct). On the use of dual-doppler radar measurements for very short-term wind power forecasts. Remote Sensing, 10(11), 1701. doi: 10.3390/rs10111701

Valldecabres, L., Peña, A., Courtney, M., von Bremen, L., & Kühn, M. (2018, may). Very short-term forecast of near-coastal flow using scanning lidars. Wind Energy Science, 3(1), 313–327. doi: 10.5194/wes-3-313-2018

van der Meer, D., Shepero, M., Svensson, A., J.Widén, & Munkhammar, J. (2018, March). Probabilistic forecasting of electricity consumption, photovoltaic power generation and net demand of an individual building using Gaussian processes. Applied Energy, 213, 195–207.

Wang, J., Botterud, A., Bessa, R., Keko, H., Miranda, V., Akilimali, J., ... Issicaba, D. (2011, November). Wind power forecasting uncertainty and unit commitment. Applied Energy, 88(11), 4014-4023.

Wang, Y., Zhang, N., Chen, Q., Kirschen, D. S., Li, P., & Xia, Q. (2018, May). Data-driven probabilistic net load forecasting with high penetration of behind-the-meter PV. IEEE Transactions on Power Systems, 33(3), 3255–3264.

Wendell, L., Wegley, H., & Verholek, M. (1978). Report from a working group meeting on wind forecasts for WECS operation. pnl-2513 (Tech. Rep.). United States Department of Commerce, 5205 Port Royal Road, Springfield, Virginia 22151, USA: Pacific Northwest Laboratory.

Wilczak, J., Finley, C., Freedman, J., Cline, J., Bianco, L., Olson, J., ... Marquis, M. (2015). The wind forecast improvement project (wfip): A public-private partnership addressing wind energy forecast needs. Bulletin of the American Meteorological Society, 96(10), 1699-1718. Retrieved from https://doi.org/10.1175/BAMS-D-14-00107.1 doi: 10.1175/BAMS-D-14-00107.1

Würth, I., Valldecabres, L., Simon, E., Mhrlen, C., Uzunoğlu, B., Gilbert, C., ... Kaifel, A. (2019, feb). Minute-scale forecasting of wind power—results from the collaborative workshop of IEA wind task 32 and 36. Energies, 12(4), 712. doi: 10.3390/en12040712

Wyngaard, J. C. (2004). Toward numerical modeling in the terra incognita. Journal of the Atmospheric Sciences, 61(14), 1816-1826. Retrieved from https://doi.org/10.1175/1520-0469(2004)061<1816:TNMITT>2.0.CO;2 doi: 10.1175/1520-0469(2004)

061⟨1816:TNMITT⟩2.0.CO;2

Yang, J., Astitha, M., Delle Monache, L., & Alessandrini, S. (2018). An analog technique to improve storm wind speed prediction using a dual nwp model approach. Monthly Weather Review, 146(12), 4057 - 4077. Retrieved from https://search.ebscohost.com/login.aspx?direct=true&db=a9h&AN=133447861&site=ehost-live

Zhang, F., Qiang Sun, Y., Magnusson, L., Buizza, R., Lin, S.-J., Chen, J.-H., & Emanuel, K. (2019). What is the predictability limit of midlatitude weather? Journal of the Atmospheric Sciences, Early Online(0), null. Retrieved from https://doi.org/10.1175/JAS-D-18-0269.1 doi: 10.1175/JAS-D-18-0269.1

Zhang, X., , & Grijalva, S. (2016, September). A data-driven approach for detection and estimation of residential PV installations. IEEE Transactions on Smart Grid, 7(5), 2477–2485.

Zhou, N., Huang, Z., Meng, D., Elbert, S., Wang, S., & Diao, R. (2014, March). Capturing dynamics in the power grid: Formulation of dynamic state estimation through data assimilation (Tech. Rep. No. PNNL-23213). Pacific Northwest National Laboratory.