The Future of Forecasting for Renewable Energy

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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.
[249 words]

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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, while a large proportion of hydro power schemes include significant storage capacity and can be dispatched at will. For a recent coverage of a broad range of topics of interest in renewable energy forecasting, the reader is referred to (Jung & Broadwater, 2014), (Gallego-Castillo, Cuerva-Tejero, & Lopez-Garcia, 2015), (Antonanzas et al., 2016), (Bessa et al., 2017).

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.

[298 words]

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

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, 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 (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 IFS model produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), and the deterministic GFS model produced by the National Centers for Environmental Prediction (NCEP).

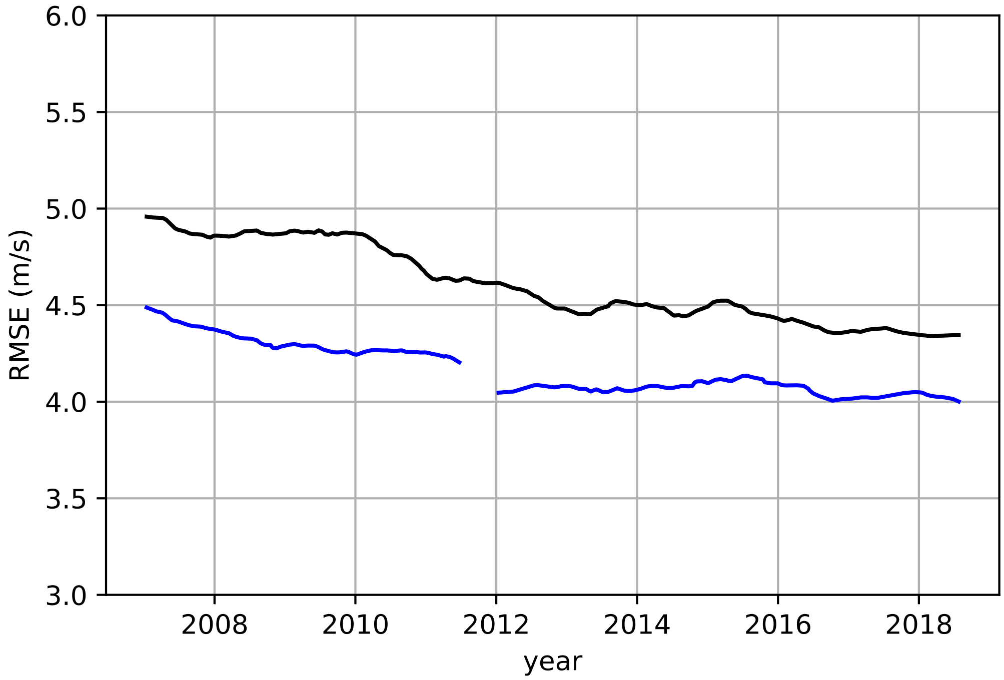

Figure 1: 12-month rolling average of the 48-hour ahead root mean square error (RMSE) forecast skill for wind speed on the 850 hPa pressure level in the Northern Hemisphere. Blue lines: old/new ECMWF IFS. Black line: NCEP GFS

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 centre	Model	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) and the ensemble Kalman filter (EnKF) (Bannister, 2017). Advances in data assimilation can lead to improved NWP forecasts, and new methods are still being tested and applied to operational NWP (Lorenc & Jardak, 2018).

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 combined to produce a probabilistic forecasts. Probabilistic forecasting has been shown to outperform deterministic forecasts, e.g. (Siuta & Stull, 2018). 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.

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 (Wendell, Wegley, & Verholek, 1978; Bossanyi, 1985; Jensenius & Cotton, 1981; Chowdhury & Rahman, 1987). Since this time there has been 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

The purpose of post-processing weather forecasts in renewable energy forecasting is three-fold: 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.

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 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.

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, 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. This information is important in decision-making problems with temporal or spatial constraints, such as energy storage management 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 for 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. And concerning timescales of minutes, a different class of physical model is required all together to resolve the necessary physical processes and these types of models are prohibitively expensive to run operationally. For these reasons, 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. 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 length and time scales of the weather match the forecast lead-time. In the simplest case forecasts are largely based on power production observations only. Recent research in this area has focused on scaling-up this methodology and conditioning spatial dependency models on different weather regimes particularly for wind energy applications (Messner & Pinson, 2018; Browell, Drew, & Philippopoulos, 2018). Augmenting power production with remote sensing is well established in solar power forecasting, where use of satellite imagery (Blanc, Remund, & Vallance, 2017) for hours-ahead forecasting and sky cameras (Chow et al., 2011; Kazantzidis et al., 2017) for cloud observation and prediction for intra-hour forecasting significantly improve performance. 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).

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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, which would have value in some electricity markets. 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 e.g. 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. 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 such models (Feist et al., 2019).

Different types of models which have traditionally 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 is being included as a wind farm parameterization within NWP (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.

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 this data available to the NWP models, and a survey of data assimilation approaches for high-resolution NWP has shown improvements in skill by assimilating data at a higher resolution, with good potential for further improvements in the future (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). 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.

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 New 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 IEA Wind Task 36 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 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 (M. A. Matos & Bessa, 2011), wind power bidding (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 (Wang et al., 2011) and storage operational planning (Haessig, Multon, Ahmed, Lascaud, & Bondon, 2015).

- 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 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, for prosumers and flexibility providers available to sell their flexibility in the electricity market, information about renewable energy sources (RES) uncertainty can be combined with flexibility from distributed energy resources (e.g., storage, controllable loads) and create a new forecasting product that consists is multi-period flexibility forecast (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 Business Models

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 2 characterising three users groups with different supply chains.

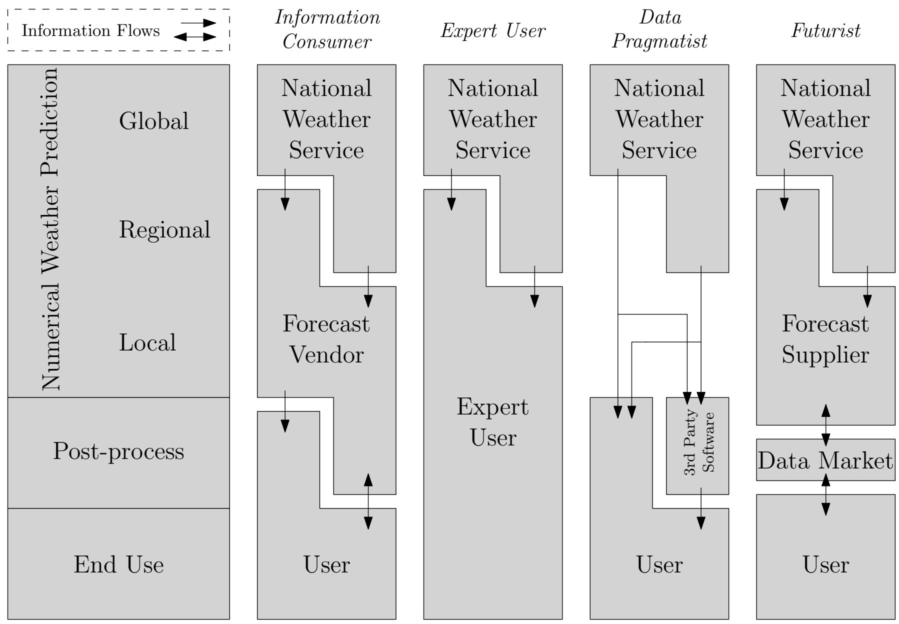

Figure 2: Graphical representation of different business models in renewable energy forecasting.

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 forecast 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 meteorologist 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 specialist 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. In addition to cost and skill, users may also consider customer service, cyber security and uptime guarantees when deciding on a forecasting solution.

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 statistical learning, 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:

- Fit a statistical learning model 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: homomorphic encryption that consists in the ability to perform computations on the ciphertext without decrypting it first (Gentry, 2010); differential privacy, which is a mechanism to guarantee that the probability of producing any particular output from an input cannot vary by more than a factor of e^ϵ for "similar" inputs differing in only one subject (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 networks (GANs), 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).

- 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[1] 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[2] uses blockchain and provides a tokenized service layer connecting data providers and consumers, which was designed so that data owners control each dataset. Numerai[3] 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 artificial intelligence and machine learning tools (Goertzel, Giacomelli, Hanson, Pennachin, & Argentieri, 2017). Finally, Algorithmia DanKu developed

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

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 main challenges emerge for power system operations: (i) decrease in system inertia due to high shares of non-synchronous generation - critical for frequency control; (ii) decentralised small-scale RES that create local technical problems in electrical grids (mainly in MV and LV levels).

The first challenge is being tackled with synthetic inertia from RES power plants (Morren, de Haan, Kling, & Ferreira, 2006) and with inertia monitoring and forecasting from synchronous generation using a network model-driven approach (Du & Matevosyan, 2018) as well as 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 in high temporal resolution weather and power forecasts that generate probabilistic forecasts of synthetic inertia from RES power plants. 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.

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 ellipsoids or polyhedra. 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 in robust optimisation (Ma, Wang, Gupta, & Chen, 2018).

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 to 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)[4] 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 S2S4E[5] Horizon 2020 project.

[3104 words]

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) and statistical modelling. 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.

[4] http://www.secli-firm.eu/

[5] https://www.s2s4e.eu

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 this 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.

Statistical modelling 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 approaching an area called the grey zone, where sub-grid scale processes like turbulence and cloud processes are partially resolved, but still partially parameterized. 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. System inertia challenges can be managed by modelling synthetic inertia from renewable energy plants as well as dispatching synchronous inertia. Managing power systems with large amounts of decentralised renewable energy generation will also require advanced forecasting skills for these energy sources, with high-resolution, probabilistic forecasts providing valuable information.

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.

[673 words]

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