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Current Methods and Advances in Forecasting of Wind Power Generation

Aoife M. Foley[a,b,*], Paul G. Leahy[a,b], Antonino Marvuglia[c] and Eamon J. McKeogh[a,b]

[a] Dept. of Civil & Environmental Engineering, School of Engineering, University College Cork, College Rd., Cork, Ireland

[b] Environmental Research Institute, University College Cork, Lee Rd. Cork, Ireland

[c] Cork Constraint Computation Centre (4C), University College Cork, Western Gateway Building, Cork, Ireland

*Corresponding author. Tel.: +353 87 2874092; fax: +353 21 427 6648

E-mail address: aoife.foley@ucc.ie

Abstract

Onshore wind power has seen considerable growth in all grid systems due to government-imposed renewable energy targets, motivated by climate change and security of supply concerns. In the coming decade offshore wind power is also expected to expand rapidly. Wind generation of electricity differs from conventional thermal generation because it is more variable and intermittent due to the stochastic nature of wind, and the power output is therefore not fully predictable over all time scales. Integration of wind generation into existing grids requires additional power system and electricity market planning, operation and management for system balancing. Low levels of wind power generally have little effect on power systems. However, as penetrations increase studies indicate additional system balancing is required with an associated extra cost. Wind power forecasting and prediction methods are used by system operators to reduce these additional integration costs and by wind farm owners to maximize profit. This paper presents an in-depth review of the current methods and advances in wind power forecasting and prediction. Numerical wind prediction from global to local scales, ensemble forecasting and upscaling and downscaling processes are discussed. Statistical and machine learning approach methods are detailed. Techniques for benchmarking and uncertainty analysis of forecasts are overviewed, and the performance of various approaches over different forecast time horizons is examined. Finally, current research activities, challenges and potential future developments are appraised.

Keywords: Meteorology, Numerical weather prediction, Probabilistic forecasting, Wind integration Wind power forecasting

1.0 Introduction

Over the last decade there has been rapid growth in wind generation of electricity, with the installed wind power capacity worldwide has increased almost fourfold from circa 24.3 GW to an expected 203.5 GW this year [1]. In power systems, balance is maintained by continuously adjusting generation capacity and by controlling demand. As wind is inherently variable, wind power is a fluctuating source of electrical energy. Short-term forecasts (ranging from 1 hour up to 72 hours) are useful in power system planning for unit commitment and dispatch, and for electricity trading in certain electricity markets where wind power and storage can be traded or hedged. Medium-term forecasts and predictions (ranging from 3 days to 7 days) are needed to plan maintenance of the wind farms, unit commitment and maintenance outages of thermal generators and to schedule grid maintenance and energy storage operations. Forecast errors typically increase as the time horizon increases. However, this is always not the case, as shown in Figure 1 [2]. When specifying a wind power prediction model, the desired time horizon will dictate the final choice, as the different models are differently suited to certain power system planning and market activities which occur over different timescales.

Wind forecasting for energy generation and power systems operations mainly focuses on the immediate short-term of seconds to minutes, the short-term of hours up to two days, and the medium term of 2 to 7 days. This is because power systems operations such as regulation, load following, balancing, unit commitment and scheduling, are carried out within these timeframes. The science of wind power prediction is described as the application of the theories and practices of both meteorology and climatology specifically to wind power generation [3]. The prediction of short-term wind power patterns is discussed in Landberg [4].

Traditional thermal generators are also intermittent but with more predictability than wind power. Nevertheless, thermal plant can experience sudden unplanned outages. In power systems a traditional generator is usually described as ‘dispatchable’, whereas wind generation is often referred to as ‘non-dispatchable’. Accurate wind power forecasting reduces the risk of uncertainty and allows for better grid planning and integration of wind into power systems. However, a common conclusion is that as the levels of wind power penetration increase additional system balancing is required. The cost of the balancing is linked to the flexibility of the existing power system. Wind power forecasting tools are therefore invaluable because they enable better dispatch, scheduling and unit commitment of thermal generators, hydro plant and energy storage plant and more competitive market trading as wind power ramps up and down. Overall they reduce the financial and technical risk of uncertainty of wind power production for all electricity market participants.

This paper provides a detailed review of current methods and recent advances in wind power forecasting. The paper contains three sections. Section 2 overviews benchmarking and uncertainty analysis, examines current forecasting methods, starting with a discussion of time horizons, followed by descriptions of numerical wind prediction, ensemble forecasting, upscaling and downscaling methods, and physical, statistical and learning approach methods. Section 3 presents current research activities and potential future advances. Finally, section 4 gives a brief summary and conclusion.

2.0 Current Forecasting & Prediction Methods

Forecasting models for wind power can be divided into two overall groups. The first group is based upon analysis of historical time series of wind, and a second group uses forecasted values from a numerical weather prediction (NWP) model as an input. However, wind power forecasting is generally described in terms of physical methods, traditional statistical or 'black box' methods and more recently the so-called learning approaches, artificial intelligence or 'grey box' methods. Hybrid methods can involve some aspect of all of these.

The models in the first group use the statistical approach to forecast mean hourly wind speed or to directly forecast electric power production. The models in the second group use explanatory variables (mainly hourly mean wind speed and direction) derived from a meteorological model of the wind dynamics to predict wind power N-steps ahead. The models of the first group provide good results, in the majority of cases, in the estimation of mean monthly or even higher temporal scale (quarterly, annual) wind speed. However, in the short-term horizon, (mean daily or hourly wind speed forecasts), the influence of atmospheric dynamics becomes more important, so that the use of the models of the second group becomes essential [5].

There are three steps in wind power forecasting: firstly determining wind speed from a model; then calculating the wind power output forecast or prediction; and finally regional forecasting or upscaling or downscaling, which may be applied over different time horizons. Very short term forecasting models are usually statistically-based. For statistical and the learning approach methods a large amount of historical time series data is essential. The persistence method, also known as the naïve predictor, can be used to benchmark other methods. Persistence usually performs better than NWP methods for short-term prediction horizons of up to about 3 to 6 hours at a local level, whereas the climatologic mean is better for prediction horizons longer than 15 hours [6]. Table 1 presents a non-exhaustive list of wind power software models developed internationally.

2.1 Numerical Weather Prediction & Wind Forecasting

In developing a NWP-based wind power prediction model the selection of the particular NWP model is a critical step. Important selection criteria include the geographical area, the resolution (both spatial and temporal) and the forecast horizon, as well as the accuracy required and the computational time and number of runs. NWP models usually have three main components, the dynamic centre, which represents the adiabatic non-viscous flow, the physical equations describing variability of the meteorological processes (e.g. turbulence and radiation) and the information gathering software code. Therefore the output of a NWP model is a detailed forecast of the state of the atmosphere at a given time, not just the wind. NWP forecasts are not specifically produced for the electricity industry and are used by a variety of industries, sectors and government agencies. NWP is sensitive to initial conditions and to overcome this ensemble forecasting is used [7]. Nielsen et al [8] demonstrated that if several NWP forecasts are used the forecast error decreases. Louka et al [9] showed that the Kalman filter can remove systematic forecast errors in NWP wind speed forecasts.

Ocean models are not included in most NWP as sea surface water temperatures are described by climatology. Specific NWP models have been developed to identify storms in the Pacific and Atlantic, which tend to be ensemble NWP models (e.g. Typhoon Ensemble Model by the Japan Meteorological Agency). Most meteorological services provide only on-shore and near-shore weather predictions to meet their client needs. Hence, the focus to date of global NWP models has been to provide more accurate weather forecasts on land. As global NWP models need boundary conditions to solve their equations, mostly land surface properties including temperature are used. NWP holds best for time horizons greater than 4 hours. Most models are multi-step and provide look-ahead times for numerous horizons but the bulk of these tools only produce a single expected value for each forecast timescale and are referred to as deterministic, spot or point forecasts. Hence their use for stochastic optimization and risk assessment is limited [10].

At a regional and mesoscale level another family of NWP models was developed to focus on particularly local weather phenomena. Examples include the hydrostatic ETA model, the HIRLAM model and the ALADIN model [11, 12 and 13]. Further examples include the freely downloadable MM5 regional model developed at the Pennsylvania State University and used by the National Centre of Atmospheric Research in the United States of America (USA) and the more recent Weather Research and Forecast (WRF) regional model [14 and 15]. Some NWP models are used at a regional level to predict wind power in a country or in a region of a country. Predicting the wind power output from each individual wind farm can be time consuming so instead an approach called 'upscaling' is used. In upscaling the wind power output from a sample number of wind farms forms the basis of reference data. Upscaling can have the apparent effect of reducing forecast error because it becomes averaged over the whole region [16]. The process of downscaling involves the production of more detailed spatial information from coarse NWP outputs using physical and/or statistical models [17]. Physical downscaling models are similar to NWP but run at higher resolution over a smaller area. Statistical downscaling models use power and/or wind speed at an actual wind farm and NWP to generate a transfer function, which can be used to predict wind power from other wind farms in a region. Table 3 provides a list of a number of NWP global and regional models in use.

2.2 Ensemble Forecasting

Ensemble forecasting employs a number of different model runs to predict a large sample of possible future weather outcomes. The results are then evaluated by examining the the distribution across all ensemble 'members' of the forecast variables. Another ensemble approach is the multi-model approach, which uses a number of NWP models to produce an ensemble [18]. It is referred to as a multi-NWP method. The members of the ensemble arise from different variants of the same NWP model (like different physical parameterization of the sub-grid physical processes, or different initial conditions, or different data assimilation techniques). They can also arise from completely different NWP models. An interesting feature of ensemble forecasting lies into the fact that it also provides an estimation of the reliability of the forecast. The idea is that when the different ensemble members differ widely the forecast is affected by a large uncertainty; when there is a closer agreement between the ensemble member forecasts, the uncertainty in the prediction is lower.

The MSEP approach is another ensemble method, based on predictions from one NWP with different schemes [19]. A study of MSEP in Ireland compared against validated results from Denmark and Germany established that forecast errors increased with increasing capacity factor due to an increase in abnormal weather events and higher than normal wind speeds [20]. In Ireland, for instance, a study showed that using a power curve derived from measured wind and power can improve the forecast root mean square error (RMSE) by nearly 20% in comparison to using the power curve only [21]. The nonlinearity of the wind power curves leads to a further amplification of the error, such that small variations in the wind speed may result in much larger deviations in the power.

2.3 Physical Methods

Several physical models based on the use of weather data have been developed for wind speed forecasting and wind power predictions [22]. The physical models generally make use of global databases of meteorological measurements or atmospheric mesoscale models, but they require large computational systems in order to achieve accurate results [23]. In the physical approach a detailed description of the lower atmosphere is used to estimate the wind power output. An overview of some of the neural, geostatistical and hybrid models used for space-temporal wind forecasting is contained in Cellura et al [24]. The numerical codes for wind field modeling over rough terrain are generally divided into two types: *dynamic models* (also called *prognostic*) and *kinematic models* (also called *diagnostic*) [25]. In these models the momentum and energy equations are not solved explicitly but considered indirectly using parametric relations and/or wind data [26]. Computational fluid dynamics (CFD) is also used as an alternative method to the power law to adjust for the local conditions of the physical terrain [27]. Model output statistics (MOS) are often used to avoid systematic forecasting errors and to correct the predicted power output for unknowns [28].

2.4 Statistical and Learning Approach Methods

In the statistical approach a vast amount of data is analyzed and meteorological processes are not explicitly represented. The link between historical power production and weather is determined and then used to forecast the future power output. Unlike physical methods, statistical methods involve only one-step to convert the input variables into power output. Hence, the methods used are described as 'black box'. Generally a statistical relationship is developed between the weather forecast or prediction and the potential power output from the wind farm.

Other statistical techniques used include autoregressive (AR), moving average (MA), autoregressive moving average model, (ARMA) and autoregressive integrated moving average model (ARIMA), the Box-Jenkins methodology and the use of the Kalman filter. Torres et al [29] found it was possible to get 20% error reduction compared to persistence to forecast average hourly wind speed for a 10 hour forecast horizon at a number of locations using nine years of historical data using an ARMA model. Classical time series analysis is not the only way to model the statistical relationship among the data. The main soft computing (or machine learning) approaches used are artificial neural networks (ANN) and fuzzy systems, but also other models, like grey predictors or support vector machines (SVM) have been applied. Learning approach methods are also often referred to as artificial intelligence (AI) methods. They are called learning approaches because they learn from the relationship between the predicted wind and forecasted power output using historical time series. More recently, they have been referred to as 'grey box' methods. Wind speed and output power were forecasted using a *grey predictor* with a look-ahead time of one hour with an accuracy respectively 11.2% and 12.2% better than persistence in terms of mean absolute error [30]. In some studies an improvement, depending on the forecast horizon, between 9.5% and 28.4% over persistence was the result of using a genetic algorithm (GA) to optimize a fuzzy inference system (FIS) model [31].

ANN's 'learn from experience' using data. For this reason, the approach they are based upon is called data-driven approach. A number of studies apply the most commonly used neural models, which is the standard multi-layer perceptron (MLP) network method [32] or the recurrent version of NN [33]. Welch at al [34] compares three types of neural networks (namely MLP, simultaneous recurrent neural network (SRN) and Elman recurrent neural network) trained using particle swarm optimization (PSO) for short term prediction of wind speed. Ramirez-Rosado et al. compared forecasting schemes in which NWP predictions were enhanced by various neural network and other machine learning approaches and combined with turbine power curve models and demonstrated significant improvements over persistence [35]. Recently, researchers have started to use decision tree techniques in data mining with interesting results [36]. The results indicate that the predictive power of individual variables is dependent on the seasons, with wind power most strongly related to atmospheric pressure in summer and to humidity in winter. Wind power forecasts were determined at 10 wind farms and compared to the NWP data at each wind farm using classical MLP ANNs, mixture of experts, SVM and nearest neighbor with PSO [37]. The main conclusion is that combining several models for day-ahead forecasts produces better results.

Jursa and Rohrig [38] presented an approach which combined the ANN and the nearest-neighbor approaches in an optimization model and the result was an improvement of 10.75% in the normalized RMSE of the prediction compared to persistence (where the improvement equals $RMSE_{persistence}$ minus $RMSE_{model}$ divided by $RMSE_{persistence}$). In summary, five data-mining models used in wind speed and wind power prediction include SVM, MLP ANN, *regression trees* and *random forests*. The review of published literature and data indicates that the MLP ANN outperforms the other four models in both very-short and short and long-term forecasts. The direct approach of feeding the wind ensemble NWP directly into the model also outperformed the integrated approach for both very-short and short and long-term models [39].

Mohandes et al [40] compared SVM to a multilayer perceptron ANN model to predict wind speed. The SVM model gave lower RMSE than the MLP ANN model and it was established that SVM outperforms MLP for system orders from 1 to 11. In data mining repeating patterns are identified. In Kusiak et al [41] four time series models with different prediction horizons were developed with data mining algorithms and it was established that the least accurate and stable was the integrated k nearest neighbor (kNN) for power prediction. Larson and Westrick [42] used a support vector classifier to estimate the forecasting error, obtaining lower mean square error and mean absolute percentage error than traditional SVM. A novel approach for the analysis and modeling of wind vector fields was introduced by Goh et al [43] and developed by Mandic et al [44] where the wind vector is represented as a complex-valued quantity and, unlike the other commonly used approaches, wind speed and direction are modeled simultaneously.

Negnevitsky et al [45] combines two AI methods, ANN and fuzzy logic in a hybrid approach to develop an adaptive neural fuzzy system model (ANFIS). Fuzzy models are employed in cases where a system is difficult to model exactly or vagueness is the problem formulation is characterized by some indefinite and vague elements. In Damousis et al [46] a fuzzy model was implemented for the prediction of wind speed and the produced electrical power at a wind park. The model was trained using a genetic algorithm-based learning. The efficiency of short-term forecasting was improved for ranges from a few minutes to several hours ahead. However, the main drawback of the proposed method is the large number of fuzzy rule base and the consequent large computational time. Pinson and G. Kariniotakis [47] developed a prediction system that integrates models based on adaptive fuzzy-neural networks configured for short and long-term forecasting.

Recently, Bayesian methods have started to be employed for wind speed prediction. Miranda and Dunn [48] used an autoregressive model based on a Bayesian approach to obtain one-hour-ahead forecasts of the wind speed. Fan et al [49] applied an integrated machine learning forecasting model, based on Bayesian clustering by dynamics (BCD) and support vector regression (SVR), to provide short-term wind power generation forecasts for a wind farm.

A general result worth noting is that there is a very strong interdependence between wind power prediction model accuracy and NWP model accuracy. In all statistical models the data gathering and accuracy is key to producing good results. The dependence of prediction error on time horizon is illustrated from a sample of models for which, RMSEs were reported is illustrated in Figure 2. The increase in prediction error as time horizons become longer can be observed, and it is also apparent that wind speed prediction models produce lower errors than models which attempt to predict wind power outputs. In Fugon et al [50], it was found that if a number of statistical models are combined for day-ahead predictions the forecast error decreases.

2.5 Benchmarking & Uncertainty Analysis

As wind power forecasting has intrinsic uncertainty, the results of any model must be tested. The verification of wind power prediction models is complicated. As wind power prediction model outputs are generally either a vast array of single value point forecasts for each look-ahead time or more recently multiple ensembles from a multi-scheme ensemble prediction (MSEP), it is difficult to establish a standard metric of accuracy. Therefore, a number of accuracy tests are used to benchmark or validate a model and to determine the percentage of uncertainty of the results. The input data and the time horizon usually determine the most appropriate accuracy test. In Madsen et al [51] three criteria were identified to establish the 'fitness for purpose' of a weather forecast. These criteria are consistency, quality and value. Consistency refers to the expectations of the model performance based on the skill and experience of the modeler. Quality is defined as the correspondence between the observed and forecasted observations. Value is related to the 'fit for purpose' or relevance of the forecast to its actual function and application.

The purpose of uncertainty analysis is to measure the degree of 'wrongness' of the model, often described by a loss (or cost) function. Uncertainty analysis has three main approaches: probabilistic forecasting, risk indices and scenario generation. In probabilistic forecasting the uncertainty in the future is estimated as a probabilistic measure. Probabilistic measures include quantiles, interval forecasts and probability density function (pdf) and probability mass function for each time step of the prediction horizon. Risk indices, also referred to as skill forecasts, include the meteo-risk index (MRI) and the normalized prediction risk index (NPRI). They are not related to the prediction method and provide a priori information on expected level of forecast error.

A model's prediction error is classically defined as the difference between the measured and the predicted value. A number of standard error measures are also used to describe the error in point forecast models. Models are assessed and compared using mean error (bias), mean absolute error (MAE), mean square error (MSE), RMSE, histograms of the frequency distribution of the error, the correlation coefficient (R), mean absolute percentage error (MAPE) and the coefficient of determination (R^2), standard deviation of the errors (SDE) and the normalized MAE and RMSE. These error measures do not depend on the size of the test set. The 'skewness' of the prediction is often determined using Fisher's equation. A negative skew implies relatively few low results, whereas a positive skew implies few high results. The skill score and measures to verify forecast models are proposed in Murphy and Epstein [52] and Murphy and Winkler [53]. It is frequently recommended that three measures are taken to reduce forecast and prediction errors. Table 2 gives a summary of some of the standard error measures.

The grouping of wind farms reduces the overall prediction error, an example of this is in Germany where the forecast error for the aggregated wind power stays below 2.5% when the three control zones of E.ON, Vattenfall and RWE are grouped together [54]. In the USA a MAE of 10 to 15% for day-ahead modeling of the nameplate capacity of the wind farm has been obtained [55]. If the model is rerun a few hours ahead on the same day the MAE range is typically 5% of the name plate capacity of the wind farm. The Danish system operator has had similar results [56]. The RMSE is usually 10% of installed capacity for most models. In Ireland the system operators (i.e. EirGrid in the Republic of Ireland and SONI in Northern Ireland) have a target accuracy of 6 – 8% [57]. The operators have quoted individual wind farm accuracy in the range of 10 – 20%.

As part of the European Union (EU) funded ANEMOS project, a number of models including Prediktor, Previento and AWPPS, were benchmarked and a standardization approach was developed [58 and 59]. A number of the key findings were that Kalman filters decrease NWP systematic error. Forecasts for offshore wind farms appear to have similar performance results to those for flat terrain on-shore wind farms and that none of the models could perform better than the others for each test case or look-ahead time. Another benchmarking study was carried out by the Asociación Empresarial Eólica (AEE) in Spain to study the effects of terrain and model selection [60].

3.0 Current Research Activities and Future Advances

Most wind power forecasting models study 'regular' wind conditions. The EU funded project called 'Safewind' aims to improve wind power prediction over challenging and extreme weather periods and at different temporal and spatial scales [61]. Development activities are on-going to reduce error in wind power prediction, to improve regionalized wind power forecasting for on-shore wind farms and to derive methods for wind power prediction for offshore wind farms. It is possible that the use of ensemble and combined weather prediction methods together may enhance forecasting.

If the error in wind power forecasting and prediction is reduced then electricity markets can trade with more certainty. Contract errors as a function of time in electricity markets can be as high as 39% for a forecasting lead time of 4 hours [62]. Gubina et al (2009) [63] presents a new tool called the WILMAR and ANEMOS scheduling MeThodology (WALT) to reduce the number of thermal generators on stand-by or in reserve using the probability of generation outages and load shedding are system reliability criteria instead of generation adequacy based solely on generation outage. The wind and load forecast errors are modeled using a Gaussian stochastic variable approach. However, in another study it was found that the prediction errors do not satisfy the Kolmogorov-Smirnov test for normal distribution [64]. In Ramìrez and Carta [65], it was shown that, the use of autocorrelated (and thus not independent) successive hourly mean wind speeds, though invalidating all of the usual statistical tests, has no appreciable effect on the shape of the pdf estimated from the data.

Offshore wind farms pose more of a challenge in terms of accurate wind power forecasting because the environment is typically flat and smooth with very few obstacles so changes in wind speed and thermal effects are felt more acutely than on land as weather fronts pass over the wind farm [66]. A review of published data has gleaned very little knowledge of methods in use for offshore wind power prediction. There are ambitious plans to develop large offshore wind farms (e.g. Horns Rev, Denmark, Arklow Bank, Ireland and Hornsea, UK). Watson et al [67] discusses some of the issues associated with offshore wind farm prediction, including:

- Current forecasting and prediction models are designed for on-shore environment and still have errors,
- Resource assessment is difficult due to completely different conditions, offshore is vast, flat and smooth (with a variable roughness) and thus weather fronts are felt more acutely than on land. Therefore thermal effects, wake affects and coastal land mass effects are amplified.
- Poor availability of meteorological data to validate NWP outputs for these offshore locations.

Current indications of best practice involve adapting existing models and using CFD adjusted for the maritime conditions. To illustrate the difficulty of accurate prediction of offshore wind, a 'nowcast' (i.e. zero time horizon) is included in Figure 2 for comparison purposes, and it can be seen that the RMSE exceeds that of many onshore forecasts [68]. The increase in prediction error as time horizons become longer can be observed, and it is also apparent that wind speed prediction models produce lower errors than models, which attempt to predict wind power outputs.

4.0 Discussion & Conclusion

One of the ultimate goals of every wind power prediction model is to estimate the wind power output as early and as accurately as possible. Wind power will become more attractive for system and market operators as NWP model accuracy improves and as easier to use forecasting techniques are developed. Wind power prediction tools are invaluable because they enable better dispatch, scheduling and unit commitment of thermal generators, hydro plant and energy storage plant and more competitive market trading as wind power ramps up and down. Overall accurate wind power prediction reduces the financial and technical risk of uncertainty of wind power production for all electricity market participants. When smart grid technology and intelligent load management techniques (such as controlled water and space heating and chilling, and electric vehicle charging) are deployed, integration of wind power will become a more straightforward task. Many aspects of existing grid systems, conventional thermal generation and the management of the power system are circa 70 years old, whereas large-scale adoption of wind energy has only occurred in just the last 15 years. Furthermore, a more diverse generation portfolio mix, which includes energy storage plant, off-shore wind, wave and tidal will also make wind power integration less operationally intensive for system operators.

In conclusion, the extensive body of literature has demonstrated that research; development and activity in wind power forecasting are very active areas and are delivering results for generators, power system operators and market operators. The rapid expansion of wind generation capacity in the past 15 years has created demand for advances in wind forecasting techniques. Improvements in NWP, driven by advances in the affordability and power of computing technology, have resulted in greater accuracy by enabling the use of more sophisticated parameterizations and finer meshes. Continuing innovations in statistical and machine learning prediction techniques have also paid dividends, particularly for forecasting on very short term and short term timescales. Hybrid methods are delivering some of the benefits of both NWPS (in terms of accuracy over medium term time horizons) and of statistical and machine learning techniques (in terms of better time resolution and better representation of winds at local scales). Further increases in wind energy penetration of power systems, with the associated issues of managing wind variability, are likely to drive future developments in wind forecasting technology, and the current plans to hugely increase offshore wind capacity will necessitate model improvements in this area.

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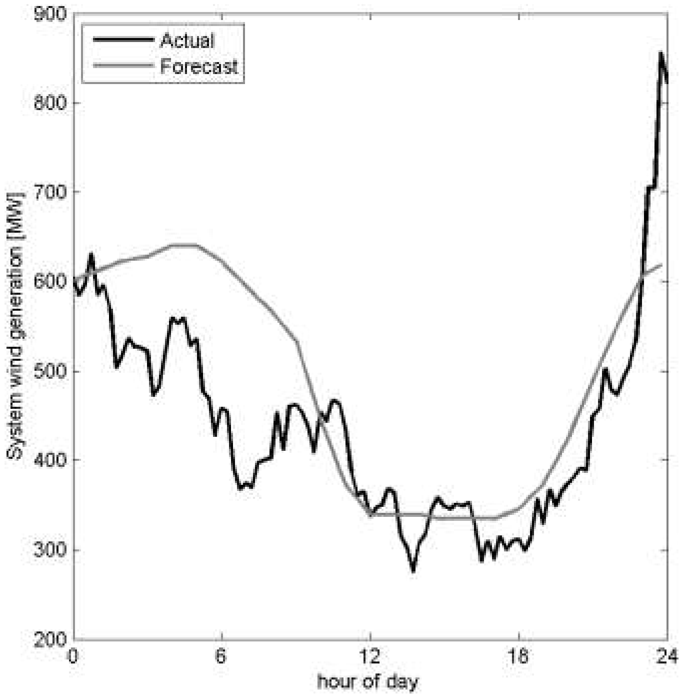

Figure 1. Actual and Short Term Forecast Total System Wind Power Generation on the 10th January 2011 on the Republic of Ireland System (data provided by Eirgrid).

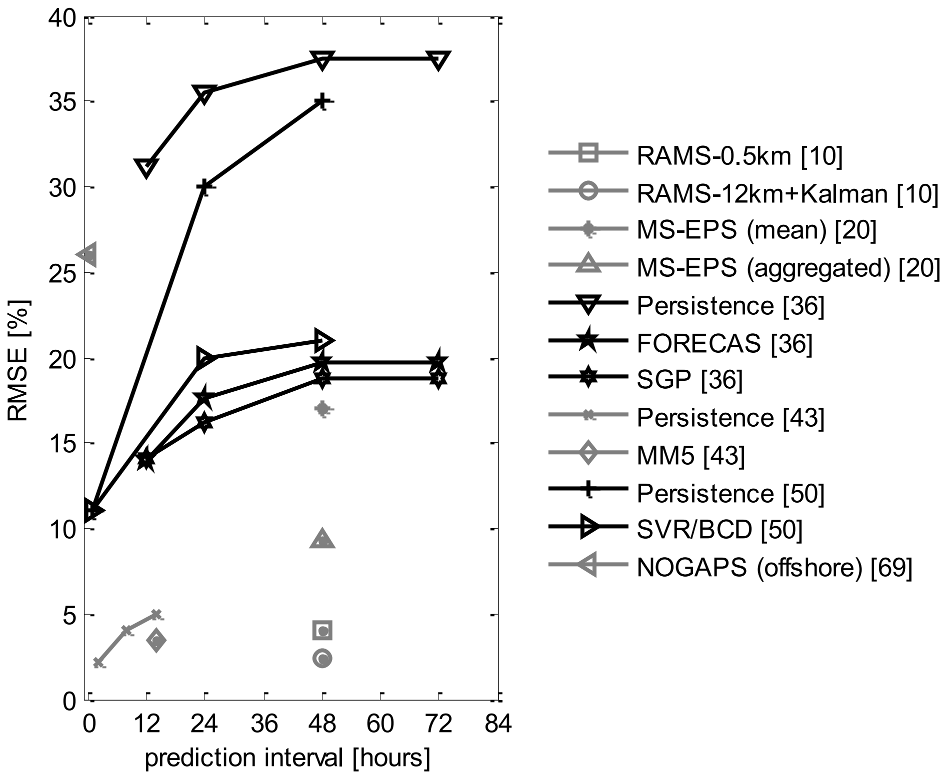

Figure 2 Some Prediction Errors (as percentage RMSE) as a Function of Forecast Horizon from different studies (Black markers indicate wind power generation prediction models, whereas grey markers indicate wind speed prediction models)

Table 1 Some Wind Power Forecasting & Prediction Models

Model Name	Developer(s)	Method	Some geographical locations of applications
Prediktor	L. Landberg at Risø, Denmark	Physical	Spain, Denmark, Republic of Ireland, Northern Ireland, France, Germany, USA, Scotland & Japan
WPPT	Eltra/Elsam collaboration with Informatics and Mathematical Modelling at Danmarks Tekniske Universitet (DTU), Denmark	Statistical	Denmark, Australia, Canada, Republic of Ireland, Holland, Sweden, Greece & Northern Ireland
Zephyr	Risø & IMM ay DTU, Denmark	Hybrid	Denmark & Australia
Previento	Oldenburg University	Hybrid	Germany, Northern Ireland
e Wind ™	True Wind Inc., USA	Hybrid	USA
Sipreólico	University Carlos III, Madrid, Spain & Red Eléctrica de Espaňa	Statistical	Spain
WPMS	Institut für Solare Energieversorgungstechnik (ISET), Germany	Statistical	Germany
WEPROG	J. Jørgensen & C. Möhrlen at University College Cork	Hybrid	Ireland, Denmark and Germany
GH Forecaster	Garrad Hassan	Statistical	Greece, Great Britain & USA
AWPPS	École des Mines, Paris	Statistical	Crete, Madeira, Azores & Ireland
LocalPred & RegioPred	M. Perez at Centro Nacional de Energias Renovables (CENER) and Centro de Investigaciones Energéticas, Medioambientales y Tecnalógicas, Spain (CIEMET)	Hybrid	Spain and Ireland
Alea Wind	Aleasoft at the Universitat Polytécnica de Catalunya, Spain (UPC)	Statistical	Spain
SOWIE	Eurowind GmbH, Germany	Physical	Germany, Austria & Switzerland
EPREV	Instituto de Engenharia de Sistemas e Computadores do Porto (INESC), Instituto de Engenharia Mecânica e Gestão Industrial (INEGI) and Centro de Estudos de Energia Eólica e Escoamentos Atmosféricos (CEsA) in Portugal	Statistical	Portugal
Scirocco	Aeolis Forecasting Services, Netherlands	Hybrid	Netherlands, Germany & Spain

Table 2 Commonly-used Error Measures

Measure	Formula	Purpose
Bias	Bias $_k = \overline{e_k} = \frac{1}{N_T}\sum_{t=1}^{N} e_{t+k/t}$ where N_T = number of prediction errors for each look-ahead time *k* for the considered time horizon	Bias signifies if the method over-estimates or under-estimates the forecast variable. It gives low results for statistical methods. If MOS are used in physical methods it also gives low results. It does not indicate the level of skill of the forecast method.
MSE	MSE $_k = \overline{e_k} = \frac{1}{N_T}\sum_{t=1}^{N}(e_{t+k/t})^2$	MSE expose the contribution of positive and negative errors to the lack of accuracy. Random and systematic errors influence MSE.
RMSE	RMSE $_k = \sqrt{MSE_k} = \sqrt{\frac{1}{N_T}\sum_{t=1}^{N}(e_{t+k/t})^2}$	RMSE is easier to interpret it is expressed in the same units as the forecasted variable.
SDE	SDE $_k = \sqrt{\frac{\sum_{t=1}^{N}[e_{t+k/t} - \overline{e_k}]^2}{N-(p+1)}}$	SDE is a guesstimate of the error distribution. Therefore only random errors are a factor in SDE.
Skill Score	$Imp_{\gamma}^{ref}(k) = \frac{\gamma^{ref}(k) - \gamma(k)}{\gamma^{ref}(k)}$ where Imp = the improvement with respect to, $\gamma^{ref}(k)$ = value for the reference approach and $\gamma(k)$ = value for the advanced approach, for time horizon k.	Skill score can use MAE, RMSE or SDE including the normalized versions of all three. The result is often changed to a percentage by multiplying by 100 and presenting it as a percentage improvement on the result of the reference approach. If the results are always less than 100, the forecast is very accurate.

Table 3 Global & Regional NWP Models

Name	Developer(s)	Type
Global Forecast System (GFS)	National Oceanic and Atmospheric Administration (NOAA), US	Global
Action de Recherche pour la Petite Echelle et la Grande Echelle (ARPEGE)	Météo-France (METEO FRANCE)	Global
Global Meteorological Model (GME)	Deutscher Wetterdienst (DWD), Germany	Global
Global Environmental Multi-scale Model (GEM)	Recherche en Prévision Numérique (RPN), Meteorological Research Branch (MRB), and the Canadian Meteorological Centre (CMC)	Global
Navy Operational Global Atmospheric Prediction System (NOGAPS)	United States Navy (USN)	Global
Intermediate General Circulation Model (IGCM)	NCAS Centre for Global Atmospheric Modelling, University of Reading, United Kingdom (UK)	Global
Unified Model (UM)	Met Office, UK	Global
Integrated Forecast System (IFS) Note uses the same code as ARPEGE	European Centre for Medium-Range Weather Forecasts (ECMWF), England	Global
GSM	Japan Meteorological Agency (JMA)	Global
Global Analysis and Prediction (GASP)	Bureau of Meteorology, Australia	Global
High Resolution Limited Area Model (HiRLAM)	Current members include: Danmarks Meteorologiske Institut (DMI), EESTI Meteoroloogia Ja Hüdroloogia Insitut (EMHI), Ilmatieteen Laitos (FMI), Veðurstofa Íslands (VI), Met Éireann, Koniklijk Nederlands Meteorologisch Instituut (KNMI), Meteorologisk instutt (met.no), Agencia Estatal de Meteorología (AEMET) and Swedish Meteorological and Hydrological Institute (SMHI)	Regional
Lokal-modell (LM)	DWD, Germany	Regional
ALADIN	Météo-France with a consortium of16 European partners	Regional
Mesoscale Model 5 (MM5)	Mesoscale Prediction Group in the Mesoscale and Microscale Meteorology Division, National Center for Atmospheric Research (NCAR)	Regional
MSM and a number of Ensemble models	Japan Meteorological Service	Regional
Weather Research and Forecasting (WRF) Model	A collaboration in the US, which includes NCAR, the National Oceanic and Atmospheric Administration (National Center for Environmental Prediction (NCEP) and the Forecast Systems Laboratory (FSL)), the Air Force Weather Agency (AFWA), the Naval Research Laboratory (NRL), the University of Oklahoma and the Federal Aviation Administration (FAA)	Regional
Consortium for Small-Scale Modelling (COSMO)	A collaboration of 6 European met services led by the Federal Office of Meteorology and Climatology MeteoSwiss	Regional