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Abstract

The need to have access to accurate short term forecasts is essential in order to anticipate the energy production from intermittent renewable sources, notably wind energy. For hourly and sub-hourly forecasts, benchmarks are based on statistical approaches such as time series based methods or neural networks, which are always tested against persistence. Here we discuss the performances of downscaling approaches using information from Numerical Weather Prediction (NWP) models, rarely used at those time scales, and compare them with the statistical approaches for the wind speed forecasting at hub height. The aim is to determine the added value of Model Output Statistics for sub-hourly forecasts of wind speed, compared to the classical time series based methods. Two downscaling approaches are tested: one using explanatory variables from NWP model outputs only and another which additionally includes local wind speed measurements. Results of both approaches and of the classical time series based methods, tested against persistence on a specific wind farm, are considered. For both hourly and sub-hourly forecasts, adding explanatory variables derived from observations in the downscaling models gives higher improvements over persistence than the benchmark methods and than the downscaling models using only the NWP model outputs.

Keywords: Wind speed forecasting, Very-short term, Wind energy forecasting, Downscaling, Statistical model, Numerical Weather Prediction

1. Introduction

Over the past two decades, the global energy market is turning increasingly to green energies. In this context, the wind energy sector has soared all over the world. Wind farms are located in more than 90 countries around the world,

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9 of them with an installed capacity of more than 10 GW, and 30 with more than 1 GW across Europe, Asia, North America, Latin America and Africa. In 2017, 52.5 GW of new wind power was installed across the globe, bringing total installed capacity up to 539 GW. In France, wind power installation increased by 14.04% in 2017 [1], especially thanks to the feed-in tariffs. The French main electricty utility company is under an obligation to purchase green electricity from smaller producers for a time period of 15 years. After this period, the producers have to sell their electricity on the competitive market. Every day a contract is established between the market and the producer about the quantity of electricity they will inject on the grid. This contract can be updated up to 10 min in advance. If the difference between the contract and the production is too big, the producer will have to pay penalties. This framework prompts the producers to have accurate short term forecasts.

Fortunately, Numerical Weather Prediction (NWP) models have improved significantly over the last 30 years. The forecast skill of the 3-days forecasts for the northern hemisphere rose from 85% to 98.5% between 1981 and 2013 and from 70% to 98.5% for the southern hemisphere [2]. Even though NWP models perform well for predicting large scale meteorological variables at short term, like mid-tropospheric pressure, they do not perform the same for variables having much variability at small scales, like surface winds. Large scale variables are well understood physically and efficiently modeled numerically but variables tied to phenomena occuring on smaller scale depend more on processes that are not resolved and so parametrized. This leads to significant model errors for variables like surface wind.

Model error has several components: part comes from the inadequate representation of physical processes, e.g. uncertainties in the parametrizations used for boundary layer turbulence. This error should be reduced by improving parametrizations. Part of the error is numerical error, coming from the discrete representation of a continuous process. Also tied to the limited resolution is the representativity error, which occurs because of the difference of the value over a grid box and the value at a specific point. Downscaling method such as Model Output Statistics (MOS) are usually used to reduce representativity error [3]. Those models have been developed in weather forecast for several decades, based on NWP models outputs. A statistical relationship is determined between observations and forecasts using past forecasts and corresponding observations, and then serves to improve predictions at that observation site.

Downscaling models can be very interesting to get accurate forecasts at a specific location of a wind farm [4]. To do so, different downscaling models and different outputs of NWP models, climate data or, if applicable, recent surface observations can be used as explanatory variables for the near surface wind speed [5]. Amongst them, markers of large-scale systems (geopotential height, pressure fields) and boundary layer stability drivers (surface temperature, boundary layer height, wind and temperature gradient) can be used [6].

However, for hourly and sub-hourly forecasts, downscaling methods are not commonly used because NWP models are only run once or twice a day due to the difficulty to gain information in short time and the associated high costs.

This usually limits its usefulness to forecasts with lead times longer than 6 hours at least. Persistence is the reference method for short term and very short term forecasts. It supposes that the wind speed at a certain future time will be the same as it is when the forecast is made. Statistical approaches are also used as benchmark for short and very short term generally. We can split this category into two sub-categories which are artificial intelligence methods such as Artificial Neural Network (ANN) using past measurements as explanatory variables and time series models such as Auto-Regressive Moving Average (ARMA) [7]. The ANN models can represent a complex non-linear relationship and extract the dependences between variables through the training process. Statistical methods are based on training with measurements and use differences between the predicted and the actual wind speed to upgrade the model. Both approaches constitute the reference methods for short term forecasts [8]. Usually ANN models outperform time series models [9] even if some very good time series models can supersede ANN methods [10, 11].

In this paper, we compare two configurations of downscaling models. One using explanatory variables available from NWP models and another adding explanatory variables derived from observations. In both cases, we compare the results with persistence methods and with the benchmark methods. The paper is organized in six parts. The next part describes the data and the different models. In section 3 the downscaling methods are used for hourly forecasts from 1 h to 11 h. Results of persistence, ARMA and ANN methods are also shown for comparison with classical results found in the literature. In section 4, all methods are applied for sub-hourly forecasts from 10 min to 170 min at a frequency of 10 min which are horizons much less investigated in the literature than hourly horizons. In section 5, preliminary results on wind energy forecasts are presented. In the last section, we discuss the results and conclude.

2. Data and methodology

Our aim is to forecast the wind speed at 100 m height using outputs from ECMWF (European Centre for Medium-Range Weather Forecasts) for a given wind plant using downscaling model. The wind farm is located in Bonneval, a small town 100 km Southwest of Paris, France (48.20°N and 1.42°E). The wind farm is operated by Zephyr ENR, a private company managing 5 other wind farms. The Bonneval wind farm, called "Parc de Bonneval", has been implemented in 2006 and is composed of 6 Vestas V80-2 MW turbines. The European Centre, ECMWF, provides global forecasts, climate reanalyses and specific dataset. In our case, we retrieve the day-ahead forecasts at hour step starting from analysis twice a day, at 0000 UTC and 1200 UTC. UTC is the Universal Time Coordinate. At the location of the wind farm, the local time is UTC+1 h in winter and UTC+2 h in summer. The downscaling model is trained using 47 variables aiming at describing the boundary layer, winds and temperature in the lower troposphere. Tables 1, 2 and 3 show the considered variables. The targeted wind speed is computed by averaging the 10-minutes

measurements over the years 2015 and 2016 of the considered wind farm. Spatial averaging is performed by averaging the data of all turbines. To retrieve measurements at the same interval than ECMWF forecasts, time averaging is performed by averaging the 10-minutes measurements. The spatial resolution of ECMWF forecasts is of about 16 km (0.125° in latitude and longitude). Explanatory variables at the location of the farm are interpolated linearly from the four nearest grid points.

Altitude (m)	Variable	Unit
10 m / 100 m	Zonal wind speed	m s^{-1}
	Meridional wind speed	m s^{-1}
2 m	Temperature	K
	Dew point temperature	K
Surface	Skin temperature	K
	Mean sea level pressure	Pa
	Surface pressure	Pa
	Surface latent heat flux	J m^{-2}
	Surface sensible heat flux	J m^{-2}
-	Boundary layer dissipation	J m^{-2}
	Boundary layer height	m

Table 1: Surface variables

Pressure level (hPa)	Variable	Unit
1000 hPa / 925 hPa / 850 hPa / 700 hPa / 500 hPa	Zonal wind speed	m s^{-1}
	Meridional wind speed	m s^{-1}
	Geopotential height	m^2 s^{-2}
	Divergence	s^{-1}
	Vorticity	s^{-1}
	Temperature	K

Table 2: Altitude variables

Altitude	Variable	Unit
10 m / 100 m	Norm of the wind speed	m s^{-1}
Between 10 m and 925 hPa	Wind shear	m s^{-1}
	Temperature gradient	K

Table 3: Computed variables

2.1. Parametric approach and low cost assimilation

Downscaling statistical methods have been widely investigated since several decades in order to forecast the wind speed, usually from few to several hours

[12, 13, 14]. In this paper, we consider a parametric approach, using linear regression. This method has been developed for NWP downscaling in the study by *Alonzo et al.* [15]. Non-parametric approaches such as random forests have also been tested in this study. The results between the two approaches do not differ significantly for the longest horizons. However, for the shorter horizons (<1 h), considered in this paper, the parametric approach give better results. It is also an easier method to implement and a faster one. That is why we choose to focus on this method. The parametric approach supposes a relation between the target at time t, $\widehat{y}_t$ and the m explanatory variables at time t, $X_{1,t}, ..., X_{m,t}$:

$$\widehat{y}_t = \beta_0 + \sum_{k=1}^{m} \beta_k X_{k,t} + \varepsilon \tag{1}$$

where β_i, $i \in \{0, ..., m\}$, are the model parameters to be estimated and ε is the residual.

Among the explanatory variables, $X_{1,t}, ..., X_{m,t}$, some provide more important information and some may be correlated. Thus, a stepwise regression (forward selection) is performed to only keep the most important uncorrelated variables [15]. This is an iterative regression, which consists in adding variables from the set of explanatory variable based on the Bayesian Inference Criterion (BIC). At each step, a model is built by adding one variable among the remaining ones. The added variable which minimizes the BIC of the model is chosen. The procedure is repeated as long as the BIC decreases.

Two configurations are tested. The first one, denoted LR_{no-obs}, consists in a classic downscaling using the explanatory variables retrieved from ECMWF outputs. The second one, denoted LR_{obs}, consists in adding the error between the observed wind speed at time t_0, i.e. when the forecast is launched, and the forecasted wind by ECMWF at time t as explanatory variable.

In the first case only one model is fitted. In the second case a model is fitted at each hour in order to take into account the error between the forecasted wind at time t and the observations at time t_0 precisely. For the second model, after the variable selection step, between 14 and 21 variables remain, depending on the horizon. This low cost assimilation has been performed and compared to the classical downscaling in Alonzo *et al.* [15]. For a 3 h lead-time, they can improve the forecast up to 9.3% by considering the initial error.

2.2. Benchmark

For short term predictions, statistical methods are the most used and are always compared to persistence [7]. Persistence assumes that the wind speed at time t will be the same as it was at time t_0.

The statistical approach aims at finding the relationship between past and future observations using measurements (and possibly exogenous variables). They can be split in two sub-categories: time series based models which are easy to model and cheap to develop and artificial neural network which can deal with non-linearity but which is known as black box model.

Time series models are mainly based on Auto-Regressive Moving Averaged (ARMA) models [16]. An ARMA(p, q) model aims at predicting the wind speed at time t, using a linear combination of the p previous wind speed values, the q previous residuals and potentialy m exogenous variables (in that case we define the model as ARMAX). The most sophisticated models are ARIMAX(p, d, q) for Auto-Regressive Integrated Moving Averaged EXogenous. They aim at removing the non-stationarity of the data by applying an initial d-order differencing step as follow

$$\widehat{y}_t = \sum_{i=1}^{p} \Phi_i \Delta^d y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{k=1}^{m} \beta_k X_{k,t} \tag{2}$$

where y_{t-i} is the observed wind speed at time $t-i$, $\Phi_i, \theta_j, \beta_k$ are the model parameters, Δ^d is the d-order lag operator defined in equation (3), ε_{t-j} is the residual at time $t-j$, and $X_{k,t}$ is the k^{th} explanatory variable at time t, which can be an output from NWP. However, in this study, benchmark methods only use endogenous parameters. Models with exogenous parameters have been investigated but they do not differ significantly for the considered lead times.

$$\Delta^d y_t = (y_t - y_{t-1}) - \sum_{i=1}^{d-1} (y_{t-i} - y_{t-(i+1)}), \quad d = 1, ..., n \tag{3}$$

Artifical neural networks (ANN) are models inspired by the biological neural networks. They are based on interconnected groups of nodes, divided in layers. Each connection can transmit a signal from one artificial neuron to another. An artificial neuron that receives a signal can process it and transmit it to another neuron. Usually, this signal is a real number and the output of each artificial neuron is computed by some non-linear function, called activation function, of a weighted sum of its input. The weights and the activation function are updated through the training process [17, 18]. Those models are very useful to model complex non-linear relationships and extract dependences between variables.

To quantify the performance of the models, we used two indicators. The Normalized Root Mean Square Error (NRMSE) defined in (4), which is often used and facilitates comparisons with classical scores. The second indicator is the improvements over persistence, defined in (5), that is to say the decrease of the RMSE between the considered model and the persistence method. This skill score is referred to as Δ_{RMSE}.

$$\text{NRMSE} = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^{N} (\widehat{y}_i - y_i)^2}}{\bar{Y}} \tag{4}$$

$$\Delta_{RMSE} = -\frac{RMSE_{model} - RMSE_{persistence}}{RMSE_{persistence}} \tag{5}$$

where, $\widehat{y}_i$ is the i-th wind forecast and y_i is the corresponding observation.

N refers to the number of forecasts that have been done to compute the skill score and $\bar{Y}$ is the mean of the observed wind speed over the same sample. By removing the normalization we obtained the skill score $RMSE$. When $\widehat{y}_i$ is forecasted using persistence, it refers to $RMSE_{persistence}$. When it is forecasted by any other model, it refers to $RMSE_{model}$ where the model is clearly identified (among ECMWF, LR_{no-obs}, LR_{obs}, ARMA and ANN).

3. Performances for hourly forecasts

In this section, the downscaling methods are used for hourly forecasts and tested against the commoly used ANN and ARMA methods. Hourly forecasts have been largely studied in the literature and the results are compared to published reference skill scores.

All the models are trained using hourly averaged of the past observations of the year 2015 and 2016. For the ANN model we used as input hourly averaged of the last 6 hours. Then, we fit different models depending on the number of layers in the network and on the number of neurons in the hidden layers. We fixed the seed in order to remove the uncertainty due to the stochastic nature of the models. The best ANN is a two-layers model with 10 neurons in the hidden layer. For the ARMA model, several models have been fitted depending on the orders p and q of the model. We chose the model that minimizes the Bayesian Inference Criterion which is an ARMA(6,3). To evaluate the models, the hourly averaged of the measurements of the year 2017 are used.

Figure 1 displays the NRMSE depending on the forecast lead times (1 h to 11 h) for persistence, ECMWF forecasts, ARMA and ANN models and for our methods LR_{no-obs} and LR_{obs}. One can note that, for models that use observations as input, performances deteriorate with lead time whereas it remains constant for models that do not. For the 1 h forecast, all the methods that consider measurements as explanatory variables outperform ECMWF and the downscaling model LR_{no-obs}. The only method outperforming all the others for all time horizons is LR_{obs} even if for the 1 h forecast this method gives similar NRMSE compared to persistence, ANN and ARMA. However, the longer the time horizon, the more significant the improvements of our methods over the references (ANN, ARMA, persistence).

The improvements over persistence of all methods are displayed in Fig 2. One can see that both reference methods, ARMA and ANN, perform very similarly. The two models, overperform persistence at every horizon and the improvements slightly increase with time from 2.7% for the first hour to 15.3% for the eleventh. Those results are consistent with those found in the literature. For instance, in [19], Torres *et al.*, used ARMA model to predict hourly averaged wind speed 1 h to 10 h lead time for five sites in Spain. They found NRMSE improvements over persistence ranging between 2% and 5% for 1 h lead time and between 12% and 20% for 10 h lead time. In [20], Sfetsos compares the performances of an ARIMA(2,1,2) and an ANN using measurements collected in Crete, Greece. Hourly averaged wind speed forecasts with ANN model overperform persistence by 4.7% while ARIMA overperforms persistence by 2.3%.

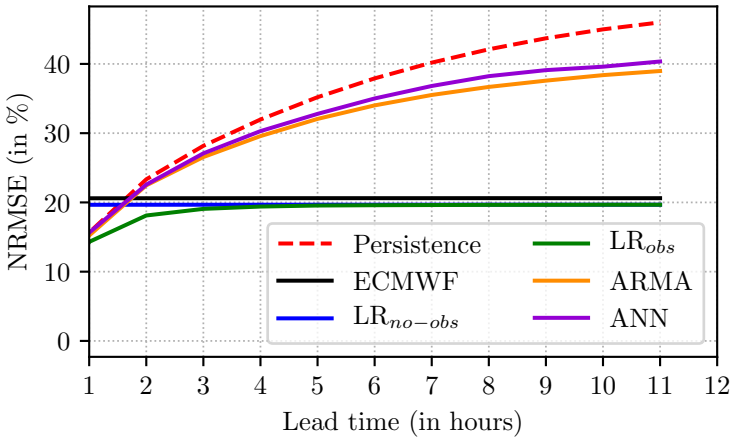

Figure 1: Performances of downscaling statistical models for hourly forecasts from 1 h to 11 h in two configurations against the performances of ECMWF and the benchmark method. LR$_{no-obs}$ displays the downscaling of explanatory variables from ECWMF outputs only. LR$_{obs}$ shows the results when the error between the measurments at t_0 and the 100-m wind speed forecasted by ECMWF at t is adding as explanatory variable. Results of persistence, ANN and ARMA are added.

Compared to these reference results, LR$_{no-obs}$ and LR$_{obs}$ are significantly better. After the fifth hour, ECMWF, LR$_{no-obs}$ and LR$_{obs}$ are better than persistence by more than 40%. For the first lead time, corresponding to t_0+1 h, LR$_{obs}$ performs better than persistence by 8.6% which is better than ARMA (Δ_{RMSE} = 2.7%) and ANN (Δ_{RMSE} = 0.1%). The improvements remain significantly better than ECMWF and LR$_{no-obs}$ until the third hour.

The performance shift at $t_0 + 2$ h between the observations based methods and the downscaling methods can easily be explained. At short lead times, an accurate initial state provided by the observations is a key. At longer lead times, the observations no longer constrain the forecast and NWP forecast then provide the needed information. Moreover, at longer lead times, ARMA and ANN models are no longer based on lattest measurements but on previous forecasts. This feature explains why LR$_{obs}$ outperforms all other methods at all lead times.

4. Performances for sub-hourly forecasts

In this section, we focus on very short term forecasts which is the key objective of this work. We apply the same methods as in section 3 to forecast 10 min averaged winds up to 3 h ahead. Again, a model is fitted at each hour using ECMWF hourly forecasts and the hourly averaged of the measurements. In

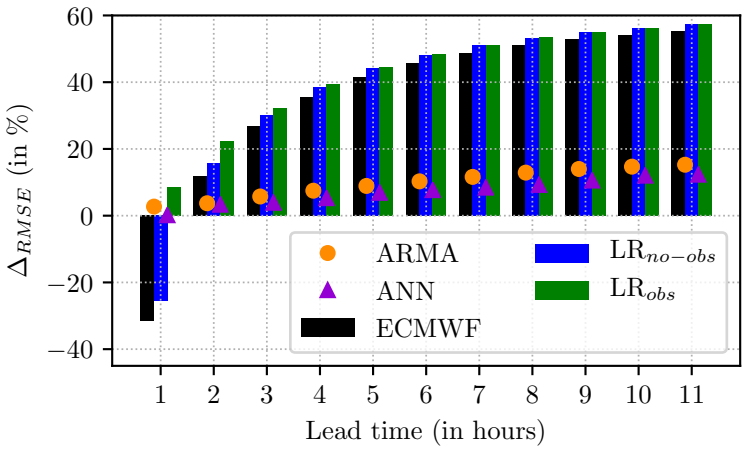

Figure 2: Comparison of the improvements over persistence in percentage for ECMWF forecasts and the downscaling models from 1 h to 11 h in the two configurations. LR_{no-obs} corresponds to the downscaling with explanatory variables from ECWMF outputs only. LR_{obs} shows the results when the error between the measurments at t_0, the time when the forecast is launched, and the 100-m wind speed forecasted by ECMWF at t is added as an explanatory variable. Improvements of ECMWF, ARMA and ANN methods are also included. For ECMWF and the downscaling models, the value of the improvement corresponds to the extremity of each bar while for ARMA and ANN it corresponds to the center of the circle and triangle, respectively.

order to retrieve 10-min forecasts, the explanatory variables are linearly interpolated every 10 min. Then, to retrieve the prediction for all hours h at minutes 0, 10 and 20, we apply the model calibrated at hour h. To retrieve the prediction for all hours h at minutes 30, 40 and 50, we apply the model calibrated at hour $h+1$. However, the calibration leads to an issue with LR_{obs}. For 10 min and 20 min, LR_{obs} is doing exactly the same as persistence. Indeed, the model fitted at time t_0 puts all the weight on the forecasted wind speed by ECMWF and on the initial error. As this model is used at 10 min and 20 min, the results are exactly the results of persistence. To let the model outperforms persistence, one solution is to do a linear regression using only past observations for the first two horizons. Hereafter, LR_{obs} denotes a linear regression over past measurements for time 10 min and 20 min and a linear regression over ECMWF outputs and the error at time t_0 for the remaining time. For the reference methods ANN and ARMA, the training is performed directly using the 10-minutes measurements. The procedure applied to choose the models is the same as in section 3. For the ARMA models, we fitted several models depending on the orders p and q of the models and we select the model which minimizes the Bayesian Inference

Criterion (BIC). This is an ARMA(4,2). For the ANN we fitted several models depending on the number of layers and the number of neurons per layer. The best model is an ANN with 4 layers and 10 neurons per layers. Moreover, we used as input the 10-min measurements over the past hour.

4.1. Statistical skill performances

Figure 3 displays the NRMSE as a function of the time horizon, from 10 min to 170 min, for persistence, ECMWF forecasts, LR_{no-obs} and LR_{obs} forecasts and reference methods ARMA and ANN.

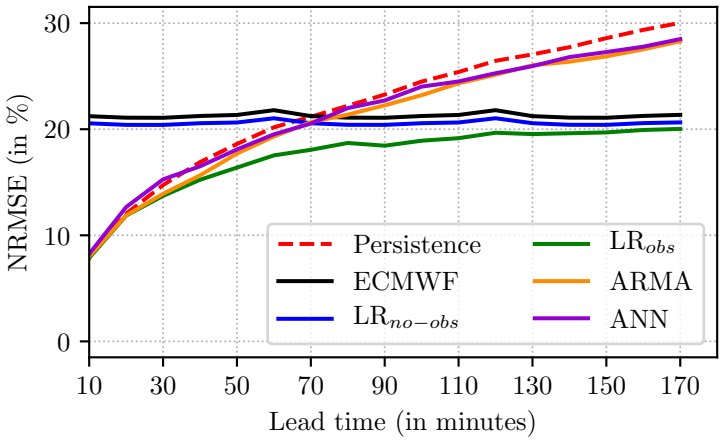

Figure 3: Performances of the different models for sub-hourly forecasts from 10 min to 170 min in two configurations against the performances of ECMWF and the benchmark method. LR_{no-obs} displays the downscaling of explanatory variables from ECWMF outputs only. LR_{obs} shows the results when the error between the measurments at t_0 and the 100-m wind speed forecasted by ECMWF at t is adding as explanatory variable. Results of persistence, ANN with 4 layers and 10 neurons per layer and an ARMA(4,2) are added.

At this time scale the differences between the models are smaller than for longer lead times but the hierarchy between them remains the same. It is hard to distinguish the best model at 10 min and 20 min but after 30 min, LR_{obs} is significantly better. For times between 30 min and 2 h, it provides clearly the best forecasts, with NRMSE less than 20%. For lead times of 2 to 3 h, its performance gradually converges to that of LR_{no-obs}.

Figure 4 is similar to figure 2 for lead times ranging between 10 min and 170 min. Only LR_{obs} overperforms persistence at every horizons. Again it is the model giving the best improvements. The differences with ARMA are not extremely significant for the first lead times especially at 20 min (1.5% for LR_{obs} and 1.3% for ARMA). After 20 min, LR_{obs} is by far the best model. The

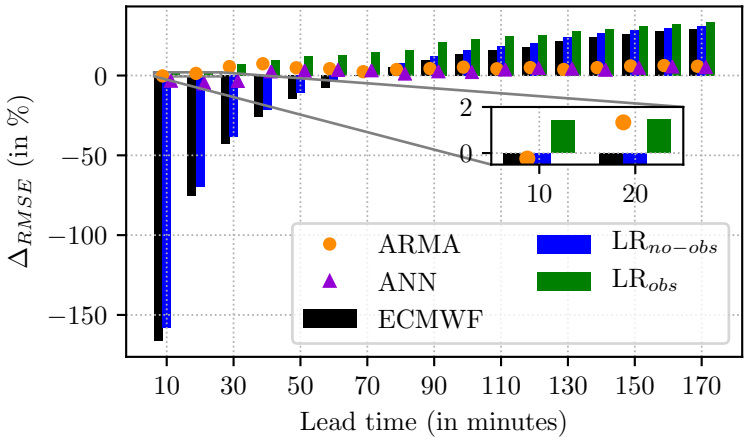

Figure 4: Comparison of the improvements over persistence in percentage for ECMWF forecasts and the downscaling models from 10 min to 170 min in the two configurations. LR_{no-obs} displays the downscaling of explanatory variables of ECWMF outputs only. LR_{obs} shows the results when the error between the measurments at t_0 and the 100-m wind speed forecasted by ECMWF at t is adding as explanatory variable. At 10 min and 20 min, LR_{obs} denotes a linear regression over the last 45 measurements. Improvements of ECMWF, ARMA and ANN methods are added. For ECMWF and the downscaling models, the value of the improvement corresponds to the extremity of each bar while for ARMA and ANN it corresponds to the center of the circle and triangle, respectively.

improvement over persistence is 6.9% at 30 min 33.3% at 170 min. If ECMWF, LR_{no-obs} and LR_{obs} converge with each other with time, ECMWF and LR_{no-obs} start to outperform persistence only from 80 min and 70 min respectively.

4.2. Case studies

Such nowcasting method should be used for decision-making process. Therefore, a statistical quantification of the performances is not enough to evaluate the usefulness of the method. Figure 5 and 6 display forecasted time series with two starting dates: the 15^{th} of January 2017 at 00:00 UTC and the 15^{th} of July 2017 at 01:00 UTC. Those dates have been choosen because the mean wind speed is around 6 m s^{-1}. This is the mean wind speed at "Parc de Bonneval" over the years 2015, 2016 and 2017 so those dates represent common situations. For both dates, a prediction using LR_{obs} and ECMWF models are shown. The measurements and confidence intervals are also included.

In both cases, three degrees of confidence are shown. Each of them are defined depending on the lead time and on the predicted wind speed. For each

lead time, we consider wind speed bins of 1 m s^{-1}. For each prediction we compute the difference : $\widehat{y}_t - y_t$, where $\widehat{y}_t$ is the forecasted wind speed by LR_{obs}, at time t and y_t is the measured wind speed at time t. Those differences are stored in the corresponding bin depending on $\widehat{y}_t$ and t. Using the data of the years 2015 and 2016, we compute for each couple lead time/wind speed bin a distribution of error. We compute, for each couple, three intervals: the 10% confidence interval, the 25% confidence interval and the 50% confidence interval.

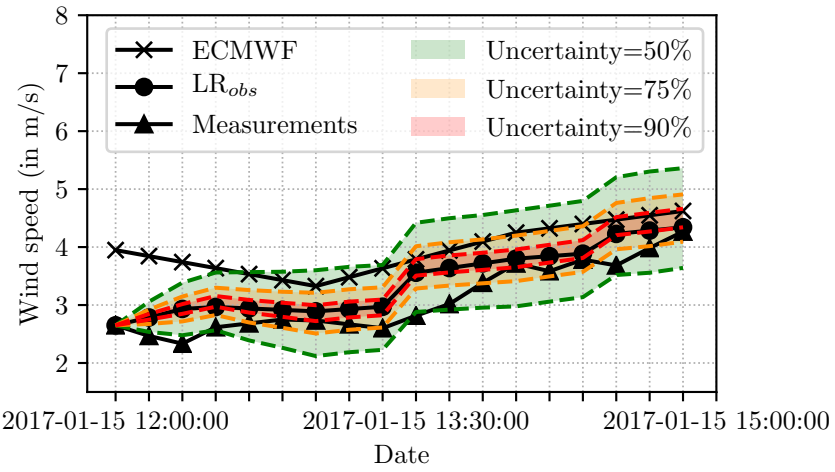

Figure 5: Forecasted time series starting on the 15^{th} of January 2017, 00:00 UTC to 02:50 UTC. ECMWF and LR_{obs} forecasts are compared to the observations. The 10%, 25% and 50% confidence intervals are added.

Figure 5 displays a winter prediction. It starts on the 15^{th} of January 2017 and ranges from 00:00 UTC to 02:50 UTC. For this forecast, the mean of the observed wind speed is around 5.93 m s^{-1} and the mean of the forecasted wind speed is around 6.30 m s^{-1} for LR_{obs} and 5.12 m s^{-1} for ECMWF model. In this case, ECMWF underestimates the wind speed while LR_{obs} overestimates it. However, the LR_{obs} overestimation is lower than ECMWF underestimation. It is clear that this model gives a more accurate prediction than ECMWF model. The mean absolute error, defined in equation (6), is around 0.45 m s^{-1} for the downscaling model and around 0.80 m s^{-1} for the ECMWF forecast. This corresponds to a normalised mean absolute error of 7.65% for LR_{obs} and of 13.57% for ECMWF. This difference is due to the bias correction using LR_{obs}. In terms of variability, a clear lack is visible. It seems to be slightly corrected by LR_{obs} but this is essentially due to the fact that several models are fitted. Consequently when a new models is used there is a rupture in the linearity of

the prediction.

$$MAE := \frac{1}{N}\sum_{i=1}^{N}|\widehat{y}_i - y_i| \tag{6}$$

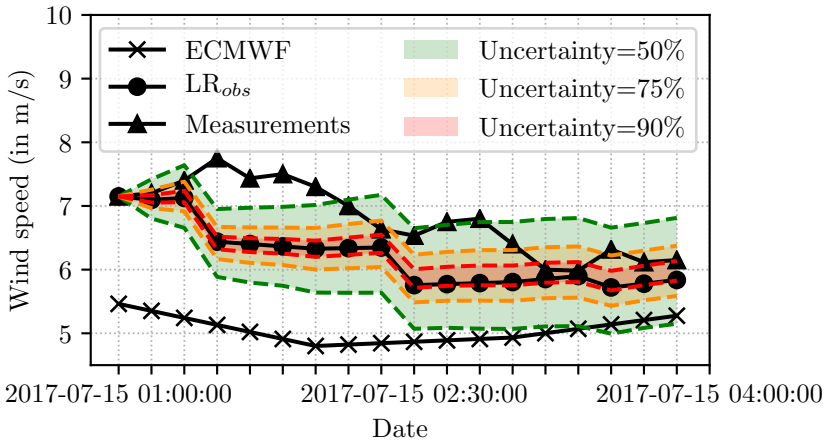

Figure 6: Forecasted time series starting on the 15^{th} of July 2017, 01:00 UTC to 03:50 UTC. ECMWF and LR$_{obs}$ forecasts are compared to the observations. The 10%, 25% and 50% confidence intervals are added.

Figure 6 displays a summer prediction. It starts on the 15^{th} of July 2017, from 01:00 UTC to 03:50 UTC. In this case, the mean of the observed wind speed is around 6.80 m s^{-1} and the mean of the forecasted wind speed is around 6.21 m s^{-1} for LR$_{obs}$ and around 5.05 m s^{-1} for ECMWF model. This time, both models understimate the wind speed but the underestimation is strongly corrected by LR$_{obs}$. Again, the lack of variability is slightly corrected by the use of several models. However, this lack of variability is a reccurent problem in the forecasts. Even with random forests, which are non-parametric models, the variability remains low. The problem comes from the fact that ECWMF outputs are hourly data and in order to retrieve data at a frequency of 10 min, a linear interpolation is made. This creates a huge lack of variability relative to the real 10 min observations. For the this forecast, the MAE is around 0.59 m s^{-1} for LR$_{obs}$ which corresponds to a normalised mean absolute error around 8.67%. This is lower than for ECMWF forecast for which the MAE is around 1.75 m s^{-1}. This corresponds to a normalised mean absolute error around 25.76%. Again this difference is due to the bias correction using LR$_{obs}$.

From Figs. 5 and 6, an "obvious alternative" would be to simply correct the whole wind forecast time series of the weather model ECMWF by the delta to the observations at the initial point. We computed the skill scores of this

"obvious alternative" and it shows that at any time step LR_{obs} overperforms this model (figure not shown).

5. From wind speed to wind energy forecasts

The next step would be to provide forecasts of the wind energy directly. To do so, two approaches are possible. The direct approach, which consists in training the models directly using the production data and the indirect approach which consists in forecasting first the wind speed, then converting it into production using power curves.

Both approaches have advantages and drawbacks depending on the target. For instance, if the target is the wind energy at each turbines, the direct approach requires to build one model for each turbines while the indirect approach just needs one model to predict the wind speed and the power curves of each turbine. The indirect approach is a modular approach, less turbine dependent than the direct approach. However, if the target is the wind energy at the farm scale, the direct approach can avoid error accumulation and it requires only one step, in contrast to two for the indirect approach.

As a preliminary in the present paper, results are shown for the forecasts of the mean power output, by the indirect approach, over the wind farm. Both approaches have been tested and they give similar results. For instance, the NRMSE of the direct approach is 8.11% while the NRMSE of the indirect approach is 7.95% after 30 min. After 60 min it is 10.05% for the direct approach and 10.02% for the indirect approach and after 170 min it is 11.19% for the direct approach and 10.92% for the direct approach. We used LR_{obs}, the best model shown previously, to predict the wind speed from 10 min to 170 min and then we used a power curve, computed at the farm scale using data averaged over the six turbines, to produce a wind energy forecast. This wind farm's power curve is computed by dividing the averaged wind speed data set into 0.5 m s^{-1} intervals. The quantiles of the distribution of the wind farm power of each interval are computed. Finally, the power curve is retrieved by fitting the means of each interval, as shown in figure 7.

Figure 8 illustrates a wind energy forecasts. It displays a forecasted time series of wind energy starting from the 15^{th} of January 2017 at 00:00 UTC, corresponding to the same time series than in part 4.2. As previously, the wind speed is forecasted by LR_{obs} and then the forecasted power is retrieved using the computed power curve shown in figure 7. The different confidence intervals computed using the power curve in figure 7 are added with the same color code than in figures 5 and 6. In figure 8, we can see that LR_{obs} forecasts is very close to measurements and inside the confidence intervals.

More generally, figure 9 shows the statistical performances of the different models for the wind energy forecast. Again it is hard to distinguish the best model for short lead time but LR_{obs} overperforms the other methods.

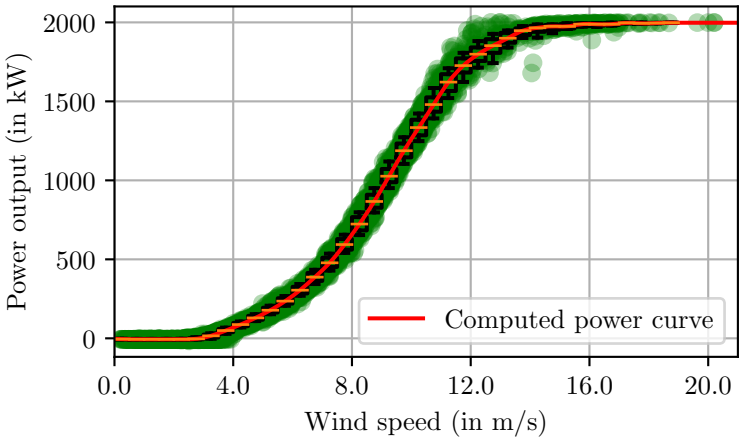

Figure 7: Computed power curve at the farm scale. For each 0.5 m s^{-1} intervals, the boxplots of the distribution are shown in green. The whiskers correspond to the first and the ninth decile. The means of each interval are fitted in order to retrieve the power curve.

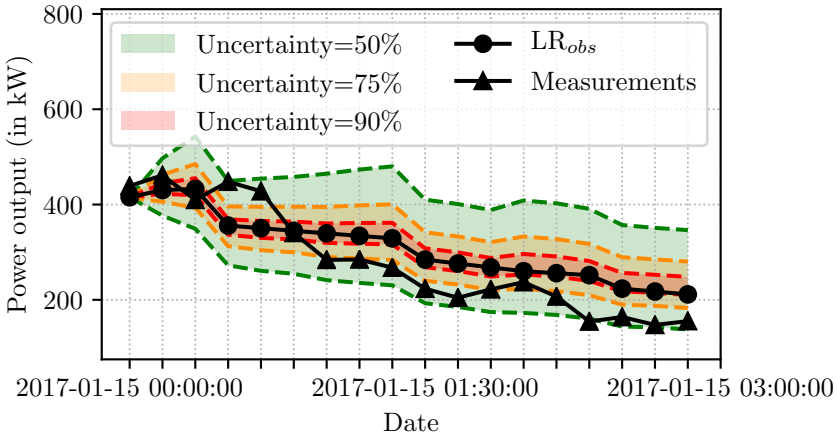

Figure 8: Forecasted time series of wind energy starting from the 15^{th} of January 2017 at 00:00 UTC. LR$_{obs}$ forecasts are compared with the measurements. First, the wind speed is forecasted by LR$_{obs}$ and then the forecasted power is retrieved using an averaged power curve. The 10%, 25% and 50% confidence intervals are added.

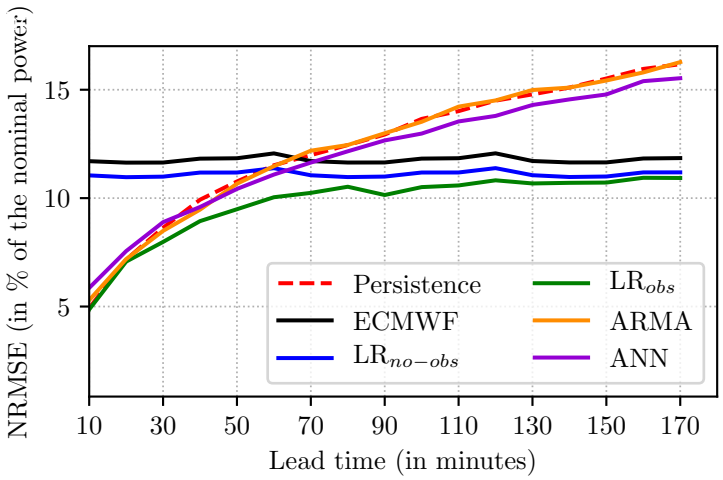

Figure 9: Performances of the different models for sub-hourly forecasting of wind energy from 10 min to 170 min in two configurations against the performances of ECMWF and the benchmark methods. The models are exactly the same than figure 3. The power curve shown in figure 7 is used to compute the wind energy forecast. The NRMSE is normalized by the nominal power (2000 kW).

6. Conclusion

In this paper, we have developed and tested approaches that combine statistical models and output from Numerical Weather Prediction (NWP) models in order to forecasts the 100 m wind speed and the wind energy production at sub-hourly time scales. Traditionally, the main methods used for those time scales are time series based methods using only local observations, while Numerical Weather Prediction (NWP) models are preferred for lead times longer than 6 h at least [21]. However for the case of the considered wind farm ("Parc de Bonneval", 100 km Southwest of Paris, France) we have used 3 years of data to show that the European Centre for Medium-Range Weather Forecasts (ECMWF) performs well even for short lead times. After 80 min the direct output of ECMWF forecasts gives better results than the classical time series based methods and improves persistence from 5.0% to 28.9%. Taking into account those good performances, we have considered a parametric approach to downscale the model outputs at farm scale using a linear regression. In order to have better results for lead time shorter than 80 min, we have corrected ECMWF forecasts by providing as explanatory variable the error between the forecasted wind speed and the initial measurement. This low cost assimilation lets the linear regression to overperform all other methods. If the improvements over the traditional time series based models may not be important for the first lead times, 0.2% at 10 min, they become significant with time, from 5.3% at

30 min to 30.1% at 170 min.

For the wind energy forecasts we considered an indirect approach. The forecasted wind speed provided by the downscaling model with low cost assimilation is used to retrieve wind energy forecasts using a computed power curve. Again, this model overperforms all other methods at all lead times, from 2.3% to 29.7%. In order to illustrate the model performances, case studies for specific times are shown. Wind speed and wind energy forecasted time series are presented. The associated confidence intervals are also display. We choose to add the 50%, 25% and 10% confidence intervals because their range, from 0.20 m s^{-1} to 1.5 m s^{-1}, correspond to the appropriate accuracy for wind energy producers. For instance, a 90% confidence would have been statistically better but not accurate enough to be useful. For the wind speed, a lack of variability is visible in the forecasts compared to the measurements. This is due to the hourly frequency of the ECMWF outputs used as predictors in the dowscaling model. This lack of variability has less impact on the wind energy forecasted time series. The inertia of the turbines generates much less variability in term of measured power than in term of observed wind speed which is measured by anemometers. The forecasted wind energy time series are smoother and the predictions are closer to measurements.

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