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Sub-hourly Forecasting of Wind Speed and Wind Energy

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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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5 9 of them with an installed capacity of more than 10 GW, and 30 with more
6 than 1 GW across Europe, Asia, North America, Latin America and Africa. In
7 2017, 52.5 GW of new wind power was installed across the globe, bringing total
8 installed capacity up to 539 GW. In France, wind power installation increased
9 by 14.04% in 2017 [1], especially thanks to the feed-in tariffs. The French main
10 electricity utility company is under an obligation to purchase green electricity
11 from smaller producers for a time period of 15 years. After this period, the
12 producers have to sell their electricity on the competitive market. Every day a
13 contract is established between the market and the producer about the quantity
14 of electricity they will inject on the grid. This contract can be updated up to
15 10 min in advance. If the difference between the contract and the production is
16 too big, the producer will have to pay penalties. This framework prompts the
17 producers to have accurate short term forecasts.

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

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

41 Downscaling models can be very interesting to get accurate forecasts at a
42 specific location of a wind farm [4]. To do so, different downscaling models and
43 different outputs of NWP models, climate data or, if applicable, recent surface
44 observations can be used as explanatory variables for the near surface wind speed
45 [5]. Amongst them, markers of large-scale systems (geopotential height, pressure
46 fields) and boundary layer stability drivers (surface temperature, boundary layer
47 height, wind and temperature gradient) can be used [6].

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

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

66 In this paper, we compare two configurations of downscaling models. One
67 using explanatory variables available from NWP models and another adding
68 explanatory variables derived from observations. In both cases, we compare the
69 results with persistence methods and with the benchmark methods. The paper
70 is organized in six parts. The next part describes the data and the different
71 models. In section 3 the downscaling methods are used for hourly forecasts
72 from 1 h to 11 h. Results of persistence, ARMA and ANN methods are also
73 shown for comparison with classical results found in the literature. In section
74 4, all methods are applied for sub-hourly forecasts from 10 min to 170 min at a
75 frequency of 10 min which are horizons much less investigated in the literature
76 than hourly horizons. In section 5, preliminary results on wind energy forecasts
77 are presented. In the last section, we discuss the results and conclude.

78 2. Data and methodology

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

94 measurements over the years 2015 and 2016 of the considered wind farm. Spa-
 95 tial averaging is performed by averaging the data of all turbines. To retrieve
 96 measurements at the same interval than ECMWF forecasts, time averaging is
 97 performed by averaging the 10-minutes measurements. The spatial resolution
 98 of ECMWF forecasts is of about 16 km (0.125° in latitude and longitude). Ex-
 99 planatory variables at the location of the farm are interpolated linearly from
 100 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	$\text{m}^2 \text{s}^{-2}$
	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

101 *2.1. Parametric approach and low cost assimilation*

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

104 [12, 13, 14]. In this paper, we consider a parametric approach, using linear
 105 regression. This method has been developed for NWP downscaling in the study
 106 by *Alonzo et al.* [15]. Non-parametric approaches such as random forests have
 107 also been tested in this study. The results between the two approaches do not
 108 differ significantly for the longest horizons. However, for the shorter horizons
 109 (<1 h), considered in this paper, the parametric approach give better results. It
 110 is also an easier method to implement and a faster one. That is why we choose
 111 to focus on this method. The parametric approach supposes a relation between
 112 the target at time t , \hat{y}_t and the m explanatory variables at time t , $X_{1,t}, \dots, X_{m,t}$:

$$\hat{y}_t = \beta_0 + \sum_{k=1}^m \beta_k X_{k,t} + \varepsilon \quad (1)$$

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

115 Among the explanatory variables, $X_{1,t}, \dots, X_{m,t}$, some provide more import-
 116 ant information and some may be correlated. Thus, a stepwise regression (for-
 117 ward selection) is performed to only keep the most important uncorrelated vari-
 118 ables [15]. This is an iterative regression, which consists in adding variables
 119 from the set of explanatory variable based on the Bayesian Inference Criterion
 120 (BIC). At each step, a model is built by adding one variable among the remain-
 121 ing ones. The added variable which minimizes the BIC of the model is chosen.
 122 The procedure is repeated as long as the BIC decreases.

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

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

135 2.2. Benchmark

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

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

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

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

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

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

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

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

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

$$\Delta_{RMSE} = - \frac{RMSE_{\text{model}} - RMSE_{\text{persistence}}}{RMSE_{\text{persistence}}} \quad (5)$$

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

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

180 3. Performances for hourly forecasts

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

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

195 Figure 1 displays the NRMSE depending on the forecast lead times (1 h to
196 11 h) for persistence, ECMWF forecasts, ARMA and ANN models and for our
197 methods LR_{no-obs} and LR_{obs} . One can note that, for models that use obser-
198 vations as input, performances deteriorate with lead time whereas it remains
199 constant for models that do not. For the 1 h forecast, all the methods that
200 consider measurements as explanatory variables outperform ECMWF and the
201 downscaling model LR_{no-obs} . The only method outperforming all the others for
202 all time horizons is LR_{obs} even if for the 1 h forecast this method gives similar
203 NRMSE compared to persistence, ANN and ARMA. However, the longer the
204 time horizon, the more significant the improvements of our methods over the
205 references (ANN, ARMA, persistence).

206 The improvements over persistence of all methods are displayed in Fig 2. One
207 can see that both reference methods, ARMA and ANN, perform very similarly.
208 The two models, overperform persistence at every horizon and the improvements
209 slightly increase with time from 2.7% for the first hour to 15.3% for the eleventh.
210 Those results are consistent with those found in the literature. For instance, in
211 [19], Torres *et al.*, used ARMA model to predict hourly averaged wind speed
212 1 h to 10 h lead time for five sites in Spain. They found NRMSE improvements
213 over persistence ranging between 2% and 5% for 1 h lead time and between
214 12% and 20% for 10 h lead time. In [20], Sfetsos compares the performances of
215 an ARIMA(2,1,2) and an ANN using measurements collected in Crete, Greece.
216 Hourly averaged wind speed forecasts with ANN model overperform persistence
217 by 4.7% while ARIMA overperforms persistence by 2.3%.

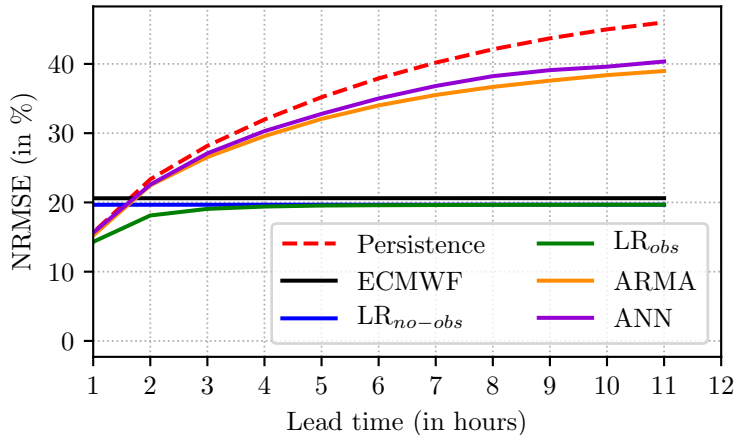


Figure 1: Performances of downscaling statistical models for hourly forecasts from 1 h to 11 h in two configurations against the performances of ECMWF and the benchmark method. LR_{no-obs} displays the downscaling of explanatory variables from ECWTF outputs only. LR_{obs} shows the results when the error between the measurements 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.

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

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

231 4. Performances for sub-hourly forecasts

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

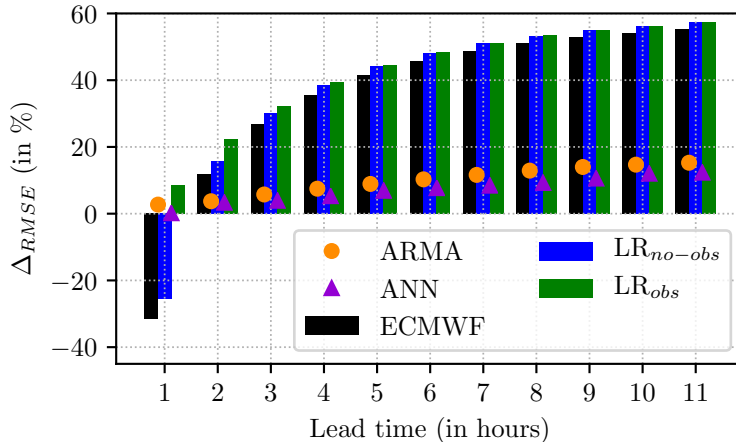


Figure 2: Comparison of the improvements over persistence in percentage for ECMWF forecasts and the downscaling models from 1 h to 11 h in the two configurations. LR_{no-obs} corresponds to the downscaling with explanatory variables from ECMWF outputs only. LR_{obs} shows the results when the error between the measurements 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.

236 order to retrieve 10-min forecasts, the explanatory variables are linearly inter-
 237 polated every 10 min. Then, to retrieve the prediction for all hours h at minutes
 238 0, 10 and 20, we apply the model calibrated at hour h . To retrieve the prediction
 239 for all hours h at minutes 30, 40 and 50, we apply the model calibrated at hour
 240 $h + 1$. However, the calibration leads to an issue with LR_{obs} . For 10 min and
 241 20 min, LR_{obs} is doing exactly the same as persistence. Indeed, the model fitted
 242 at time t_0 puts all the weight on the forecasted wind speed by ECMWF and on
 243 the initial error. As this model is used at 10 min and 20 min, the results are
 244 exactly the results of persistence. To let the model outperforms persistence, one
 245 solution is to do a linear regression using only past observations for the first two
 246 horizons. Hereafter, LR_{obs} denotes a linear regression over past measurements
 247 for time 10 min and 20 min and a linear regression over ECMWF outputs and
 248 the error at time t_0 for the remaining time. For the reference methods ANN and
 249 ARMA, the training is performed directly using the 10-minutes measurements.
 250 The procedure applied to choose the models is the same as in section 3. For
 251 the ARMA models, we fitted several models depending on the orders p and q
 252 of the models and we select the model which minimizes the Bayesian Inference

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

257 *4.1. Statistical skill performances*

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

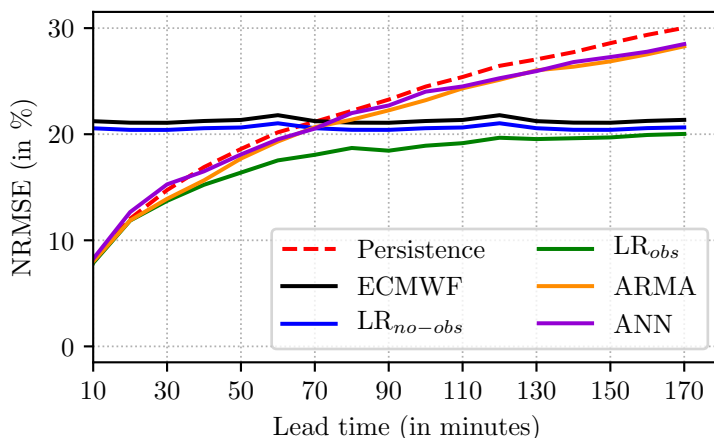


Figure 3: Performances of the different models for sub-hourly forecasts from 10 min to 170 min in two configurations against the performances of ECMWF and the benchmark method. LR_{no-obs} displays the downscaling of explanatory variables from ECWMF outputs only. LR_{obs} shows the results when the error between the measurements 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.

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

267 Figure 4 is similar to figure 2 for lead times ranging between 10 min and
 268 170 min. Only LR_{obs} overperforms persistence at every horizons. Again it
 269 is the model giving the best improvements. The differences with ARMA are
 270 not extremely significant for the first lead times especially at 20 min (1.5% for
 271 LR_{obs} and 1.3% for ARMA). After 20 min, LR_{obs} is by far the best model. The

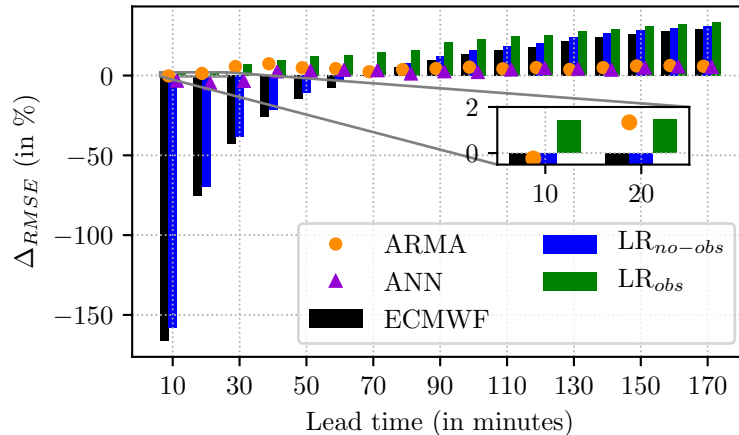


Figure 4: Comparison of the improvements over persistence in percentage for ECMWF forecasts and the downscaling models from 10 min to 170 min in the two configurations. LR_{no-obs} displays the downscaling of explanatory variables of ECMWF outputs only. LR_{obs} shows the results when the error between the measurements at t_0 and the 100-m wind speed forecasted by ECMWF at t is added 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.

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

275 4.2. Case studies

276 Such nowcasting method should be used for decision-making process. There-
 277 fore, a statistical quantification of the performances is not enough to evaluate
 278 the usefulness of the method. Figure 5 and 6 display forecasted time series with
 279 two starting dates: the 15th of January 2017 at 00:00 UTC and the 15th of July
 280 2017 at 01:00 UTC. Those dates have been chosen because the mean wind
 281 speed is around 6 m s^{-1} . This is the mean wind speed at “Parc de Bonneval”
 282 over the years 2015, 2016 and 2017 so those dates represent common situations.
 283 For both dates, a prediction using LR_{obs} and ECMWF models are shown. The
 284 measurements and confidence intervals are also included.

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

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

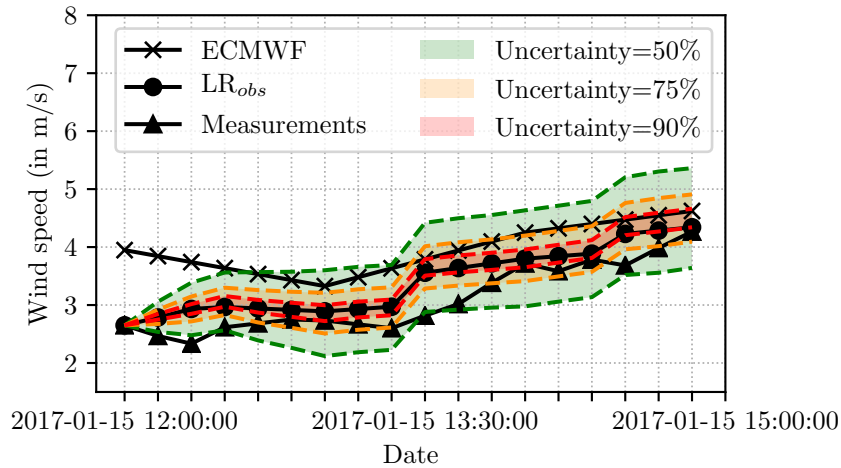


Figure 5: Forecasted time series starting on the 15th of January 2017, 00:00 UTC to 02:50 UTC. ECMWF and LR_{obs} forecasts are compared to the observations. The 10%, 25% and 50% confidence intervals are added.

294 Figure 5 displays a winter prediction. It starts on the 15th of January 2017
 295 and ranges from 00:00 UTC to 02:50 UTC. For this forecast, the mean of the
 296 observed wind speed is around 5.93 m s^{-1} and the mean of the forecasted wind
 297 speed is around 6.30 m s^{-1} for LR_{obs} and 5.12 m s^{-1} for ECMWF model. In
 298 this case, ECMWF underestimates the wind speed while LR_{obs} overestimates it.
 299 However, the LR_{obs} overestimation is lower than ECMWF underestimation. It
 300 is clear that this model gives a more accurate prediction than ECMWF model.
 301 The mean absolute error, defined in equation (6), is around 0.45 m s^{-1} for
 302 the downscaling model and around 0.80 m s^{-1} for the ECMWF forecast. This
 303 corresponds to a normalised mean absolute error of 7.65% for LR_{obs} and of
 304 13.57% for ECMWF. This difference is due to the bias correction using LR_{obs} .
 305 In terms of variability, a clear lack is visible. It seems to be slightly corrected
 306 by LR_{obs} but this is essentially due to the fact that several models are fitted.
 307 Consequently when a new models is used there is a rupture in the linearity of

308 the prediction.

$$MAE := \frac{1}{N} \sum_{i=1}^N |\hat{y}_i - y_i| \quad (6)$$

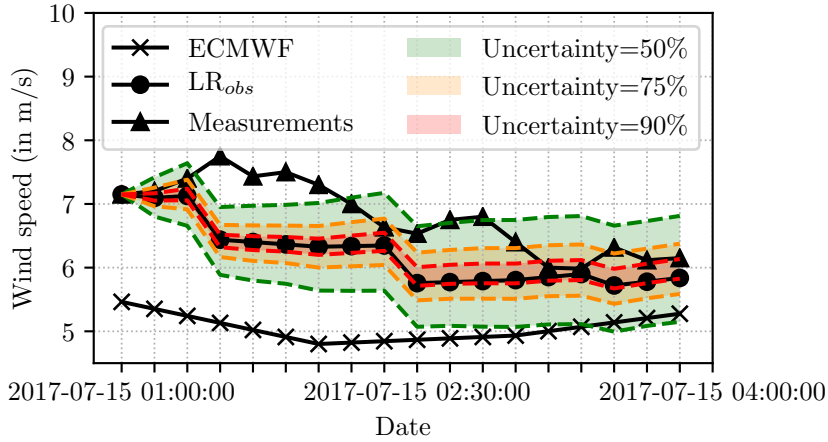


Figure 6: Forecasted time series starting on the 15th of July 2017, 01:00 UTC to 03:50 UTC. ECMWF and LR_{obs} forecasts are compared to the observations. The 10%, 25% and 50% confidence intervals are added.

309 Figure 6 displays a summer prediction. It starts on the 15th of July 2017,
 310 from 01:00 UTC to 03:50 UTC. In this case, the mean of the observed wind
 311 speed is around 6.80 m s⁻¹ and the mean of the forecasted wind speed is around
 312 6.21 m s⁻¹ for LR_{obs} and around 5.05 m s⁻¹ for ECMWF model. This time,
 313 both models underestimate the wind speed but the underestimation is strongly
 314 corrected by LR_{obs}. Again, the lack of variability is slightly corrected by the
 315 use of several models. However, this lack of variability is a recurrent problem
 316 in the forecasts. Even with random forests, which are non-parametric models,
 317 the variability remains low. The problem comes from the fact that ECMWF
 318 outputs are hourly data and in order to retrieve data at a frequency of 10 min,
 319 a linear interpolation is made. This creates a huge lack of variability relative
 320 to the real 10 min observations. For the this forecast, the MAE is around
 321 0.59 m s⁻¹ for LR_{obs} which corresponds to a normalised mean absolute error
 322 around 8.67%. This is lower than for ECMWF forecast for which the MAE
 323 is around 1.75 m s⁻¹. This corresponds to a normalised mean absolute error
 324 around 25.76%. Again this difference is due to the bias correction using LR_{obs}.

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

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

330 5. From wind speed to wind energy forecasts

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

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

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

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

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

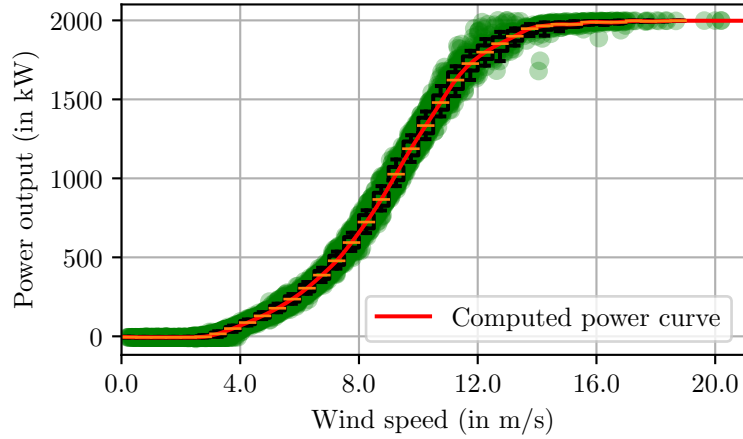


Figure 7: Computed power curve at the farm scale. For each 0.5 m s^{-1} intervals, the boxplots of the distribution are shown in green. The whiskers correspond to the first and the ninth decile. The means of each interval are fitted in order to retrieve the power curve.

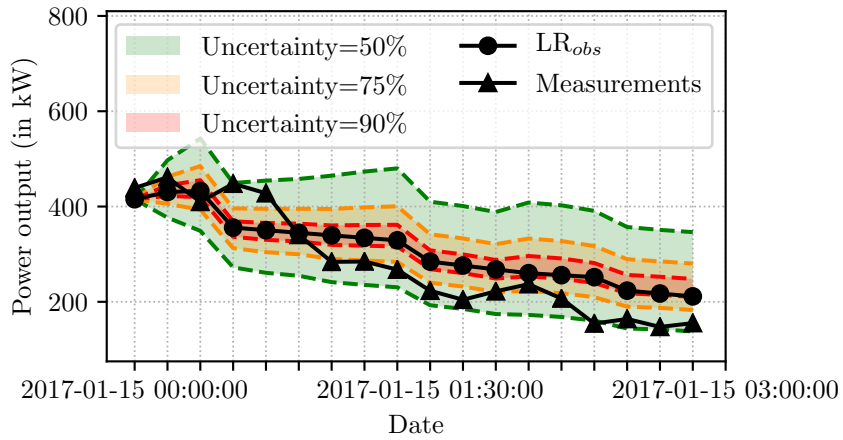


Figure 8: Forecasted time series of wind energy starting from the 15th of January 2017 at 00:00 UTC. LR_{obs} forecasts are compared with the measurements. First, the wind speed is forecasted by LR_{obs} and then the forecasted power is retrieved using an averaged power curve. The 10%, 25% and 50% confidence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

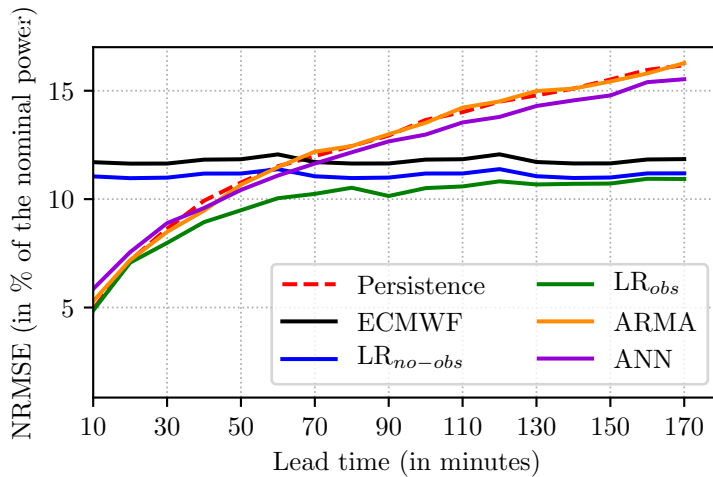


Figure 9: Performances of the different models for sub-hourly forecasting of wind energy from 10 min to 170 min in two configurations against the performances of ECMWF and the benchmark methods. The models are exactly the same than figure 3. The power curve shown in figure 7 is used to compute the wind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

369 6. Conclusion

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

390 30 min to 30.1% at 170 min.

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

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