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Multiple linear regression MOS for short-term wind power forecast

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Abstract

Short-term (0 – 36 h ahead) wind power forecast is a central issue for the correct management of a grid connected wind farm. A combination of physical and statistical treatments to post-process Numerical Weather Predictions (NWP) outputs is needed for successful short-term wind power forecasts. One of the most promising and effective approaches for statistical treatment is the Model Output Statistics (MOS) technique. In this study a MOS based on multiple linear regression is proposed: the model screens the most relevant NWP forecast variables and selects best predictors in order to fit a regression equation that minimizes the forecast errors, utilizing wind farm power output measurements as input. The performance of the method is evaluated in two wind farms, located in different topographical areas and with different NWP grid spacing. Due to the high seasonal variability of NWP forecasts, it was considered appropriate to implement monthly stratified MOS. In both wind farms, first predictors were always wind speeds (at different heights) or friction velocity. When friction velocity is the first predictor, proposed MOS forecasts resulted to be highly dependent on the friction velocity – wind speed correlation. Negligible improvements were encountered when including more than 2 predictors in the regression equation. Proposed MOS performed well in both wind farms and its forecasts compare positively with actual operative model in use at Risø DTU and other MOS types, showing minimum BIAS and improving NWP power forecast of around 15% in terms of root mean square error. Further improvements could be obtained by the implementation of a more refined MOS stratification, e.g. fitting specific equations in different synoptic situations.

Resumen

La predicción a corto plazo de la energía eólica producida es de fundamental importancia para la correcta gestión de un parque eólico. Generalmente, para optimizar las previsiones a corto plazo de la producción eólica es necesaria una combinación de métodos físicos y estadísticos para el tratamiento de las salidas de los modelos meteorológicos (NWP). Entre los métodos estadísticos, la técnica del Model Output Statistics (MOS) es actualmente la más efectiva y prometedora. En este estudio, se propone un MOS basado en regresión multilíneal: a partir de las medidas de producción eólica, el modelo examina las más relevantes variables de pronóstico y diagnostico del NWP y selecciona los mejores predictores para ajustar una ecuación de regresión que minimice los errores de predicción. Las prestaciones del método se evalúan en 2 parques eólicos europeos, situados en áreas de diferente conformación topográfica y con diferentes pasos de malla del modelo meteorológico. Debido a la elevada variabilidad estacional de las prestaciones del NWP, se ha considerado apropiado implementar MOS estratificados mensualmente. En ambos parques eólicos, los mejores predoctores han resultado ser la velocidad del viento a diferentes alturas y la velocidad de fricción. Cuando la velocidad de fricción es el primer predictor, las previsiones del MOS propuesto son altamente dependientes de la correlación entre la velocidad del viento y la velocidad de fricción, obtenidas por el NWP. Mejoras despreciables se aprecian al incluir más de 2 predictores en las ecuaciones de regresión. Al aplicar el método propuesto se obtienen buenos resultados y sus predicciones comparan positivamente con las obtenidas por el MOS actualmente en uso al Risø DTU y con otros tipos de MOS analizados. El MOS presentado es capaz de minimizar el BIAS de las previsiones y mejorar las predicciones del modelo meteorológico de un 15% en término de la raíz del error cuadrático medio (RMSE). Una posible línea de investigación para futuros trabajos podría enfocarse en el estudio de una estratificación más detallada, de manera que se ajusten ecuaciones específicas para diferentes situaciones sinópticas reales.

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1. Introduction

The amount of wind energy-produced electricity which is fed into the electrical grid has grown rapidly in recent years and wind energy penetration levels reached appreciable values in many Europeans countries, e.g. more than 10% in Spain and up to 20% in Denmark in 2007 (EWEA, 2008). The overall penetration for the EU-27 in 2020 will be around 12-14% according to the European Commission (EC) targets (EWEA, 2008). It is therefore necessary to have some kind of system which predicts the power production over the next 1–2 days in order to control the dispatch of the conventionally fired plant, to increase its value in the markets operating on a 48 h time scale, and to take full advantage of the produced wind energy. In this situation, the necessity and advantages of wind power short-term forecasting are generally accepted and highly evaluated by most wind energy utilities. Studies that investigated economical benefit of forecast agree that important savings were reached by wind production companies thanks to good forecasts (Giebel et al, 2011); a recent study for the UK market that quantifies the benefit of using forecast indicates that this could be up to £4.5/MWh, measured as increase in value of the produced and traded MWh of wind energy (Barthelmie et al, 2008). Therefore, short-term (0 – 36 h ahead) wind power forecast is a central issue for the correct management of a grid connected wind farm and to make wind energy a more competitive and reliable resource.

Numerical Weather Prediction (NWP) models are generally the primary input for short-term forecasting of wind power (Landberg et al, 2003). It is, however, well-known that NWP models usually exhibit systematic errors in the forecast of certain meteorological parameters especially near the surface (Giebel et al, 2011). Furthermore, it is an open question whether the use of higher resolution limited area models improves the forecast skill, and whether such improvements compensate the increasing computational requirements for such calculations. In order to deal with these issues, a variety of different approaches is currently implemented to post-process NWP outputs (Nielsen et al, 2006). In general, a combination of physical and statistical treatments is needed for successful forecasts (Giebel et al, 2011).

Statistical models for power predictions have basically the aim of finding relationships between some explanatory variables and some measured values of the interested predictand (power production, wind speed, etc.) usually employing recursive techniques. When the model, generally a regression equation, is developed and implemented using NWP (or NWP-based) forecast variables as predictors, the method is known as Model Output Statistics (MOS) (Wilks, 2006). The MOS approach to statistical forecasting has mainly two characteristics that make it the state-of-the-art between other statistical methods, such as classical approach or perfect prog. The first is that NWP calculated but unobserved variables such as vertical velocity can be used as predictors. The second characteristic is that systematic errors exhibited by the dynamical NWP model are accounted for in the process of developing the MOS equations. Main limits of the MOS technique are the need of good database of measured data of the predictand (e.g. wind farm power productions) and the fact that the regression equations of the MOS should be calibrated for every type of NWP and for a specific forecast length. Generally, regression is developed using the current NWP model for retrospectively re-forecast weather for previous years of data.

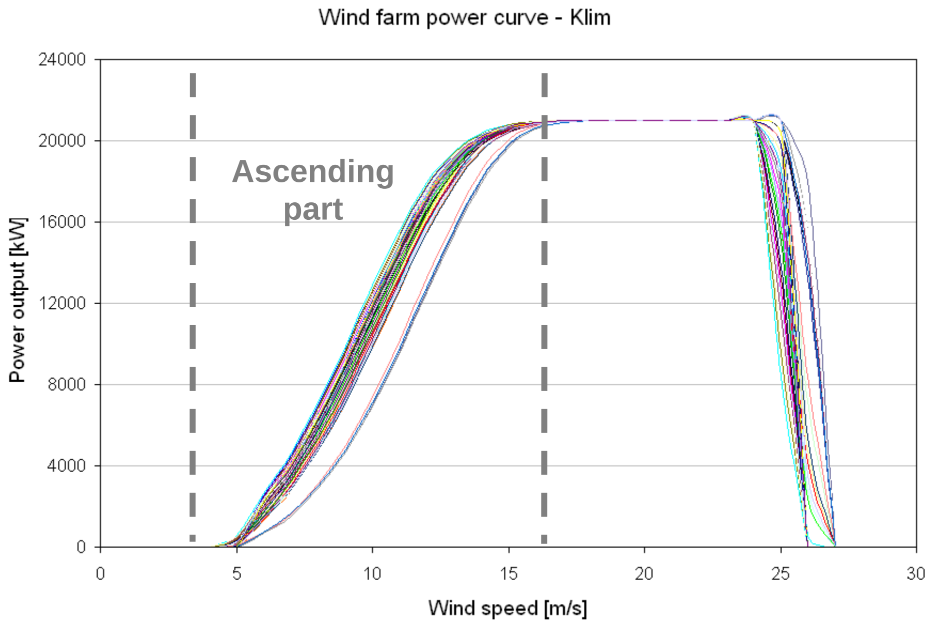
During the ANEMOS EU Project (Kariniotakis et al, 2004), a large number of next generation tools for facilitating short-term wind power predictions of different Europeans countries have been developed, tested and implemented in different atmospherics and topographic conditions (Giebel et al, 2006), aiming to provide guidelines for the state-of-the-art of short term forecast of wind power production. Analyses during the ANEMOS project have confirmed that statistical methods for downscaling (as the MOS) are a powerful tool in order to improve numerical models results and that the statistical treatment reduces forecast errors significantly (Nielsen et al, 2006). In highly complex terrain, it has been even observed that the error reduction, respect to NWP forecast alone, due to the statistical MOS corrections can be better than the error reduction obtained by a CFD (Computational Fluids Dynamics) model (Giebel et al, 2006).

The short-term forecast model currently in use at Risø DTU is called Prediktor (Landberg, 1994). The basic idea of the model is to use the wind speed and direction from a NWP, then transform this wind to the local site, using the WAsP method (Mortensen et al, 1993), and finally use the wind farm power curve (considering wake losses and efficiency with the Park model) to obtain the predicted power production. The statistical module MOS can be used at any stage of the modelling: it can either set in before the transformation to the local wind or before the transformation to power, or at the end of the model chain trying to change the power. Different statistical approaches for Prediktor, such as Kalman filters or genetic algorithms for the determination of the MOS parameters have been analyzed by Giebel PhD thesis (Giebel, 2001) for treatment of Prediktor model output. The MOS technique was found to be the most effective one showing the best results. Recent studies found that the MOS process should be trained utilizing generated power measurements instead of wind speed measurements, which are not so easy to directly relate with power output (Giebel et al, 2011). One of the reasons is the uncertainty in the turbines power curve, which could be more than 10%, leading met mast and nacelle measurements being not completely representative of the real generated power (Giebel, 2001). Furthermore, defining a single local wind speed representative for the total wind farm should be considered a hard task.

The objective of this study is the proposal of a statistical approach based on multiple linear regression for short-term power forecast using measured wind farm power output and NWP variables. The performance of the proposed method is evaluated in two different wind farms and compared with the actual operative method in use at Risø DTU and with other MOS types.

2. Methods

The main idea of the proposed method is to find a statistical relationship between some NWP forecast variables and a local wind speed that is representative of the mean wind farm wind speed (chapter 2.1). Most relevant NWP variables that could have a prediction potential on wind speed are evaluated and screened in order to define best multiple linear (or "multilinear") regression equation, as described in chapter 2.2. A wind farm power curve (Figure 1), that considers turbines' position, power curves and wake losses, is needed in order to derive generated power from wind speed and viceversa. The performance of the method is tested in 2 wind farms: sites location and NWP input data are described in chapters 2.3 and in chapter 2.4 NWP forecasts performance are briefly analyzed.



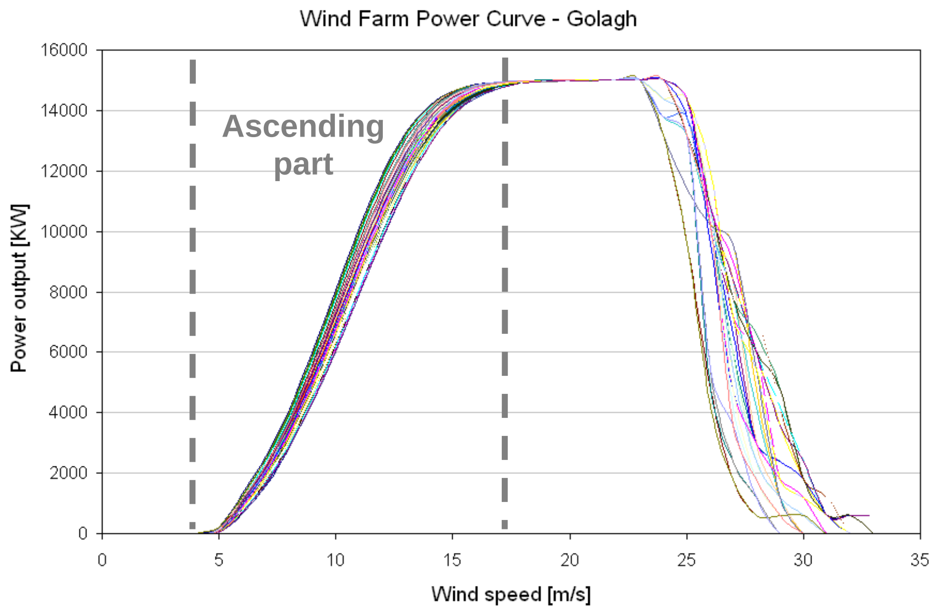


Figure 1 – Power curves of Klim and Golagh wind farms. As wake losses depend on wind direction, there is a power curve for each of the 60 wind direction sectors considered in both wind farms. The wind farm power curves were obtained utilizing the WAsP – Park model (Mortensen et, 1993)

2.1 Proposed method and analyzed MOS types

The proposed approach is schematically described in Figure 2. The only measured data required is the wind farm generated power and no wind data (or nacelle measurements) are needed. The wind farm power curve (Figure 1) is firstly utilized to derive a wind farm wind speed ("*WF_ws*") from power measurements and wind direction forecast (Step 1).

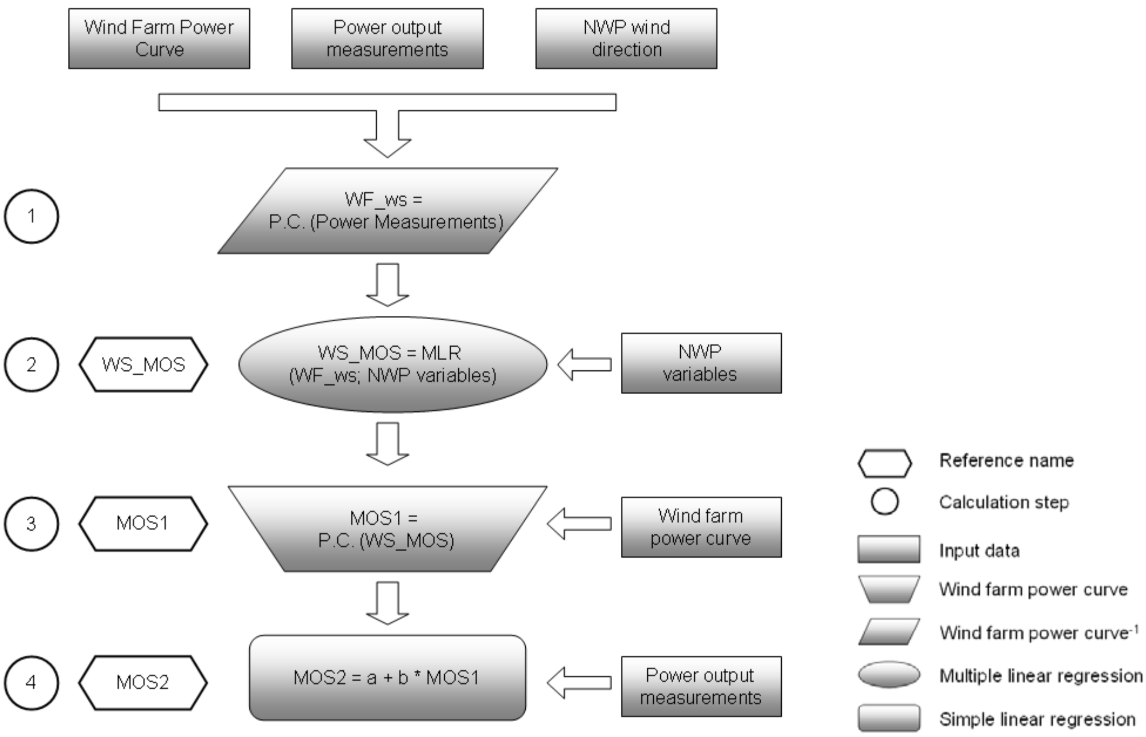


Figure 2 – Diagram chart of the proposed MOS method. Shapes on the bottom right indicate the type of calculation or method implemented at each step: wind farm power curve, multilinear and linear regression

The method assumes that the wind farm power curve is highly reliable and the encountered wind speed could be a good estimator of a spatial mean wind farm wind speed. In order to obtain a univoque value, only power data in the ascending part of the power curve have been considered (see Figure 1), disregarding data of null and maximum power production and those in the descending part (where wind speed is higher than maximum wind speed for nominal power generation). The ascending part is actually the most critical, as small wind speed forecast error are converted in bigger power forecast errors, thus those values are the most important to predict and forecast (Lange & Focken, 2006). In step 2, an iterative technique for multiple linear regression ("*MLR*") is then followed in order to identify best predictors between NWP forecast variables utilizing the previously obtained wind farm wind speed as the predictand (details of this procedure are described in chapter 2.2); the resulting wind speed forecast is referred to as "*WS_MOS*" in Figure 2. The wind farm power curve is then applied to obtain power forecast ("*MOS1*") from wind speed forecast (Step 3). Finally, a simple linear regression is implemented using measured power production as predictand in order to correct remaining *BIAS* (Step 4) and final power forecast is obtained ("*MOS2*").

In this study, the performance of the proposed method (Figure 2) is analyzed in comparison with results obtained with other types of statistical treatments (MOS). The models used for comparison are:

NOMOS: Power = P.C. [NWPws]
MOS1: Power = P.C. [MLR (WF_ws; NWPvariables)]
*MOS2: Power = a + b * P.C. [MLR (WF_ws; NWPvariables)]*
*MOS3: Power = a + b * P.C. [NWPws]*
MOS4: Power = MLR (Pow_meas; NWPvariables)
*PrediktorMOS: Power = aMOS * P.C.(bMOS * localWind + sectMOS)*

Where:

- *P.C.* is the wind farm power curve as derived from WAsP (Figure 1), valid for the wind direction given by the NWP;
- *MLR (x;y)* means the implementation of a multiple linear regression obtained following forward selection (described in chapter 2.2) where *x* is the predictand and *y* is the pool of predictors;
- *NWPvariables* are the values of the variables obtained from the NWP modelling considering the grid point closest to the wind farm. *NWPws* is the wind speed at the closest height of the turbines (see chapter 2.4.1);
- *WF_ws*: wind farm wind speed derived from power measurements and NWP wind direction utilizing the wind farm power curve;
- *localWind*: Predictor wind speed forecast. i.e. the *NWPws* and a height correction plus a correction for orography and roughness issues.
- *aMOS, bMOS* and *sectMOS* are the overall and sectorwise Prediktor MOS parameters.

MOS1 and MOS2 refer to the proposed method visualized in Figure 2. NOMOS, MOS3 and MOS4 calculation steps are shown in Figure 3. NOMOS represents the direct transformation of the wind speed forecast by the NWP in power forecast using the wind farm power curve. MOS3 is the simple linear regression between NOMOS results and power measurements (*BIAS* removal). In respect of MOS4, the same multiple linear regression method "*MLR*", described in chapter 2.2, is implemented between power measurements and NWP variables in order to obtain a direct power forecast.

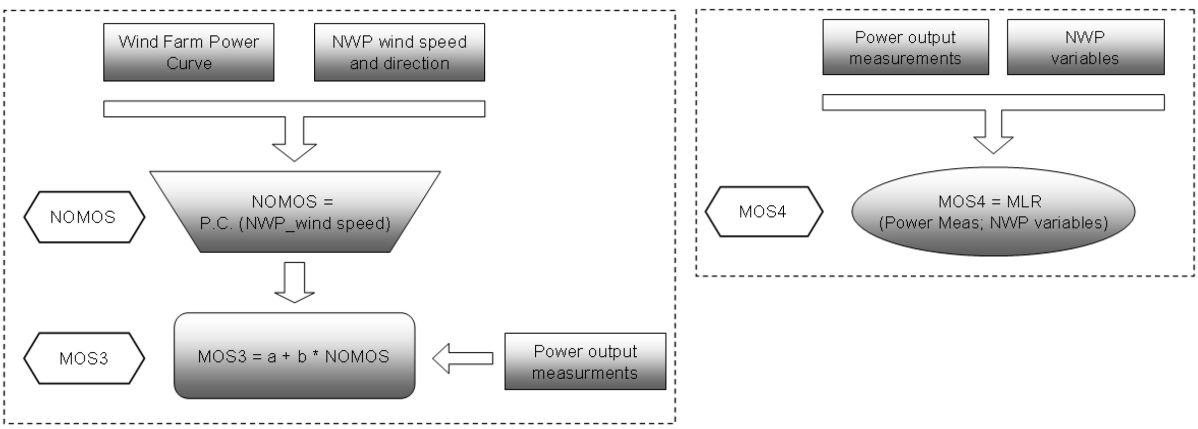


Figure 3 – Diagram charts of the NOMOS, MOS3 and MOS4 forecasts

PrediktorMOS refers to the actual MOS type in use at Risø DTU. Between the different Prediktor MOS types (Giebel, 2001), the one that shows best performance in terms of *RMSE* reduction was chosen. Since the aim of the study is to evaluate different MOS systems, and the height correction is (sectorwise) linear, i.e. subsumed under the MOS correction factor once established, the difference in no-MOS performance between Prediktor proper and the one shown here (NOMOS of Figure 3) is irrelevant. All MOS types forecast errors will be analysed in comparison with the NOMOS performance (see chapter 3.2).

2.2 Multiple linear regression (MLR): predictors' selection and model validation

Landberg (Landberg, 1998) has shown that a simple NWP (+ physical downscaling) approach is effectively linear, thereby being very easily amenable to improvements by a MOS based on multiple linear regression.

Multiple linear (here also called "multilinear") regression is the more general (and more common) situation of linear regression. As in the case of simple linear regression, there is still a single predictand, y, but in distinction there is more than one predictor x variable. The regression is based on the least squares method. The best fit in the least-squares sense minimizes the sum of squared residuals, a residual being the difference between an observed value and the fitted value provided by the regression.

Let K denote the number of predictor variables, the prediction equation is then

$$y = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_K x_K$$

Initially a set of potential predictors is defined including NWP variables that could be physically meaningful predictors of the wind speed.

Even if it could be, however, it is generally not useful to include all the potential predictors in the final equation. In fact, minimum number of predictors should be finally considered in the regression in order to avoid over-fitting problems and inclusion of predictors with strong mutual correlation (Wilks, 2006).

The problem of selecting a good set of predictors from a pool of potential predictors is called screening regression; the screening procedure here utilized is known as *forward selection* (Wilks, 2006) and is briefly described in the following. The best regression for the predictors' selection is evaluated in terms of Mean Square Error (*MSE*) and correlation coefficient (R^2). The *MSE* and the correlation coefficient are calculated as

$$MSE = \frac{SSE}{n - K - 1}$$

$$R^2 = 1 - \frac{SSE}{SST}$$

Where SSE is the sum of squares of the residuals, SST is the sum of squares of the total (variance of the observed values), n is the number of data for the regression and K is the number of predictors of the regression ($K = 1$ for a simple linear regression). The root of the MSE ($RMSE$) is known as the standard error and gives an idea of the error of the estimate; R^2 is often described as the proportion of variance "explained" by the regression. If the regression is perfect MSE is close to 0 and R^2 is 1.

Suppose there is certain number, M, of potential predictors. On the first selection step, all M potential predictors are examined for the strength of their linear relationship to the predictand, in terms of lowest MSE and highest R^2. In effect, all the possible M simple linear regressions between the available predictors and the predictand are computed, and that predictor whose linear regression is best among all candidate predictors is chosen as x_1. At this stage of the screening procedure, then, the prediction equation is $y = b_0 + b_1 x_1$. At the next stage of the forward selection, trial regressions are again constructed using all remaining $M - 1$ predictors. However, all these trial regressions also contain the variable selected on the previous step as x_1. That is, given the particular x_1 chosen on the previous step, that predictor variable yielding the best regression $y = b_0 + b_1 x_1 + b_2 x_2$ is chosen as x_2. This new x_2 will be recognized as best because it produces that regression equation with $K = 2$ predictors that also includes the previously chosen x_1, having the highest R^2 and the smallest MSE.

Subsequent steps in the forward selection procedure follow this pattern exactly: at each step, that member of the potential predictor pool not yet in the regression is chosen as the one that produces the best regression in conjunction with the $K - 1$ predictors chosen on previous steps.

At each cycle results of the regression with the new predictor are validated utilizing an independent data set for which the R^2 and MSE have been evaluated. The validation method here utilized is the leave-L-out method that consists in leaving out for the training data a number of consecutive observations, L, so the fitting procedure is repeated $n - L + 1$ times on samples of size $n - L$ (Burman et al, 1994), where n is the total number of data. The block length L is chosen to be large enough for the correlation between its middle value and the nearest data used in the cross-validation fitting to be small. The final MSE of the validation is the mean value of the MSEs of the n - L - 1 validation cycles. A very large difference in performance between the dependent and independent samples would lead to the suspicion that the equation had been overfit (Wilks, 2006). In order to reach the right number of final predictors a stopping rule must be implemented. The stopping criterion of the forward selection methods is generally based on a combination analysis of the MSE decrease and R^2 increase between training cycles and of the cross-validation results.

As the NWP models generally show different performance in different atmospheric conditions (seasonal variations, different synoptic situations, etc.), it is generally preferred to divide input data into sections and calibrate the MOS equations for each section. This procedure is called stratified MOS and is discussed in chapter 2.4.

2.3 Case studies: NWP dataset and wind farm descriptions

Two wind farms of the ANEMOS Project (Kariniotakis et al, 2004) are analyzed: Klim (Denmark) and Golagh (Ireland). The power curves of Klim and Golagh wind farms are shown in Figure 1.

The NWP dataset used in this study comes from a dynamical downscaling study where the global NCEP/NCAR 2.5 degree reanalysis dataset 2 and a LAM (limited area model) WRF version 3 (Shamarock et al, 2008), were used to compute 10 year long time series for all grid points in Europe. The WRF model was run in a 2 times nested setup with horizontal resolutions of 45 and 15 km respectively (Figure 4) and data post processed by Risø DTU. The NWP was constantly aligned with observations by updating the simulations every 6 hours utilizing grid and observational nudging (WRF to the NCEP/NCAR and observations). The dataset therefore represents closely the state of the atmosphere in the 10 years long simulated period and the extracted time series for this study is directly comparable to observations.

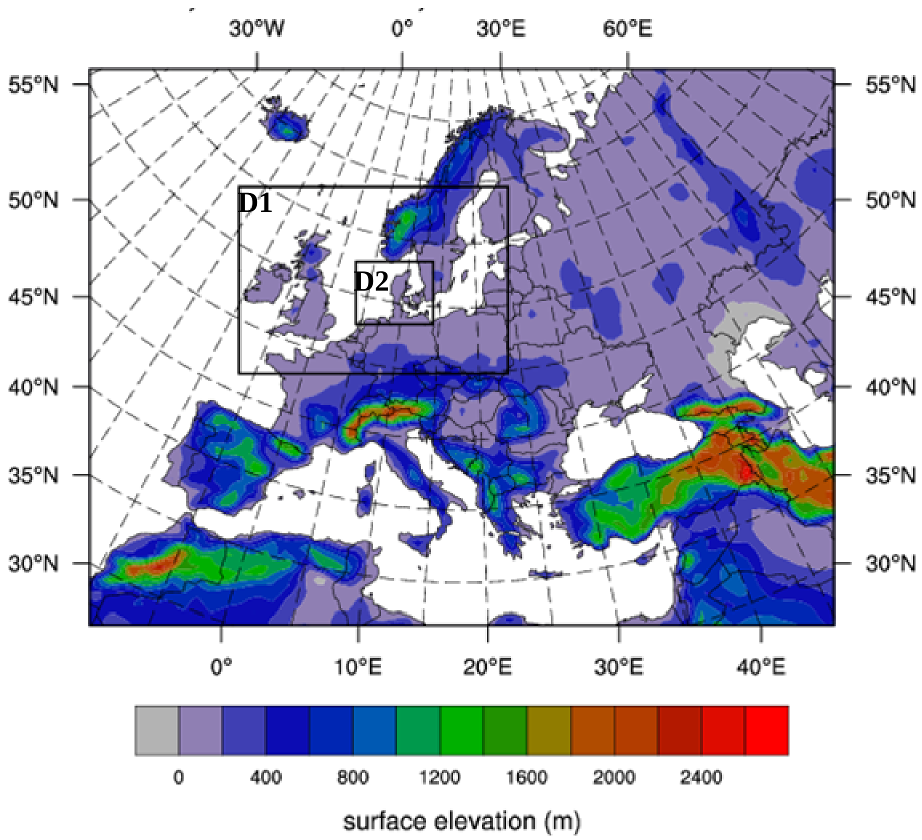


Figure 4 – NWP domains utilized: D1 has a grid spacing of 45 km and D2 15 km.

The Klim wind farm is located in the north-western part of Jutland (Denmark), with coordinates 9°09' East 57°04' north, 8 km from the north coast. The area is called Klim Fjordholme. The wind farm contains 35 wind turbines, all Vestas V44 (44 m rotor diameter), 600 kW, with typical spacing: 4.5 rotor diameters in rows and 5.5 – 7 between rows. The total capacity of the wind farm is 21.0 MW. For the Klim wind farm, power and wind speed data were available since 1st January 1999 till the 31st of December 2003. The area is mainly flat with a ruggedness index RIX (Bowen & Mortensen, 1996) value of 0. The wind farm is located in WRF domain D2 (Figure 4) and NWP grid spacing is 15 km.

The Golagh wind farm is located in the northwestern part of Ireland (Donegal County) 370 m above sea level. The turbines are 25 Vestas V42 600 kW machines corresponding to a rated capacity of 15.0 MW. Power production is the only measured data available and data covers a period from August 1st 2002 onto March 31st 2003. The RIX value of the area is 7.3 (medium complex terrain). Golagh wind farm is located in WRF domain D1 (Figure 4) and NWP grid spacing is 45 km.

2.4 NWP performance analysis

NWP performance is analyzed in terms of wind speed and wind direction. Firstly NWP wind speed forecast performance variation along the year is analysed and then it is verified that NWP direction doesn't deviate much from measured wind direction.

2.4.1 Wind speed forecast and MOS stratification

NWP performance variation along the year is hereby analysed. Forecast performance is shown in terms of *RMSE* and Mean Error (*BIAS*) for the wind speed and in terms of normalized root mean square error (*NRMSE*) for the power production (normalization with respect to the installed capacity of the wind farm), as recommended by Madsen et al (2005).

Differences (in m/s) between wind speed from power measurements ("*WF_ws*" in Figure 2) and wind speed forecast at 40 m are visualized for the Klim wind farm in Figure 5. As shown, the monthly mean error (red line) follows a clear seasonal variation with typical overestimations in winter and underestimations in summer.

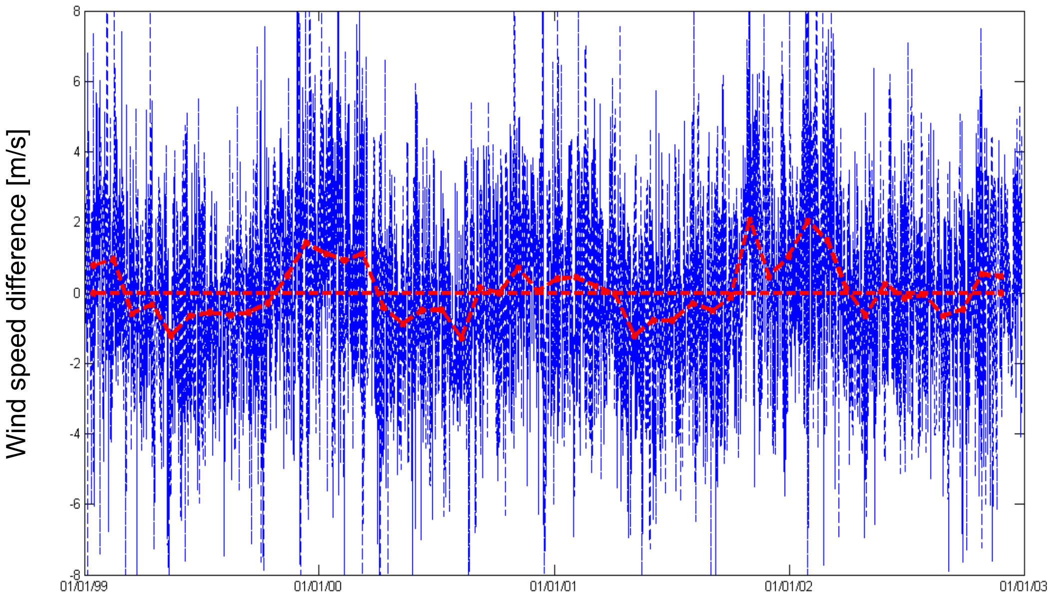


Figure 5 – Difference between NWP wind speed forecast and wind farm wind speed obtained by power measurements (Klim wind farm)

In order to have an idea of the NWP performance along the year, data are divided by month, and *RMSE* and Mean Error (*BIAS*) between NWP forecast and wind farm wind speed obtained by power measurements are calculated for each month (Figure 6). NWP wind speed at 40 and 80 m are considered in the analysis (considering that hub height is around 40-45 meters in both wind farms).

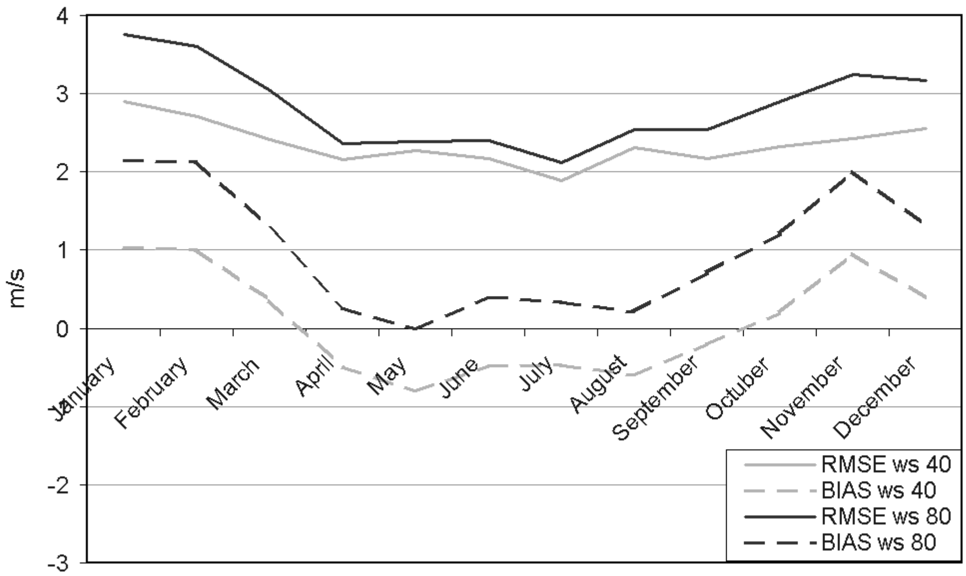


Figure 6a – RMSE and BIAS between wind farm wind speed and NWP wind speed forecast at 40 and 80 m (Klim)

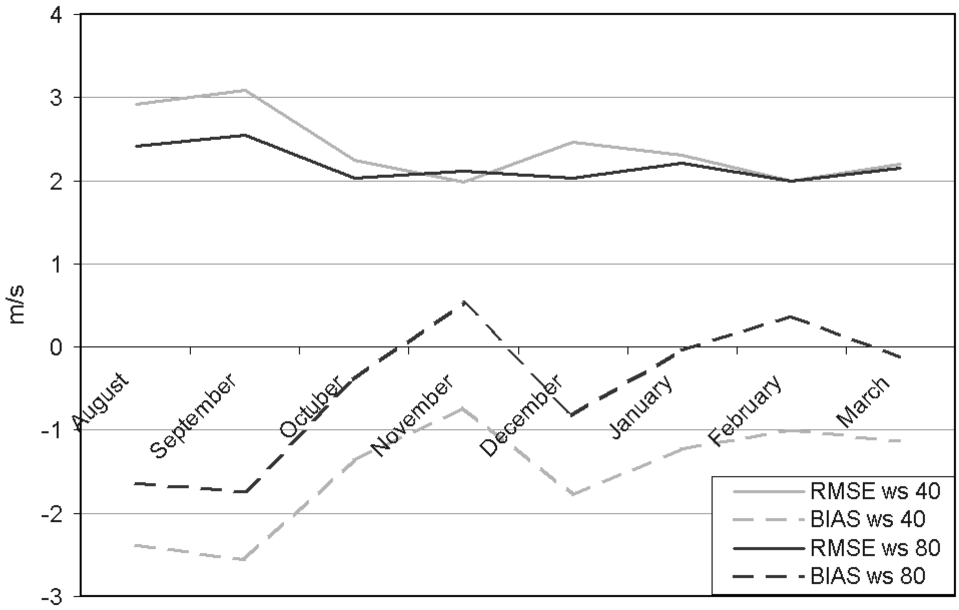


Figure 6b – RMSE and BIAS between wind farm wind speed and NWP wind speed forecast at 40 and 80 m (Golagh)

For the Klim wind farm forecast wind speed at 40 m is the better predictor, while for the Golagh wind farm better forecast is obtained by the 80 m wind speed. This could be due to a more complex terrain in Golagh that results in an increased wind speed (speed-up) at the top of the hills where turbines are located. In both sites, NWP performance varies considerably along the year, in particular the Mean Error (*BIAS*). For Klim wind farm, *BIAS* is quite high and positive in winter, while it is smaller and negative in summer. On the other side, in Golagh site *BIAS* is higher in summer than in winter.

Therefore, it has been considered appropriate to implement monthly stratified MOS: data are divided by month (when many years of data are available, data of the same month of every year are grouped together) and separate month-by-month MOS equations are obtained. This method allows the MOS forecast to incorporate different relationships between predictors and predictand at different times of the year and therefore improve the effectiveness of the regression equations.

The NWP forecasts used here are continuously calibrated with observational data; therefore performance of the NWP model considered here is basically constant for different forecast lengths; data are thus not divided by forecast lengths (as is preferred in operational models) and MOS equations are developed for the whole data. As the aim of this study is to analyse and compare MOS performance and not the NWP forecast, the use of the continuous run is acceptable for our purpose. Furthermore MOS is basically looking at improvement of a localised error ("background error" in Möhrlen & Jorgensen (2006)), not an error in the NWP model formulation, which essentially is due to a sub-optimal representation of the single point used for verification with the grid cell average calculated by the NWP and is not dependent on the forecast horizon (Möhrlen & Jorgensen, 2006). Anyhow, in order to improve its performance, MOS equations should be trained and validated for different forecast horizons when implemented in an operational model.

2.4.2 Wind direction forecast

For the Klim wind farm wind direction measurements are available and a comparison is carried out between observed wind direction and NWP forecast wind direction (Figure 7).

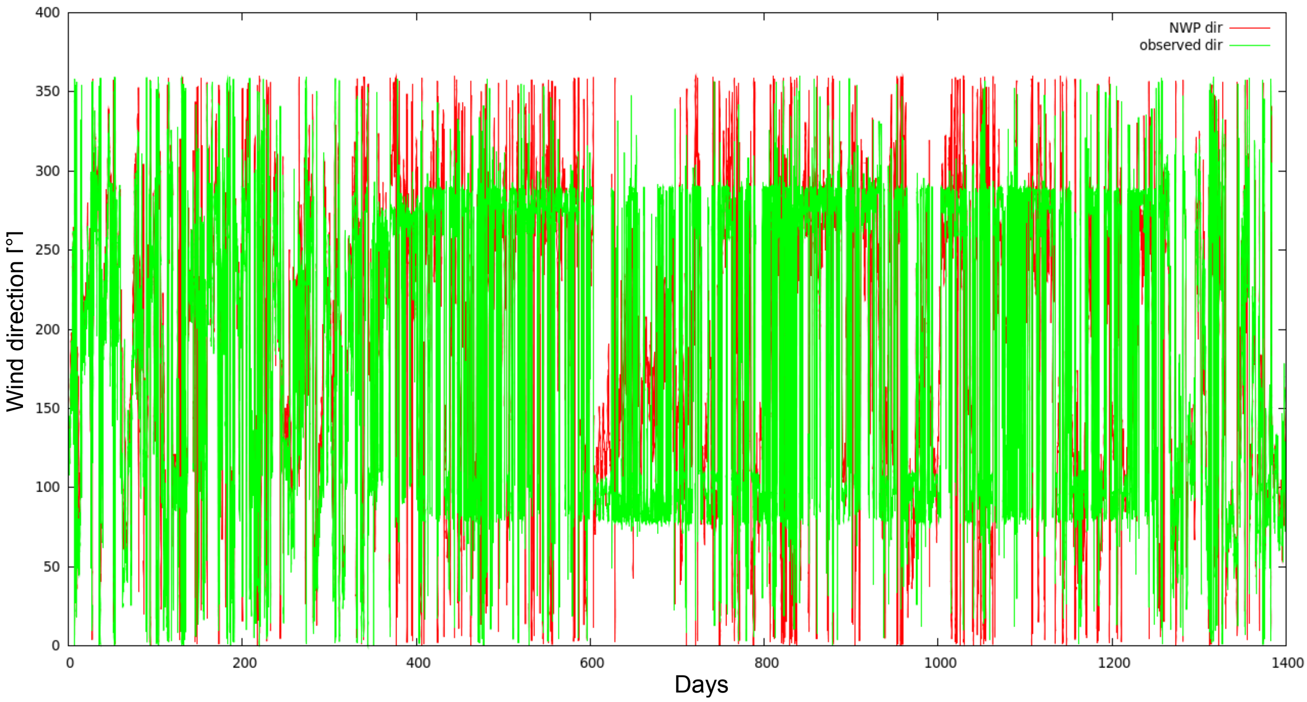


Figure 7 – Comparison between measured (observed) and NWP wind direction in Klim area

It is clear that wind direction measurements (green line) are not valid since day 350 as their value varies just from 80º to 280º. Comparison have been then calculated only for the first year (days from 1 to 350) and resulting *RMSE* and *BIAS* are respectively 45º and 15º.

Taking into account NWP grid spacing (15 km), possible wake effects and typical measurements errors, NWP wind direction forecast results to be sufficiently accurate and could be then considered a good approximation of the main wind direction sector for the purpose of the study.

3. Results and discussion

In this section, performance of the proposed MOS in Klim and Golagh wind farms is analysed. Results of the predictors' selection for the wind speed MOS are firstly discussed and then different MOS types performance for power forecast are compared. MOS performance is shown in terms of decrease in the power forecasts' *RMSE* respect to direct NWP forecast (NOMOS in Figure 3) and final *BIAS* is also evaluated, as recommended by Madsen et al (2005).

As previously defined, only power data in the ascending part of the power curve are considered for MOS implementation (see Figure 1), disregarding data of null and maximum power production and those in the descending part (where wind speed is higher than the cut-off value). Notice that power data in the descending part of the power curve (forecast wind speed higher than 17 m/s) are less than 1% and total used data for the MOS are 92% for Klim wind farm. In the Golagh wind farm, data in the descending part are less than 2% and total used data for the MOS calibration are 88%.

3.1 Predictors selection

The iterative process of predictors' selection for the multiple linear regression between wind farm wind speed derived from power data "*WF_ws*" (predictand) and NWP forecast variables (predictors) is described in chapter 2.2. A certain number of forecast prognostic variables are considered as potential predictors: wind speeds at the first 5 model levels close to ground (40m, 80m, 100m, 125m and 150m), surface temperature and temperature at 40m, 80m. During the ANEMOS project, atmospheric stability was found to play an important role in determining how the local wind is influenced by topography and it deeply affects flow in complex terrain (Giebel et al, 2006). Therefore, the following diagnostic variables were also part of the initial predictors' pool: planetary boundary layer height, heat flux, friction velocity, Monin Obukhov length and Richardson number. The last two variables were calculated according to Stull (Stull, 1988). Due to the high grid spacing of the NWP simulations, pressure gradients are not considered as potential predictors, even those it would be interesting to include them in future studies with higher resolutions as recommended by Nielsen et al (2006).

Correlation coefficients and *RMSE* obtained by linear regressions encountered between the different NWP variables and the wind farm wind speed at the first cycle of the forward selection are shown for Klim (Figure 8a) and Golagh wind farm (Figure 8b). Here results for a summer (July and August) and a winter (January) month are shown.

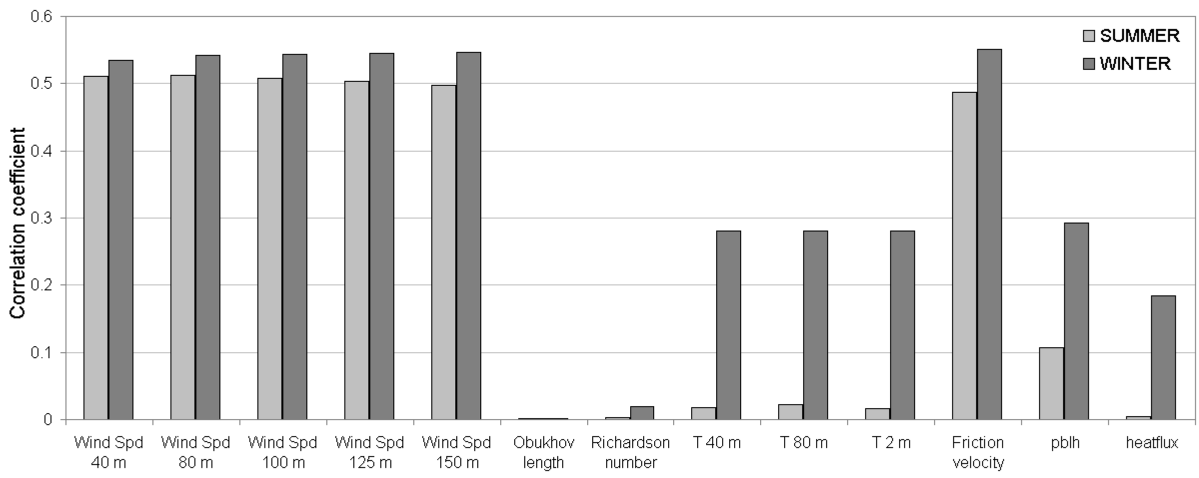


Figure 8a – Correlation coefficient for cycle1 of the predictors' selection for a summer (July) and a winter (January) stratified MOS in Klim wind farm

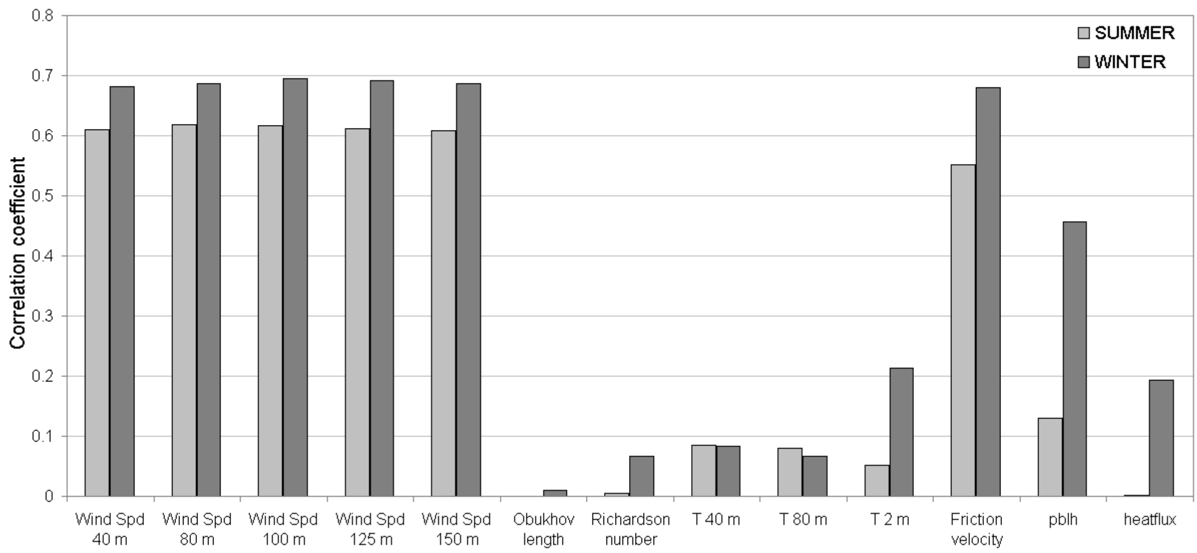


Figure 8b – Correlation coefficient for cycle1 of the predictors' selection for a summer (August) and a winter (January) stratified MOS in Golagh wind farm

Similar results are obtained in both wind farms. Predictors that show highest correlations and lowest errors are NWP wind speeds (at different heights) and friction velocity. Planetary boundary layer height, heat flux are seasonally dependent predictors: small or null correlations in summer and higher correlations in winter. Similar pattern is observed for potential temperatures in Klim wind farm, while minimal correlations in both winter and summer periods are obtained in Golagh wind farm for potential temperatures. In both wind farms, Monin Obukhov length and Richardson number have basically no correlation with wind farm wind speed and are bad predictors for the forecast in both seasons.

Results of MSE decrease for different cycles for regression training data, in comparison with MSE variation for the validation data are shown in Figure 9. July and August monthly stratified MOS are considered for Klim and Golagh wind farms respectively. Similar results are obtained for all the monthly stratified MOS. With respect to the cross-validation process (dark and light grey diamonds), slightly higher forecast errors result when considering a bigger block length *L*, as expected.

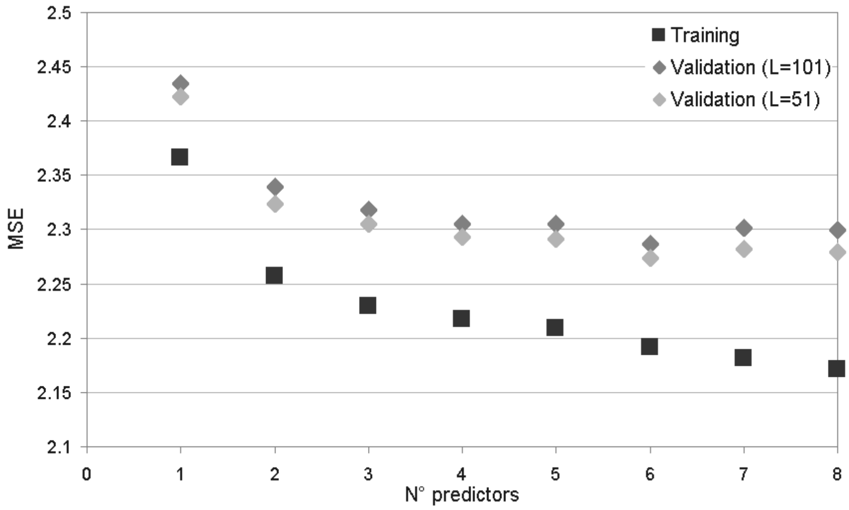


Figure 9a – MSE at different predictors' selection cycles of the WS MOS for July data in Klim wind farm

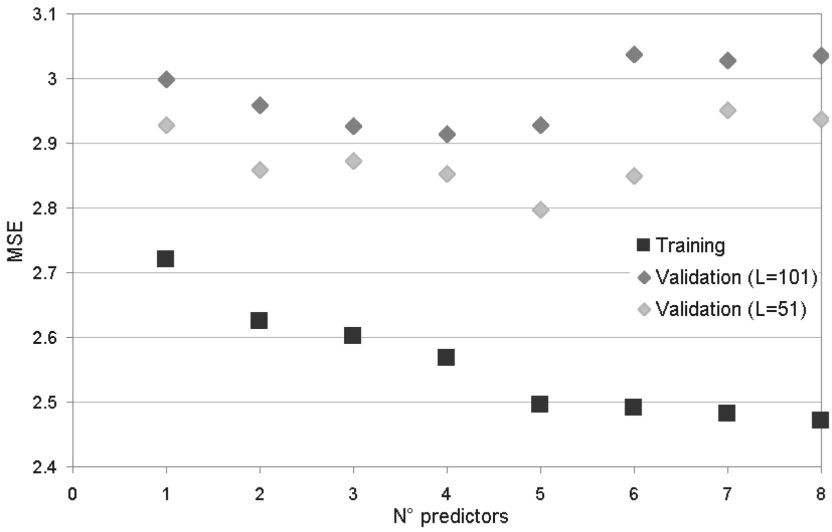


Figure 9b – MSE at different predictors' selection cycles of the WS MOS for August data in Golagh wind farm

In the Klim wind farm, the improvement of the forecast is important when adding a second predictor, both for the training and the validation data. A smaller decrease in the *MSE* (mean square error) is observed after the second cycle (less than 1% for the validation data). When considering more than 3 predictors, minimal variations in the *MSE* are encountered for validation, which even tends to increase after 4th cycle. In the Golagh wind farm, a small improvement of the forecast is reached when adding a second predictor, both for the training and the validation data. When considering 3 predictors, *MSE* of the validation data increases (for the lower validation blocklength) indicating a possible overfit in the regression equation (Wilks, 2006).

Considering a stopping criterion of a 1% decrease in the MSE in the monthly stratified MOS, the selection process stops at the second cycle for most of the cases in both wind farms. Therefore, as a common rule, forward selection of the predictors has been stopped after the second cycle and two predictors are selected for each monthly stratified WSMOS. When 2 predictors are considered, differences between MSE for training and validation data are expected to be less than 3% for Klim wind farm (Figure 9a) and around 10% for Golagh wind farm (Figure 9b).

First and second predictors obtained by the forward selection process for all the monthly stratified WSMOS are shown in Table 1. As expected, first predictor is always friction velocity or wind speed. It should be noted that wind speeds at higher levels resulted better predictors than wind speed at hub height (around 40 m). The selection of wind speeds at different heights (80 m, 100 m and even 125 m in Golagh) could be related to the variation of boundary layer stability along the year: wind speed at 80 m is a better predictor during summer (April to September) while wind speeds above 100 m are generally selected for winter data (October to March). According to this, it is expected that increasing the number of forecast levels close to the ground could improve the effectiveness of the MOS and forecast performance (Giebel et al, 2006).

In the Klim wind farm, friction velocity is the best predictor in the majority of the cases, even better than wind speed in 8 on 12 monthly MOS. In the Golagh wind farm, wind speed and friction velocity are the best predictors in respectively 6 and 2 monthly stratified MOS. When friction velocity is the first predictor, second predictors are generally planetary boundary layer height (Pblh) and potential temperatures. On the other side, when wind speed is the best predictor, second predictors are mainly heat flux followed by potential temperatures (Pblh in just one case). In Golagh wind farm, friction velocity resulted second predictor in 2 stratified MOS, probably due to its relatively low correlation with wind speed (first predictor).

Even if diagnostic stability parameters (Monin Obukhov length and Richardson number) are not good predictors, the fact that friction velocity, wind speeds at different heights and planetary boundary layer height always appear in the regression equations confirms that atmospheric stability has a fundamental role in wind power forecast (Giebel et al, 2011).

Table 1 – First and second predictors for the monthly stratified WSMOS

Month	*Klim wind farm*		*Golagh wind farm*	
	First predictor	*Second predictor*	*First predictor*	*Second predictor*
January	Friction velocity	Pblh	Wind spd. at 100m	Temp. at 40m
February	Friction velocity	Temperature at 2m	Wind spd. at 80m	Pblh
March	Friction velocity	Pblh	Wind spd. at 125m	Heatflux
April	Wind spd. at 80m	Heatflux		
May	Wind spd. at 80m	Heatflux		
June	Friction velocity	Temp. at 2m		
July	Wind spd. at 80m	Heatflux		
August	Friction velocity	Temp. at 2m	Wind spd. at 80m	Friction velocity
September	Friction velocity	Pblh	Wind spd. at 80m	Friction velocity
October	Wind spd. at 100m	Temp. at 80m	Friction velocity	Temp. at 80m
November	Friction velocity	Pblh	Wind spd. at 100m	Heatflux
December	Friction velocity	Temp. at 40m	Friction velocity	Heatflux

3.2 Different MOS types comparison

Performance of different MOS types, described in chapter 2.1, is analysed and compared. In order to carry out a consistent analysis, NWP and power measurements input data are the same for all the considered MOS types.

Forecasts' performance of different MOS approaches is evaluated in terms of decrease in the power forecasts' *RMSE* in respect to the direct transformation of the wind speed forecast by the NWP in power forecast using the wind farm power curve (NOMOS in Figure 3), for all the monthly stratified MOS (Figure 10 and 11). According to Figure 6, wind speed forecast at 40 m and at 80 m, for Klim and Golagh wind farms respectively, have been considered for the whole period as the reference NWP forecast for NOMOS and MOS3 models (Figure 3).

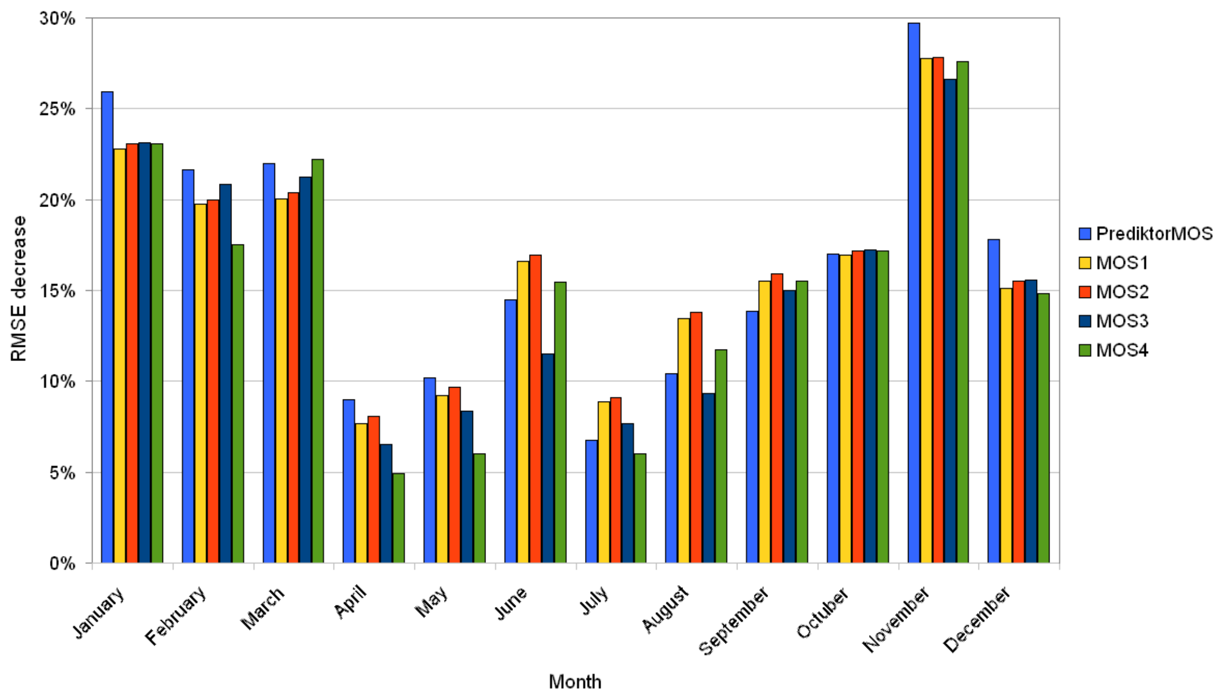


Figure 10a –Improvements in respect to NWP forecast with different MOS types (monthly stratified MOS) in Klim wind farm

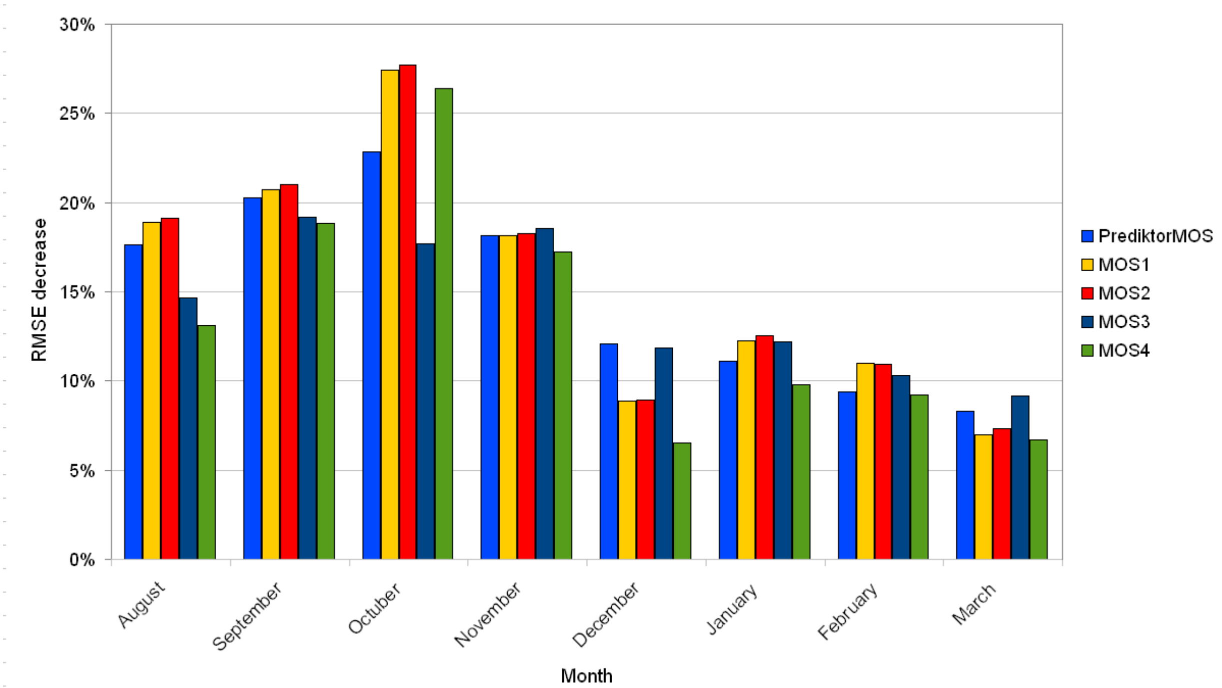


Figure 10b –Improvements in respect to NWP forecast with different MOS types (monthly stratified MOS) in Golagh wind farm

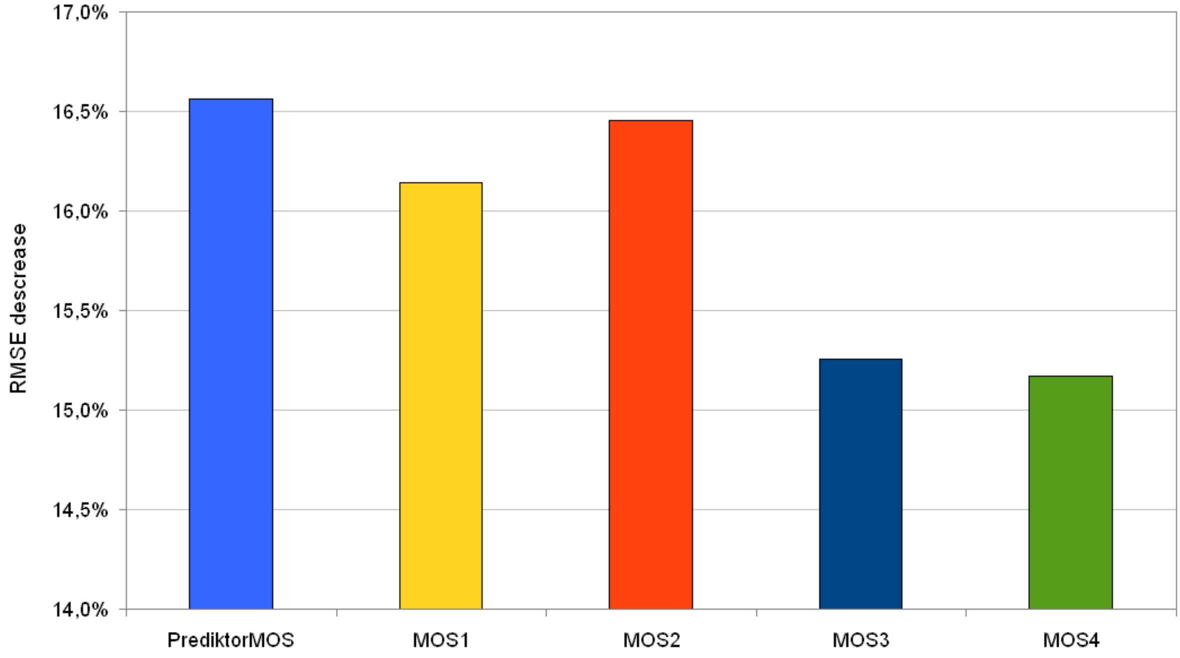


Figure 11a –Mean improvements of different MOS types in respect to NWP forecast in Klim wind farm

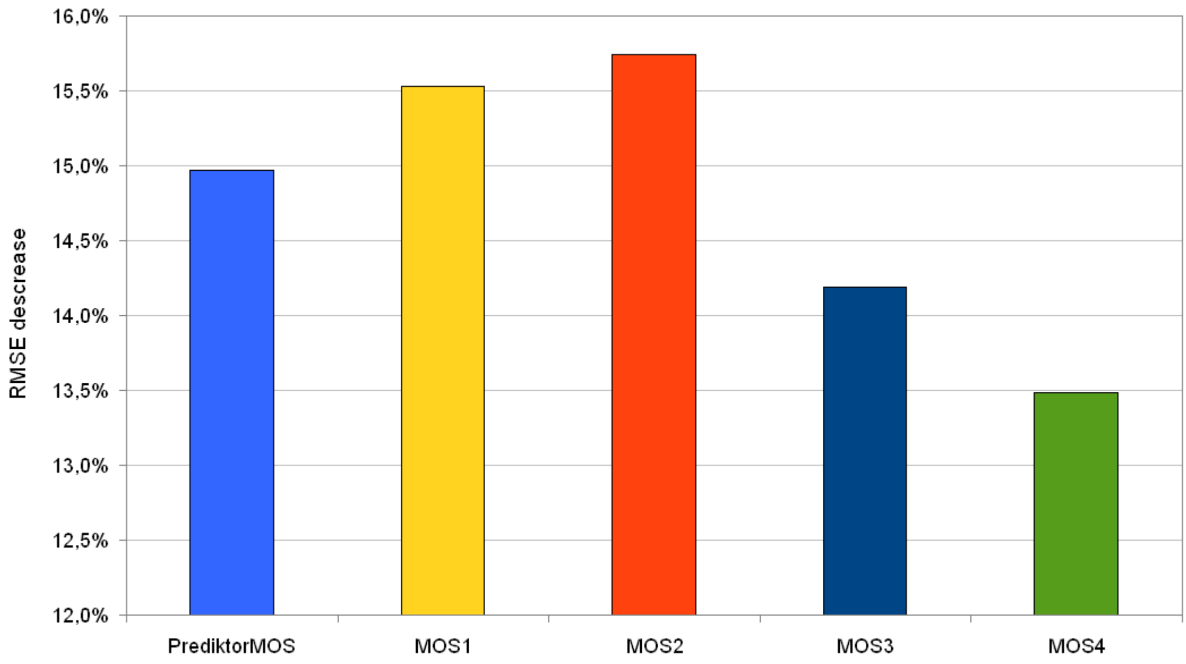


Figure 11b –Mean improvements of different MOS types in respect to NWP forecast in Golagh wind farm

All the MOS types reduce the *RMSE* in respect to the NOMOS forecast for all the monthly stratified MOS and mean *RMSE* reductions seem to be seasonally dependent in both wind farms and highly correlated to NWP forecast *BIAS* (Figure 10). Mean improvements obtained are lower in summer (5-15%) than in winter (15-30%) in Klim wind farm, the difference is mainly due to the much higher *BIAS* of the NWP forecasts during winter (Figure 6a). In Golagh wind farm, higher MOS improvements are observed in summer (15-25%) and lower in winter (around 10%) as NWP *BIAS* is higher in summer than in winter

(Figure 6b). MOS improvements are in accordance with literature where mean improvements obtained by static MOS for Prediktor in Denmark were between 10 and 15% (Giebel, 2001).

Proposed method is represented by MOS1 and MOS2 (see Figure 2). Differences between these two MOS types are minimal as small *BIAS* is encountered by MOS1 power forecasts.

Unless a few exceptions, in both wind farms the improvements associated with the utilization of proposed method (MOS1 and MOS2) are higher than MOS3 and MOS4, as confirmed by mean *RMSE* reductions (Figure 11). This leads to believe that application of the statistical treatment to wind speed, utilizing the wind farm power curve, gives better results than implementing the MOS directly on power output (MOS4) (Giebel et al, 2011), and than implementing a simple regression approach (MOS3).

The overall performance of proposed MOS is similar to those of the actual Prediktor MOS in Klim wind farm (Figure 11a) and slightly better in Golagh wind farm (Figure 11b). It should be noted that in both wind farms, big differences are encountered in the final forecast *BIAS*: PrediktorMOS could show pretty high *BIAS* (till 10% of the nominal power) while *BIAS* of proposed MOS is much lower (less then 2% of the nominal power in Klim and between 2 and 5% in Golagh wind farm). In Klim wind farm, Prediktor MOS (light blue column) improves more the NWP forecasts in winter (since November to March), while better forecast are obtained by MOS2 (orange column) during summer (June to September). Similar results are encountered in April, May and October. In Golagh wind farm higher *RMSE* decreases are observed utilizing Prediktor MOS in December and March, while similar or better forecast are obtained by proposed MOS types in the rest of the monthly stratified MOS.

3.3 Proposed MOS performance analysis

In Figure 12, the improvements of MOS2 respect to the actual Prediktor MOS are plotted as a function of the correlation coefficient (R^2) between NWP forecasted friction velocity and wind speed. Improvements are calculated as the difference between the *RMSE* decreases obtained by the 2 methods.

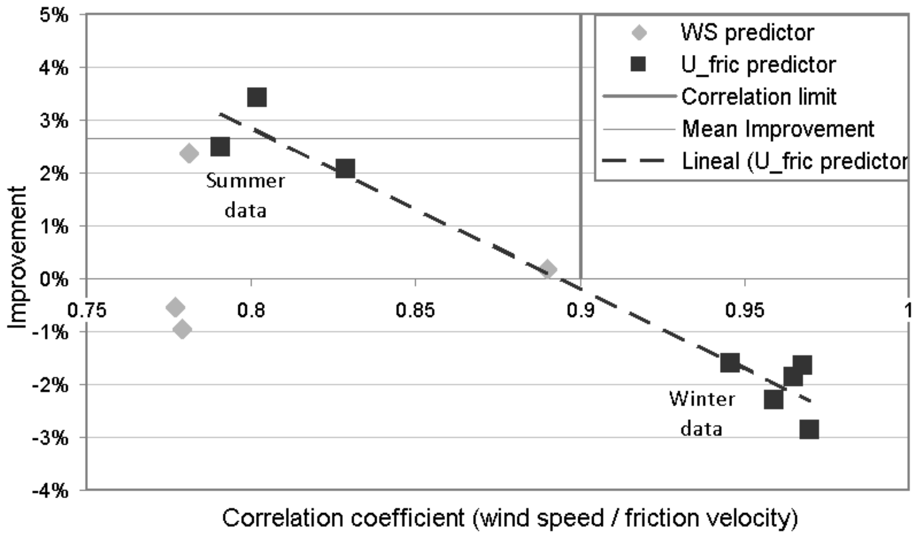


Figure 12a – Improvements in utilizing MOS2 respect to PrediktorMOS in function of correlation between wind speed and friction velocity (Klim wind farm)

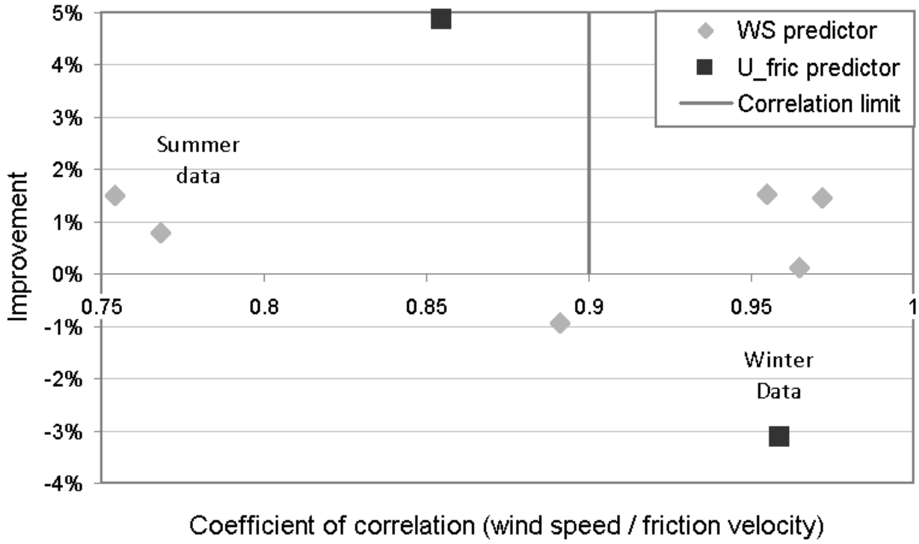


Figure 12b – Improvements in utilizing MOS2 respect to PrediktorMOS in function of correlation between wind speed and friction velocity (Golagh wind farm)

When the forecast wind speed is the first predictor of the WSMOS (grey diamonds), performance of both MOS is quite similar: differences are lower than 1.5% in most of the monthly stratified MOS in both wind farms. *RMSE* reduction achieved by the proposed MOS is generally higher than actual PrediktorMOS (7 cases on 10). On the other hand, when the friction velocity is the best predictor (black squares), differences are quite pronounced and show a dependence on the correlation between the friction velocity and the wind speed. The PrediktorMOS performs better when the correlation between the two variables is high, while proposed MOS is better when the correlation is low. For the Klim wind farm, the linear regression (visualized by the black dashed line in Figure 12a) equation shows a pretty high a correlation coefficient and it passes by 0% difference when the correlation coefficient is around 0.9 (Correlation limit). For R^2 lower than 0.9 the improvement by utilizing MOS2 respect to PrediktorMOS is remarkable with a mean increase in performance of almost 3%

(Mean improvement). In the Golagh wind farm, a similar pattern is observed but, as only 2 monthly stratified MOS have friction velocity as the first predictor, no regression could be developed. When the correlation is higher than 0.9 PrediktorMOS performs better, while when correlation is lower than 0.9 the improvement of MOS2 with respect to PrediktorMOS is around 5%.

Notice that, in both wind farms, lower correlations between wind speed and friction velocity are encountered during summer and higher in winter. This leads to suppose that correlation is related with boundary layer stability, which generally depends on wind speed: when high wind speeds are observed, stability tends to be neutral and friction velocity is proportional to wind speed (Stull, 1988). Temperature profiles confirm neutral stability in winter and unstable stability (in the first 40 m above surface) in summer. Figure 13 shows the relation between NWP wind speeds and its correlation with friction velocity. Effectively, high correlations between wind speed and friction velocity are encountered during winter months when high NWP wind speed are obtained and neutral stability is observed. On the other side, during summer, when unstable stability is generally developed close to the surface, lower NWP wind speeds are observed and lower correlations with friction velocity are encountered.

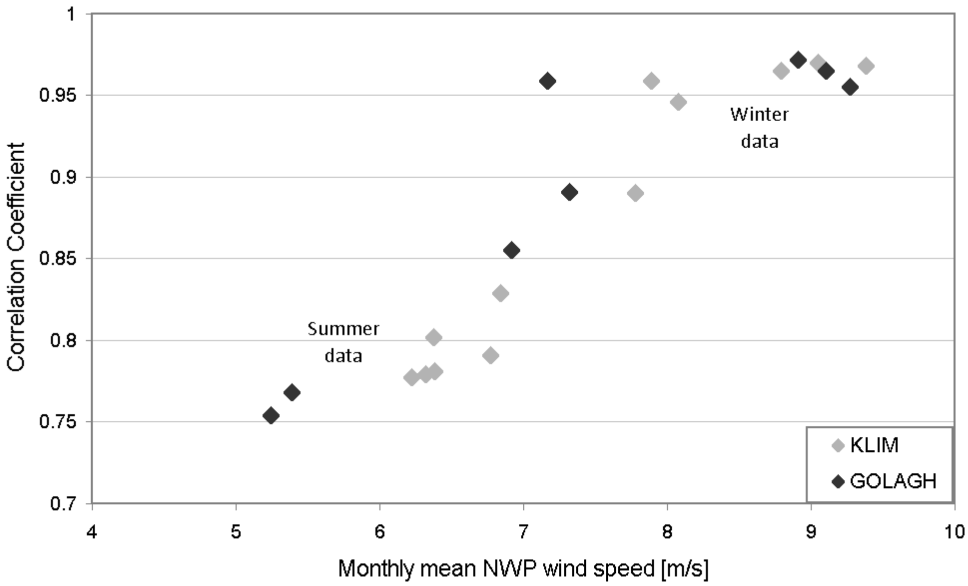


Figure 13 – Correlation coefficient between NWP wind speed and friction velocity as a function of NWP wind speed

4. Conclusions

In this study, an approach for statistical treatment (MOS) of the NWP output for the improvement of short-term wind farm power forecast is discussed. The proposed approach is mainly based on the fitting of a multilinear regression for calculating a representative wind farm wind speed, obtained from power measurements. An iterative process is implemented in order to identify which are the best predictors for the wind speed among different NWP forecast prognostic and diagnostic variables, and whereas their inclusion in the MOS could improve the forecast. The performance of the proposed approach is evaluated in Klim (Denmark) and Golagh (Ireland) wind farms of the ANEMOS project and compared with the operational Prediktor MOS and other MOS types.

The method requires only power measurements as input and could be applied to data in the ascending part of the power curve, that is the range where highest power forecast error are generally encountered. Data utilized for MOS training were around 90% of total data for both wind farms.

The NWP performance (WRF model) was found to be variable along the year and highly seasonal dependent and it resulted really useful the implementation of stratified MOS (in here monthly stratified). As future development, a detailed study should be carry out in order to identify whether synoptic conditions are mostly affecting the forecasts and implement MOS stratified according to those situations. As the simulations were constantly kept on track by utilizing grid and observational nudging, data were not subdivided in different forecast lengths for MOS development.

In respect to the wind farm wind speed multilinear regression, NWP friction velocity and wind speed resulted to be the best predictors of the wind farm wind speed. Friction velocity is the first predictor in most of the monthly stratified MOS in the Klim case (8 months on 12), while NWP wind speed forecast was better in the Golagh wind farm (6 months on 8). Other prognostic variables shown considerably lower correlations with wind farm wind speed and some of them are highly seasonally dependent, such as boundary layer height and heatflux. Stability diagnostic parameters, Monin Obukhov length and Richardson number, revealed to be very bad predictors with almost null correlations and they don't appear in monthly stratified MOS equations neither as second predictors. It should be noted that the stability affects the wind profile and is already taken into account in the MOS when selecting as first predictors friction velocity or wind speed at higher levels (80 m, 100 m or even 125 m) than the hub height.

MOS equations have been developed considering 2 predictors in each stratified MOS. Null or negligible improvements were generally encountered in selecting more than 2 predictors and overfitting risk highly increase if selecting more predictors. When considering 2 predictors, differences between training and validation data are small: less than 5% in Klim wind farm and around 10% in Golagh wind farm.

Performance in power forecast of the different analysed MOS types is evaluated in respect to direct NWP forecast (NOMOS). Results confirm that, when power measurements data are available (at least one year data), statistical treatment is highly recommended and all MOS types averagely improve NWP power forecast of around 15% in both wind farms. Proposed method (MOS1 and MOS2) shown better results comparing to a simple regression MOS based on power measurements (MOS3). *RMSE* reductions obtained by the comparison confirm that adjusting the wind speed before calculating the power output is much better than MOS performed directly on the power output (MOS4). Therefore, the utilization of the wind farm power curve, as by the WAsP-Park model, for calculating a mean wind farm wind speed was found to be important in order to improve the forecast.

The overall performance (in terms of RMSE) of proposed approach is similar to the operational Prediktor MOS in the Klim wind farm and slightly better in the Golagh wind farm. In both wind farms, *BIAS* obtained by PrediktorMOS is relevant (up to 10% of the nominal power) while *BIAS* of the proposed method is negligible. When the wind speed is the first predictor, similar results are obtained by actual PrediktorMOS and proposed MOS (differences are generally less than 1,5%). On the other side, when friction velocity is the best predictor of the WSMOS, forecasts of the proposed MOS are shown to be highly dependent on the correlation between the first predictor (in this case friction velocity) and the wind speed. Better results are obtained when the correlation between those two variables is small. Improvements in respect to actual operational Prediktor MOS are expected when the correlation R^2 is lower than 0.9 and the best predictor is not the forecast wind speed. Stability plays an important role in determining the correlation between wind speed and friction velocity: higher correlation were found in winter months when neutral stability is observed, while lower correlations are obtained in summer under unstable surface layer stability.

The proposed MOS performed well in both Klim and Golagh wind farms, located in different topographical areas and with different NWP grid spacing and its forecasts compare positively with other MOS types. The methodology described should be carried out for every wind farm in order to select best predictors and stratification the better fits in each site. Further research should be carry out in order to analyse more diagnostic variables as possible predictors, such as pressure gradients, to define a new criteria for the MOS stratification, more related to real synoptic features of the studied wind farm and to make the MOS operatively reliable.

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