Wind power prediction in complex terrain: from the synoptic scale to the local scale

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Abstract:

In this paper operational results of CENER prediction model are presented. This model has been developed at CENER and it is specially designed for complex terrain. The prediction model includes a complete set of models that ranges from the synoptic scale to the local scale of the wind farm:

- MM5 model reads as inputs the status and expected evolution of the atmosphere at synoptic scale, from global or regional meteorological models (like AVN, HIRLAM, etc); and forecasts all the relevant atmospheric variables like wind speed, direction and air density at different domains. The nesting capabilities of MM5 allow increasing the spatial resolution of the domains in a hierarchical way up to 1 km^2 around the wind farm. The effects of the spatial resolution and nesting options have been tested at different forecast horizons.
- In order to include smaller scale phenomena (smaller than 1 km^2), a CFD model has been developed to be coupled with MM5. This model reads the wind predictions of MM5 for the area of the wind farm, and transforms them into specific wind forecasts for wind turbines or groups of wind turbines. This model can increase the spatial resolution of the wind forecasts up to the scale of meters.
- A final MOS correction is included in order to detect and remove systematic errors that could appear in the previous process. This module is based on an automatic selection of input variables, principal components regression and fuzzy logic.
- Wind forecasts are transformed into power production forecasts by the wind farm power curve statistical module. Different sets of power curves are calculated considering wind direction and air density. Fuzzy logic models are compared versus simple binning models.
- In order to improve the very short tem forecasts (up to 10 hours ahead), CENER prediction model includes a time series statistical forecasting module. This module is based on autoregressive techniques that allow modelling the persistence of the wind and its effect on the forecasted power production.

The prediction model has been operational since the beginning of 2002 and it has been running on-line since June 2003 at different wind farms in Spain, mainly located in complex terrain. The paper shows the results of the prediction model for some of the wind farms.

Keywords: wind power prediction, forecasting, power curve, fuzzy logic, MM5, time series

1 Introduction

The use of wind power forecasting tools is becoming a need, especially in the countries with an important wind energy capacity installed. Prediction tools can help wind energy to compete with the conventional energy sources in a liberalized energy market context. In general terms, according to the basic rules of the market the deviations of the scheduled production have a penalty. The unknown fluctuations of the wind energy production are thus an important obstacle for wind energy producers to enter in the energy market.

From the point of view of the system operators the unpredicted variability of the wind farms production reduces the efficiency of the system, with an increase in the price of the kWh.

Another problem related to the unpredicted variability of the wind is the efficient use of the electrical network. Prediction tools are of special interest in areas with a high concentration of wind farms and a limited capacity of the network, the prediction of the energy production for the wind farms connected to a certain node can be used by a grid manager to optimize the load of the network, minimizing the loses of energy.

In this context, the accuracy of the predictions is a critical point that determines the value of the forecasts. In the case of Spain, the majority of the wind farms are located in complex terrain. In general, wind forecasting in complex terrain is more difficult than in flat areas. In complex terrain local effects (topography and thermal effects) play an important role that cannot be solved completely by the meteorological forecast models.

One of the main limitations of numerical weather predictions is the spatial resolution of the grid that is used to solve the equations. This limitation causes that the effects having a characteristic dimension (spatial and temporal) smaller than the grid resolution cannot be solved explicitly. In the case of wind forecasts in complex terrain, the features of the terrain surrounding the area of the wind farm modify significantly the wind flow, and are not adequately considered in numerical weather predictions.

2 Description of the test case

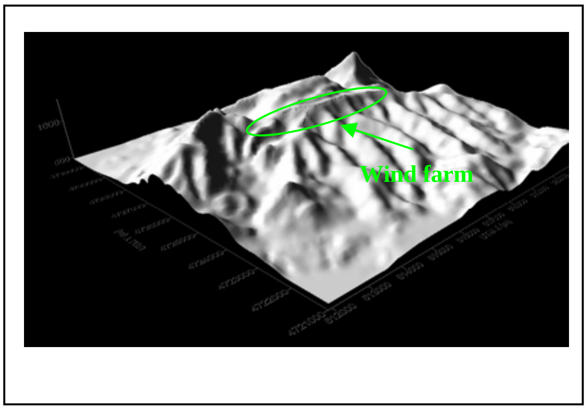

Figure 1. 3D map of Alaiz wind farm area.

Figure 1 shows the terrain characteristics where Alaiz wind farm is installed. The prediction model has been tested in several wind farms in Spain, for this paper Alaiz wind farm has been selected as test case. Alaiz is a mountainous area with steep slopes and big changes in the altitude. Figure 2 shows the spatial distribution of the ruggedness index (RIX) [1], this index represents the percentage of slopes steeper than 30%. It can be seen in figure 2, the RIX varies between 10% and 38%, being a clear indication of the high level of complexity of the terrain. Alaiz wind farm is situated in Navarra at the North-East of Spain, owned by Energía Hidroeléctrica de Navarra (EHN). It has 50 wind turbines (660 kW rated power). The average height above sea level is 1050 m.

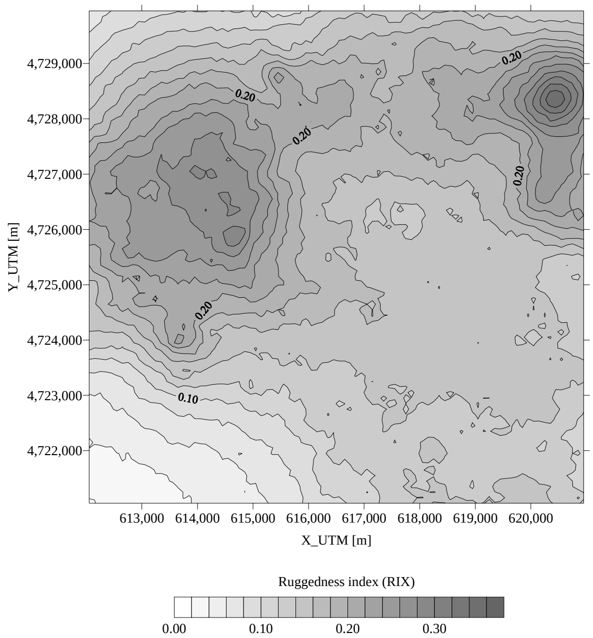

Figure 2. Spatial distribution of the ruggedness index (RIX).

Wind and power forecasts have been produced for the period 23/05/2003 – 31/10/2003. The wind measurements used for the test case come from a meteorological mast located in Alaiz wind farm. The anemometer and vane are located at 55m a.g.l.

3 Description of the prediction model

CENER prediction model has been designed to improve the quality of the wind and power production forecasts especially in complex terrain.

The prediction model has a modular design, including physical modules (MM5 and CFD) and statistical modules (MOS, wind farm power curve and time series forecast).

The prediction model uses as input data the numerical weather predictions (NWP) given by a global or regional model and the wind speed, temperature, pressure and power production measured at the wind farm. The mesoscale meteorological model MM5 uses the NWP as initial and boundary conditions and generates a high resolution wind forecasts in the area of the wind farm reaching up to 1 x 1 km^2 resolution. The CFD module reads the forecasted wind speed and direction of MM5 at different nodes and performs a very high resolution simulation of the wind flow over the wind farm, reaching a spatial resolution of meters. An advanced Model Output Statistics module (MOS) improves even more the wind forecasts detecting and removing the systematic errors through a powerful

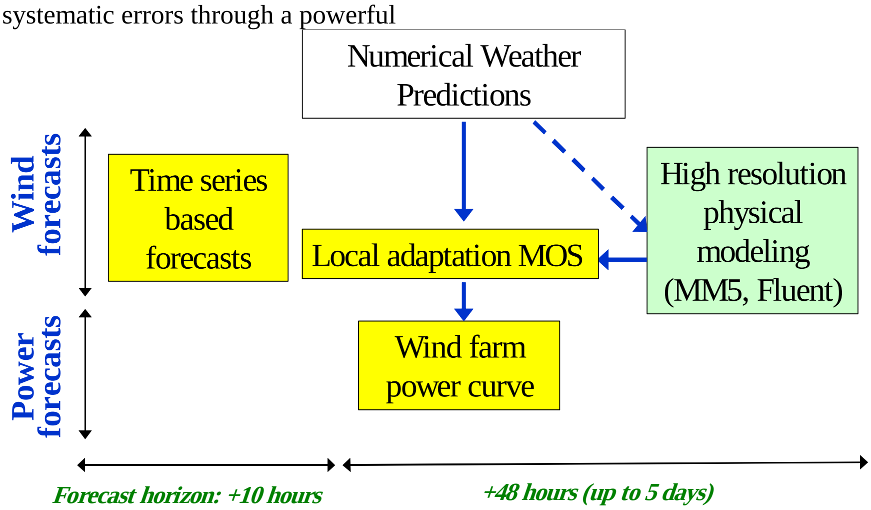

Figure 3. CENER prediction model structure.

statistical process that is based on historical wind predictions and simultaneous data. Finally, the wind forecasts are transformed into power forecasts through the wind farm power curve module. In parallel, the time series module generates a forecasts based only on wind and power productions measurements.

3.1 MM5

MM5 is a numerical short-time prediction model; it is a well known model amongst meteorological modellers.

The version used corresponds to the Fifth-Generation of the known Mesoscale Model, it was developed between the University Pennsylvania State (PSU) and the National Center for Atmospheric Research (NCAR) from United States. The main aspects that can be relevant for the generation of wind forecasts are:

- Capability of multiple nesting with up to nine domains running at the same time and completely interacting in two-way. Two-way interaction means that the nest's input from the coarse mesh comes via its boundaries, while the feedback to the coarse mesh occurs over the nest interior.
- Non-hydrostatic Dynamic Formulation, which adds vertical acceleration that contributes to the vertical pressure gradient. This characteristic is especially important for wind simulations in complex terrain, where the vertical acceleration of the wind plays an important role.

independent forecast based on wind and power measurements of the wind farm; this statistical forecast reduces the errors for the first hours taking advantage of the persistence of the wind. Figure 3 shows CENER prediction model structure.

- Automatic initialization with bucket meteorological datasets (AVN global model, ECMWF global model, HIRLAM, etc.). And also MM5 allows four-dimensional data assimilation (FDDA) while the model is executed. Essentially FDDA makes the model run with forcing terms that "nudge" it towards the observations or analysis.
- This model incorporates the recently developed parameterizations schemes for the physics process related with: atmospheric radiation, clouds, precipitation, turbulence, cumulus, convection and surface fluxes.

The conditions used for the test case are:

- The wind farm's topography is represented in a terrain file generated at NCAR using a USGS (United States Geological Survey) database for terrain and land use. The resolution of the source terrain and land use data are: 111 Km, 56 Km, 19Km, 9Km, 4km and 1Km.
- Boundary conditions such as horizontal winds, temperature, pressure and moisture fields depend on a global model used to initialize MM5. In this case, the AVN global

model has been chosen, with 6 hour data and 1ºx1º grid.

- For these calculations, four domains have been nested, in order to obtain a fine grid in the last domain near to 3x3 km^2. These domains are centred in the Alaiz's wind farm. See the figure 4. The last domain has a dimension of 49x49 nodes.

- The four domains are nested as two-way. The nesting ratio is 3:1 between domains, in order to guarantee stability and convergence in the equations resolution.

- The model has been vertically interpolated in 23 sigma levels. Sigma surfaces near the ground follow the terrain, and the higher-level sigma surfaces tend to approximate isobaric surfaces.

With the above conditions, the model has been run once per day for the test case during the period 23/05/2003 – 31/10/2003, using the boundary conditions from AVN model at 00 hours run. The results obtained have been 72 prediction horizons, each day.

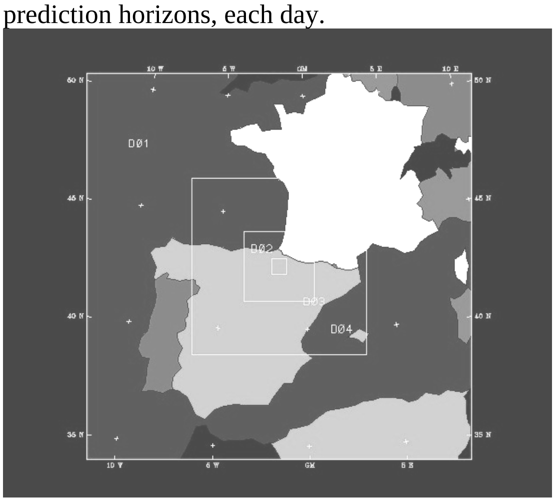

Figure 4. Four nested domains centred in Alaiz's Wind Farm.

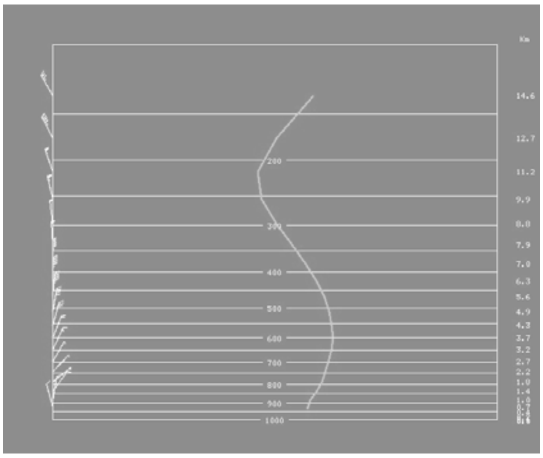

Figure 5. Simulating the wind profile for Alaiz's wind farm. Sample of vertical profile calculated by MM5: pressure levels, temperature profile and wind vector variations with height.

The results of the MM5 model for Alaiz test case are presented in the MOS section.

3.2 CFD

The simulation of the wind flow over the area of the wind farm is carried out by a CFD model developed by CENER. This simulation takes into account the topography and roughness with a very high spatial resolution (some meters).

This CFD model has been coupled with MM5 and it takes as inputs the output of MM5 in the last domain (3 x 3 km^2), the CFD model modifies the wind prediction for the area given by MM5.

The results of this model are presented in a different paper [2]

3.3 MOS

The MOS module of the prediction model is designed to improve the wind forecasts statistically. Part of the errors that affect the forecasts are systematic, this means that they can be detected statistically. This MOS module is based on a principal components regression with a self-tuning algorithm.

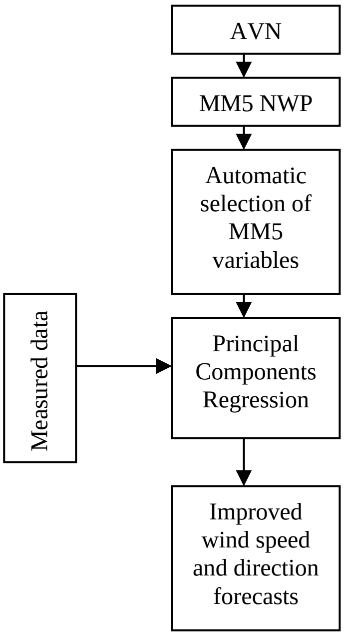

Figure 6: MOS structure.

A training period has been determined in order to fit MOS algorithms, and an independent validation period has been used to evaluate the results. This procedure avoids the overfitting problem. The training period was defined as the last three weeks of each month, and the validation period is the first week of each month (five weeks in total). All the results presented here correspond to the validation period.

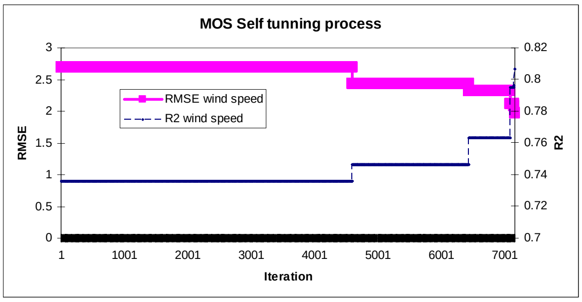

Figure 7. Automatic selection of MM5 variables for the MOS corrections. Evolution of rmse and R^2 of wind speed forecasts for the 12 hours horizon.

After the MOS correction an improved wind forecasts is produced. The forecasts are made daily using AVN 00 run as input data to MM5, the forecast horizons are +01 to +72 hours.

The previous figure shows the rmse (root mean square error) and R^2 (determination coefficient) evolution of the wind forecasts, in the automatic selection of MM5 variables for the MOS. This process searches the optimum set of MM5 output variables that allow the MOS module to detect and remove the systematic errors of the wind forecasts. The final set of variables gives the minimum value of the rmse for the wind speed forecasts.

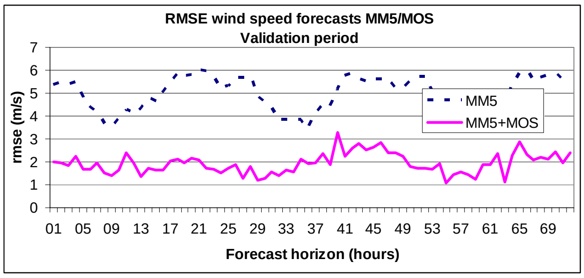

Figure 8. Rmse of wind speed forecasts obtained with MM5 and MM5+MOS for the validation period.

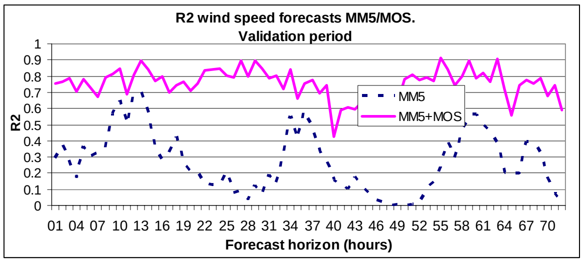

Figure 9. R^2 of wind speed forecasts obtained with MM5 and MM5+MOS for the validation period.

The previous graphs show the errors (rmse) and the determination coefficient R^2 of the MM5 wind speed forecasts for the validation period, with and without the MOS corrections. It can be seen that the MOS corrections improve significantly the forecasts, reducing the rmse and increasing the R^2 for every forecast horizon.

MM5 performance varies for the different horizons, since there is a single run of the model per day; this means that the diurnal variations of the wind are not yet well captured by MM5 in this area. Another explanation for the fluctuations of MM5 performance could be the effect of the boundary conditions over the last domain. MOS corrections smooth the fluctuations of the errors, giving a more homogeneous performance of the forecasts for all the horizons.

	MM5	MM5+MOS
RMSE wind speed forecasts	4.9 m/s	1.9 m/s
R^2 wind speed forecasts	0.27	0.75

Table 1. Rmse and R^2 of wind speed forecasts. MM5/MOS. Average values for all the horizons (1-72 hours). Comparison between 10 m a.g.l. MM5 forecasts and 55m a.g.l. wind measurements, for the validation period.

A new MOS algorithm based on fuzzy logic is now under development.

3.4 Wind farm power curve

Power curve modelling allows the prediction of wind farm power for a predicted wind speed and direction. This modelling has been carried out by means of different methods based on statistical tools. Except for the last one, all the methods obtain as a result a matrix-shaped power curve in which the mean output power is obtained entering a certain wind direction and wind speed.

The interest of using different methods is based on the diverse situations related to available measurements at wind farms. In some cases there is only a global measure of power production and the wind at the meteorological station, in other cases there are more detailed measurements like individual power production and nacelle anemometers. The use of each method is conditioned on the availability of data, in general, the more data are available, the more accurate the results are because of the use of a more sophisticated model.

Power production, wind speed, wind direction, temperature and pressure data measured at Alaiz wind farm have been used to fit the models. For all the methods, a training period has been determined during which the models are fitted, and an independent validation period has been determined.

The general training period is Jan01-Aug01, and the general validation period is Sep01-Dec01. As these periods were conditioned to the availability of data, they changed in some cases. The number of wind speed bins and sectors for the definitive power curve was optimised during the modelling.

In order to avoid the effect of air density over the measurements, all wind speed and output power data were corrected by means of atmospheric pressure and air temperature. This correction was made according to IEC 61400-12 that depends on the kind of regulation (pitch controlled: correction over wind speed or stall regulated: correction over output power). The turbines installed in Alaiz are pitch regulated. A normalised wind speed was calculated for a standard density of 1.225 kg/m3.

Three parameters were used to evaluate power prediction during the validation period:

- Determination coefficient (R^2)
- Root mean square error (rmse)
- Relative error to the wind farm nominal power

The tables 2 and 3 and figures 10 to 14 show for some models the training and validation period used as well as the three parameters explained above and the comparison between the real and the simulated power curves during the validation period.

Five models were tested:

- Model 1: Global power curve referred to the meteorogical mast.
- Model 2: Global power curve referred to the nacelle anemometers.
- Model 3: Cluster analysis to determine subsets of wind turbines. Cluster power curves referred to the nacelle anemometers.
- Model 4: Turbine power curves referred to the nacelle anemometers.
- Model 5: Fuzzy logic power curves.

Model 1: Global power curve referred to the meteorogical mast.

This model compares directly the global wind farm power to the normalised wind speed measured at the meteorological mast. All the measurements were filtered and singular points ignored in the analysis. A discretization for different number of sectors (4, 6, 8, 12 and 16) and bin widths (0.5 and 1 m/s) was made so that optimum results were obtained for 16 sectors and a bin width of 0.5 m/s. No data was available for air pressure and temperature during June 01 so this month could not be included in the training period for this model and for the subsequent ones.

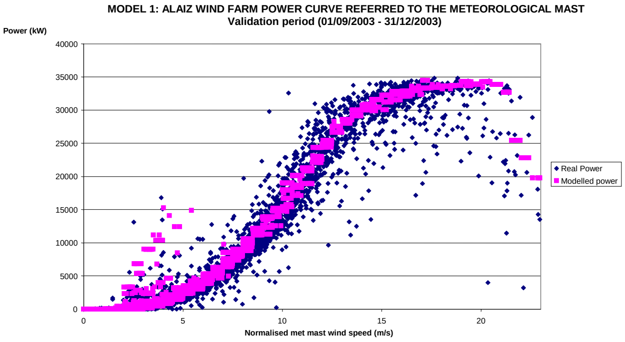

Figure 10. Modelled and real power curves during the validation period for MODEL 1

As it was said before, a global power curve in a matrix form (sectors in rows-wind speed bins in columns) was obtained using the specified training period and taking a mean value for the wind farm power corresponding to each sector and wind speed bin. This power curve was applied for the validation period (Sep01-Dec01).

Model 2: Global power curve referred to the nacelle anemometers.

This second model uses wind speed measured at the nacelle anemometers assuming this is a more representative measurement around the area.

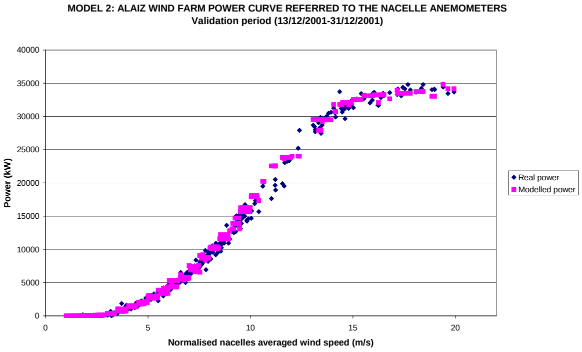

Figure 11. Modelled and real power curves during the validation period for MODEL 2

Unfortunately, these speeds were not measured in Alaiz since June 01 until 13 December 01 so that the validation period was reduced to the 2nd half of December 01.

The available nacelle wind speeds were filtered, averaged for the whole period and synchronized again to the wind direction at the meteorological mast and global output power. The table 2 shows an improvement on the results. The validation period is not the same; therefore the comparison between model 1 and the other ones could be considered only in a qualitative way.

Model 3: Cluster analysis to determine subsets of wind turbines. Cluster power curves referred to the nacelle anemometers

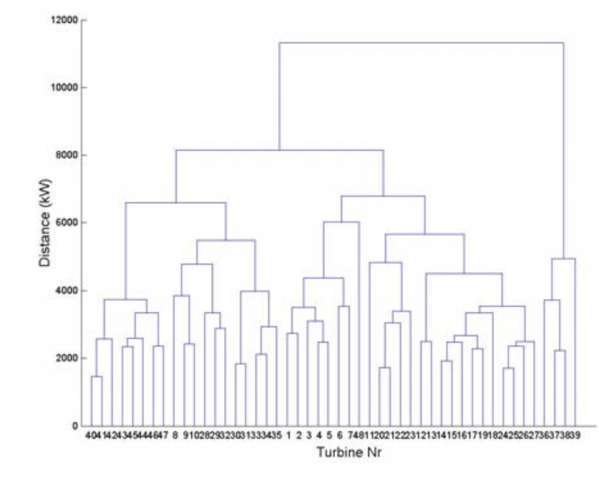

Figure 12. Dendrogram of the cluster analysis.

Once tested that nacelle anemometers gave better results, a new method was employed in order to adjust different power curves to different turbine subsets. These subsets were formed by means of a cluster analysis applied to the power data of every turbine so that a group of turbines was obtained attending to production homogeneities criteria. Five turbine subsets were obtained after the cluster analysis based on hierarchical clustering and complete links (maximum distances between groups). Figure 12 shows the dendrogram, it identifies the groups of wind turbines with homogeneous behaviour. From this point, a similar method to the one explained above was carried out so that five different power curves were developed from averaged nacelle wind speeds corrected by density, wind direction measured at the meteorological mast and cluster output power. These curves were applied during the validation period in order to get a predicted power output for each cluster. By adding these cluster productions, a global wind predicted power was obtained and compared to real data. The table 2 below shows a new improvement in terms of rmse.

Model 4: Turbine power curves referred to the nacelle anemometers

An extreme case derived from the previous model consists of obtaining different power curves for every turbine instead of making groups, and applying the same process as explained above. This modified-model 3 uses normalised nacelle wind speed, meteorological mast wind direction and turbine output power. Once filtered, these measurements produced a power curve for each turbine, which was applied later over the validation period.

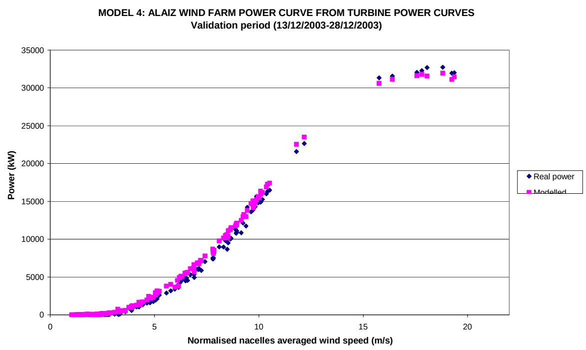

Figure 13. Modelled and real power curves during the validation period for MODEL 4

The output power for this period was added in order to get the global wind farm power so that it was compared to real output power. The table 2 below shows a new small decrease in rmse to 632 kW (1.91% of the nominal wind farm power).

Model 5: Fuzzy logic power curves

Fuzzy logic statistical tool defines input variables (normalised wind speed, wind direction and optionally other variables like air pressure and air temperature) and an output variable (wind farm power) by means of membership functions and finds proper transfer functions for relating them. As in the previous models, fuzzy logic method fits these functions for a training period attending to minimum rmse criteria and applies them during the validation period giving as a result the simulated power which is compared to real power.

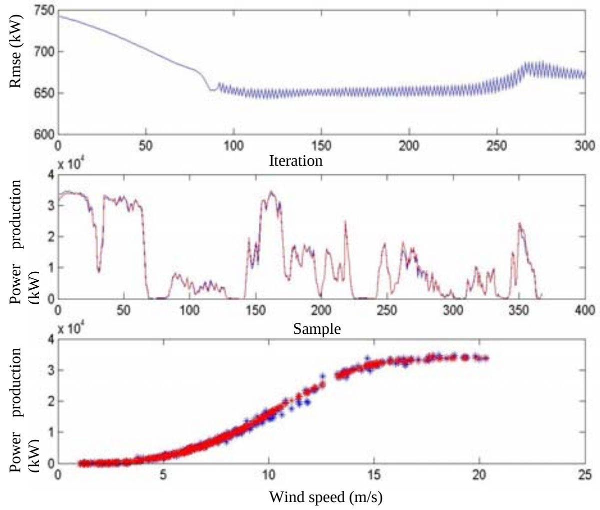

Figure 14: a. Evolution of rmse with the number of iterations, b. Predicted power vs measured power during the validation period, c. Modelled power curve vs real power curve during the validation period

A certain number of iterations is needed to get the optimal fitting so that there is a critical number of them from which an improvement in terms of rmse is not expected (see figure 14a). As it can be observed, rmse between modelled and measured power is minimum at approximately 80 iterations. From this point, rmse fluctuates considerably and no improvement is observed.

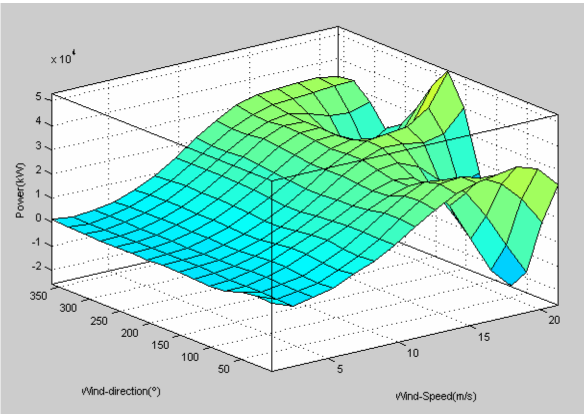

Figure 15: Transfer functions between wind speed-direction and output power (fuzzy logic power curve)

Fuzzy logic model was applied to two groups of data:

- Wind farm data: averaged nacelle wind speed, meteorological mast wind direction and wind farm power. An only transfer function is obtained for this case (see figures 14 and 15).
- Wind turbine data: turbine nacelle wind speeds, meteorological mast wind direction and wind turbine power. Fuzzy logic is applied separately to every turbine to get different transfer functions one for each wind turbine.

Figure 14 also shows the time evolution for the modelled and measured power as well as their corresponding power curves during the validation period. The fitting for both series is accurate with a high degree of explanation of the measures by the model.

The next tables show the results obtained for all the models for R^2 and rmse. The results for the fuzzy logic model are separated for both groups of data explained above.

Model Nr.	Training period	Validation period	R2	rmse (kW)	rmse (%)
1 Global power curve, met. mast	Jan01-May01 Jul01-Sep01	Oct01-Dec01	0.947	2863	8.65
2 Global power curve, nacelle anemometers	Jan01-May01	2^{nd} half Dec01	0.995	851	2.68
3 Cluster power curve, nacelle anemometers	Jan01-May01	2^{nd} half Dec01	0.996	673	2.11
4 Turbine power curve, nacelle anemometers	Jan01-May01	2^{nd} half Dec01	0.996	632	1.91

Table 2: R^2 and rmse of the wind farm power curves (without prediction) for the linear models (1 to 4).

Model Nr. 5		Tr. period	Val. period	Nr iterations	R2	rmse %
Fuzzy logic power curves	Wind farm	Jan01-May01	2nd half Dec01	5	0.9979	2.44
				20	0.9980	2.40
				70	0.9982	2.29
				100	0.9984	2.21
				200	0.9984	2.19
				300	0.9984	2.19
	Wind turb.	Jan01-May01	2nd half Dec01	5	0.9982	1.78
				20	0.9982	1.78
				100	0.9989	1.56
				300	0.9989	1.53

Table 3: R^2 and rmse of the wind farm power curves (without prediction) for the non-linear model (fuzzy logic).

3.4.1 Power production forecasts

The first wind farm power curve model has been coupled with MM5 and the MOS system to generate power production forecasts at the test case.

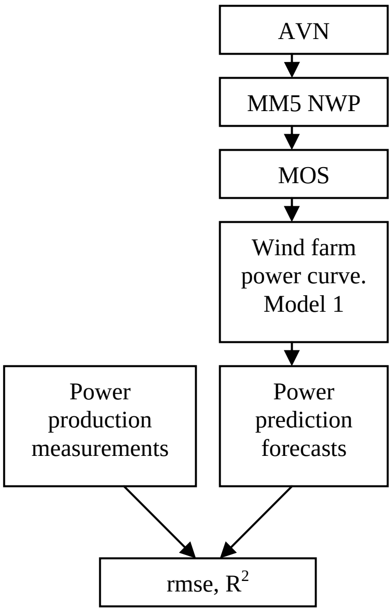

Figure 16: Structure of the prediction model used to generate power production forecasts at the test case.

Only the first model of wind farm power curve has been tested, this means that an improvement of the power production forecasts can be achieved when the fuzzy logic power curve model is tested.

Figure 17 shows the rmse and R^2 of the power production forecasts for the test case during the validation period.

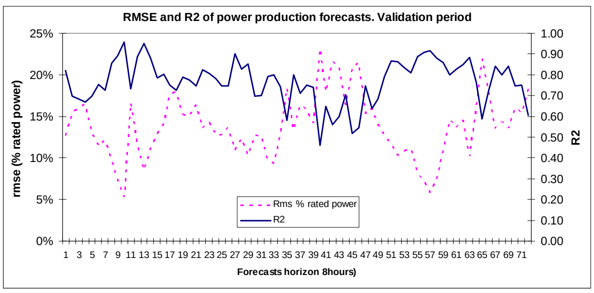

Figure 17: R^2 and rmse of the power production forecasts for every forecast horizon and for the validation period.

	MM5+MOS+Power curve 1
RMSE power production forecasts	14% nominal power
R^2 power production forecasts	0.77

Table 4: Rmse and R^2 of power production forecasts. MM5+MOS+Wind farm power curve 1. Average values for all the horizons (1-72 hours). Results for the validation period.

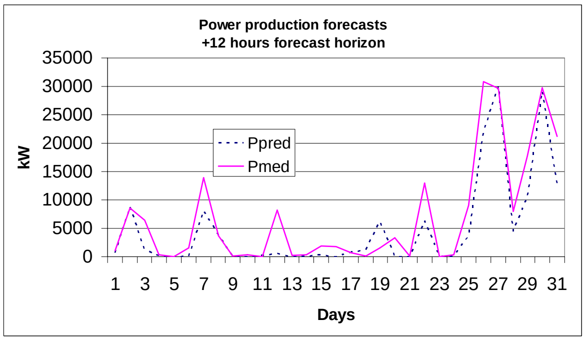

Figure 18. Power production forecasts vs measurements during the validation period. +12 hours horizon. Pmed is measured power, Ppred is predicted power.

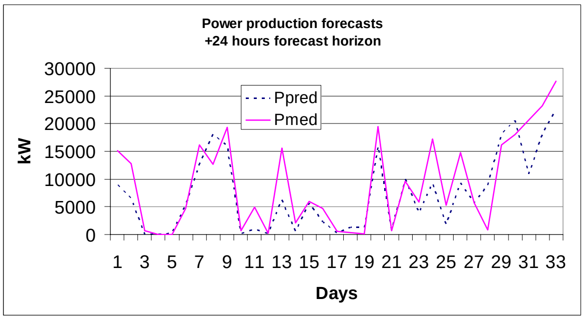

Figure 19. Power production forecasts vs measurements during the validation period. +24 hours horizon.

The previous graphs represent the measured power production of the wind farm and the predictions of the model for the validation period. The measures are different because there is only one forecast per day. It can be seen that the tendencies are well captured by the model as well as the amplitude.

3.5 Time series forecast

A time series model is a useful tool in order to characterize and forecast the behaviour of any time series in the first prediction horizons. In these horizons normally this kind of model presents better results than the ones obtained based on a meteorological model as MM5.

The models based on time series, both linear and non-linear, predict the behaviour of the time series using only the empirical data. The absence of information about the evolution of the atmosphere at synoptic scale implies that the forecasts calculated with time series models are good only for short forecast horizons. For that reason, the optimum prediction can be obtained by the combination of the meteorological forecasts (like MM5) and the time series ones.

It is possible to use the time series models in two ways in order to generate power production forecasts:

1. Forecast the wind field (velocity and direction) and use the wind farm power curves to transform wind the wind predictions into power production forecasts.
2. Forecast the power production directly, using power production data as the main time series

The time series model used is an ARMA model (1) considering the time series as stationary [6]. This is the general formulation of the model:

$$Z_t = \sum_{j=1}^{p} \phi_j Z_{t-j} + \sum_{j=0}^{q} \psi_j a_{t-j} \qquad (1)$$

Where

- $\{\phi_j\}$ corresponds to the autorregresive parameters, whose general order is *p*.
- $\{\psi_j\}$ refers to the moving-average parameters, whose general order is *q*.
- $\{a_t\}$ is a white noise series, a random and independent series that is normally distributed.

The orders of the best fitted model can be estimated through the shape of the autocorrelation function (2) and the partial autocorrelation function (3).

$$\rho_k = \frac{E[(z_t-\mu)(z_{t-k}-\mu)]}{\sqrt{E[(z_t-\mu)^2(z_{t+k}-\mu)^2]}} = \frac{E[(z_t-\mu)(z_{t+k}-\mu)]}{\sigma_z^2} \qquad (2)$$

$$P_k = \frac{Cov[(Z_t-\tilde{Z}_t)(Z_{t+k}-\tilde{Z}_{t+k})]}{\sqrt{Var(Z_t-\tilde{Z}_t)}\sqrt{Var(Z_{t+k}-\tilde{Z}_{t+k})}} \qquad (3)$$
$$\tilde{Z}_{t+k} = \phi_1 Z_{t+k-1} + \phi_2 Z_{t+k-2} + \ldots + \phi_{k-1} Z_{t+1}$$

The following step in the process of fitting a model is the parametric estimation of the coefficients. They can be estimated resolving the *Yule-Walker* equations (4), taking into account the orders of the model.

$$\rho_k = \phi_1\rho_{k-1} + \phi_2\rho_{k-2} + \ldots. + \phi_p\rho_{k-p} \qquad (4)$$
$$k \geq q+1$$

An important step to adequate the model to the data is to look for possible hidden periodicities. Usually, it is made using *Fourier analysis*, either through harmonics analysis or through spectral analysis with variable window. But the wind velocity is so fluctuant than this kind of analysis is not sufficient to eliminate these fluctuations. In this case it is preferable to carry out a filtering of the data through non-parametric wavelets analysis.

Wavelet Analysis is a relative new technique to analyse the time series in time-frequency domains. The wavelet analysis is able to detect the signal and the noise that are behind of the measured data. In this way, this kind of analysis is optimum to pre-process whichever time series previous to adjust a stochastic model. This methodology allows removing the noise from measurement data while preserving the features of the signal. [7, 8]

After the wavelets filtering, two linear models ARMA have been estimated: one of them for the wind velocity data and the other for the wind farm power production. Both of them correspond to an autorregresive model of order 1.

The parametric estimation has been carried out solving the Yule-Walker equations, the obtained optimized parameter for the wind velocity is $\phi_v = 0.9910$, and the corresponding parameter for the wind power $\phi_v = 0.9432$. The best lineal model for the velocity is presented in (5), and it can be seen the equation (6) for the power.

$$v(t) = 0.9910\, v(t-1) + \varepsilon(t) \qquad (5)$$

$$p(t) = 0.9432\; p(t-1) + \varepsilon(t) \qquad (6)$$

The previous models have been used to estimate the forecasts for the different prediction horizons, from 1 to 24 hours. The validation results are presented for each prediction horizon. In order to characterise the performance of the time series models, two parameters have been calculated for each model: the root mean square error (rmse), and the determination coefficient R^2 between the forecasts and the measured data.

Figure 20 shows the rmse for the wind speed and figure 21 shows the relative rmse to the nominal power. As it can be seen, this error parameter increases with the forecast horizon, following a logarithmic function for both velocity and power.

The determination coefficients between forecasts and measurements for the different horizons are shown in the figure 22; they decrease as the forecast horizon increases following an exponential function. It is also remarkable that the numerical value of this parameter is very similar for the wind speed predictions and power production predictions obtained by the time series models.

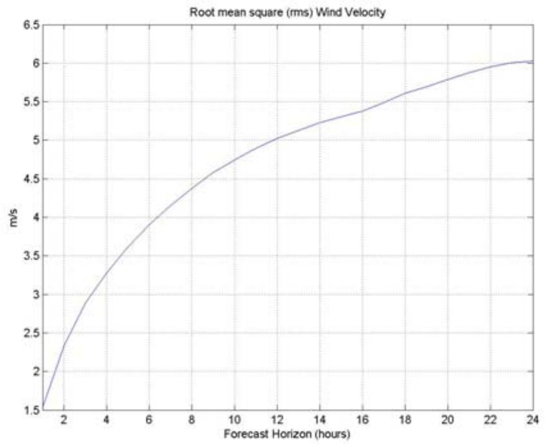

Figure 20: Root mean square error between the AR model and wind speed measurements, forecast horizons between 1 and 24 hours.

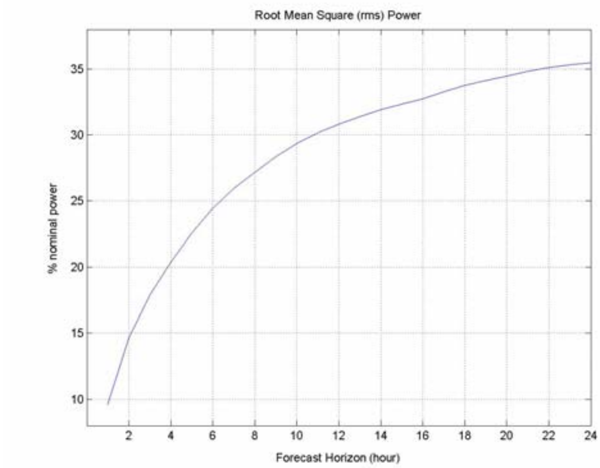

Figure 21: Root mean square relative to the wind farm nominal power, forecast horizons between 1 and 24 hours.

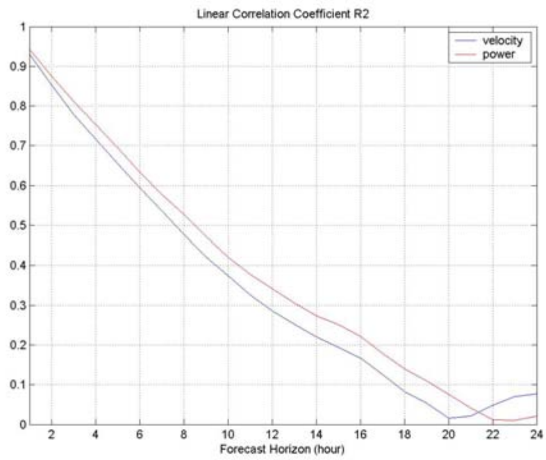

Figure 22: R^2 coefficient of the fitted model for wind velocity and for the wind power, forecast horizons between 1 and 24 hours.

According to the results obtained with the time series model, it can be seen that the first 3 or 4 hours forecasts are improved by the use of the time series when they are compared to the predictions calculated with MM5+MOS.

3.6 Conclusions

CENER prediction model has been tested in a complex terrain wind farm. All the modules included in the model have been tested individually, showing that a high quality power prediction can be obtained.

The simulation of the wind farm can be done with a high level of precision by means of the developed power curve models. The error of this simulation is below 2% of the installed capacity.

As it has been shown, the main error source is the wind forecast. MM5 predictions have been calculated using a nested domain configuration, being the last one a high resolution domain (3 x 3 km^2) in order to improve the quality of the wind predictions. With this configuration and the use of the advanced MOS module, the errors of the wind speed forecasts are below 2 m/s in average (rmse).

The combination of MM5 forecasts with the MOS corrections and the wind farm power curve gave an accurate prediction of the wind farm power production. The average error of the power production is 14% of the wind farm nominal power (rmse), with a high level of correlation (determination coefficient R^2 = 0.77 in average).

The validation period used is relatively short (5 weeks) although it is homogeneously distributed between June and October 2003, a larger validation period is presently under calculation.

The results will be improved when the non-linear wind farm power curves will be used in conjunction with the MOS module.

The time series module give an accurate prediction of both wind speed and power production for the first prediction horizons (up to 4 hours), with errors below 10% of installed capacity and R^2 above 0.9. The combination of the forecasts generated by the time series module, with the forecasts generated by MM5+MOS+Power curve provides the optimum power production forecast for each prediction horizon.

3.7 Aknowledgements

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