# COMPARISON OF METHODS FOR POWER CURVE MODELING

**SESSION *FORECASTING CHALLENGES AND SOLUTIONS***

**Wednesday, March 31, 2004, 10:30 am – 12:00 pm**

**GLOBAL WINDPOWER 2004 Chicago, Illinois (USA)**

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## 1. Abstract

Power curve modeling from wind speed, wind direction and power output measurements allows forecast wind farms power once the prediction of wind speed and direction has been made. Therefore it is important to obtain a reliable empirical dependence between these variables.

In this paper, a comparison of five different methods based on statistical tools is presented. The methods are conditioned to the availability of data and are named as follows:

a) Global power curve referred to meteorological mast
b) Global power curve referred to nacelle anemometers
c) Cluster power curves referred to nacelle anemometers
d) Turbine power curves referred to nacelle anemometers
e) Fuzzy logic power curves

The comparison is made for a validation period so that two parameters are used to evaluate the prediction of output power:

1) Determination coefficient $(R^2)$
2) Root mean square error (rms)

A substantial improvement is observed over the evaluation parameters as the models are more accurate and take into account more effects (models a. to e.)


## 2. Introduction

Wind power forecasting tools are becoming helpful especially in countries with an important wind energy installed power. Prediction tools can make wind energy be competitive with other energy sources in a liberalized energy market context. Deviations between scheduled and real production have always a penalty which is in most cases an important obstacle for wind energy producers in order to access to the energy market.

A significant aspect is related to the efficient use of electrical networks. Prediction tools are very useful in areas characterised by a high concentration of wind farms and a limited capacity of network. The load at a certain node can be optimised by an operator by means of this type of tools, minimizing the losses of energy.

That's why the accuracy of predictions is a critical point that determines the value of forecasts. The most of Spanish wind farms are located in complex terrain where wind forecast is normally more difficult than in flat areas mainly due to terrain local effects (topographical and thermal) that modify wind flow.

One way for predicting a wind farm power would be forecast wind speed and direction through a numerical weather prediction (NWP) model and convert them into a production value by means of a wind farm power curve. However, these NWP models are limited by their grid scale so that effects with a characteristic dimension (spatial and temporal) smaller than this resolution cannot be solved explicitly. These circumstances recommend adding other techniques in complex terrain areas in order to decrease prediction errors such as high resolution physical modelization, statistical downscaling, power time series, etc.

CENER prediction model comprises all these facilities and gives a solution to power prediction at different levels.

Input data to the model consist of numerical predictions given by a global or regional model and local measurements (wind speed, wind direction, air temperature, air pressure and power production) at a meteorological mast located in the wind farm. A mesoscale meteorological model (MM5) uses the outputs of a global or regional model as initial and boundary conditions and generates high resolution wind forecasts in the area of the wind farm with a 1x1 $km^2$ resolution. The CFD module reads the MM5 forecasts at the nodes over the grid and performs a simulation of wind flow with a spatial resolution of meters.

An advanced Model Output Statistics module (MOS) improves more wind forecasts detecting and removing the systematic errors through a powerful statistical process based on historical wind predictions and simultaneous meteorological mast data.

Wind forecasts are finally transformed into power forecasts through the wind farm power curve module, which is specially analyzed in this paper.

The time series module generates in parallel an independent forecast based on wind and power measurements of the wind farm. This module reduces the errors for the first hours taking advantage of the persistence of the wind. Figure 1 shows CENER prediction model structure.

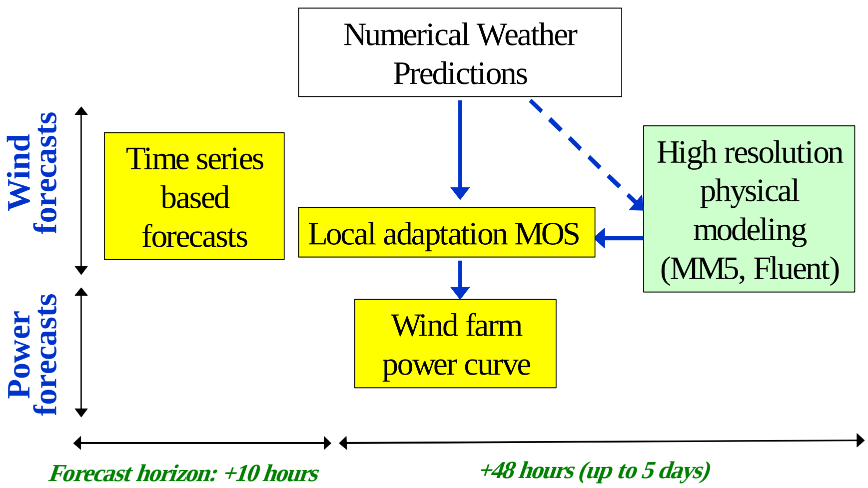


Figure 1 CENER prediction model structure

Another application of the developed wind farm power curve models is to characterize the performance of a wind farm or a wind turbine being possible to detect variations in the power curve with a high degree of precision.

## 3. Power curve modeling

### 3.1 General features

Power curve modeling allows predict wind farm power for a predicted wind speed and direction. This modeling 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 use of each method is conditioned to the availability of data (historical data of wind speed, wind direction and wind farm output power) so that the more data are available, the more accurate the results are. All the methods have a tunning period during which they are fitted and a checking period for validating them.

The study used the same tunning and validation period so that one or more power curves were obtained during the tunning period (Jan01-Aug01) and applied for the validation period (Sep01-Dic01). 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 first modeling.

The data used in the analysis belong to Alaiz wind farm located in Navarra, at the North-East of Spain. The terrain in the area is classified as complex (figure 2) with steep slopes and considerable changes on altitude. Alaiz wind farm is formed by 50 turbines (660 kW rated power) installed on the top of a hill with an average height above sea level of 1050 meters.

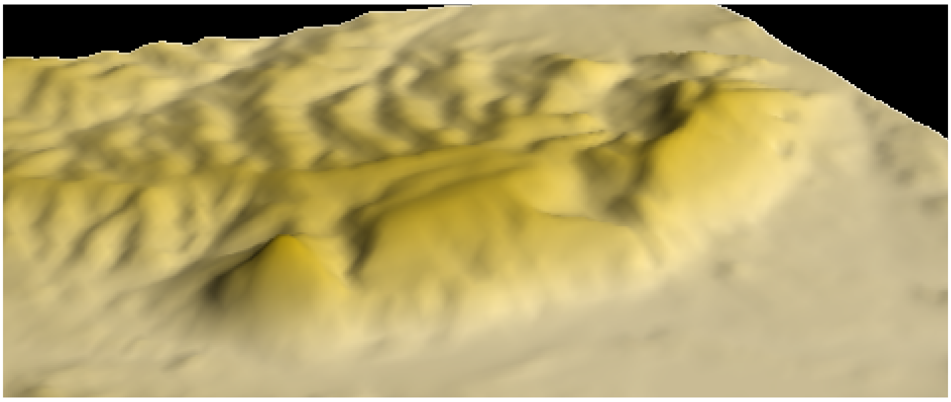

Figure 2 Alaiz wind farm area

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 depending on the power control (pitch controlled: correction over wind speed or stall regulated: correction over output power). Taking into account that 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:

1) Determination coefficient (R2)
2) Root mean square error (rmse)
3) Relative error to the wind farm nominal installed power

### 3.2 Linear models. Binning methods

Binning methods consist of discretizing wind speed and wind direction data measured at the mast into speed bins and direction sectors so that a mean output power is obtained for each corresponding speed bin and direction sector.

The bin width and the number of sectors were optimised in the analysis for a bin width of 0.5 m/s and 16 sectors. The result is a power curve (output power vs wind speed) for each sector and a global power curve.

- Model 1: <u>Global power curve referred to meteorological mast</u>

This model compares directly the global wind farm power to the normalised wind speed measured at the met 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 indeed for 16 sectors and a bin width of 0.5 m/s, as it was expected.

There were not available data for air pressure and air temperature during Jun01 so this month could not be included in the tunning period for this model and for the subsequent ones.

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-Dic01) and a simulated power was obtained. Figure 3 shows the comparison between this simulated power and the measured one.

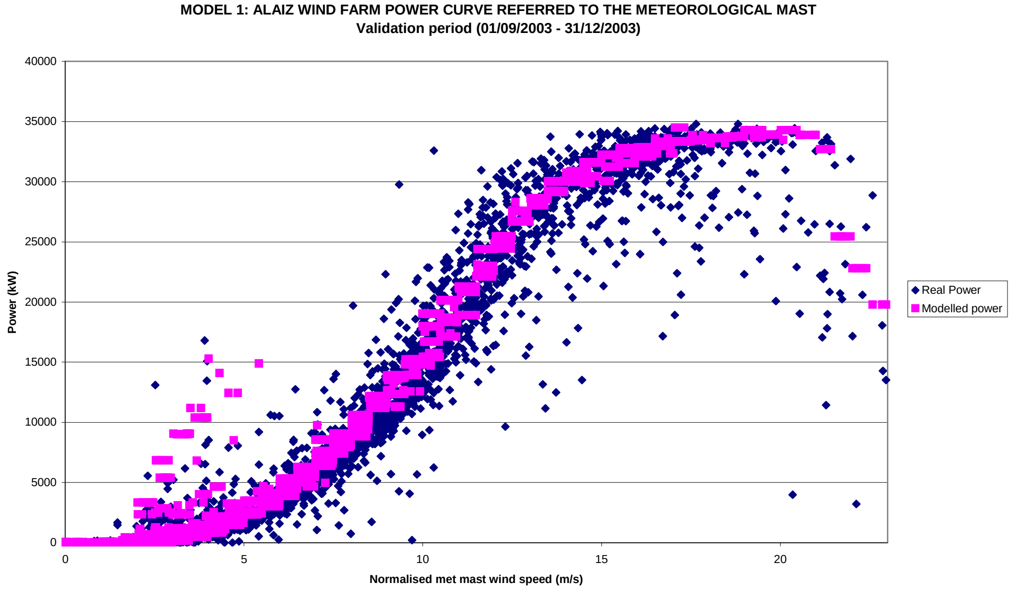


Figure 3 Modelled and real power curves during the validation period for MODEL 1

- Model 2: <u>Global power curve referred to nacelle anemometers</u>

This second model uses wind speed measured at the nacelle anemometers assuming this is a more representative measurement around the area. Unfortunately, these speeds were not measured in Alaiz since Jun01 until 13Dic01 so that the validation period was reduced to the 2$^{nd}$ half of December 2001. The available nacelle wind speeds were filtered and an only wind speed series averaged for all the turbines was obtained. This series was synchronized again to wind direction at the met mast and to global output power.

The resulting power curve obtained during the tunning period was again applied during this second validation period so that the simulated power was compared to the measured one.

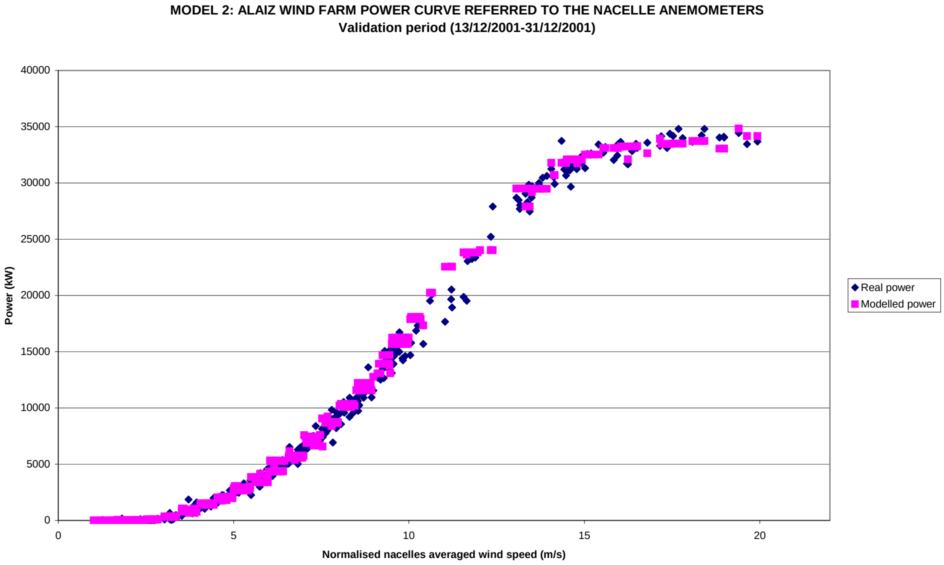


Figure 4 Modelled and real power curves during the validation period for MODEL 2

- Model 3: <u>Cluster analysis to determine subsets of wind turbines. Cluster power curves referred to nacelle anemometers</u>

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 arranged by means of a **cluster analysis** applied to the turbines power data so that a group of turbines was obtained attending to production homogeneities criteria.

According to the dendrogram in figure 5, five turbines subsets could be obtained after filtering output power data and applying a cluster analysis based on a hierarchical clustering and complete links (maximum distances between groups). From this point, a similar method to the 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 met mast and cluster output power. These curves were applied during the validation period in order to get an output predicted power for each cluster. By adding these cluster productions, a global wind predicted power was obtained and compared to real data (figure 6).

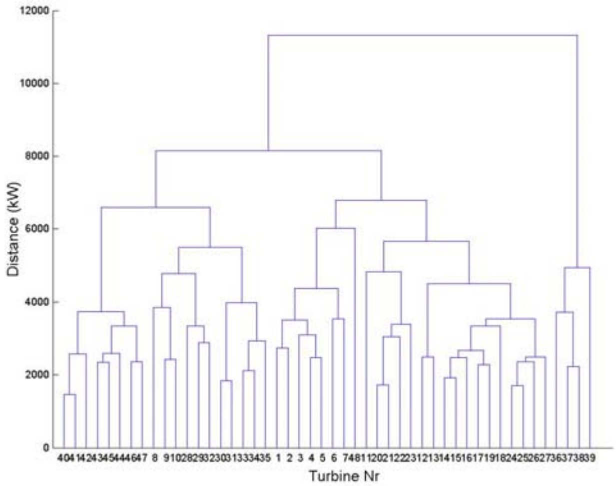


Figure 5 Cluster analysis dendrogram

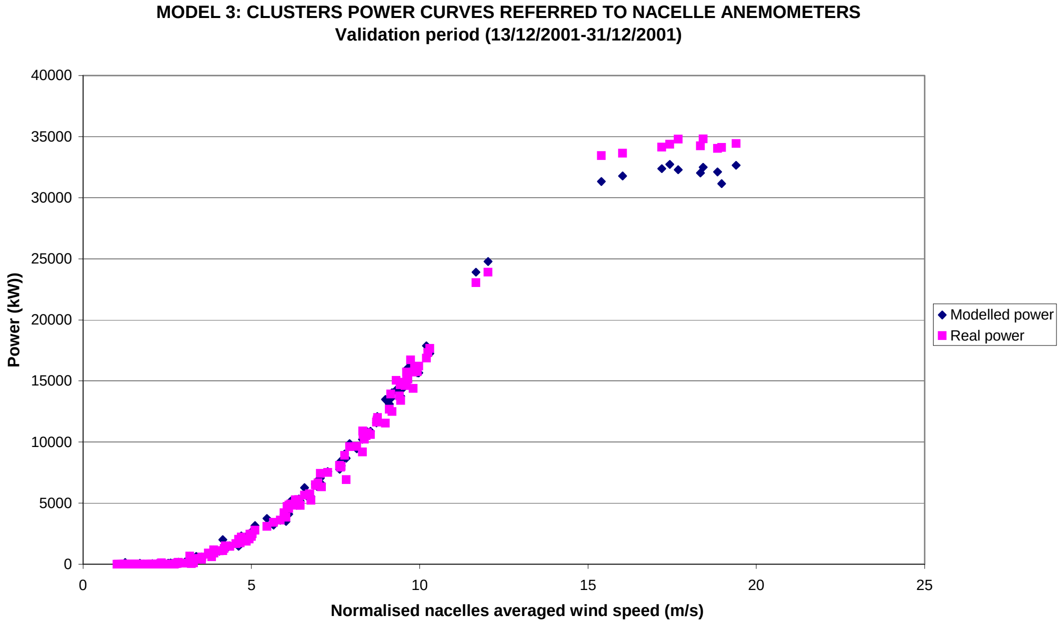


Figure 6 Modelled and real power curves during the validation period for MODEL 3

- <u>Model 4: Turbine power curves referred to nacelle anemometers</u>

An extreme case derived from the model before consists of obtaining different power curves for every turbine instead of making groups and applying the same process as explained above. Therefore, this modified-model 3 uses as inputs normalised nacelle wind speed, meteorological mast wind direction and turbine output power. Once filtered, these measurements allowed obtain **a power curve for each turbine**, which was applied later over the validation period. The output power for this period was added for all the turbines in order to get the global wind farm power and was compared to real output power.

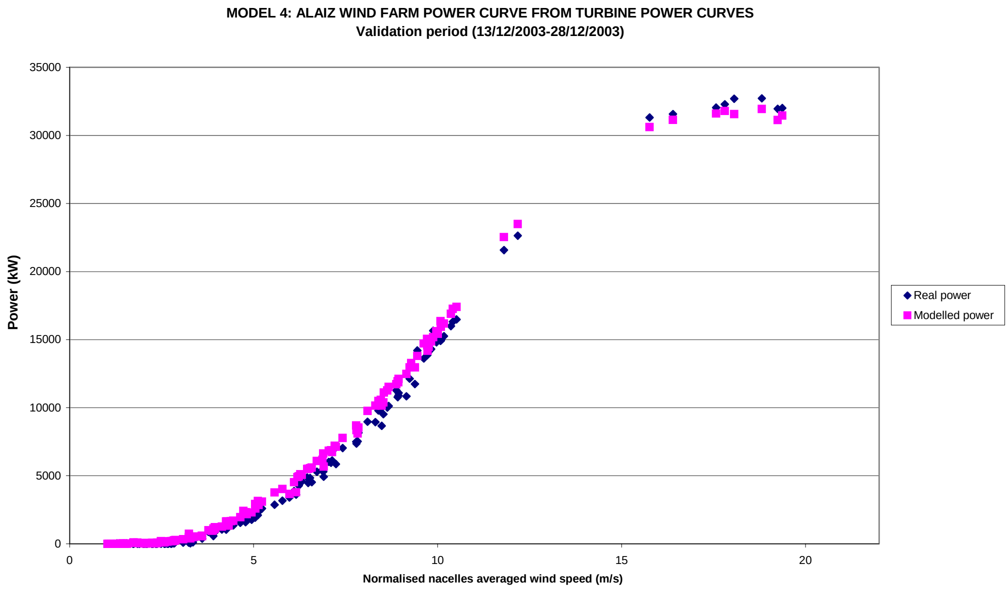


Figure 7 Modelled and real power curves during the validation period for MODEL 4

## 3.3 Non-linear models: fuzzy logic power curves referred to nacelle anemometers

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. Like in the models before, fuzzy logic method fits these functions for a tunning period attending to minimum rms criteria over another validation period. Once tunned, these transfer functions are applied during the validation period giving as result a simulated power which is again compared to real power.

Several iterations are needed to get the optimal fitting so that there are a critical number of them from which an improvement in terms of rms is not observed (see figure 8.a). As it can be observed, rms between modelled and real power is minimum at approximately 80 iterations. From this point, rms fluctuates considerably around 600 kW approximately.

Fuzzy logic model was applied over two groups of data:

1) Wind farm data: averaged nacelle wind speed, meteorological mast wind direction and wind farm power. An only power curve was obtained for this case (see figures 8 and 9).
2) Wind turbine data: turbine nacelle wind speeds, met mast wind direction and wind turbine power. Fuzzy logic was applied separately to every turbine to get different power curves so that a different turbine power curve was simulated during the validation period.

Figure 8 also shows the time evolution for the modelled and measured power as well as their corresponding power curves during the validation period. Tunning for both series is acceptable and big discrepancies were not detected.

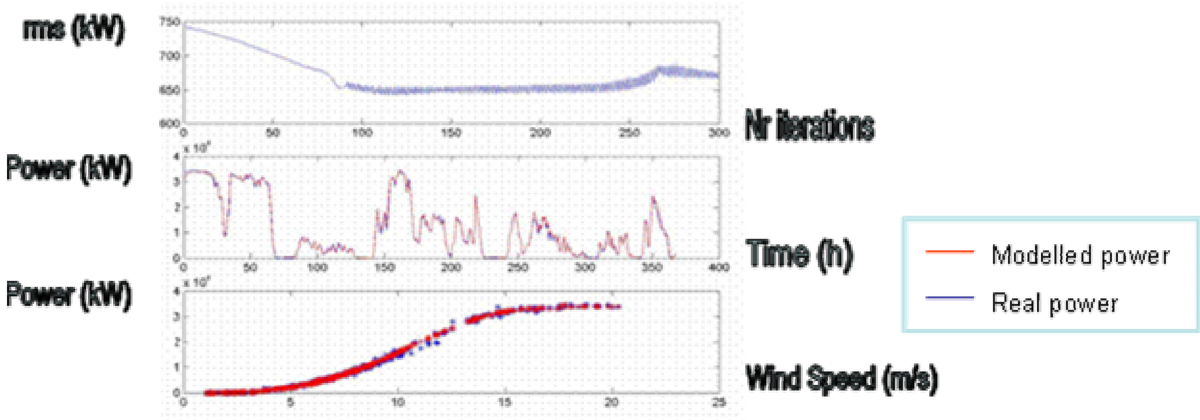


Figure 8 a. Evolution of rms with the number of iterations b. Predicted power vs measured power during the validation period c. Modelled power curve vs real power curve during the validation period

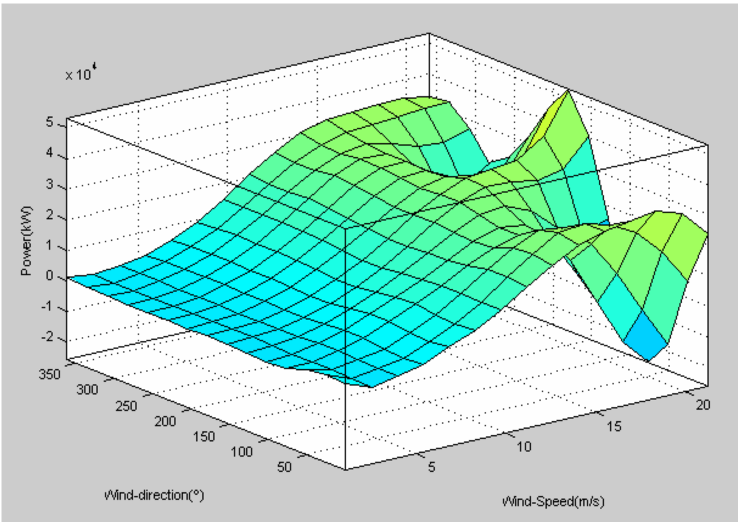


Figure 9 Tranfer functions between wind speed-wind direction and output power

## 4. Results

The table on the next page shows the results obtained for all the models as for R2 and rms **always between modelled and real power during the validation period** as well as the tunning and the validation period used for everyone. The results corresponding to the fuzzy logic model are separated for both groups of data explained above.

Model 1 afforded an rms of 2863 kW (8.65% of the nominal installed wind farm power) and a determination coefficient of 0.947. The best improvement was observed between model 1 and 2 when nacelles anemometers wind speeds were used getting a decrease in rms from 2863 to 851 kW and resulting in a 2.68% of the nominal power.

From this point, small improvements were observed for model 3 and 4 by making the analysis with groups of turbines (cluster analysis) or even with each wind turbine, getting as much a production rms of 1.91%.

Similar results to the ones in model 3 were achieved for the fuzzy logic tool applied over the wind farm with a minimum production rms of 696.24 kW (2.19% of the nominal power).

The best results were obtained when the fuzzy logic tool and the tunning over the transfer functions were applied for each wind turbine. This method afforded for 300 iterations a rms of 496.43 kW (1.53% of the nominal power) and a R2 value of 0.9989.

| Model Nr. | Training period | Validation period | R2 | rms (kW) | rms / Nominal Power (%) |
|---|---|---|---|---|---|
| 1 | Jan01-May01 Jul01-Sep01 | Oct01-Dic01 | 0.947 | 2863 | 8.65 |
| 2 | Jan01-May01 | $2^{nd}$ half Dic01 | 0.995 | 851 | 2.68 |
| 3 | Jan01-May01 | $2^{nd}$ half Dic01 | 0.996 | 673 | 2.11 |
| 4 | Jan01-May01 | $2^{nd}$ half Dic01 | 0.996 | 632 | 1.91 |

| Model Nr. | | Training period | Validation period | Nr iterations | R2 | rms (kW) | rms / Nominal Power (%) |
|---|---|---|---|---|---|---|---|
| 5 | Wind farm | Jan01-May01 | $2^{nd}$ half Dic01 | 5 | 0.9979 | 777.96 | 2.44 |
| | | | | 20 | 0.9980 | 762.38 | 2.40 |
| | | | | 70 | 0.9982 | 728.05 | 2.29 |
| | | | | 100 | 0.9984 | 701.76 | 2.21 |
| | | | | 200 | 0.9984 | 696.24 | 2.19 |
| | | | | 300 | 0.9984 | 696.24 | 2.19 |
| | Wind turbine | Jan01-May01 | $2^{nd}$ half Dic01 | 5 | 0.9982 | 565.73 | 1.78 |
| | | | | 20 | 0.9982 | 566.43 | 1.78 |
| | | | | 100 | 0.9989 | 495.85 | 1.56 |
| | | | | 300 | 0.9989 | 486.43 | 1.53 |

## 5. Acknowledgements

This study has been carried out thanks to Alaiz wind farm data provided by Energía Hidroeléctrica de Navarra (EHN).

## 6. References

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