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Local Short-term forecasting for Wind Power Plants in Brazil

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Wind Power in Brazil

The Brazilian government aims to increase the share of renewables to 10% of annual electriciy consumption within the next 20 years. Over the last years shortages in rainfall and reservoirs caused problems in the supply by hydroelectric plants.
The PROFINA programme started in 2002 to promote biomass, wind and small hydro generation to 3300MW by the end of 2006. Although this ambitious target was not met, wind power is believed to complement hydro generation in a much larger scale in the coming years.
Despite the currently low wind power penetration, wind power predictions are vital, because of the comparably weak grid infrastructure. In particular single site forecasts are needed as aggregating effects (smoothing of the forecast error) are small. 300 MW will be rated by the end of 2006.

Wind Farm Usina Eólica de Horizonte

Wind power predictions are computed for the wind farm Usina Eólica de Horizonte that is located in the East of the state Santa Catarina (South of Brazil). The terrain is complex and about 1200m above sea level. The eight E40 turbines with 600kW nominal power (hubheight 46m) are owned by a group of private investors (CENAEEL).

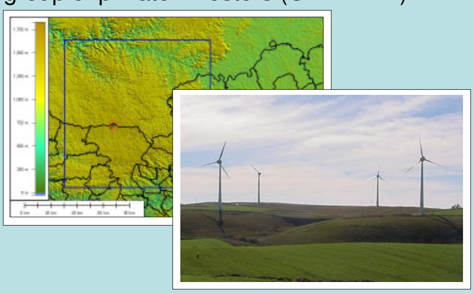

Fig. 1: Brazilian wind farm Usina Eólica de Horizonte (Santa Catarina, Brazil)

Wind Forecast Data

ECMWF 10m wind components and 2m temperature forecasts are interpolated to the site from 0.4° model fields. NCEP's GFS winds at 900hPa height are used at the four surrounding grid points (1.0° resolution) and are also interpolated to the site.

Forecasting Algorithm

A Neural Network (NN) is used as a statistical wind power forecasting algorihtm. The NN acts as a vertical extrapolation system to hubheight, Model Output Statistics (MOS) and fits the sectoral wind power curve. u, v wind components are the input and the produced wind power is the output.

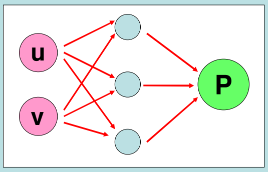

Fig. 2: Architecture of the Neural Network

Two examples of the sectoral power curve are shown in Fig. 3. As the plots are not radial-symmetric, winds from different directions are converted differently to wind power. In general 10m speeds are lower for the same power yield compared to 900 hPa wind speeds.

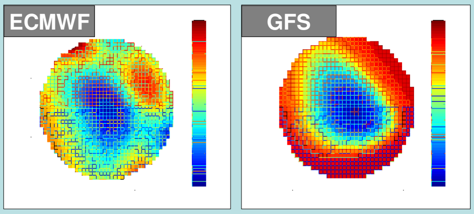

Fig. 3: NN wind power forecasting algorithms for ECMWF's 10m and GFS' 900hPa winds.

The NN algorithms are updated every 15 days and are derived with data pairs (forecasted winds and produced wind power) of the last 120 days.
The forecast horizon is 60h with 3 hourly resolution. Wind power production data is smoothed to hourly values. The study period is June 2004 to October 2005.

Wind Power Forecasting Performance

The root mean square of the error (RMSE) between forecasted and produced wind power is shown for several experiments against the look ahead time.
The usage of 10m ECMWF winds can be improved when the 2m air temperature is included (Fig. 4, left). The strong diurnal signal in the forecasting error is very much reduced, i.e. the 2m temperature alone can facilite the extrapolation to hubheight.

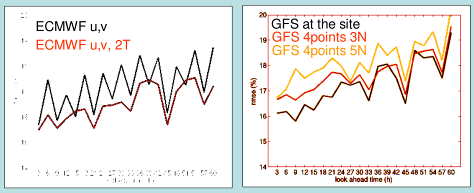

Fig. 4: Wind power prediction error for experiments with ECMWF and GFS winds.

It is not approriate to include wind information of all four surrounding grid points for GFS compared to wind information at the wind farm site (Fig. 4, right). The increased number of neurons (5) even degrades results.
The results are better for ECMWF forecasts compared to GFS. The combination of input of both weather models is the best choice. In this case five input neurons are used (u10, v10, u900, v900 and 2m temperature).

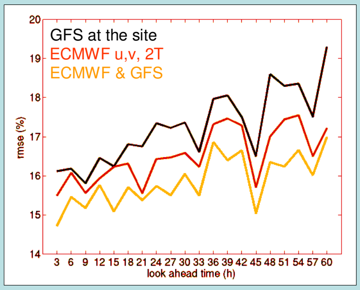

Fig. 5: Wind power prediction error for combination of ECMWF and GFS winds.

Conclusion

A Neural Network wind power forecasting approach for a single wind farm in Brazil shows errors between 15% and 17% of the installed capacity for look ahead times up to 60h. Results can be improved with additional use of the 2m air temperature, while the wind information from surrounding grid points is not benefitial and even prevents the NN from learning the statical relation. Combining wind forecasts from GFS and ECMWF is superior.

Acknowledgement

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