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Forecasting Wind Energy Production in complex terrain: impact of mesoscale modeling in a forecasting system

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Abstracts

DEWI has developed a short term wind power forecasting system based on a combination of physical and statistical methods. The physical model is based on global circulation forecasts, downscaled to mesoscale resolution with the atmospheric research model WRF. A set of artificial neural network (ANN) is then applied to describe statistically the relationship between the wind forecasts and the observed response of a wind farm.
Whistle the importance of both general circulation models and statistical methods have been extensively discussed in details by previous research activities, the effects of mesoscale models as intermediate step between global forecasts and statistical model is still under debate and questioned.
This work outlines the results of a comparison of three forecasts systems, the first based on the application of the mesoscale model WRF, a second on a direct linkage between the global forecasts to the ANN models and a third one which includes both global circulation data and WRF forecasts. The results of the three forecasting systems have been compared with real production data. The observational dataset used for the comparison is derived by 12 months of operational data collected at four wind farms in Italy. The wind farms are sited in complex terrain and affected by strong local atmospheric effects, such as stability and land-sea breezes.

Objectives

The aim of the work was to identify the value of mesoscale modeling in a short term power forecast chain. In particular the comparison has been focused to assess the ability of the mesoscale model to predict phenomena at a temporal resolution higher than the typical ones of the global forecasts.

Methods

Three forecasts systems have been developed: the first (**A**) based on GFS forecasts and Artificial Neural Networks (ANN) . The second (**B**) based on GFS fed into the mesoscale model WRF and ANN. A third system (**C**) differs from system **A** only for the presence of GFS time series as additional input to the ANN. Each of the three systems produced 72 hours ahead forecasts for a period of 12 months (2012-01-01 to 2012-12-31) with a 12 hours frequency cycle (703 forecasts over 732). The results of the forecasts have been compared with production data collected at 4 wind farms in southern Italy sited in medium and high complex terrain; the wind farms differ each other for climatology, number and models of wind turbines.

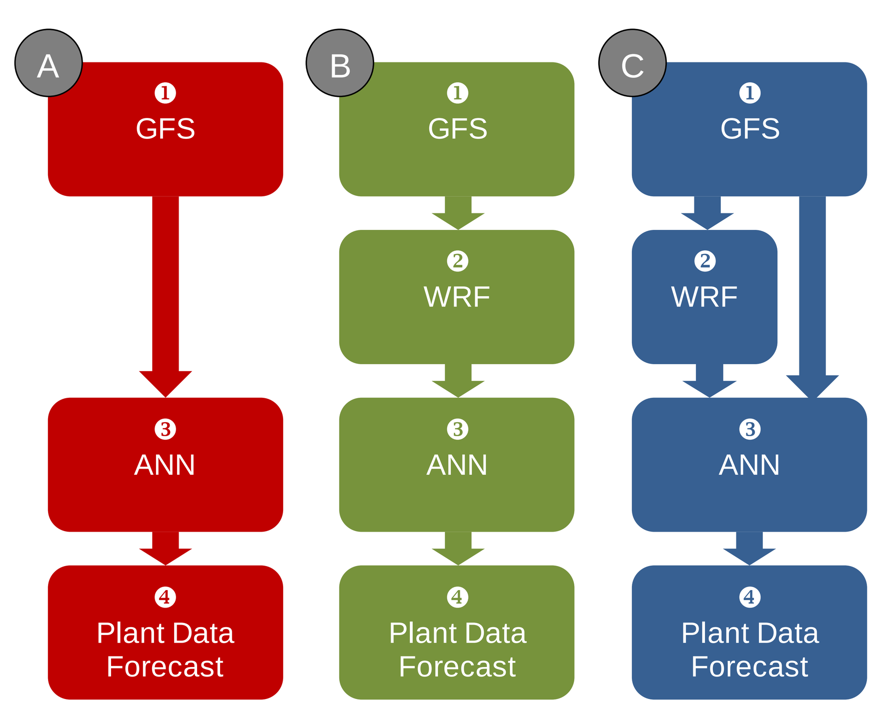

Figure 1: Scheme of the three forecasts systems

❶ GFS

NOAA GFS forecasts have been applied as principal input of all forecasting systems. U and V have been used for the forecasting system **B**. Several atmospheric parameters have been used to nest the mesoscale model WRF for systems **A** and **C**.

❷ WRF

The WRF model has been run for systems **B** and **C**. The model have been setup for an area of about 1100 km x 800 km at 5 km resolution over southern Italy for year 2012. Each forecast spans over a period of 72 hours.

❸ ANN

The artificial neural networks (ANNs) have been built with 16 input parameters and a single hidden layer for system **A** and **B**. In case of system **C**, a two hidden layers ANN has been designed, with 20 input parameters. In all systems a single output parameter (wind speed) has been used. A back-propagation algorithm has been applied to train the network with the plant data.

❹ Plant Data Forecasts

SCADA data have been collected for 4 wind farms. The database comprises values of production, wind speed and wind direction at a sampling rate of 10 minutes along with information about the operational status of the wind farm. An additional ANN has been used to reproduce the relationship between the wind farm representative speed and the farm power curve.

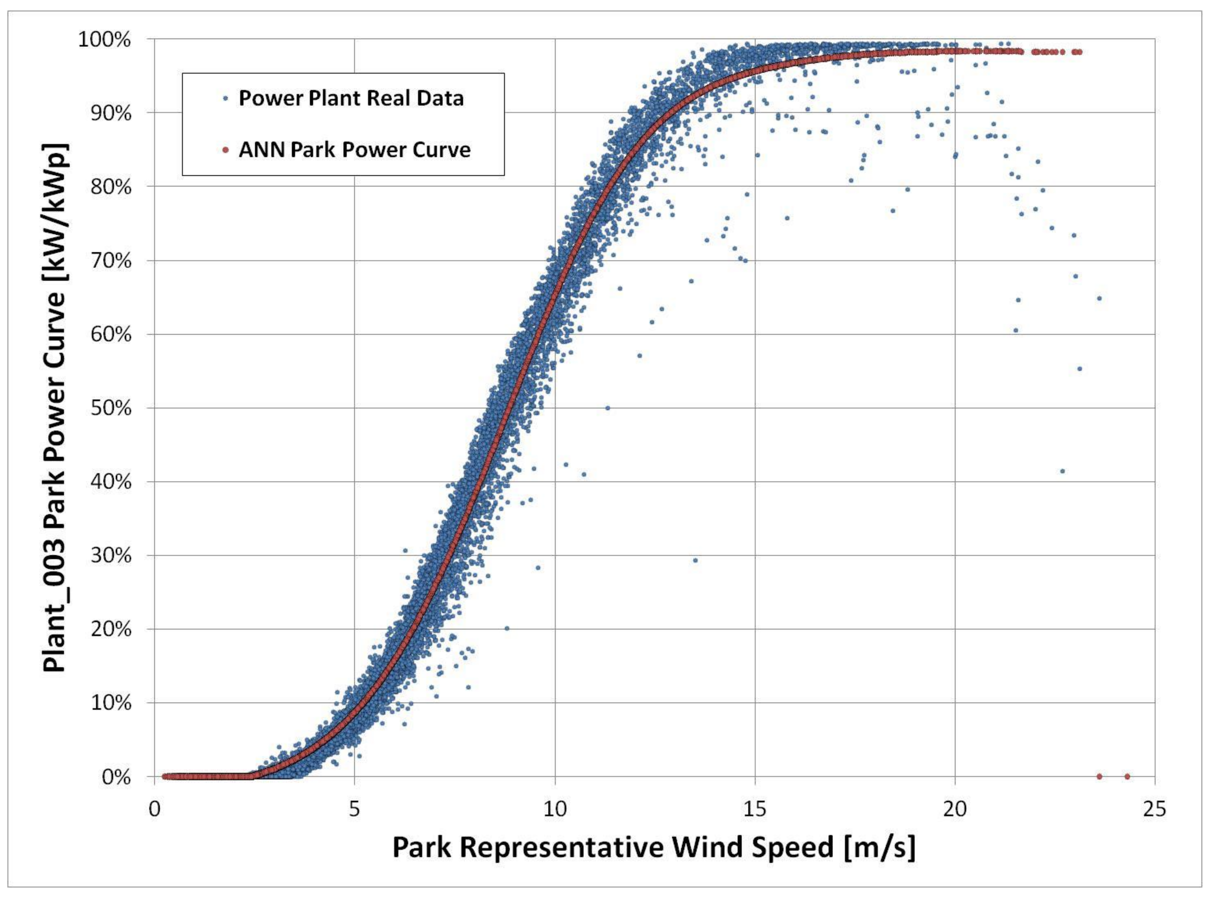

Figure 2: Park Power Curve for operational data and representation by ANN

Results

Short term power forecasts of the three different methods have been evaluated with usual statistical indexes (NMAE, NRMSE, MAE) (2). The results are compared with the persistency as metric of the predictability of the power production and, indirectly, of the complexity of the forecast.

For all the analyzed plants the forecasting system **C** produced more accurate predictions.

For the forecast system **C**, the average NMAE of the 72 hours ahead varied between 7.7% and 11.2% while the average NRMSE of the 72 hours varied between 12.4% and 18.2%.

The error growth with the lead time ($NMAE_{day3}/NMAE_{day1}$) has been contained an average value of 13% for the 4 wind farms. As a comparison, forecasts based on persistence would present an error growth of 64%. This suggest a good ability of the forecasts to reproduce the evolution of the power production even with strong temporal variations of energy production within the forecasting period.

The forecast system **B** based on only GFS simulations and system **A** based only on WRF simulations presented worse skill scores. In particular the system **B** appeared to reproduce realistic evolutions of wind speed in case of fast increase of power production (ramps, see figure 4, top). Nevertheless the ramps have been often affected by phase errors that the ANN was not able to correct (see figure 4, bottom). The system **A** even without describing the temporal evolution in detail presented better skill scores than system **B**.

Plant 001	Forecast Performace - 00:72 h Ahead				Improvement referred to Persistence		
	Samples	NMAE	NRMSE	Error Energy	NMAE	NRMSE	Error Energy
Persistence	38'008	17.9%	27.5%	104.3%	0.0%	0.0%	0.0%
Forecast Mod A	38'340	10.3%	16.4%	57.8%	-7.7%	-11.1%	-46.5%
Forecast Mod B	41'506	11.2%	17.4%	63.8%	-6.7%	-10.1%	-40.6%
Forecast Mod C	37'404	8.9%	14.2%	49.8%	-9.0%	-13.4%	-54.5%

Plant 002	Forecast Performace - 00:72 h Ahead				Improvement referred to Persistence		
	Samples	NMAE	NRMSE	Error Energy	NMAE	NRMSE	Error Energy
Persistence	41'147	25.9%	36.9%	101.9%	0.0%	0.0%	0.0%
Forecast Mod A	40'293	12.5%	19.8%	49.1%	-13.4%	-17.1%	-52.8%
Forecast Mod B	43'777	16.4%	23.9%	65.5%	-9.4%	-13.0%	-36.5%
Forecast Mod C	39'267	11.2%	18.1%	43.9%	-14.7%	-18.8%	-58.0%

Plant 003	Forecast Performace - 00:72 h Ahead				Improvement referred to Persistence		
	Samples	NMAE	NRMSE	Error Energy	NMAE	NRMSE	Error Energy
Persistence	34'031	21.8%	32.8%	92.4%	0.0%	0.0%	0.0%
Forecast Mod A	35'452	11.2%	17.0%	47.2%	-10.6%	-15.8%	-45.2%
Forecast Mod B	38'477	13.8%	21.2%	58.5%	-8.0%	-11.6%	-34.0%
Forecast Mod C	34'597	9.9%	15.6%	41.3%	-11.8%	-17.3%	-51.1%

Plant 004	Forecast Performace - 00:72 h Ahead				Improvement referred to Persistence		
	Samples	NMAE	NRMSE	Error Energy	NMAE	NRMSE	Error Energy
Persistence	44'187	18.6%	28.2%	102.5%	0.0%	0.0%	0.0%
Forecast Mod A	40'901	9.0%	14.2%	49.1%	-9.6%	-14.1%	-53.4%
Forecast Mod B	44'398	10.8%	17.1%	60.0%	-7.9%	-11.2%	-42.5%
Forecast Mod C	39'986	7.7%	12.4%	41.8%	-10.9%	-15.9%	-60.6%

Table 1: Skill scores for the three forecasts systems

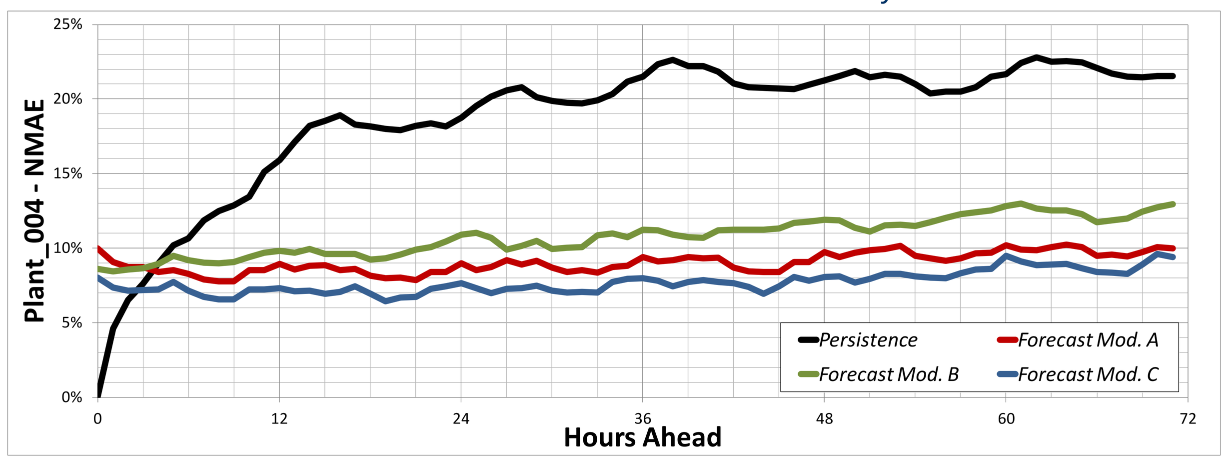

Figure 3: Forecast errors and lead time for Plant04

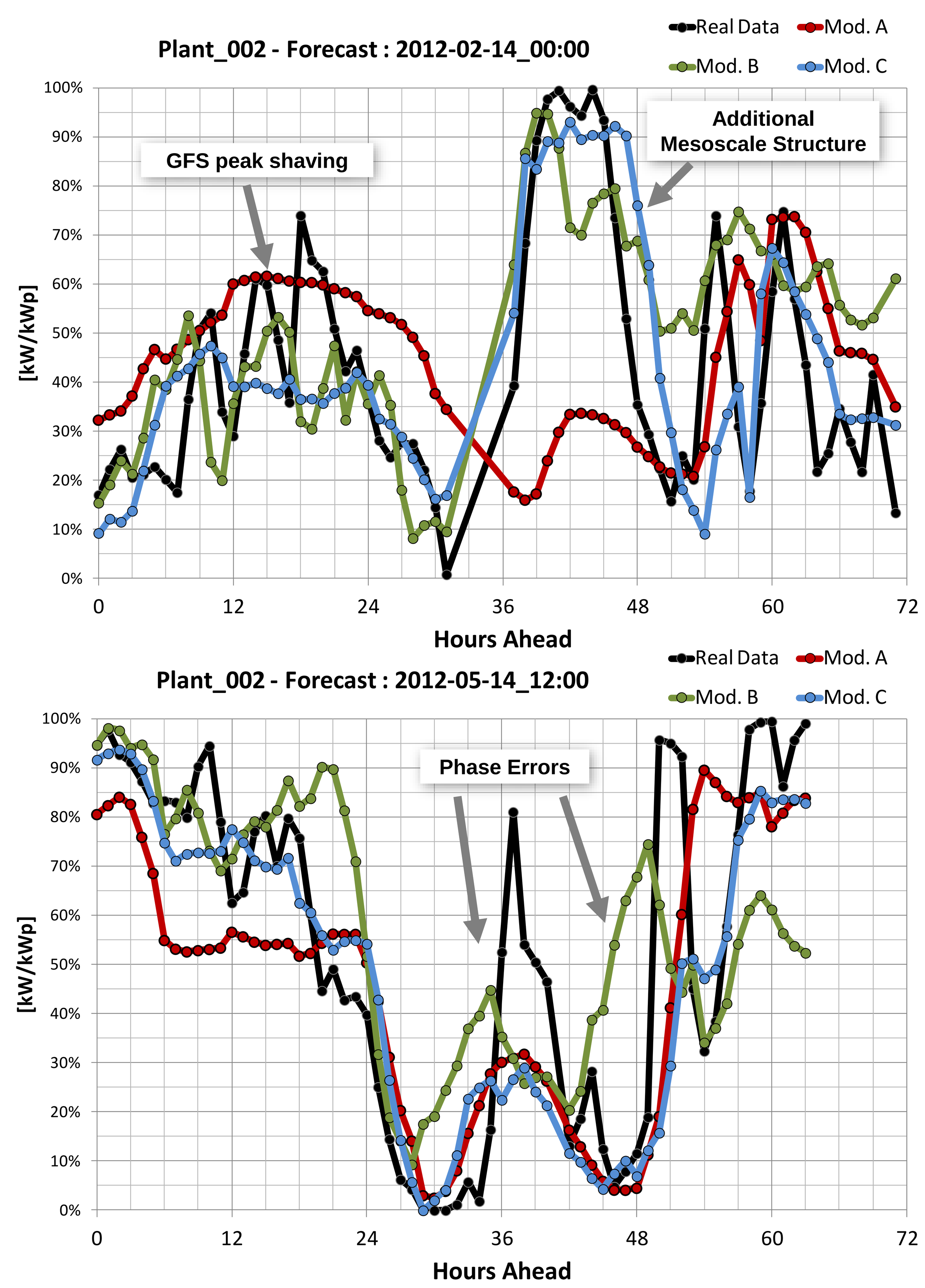

Figure 4: Evolution of the forecast systems during different events.

Conclusions

Results show that mesoscale modeling introduces additional information to the prediction of the power output in complex terrain. A direct improvement of the skill scores was only visible when mesoscale modeling time series have been fed to the ANN along together with GFS time series. In particular a qualitative analysis suggests that small scale phenomena like land-sea breezes and ramp-ups are often predicted more realistically by the system based on the mesoscale model than the one based on GFS. Nevertheless the metrics which was here applied penalizes the system based on pure mesoscale modeling since the predicted values are often affected by phase errors that the applied ANN is not able to mitigate

References

1. J Skamarock, C. et al. A Description of the Advanced Research WRF Version 3, NCAR Technical Note NCAR/TN-475+STR, 2008
2. Gong. L. Jing S.: On comparing three artificial neural network for wind forecasting, Applied Energy, 2010

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