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SHORT-TERM FORECASTING OF ENERGY PRODUCTION USING CFD SIMULATION

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Abstract

More and more governments require wind farm owners to deliver production forecasts for their wind farms. In Italy, the government will require regular forecasts beginning in January 2013. This has increased the demand from Italian wind farm owners to find good in-house forecasting solutions which can be adjusted based upon experience.

To meet these requirements, a forecasting tool has been developed combining wind speed forecasts from numerical weather prediction models (NWP), Neural Network (NN) corrections, and high resolution CFD simulations. Downscaling NWP by CFD simulations have proven added value, but there are some bottlenecks. These include the quality of the weather forecasts, and the accuracy of the power curve used for the energy calculation. To overcome these problems, a NN correction is used to adjust the forecasted wind speeds before they are used by the CFD. The CFD power forecast can be corrected by one NN or many NNs to improve the performance of the CFD forecast.

Method

The objective of this study is to compare the forecasted power of different NN approaches. The developed method is explained in *Fig.1*. A NN is trained to correct the NWP forecasted time series at the position of the met mast. Using this corrected data as real measurements, a CFD power forecast is performed for each turbine (*Fig.1* a). The NN is trained using long time series of NWP forecasts and wind measurements. The careful cleaning of this data is important to avoid an error affected training. The added value of a NN correction for the wind speed forecasts of this method has been proven in earlier published works [1].

The NN method that we present here is focused on the correction of the CFD power output. The first correction method uses a single NN for the whole wind farm (*Fig.1* b), while the second one uses a NN for each turbine (*Fig.1* c).

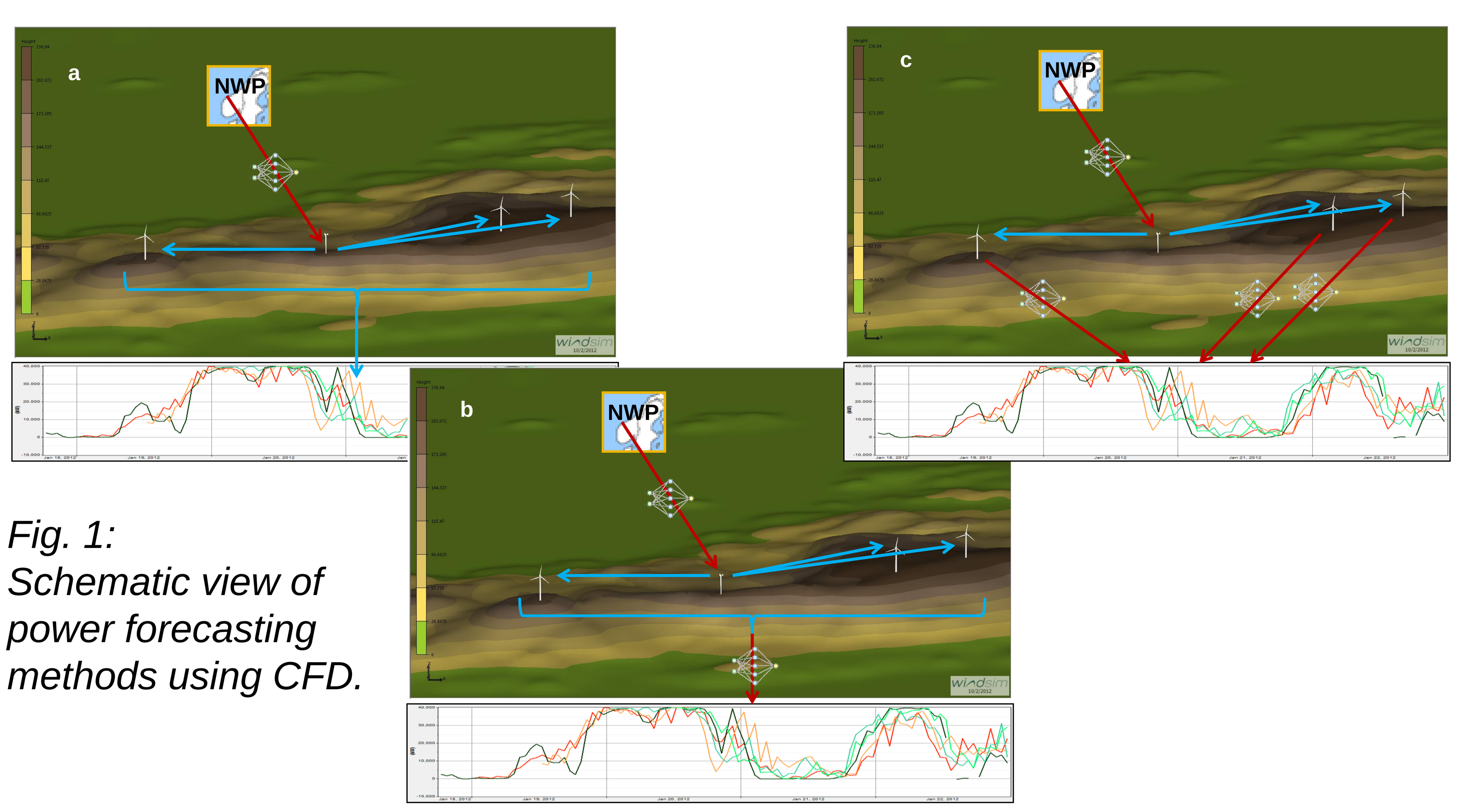

Fig. 1: Schematic view of power forecasting methods using CFD.

The NNs are trained using a long time history of power production data from SCADA. The calculation of the performance is done on the same data but on a time period which is not used in the training.

Site

The wind farm is located in central Italy. It consists of 20 turbines each 80m high. The nominal power of the WTG is 2MW and the rotor diameter is 60m.

The layout is quite wide, the main diagonal is almost 10km. The anemometer used as reference for the whole wind farm is 30m high and has several years of data.

The anemometrer data and the SCADA data are covering almost 3 years, from April 2010 to May 2012. Data from the entire year 2011 is used to train the NN. A complete year is used to avoid seasonal bias. The other periods are used to validate the performance of the different methods.

This site is quite complex and accurate NWP forcasts for central Italy are very difficult due to the complex orography and the warm sea.

The wind farm is wide and the anemometer is much lower than the hub height.

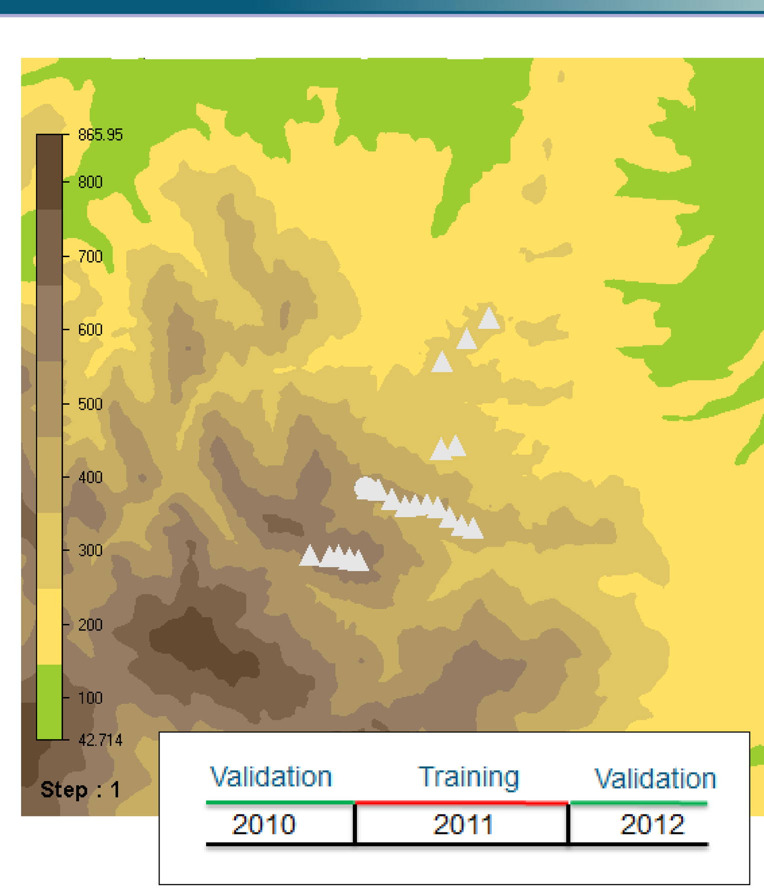

Fig. 2: Site layout and time series of wind and power data used for training and validation.

Results

To quantify the performance of the different methods, we calculated the Normalized Mean Average Error (NMAE), which is normalized towards the nominal power of the wind farm.

First we calculate the energy in the CFD model. Then the resulting time series of power production is used as input of a NN. Three cases are presented. In each case we add different inputs in the NN training:

- case 1 : pressure and temperature
- case 2 : wind speed and direction
- case 3 : use of the power series of case 2 and CFD output in a Hybrid Solution

We noticed that the CFD and the NN correction perform better at different power levels. The CFD is more accurate in the extreme cases: high production periods and calm periods. *Fig.3* displays the measured and the forecasted production during a period between March and April 2012. The two yellow lines divide the power history horizontally in three areas. In the central area, the NN corrected time series is the better forecast, while in the upper and lower area, the CFD describes the power production better. The Hybrid Solution, depending on the area we are, use the method performing best.

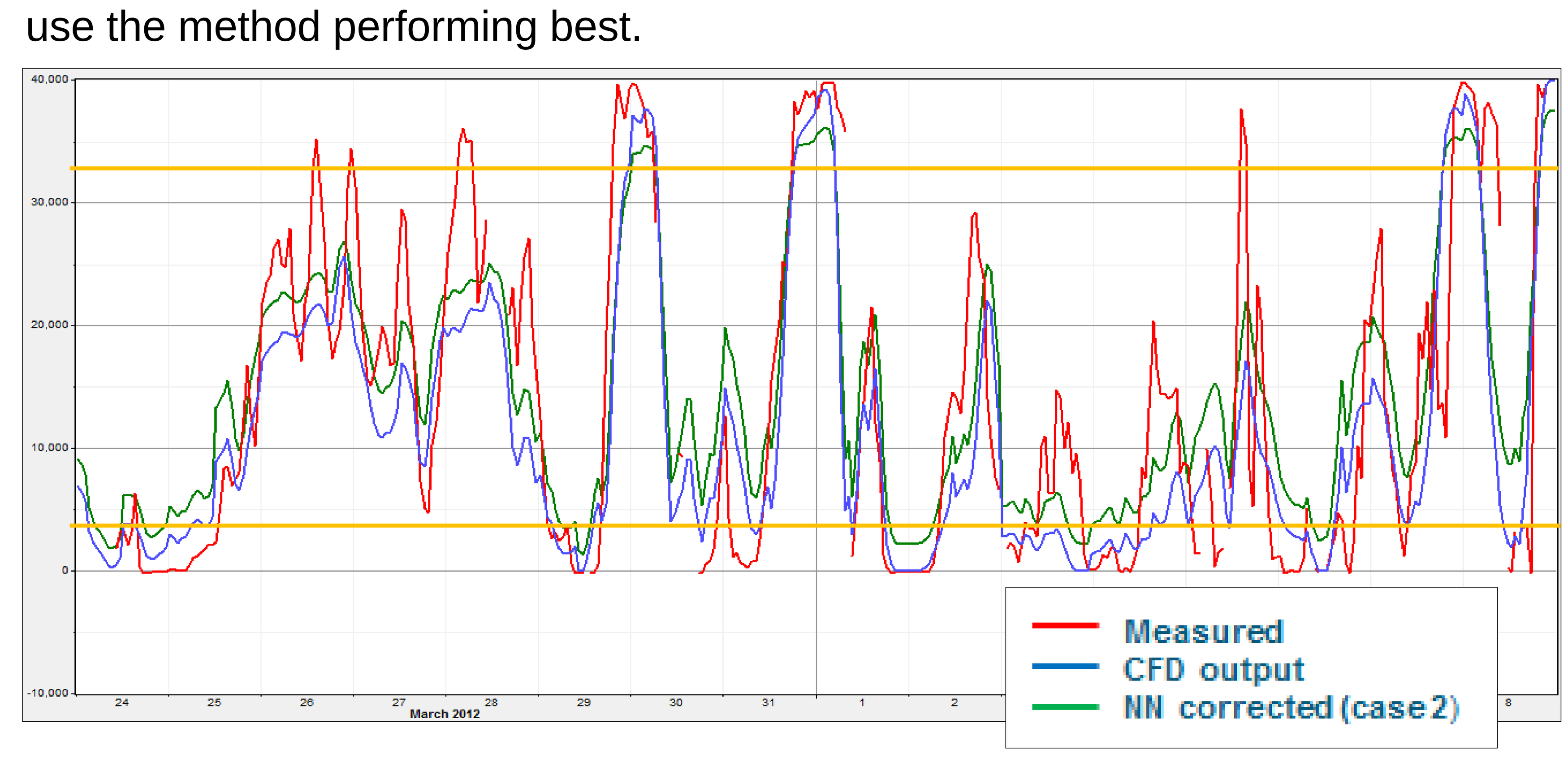

Fig. 3: Comparison of observed, CFD calculated, and NN corrected power.

All the cases are calculated; both using a single NN for the complete wind farm production, and with 20 NNs, one for each turbine production.

The left plot of *Fig.4* describes the gain in terms of normalized error of the NN correction for the single NN, and we can see the improvement of the performance in the three cases. The right plot displays the gain using 20 NNs instead of one.

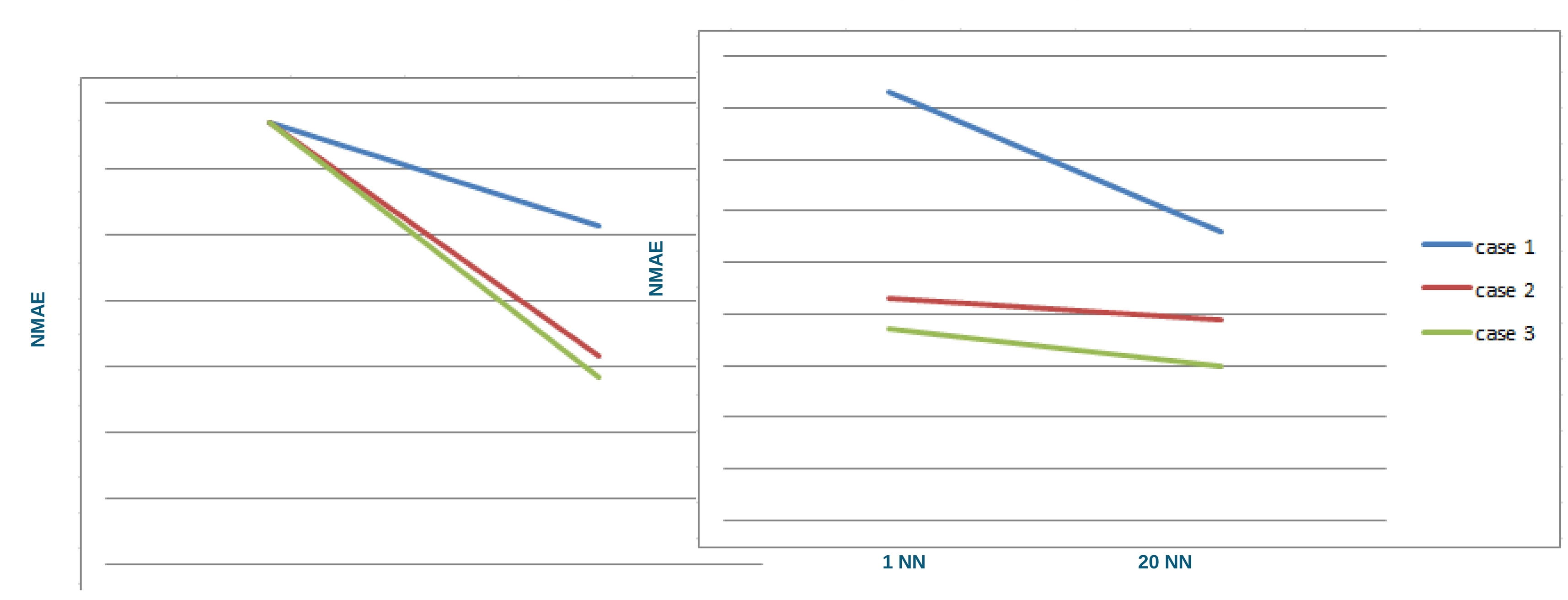

Fig. 4: Plots of NMAE improvement in the NN input cases (case 3: Hybrid S.)

The results describe, as expected, an improvement of the performance using the forecasted wind speed and direction, instead of pressure and temperature, and a further improvement using a Hybrid Solution. All these cases perform better training 20 NNs instead of one.

These improvements are time consuming, both for the training from 1 to 20 NNs and for the preparation of the production data used in the training. The CFD case does not need any production data, only the wind farm layout information: position and turbine characteristics.

Conclusions

A short-term power production forecasting system has been developed which has several forecasting modes; different training cases and number of NNs are used.

Depending upon the data availability and data quality of the wind farm, the forecasting can be further improved by using a Neural Network approach.

The NN method corrects the forecasted wind speed and the CFD calculated energy output of the wind farm. Validation results are promising, but using NN on the energy CFD output needs special attention: the quality of the production data used in the training can effect the performance significantly.

Using CFD improves the forecast for the high production and the calm periods. This is used to create a Hybrid Solution between CFD and NN forecasts.

[1] "SHORT-TERM FORECASTING USING MESOSCALE SIMULATIONS, NEURAL NETWORKS AND CFD SIMULATIONS" C. Meißner, A.R. Gravdahl , X. Wu, EWEA 2012