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Wind energy forecast in complex sites with a hybrid neural network and CFD based method.

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Abstract

The wind is an intermittent renewable energy source and the energy production forecast is a fundamental activity for many reasons (grid regulation, maintenance, etc.…).
In this work a hybrid method (based on weather forecast data, neural networks and computational fluid dynamics) and a pure neural network approach are compared in a complex terrain site.
The post processing of real production data has been discovered to be a key activity. Treatment and filtering of data spreading out from the supervisory control and data acquisition system are fundamental both for training and testing methods reliability.

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Nomenclature

RES	Renewable Energy Source
CFD	Computational Fluid Dynamics
SCADA	Supervisory Control And Data Acquisition
(A)NN	(Artificial) Neural Network
WRF	Weather Research Forecast
NWP	Numerical Weather Prediction
RANS	Reynolds Averaged Navier-Stokes

1. Introduction

Due to the stochastic nature of wind energy source, power production forecast is fundamental in order to balance energy production with programmable sources in a complex electric grid, especially with the increase of wind farm installations.

Transmission and dispatching of electricity into the grid are submitted to very strong constraints, in order to maintain continuous and instantaneous balancing between energy entered and requested and to guarantee energy frequency and voltage into a narrow range. Renewable energy dispatching has priority with respect to other kinds of energy.

Respecting these constraints is awkward because of the variability of production, transmission and demand and due to the absence of storage systems.

A program of injection and withdrawal is defined for each dispatching zone with 24 hours of advance: fees are assigned to the producers by the electric service provider due to mismatch between energy forecasted and actually entered into the grid.

An error on the forecasted power is allowed but after the first 6 months of 2013 such limit is set to 10%. The accuracy on wind power production forecast on 24 hours basis is therefore fundamental in order to limit charges due to the unbalance.

Wind power production forecast is an application of physical modeling [1] which can involve several different approaches: numerical methods from global to local scales, ensemble forecast, upscaling and downscaling methods; the prediction is implemented also with statistical methods and learning machines, or benchmarking techniques and uncertainty analysis [2].

The choice of forecast methods depends on the scale of prediction and on the tasks; a forecast of 3-7 days is useful for maintenance, while for power balancing a 1-72 h forecast is needed.

In wind power forecast models can be arranged in two main groups [2]:

1) wind time series analysis methods, with a statistical approach (this approach is generally used for long-term forecast [2]);

2) methods based on the input of weather forecast data for power prediction (this approach is used for short term forecast, because of the influence of the atmospheric dynamics on the flow [3]).

Forecast methods are further divided generally in physical methods, traditional statistical methods (named also black box methods) and learning approaches. Some hybrid methods involve features of all the approaches. The limitation in the applicability of learning or statistical approaches usually lies in the large amount and the quality of historical data needed, which might not be available.

From NWP it is possible to find the best configuration for wind speed and wind power forecast with the use of Kalman filtering [4] of numerical meteorological predictions.

There are many different statistical methods that attempt a link between historical data and power output in a unique step (black box), using NN tools [5] with different techniques, for example multi-layer perceptron (MLP) [6] or recurrent version [7].

NN are used also for long-term energy forecast or for predicting wind speed at a target site from wind speed and direction measurement at a reference site [8].

A lot of models are based on weather forecast data in order to provide a good power production prediction. Recently [9] the CFD was used in order to take into account local orography and wake effects in power forecast. In the present work weather forecast is provided by the WRF model that is used for meso scale predictions [10].

In the paper we compare different approaches to wind power forecast for a wind farm sited in the south of Italy.

The first method, which we shall name Full NN, is based on a pure Neural Network approach, while in the second method we employ a hybrid procedure, linking weather forecast data to speed and direction measures of a meteorological mast, and with a CFD procedure we estimate the power production for each turbine, simulating rotor effect on the wind flow with the actuator disc theory. The importance of employing Neural Networks techniques lies in the non linearity between the results of WRF meteorological simulation and the power output throughout the wind farm: actually in the present work we analyze how powerful this tool is for performing consistent forecast.

Also expertise on the SCADA control system of the wind turbines is employed: the SCADA is a control system spreading out on a 10 minute time basis a series of measurement and control counters channels for each turbine, building grounds for knowledge of the exact operational behavior of each turbine and of the whole park. There is a vast amount of literature on SCADA control systems: it can be applied for numerical investigation of wind turbine behavior, or even for training neural networks for predictive models, or on the other way round for providing a posteriori validation datasets for predictive models [11, 12, 13, 14]. In this work, the SCADA database has been judiciously filtered: only time steps during which all the farm was productive have been kept, and such filtered dataset of nacelle wind speed and power output of each turbine has been employed for training Neural Networks. This procedure automatically encodes in the ANN the knowledge of the orography of the farm and of the wake interactions and somehow bypasses the physical modeling. Actually it shall be shown that it significantly improves the quality of the forecast.

The plan of the Paper is as follows: in the first paragraph we briefly sketch our methods, first introducing the weather forecast model WRF used for our analysis, and subsequently discussing the NN models and the algorithms for the pure NN approach and the CFD methodology for the hybrid procedure. In the last part of the first paragraph the test case, the turbine technology, the wind farm and the SCADA data filtering process are discussed.

In the third paragraph we display the results of our simulations and analysis, including discussion and a benchmark of the methods, and a brief sketch of further developments of the present work.

2. Methodology

WRF is a mesoscale numerical weather prediction model which has been developed both for operational forecasting as well as atmospheric research [15]. It is based on two dynamic solvers, physics packages that interface with them, and pre-processing and post-processing packages. The solvers integrate numerically the compressible, nonhydrostatic moist Euler equation, using a terrain-following hydrostatic pressure vertical coordinate system. With such model, the forecasted variables are the two horizontal components of the velocity, the vertical velocity, the perturbation potential temperature, the perturbation geopotential and the perturbation surface pressure.

There is no linear relation between results of WRF and actual wind condition in the met mast point and amount of power generation in different turbines through the wind farm. As a matter of fact ANN have been the focus of great attention, due to their capacity in solving non-linear problems [16]. Hence, artificial neural network method can be useful to predict the wind condition in the met mast point and amount of power generation for each wind turbine. In [17] how powerful ANN method is in predicting the missing wind speed of target station depending on the correlation between the target and reference stations.

An ANN model has several layers: first, hidden and last. The first is an input layer, which includes all the input factors, and the last one is the output layer. The hidden layers process all data from the input layer. In the following step, the next hidden layer computes the output vector, which is finally processed in the last layer (output layer) to create the final result. The hidden and output layers have a transfer function. In this paper, hyperbolic tangent sigmoid, Log-sigmoid and Linear functions are used as a transfer function, whose output lies between -1 to 1, 0 to 1 and $-\infty$ to ∞ respectively.

In an artificial neural network, the first important step is the training. In the training step, an input is introduced to the network accompanied with the desired output. Initially, the weights and biases are set randomly. Since the output may not be what is expected, the weights and biases need to be finely tuned. During the training phase, random weights are changed by the back-propagation algorithm to produce a satisfactory level of performance. After training, the weights and biases contain meaningful information, whereas before training they are random and have no meaning. When a satisfactory level of the performance is achieved, the training will stop. Then the network uses these weights to make predictions.

In the present work, inputs in all of the created ANN models are the same. They are wind speed, wind direction and ambient temperature at three different heights (200, 300 and 400 meters above ground level) calculated by the WRF model. So we have 9 inputs for the each ANN model. We have studied the power output of 8 aerogenerators (turbines numbered from 3 to 10) and the wind speed and direction of the met mast sited inside the wind farm, so we totally have nine ANN models created for predicting wind speed and amount of power generation.

To evaluate model performance, coefficient of determination (R^2) was calculated from the results produced by the ANN model. R^2 measures the proportion of the variation around the mean. R^2 is 1 if the model fits perfectly, while a vanishing R^2 indicates that the fit is no better than the simple mean model. The coefficient of determination is defined by equation 1:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(T_i - O_i)^2}{\sum_{i=1}^{n}(O_i)^2}\right) \tag{1}$$

T is target value, O is output value.

For each ANN model, different architectures with different transfer functions were created in Matlab software in order to achieve the best performances. The best architecture for each model is shown in the Results section.

All WRF data, experimental wind condition at met mast point and amount of power generation in each turbine have been synchronized. After synchronizing all data, the set is built of 1366 stamps (hourly averaged values) from 24 Jan 2013 to 27 May 2013. All of the data from 24 Jan 2013 to 30 Apr 2013 were used for training and all of the data in May 2013 were used for testing. The training data have been used for training the ANN model and testing data were used for distinguishing ANN model accuracy in estimating output.

The validity of the ANN models was ascertained by comparing their result with the corresponding experimental data.

In the hybrid-model the wind speed and direction time series predicted by ANN in the met-mast position have been used as input to forecast the power production of the wind turbines through CFD (Computational Fluid Dynamics) simulations.

The numerical calculations were implemented using the Windsim CFD model: a numerical code based on PHOENICS, which solves the Reynolds Averaged Navier-Stokes (RANS) equations with a multigrid-coupled solver (MIGAL).

The wind field was simulated for twelve different wind directions (starting from 0° with a step of 30°).

All the simulations were performed using a boundary wind speed condition of 10 m/s at the top of the meso-scale domain; then the nesting methodology was used to calculate the local tridimensional wind field.

The use of CFD calculations can be coupled with different approaches (analytical, CFD based models or vortex) for wakes simulations.

The aerodynamics of wakes is exhaustively described in [18], while a review of the models can be found in [19].

Generally, when using analytical models, only very simple calculations are needed in order to have an estimate of the wakes losses; for a more detailed description of the wind farm aerodynamics more complex models can be applied to simulate the physics of energy exchanges.

Increasing the computational effort, the action of the blades on the wind flow can be represented through the actuator disc/surface/line model or the full rotor simulation. With the actuator disc model the interaction of the blades is simply represented through axial forces on the rotor surface disregarding the flow rotation; with the actuator surface model the force is distributed only on part of surface are swept by the rotor; in the actuator line model the forces are applied on radial line representing the blades.

A comparison of results from the different approaches can be found in [20]; in the present work the actuator disc method was applied to simulate the overall wind farm interaction with the terrain.

The flow field was calculated solving RANS equations; this technique can be considered one of the easiest ways to solve wake interaction flow with reasonably short calculation times [21] even with complex terrains and complex wind farm layouts.

Despite RANS solutions can not manage a turbulence modeling scheme able to reproduce faithfully the complex physics of wakes [22], this method can be successfully used for giving good results in term of energy losses and rough wind flow characterization [23, 24].

Inside the wind flow the action of the rotor is described, according to the Betz theory, though the axial induction factor:

$$u_r = (1 - a) * u_\infty \tag{2}$$

where u_∞ is the free stream velocity and u_r is the wind speed on the rotor surface at the hub height (center of the rotor).

The thrust coefficient for the whole rotor C_T is defined as:

$$C_T = \frac{F_a}{\frac{1}{2}\rho \cdot u_\infty^2 \cdot A} \tag{3}$$

where F_a is the thrust force, ρ is the air density and A is the rotor swept area.

CFD results have been used to evaluate the speed up from anemometer to turbine positions; the speed up is defined as the ratio between the speed at the center of the rotor and the speed at the anemometer. Starting from wind speed and direction estimated by ANN in the anemometer position, the wind speeds for turbine rotors is calculated for all the sectors using the following formula:

$$u_{jk} = S_{jk} \cdot u_{a,k} \tag{4}$$

where u_{jk} and $u_{a,k}$ are respectively the wind speed for turbine j in the sector k and the wind speed for the anemometer in the sector k. The speed up $S_{jk}$is computed from numerical results in the position of turbine j for the direction sector k:

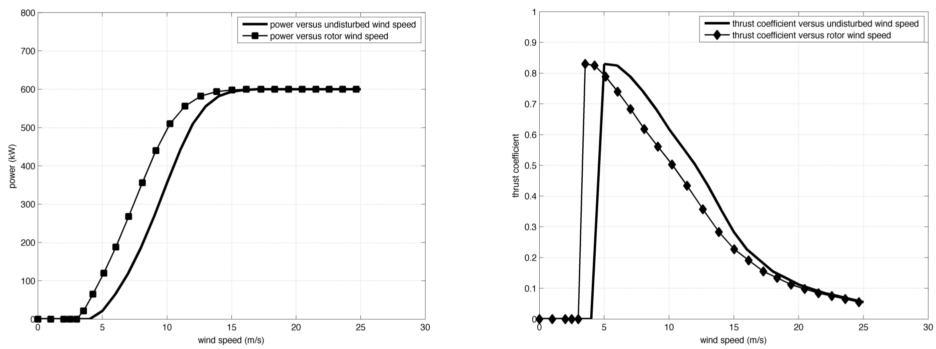
$$S_{jk} = \frac{(\text{wind speed})_{\text{turbine}}}{(\text{wind speed})_{\text{anemometer}}} \tag{5}$$

With this method it is possible to transfer the time history calculated by ANN from the anemometer position in each rotor position. With the rotor wind speed and direction on the turbine positions it is possible to compute the power output of each turbine.

The numerical simulations were performed twice: considering only the effect of the terrain (undisturbed wind field) and including the effect of the rotor (with the actuator disc model).

The power output can be calculated using turbine power curve; anyway, when dealing with actuator discs, it is necessary to refer the power curve to the rotor wind speed; in this case the axial induction factor a can be estimated using the thrust coefficient and the following equation from the 1-dimensional theory:

$$C_T = 4a(1 - a) \tag{6}$$



(a) (b)

Fig. 1. Power curve (a) and thrust coefficient (b) considered for the aerogenerators.

Using the speedups it is possible to have two different version of power output estimation: one considering the free wind field and one considering wakes and the action of the actuator discs. Dealing with real data we can have many different intermediate operational conditions according to wind variability and to the thrust coefficient curve of the aerogenerator, so that weighting of results from CFD is necessary.

In this way the hybrid approach provides three different scenarios:

- a forecast obtained using free wind field results (HYBRID 1)
- a forecast obtained using numerical results from the CFD model with actuator discs (HYBRID 2)
- an intermediate forecast obtained weighting the above mentioned cases (HYBRID 3).

The weighting procedure for the HYBRID 3 solution was formulated according to the actual thrust conditions as follows:

$$w_1 = \left|\frac{C_t - C_{tmax}}{C_{tmax}}\right| \qquad w_2 = \frac{C_t}{C_{tmax}} \tag{7}$$

$$P = \mathrm{w}_1 \times \mathrm{P}_1 + \mathrm{w}_2 \times \mathrm{P}_2 \tag{8}$$

where C_t and C_{tmax} are respectively the actual and the maximum thrust coefficient. P_1 is the forecasted power in the free wind field conditions and P_2 is the forecasted power when including the actuator discs.

Summarizing, the forecast analyzed in the present work is finally proposed with two different approaches, whose performances for the test case are compared:

1. the full neural network approach, where ANN methods are used directly to forecast the power production of each turbine;
2. the HYBRID approach, where ANN are trained to forecast wind speed and direction for a reference met-mast and CFD methods are then used to compute the power output of each turbine using the wind climatology estimated for the anemometer.

The forecast techniques were tested for a wind farm operating on a very complex terrain in southern Italy, where 12 pitch-controlled aerogenerators with an hub height of 50 m and a rotor diameter of 42 m are operating in a very windy area.

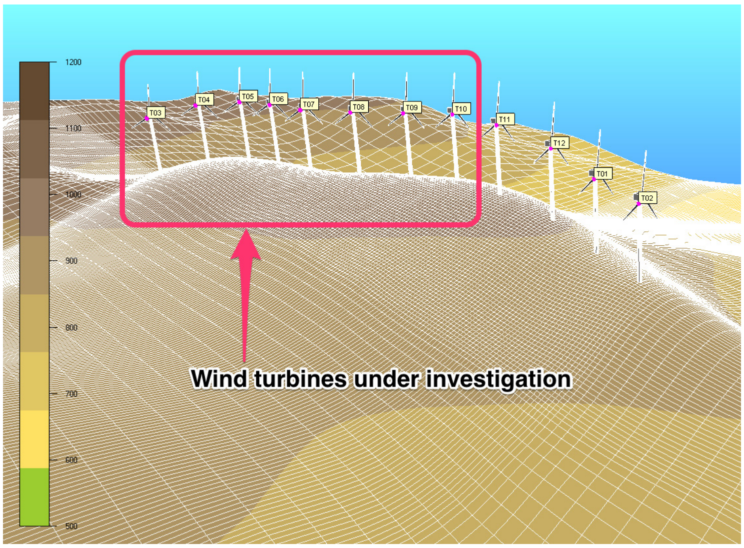


Fig. 2. The wind farm layout with the turbines under investigation.

The study is focused on a group of turbines, numbered from 3 to 10, for which the SCADA database is sufficiently complete.

The SCADA (Supervisory Control And Data Acquisition) is a control system spreading out a database for each wind turbine on a ten minute time basis. The most common channels are those more directly related to wind flow, turbine response to it and power output, i.e. rotor wind speed, nacelle position, pitch angle, active power and so on.

The SCADA dataset of interest for the present study also includes a series of counters in order to check step by step the operating state of the turbine (for example Grid OK, Grid On, Wind OK, Turbine OK, Manual Brake, Maintenance). Further a separated log alarm database has been provided, which can be crosschecked against the SCADA counters in order to verify consistency of the information.

The counters are in the form of a number between 0 and 600, indicating how many seconds of the ten minutes interval each turbine has been in the state described by the counter itself. This information might be considered a sort of read-only database, which can be interactively used to filter the SCADA dataset, in order to investigate wind turbine behavior under certain operative conditions. A judicious SCADA data mining provides useful awareness on the behavior of each turbine and on the interactions (for example wake effects) between them and has a huge number of applications.

Being the goal of the present study a forecast simulation of the wind turbine output in the state of functionality of the whole park, the counters have been used for filtering: only the time stamps during which each of the "functionality checkers" of each turbine were on for at least the 90% of the time have been kept. The main counters used for this aim, ensuring grid availability, enough wind speed to provide power production and turbine proper functionality, have been Grid On, Grid Ok, Turbine Ok and Wind Ok.

Further the filtered SCADA database can be divided and part of it can be used for training the neural network, both in the full and hybrid approaches, and part for testing: it can be appreciated that the quality of the forecast significantly increases, as intuitively expected, if one trains the neural network directly with the refined filtered database which contains the awareness of the behavior of the park when it is fully productive. It is therefore expected that, as shown in the Results section as a key point of the present work, such training naturally leads to a sensibly better forecast than any hybrid method which artificially simulates the orography of the terrain.

3. Results and discussion

All the available data (WRF data, met-mast data and SCADA) were arranged in a unique synchronized database; the first part of the database was used for training and the final part (all the hourly timesteps during May 2013) was used for testing the reliability of the different approaches.

The best results were obtained with the full NN approach; the value of R^2 is appreciable in the prediction of production for all the turbines with a peak of 0.828 for T4 (see Table 1).

For each specific model the ANN architecture was optimized in term of number of neurons in the hidden layer; training and testing was done using the filtered SCADA database.

Results from the different versions of the HYBRID approach are sensibly worst with respect to the full NN method, the performance peak is an R^2 of 0,7582 for turbine T10 with the HYBRID1 model.

This results demonstrate the importance in training the NN directly against the final output, i.e. the power output of each turbine; when SCADA data are not available the only way for power forecast is the HYBRID model but the results shall be affected by a larger error due to the longer modeling chain.

In figure 3 all the approaches are compared in a daily forecast for turbine T4; it is quite clear that the full NN method is the best in following the real production variations due to changes in wind speed and wind direction.

The CFD fails also because of site complexity, which introduces many issues on the calculation side; the numerical simulations were successful only on a grid too coarse to realistically encode the orography of the terrain.

Anyway numerical simulations can be very useful at the beginning of the operation of the wind farm when the SCADA database is very poor and could be very important to understand the wind farm behavior against different wind speed and directions.

Table 1: R^2 for target data and the outputs of the created ANN models

ANN Model for Prediction of	ANN Architecture	Transfer Function	R-Squared
Wind Speed in Met Mast	9-300-1	Logsig- Purelin	0.750
Wind Direction in Met Mast	9-100-1	Logsig- Purelin	0.799
Turbine 3	9-100-1	Logsig- Purelin	0.824
Turbine 4	9-400-1	Tansig- Purelin	0.828
Turbine 5	9-210-2	Tansig- Purelin	0.818
Turbine 6	9-200-1	Logsig- Purelin	0.796
Turbine 7	9-110-1	Logsig- Purelin	0.752
Turbine 8	9-150-1	Logsig- Purelin	0.775
Turbine 9	9-100-1	Logsig- Purelin	0.794
Turbine 10	9-190-1	Logsig- Purelin	0.784

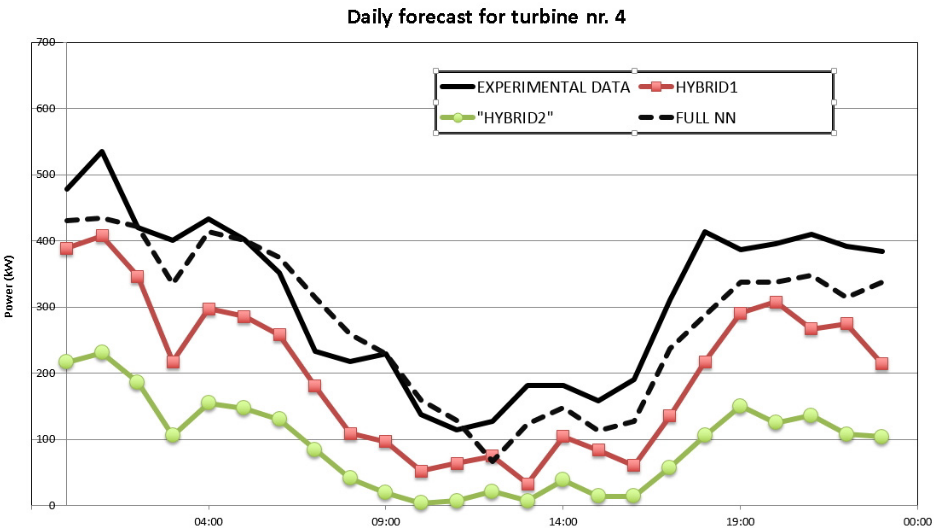


Fig. 3. Sample of daily forecast for turbine nr. 4.

Comparing the results obtained with the different approaches in the HYBRID model (Table 2) it is interesting to notice that the R^2 obtained with the free wind field are generally higher to those obtained with the other two methods involving also wakes calculations. This is mainly due to the difficulties for the model to simulate the wakes and to the wind speed distribution of the site that is well populated in the high wind conditions for which wakes are not strong (low thrust coefficient values).

Table 2. R^2 for T4 using the different versions of HYBRID model.

Only terrain and free wind speed	With Wakes	Mixed
0.723	0.611	0.709

Comparing the R^2 obtained for each turbine with all the methods it is interesting to notice a similar trend (fig. 4) with lower values for turbine T6, T7 and T8. This is due to wind field complexity in that part of the wind farm layout.

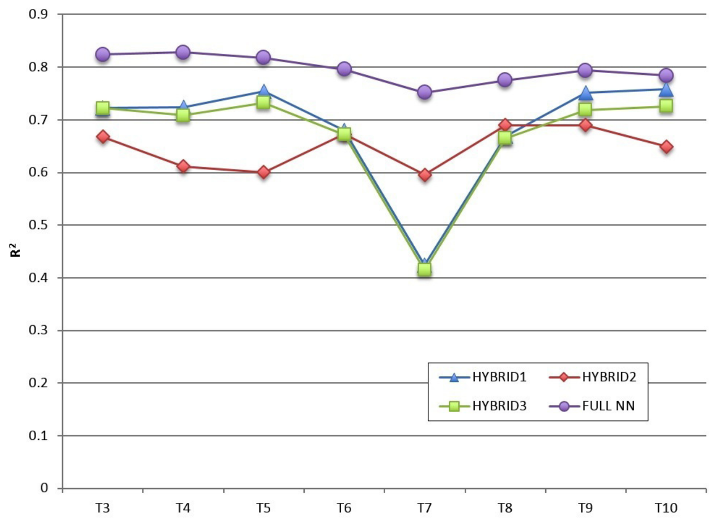


Fig. 4. R^2 obtained in testing all the methods.

The full NN approach seems also to be very robust: if one trains the ANN with post-processed SCADA data, but uses as input non filtered time-series, the quality of results (see Table 3) is only marginally reduced. The R^2 actually decreases from 0,828 to 0,820.

Table 3. R^2 for T4 using the different training and testing conditions for ANN.

Data for training NN	Data for testing forecast	R^2
Non filtered	Non filtered	0.787
Filtered	Non filtered	0.820
Filtered	Filtered	0.828

4. Conclusions

From the Results section above, a certain number of interesting issues arise: first of all the comparison, from the point of view of goodness of forecast, between the pure NN and the hybrid approaches. The hybrid approach has its strength, through turbulent flow modelling, in capability of reproducing the physical effects (most of all wake interactions and its relation with wind rose). Yet, the orography of the terrain is too complex, and the grain of the simulation necessarily too rough, to reproduce turbulence and orography effects so precisely as to forecast excellently the power output throughout the park.

As shown in Fig. 4 the R^2 between target test data and forecasted data is systematically higher using the pure NN approach; actually also the procedure for training and testing the forecast method deserves some interesting discussions. The Table 3 encodes an interesting summary sketching the power of the proposed approaches: actually one sees that training the NN with postprocessed SCADA measurements, filtered in the regime of park productive, significantly improves the quality of the forecast. Yet, it might not a priori be consistent to validate such models against similarly filtered data, since one of course shall not be aware of the state of the park in the future and of possible fault onsets. The most consistent route is therefore to validate the forecast against non filtered measurements: it is instructive to notice that the R^2 does not significantly change. The lesson is therefore that historical database of judiciously filtered SCADA measurements provides a significant improvement for actual and realistic forecast requests, because it needs to be applied only to the phase of training of the neural network. In this way a powerful support in forecast of production and optimal operation can be offered through the use of artificial neural network.

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