Evaluation of two ANN Approaches for the Wind Power Forecast in a Mountainous Site

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Received: 13.03.2017 Accepted:20.04.2017

Abstract- Accurate wind power forecast is very important in order to construct smart electric grids. Nevertheless, this task still constitutes a challenge because wind is a very variable and local phenomenon. It is difficult to downscale information coming from Numerical Weather Prediction (NWP) models down to wind farm level and this is especially true onshore, in complex terrain conditions. Artificial Intelligence often comes at hand, for its power in learning what is hidden inside data: Artificial Neural Networks (ANN) are therefore commonly employed for wind power forecast. In this work, a pure ANN method is compared against a hybrid method, based on the combination of ANN and a numerical method based on physically-consistent assumptions (Computational Fluid Dynamics). Both approaches are validated against the SCADA data of a wind farm sited in Italy in a very complex terrain. It arises that the two methods have overall similar performances on average. However, pure ANN turns out to forecast better at mid-energy levels and during cut-off events at the highest wind speed, whereas the hybrid method forecasts better during low and high wind speed ranges. This makes the two approaches complementary and promising for future applications through an ensemble strategy.

Keywords wind energy, power forecast, Computational Fluid Dynamics, Artificial Neural Network, SCADA control system.

1. Introduction

The efficiency in the exploitation of renewable energy sources passes also through the precision in forecasting how much energy shall be fed into the grid. The expected power production is very complex to quantify when the source is stochastic, as wind is. Nevertheless, wind farm owners are usually expected to provide a forecast in the morning for the 24 hours of the day ahead and this information, if it has a good quality, can be crucial to build smart grids [1, 2, 3].

Wind power forecast is technically very challenging for one main reason: it is very difficult to downscale locally the mesoscale conditions [4] coming from Numerical Weather Prediction Models (NWP), which are nowadays the only available tool to obtain deterministic forecast. This is especially true onshore in complex terrain, where the wind field can encounter so severe variations in few meters that it is even challenging to simulate it locally through numerical modelling by Computational Fluid Dynamics [5-10]. Further, the interaction between the wind field and the single turbine in complex terrain [11] is difficult to model too and it is even more challenging to take into account wake interactions between nearby turbines [12-18].

Two are the keystones for circumventing the above issues, about wind power forecasting: Artificial Intelligence and data. Artificial Neural Networks (ANN) are often used for their capability in reconstructing non-linear dependency between input and outputs and they are often used to connect directly the mesoscale wind conditions to the power output of the wind turbines on site [19-23]. The ingredient to feed (and train) the ANNs with are data: the inputs (mesoscale) and the outputs (typically, the power of the wind turbines). For this reason, statistical models for wind power forecast are based on the disposal of large data sets describing wind turbines in operation. Supervisory Control And Data Acquisition (SCADA) data are therefore crucial. Those are, becoming ubiquitous in modern wind turbine technology because they conjugate low cost to versatility and effectiveness. They can be used for fault diagnosis [24-33], for performance assessment [34-42]: these two tasks are intimately connected and the border between them is fleeting because, for example, unsteady load conditions due to extreme winds [43] might make it difficult even to distinguish if degraded performances are due to incoming faults or not [44].

As argued above, ANN techniques for wind power forecast are characterized by several critical issues, first because vast data sets are needed in order for the algorithm to learn the relation between inputs and outputs and because there might be instabilities, especially in reproducing what happens at the tails of wind distributions [45]. The strategies to overcome these issues are several: one can point at optimizing the machine-learning algorithm: in [46], for example, the focus is on the clustering of the events after the post processing of three NWPs. In [20], wavelet neural networks are employed and the error in the wind power forecast is minimized through the maximum correntropy approach. In [47], heterogeneous machine learning methods are adopted, in [48] a Gaussian mixture model-based neural network model is proposed. In [49], a full probabilistic density forecast for the wind power for each wind speed predicted by time series methods for each lead time, using Double Seasonal Holt Winters and conditional density kernel estimation. In [50], a wind speed forecasting using feature selection method and bagging neural network is proposed. In [51], the attention is devoted to the optimal selection of meteorological data and the random forest algorithm is adopted for hour-ahead wind power forecast. In [52], the optimization of the machine-learning algorithm is achieved through an improved radial basis function neural network-based model with an error feedback scheme. In [53], five ANN models are formulated and their performances are compared. In [54], Elman neural network and Particle Swarm Algorithm are proposed to predict wind power. In [55], discrete wavelet transform and singular spectrum analysis are used to filter out the noises from wind power series and an optimized local linear fuzzy neural network is adopted to forecast the wind power. A similar approach is proposed in [56] and [57], where the combination of variational mode decomposition (for cleaning the time series) and machine learning is adopted. Pushing to the limits the time scale of the forecast is a very interesting issue in the scientific literature: in [58], for example, strategies for very short term forecast (five minutes ahead) are proposed and tested. In [59], a framework is proposed for wind power forecasts, by combining a dynamic power curve with a stochastic model for wind speed based on stochastic differential equations. In [60], the randomness is tackled by using the cloud model. Quantifying the impact of uncertainties and minimizing them is a very pressing topic in the literature about wind power forecast. In [61], day-ahead forecast errors from four Nordic countries and the impacts of wind power plant dispersion on forecast errors in areas of different sizes are studied. About uncertainties in wind power forecast, see also [45], and [62] where a conditional probabilistic dependent method of modeling wind power forecast error is proposed, and [63] where a piecewise exponential distribution model has been proposed for analysis of short term wind power forecast errors. For a review of the approaches in wind power forecast, see [64-67] and for a review of uncertainty analysis in wind power forecast, see [68].

Another possible approach for improving wind power forecast can be retaining, in some sense, a certain degree of determinism: physical hybrid methods [69-70] are based on targeting wind conditions from the mesoscale on site (at a reference point) through ANNs and then transferring them at turbine sites through physical methods as CFD is. As arises from the above discussion on the state of the art in the literature about wind power forecast, this approach has been little explored. In [71-72], this hybrid method is proposed and in particular the impact of the wake modelling is discussed. In [73], a case study like the one of this work is proposed: the approach is Weather Research Forecast to WindSim software and it is employed for the forecast on a Turkish site. On these grounds, the motivations of the present work are based: the use of hybrid (ANN+CFD) approach to wind power forecast has been very little explored especially in complex terrain, where wakes and terrain-induced flow acceleration heavily combine [13, 17, 74, 75, 76, 77]. The complex environment introduces an additional challenge: the interaction between wind field and turbines, occurring locally, might be modelled as in the hybrid approach of this work, or one might trust the ability of machine-learning algorithms in capturing also this issue. It is reasonable to expect that the two approaches might capture different features of the wind field and of the interaction between wind and turbines, and then might provide a good forecast under different conditions.

Summarizing, this work is therefore a comparison of a pure ANN and a hybrid ANN + CFD approach for wind power forecast: the validation case is very valuable, because it is a wind farm sited in complex terrain on a vast layout. Further, the philosophy of this work is trying to stretch both approaches to their limits and investigate where the added value of each method is.

The structure of the Paper is as follows: in Section 2, the approach is described and the details of the computational set up and of the data sets are provided. In Section 3, the results are collected and discussed. The conclusions and the further directions are sketched in Section 4.

2. Materials and Methods

The input for both pure ANN and a hybrid ANN + CFD approach, employed in this work, is the same: data coming from a NWP model. The selected NWP model is the Weather Research and Forecasting (WRF) – Advanced Weather WRF (WRF-ARW) model [78], initialised by means of the Global Forecast System (GFS) analyses. From WRF simulations, time series of wind direction and wind speed at 5 heights (10, 100, 200, 300 and 400 meters) above ground level are extracted and are fed to two post processing methods:

- In the pure ANN approach, an ANN for each wind turbine directly connects the input (mesoscale wind conditions) to the power output of the wind turbine (Fig. 1).

➢ In the hybrid method, an ANN connects wind conditions at the mesoscale to wind conditions at a reference point in the wind farm area. Therefore, in this case the ANN is wind – wind. The wind conditions at target site are transferred at turbine site using CFD simulations and the final output (wind power forecast) is obtained employing the theoretical power curve of the wind turbines (Fig. 2)

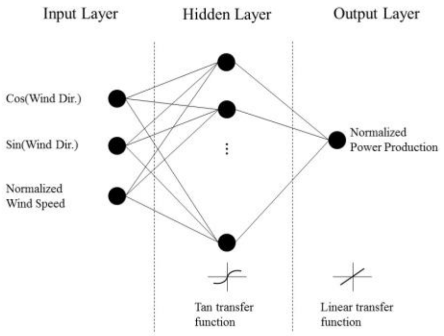

Fig. 1. Structure of the two ANNs: pure ANN approach.

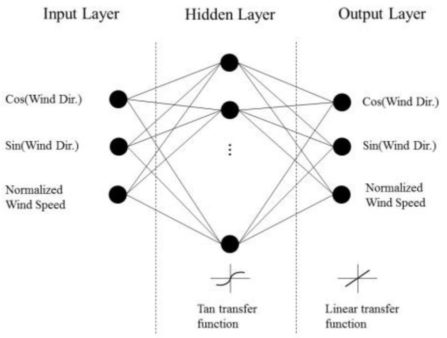

Fig. 2. Structure of the two ANNs: hybrid approach.

In both cases, the ANNs are single layer perceptrons, trained by a feed-forward back-propagation method, not supervised training. The structures are represented in Fig. 1 and 2 and the flow chart is shown in Fig. 3; the inner layer has tangent transfer function, while the output layer has linear transfer function. The ANNs can be set with different number of neurons in the inner layer and the performance is sensitive to such a setting. Therefore, many configurations have been tested and the best performing one has been chosen.

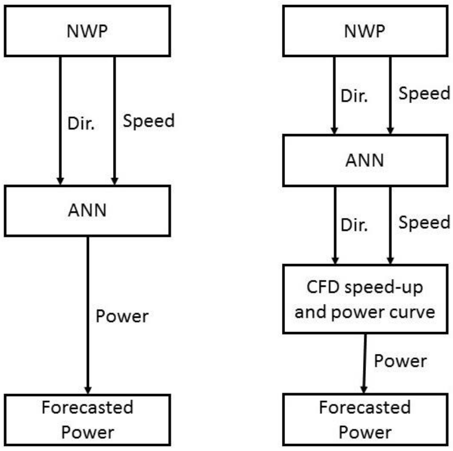

Fig. 3. Flow chart of the two methods: pure ANN (left) and hybrid (right).

The first approach is purely statistical and it accounts implicitly that the same conditions at the mesoscale can correspond to different local conditions, different wake patterns and different power outputs. Using the pure ANN, one trusts that the algorithm might capture all that is hidden inside the data. Using the hybrid method, one transports the wind conditions at turbine sites through the CFD and takes into account different wake patterns explicitly. In this work, the Jensen model [79] is adopted. The CFD simulations are performed with the WindSim software [80-83].

The computational set up for the CFD simulations is the following: the Reynolds-averaged Navier Stokes (RANS) equations are solved using the RNG k-ε turbulence closure. RNG k-ε is selected because it is considered superior for complex terrain [6]. In order to reduce the computational cost of the forecast, a set of idealized simulations is run. Logarithmic wind profiles are given at the inlet of the domain for different wind directions. A reference point inside the domain is selected, where the NWP forecast is extracted and used as external forcing to the CFD simulations. According to the forecast at the reference point, the whole three-dimensional wind field calculated by the CFD can be scaled from the idealized simulations through appropriate transfer coefficients that are usually defined as the ratio between the wind speed at the reference point and the wind speed at another whatsoever grid point. Simulations have been performed with a wind speed equal to 15 m/s at the top of the boundary layer, and 12 wind directions equally spaced of 30 degrees. A sector interpolation is performed to define the transfer coefficients at intermediate directions.

The test layout of the test case wind farm is reported in Fig. 4. On site, 24 turbines are installed. 18 turbines have 50 meters of hub height and 42 meters of rotor diameter. 6 turbines have 55 meters of hub height and 52 meters of rotor diameter. The total rated power of the wind farm amounts to 15.9 MW. To give an idea of the complexity of the terrain, consider that the highest point of the wind farm is at 1000 meters above sea level, while the lowest is at 400 meters.

Due to the vastness of the wind farm, it has been divided in two computational domains for the CFD simulations. Each domain has a refined computational grid in the middle, with a minimum horizontal grid resolution down to 40 meters along x and y directions. The horizontal resolution decreases from 40 m in the middle to 380 m at the boundaries. The computational domains are respectively made of 119 × 124 × 20 and 120 × 130 × 20 cells and the height of the boundary layer is 1000 meters in both cases. One position inside each domain is selected as reference point to extract the NWP wind condition: the met-mast site is selected for domain 1, the position of one turbine is selected for domain 2 (blue markers in Fig. 4).

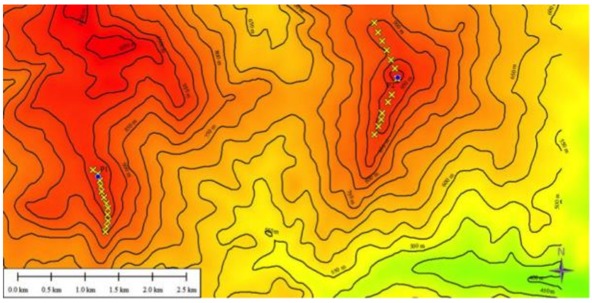

Fig. 4 The two layouts of the wind farm (layout 1 to the left and layout 2 to the right). The blue dots indicate the position of the met-mast and the turbine used as reference point for the computational domains 1 and 2, respectively.

SCADA data are another crucial ingredient of the method: they are fed to the ANNs for the training and then are used in the validation to crosscheck how much simulation (and then forecast) resembles reality. For the pure ANN method, the power outputs of each turbine are used. For the hybrid method, the wind direction and intensity at reference points are used. In both cases, the structure of the SCADA is the same. SCADA data are stored on 10-minute time basis and they are post-processed for this study as follows: the data set of each turbine is filtered on the requirement that the turbine itself is in production and the data are hourly averaged in order to be synchronized to the NWP data. NWP and SCADA data are employed half for training and half for validation.

The total data set employed for this work is visualized in the following Figs. 5 to 8. On the left of each of the figures, the wind rose is shown and, on the right, the wind speed frequency distribution and the Weibull best fit are shown. This is done for each layout and for the NWP data and the SCADA data sets at each reference point.

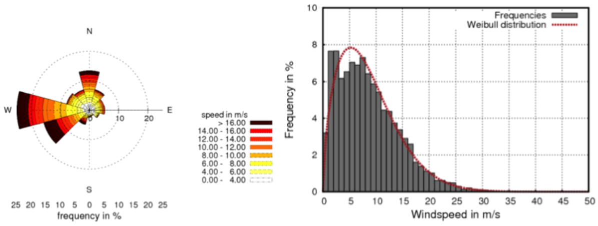

Fig. 5 The NWP data set for layout 1. Wind rose (left) and wind speed distribution (right).

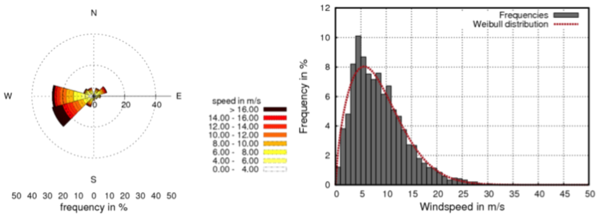

Fig. 6 The SCADA data set at the reference point for layout 1. Wind rose (left) and wind speed distribution (right).

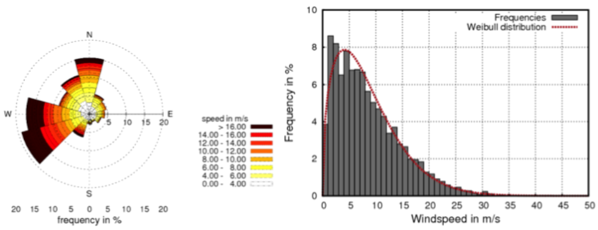

Fig. 7 The NWP data set for layout 2. Wind rose (left) and wind speed distribution (right).

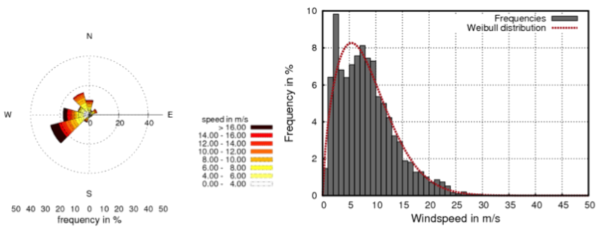

Fig. 8 The SCADA data set at the reference point for layout 2. Wind rose (left) and wind speed distribution (right).

The size of the data set is in total seven months and this size is fit for the purposes cited in Section 1: stretching ANNs to their limits with reasonably short data sets. In order to avoid bias due to seasonal effects, the data set is split in weeks and weekly subsets are employed alternatively for training and validation. To simulate the run of a real day ahead, as the forecast has to be done in the morning for the day after, 18 hours of each forecast run are cut out and the following 24 hours are used. The dependency of the quality of the forecast on the time scale has been addressed too: the forecast has also been validated on 6-hours spaced intervals inside the 24 hours. It arises that the overall quality of the forecasted doesn't vary appreciably and, for this reason, in the following, results are reported only on the standard 24 hours scale. It would be interesting to consider longer intervals too but, in this validation case with short data sets, this would compromise the statistical significance of the results. It is planned to project on longer time scales as a further direction of this work.

3. Results

The validation metrics, adopted for evaluating the goodness of the forecast, are the normalized mean absolute error (NMAE) and the normalized root mean square error (NRMSE). In [20], it is argued that these two metrics are among the most common and meaningful for evaluating the quality of the forecast. Further, they are the same which have been selected in [71, 72] and it is therefore interesting to compare the order of magnitudes of the metrics, when employing basically the same methods and very different testing grounds: complex terrain and short data sets, in this case. The normalization factor is the nominal power of each layout (6.6 MW and 8.7 MW respectively for layout 1 and 2). Two main issues are investigated: the dependency of the quality of the forecast on the height of extraction of the NWP data and the behaviour of the forecast, global and at the level of time series (hour by hour). The results are reported in the following Fig. 9-12.

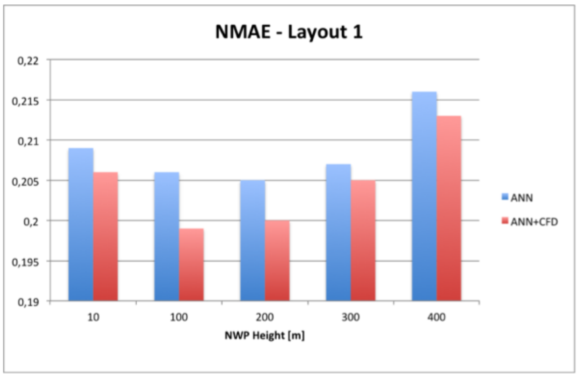

Fig. 9 NMAE for layout 1.

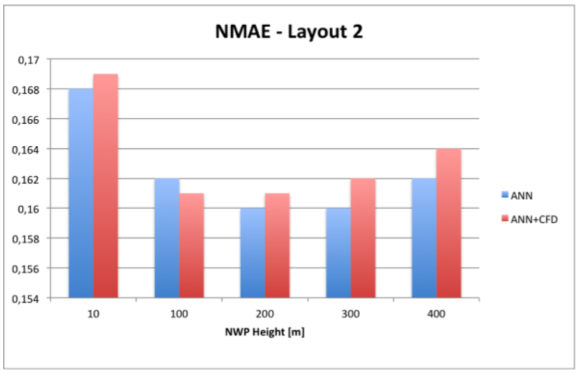

Fig. 10 NMAE for layout 2.

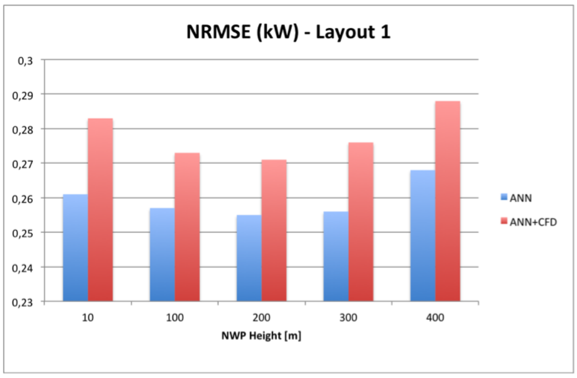

Fig. 11 NRMSE for layout 1.

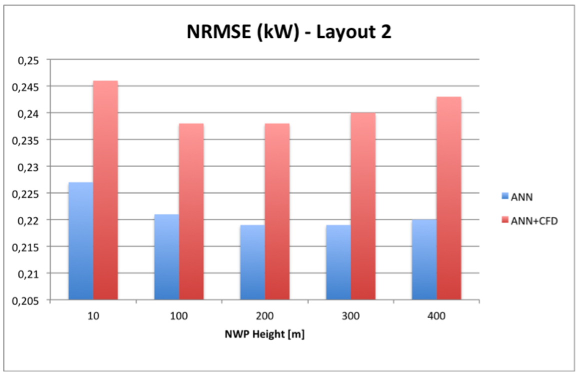

Fig. 12 NRMSE for layout 2.

From Figs 9 to 12, it arises the lowest NMAEs are obtained with the NWP height of 100 and 200 meters. This is reasonable, because the wind field at 10 meters is probably too close to the surface of the terrain to capture what happens at hub height, whereas 300 and 400 meters of height are instead too far from the ground. In general, the performances of the two methods are similar: NMAE is about 20% for layout 1 and about 16% for layout 2. It is interesting to notice that, while the hybrid method is comparable, if not even better than the pure ANN as regards NMAE, pure ANN performs better than the hybrid method as far as the NRMSE is concerned. This is reasonable because the training of the ANNs is targeted on minimizing the sum of squares error, calculated on the training period. This point ex post supports the choice of the metrics for validating the forecast, because each of them can capture slightly different features and it is therefore interesting to visualize both of them.

Further, the CFD in the hybrid method introduces more physical information than the statistical approach of the pure ANN and, as a drawback, it introduces additional sources of uncertainties due to the more complex flow. It is notable that the hybrid method averagely performs even better than pure ANN, but the results have a larger spread (higher NRMSE). From this point of view, therefore, it is necessary to investigate the differences between the two approaches hour by hour.

From the following Fig. 13, a very interesting feature arises about this issue. The ANN performs better in forecasting mid-energy levels; the hybrid method is better to reproduce wind flow acceleration, especially in the ascending ramps. This happens because the CFD simulates properly the wind flow accelerations, i.e. speed-up, in complex terrain and is therefore more suitable to follow the dynamics of the power output oscillation. This shows that even though both methods are overall similar on average, they perform quite differently hour by hour.

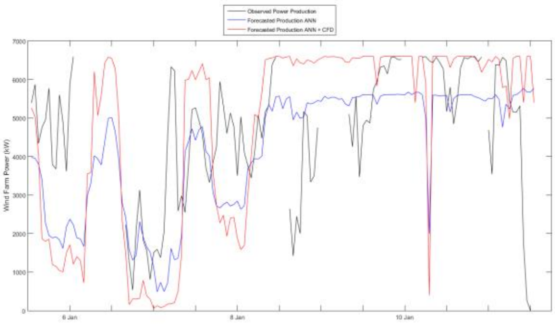

Fig. 13 Plots of measured (black line) and simulated power production: ANN (blue lines) and ANN+CFD (red lines), corresponding to using the NWP wind field input at 200 m. Layout 1.

The following Fig. 14 and 15 show the forecasted power in three-dimensional view as a function of wind direction and wind speed; the speed and the direction are extracted from the 200 m. NWP height because it averagely provides the best performance. The forecasted power corresponds to the complete wind farm production in the considered period.

From Fig. 14, it arises that the ANN approach increases more slowly and on different “plateaux” with increasing wind speed, while the hybrid case has a linear and faster increase. Nevertheless, both methods can recognize the different behaviour of the wind farm production as a function of the direction.

Fig. 15 is following the same behaviour of Fig. 14, while it is notable that the ANN can catch the decrease of production due to extreme winds, i.e. the stop of the turbines at the power curve cut-out speed. Actually, for wind directions about 230° and 270° and wind speed greater than 25 m/s, the forecasted power production decreases with speed increasing. This highlights an added value of the ANN approach: it is able to simulate the real dynamics of the wind turbines for high wind speeds, instead of using the theoretical power curve as in the ANN+CFD approach.

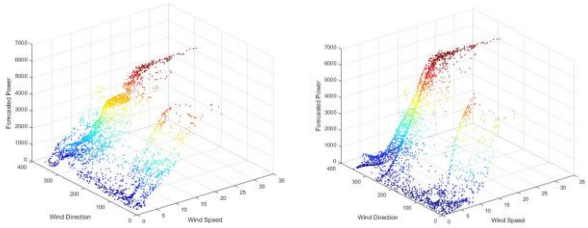

Fig. 14: Plots of forecasted power per wind speed and direction of ANN (left) and ANN+CFD (right), corresponding to using the NWP wind field input at 200 m for layout 1.

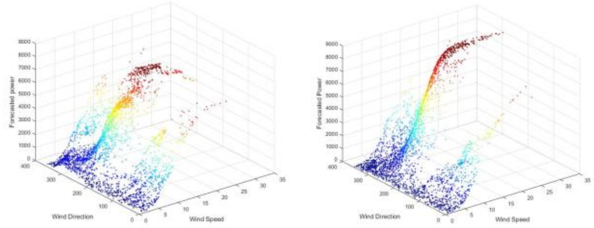

Fig. 15: Plots of forecasted power per wind speed and direction of ANN (left) and ANN+CFD (right), corresponding to using the NWP wind field input at 200 m for layout 2.

The improved awareness on the key points of both approaches can improve the overall performance of the forecast: in perspective, the idea is a more complex forecast where the two approaches concur in an ensemble picking the best from each other.

4. Conclusions

This work was devoted to the issue of wind power forecast in complex terrain. Complex terrain is a very challenging testing ground for forecast methods because the wind can encounter severe variations in space: therefore, the relationship is very elusive between what happens at the mesoscale in terms of wind conditions and what happens at each turbine site (and therefore how much power can be extracted). In this work, a very valuable validation case was proposed: a wind farm sited in Italy in a very complex terrain, featuring 24 turbines distributed in two layouts a few kilometres far each other. Two forecast methods have been compared: a pure ANN method, i.e. an ANN connecting directly wind conditions at the mesoscale to power output of each wind turbine; a hybrid method, where an ANN wind – wind connects the wind conditions at the mesoscale to the wind conditions at a selected point in the domain, and the wind field is then transferred at turbine site using a deterministic CFD method.

The two methods resulted in similar overall performances as regards NMAE, but their behaviour is different hour by hour because they have different advantages: the pure ANN method captures better mid-energy level because, being purely statistical, it better performs “averagely”. The hybrid method better describes the acceleration of wind flow and is therefore very promising for reproducing the regime of complex dynamics of the wind farm. Further, the hybrid method performs better in high and low wind speed range and the ANN recognizes cut-off events due to high wind speed. Summarizing, the performances of the two methods (overall similar, different hour by hour) suggest that the approaches could be used reciprocally, for improving the performance of the forecast. This is actually the main further direction of the present work and one possible idea is switching from one method to the other using genetic algorithm techniques [84]. A valuable further direction is also a most extensive use of SCADA data: as for example in [85], the quality of the forecast can be improved by modelling the power curve [86] of the wind turbine by learning from the SCADA data. This wouldn't have been effective in our test case because the data set was deliberately chosen to be reasonably short, but it would be an interesting direction to be explored further. Another very interesting further direction is testing the above method on very valuable test cases as the ones of the IEA-Task 31 Wakebench project for the assessment of microscale flow models [10, 18], which are characterized by vast layout, very complex flow intertwining with wake effects, not rare occurrence of harsh wind regimes with very high turbulence. For a reliable wind power forecast in such a testing ground, the missing final link in the modelling chain of the present work must necessarily be addressed: the role of the technology, i.e. the control system of the wind turbine.

Acknowledgments

The authors acknowledge the Italian company Lucky Wind spa for providing the production data and all the technical information used in the validation of the methods.

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