Weather-based Machine Learning Technique for Day-Ahead Wind Power Forecasting

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***Abstract*— This paper presents the development of forecast models for a wind farm producibility with a 24 hours horizon. The aim is to obtain accurate wind power predictions by using feedforward artificial neural networks. In particular, different forecasting models are developed and for each of them the best architecture is researched by means of sensitivity analysis, modifying the main parameters of the artificial neural network. The results obtained are compared with the forecasts provided by numerical weather prediction models (NWP).**

Keywords— Wind Power Forecasting; Wind Energy; Wind Farm; Artificial Neural Network.

I. Introduction

In the last few decades, due to the increasing concern regarding the excessive use of fossil fuels and the environmental consequences linked to the global atmospheric emissions, wind power industry has quickly expanded, increasing wind turbines installed capacity [1].

This expansion of wind power requires to face new challenges: in particular, being wind a non-programmable energy source, the stability of the grid and the balancing of demand and supply [2].

In view of the strong and continuous growth of wind power in Italy and in the world, it becomes essential to get wind energy source involved in the electric system functioning. The improvement in the forecasting of electrical energy fed into the power grid by wind farms is fundamental to decrease the unpredictability due to the stochastic nature of renewable energies, and to improve dispatch and commitment of the power units connected to the grid [3].

Proper wind power forecasting is thus essential for:

- grid operators, in order to avoid power grid balance problems,
- wind farm operators, to reduce imbalance charges and penalties,
- consumers, affected by the increase of imbalance costs due to low predictability.

This work will be focused on forecasting models for a day ahead wind power production based on meteorological predictions.

Various forecasting approaches have been studied and developed in literature with several techniques [4],[5],[6],[7], in order to improve the prediction and to reduce its error: these method can be classified considering their time-scale, ranging from a very short-term (few seconds or minutes) until a long-term (one day to one week or more ahead) time horizon [8], [9]. The most common forecasting methods presented in literature are *Persistence Method*, *Physical Method*, *Statistical Method* and *Hybrid Method* [2].

The aim of this work is to obtain accurate wind power predictions using well known machine learning techniques, i.e. feedforward neural networks (FFNN). It will be also presented a hybrid model in order to gain advantage of both the physical and the statistical models.

II. Case Study

This paper focuses on a real-world application, i.e. a wind farm located in Southern Italy. The generators in this wind farm are three-blades horizontal axis wind turbines with a 90 m rotor diameter; their rated power is of 2 MW each.

In particular, the plant covers an area of about 4.4 km² at an altitude varying between 180 m and 235 m above the sea level. The average annual wind speed value in the considered region is about 5-6 m/s (measured at 100 m above the ground level), according to the Global Atlas for Renewable Energy (developed by IRENA [10]); this value is confirmed by the wind farm records for the year 2015, reported in Figure 1.

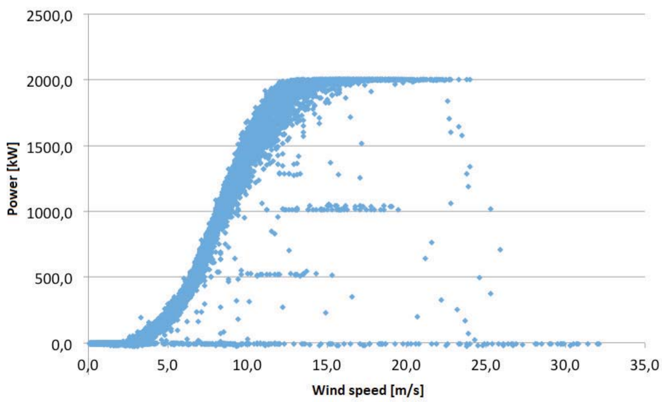

Fig. 1. Measured power vs wind speed for the considered plant.

III. Numerical analysis

In this paper, forecasting models for a day ahead wind power production based on meteorological predictions are considered; in particular, different FFNN architectures are developed and compared by means of sensitivity analysis, modifying the principal parameters of the network and the training methods and dataset. The results obtained are compared with the forecasts provided by a commercial weather service using numerical weather prediction models (NWP). The considered forecasting models and training techniques are briefly described in the followings.

A. Models

The *Direct Power Prediction* uses the neural network to predict the wind turbine output power.

The *Indirect Power Prediction* model predicts the on site wind speed. The neural network is used to correct the systematic errors in the weather forecasts. The predicted wind speed is converted to the wind turbine output power by using its ideal power vs. wind speed curve.

B. Dataset and training

The *Fixed Window* training set consists of a fixed data window over time. The forecasts are always made using as inputs and training targets the values of the same days previously set.

The *Moving Window* training set consists in considering a fixed size window that moves daily as the forecasts proceed, incorporating in training the values of the last forecast data and discarding the data of the oldest day in the dataset.

The *Increasing Window* training set consists of a data window that increases in size day by day, incorporating the last forecast data without discarding the data of the oldest day in the dataset.

The *Random Samples* training set consists of a finite and fixed dimension set of randomly extracted data from the complete dataset, which increases its size day by day.

C. Analysis of results

In order to properly compare the simulation results, the following error indexes have been considered, as suggested in literature:

- *Absolute hourly error* ($e_{h,abs}$), given by the difference by the measured power and predicted power:

$$e_{h,abs} = \left| P_{m,h} - P_{p,h} \right| \quad (\mathrm{W}) \tag{1}$$

- *Weighted mean absolute error (WMAE)*:

$$WMAE = \frac{\sum_{h=1}^{N} e_{h,abs}}{\sum_{h=1}^{N} P_{m,abs}} \quad (\%) \tag{2}$$

- *Normalized mean absolute error (NMAE)*, based on the plant rated power *C*:

$$NMAE = \frac{1}{N} \cdot \sum_{h=1}^{N} \frac{e_{h,abs}}{C} \quad (\%) \tag{3}$$

- *Normalized root mean square error (nRMSE)*:

$$nRMSE = \frac{\sqrt{\dfrac{\sum_{h=1}^{N} \left(e_{h,abs}\right)^2}{N}}}{\max\left(P_{m,h}\right)} \quad (\%) \tag{4}$$

IV. Numerical results

The results obtained by different methods are briefly summarized in Table 1.

TABLE I. Comparison among the best neural network configurations.

Prediction model	Best Configuration	WMAE [%]	NMAE [%]	nRMSE [%]	$\Sigma e_{h,abs}$ [MWh]
Direct Power	*Increasing window, 49 days*	61.5	17.2	23.4	7298
	Fixed window, 49 days	61.4	17.2	24.1	7283
Indirect Power	*Increasing window, 49 days*	64.3	18.0	26.7	7626
	Fixed window, 40 days	62.9	17.6	24.8	7461
Hybrid	*Fixed window, 49 days*	61.4	17.2	24.0	7279
	Fixed window, 40 days	62.2	17.4	24.6	7381

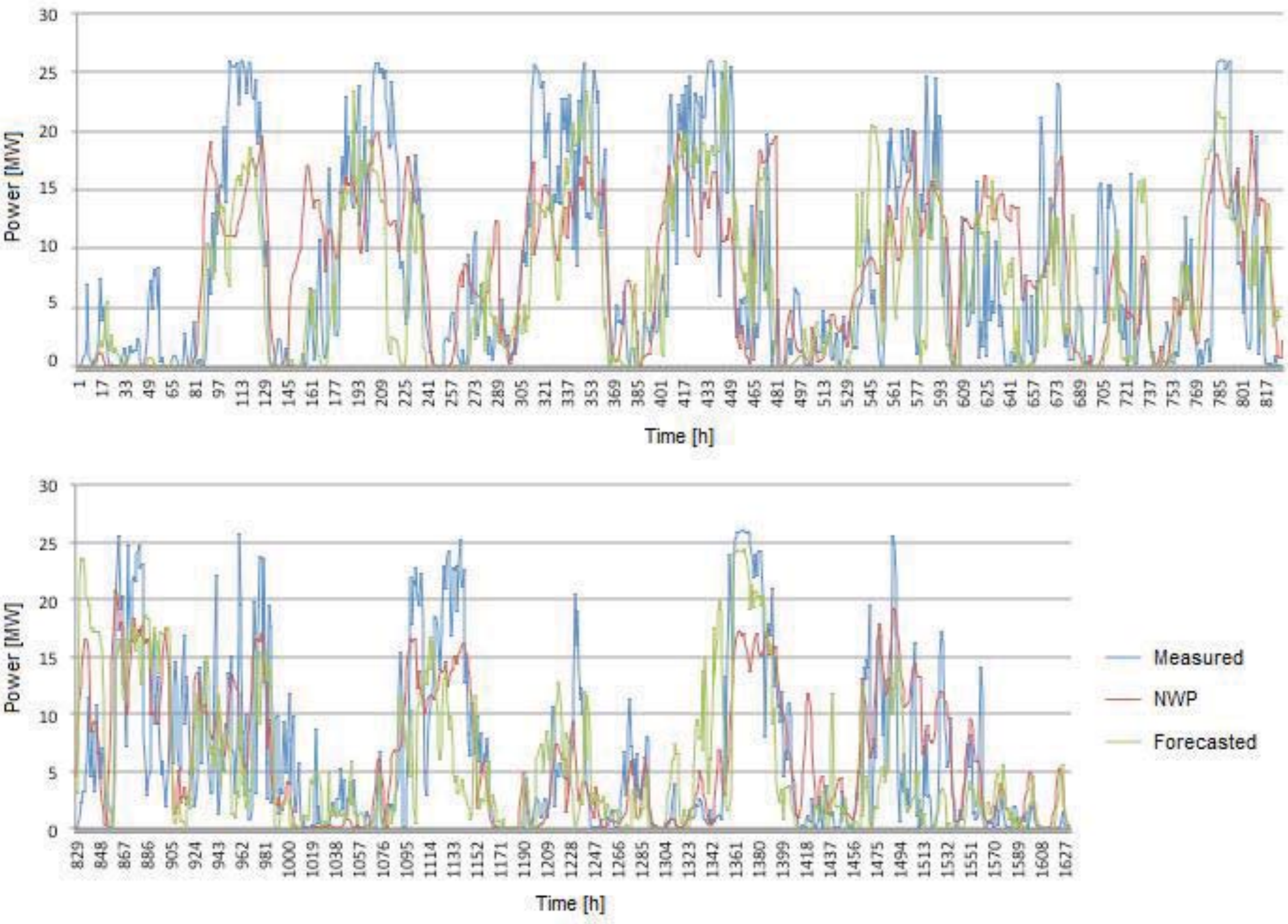

Fig. 2. Comparison among the measured, forecasted and NWP power.

Figure 1 reports the performance of the forecasted power vs. the measured power, and an additional comparison with the forecasts provided by numerical weather prediction models (NWP).

The results obtained have been compared with those reported in previous studies: in particular, [11] and [12] have been considered. According to [11], the obtained NMAE values with 24-hour forecast horizons can vary between 21% and 35% when the complexity of the soil is relevant, and for medium-complex plants such as the one considered in this study, *NMAE* could reach values between 10% and 19%, depending on the change in the forecast horizon.

Despite the difficulty of comparing with other studies in literature, due to the diversity of analyzed plants, the duration of forecasts and the considered forecast horizons, also results reported in [12] have been considered to compare the adopted approach with respect to Bayesian clustering and Support Vector Machine. Considering a 24h time horizon, the *NMAE* values obtained in our study (around 17%) are well below the reported 21% obtained with a persistent approach.

V. Conclusions

In this work, different forecasting models for a day-ahead wind power production based on meteorological predictions were presented and analyzed. In particular, the hybrid model provides an improvement of all error indicators, obtaining an efficient forecast model, also in comparison with published literature.

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