Neural Networks model to detect wind turbine dynamics

Gino Iannace [1], *, Giuseppe Ciaburro [1], and Amelia Trematerra[1]

[1] Department of Architecutre and Industrial Design Università degli Studi della Campania Luigi Vanvitelli, Borgo San Lorenzo - 81031 Aversa (Ce) - Italy

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*Corresponding author: gino.iannace@unicampania.it

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Abstract: The wind has been a source of energy for the human being since ancient times, mainly because it is widely available in different areas of the world. Several companies are investing huge capital to build wind farms with the aim of obtaining the maximum possible economic return. Therefore, a precise definition of the dynamics of operation of the turbines is necessary in order to appropriately define a system that takes full advantage of the wind energy. In this study, the measurements of the noise emitted by different wind turbines were used to obtain information on the dynamics of operation. A selected range of average spectral levels was extracted in a 1/3 octave band. A model based on the neural network for detection has been developed and applied to identify the operating conditions of wind turbines. The prediction and identification model have returned a high precision that suggests the adoption of this tool for several other applications.

Keywords: Artificial neural network; feature selection; low-frequency sound; random forest; wind turbine noise.

Introduction

Since the beginning of civilization, humanity has used wind energy to produce mechanical energy. The first examples are a propulsion system like the sail and then move on to the first wind turbines like windmills. Sailing as a propulsion system for boats and the windmill as an industrial engine were developed on purely empirical models and perfected in numerous variants. They were left out with the discovery of thermal machines that made it possible to exploit the large reserves of chemical energy stored in fossil fuels, converting it into motive power and electricity. The problem arose when it was discovered that these energy sources are in limited quantities and once consumed in their entirety, they cannot be replaced [1].

Non-renewable energy sources produce gas emissions that pollute the atmosphere and are toxic to life, are found in limited quantities, and reduce the raw materials used to manufacture products. This imposes the need to start using renewable energies, which are those whose potential is inexhaustible. The importance of these renewable energies is that day after day they become more necessary due to the significant shortage of fossil fuels [2].

Wind energy does not pollute, is inexhaustible and slows the depletion of fossil fuels helping to avoid climate change. The generation of electricity without a combustion process or a phase of thermal transformation implies, from an environmental point of view, a very favorable procedure to be clean, free from contamination problems, etc. The negative impacts caused by fuels during their extraction, transformation, transport and combustion are radically suppressed, to the benefit of the atmosphere, soil, water, fauna, vegetation, etc [3].

The use of wind energy for electricity generation has no impact on the physico-chemical characteristics of the soil or on its erodibility, since there is no pollutant that affects this environment [4].

Contrary to what can happen with conventional energies, wind energy does not produce any type of groundwater alteration or consumption or contamination from waste or spills. It does not cause dangerous secondary products or polluting waste [5].

Knowledge of the characteristics of the wind is fundamental for all aspects concerning the use of wind energy, from the identification of wind sites to the evaluation of the technical and economic feasibility of a wind power plant, up to to the design of wind turbines and to the understanding of the effect of the variability of electricity production on the distribution system. The wind is generated by a difference in atmospheric pressure to be attributed to a temperature difference and has a translation trend from areas where the atmospheric pressure is greater to areas where it is lower. The wind is the result of the expansion and convective motion of the air caused by the irregular heating of the Sun over large areas of the earth's surface. Solar radiation induces a series of natural convective motions in the atmosphere due to the uneven heating of the earth's surface. This creates a cell macrocirculation: the air masses heat up, decrease in density and rise, attracting cooler air that flows on the earth's surface towards the equator. This movement of hot and cold air masses produces the typical high- and low-pressure areas, permanently present in the atmosphere [6].

In this work we will study how to use the measurements made on the noise emitted by a wind turbine to develop an automatic system for identifying its operating conditions. Wind turbines produce a noise characterized by two components: the mechanical noise coming from the generator and the aerodynamic noise due to the rotation of the rotor blades [7]. The mechanical noise produces a sound level lower than that due to the rotation of the blades and already at a distance of a few tens of meters from the turbine, it is no longer perceptible. On the contrary, the aerodynamic noise is persistent, even if at 200 meters it can be confused with the wind noise in the surrounding environment. To begin with, measurements were made of the noise emitted by a wind turbine. The results were elaborated to use them as input of a model based on artificial neural networks for the recognition of the operating conditions of wind turbines.

Methodology

The acoustic measurements were made in a rural area of southern Italy. It is a hilly area with the presence of tree crops. In this area a wind farm with several wind turbines has been built. The analyzed wind turbine has a horizontal axis with a nominal power of 200 kW. The tower is of the monopolar tubular type and 80-meter hub height, equipped with three blades with a diameter of 95 meters, made of glass fibers. The maximum power is obtained in wind conditions that has a speed ranging from 10.5 m/s to 25 m/s. Beyond this speed the blades are stopped by the safety system to guarantee the integrity of the system.

Noise measurements were performed in the condition of maximum disturbance, inside a private house with open windows. For the measurement, an LXT1 Larson Davis sound level meter was used, which integrates a "Class 1" sound level meter model and a Larson Davis CAL 200 calibrator. The sound level meter complies with the requirements of the IEC61400-11 standard [8]. The sound level meter was installed at a height of 1.60 meters from the floor and 1.2 m from the window. The window has the following dimensions: 2 m wide and 1.2 m high. The room is 5 m wide, 4 m long and 3 m high, and is normally furnished. The sound level meter was configured for the acquisition of the equivalent level of linear sound pressure, weighted "A", and for the frequency spectra in 1/3 octave band, with a fast time constant.

Noise measurements were performed during the day with two operating conditions: wind turbine turned on and off. To identify the operating conditions of the wind turbine, the measured sound levels were compared. The temporal history and frequency spectrum in thirds of the octaves were analyzed. The results of the measurement processing were used as input to implement a model based on neural networks for the automatic recognition of the conditions of the wind turbine turned on and off.

Machine learning algorithms are widely used in various fields of use [9-19], in many cases these algorithms have been used to solve various problems related to the operation of wind turbines [20-23]. Artificial neural networks are information processing systems. Artificial neural networks are structured in such a way as to return the link between input and output data. The correlation between the quantities detected is often unknown a priori. The use of sensors for detecting physical quantities in conjunction with a system based on artificial neural networks makes it possible to determine the correlation sought and therefore possible to control the automation system.

The system based on neural networks, like the human mind, can process large amounts of input data, apparently unrelated to each other, and to produce a usable decision in output. This ability to learn is the fundamental characteristic that makes it possible to discover the correlation sought in the data.

The identification model developed is based on a feed-forward artificial multi-layer neural network, with 1 hidden layer and 2 output classes representing the two operating conditions (on, off). A supervised learning paradigm was adopted. In the training phase 70% of the input data and the respective binary outputs were randomly selected. In this phase, the training data set was sent to the network for weighing and error minimization. The resilient backpropagation algorithm with backtracking was used. In this way the weights of the network have been updated iteratively for the purpose of minimizing the error function in finding the local minimum. In backtracking the weights are updated restoring the previous iteration and adding a small value to the weight. After the training phase, a test phase was performed, using 30% of the remaining data.

Results

During the acoustic measurements an average wind speed of 6.9 m was measured with a maximum wind speed peak of 11.7 m/s. During the monitoring period the turbine was switched on and off according to the following schedule: The acoustic measurements started at 10:58 and ended at 15:32 with a duration of 4 hours 34 minutes and 15 seconds. During the measurements the following operating conditions were monitored in order: Tower ON; Tower OFF; and Tower ON. Figure 1 shows the trend of the sound pressure level for the operating conditions monitored during the measurement session. The figure shows the dynamics of the turbine's operation to make the differences in the measured levels more noticeable.

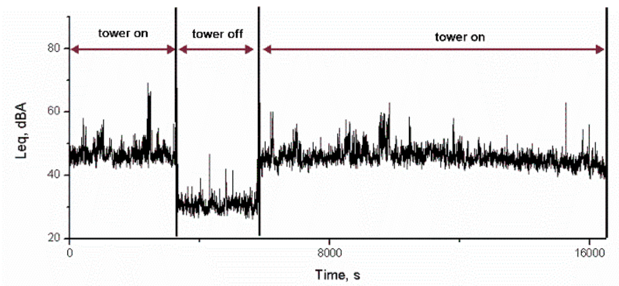

Figure 1. Sound pressure level time history in the measurement sessions.

In Figure 1, the operating conditions are clearly identified, also thanks to the labels we have added. In the off-turbine monitoring period, sound levels are significantly reduced. This confirms that the source that characterizes the environmental noise is precisely the wind turbine under investigation. To obtain further information, in Figure 2, the average spectral levels in the 1/3 octave band between 50 Hz and 5 kHz are shown for the entire measurement session.

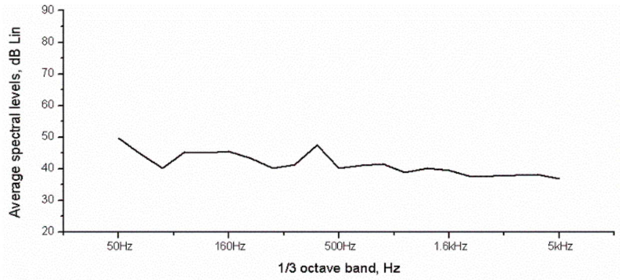

Figure 2. Average spectral levels in 1/3 octave band during the entire monitoring period.

The data acquired during the measurements were subsequently processed to identify features capable of distinguishing the different operating conditions of the wind turbine. As shown in Figure 1, the following three operating periods have been isolated, in order: Torre ON, Torre OFF and Torre ON. Table 1 shows the information relating to the three operating conditions detected in the measurement session. From the analysis of the acquired data it is possible to verify that the three different operating conditions are confirmed by the noise levels recorded by the sound level meter. Operating conditions with the tower on have higher sound pressure levels (49.9-47.0 dBA). In operating conditions with tower off the sound pressure levels are lower (31.1 dBA).

Table 1. Acoustic measurements for the three operating conditions monitored.

Operating conditions	*Duration (hour)*	*LeqA (dBA)*
Tower ON	0:48:39	49.9
Tower OFF	0:35:36	31.1
Tower ON	2:55:11	47.0

Figure 3 shows the pressure levels measured in the three different identified operating conditions, one above the other to make a comparison easier. In the three monitoring periods there are no anomalous and occasional phenomena. This tells us that the acquired data can be used as input for the classification model. To elaborate the classification model of the operating conditions of the wind turbine, the measured data were resampled by setting an integration time of 1 second. For each observation, the A-weighted equivalent levels for each 1/3 octave band were calculated. In this way, 15569 observations were collected and 21 variables were selected. To characterize the three periods, it was decided to use the average spectral levels in 1/3 octave bands between 12.5 Hz and 20 kHz as descriptors. Figure 4 shows the average spectral levels in 1/3 octave bands between 50 Hz and 5 kHz for each of the three identified observation periods.

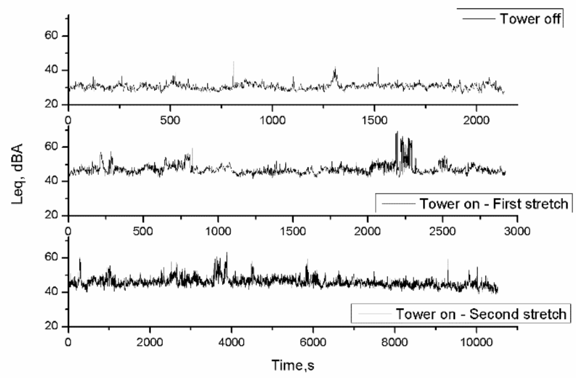

Figure 3. Sound pressure level measured in the three different operating conditions.

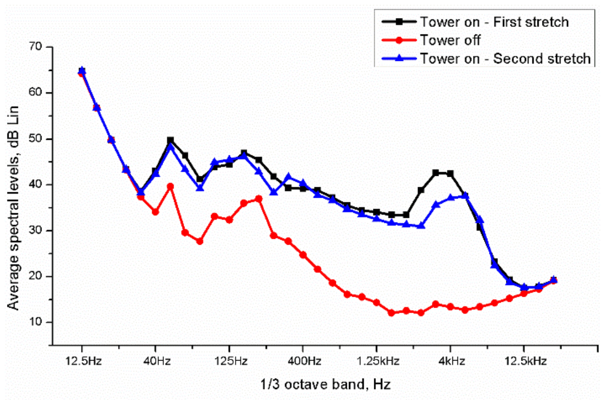

Figure 4. Average spectral levels in 1/3 octave band between 12.5 Hz and 20 kHz for each of the three different operating conditions.

Figure 4 shows that the operating conditions can be identified in the central part of the graph. The extremes do not contribute to the identification of operating conditions. Thus, not all frequencies are necessary for setting up the model. We omit the low and high frequencies in which the three curves overlap, we limit the range from 50 Hz to 5 kHz. In this way the curves are distinct and the different operating conditions are identifiable, as shown in Figure 5.

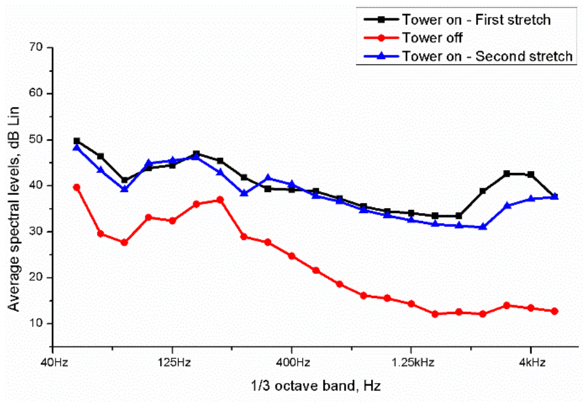

Figure 5. Average spectral levels in 1/3 octave band between 50 Hz and 5 kHz.

In Figure 5 it is possible to notice that when the turbine is on, the spectral values are higher. Below this curve, we find the values relating to the operating condition with the turbine turned off. Visual analysis allowed us to perform a first selection of features. For the correct identification of the operating conditions, in addition to the extreme frequencies, it is possible that other frequencies are not necessary. A visual analysis through a wrapper for density lattice plots could identify the characteristics able to discriminate between the different operating conditions (Fig.6).

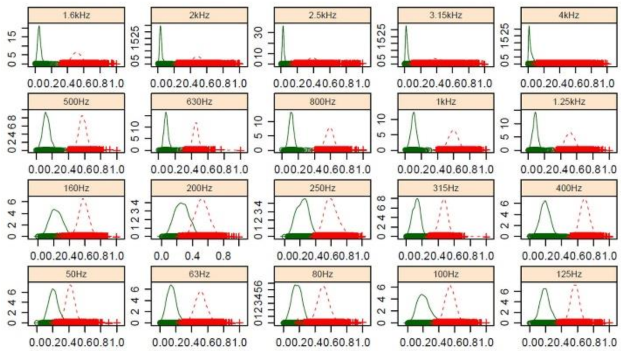

Figure 6. Density lattice plots for average spectral levels in 1/3 octave band from 50 Hz to 4 kHz.

Analyzing Figure 6 it is possible to notice some characteristic bell-shaped curves that identify the distribution for each frequency of the two identified operating conditions. In the central frequencies ranging from 50 Hz to 5 kHz, some frequencies discriminate better than others. To identify the most relevant frequencies for the model's performance, we need to perform a feature selection procedure.

The objective of the feature selection procedure is to identify features that allow objects to be identified and that are insensitive to translation, rotation or scale problems. A procedure is then performed that reduces the complexity of the information to be processed and makes the system more efficient. An extracted parameter must be obtained in a simple way but must have a high discriminating power.

However, the Boruta algorithm [24] was used to select the features. It is a wrapper built around the random forest classification algorithm [25]. Random forest is a supervised algorithm based on learning multiple forecast models to form a single, more powerful forecasting model. Each model used by the Random Forest prediction is usually a decision tree. This means that a random forest combines many decision trees into a single model. Individually, the forecasts made by the individual decision trees may not be accurate, but combined, the forecasts will be closer to the result on average. The random forest algorithm can be used for both regression and classification problems.

The Random Forest algorithm evaluates the importance of a variable by analyzing how much the prediction error increases as the variable changes, when the values of all the other variables are kept unchanged. The calculations are tree-by-tree.

The Boruta algorithm iteratively compares the import of attributes with the import of shadow attributes, created by mixing the original ones. The features that return worse performance than the shadow ones are progressively eliminated. In this way, significantly better shadow features are selected. Shadows are recreated in each iteration. The algorithm stops when only the confirmed attributes remain or when the maximum number of operations is reached.

Table 2 shows the mean, median, maximum and minimum importance, the number of normalized hits to the number of analyzes of the source of importance performed and the decision for each function contained in the data frame. Table 2 is shown at the end of the paper.

To get an overall view of the analysis performed and to appreciate the differences between the contributions that each feature provides to the final result, we have drawn a diagram. Figure 7 shows the attribute plot boxes as they are shown in Table 2. Furthermore, the features are plotted in order of importance starting from the far right.

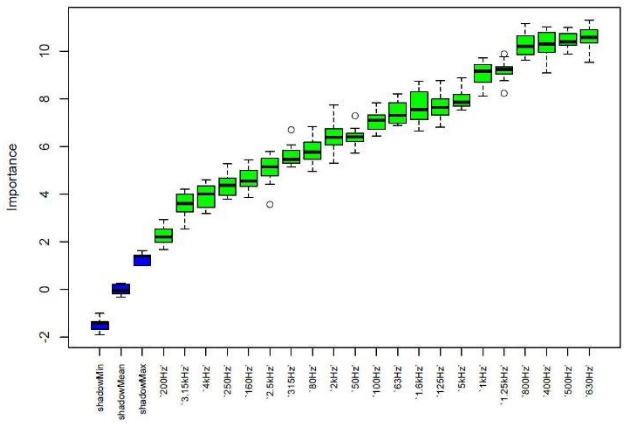

Figure 7. Boxplots of features ordered for importance.

Both Figure 7 and Table 2 allow us to identify the variables that have obtained the highest values in importance. To lower the cost of the calculation and to avoid over-adaptation, we have further reduced the number of features to be used as input of the classification model based on neural networks. Only the first 10 of those that recorded the highest values in the **meanImp** were selected. Table 3 shows the first 10 variables selected from the model in order of importance.

Table 3. The best features selected.

630Hz	500Hz	400Hz	800Hz	1.25kHz
1kHz	5kHz	125Hz	1.6kHz	63Hz

The Boruta method has returned the features in order of importance. We have selected the first 10 in order of importance to be used as input variables for a supervised classification model. This model creates a neural network to identify the operating conditions of the wind turbine.

The following neural network architecture has been implemented:

- Input level with 10 nodes (input variables)
- Hidden layer with 10 nodes
- Output level with a dichotomous value (ON, OFF)

The neural network has been trained with resilient backpropagation with the weight backtracking algorithm. The resilient backpropagation algorithm modifies the weights of a neural network in an iterative way in order to find a local minimum of the error function [26-27].

Before proceeding with the training of the network, it is necessary to subdivide the data. The data subdivision procedure adopted can have a significant effect on the quality of the subsets that will be used for training and on the test. Inaccurate model performance may result from poor data breakdown [28]. The data were divided into two randomly selected groups:

- A training set equal to 70% of the available observations (10899 samples): these are presented to the network during training and the network is adjusted based on its error.
- A set of tests equal to the remaining 30% of the available observations (4670 samples): these have no effect on training and therefore provide an independent measure of network performance during and after training.

Figure 8 shows the architecture of the neural network model adopted. In it it is possible to identify the value assigned to the weights of the connections as well as the bias values.

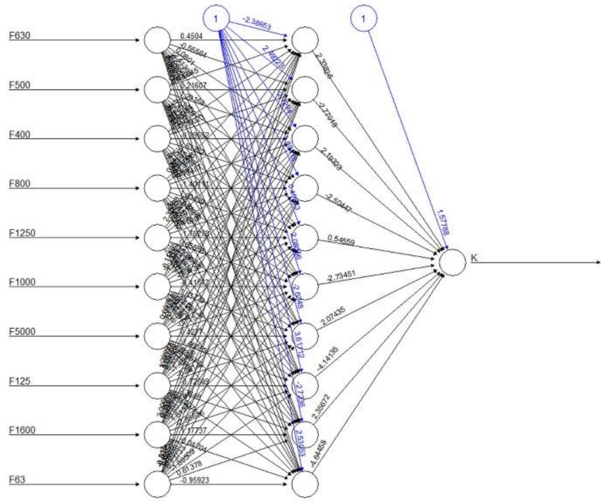

Figure 8. Neural network architecture with input, weights, and biases.

Table 4. Confusion matrix.

	Predictions	
Actual	OFF	ON
OFF	622	18
ON	17	4013

Table 4 shows the confusion matrix of the model. The confusion matrix describes the performance of a classification model on a set of data for which the real values are known. The results are presented in tabular form. The rows contain the occurrences of the expected class while the columns contain the occurrences of the true class. The diagonal cells contain the occurrences of correctly classified observations. The data contained in the cells outside the diagonal correspond to incorrectly classified observations [29].

The confusion matrix presents excellent results. There are only 35 errors out of 4670 occurrences. So the accuracy of the model is high (Precision = 0.99), this tells us that the model based on neural networks is able to identify the operating conditions of a wind turbine.

Conclusion

In this study the measurements of the noise emitted by the wind turbine were used to train a classification model based on neural networks. First, the average spectral levels in a 1/3 octave band were examined through a visual analysis in order to select the frequency range able to identify the turbine operating conditions. Later, a model for assessing the importance of variables was used to select features based on relative importance. The results of this model have been used to reduce the number of predictive variables, using the random forest algorithm. The subset of predictors so selected was used to develop an accurate forecasting model. Finally, a model based on a neural network for detecting the operating conditions of a wind turbine has been designed and trained. The results obtained suggest in-depth studies on the development and application of this technique in these contexts. In particular, the high precision of the model (Precision = 0.99) proposes the adoption of this tool for different applications.

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Table 2 Attribute statistics of the feature importance analysis.

Frequency	***meanImp***	***medianImp***	***minImp***	***maxImp***	***normHits***	***decision***
630Hz	10.588.677	10.569.419	9.530.693	11.303.876	1	Confirmed
500Hz	10.437.252	10.390.159	9.870.818	10.988.832	1	Confirmed
400Hz	10.303.382	10.297.387	9.079.808	11.020.370	1	Confirmed
800Hz	10.299.554	10.210.500	9.634.459	11.164.620	1	Confirmed
1.25kHz	9.194.757	9.222.337	8.230.829	9.882.266	1	Confirmed
1kHz	9.031.084	9.165.310	8.114.298	9.706.277	1	Confirmed
5kHz	7.964.806	7.852.242	7.529.921	8.876.685	1	Confirmed
125Hz	7.711.010	7.635.726	6.822.084	8.760.154	1	Confirmed
1.6kHz	7.697.697	7.558.887	6.645.246	8.750.942	1	Confirmed
63Hz	7.402.964	7.311.983	6.882.303	8.217.014	1	Confirmed
100Hz	7.063.215	7.107.488	6.442.282	7.835.868	1	Confirmed
50Hz	6.420.612	6.405.997	5.728.199	7.290.249	1	Confirmed
2kHz	6.364.333	6.383.840	5.312.907	7.752.230	1	Confirmed
80Hz	5.829.579	5.764.305	4.957.193	6.840.125	1	Confirmed
315Hz	5.609.310	5.466.688	5.140.460	6.700.957	1	Confirmed
2.5kHz	5.051.933	5.153.177	3.571.474	5.797.949	1	Confirmed
160Hz	4.653.575	4.553.002	3.872.390	5.450.479	1	Confirmed
250Hz	4.381.987	4.376.984	3.790.141	5.272.184	1	Confirmed
4kHz	3.933.503	4.016.383	3.179.093	4.611.066	1	Confirmed
3.15kHz	3.534.830	3.611.499	2.534.415	4.201.253	1	Confirmed
200Hz	2.261.011	2.205.732	1.677.495	2.925.925	1	Confirmed