Short term wind speed prediction using Multi Layer Perceptron

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ABSTRACT

Among renewable energy sources wind energy is having an increasing influence on the supply of energy power. However wind energy is not a stationary power, depending on the fluctuations of the wind, so that is necessary to cope with these fluctuations that may cause problems the electricity grid stability. The ability to predict short-term wind speed and consequent production patterns becomes critical for the all the operators of wind energy.
This paper studies several configurations of Artificial Neural Networks (ANN), a well-known tool able to estimate wind speed starting from measured data. The presented ANNs, t have been tested through data gathered in the area of Trapani (Sicily). Different models have been studied in order to determine the best architecture, minimizing statistical error. Simulation results show that the estimated values of wind speed are in good accord with the values measured by the anemometers.

Keywords: Artificial neural networks, Multi layer perceptron, Feed forward network Forecasting, Renewable energy, Wind energy, Wind speed

INTRODUCTION

Among the renewable resources the one that had a faster technological innovation and a more rapid diffusion is wind energy. The power generated by wind turbines depends on the intensity and persistence of the wind in the area under consideration. Therefore a good knowledge of the characteristics of the wind is a prerequisite for a good planning and construction of any wind power project. In the literature several statistical methods are reported to estimate the wind speed [1,2,3]. These methods aim to find the relationships between the climatic data recorded in the site and then the quality of the collected data is extremely important.
The simple knowledge of wind speed data is not sufficient to calculate the energy production available in a site. To get more complete information is necessary to know probability distribution of wind speed over the time.

In fact the knowledge of the probability density functions (PDF) of the wind speed is very important for the assessment of the performance of wind turbines. Actually, the quality of the productivity analysis in wind farm planning depends on the capability of the PDF, for example the Weibull distribution, to describe the measured wind speed frequencies distribution [4,5].

Anyway, because the wind is an intermittent resource the instantaneous power generated by a wind farm varies rapidly. The fluctuation of wind power generation in many cases causes problem of grid stability [6, 7]. For this reason becomes crucial to apply forecasting methods of the wind speed and the consequent production of a wind energy installation in the short term, i.e. some hours.

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The learning approach, based on artificial neural networks, is a valid tool to predict wind speeds. ANNs have the capability to process complex input-output data sets (even if not physically related) in order to forecast an event starting from learning of a past phenomenon.

Artificial neural networks are network systems which are built by simulating the learning behavior of human being [8]. In fact they have the ability to learn from past experience and then apply their knowledge to new event. There are many different typologies of ANN [9] but in this study the Multi Layer Perceptron (MLP), also called feed forward network, has been used for predicting the wind speed [10].

In this work different configurations of MLP have been proposed in order to find the best exploitation of the wind data in gathered in the area of Trapani (Sicily). Three different models with single or double hidden layers (and with a different number of neurons) have been tested in order to find the best network architecture [11].

ARTIFICIAL NEURAL NETWORKS

In the last years the artificial neural networks have been applied in different sectors like engineering, medicine, physics. In fact they can be used in problems of prediction, classification or control. ANNs are indeed a tool for modelling and forecasting, which is widely used as a valid alternative to solve complex problems arising when variables are not clearly related by physical laws.

The ability of the ANN to approximate large classes of non-linear functions with a good accuracy makes them very appropriate for the representation of dynamic non-linear systems [12].

Artificial neural networks are characterized by an interconnection of few simple elements whose functionality is based on the human biological neurons.

There are several typologies of neural networks described in literature (Feedforward neural network, Kohonen self-organizing network, Radial basis functions, Recurrent neural network etc..) but in this study the Multi Layer Perceptron (MLP), also called feed forward network, has been used for predicting the wind speed.

The communication within the network is based on a layered structure. Each layer makes independent computations. The first and the last layers are respectively the input and output layers. The layers placed between those are the hidden layers [13]. The neurons (or processing elements) of the hidden layer receive information from the previous layer and are related with neuron of the next layer. They can only interact with neurons of the neighbouring layers while there are no connections between the neurons of the same level. Each processing element makes its computation based upon a weighted sum of its inputs.

Figure 1 show a generic topology of artificial neural network.

The basic elements in the neuron model are the synapses and the activation function (back propagation algorithm). The synapses are represented as connections between units.

Input initializes the activation weightings of the neurons in the input layers.

The activation level on the first layer is the then passed to the next layer. The set of the weights to be applied to these inputs is re-calculated in every calculation step by a back propagation algorithm in order to minimize the squares of the differences between the actual and the desired outputs.

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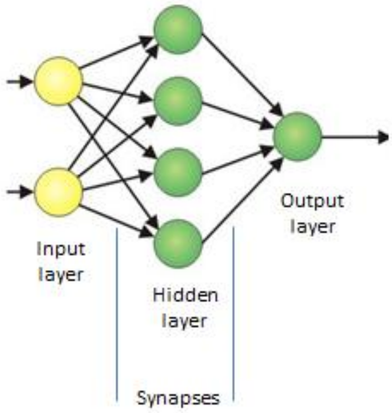

Figure 1. The neural network architecture

Different configurations of MLP based on variable number of layers and neurons have been studied for the specific application to Trapani (Sicily).
Three different models with single or double hidden layers (and with a different number of neurons) have been verified in order to identify the best neural architecture able to provide a short–term wind speed forecasting. In a first step of this study data collected by two anemometers with the frequency ten minutes have been utilised. In a second phase data captured every ten minutes have been averaged in order to obtain hourly figures.

DESIGN PROCESS OF ANN SYSYSTEM

The process of set-up and validation of a neural system [14] generally includes the following steps:

- Data acquisition and pre-processing;
- Statistical analysis and normalization;
- Design of ANN structure;
- Training and validation phases;
- Testing phase.

Usually the design process is iterative. In fact it is possible that a particular structure falls on default in one of the steps listed above. In this situation it is necessary to change the model and the ANN should be retrained [15].
The wind speed data vectors, v_1 and v_2, adopted in this study, have been acquired by two anemometers installed at hub height of 50 m with a frequency of ten minutes [7]. The data set contains the wind speed recorded from 28 April 2005 to March 2008.
As a preliminary phase, it was necessary to process the raw data in order to assess their quality. To fulfil this task it is necessary to identify, according to the period of observation, the expected number of data, the number of missing data, the number of data with not null wind speed, the measurements of calm and discard incorrect values.
In order to have further confirmations of the consistence and reliability of the data it is possible to perform additional statistical analyses such as the calculation of Weibull or Rayleigh distributions.
Once the pre-processing phase has been fulfilled, data are normalized and processed through a correlation analysis in order to identify the best period of data set to be used in the training and in the testing phases [14]. The aim of this analysis is to assess the strength of a linear or nonlinear relationship between the two vectors v_1 and v_2. The correlation coefficient can assume values

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between -1 and 1. It is equal to -1 when there is a negative correlation between the two data sets, is equal to 0 when data are not correlated and to 1 when there is a positive correlation.
During the training phase the best data set is represented by the one with the best correlation coefficient while during the testing phase the data with the worst correlation must be used.
From the result of correlation analysis (Table 1) authors decided to use the data measured in May 2006 for the training phase and the data detected in May 2005 for the testing phase.

Table 1. Result of correlations

Month	Correlation coefficient		
	2005	2006	2007
January		1	1
February		0.99	1
March		1	1
April	0.87	1	0.99
May	0.80	1	1
June	0.86	1	1
July	0.85	1	1
August	0.81	1	1
September	0.85	1	1
October	0.88	1	1
November	0.82	1	1
December	0.84	1	1

In order to control the generalization ability of the network in adapting the experience acquired in the training phase, the technique of cross validation (CV) has been applied. With the cross validation the data of training phase are divided in a subset of estimation and a subset of validation. The first subset (70 % of data) is used to obtain estimates of parameters and the second (30% of data) is used to validate the performance of the estimate.
In order to identify the best model among the ones analysed, authors have adopted the criteria of minimization of the Mean Square Error (MSE) with a tolerance limit set to 20% [16].
If y_t is the actual observation for a time period t and F_t is the forecast for the same period, the error is the MSE can be defined by:

$$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2; \qquad e_t = y_t - F_t \tag{1}$$

Where n is the number of periods of steps.
The MSE was calculated not only during the training phase but also in the validation and testing phases.

PROPOSED MODELS OF MULTY LAYER PERCEPTRONS FOR PREDICTION OF WIND SPEED

Three different configurations of MLP with different complexity have been tested to perform forecast of wind speed data from one to five time steps forward.
The network called “Low” has only one hidden layer, the “Medium” and “High” networks have two hidden layers but a different number of neurons. The input data that were provided to the

networks are the wind speeds v_1 and v_2 recorded by two anemometers placed in the same area. The forecast processing was carried out for different number of time steps (ten minutes): from zero to five.

Above the described configurations the authors have tested the following networks:

- Networks v_1-v_1 where v_1 is used as input and output;
- Networks v_2-v_2 where v_2 is used as input and output;
- Networks v_1v_2-v_1 where v_1 and v_2 are the input data and the output is the speed v_1;
- Networks v_1v_2-v_2 where v_1 and v_2 are the input data and the output is the speed v_2.

Therefore the acronym of the different models is composed by three elements: input data vector, forecast length and type of architecture. For example in the network (v_1_1_L), in table 2, v_1 is the input, 1 is the forecast horizon (ten minutes) and L is the network architecture with low complexity.

The obtained results are presented in following tables. Tables 2 and 3 show the calculated MSE for the networks with only one input while tables 4 and 5 show the MSE for the networks with two inputs.

It is worth noting that the ANNs with two inputs and one hidden layer (Low) are certainly the best models.

Table 2. Mean square errors for the neural networks with v_1 for input and output

Network	MSE Train	MSE CV	MSE Test
v_1_0_L	0.00000057	0.00000076	0.0000000001
v_1_1_L	0.00334762	0.00364580	0.0000000067
v_1_2_L	0.00612936	0.00733753	0.0000000280
v_1_3_L	0.00886840	0.01067830	0.0000000644
v_1_4_L	0.01090821	0.01365200	0.0000000781
v_1_5_L	0.01344239	0.01625730	0.0000001005
v_1_0_M	0.00067529	0.00106042	0.0000001165
v_1_1_M	0.00679159	0.00922480	0.0000005620
v_1_2_M	0.00670291	0.00871230	0.0000001430
v_1_3_M	0.01405680	0.01887690	0.0000009275
v_1_4_M	0.01154532	0.01509001	0.0000002109
v_1_5_M	0.01433278	0.01888038	0.0000004094
v_1_0_H	0.00796097	0.01493450	0.0000016659
v_1_1_H	0.00815784	0.01453130	0.0000010978
v_1_2_H	0.00960655	0.01253950	0.0000008668
v_1_3_H	0.01189107	0.01417621	0.0000007623
v_1_4_H	0.01303969	0.01830570	0.0000005747
v_1_5_H	0.01364650	0.01839424	0.0000003863

Table 3. Mean square errors for the neural networks with v_2 for input and output

Network	MSE Train	MSE CV	MSE Test
v_2_0_L	0.00000050	0.00000074	0.00001712
v_2_1_L	0.00340190	0.00362519	0.00013141
v_2_2_L	0.00621156	0.00734003	0.00087517
v_2_3_L	0.00898109	0.01069069	0.00082469
v_2_4_L	0.01131379	0.01359214	0.00140055
v_2_5_L	0.01305820	0.01604964	0.00197225
v_2_0_M	0.00055900	0.00082680	0.33980218

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v_2_1_M	0.00863774	0.01140980	0.01276821
v_2_2_M	0.00662890	0.00841130	0.00180536
v_2_3_M	0.00930510	0.01175050	0.00264751
v_2_4_M	0.01421550	0.01824130	0.00948332
v_2_5_M	0.01338553	0.01659220	0.00320692
v_2_0_H	0.01809274	0.01411125	0.00685920
v_2_1_H	0.00651950	0.01033940	0.01272843
v_2_2_H	0.00956068	0.01018382	0.00780280
v_2_3_H	0.01228585	0.01855370	0.01446880
v_2_4_H	0.01329478	0.01839603	0.00463121
v_2_5_H	0.01741058	0.02189950	0.01481504

Table 4. Mean square errors for the neural networks with two input and v_1 for output

Network	MSE Train	MSE CV	MSE Test
v_1v_2_0_L	0.000000224	0.000000273	0.000000000028
v_1v_2_1_L	0.003223600	0.003619700	0.000000013944
v_1v_2_2_L	0.006275820	0.007637000	0.000000047509
v_1v_2_3_L	0.008872400	0.010854700	0.000000099515
v_1v_2_4_L	0.011205780	0.013751800	0.000000108993
v_1v_2_5_L	0.013488754	0.016417000	0.000000132973
v_1v_2_0_M	0.000566651	0.000918420	0.000000092089
v_1v_2_1_M	0.003652880	0.004586410	0.000000093628
v_1v_2_2_M	0.006553250	0.008482700	0.000000114684
v_1v_2_3_M	0.008933580	0.011280140	0.000000113543
v_1v_2_4_M	0.011352500	0.014577740	0.000000164365
v_1v_2_5_M	0.013218870	0.016708900	0.000000181975
v_1v_2_0_H	0.003021920	0.006362070	0.000000639601
v_1v_2_1_H	0.006717400	0.012650300	0.000000957869
v_1v_2_2_H	0.011288290	0.018646500	0.000001318420
v_1v_2_3_H	0.022805550	0.030301200	0.000000460971
v_1v_2_4_H	0.013574470	0.022353800	0.000001217575
v_1v_2_5_H	0.015183530	0.021027510	0.000001066649

Table 5. Mean square errors for the neural networks with two input and v_2 for output

Network	MSE Train	MSE CV	MSE Test
v_1v_2_0_L	0.00008500	0.00023692	0.0000000203
v_1v_2_1_L	0.00322066	0.00367138	0.0000236788
v_1v_2_2_L	0.00617680	0.00753680	0.0000000965
v_1v_2_3_L	0.00881186	0. 0107297	0.0000231019
v_1v_2_4_L	0.01110347	0.01348470	0.0000001620
v_1v_2_5_L	0.01288910	0.01609230	0.0000001725
v_1v_2_0_M	0.00063298	0.00091802	0.0000001037

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v_1v_2_1_M	0.00381116	0.00488440	0.0000001205
v_1v_2_2_M	0.00977035	0.01310015	0.0000005951
v_1v_2_3_M	0.00910830	0.01173160	0.0000001512
v_1v_2_4_M	0.01134850	0.01458897	0.0000001782
v_1v_2_5_M	0.01327440	0.01690310	0.0000001974
v_1v_2_0_H	0.00785680	0.00788916	0.0000238310
v_1v_2_1_H	0.00553737	0.00772170	0.0000005244
v_1v_2_2_H	0.00810041	0.01104280	0.0000005570
v_1v_2_3_H	0.01281810	0.01865220	0.0000008167
v_1v_2_4_H	0.01555260	0.02733420	0.0000018408
v_1v_2_5_H	0.01591726	0.02334670	0.0000012571

A further comparison of the network architectures with the lowest values of MSE has been done by assessing the average and standard deviation of desired and actual outputs and thus percent deviation between the generated and that expected values. The results of the Table 6 show that the smaller values of percent deviation are obtained for networks with two inputs and v_1 as outputs.

Table 6. Analysis of MSE

Networks		Desired output	Actual output	Percent Deviation
v_1_0_L – v_1	Average	5.68	5.68	0.03
	St. Deviation	3.76	3.76	0.03
v_1_0_M- v_1	Average	5.68	5.77	1.54
	St. Deviation	3.76	3.79	0.72
v_1_1_H- v_1	Average	5.68	5.71	0.44
	St. Deviation	3.76	3.77	0.21
v_2_0_L-v_2	Average	5.68	5.73	0.12
	St. Deviation	3.76	3.72	0.36
v_2_2_M-v_2	Average	5.68	5.77	0.82
	St. Deviation	3.76	3.60	3.12
v_2_4_H-v_2	Average	5.68	5.72	0.10
	St. Deviation	3.76	3.30	11.13
v_1v_2_0_L-v_1	Average	5.72	5.73	0.15
	St. Deviation	3.71	3.74	0.71
v_1v_2_0_M-v_1	Average	5.72	5.80	1.42
	St. Deviation	3.71	3.75	1.16
v_1v_2_0_H-v_1	Average	5.72	4.71	17.70
	St. Deviation	3.71	3.91	5.26
v_1v_2_0_L-v_2	Average	5.68	5.68	0.002
	St. Deviation	3.76	3.76	0.018
v_1v_2_0_M-v_2	Average	5.68	5.77	1.572
	St. Deviation	3.76	3.78	0.601
v_1v_2_0_H-v_2	Average	5.68	5.50	3.215
	St. Deviation	3.76	3.49	7.215

PREDICTION OF HOURLY AVERAGED WIND SPEEDS

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Authors have carried out an additional analysis in which the data collected every 10 minutes were averaged on hourly basis. The same structures of ANN have been used for the wind speed hourly prediction. In this case the network output is a vector of five hourly values. The results obtained show that the best networks are those having low complexity and v1 as output. Compared to the networks application for the forecast of values for sampled every 10 minutes, there is an increase of the error. Table 7 and 8 show respectively the values of MSE for the networks with hourly forecast with one or two inputs and v1 for output. Table 9 shows the average, the standard deviation and the percent deviation between the value generated and the one expected.

Table 7. Mean square errors for forecasting max five values of hourly averaged data with v_1 for input and output

Network	MSE Train	MSE CV	MSE Test
v_1_0_L	0.000001	0.000001	0.000000000024
v_1_1_L	0.009653	0.012356	0.000000008450
v_1_2_L	0.019907	0.026790	0.000000024770
v_1_3_L	0.028060	0.037530	0.000000109036
v_1_4_L	0.035672	0.043502	0.000000098429
v_1_5_L	0.0134423	0.0162573	0.000000184865
v_1_0_M	0.000301	0.000409	0.000000007951
v_1_1_M	0.009632	0.014203	0.000000025767
v_1_2_M	0.019786	0.029321	0.000000072453
v_1_3_M	0.025815	0.042474	0.000000155792
v_1_4_M	0.034670	0.044968	0.000000191115
v_1_5_M	0.039508	0.053926	0.000000260284
v_1_0_H	0.000335	0.000400	0.000000010828
v_1_1_H	0.010180	0.013291	0.000000027174
v_1_2_H	0.020149	0.028046	0.000000076288
v_1_3_H	0.029159	0.039595	0.000000208403
v_1_4_H	0.037417	0.045626	0.000000274167
v_1_5_H	0.042210	0.049784	0.000000207080

Table 8. Mean square errors for forecasting max five values of hourly averaged data with two input and v_1 for output

Network	MSE Train	MSE CV	MSE Test
v_1v_2_0_L	0.000173	0.000030	0.0000000003
v_1v_2_1_L	0.009646	0.012127	0.0000000100
v_1v_2_2_L	0.010572	0.027039	0.0000000269
v_1v_2_3_L	0.027485	0.039845	0.0000001309
v_1v_2_4_L	0.034067	0.048339	0.0000000892
v_1v_2_5_L	0.039193	0.056843	0.0000001295
v_1v_2_0_M	0.002246	0.000342	0.0000000058
v_1v_2_1_M	0.009305	0.013672	0.0000000247
v_1v_2_2_M	0.018654	0.030343	0.0000000943
v_1v_2_3_M	0.024841	0.046203	0.0000001668
v_1v_2_4_M	0.031165	0.065871	0.0000002135
v_1v_2_5_M	0.034898	0.062296	0.0000002843

v_1v_2_0_H	0.000476	0.000770	0.0000000148
v_1v_2_1_H	0.010233	0.013212	0.0000000335
v_1v_2_2_H	0.019692	0.027589	0.0000000802
v_1v_2_3_H	0.027757	0.038128	0.0000001718
v_1v_2_4_H	0.033721	0.052073	0.0000003490
v_1v_2_5_H	0.051663	0.053404	0.0000007377

Table 9. Analysis of MSE for the best neural networks architectures for hourly forecast

Networks		Desired output	Actual output	Percent Deviation
v_1_0_L	Average	5.69	5.69	0.02
	St. Deviation	3.66	3.67	0.04
v_1_0_M	Average	5.69	5.73	0.72
	St. Deviation	3.66	3.71	1.14
v_1_1_H	Average	5.69	5.74	0.96
	St. Deviation	3.66	3.66	0.11
v_1v_2_0_L	Average	5.69	5.69	0.06
	St. Deviation	3.66	3.67	0.08
v_1v_2_0_M	Average	5.69	5.73	0.70
	St. Deviation	3.66	3.69	0.82
v_1v_2_0_H	Average	5.69	5.77	1.44
	St. Deviation	3.66	3.67	0.06

Table 9 shows that the network with architecture Low have the lower values of percent deviation compared to more complex architectures. Comparing the results with the same networks with a time step of ten minutes we have a decrease in the performance while remaining within the limit of 20%.

CONCLUSION

Speed profiles of the wind are known for having a great variability in time due to a stochastic nature of the driving phenomena. Mapping and modelling of wind speed are the essential prerequisite for any wind energy project. Therefore, the conversion and efficient utilization of wind energy resource needs an accurate knowledge of the wind characteristics on the site under investigation.

Artificial neural networks can be a valuable tool for short term prediction. Indeed they are characterized by an adaptive nature in which “learning through example” replaces classical physical or statistical models. This characteristic makes the ANN techniques very attractive to solve non-linear phenomena.

In this study different configurations of neural networks have been generated and tested to predict the wind speed. In order to compare the performances of several architectures and then to assess the best model the statistical standard error has been considered.

The result obtained are in good agreement with the measured values for many ANN configurations.

The simplest models have better performance than the more complex ones either in training either in testing phases, well describing the presence of the wind in the area where the data was collected.

By increasing the complexity of the network and the number of the input the MSE assumes highest values, however, remaining under the tolerances limit set to 20%.

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