Estimation of Wind Power Generation Using Neural Networks

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Abstract—**This paper uses data collected by weather stations to develop a neural network solution for extrapolation of wind speeds at heights ranging. Work aims to improve the foundations for a prediction of a wind profile of quality, at short and long terms. This paper begins with a comparison between different actual methods of extrapolation wind speed, and then describes an artificial neural network (ANN) approach for the vertical wind speed extrapolation. The outputs of models are compared with the real measured data so the results show a significant improvement. We conclude with the improvement of results when the assumed SISO (single-input-single-output) system is considered as a non-linear multi variable system.**

Index Terms— **Extrapolation, Neural networks, Nonlinear systems, Wind speed, Wind turbine.**

I. INTRODUCTION

TODAY, energy generated from wind is often seen as the most promising renewable energy to be developed to replace coal, oil, gas and nuclear power.

Wind resource estimation consists of the determination of the productivity (with the greatest precision possible) of a given wind turbine at a given site, for installation height of the mast of the wind turbine. Where wind speed information is available in either time series format or in a summary format. . Wind data provided by weather stations were measured at the standard height of 10 m above the surface; the researchers have embarked on extrapolation parameters winds at the height of the axis of the wind generator (50 m or more).

The choice of turbines and their precise location then requires a more precise wind conditions and turbulence taking into account local factors. The producible theory is then considered, with a calculation of uncertainty. However, the return of experience in operating the parks frequently shows a production staged less than estimated production, with gaps of up to 20%. The main contribution to these differences probably stems from the uncertainty in the determination of meteorological quantities. This is especially true when methods and tools currently in use are often found wanting.

II. MODEL AND ALGORITHM

The static and dynamic modeling is one of the main areas of use of neural networks RNs. These are nonlinear functions modular able to approximate any function in a bounded closed interval of its inputs. In first time, our system is supposed single-input-single-output (SISO) which can be modeled by the following equation:

$$y(k) = g(\varphi(k)),$$

With

$$\varphi(k) = [y(k),.....,y(k-n),u(k),..,u(k-m)]$$

And g is a non-linear function assumed unknown. The parameters m and n represent, respectively, the order of the regression on the inputs u (k) and the order of the regression on the output y (k).The output of a hybrid network will be:

$$y_{yet} = W_{2a}[W_{1a}U] + W_{2b}F[W_{1b}U]$$

Where the input vector of a neural network is $\boldsymbol{U}$, the scalar output of a network is y_{yet}, the nonlinear vector is $\boldsymbol{F}$, and the weight matrices of the linear, nonlinear, and hybrid net works are respectively $W_1, W_2, W_{1a}, W_{1b}, W_{2a}$ and $\boldsymbol{W}_{2\boldsymbol{b}}$. Further, our system will be supposed multi-input.

Neural network consist of a number of interconnected processing elements or neurons. How the inter-neuron connections are arranged determine the structure of a network. In term of their structure neural network can be divided into two types: feed-forward networks and recurrent networks.

Our choice is focused on a multilayer non-recurring. The network consists of three layers of neurons, called input layer, output layer and hidden layer. Figure 1 shows the architecture of this network.

Several learning process are available. In this work, we use learning by reverse propagation. The purpose of the learning algorithm is to minimize the total error E defined as:

$$E = \frac{1}{2}\sum_{i=1}^{N}(y_t - \hat{y}_t)^2$$

yt is the output obtained by the network and yˆt is the target

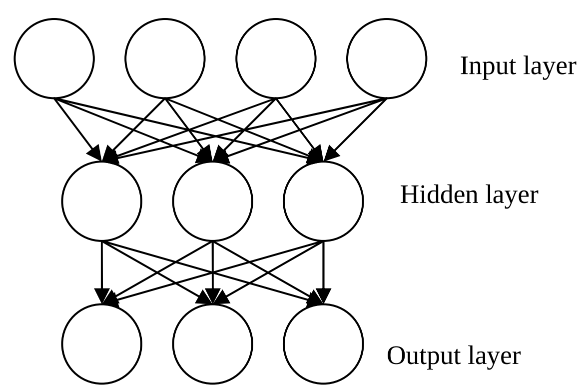

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Fig. 1. Basic Neural Network NN.

III. Results

A. *Extrapolation of wind speed between two heights*

We started by extrapolation of the wind speed from a level Z_1 = 10m to Z_2 = 50m using MatLab 7 and meteorological data. Data was collected from towers located in different regions (Algeria, Canada and USA). The data are changes of hour average wind speeds recorded every hour at heights ranging from 10m to 103m.

In this work two forms of representation are adopted:

-Figure 2 illustrated a typical plot of real wind speed (time series) at 10m and 50m.

- Figure 3 illustrated a plot of dependence structure between wind speed at 10m and wind speed at 50m, without time.

In Figure 3, we will resume under a different aspect, the same data in figure 2 but without the time variable. This second representation helps a lot to determine Input fields OF ANN, and for model validation.

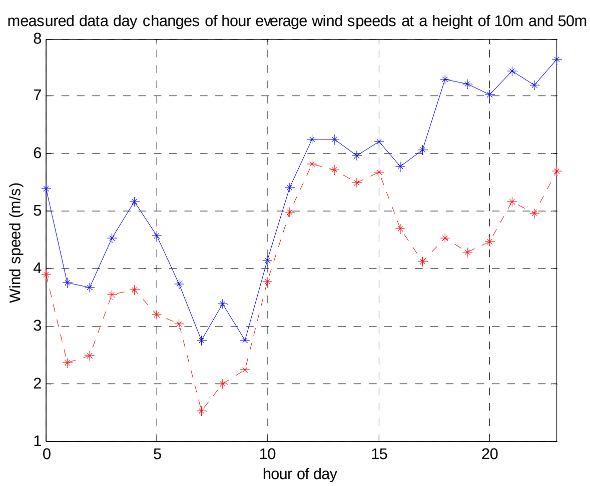

Fig. 2. Measured data day changes of hour average wind speeds at a height of 10m and 50m

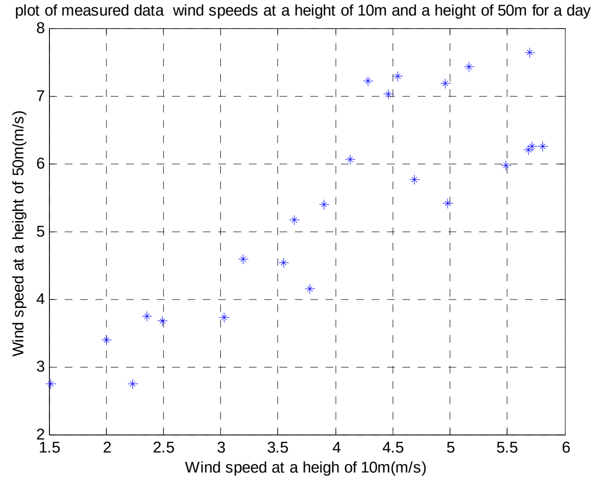

Fig. 3. Plot of measured data wind speeds

We have studied the possibilities of the neural networks for the extrapolation of wind speed from height of 10m to 50m. The Akaike criterion was used to evaluate the performance of the MLP neural networks. In order to check the most appropriate parameters for extrapolation, we carried out a sweeping in the number of neurons of the hidden layer The best results are obtained with R-S1-S2-S refers to network with two hidden layers one input and one output. The AIC is a number associated with each model:

$$AIC = N\log(EQM) + 2(q+1)$$

Where q is the number of parameters in the model, N the number of observations, and EQM the Root Mean Square Error.

The criterion may be minimized over choices of q to form a tradeoff between the fit of the model (differences between observed and estimated values) and the model's complexity, which is measured by q.

Although there are a number of ways to arrive at a prediction of a wind profile or extrapolation of the wind speed from 10m to 50m .Figure 4 illustrated Validation and comparison of results for models of vertical extrapolation wind speed.

Comparison models chosen are:

-One-seventh power law
-Justus & Mikhail power law
-Power law
-Logarithmic law
-Mikhail & al power low.

In figure 4 and table I we notice that the results of Somme methods are near to the measured data such as 1/7 law .whereas others go far such as Justus law. And the error range is too great for economic decisions

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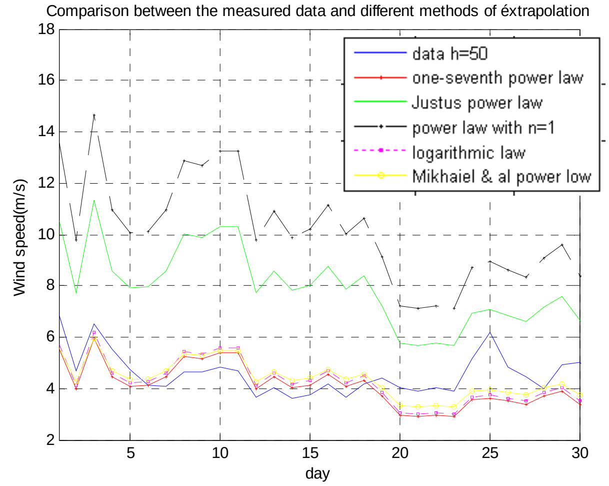

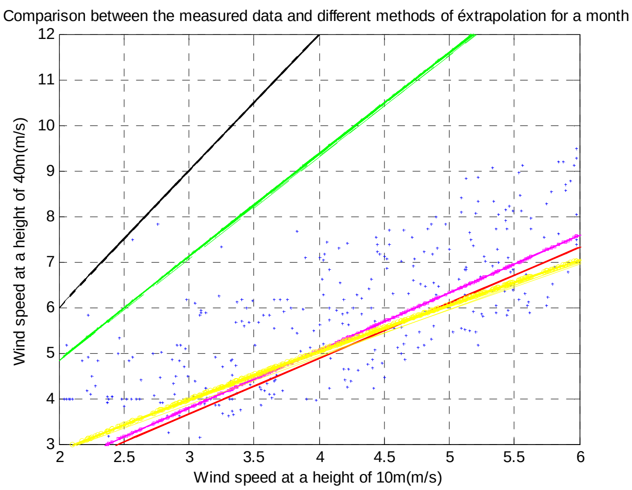

Fig. 4. plot of comparative graph of measured and estimate data wind speeds at 50m for a month

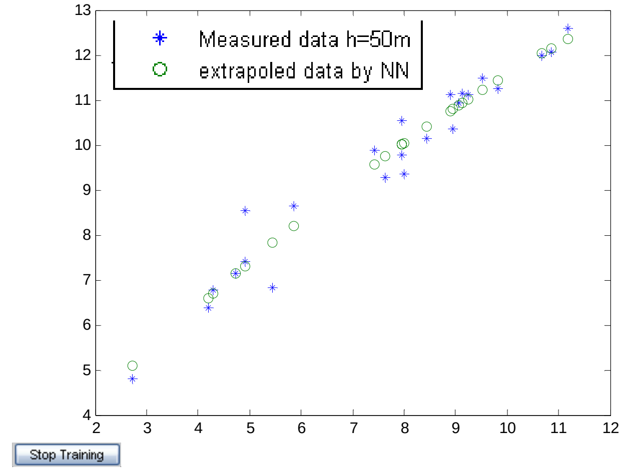

Fig. 5.Training of Neural Network.

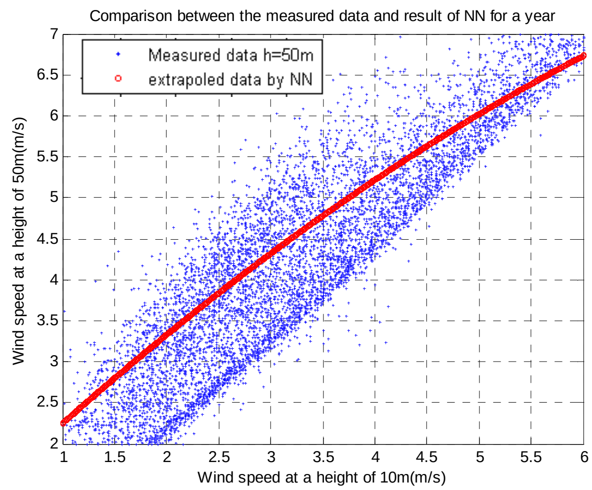

Fig. 6. Plot of measured and estimate data wind speeds for one day training and one year test phase.

The RMS error and Mean relative error has been calculated for the different estimation of the wind speeds compared at real measured data wind speed. The resultants are given in table I.

TABLE I
ROOT-MEAN-SQUARE ERROR AND
MEAN RELATIVE ERROR (IN %)

model Name	Estimation for a day	Estimation for a month	Estimation for a year
1/7 law	0.8700 (14.67%)	7.0118 (16.98%)	50.6295 (149.08%)
Justus law	3.4969 (73.62%)	33.2508 (92.86%)	90.8401 (307.25%)
power law	5.6284 (120.54%)	64.4730 (172.56%)	141.6425 (491.31%)
Log law	0.8066 (13.59%)	8.4068 (19.91%)	52.7176 (156.86%)
Mikhail & al law	0.7398 (12.73%)	9.0998 (21.75%)	29.9348 (96.25%)

In order to check the most appropriate parameters for the extrapolation, we carried out a continuation of the training time. In this way, we trained the networks, varying the training time (just one day, one month, for all year) ,the results obtained are presented in table II .

TABLE II
ROOT-MEAN-SQUARE ERROR AND MEAN RELATIVE ERROR (IN %)
FOR OUR MODEL

training time	test phase one day	test phase one month	test phase a year
One day	0.4649 3.76	1.0802 9.83	19.6531 44.10
One month	0.5259 4.13	19.6406 44.07	19.7026 42.94
One year	- -	- -	0.9965 6.10

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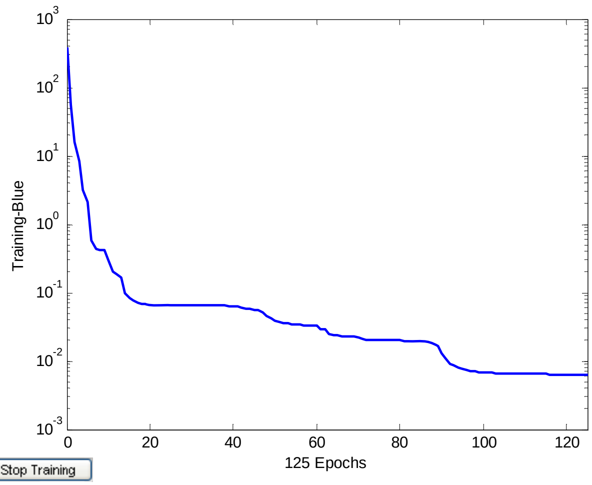

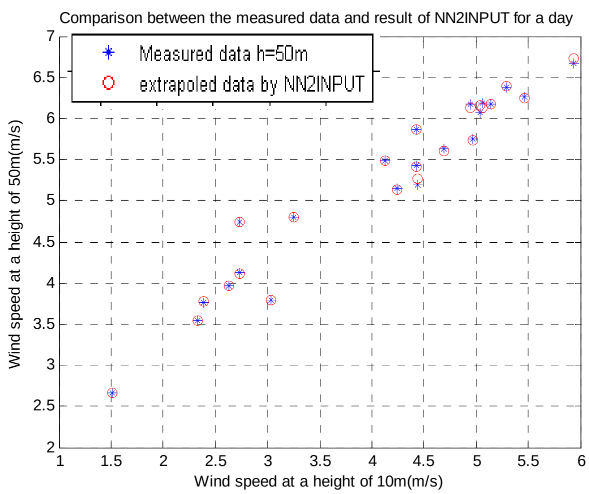

Fig. 7. plot of measured and estimate data wind speeds at 50m by two inputs Neural Network NN2INPUTS.

In table II the Root Mean Square Error (RMS) differences between observed and estimated values were used to evaluate the performance of the MLP neural networks for different training times.

Our first result has given an approximate function of extrapolation of wind speed from height of 10m to 50m, in given site, by just one day of observation. The transition from one site to another requires an adjustment in the number of neurons in the hidden layers.

After this result we will make a remark:Following the methods, if we take a given speed at 10m it will corresponds at just one value at any time. Whereas according to measure data a given speed at 10m will correspond at many values in time. To bridge this gap we have introduced other parameters like the temperature. So the results are better with an acceptable error range. Air Temperature is used as second input of network .the results are illustrated in figure 7.

B. . Vertical profile of wind speed

For this test our network includes two inputs (speed and altitude). Figure8 and 9 illustrates the changes in output (system and models)

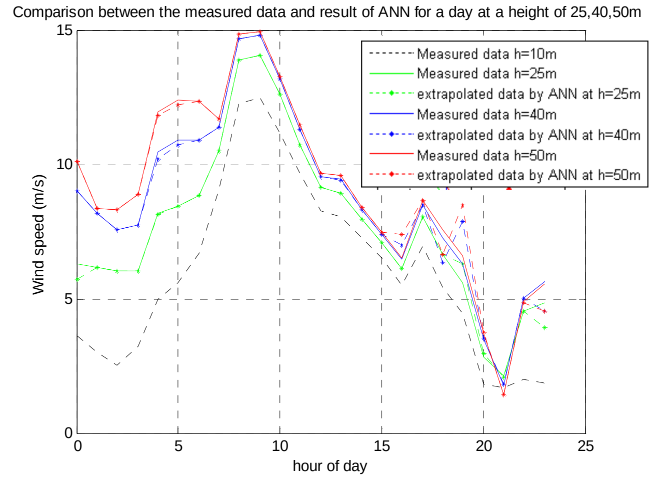

Fig. 8. Wind speed profile by reference to the 10m height by .

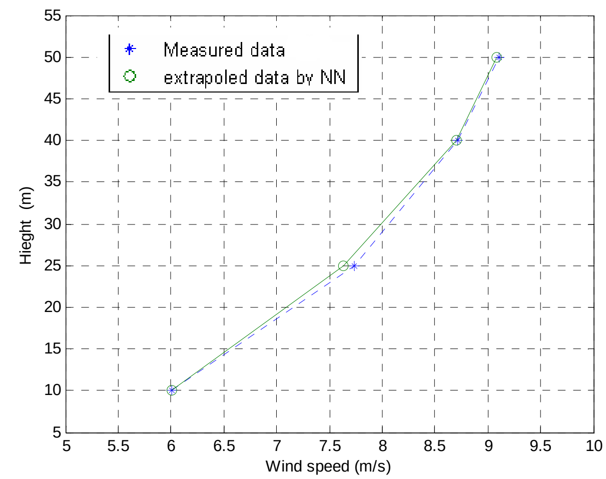

Fig. 9. Average wind speeds profile of tower.

IV. Conclusions

In our comparative study between the wind speeds measured and the results of the extrapolation methods we notice that the results of Somme methods are near to the measured; whereas others go far, because these empirical methods are developed after years of regional measures. But the error range is too great between average speeds estimated by the models and measured speeds. This effect becomes more significant for power generated by electric wind turbines (cubic speed).

In order to have an idea about the impact of actual precision estimation, obtained with most currently models used, we carried out a computing of error estimation basis of RMSE criterion. Really error range is too great for economic decisions in our site.

In this paper we have studied the possibilities of the neural networks for the extrapolation of wind speed from height of 10m to 50m.Our preliminary results have clearly indicated the feasibility of our approach. This new algorithm empirical extrapolation of the vertical wind speed based on neural networks presents an acceptable precision, witch can be improved by introduction of other parameters

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According the test results, we can conclude that training of just one day enables the validation of a network which generated an approximated function of a good ranking precision for industrial development projects.

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