Estimation of wind power in coastal areas using a Model based on the learning of a Multilayer Perceptron: Case of Douala, Cameroon

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Abstract. In recent years, the scientific community has been concerned about the threat of global warming. This phenomenon is due to the increase of greenhouse gas emissions greenhouse gas emissions due to human activity. Renewable energies present themselves as a potential solution to reduce to reduce greenhouse gas emissions. Among the promising means of production As part of its policy of promoting renewable energy, the Cameroonian government launches each year projects in this area, hence the need to study the various sites and according to the parameters that are most often stochastic, hence the problem of choosing the type of wind power choose and implement. Thus this paper proposes a method of estimating the power produced according to the wind speed data of the scale coefficient and the shape on the station P/30 of Douala of the site of ASECNA - Douala Cameroon over a period of one year which presents different characteristics on the four seasons of the coastal areas of Cameroon by using the distribution of Weibull and by proposing another method using artificial intelligence ; This instability offers the opportunity to study other methods of power estimation using, as in this work, a multilayer perceptron type neural network. Based on the Weibull parameters, the power estimation is done by both approaches according to the different coastal seasons: hard dry season, short rainy season, short dry season and long rainy season. In addition, the form factor and scale factor fluctuated over the year from 1.36 to 1.94 and from 2.74 m/s to 3.80 m/s for different periods respectively. It was found that the average wind speed is 1.309 m/s, the average power for this site is 289.46 MW, and the months of March and July have high powers because the winds are warmer in these periods. For estimation we used a multi-layer perceptron consisting of: 03 input layers (wind speed, form factor and scale factor), 02 hidden layers of 10 neurons each and one output layer (wind turbine power), for training we used the gradient back-propagation algorithm using Matlab software. After an average of 200 training runs and a training step of 0.001, we obtained an RMSE for each of the four seasons of 0, 0065361; 0.00165361; 0.00052543; 0.0000011564. It was concluded that the algorithm improves the accuracy of power estimation by the MLP model and can be recommended for wind turbine power estimation.
Keywords: Estimation**,** wind power, Multilayer Perceptron

1 Introduction

The energy question is a global issue requiring the development of new energy sources to overcome the current deficit. It probably coincides with the depletion of conventional energy sources in view of the decline in oil prices. Renewable energies present themselves as a potential solution to the reduction of greenhouse gas emissions. Among the promising means of production, we can mention wind power, biomass and photovoltaic. Moreover, these energies present themselves as a very promising means of electricity production for several reasons. We can mention among others: the technology which presents qualities on the ecological plan, because the finished product is not polluting, silent and does not involve any disturbance of the environment, if it is not the occupation of space for the installations of big dimensions. Renewable energies can be used in the mountains, in a remote village or in the center of a large city.

The rapid development of wind technologies is an alternative to conventional energy systems in recent years. The equatorial zone, which extends from the second to the sixth degree of north latitude, in which the city of Douala is located, has a low wind speed but is exploitable for the production of electrical energy. Douala is characterized by an average hourly wind

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speed that has a moderate seasonal variation throughout the year. The windiest period of the year lasts 3.5 months, from June 11 to September 26, with average wind speeds above 6.3 kilometers per hour. The windiest day of the year is August 3, with an average wind speed of 7.5 kilometers per hour. The calmest period of the year lasts 8.5 months, from September 26 to June 11. The calmest day of the year is November 30, with an average hourly wind speed of 5.1 kilometers per hour. More than 73% of its electricity comes from the Édéa hydroelectric dam. Located on the Sanaga River in the city of Edea, which is gradually experiencing a decrease in water supply due to insufficient rainfall as a result of climate change. This condition leads to a low water reserve and close to the reference value of the dam operation which is increasingly the cause of power cuts. However, the demand is increasing and the supply is insufficient. These situations cause damage in the production and distribution of electricity.

Due to the economic conditions, and high stochastic variability of wind, the estimation and accurate prediction of wind potential is too complicated. Therefore, it is clear that the efficient processing and application of wind energy resources require accurate and complete information on the wind characteristics of the Region.

The way to estimate the potential of wind energy in a selected site is to analyze and explain the data collected from the metrological station that is installed at the same location to ensure the accuracy of the analysis. The data can also be classified on daily, monthly or annual basis [1]. Identifying wind potential Energy is very important in determining site efficiency. In this paper, the analysis of station characteristics will be implemented to evaluate the wind potential of site P/30 based on the Weibull distribution. Now Wind energy forecasting relies on the estimation of wind speed. Over the past decades, various models have been established to predict wind speed to obtain accurate wind energy information and these power forecasting methods can be used to plan unit commitment, scheduling and dispatch by system operators. In general, these models are divided into three types: physical, statistical learning and intelligent models. Physical approaches, which rely on a detailed physical description of the atmosphere, use meteorological data such as air temperature, topography and pressure to predict wind speed. These types of methods have not been applied to short-term wind speed prediction due to complex computational methods, high costs and poor performance. Yet they can have more accurate long-term predictions compared to other types of prediction models [2]. We have thus in the literature [3] present a methodology for accurate prediction of wind speed and wind power using machine learning algorithms set. The objective of this study is to consider the failure to improve the predicted wind power output for Agartala using two combined methods AdaBoost and XGBoost to predict the wind power of the station. [4] present three models (Boosted Trees, Random Forest and Generalized Random Forest) to provide reliable short term wind power prediction. incorporating lagged data has been shown to improve prediction performance compared to static models. experiments conducted have shown that ensemble models taking into account lagged data can achieve better wind power prediction performance. [5] make a generalized regression neural network (GRNN), radial basis function neural network (RBFN) and a hybrid of GRNN and RBFN are applied for wind energy estimation and their performance is with respect to short-term wind energy prediction. The research in this paper interprets that GRNN has consistently better than RBFN.

The GRNN-RBFN hybrid also showed good accuracy in one week ahead wind power prediction. [6] Propose a method based on Gaussian processes (GPs) to improve the probabilistic prediction of wind power in a region. They conclude that this study went through two types of comparisons of dynamic and static GP as well as direct and indirect prediction scheme. The result of the comparison between dynamic and static GP revealed that the dynamic GP generates Prediction Intervals (PI). In addition, comparing the accuracy of direct and indirect prediction plan, it shows that the indirect prediction strategy results in wider prediction intervals with higher probability coverage of the net demand forecast share. Moreover, the proposed model provides accurate results of predicted energy at each time step.[7] propose a multi-resolution forecasting model to improve the current wind power forecasting performance. The proposed model contains three steps, including a multi-resolution ensemble, adaptive multiple error corrections and uncertainty estimation. This allows them to conclude that the techno-economic analysis allows to conclude that the proposed model has the potential to be applied to improve the power integration performance.

2. Data acquisition

2.1. Location of the site

The station of Douala P/30 of the site of ASECNA - Douala Cameroon is located in the littoral region with an altitude of 13 m. The coordinates of the site are (4.012936 longitude, 9.71835 latitude).

Fig. 1. Geolocation of the ASECNA site P / 30

2.2. ASECNA site data P / 30

Wind data were acquired from the metrological mast at ASECNA P/30 (Douala city) in Cameroon. The data include Wind speed, Weibull (k), and Weibull (C) for the 12 months of the year 2020. The data were recorded on a ten-minute interval, as required by the international standard for wind measurement.

Table 1. Table Data from the ASECNA P / 30 wind station for the year 2020

Year	Month	Wind speed C(m/s)	Weibull k	Weibull C (m/s)
2020	January	1,3903226	3,6999272	1,550865354
2020	Fébruary	1,6322581	3,7989791	1,943513735
2020	March	1	3,0082408	1,366398328
2020	April	1,1645161	2,8676263	1,404950669
2020	May	1,3935484	2,9698441	1,570712247
2020	June	1,2258065	2,753343	1,431598643
2020	July	1,4774194	3,401074	1,655192164
2020	August	1,3967742	3,4936381	1,562742886
2020	September	1,4233871	3,1628053	1,653439841
2020	October	1,3933333	2,7472998	1,542298142
2020	November	1,2166667	3,0747985	1,439902028
2020	Décember	1	3,0375622	1,396369078

Table 2. Data from the ASECNA P / 30 wind station for the year 2020

Year	**Month**	**Wind speed C(m/s)**	**Wind Power(MW)**
2020	January	1,3903226	29,99
2020	Fébruary	1,6322581	131,09
2020	March	1	258,04
2020	April	1,1645161	79,46
2020	May	1,3935484	27,67
2020	June	1,2258065	25,18
2020	July	1,4774194	289,46
2020	August	1,3967742	17,54
2020	September	1,4233871	52,85
2020	October	1,3933333	23.59
2020	November	1,2166667	39,55
2020	Décember	1	74,66

3. Methods

3.1. Weibull probability distribution function

There are many continuous probability density functions that can model several phenomena [8], but in literature we found that the two-parameter Weibull distribution has been increasingly put forward for problems of wind potential estimation in different areas [9]. The two-parameter Weibull model is given as follows [10]-[12];

$$f(V) = \frac{K}{C}\left(\frac{V}{C}\right)^{K-1} exp(-(V|C)^{K}) \quad (1)$$

$$F(V) = 1 - exp(-(V|C)^{K}) \quad (2)$$

Where

$f(V)$ =*Probability density function*

$F(V)$ =*Cumulative density function*

K = *Dimensionless shape parameter*

C = *Scale parameter* (m/s)

There are several methods for determining the K and C parameters from the wind data of a site. The most common methods are: the graphical method, the moment method, the maximum likelihood method, the modified maximum likelihood method and the standard deviation method [13].Since the available wind data are in frequency distribution format, the recommended method is the modified maximum likelihood method. The Weibull parameters are determined using the following equations:

$$K = \left(\frac{\sum_{i=1}^{n} V_i^k \ln(V_i)\times f(V_i)}{\sum_{i=1}^{n} V_i^k \times f(V_i)}\right)^{-1} \quad (3)$$

$$C = \left(\frac{1}{F(V\geq 0)} \times \sum_{i=1}^{n} V_i^k \times f(V_i)\right)^{\frac{1}{k}} \quad (4)$$

Where $\boldsymbol{V_i}$ is the midpoint of the intervals *i* of the velocities and *n* the number of intervals, $\boldsymbol{f(V_i)}$ the frequency for which the wind speed falls on *i*. $\boldsymbol{F(V \geq 0)}$ the probability that the wind speed is greater than or equal to zero. Equation (3) is solved numerically by successive iteration until the value of k converges. The calculations are initialized with k=2. After convergence, equation (4) is now solved explicitly using the value of k to find that of C.

3.2. Estimating and fitting Weibull distribution

The capacity of wind resources can be determined by the density of wind power at a specified location. There are several approaches to estimate the monthly or annual power density per unit area of a site based on the Weibull distribution. The probability density function is expressed from the mathematical relationships as below, [14], with WPD (Wind Power Density) and WED(Wind Energy Density) [14], [15].

$$WPD = \int_0^{\infty} \frac{1}{2}\rho V^3 f(V) dV = \frac{1}{2}\rho\, C^3 \Gamma\left(1+\frac{3}{K}\right) \quad (5)$$

$$WED = \frac{1}{2}\rho\, C^3 \Gamma\left(1+\frac{3}{K}\right) T \quad (6)$$

$T = Required\ time\ period$

Where ρ is the air density ($\rho = 1.225\ kg/m^3$) at standard atmosphere at sea level, *Γ* is the gamma function.

Here the wind potential depends first of all on the average wind speeds but also on wind power density and wind energy density because the average wind speeds can take the same values at different locations, although they possess the same or different wind energies or wind energy densities [10].

3.3. Estimating and fitting Weibull distribution

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3.4. Multi-layer perceptron neural networks

Multi-layer perceptron models, which are based on the nervous system of the human brain, are suitable for modeling the nonlinear behavior of complex systems. In the multi-layer back propagation perceptron, the neurons of one layer are linked to all the neurons of the adjacent layers. These links are subject to a coefficient altering the effect of the information on the destination neuron. Thus, the weight of each of these links is the key element of the network's operation: the implementation of a multilayer Perceptron to solve a problem thus requires the determination of the best weights applicable to each of the inter-neuronal connections. Here, this determination is done through a back propagation algorithm. Moreover, the nature of these models allows them to make predictions for problems of nonlinear structure. This model works on the basis of learning the problem solving process to achieve the desired or desired output. To achieve this goal, it is necessary to analyze data starting with a preprocessing of it and then training using specific algorithms and minimizing the error at most, the appropriate output is calculated. There are several examples of neural networks, among which we have the multilayer Perceptron with its learning and training algorithm which is the gradient back-propagation that is more and more used than others. This network consists of 3 layers (input, hidden and output), which are composed of interconnected neurons in front and after each. Each layer is fully connected to the layer before and after itself [2].

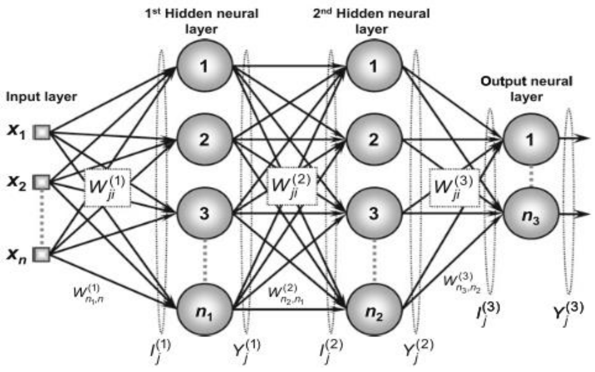


Fig. 2. Architecture of a multi-layer perceptron

3.4.1. Training process of the multi-layer perceptron

The training process of MLP networks using the backpropagation algorithm, also known as the generalized Delta rule, is usually done by the successive application of two specific stages. The figure below shows *n* MLP configuration composed of two hidden layers, ***n*** signals on its input layer, n_1 neurons in its first hidden neural layer, n_2 neurons in its second hidden neural layer, and n_3 signals associated with the output neural layer (third neural layer).

The first stage is called forward propagation, where the signals { x_1 , x_2, ………, x_n } of a given sample from the training set are inserted into the network inputs and are propagated layer-by-layer until the production of the corresponding outputs. Thus, this stage intends solely in obtaining the responses from the network, taking into account only the current values of the synaptic weights and thresholds of its neurons, which will remain unmodified during the execution of this stage.

Next, the responses produced by the network outputs are compared to the respective available desired responses, since it is a supervised learning process, as mentioned earlier. It is important to note that, considering an MLP network with n neurons in its output layer, the respective n_3 deviations (errors) between the desired responses and those produced by the output neurons are calculated and will be used after that to adjust the weights and thresholds of all neurons.

Therefore, because of these errors, it is applied the second stage of the backpropagation algorithm, known as backward propagation. Unlike the first stage, the modifications (adjustments) of the synaptic weights and thresholds of all neurons of the network are executed during this stage[16].

3.4.2. Deriving the Backpropagation Algorithm

From Fig.2 the following terminology will be assumed for its fundamental parameters:

- $W_{ji}^{(L)}$ are weight matrices whose elements denote the value of the synaptic weight that connects the *jth* neuron of layer (L) to the *ith* neuron of layer (L - 1).
- $W_{ji}^{(3)}$ is the synaptic weight connecting the *jth* neuron of output layer to the *ith* neuron of layer 2.
- $W_{ji}^{(2)}$ is the synaptic weight connecting the jth neuron of hidden layer 2 to the *ith* neuron of hidden layer 1.
- $W_{ji}^{(1)}$ is the synaptic weight connecting the *jth* neuron of hidden layer 1 to the *ith* signal of the input layer

$I_j^{(L)}$ are vectors whose elements denote the weighted inputs related to the *jth* neuron of layer L, and are defined by:

$$I_j^{(1)} = \sum_{i=0}^{n} W_{ji}^{(1)} . x_i \Longrightarrow I_j^{(1)} = W_{1,0}^{(1)} . x_0 + W_{1,1}^{(1)} . x_1 + \cdots\cdots\cdots + W_{1,n}^{(1)} . x_n \quad (7)$$

$$I_j^{(2)} = \sum_{i=0}^{n1} W_{ji}^{(2)} . Y_i \Longrightarrow I_j^{(2)} = W_{1,0}^{(2)} . Y_0^{(1)} + W_{1,1}^{(2)} . Y_1^{(1)} + \cdots\cdots + W_{1,n1}^{(2)} . Y_{n1}^{(1)} \quad (8)$$

$$I_j^{(3)} = \sum_{i=0}^{n2} W_{ji}^{(3)} . Y_i \Longrightarrow I_j^{(3)} = W_{1,0}^{(3)} . Y_0^{(2)} + W_{1,1}^{(3)} . Y_1^{(2)} + \cdots\cdots\cdots + W_{1,n2}^{(3)} . Y_{n2}^{(2)} \quad (9)$$

- $Y_j^{(L)}$ are vectors whose elements denote the output of the *jth* neuron related to the layer L. They are defined as:

$$Y_j^{(1)} = g(I_j^{(1)}) \quad (10)$$
$$Y_j^{(2)} = g(I_j^{(2)}) \quad (11)$$
$$Y_j^{(3)} = g(I_j^{(3)}) \quad (12)$$

3.4.3. Root mean Square error

The Root Mean Square Error (**RMSE**) (also called the root mean square deviation, RMSD) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power.
The RMSE of a model prediction with respect to the estimated variable X_{model} is defined as the square root of the mean squared error:

$$RMSE= \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}} \quad (13)$$

where X_{obs} is observed values and X_{model} is modelled values at time/place *i*.
The calculated RMSE values will have units, and RMSE for phosphorus concentrations can for this reason not be directly compared to RMSE values. However, the RMSE values can be used to distinguish model performance in a calibration period with that of a validation period as well as to compare the individual model performance to that of other predictive models.

4. Results and discussions

In this study, the composition of an input layer, two hidden layers, and an output layer is used as a structure of the multilayer perceptron. The parameter in the input layer consists of the wind speed. The dependent variable that used as output is the power of the station P/30. The network design includes 1, 20, and 1 neurons for the input, hidden and output layers, respectively. In addition, sigmoid, tangent, and linear functions using the gradient back propagation algorithm with 200 repetitions were used for the input and output layers. These functions were selected based on the trial and error procedure to obtain the accurate wind speed estimates to better predict the station power. In addition, the complexity of each machine learning network increases by adding configuration in the internal nodes. Based on 20 neurons from both hidden layers we trained our perceptron from our proposed program. This allowed us to also play with such sensitive parameters as the training step.

To obtain our results we used the scientific computing software Matlab 2020 on an HP Core i3 machine. Following the exploitation of the raw data obtained in our site, the profiles of the speed and then of the seasonal and annual wind power at the altitude of (13 m) in the city of Douala are expressed and displayed during the days of the month and the whole year.

4.1. Wind power estimation using the Weibull model

It should be noted that the months of March and July, which represent (the great and small dry season and hard) have a high wind speed unlike the other months. This implies that out of the 4 seasons found in the Littoral, the dry seasons present ideal periods to have a good estimate of the power of the site which oscillate around 258.06 MW for the month of March and 289.46Mw in July.

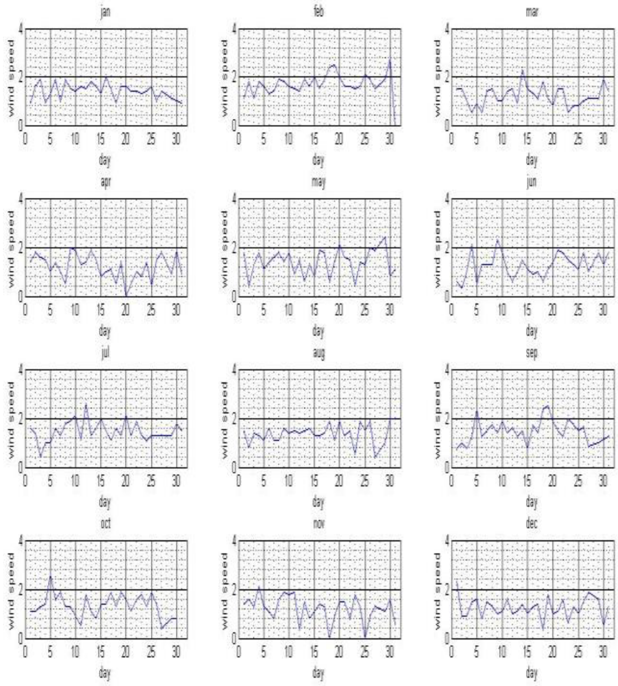


Fig. 3. Monthly wind profile at site P / 30 for the year 2020

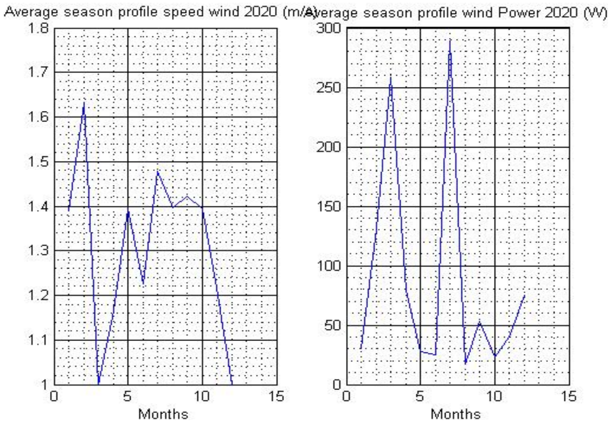
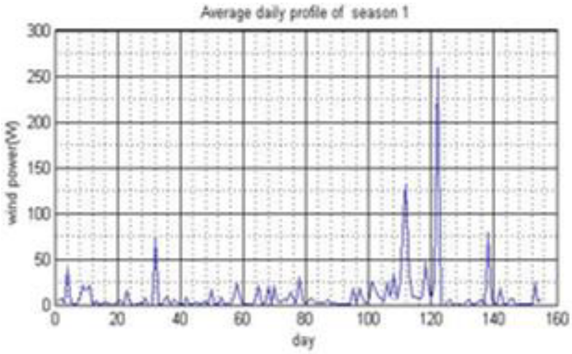


Fig. 4. Seasonal wind and power profile for the year 2020



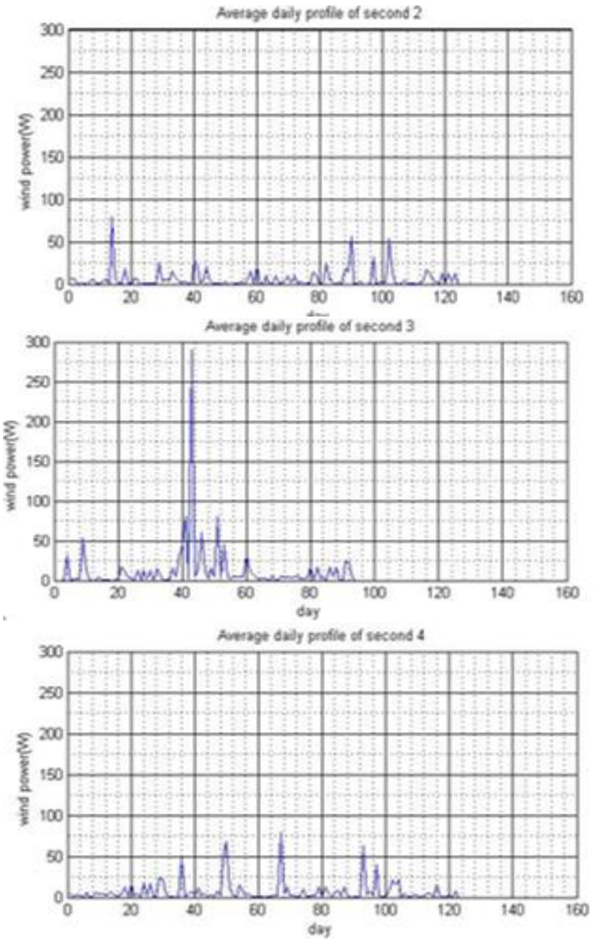


Fig. 5 Power estimation over the 4 seasons with Weibul (big dry season, small rainy season, small dry season and big rainy season)

4.2. Estimation de la puissance pour la station P / 30 en utilisant le Modèle perceptron multicouche

In this part we proposed an estimation method using an intelligent approach from a neural network model which is the multilayer perceptron. For the big dry season we obtained the model of (**Fig. 6)** after 200 trainings with a learning step of 0.1 we compared the different errors of our predictive model and we obtain a Root Mean Square Error of 0, 0065361; Thus the model has reproduced the behavior of the data curve. Hence the month of March is the period during which we have good winds and a good power 258.06MW. For small rainy season after 20 trainings with a learning step of 0.001 we get a Root Mean Square Error of 0.00165361 (**Fig. 7**). Thus the month of May is the period during which we have good winds and a power around 79.46MW.For the small dry season after 200 trainings with a learning step of 0.1 we obtain a Root Mean Square Error of 0.00052543(**Fig. 8**).Thus the month of July is the period during which we have good winds and a power around 289. For the great rainy season, after 200 training sessions with a learning step of 0.1, we obtain a Root Mean Square Error of 0.0000011564 (**Fig. 9**). Thus, the months of September and October are the period during which we have good winds and a power around 68MW to 80MW.

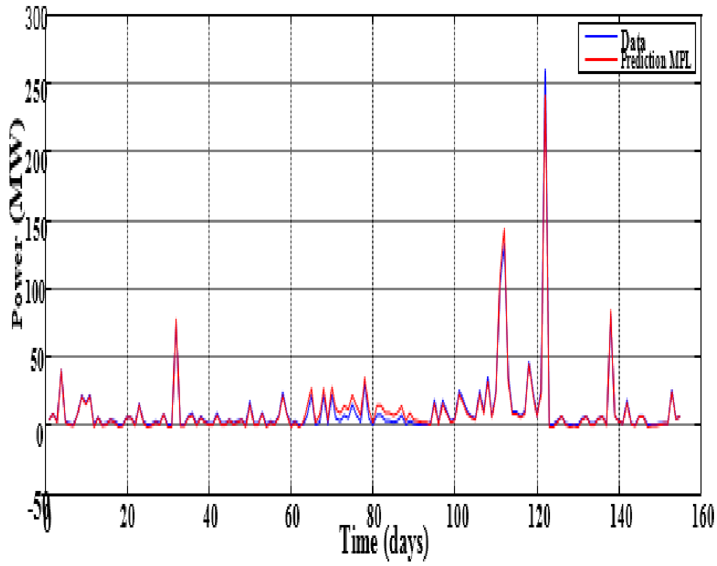


Fig. 6 Power estimation during the long dry season

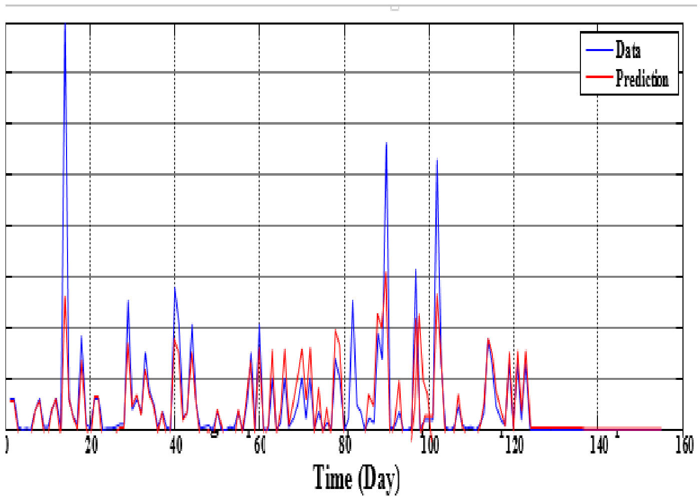


Fig.7 Power estimation during the short rainy season

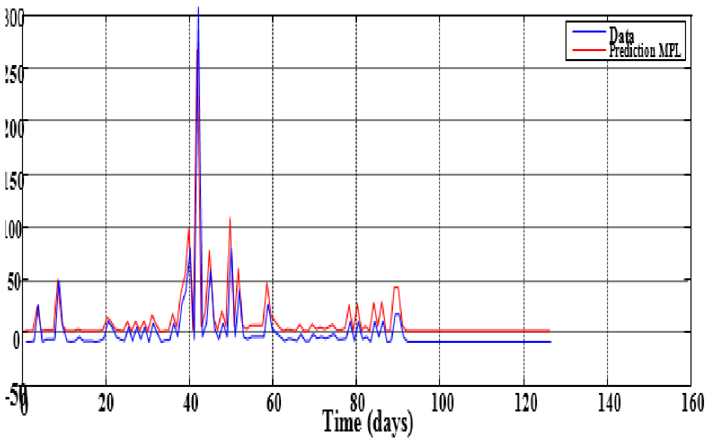


Fig. 8 Estimated power during the short dry season

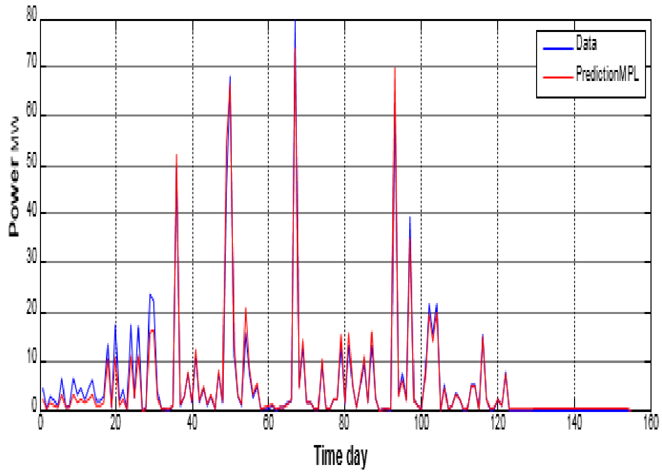


Fig.9 Power estimation during the main rainy season

Table 2: Summary of the RMSE

	Rmse
Power estimation during the long dry season	0, 0065361
Power estimation during the short rainy season	0,00165361
Estimated power during the short dry season	0,00052543
Power estimation during the main rainy season	0,0000011564

Here we present the tabulated results of the RMSE in our test between the two methods and we find that our model has very good ability to estimate the power as a function of seasons.

Conclusion

The purpose of this work was to estimate the wind power at the site using two methods, the Weibull distribution and a multilayer Perceptron neural model over each season with varying wind profile. The seasonal wind speed profiles were plotted. From the results, it can be concluded that the power prediction method based on a particular type of neural networks was used to estimate the output value. Furthermore, this paper provides an alternative power estimation model that can be a solution for the problems and challenges associated with wind power prediction. To further validate this work it is necessary to combine this work with comparisons to experimental results to validate our model which is the focus of our current work.

Abbreviations:

ASECNA : Agence pour la sécurité de la navigation aérienne
GRNN: Generalized regression neural network
RBFN: Radial basis function neural network
K = Dimensionless shape parameter
C = Scale parameter (m/s)
WPD : Wind Power Density
WED: Wind Energy Density
$\rho = 1.225$ *Air density* (kg/m^3)
MLP: Multi-layer perceptron
ANN: Artificial neural networks
RMSE: The Root Mean Square Error
RMSD: The root mean square deviation

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