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Energy production predication via Internet of Thing based machine learning system

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HIGHLIGHTS

- Estimation of the electric power production of a wind turbine.
- IoT-based machine learning to predict energy production.
- Real wind and power data generated in aerogenerators installed in a wind farm in Ceará State, Brazil.
- To obtain the power curve using logistic regression, integrated with Recursive Neural Network to forecast wind speeds.

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ABSTRACT

Wind energy is an interesting source of alternative energy to complement the Brazilian energy matrix. However, one of the great challenges lies in managing this resource, due to its uncertainty behavior. This study addresses the estimation of the electric power generation of a wind turbine, so that this energy can be used efficiently and sustainable. Real wind and power data generated in set of wind turbines installed in a wind farm in Ceará State, Brazil, were used to obtain the power curve from a wind turbine using logistic regression, integrated with Nonlinear Autoregressive neural networks to forecast wind speeds. In our system the average error in power generation estimate is of 29 W for 5 days ahead forecast. We decreased the error in the manufacturer's power curve in 63%, with a logics regression approach, providing a 2.7 times more accurate estimate. The results have a large potential impact for the wind farm managers since it could drive not only the operation and maintenance but management level of energy sells.

1. Introduction

Lee and Lee [1] categorize the Internet of Thing (IoT) as (i) a monitoring and control tool for the automation of systems to track variables and calculate their performance in real time from anywhere. This is particularity interesting for technologies that require advanced monitoring and control, such as electrical grids. (ii) Big data and business analyses are another categories, and are based on systems that can generate large amounts of data, which may come from sensors. This data might be used to find relationships between different information systems, in order to improve business issues and strategies. The last category, (iii) Information sharing and collaboration, concern the tracking of information based on predefined thresholds, which might share data with other devices and services. For example, having information as soon as possible in a supply chain service could guarantee optimization of this service. However, a real system is not exclusive to one of the categories above, it has, in fact, features from each one of these categories, such as the various monitoring tools developed under these basis [2–4].

Various researchers have studied the benefits of inserting IoT devices in energy industries. Faheem and Gungor [5] presented a work that gathers wireless sensor networks and applying algorithms to optimize smart grid integrations. This field of study lines up with another area, the pattern recognition, which consists of various kinds of data-driven methods that aim to find

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useful information in large database. Among electrical energy generation, the wind energy stands out among all sources, since it is one of the cleanest and most preferable [6]. It is growing 17% per year, and it is expected to supply 17%–20% of the world's energy demands by 2020 [6]. However, the inconsistent behavior of the wind poses as a disadvantage for the wind energy, making it a less reliable source than others, because it is hard to integrate with the power grid systems [7]. According to Zhang et al. [7], this problem might be mitigated if the operation was driven by an accurate system to monitor and forecast wind patterns.

Qureshi et al. [8] used a trend machine learning algorithm, based on artificial neural networks for wind power prediction and Faheem and Gungor [5] used it to forecast wind speed. Both works applied machine learning techniques to solve wind energy problems. We believe that the uncertainty of the electricity generation of wind farms might be tackle by gathering information from sensors already installed in an set of operating wind turbines. Therefore this work was developed in a partnership with a wind farm, by analyzing one year of the data. Two approaches are proposed: (i) regression of the power curve of a wind turbine, and (ii) forecast wind speed, based on the time series data of measurements. Together, these approaches will provide an energy power estimation for the wind farm, which might serve as an input to a high-level layer of management, *i.e.* the decision making of how much energy could be sold to the grid.

The paper is organized as follows: in Section 2 the state of the art surrounding the problem of energy estimation is presented. Our methodology is presented in Section 3, followed by the results in Sections 4, 4.2 and 4.4. Conclusions are laid out in Section 5.

2. State of the art

Reviews in the literature show there are different techniques to maximize the power of a wind farm. There are methods that study layout optimizations, as in [9–11]; however, these methods are strict to wind farms that are still on concept design, and not to the ones already in operation. Serrano González et al. [12] on the other hand, show a different approach. They suggested an algorithm to optimize the operations individually in each wind turbine. There are only a few approaches that aim to optimize the electric energy production of a wind farm already in operation, such as Serrano González et al. [12].

In addition, the literature review has shown that all works that aim to estimate, measure or optimize the electric energy produced in a wind farm, rely on two factors: one is the wind speed value, that comes from measurements in the region of interest; another is the operational power curve of the wind turbine. So, this Section has two main parts, which are Section 2.1, that presents methods found in the literature to predict the wind speed, and discusses their applicability. And, Section 2.2, that discusses the methods used for regression of the power curve of wind turbines.

2.1. Wind speed forecast

Researchers have been striving for some time to assess the impacts of wind power generation on operations and costs of electrical power systems. Holttinen [13], for example, estimates how much the variations in electricity generation by a wind power triggers auxiliary and costly energy resources for generation, such as thermoelectric plants. Ummels et al. [14] presents a study of the mismatch in the energy generated by a wind park and the load balance of the electrical systems. Based on these variations, companies such as GE [15], have created manuals to model the amount of additional services required. In these surveys, the importance of the prediction of the wind conditions is clear, since they all use temporal data to model and predict variations of the wind pattern and try to correlate it with variations of the electric power added to the grid.

Thus, the first step in determining the power of a wind farm is to model the behavior (*i.e.* velocity) of the wind [16]. There are two classical and stable methods for modeling the wind conditions, which assume wind behavior according to the statistical distribution, such as the Weibull [17] and the time series methods [18]. However, recent trends exhibit methods, mainly based on artificial intelligence techniques, may be highlighted [19]. These authors believe that some machine learning methods overlap with the classical statistical methods [20].

Yesilbudak [21] uses the classical k-nearest neighbor algorithm (k-NN) to provide short-term predictions (*e.g.* 10 min) of wind speed. The authors agree on different wind velocities as distinct classes and use the Euclidean, Manhattan and Minkowski distance metrics as measures of dissimilarities for the k-NN method. The disadvantages in using this method is the high computational cost, since a large number of samples in the database can make the use of this method impractical for real-time estimates. The author also highlights the sensitivity to noise in the data, making it imprecise for forecasts over 10 min. There is also the use of random forests in the literature, but with efficacious demonstrations for forecasts of only 1 h ahead [20].

There is a prominence for neural networks, which are promising and already confirm that they are able to provide wind information without knowledge of topographic or meteorological details [19]. Velo [22] uses a Multi-layer Perceptron (MLP) network to estimate the average annual wind speed at a location where there is no weather station available to measure wind speed. These authors used data of wind speed and direction of meteorological stations near the place of interest as input to the neural network. This methodology showed that data from 60 days of observation was necessary to obtain an acceptable generalization capacity, with results having errors less than 6%.

In spite of this, different architectures of standard neural networks are exposed for time-series analyses and have gained space in the scientific community in recent years. Nonlinear Autoregressive (NAR) networks and their applications in temporal signals prove effective and advantageous to traditional recursive neural networks [23]. Based on the wind forecasting need for wind applications and the imprecision of long-term forecasts, Azad et al. [24] proposed NAR network for wind forecasts in Malaysia and obtained promising results: absolute errors in wind speed predictions of 0.17 m/s for monthly averages forecasts, 0.64 m/s for forecasts of 30 days ahead and 0.8 m/s for forecasts of 1 year ahead. So, the author demonstrated that the NAR network is a suitable tool for predicting wind speed.

Baptista et al. [25] proposed a similar methodology to ours, and used a artificial neural network alongside with a fuzzy modeling, reducing the error in 5.01% of a baseline-model, which means 750 kWh in a 1-hour ahead prediction. Hernández-Travieso et al. [26] reports promising results, since by using neural networks with and immersion dimension of five it reaches 0.29 m/s of mean absolute error in the wind speed forecasting. However the authors were not clear how much time a prediction ahead represents in the matter of hours or minutes.

Huang and Kuo [27] exhibits in his studies a analytical tool for a database of wind speed records, from a region in Taiwan, and uses a convolution neural network to estimate wind speed. They were able to reach a RMSE of 0.99 m/s for a seven day ahead prediction. Huang and Boland [28] proposed a framework of NAR model to estimate electricity production in a hybrid (*i.e* solar-wind) plant. They reached very promising results or 0.17 m/s of RMSE for a 30 min ahead prediction.

Based on the research carried out in the literature, this work chose the NAR network as the tool for wind speed prediction, in the wind turbine environment, located on the sea-coast of Ceará.

2.2. Regression of the power curve of a wind turbine

Estimating the annual energy production is one of the most important applications of the power curve of aerogenerators [29]. Lydia [30] showed the importance of having models representative of the power curves because they reflect the performance of the equipment and even indicate anomalies in the operation. Since there is a prediction of wind speed, it is also possible to work predictively, providing information on future energy availability [30]. Thus, the next step to estimate the power output of a wind farm is to know the power curve of the wind turbines installed at that site.

The research in [29] aims to validate the annual power of a wind farm in a region of Italy by carrying out power measurements on a 12 kW turbine and wind speeds around it for a period of one year . The authors proposed an analytical method to estimate the power curve model from the data and compare it with the curve provided by the turbine manufacturer. The results indicate that the real model, evaluated [29], has a production deficit of 10.2%, concluding that the curve stipulated by the manufacturer is an optimistic representation of the process. Some years later, Zolfaghari et al. [16] indicated in their study that the actual output power of the wind turbine does not follow the behavior of the theoretical curve recommended by the manufacturer. According to Zolfaghari et al. [16] the reason for the imprecision of the theoretical curve is its benchmarking in laboratory tests, which control the direction and speed of the wind, and relative humidity of the air.

Therefore, it is important to estimate the power curve of a wind turbine starting with the real data, and the result will provide the real power potential of the turbine. Lydia et al. [31] presented in their bibliographic review the most common methods for modeling power curves. The authors classified the methods in a basic dichotomy: (i) parametric methods, which are based on solving mathematical models that explain the behavior of the system. As examples, Lydia et al. [31] reported the use of linear and polynomial regression techniques, probabilistic models and logistic regression. And (ii) non-parametric, which aims to find connections between inputs and outputs of a dataset, not only considering a specific mathematical model. Among these, there are applications of copula models, neural networks and fuzzy logic [31].

Lydia et al. [30] compared the methods of linear regression by Least Squares (LS) and logistic regression to estimate the power curve. However, the linear regression applied by parts obtained better results than the logistic regression. Shokrzadeh et al. [32] pointed out that Simple Polynomial Regression is susceptible to noise and proposes the use of interpolated polynomial models and obtained satisfactory results. Taslimi-Renani et al. [33] used a variation of logistic regression in their research and obtained results superior to the least squares linear regression. Based on the literature reviews, the present work chose to use the parametric method of linear and polynomial regression, due to their simplicity; and logistic regression due to its non-linear characteristic.

Panahi et al. [34] compared the performance, through the analysis of the Mean Square Error (RMSE) and the absolute mean error, of parametric and non-parametric methods for power curve modeling. According to the results, the robust polynomial regression has a smaller average error, but with overlapping results of the linear and polynomial regressions. However, Panahi et al. [34] proposed a two-layer MLP type network and obtained results similar to the robust regression. The authors pointed out that artificial neural networks are a promising tool for their analysis, but because of the non-parametric nature of the model, it is important to find the optimal structure for each specific problem. However, Panahi et al. [34] did not justify the choice of the architecture or even compare it with other methods of the same category.

Pelletier et al. [35] proposed the use of an MLP network, but in addition to performing a simple regression between wind speed and power, the authors believed that using other information (air density and turbulence intensity) as input from the network would help make the model more representative. The results were better than those of other parametric and non-parametric models, noting the ability of neural networks to function as universal approximations of functions.

However, the main disadvantage of the MLP network is in the arduous and time consuming training. Therefore, researchers proposed structural alternatives to the process of backpropagation of the error for MLP training, in order to make it more effective. Miller et al. [36] exposed the ineffectiveness of the backpropagation algorithm in applications that require real-time learning, and thus proposed a different approach. Years later, Huang et al. [37] proposed the current model of the neural network called Extreme Learning Machine (ELM), based on random distribution for part of the network parameters, and in the least squares technique to estimate the other part. Huang et al. [37] demonstrated the advantage of ELM over the classical algorithms like MLP and Support Vector Machines (SVM): rapid training without losses in the generalization capability of the model, and may also be used for regression problems.

The use of ELM has been reported in the literature for solving regression problems, including forecasting time series with real-time learning [38,39]. Therefore, this work chose the ELM as the nonparametric method to be used for regression of the power curve of the aerogenerator. An estimation of the local wind speed and the actual power curve of a wind turbine can provide information on future energy production which is a crucial factor for the efficient management of a wind farm.

3. Methodology to predict energy production in wind turbines

This section presents the methodology, used in this work, to estimate the wind energy production in wind turbines, and which has three stages: wind turbine power curve modeling, wind speed estimation and energy production estimation. The flow diagram of Fig. 1 illustrates the wind energy estimation process, where it is first necessary to find a model for the power curve of the wind turbine that best represents the behavior and predicts the wind speed.

Before making a deeper analysis of each step in this work, it is necessary to present the database in use, because small variations of wind velocity imply large variations in the power generated by the aerogenerator. Therefore accurate data collection must be of good quality to be able to carry out a reliable analysis.

3.1. Databases

56,838 data samples of wind speed and power produced by the wind turbine in operation make up the Database in the period between 0:0h on 05/25/2014 and 23:50 on 07/27/2015. There is a wind turbine daily availability record, for the same time period. The database was made using the mean value of the wind speed and power generated for each 10 min. The availability is the percentage of time that the generator spent with real production. Fig. 2 shows a sample of data collected over 140 days.

The availability of the wind turbine is very important because it influences the productivity of this wind turbine. As in Fig. 2, on day 40 the productivity of the VSWT wind turbine was 0 kWh, although there was wind with an average velocity of 8 m/s, because the VSWT availability was 0%. The model of wind turbine in use to generate the database in this work is presented in Table 1.

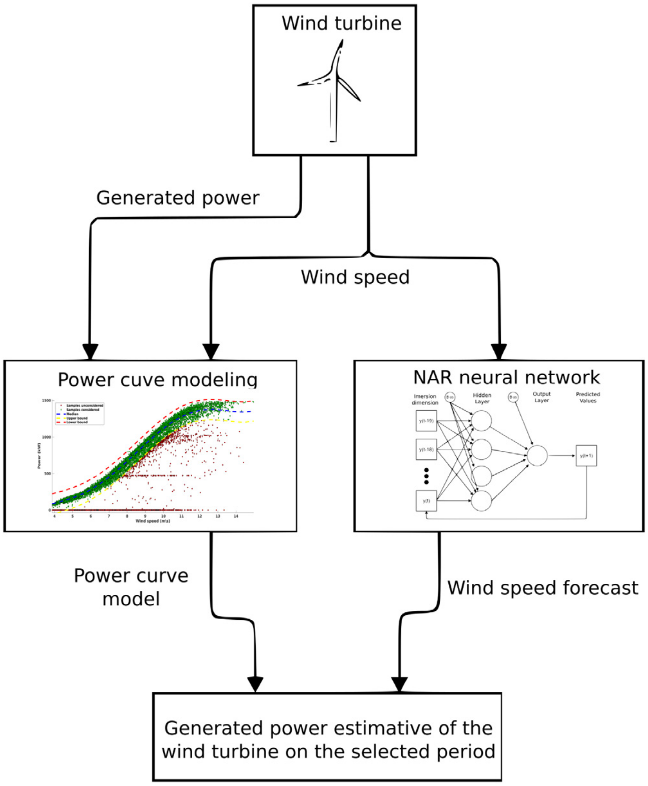


Fig. 1. The proposed methodology.

3.1.1. Data preprocessing

There are some factors that contribute to the power curve of the wind turbine presenting a variance of power values for similar wind speed. One of the factors occurs because the wind turbine control process does not update instantaneously; this is because the wind turbine control system only considers the average wind speed every ten minutes. Within this ten-minute interval, the wind speed may vary and the control system does not follow this variation, for this reason the wind turbine is not in maximum efficiency all the time. Another important factor is the turbulence that one wind generator causes other aerogenerators. This turbulence acts as a "shadow". The wind, when changing direction, focuses on the wind farm so that the wind coming from one wind turbine enters into another. This causes turbulence that disrupts wind turbine control. In addition to these reasons, the aerogenerator may be malfunctioning, or even with a deliberate limitation of its maximum generation power.

Table 1
Wind turbine specifications.

Rated power	1500 kW
Minimum wind speed	3 m/s
Rated wind speed	12 m/s
Maximum wind speed	22 m/s
Angular speed range	9 – 17.3 rpm
Diameter	82 m
Scan area	5.325 m^2
Cube height	85 – 100 m

Therefore, before applying the techniques for modeling the power curves it was necessary to filter the data from an analysis of the power curve graph. Fig. 3 shows that there are samples very distant from the average value of the power curve. Data collection involves disregarding the samples that correspond to the operation of the wind turbine under abnormal conditions. Thus valid data was considered to be that which was at a distance of twice the mean variance of the median value of the power curve. Fig. 3 shows the Limits and Data under consideration, as well as those in contempt in the modeling step of the power curve.

3.2. Power curve regression

The regression step of the power curve aims to find a function that represents the behavior of the wind turbine. Regression methods in use are based on parametric approaches. Parametric models are basic mathematical expressions. There are several different types of functions ready to use to model phenomena [40]. The method used in this work has satisfactory accuracy. The first step is to find a basic function or a set of functions that are closest to the control function (model) [30], seeking to balance the complexity and precision of the factors. The power curve, for example, is compared to the linear, exponential, sigmoidal, or polynomial functions or associations between them.

3.2.1. Approximate cubic power curve

This method is based on the fundamental equation of the maximum energy capable of being absorbed by the turbine. The model uses the following equation:

$$P(v) = \frac{1}{2}\rho A C_{p,max} v^3, \tag{1}$$

where ρ is the air density, A is the wind turbine sweep area, $C_{p,max}$ is the maximum power coefficient and v is the wind speed.

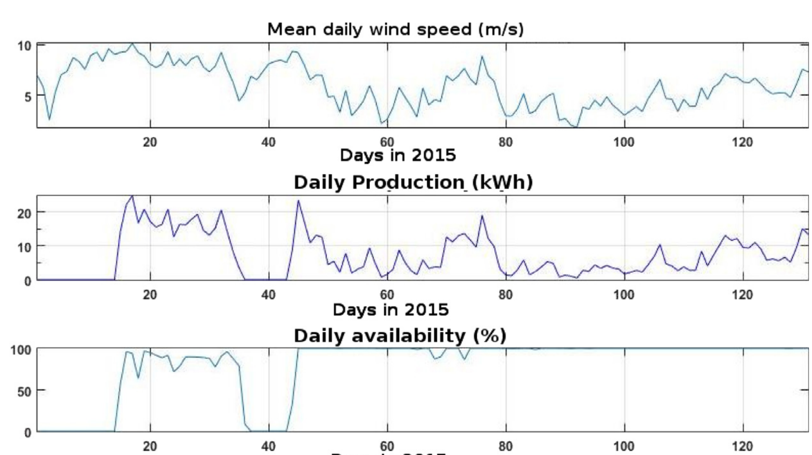


Fig. 2. Example of the relation between wind speed, energy production and availability of the wind turbine.

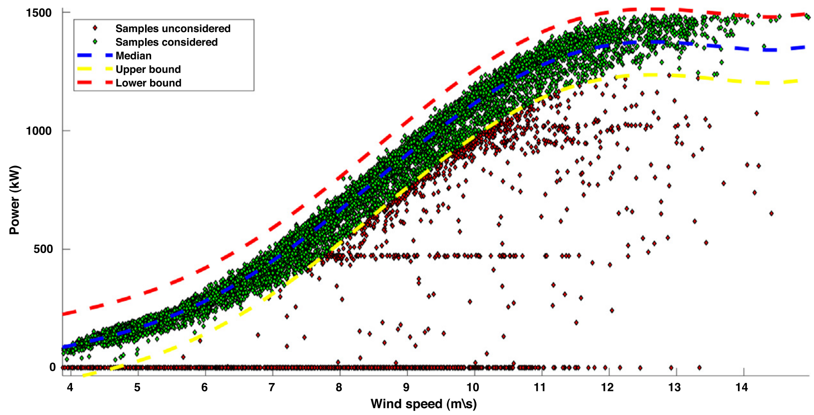


Fig. 3. A scatter plot with original raw data, the samples considered for modeling, and limits for data filtering.

Parameter models are defined using wind turbine data. These data are given in Table 1.

3.2.2. Exponential power curve

This model is based on a presumed form of power curve. It responds satisfactorily to higher average annual wind speeds [41]. This proposal is presented in Eq. (2):

$$P(v) = \frac{1}{2}\rho A K_p (v^{\beta} - v_{ci}^{\beta}), \tag{2}$$

where k_p and β are constants that need to be parameterized and v_{ci}^{β} is the cut-in wind speed.

3.2.3. Polynomial power curve

The polynomial Power function, P, is expressed as:

$$P(i) = b_k v_i^k + b_{k-1} v_i^{k-1} + \cdots + b_2 v^2 + b_1 v_i^1 + b_0, \tag{3}$$

wherein $b_0, b_1, \ldots, b_k$ are coefficients of the polynomial, and k is a non-negative integer.

Therefore, to obtain better results in power curve modeling it is necessary to use combinations of linear functions, as shown in Fig. 4.

$$P = b_1 v^1 + b_0 \tag{4}$$

The approximation of the polynomial power curve in [41] uses a second-degree polynomial equation to find $q(v)$, as follows

$$P(v) = C_2 v^2 + C_1 v + C_0, \tag{5}$$

wherein, C_0, C_1 e C_2 are calculated with v_{ci} and v_r.

$$C_0 = \frac{1}{(v_{ci} - v_r)^2}\left[v_{ci}(v_{ci} + v_r) - 4 v_{ci} v_r (\frac{v_{ci} + v_r}{2v_r})^3\right] \tag{6}$$

$$C_1 = \frac{1}{(v_{ci} - v_r)^2}\left[4(v_{ci} + v_r)(\frac{v_{ci} + v_r}{2v_r})^3 - 3v_{ci} - v_r\right] \tag{7}$$

$$C_2 = \frac{1}{(v_{ci} - v_r)^2}\left[2 - 4(\frac{v_{ci} + v_r}{2vr})^3\right] \tag{8}$$

3.2.4. Logistic function

The logistic function is the one that most closely represents the power curve of wind turbines [42]. For this approximation are used three, four or five parameters as in Eqs. (9)–(11) [30], where θ is the parameter vector; $\theta_3 = (a, b, c)$, $\theta_4 = (a, m, n, \tau)$ and $\theta_5 = (a, b, c, d, g)$, with $c > 0$ and $g > 0$ [40].

$$P(v, \theta_3) = a\frac{1}{1 + e^{-b(v-c)}} \tag{9}$$

$$P(v, \theta_4) = a\frac{1 + me^{-v/\tau}}{1 + ne^{-v/\tau}} \tag{10}$$

$$P(v, \theta_5) = \frac{d + (a - d)}{\left(1 + \left(\frac{v}{c}\right)^b\right)^g} \tag{11}$$

To find the parameters of the vector θ, Lydia [40] uses an optimization equation like the following:

$$min \sum_{i=1}^{N} [P(v, \theta) - P_a(i)]^2, \tag{12}$$

which searches for the value of the vector parameter $\hat{\theta}$ that results in the output $P(v, \theta)$ closest to the actual output $P_a(i)$.

3.3. Wind speed forecast

The state space reconstruction is the prediction process of the state vector from a single time series. In this work, we used a database with 5040 wind speed samples from a wind turbine, where 4320 samples were for test and 720 for training. Each sample corresponds to the average wind speed in a ten minute period. The 5040 samples correspond to a period of thirty-five days and the 4320 training samples correspond to a period of thirty days. The five days after the training period were all for testing. The NAR method is applied for wind speed prediction was under analysis.

As already used by Piazza et al. [43], the NAR method predicts wind speed, which according to the author is interesting because the method is neuro-statistical. The network topology results in heuristics through tests, as shown in Fig. 5. The fit of the topology elements such as the number of delay samples, the number of training data, and the number of neurons and layers of the neural network influence the result. So, one may not assume the right number of neurons by arbitration and the questions arises: How can define the proper number of neurons? We performed a preliminary investigation following a grid search of: the immersion dimension within the range of [2, 30] ∈ ℕ and the number of hidden neurons are in [2, 100] ∈ ℕ. A 10-fold cross validations is also performed, computing the RMSE is the metric to establish a comparison.

The topology that showed best results uses a immersion dimension of 20 units (*i.e.* 19 delays in the time-series) and is composed of 4 neurons in the hidden layer and one neuron in the output layer. It worth note that a 20 delays in the immersion layer represents in our problem a 5-hours of records sampled each 15 min.

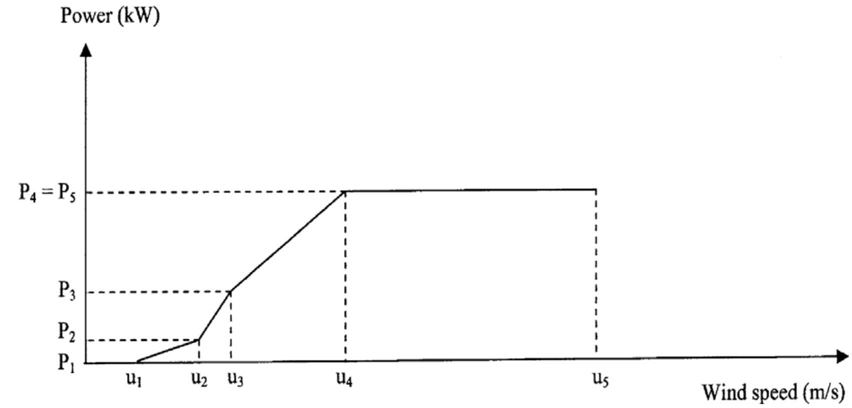


Fig. 4. Model with combinations of linear functions.

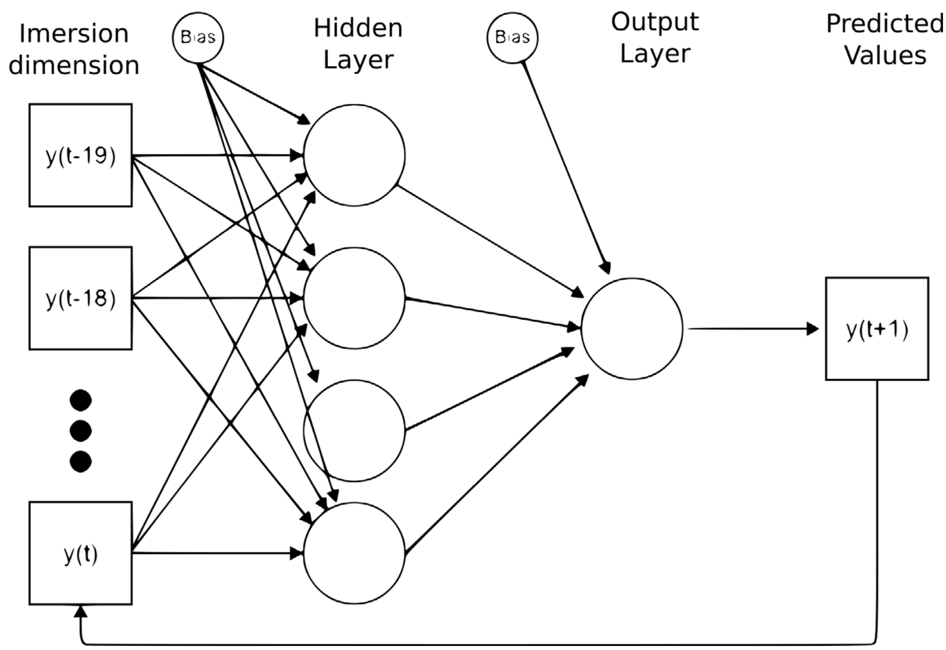


Fig. 5. NAR topology for wind speed forecast.

3.4. Simulation settings

To chose the best model configuration we used a hold-out cross-validation with 50 independent trials, in order to design a Monte-Carlo simulation. In our case, the test set for the (i) wind speed database are the five last days of each time-series, as aforementioned; and, (ii) for the power curve data the test set are randomly chosen among the processed data. The reports on the results will be from the best configurations from all trials.

The experiments were computed in a PC Intel i7 running at 3.1 GHz and 8 GB of RAM on a Linux Ubuntu operating system installed in a solid-state drive. We coded all the experiments using Matlab.

3.5. Energy potential estimation

In this work, the estimation of wind resources was performed in non-linear self-correcting models and in the power curve modeling of the wind turbine. The wind velocity predictors are the non-linear self-correcting models, which in combination with the power curve models can estimate the energy potential of a wind turbine. In summary, to obtain an estimation of the production the wind speed forecast must be combined with the power curve model, following the steps in Fig. 6.

4. Results analysis

This section contains the results of the wind power estimation analysis, applying the methodology described in Section 3, which presents the results of the evaluation methods in obtaining the power curve of the wind turbine, and then the results of the wind speed forecast. Finally, the results of the estimation of energy production are presented.

4.1. Power curve modeling

In this work, the cubic approximation, the exponential power curve, the polynomial model and the logarithmic function approximation are used in the modeling of the power curve by parametric models. The details of how each method was used and a comparison between them has been added to this topic.

4.1.1. Cubic approximation

In order to obtain the power curve through cubic approximation, the turbine parameters are applied to Eq. (1), where $C_{p,max}$

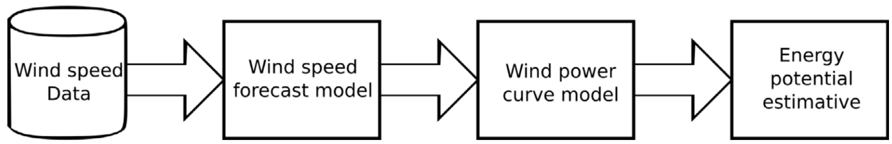


Fig. 6. Stages to estimate wind generation potential, based on the proposed approach.

Table 2
Results obtained.

θ	Parameters				
θ_5	a = 0.3	b = 3.7	c = 26	d = 1500	g = 56
θ_4	a = 1500	m = −5.2	n = 71	τ = 1.9	
θ_3	a = 1500	b = 0.6	c = 8.4		

Table 3
Logistic regression analysis.

Model	RMSE	R^2	Time (s)
Manufacturer	127.3423	0.8867	0.0219
Cubic	358.3626	0.1026	0.0550
Exponential	60.5159	0.9744	0.0578
Polynomial	234.5492	0.6156	0.0819
Logistic^3	**47.3406**	**0.9843**	**0.0047**
Logistic^4	52.9304	0.9804	0.0031
Logistic^5	96.5083	0.9349	0.0051

$= 0.45$ and $\rho = 1.225$, resulting in

$$P(v) = \frac{1}{2}(1,225)(5,325)(0.45)v^3. \quad (13)$$

4.1.2. Exponential power curve

The modeling by the exponential method, as in Topic 3.2.2, mainly consists of determining the value of the constants K_p and β. Here, it is necessary to use the trial and error method, changing the values of the constants and analyzing the results through the calculation of R^2 for each resulting model, and the parameters obtained were: $K_p = 4.5$, $\beta = 1.9$. The results of the analysis of R2 are found in Fig. 7(a) and (b). Applying the constants in Eq. (2) we arrive at Eq. (14).

$$P(v) = \frac{1}{2}(1,225)(5,325)(4,5)(v^{1,9} - v_{ci}^{1,9}) \quad (14)$$

4.1.3. Polynomial model

The polynomial model of power and the coefficients C_0, C_1 and C_2, calculated from Eqs. (6)–(8) respectively, were calculated considering the characteristics of the wind turbine present in Table 1 resulting in the following equation:

$$q(v) = 0.0116v^2 - 0.0745v + 0.1191. \quad (15)$$

4.1.4. Approximation by logistic function

As discussed in Section 4, the determination of the model from the logistic function is given by the search of values of parameter vectors (θ) that result in the model that shows the greatest similarity with the real data. The search for the logistic function parameters (θ) was performed using Eq. (16).

$$min \sum_{i=1}^{N} [P(v,\theta) - P_a(i)]^2, \quad (16)$$

where $P(v,\theta)$ corresponds to the logistic function output for a wind speed v and a vector of parameters θ and $P(P_a(i))$ corresponds to the output of the real system.

Fig. 8 was generated from the analysis of R^2 according to the variation of b and c of the vector θ_3, maintaining the a constant (see Table 2).

4.1.5. Comparison of the results of parametric models

Comparing the results of the parametric model approximations in Table 3, the logistic function of three parameters obtains the best approximation result, and is the method with the lowest RMSE value, higher R^2 value and higher approximation speed, and also one of the least complex metrics.

To visualize the models described in Table 3, the projection of the approximate curves by the parametric models, as well as the curve given by the manufacturer are presented in Fig. 9.

Observing the curves shown in Fig. 9, the polynomial and cubic model have curves below the cloud of real points and the curve given by the manufacturer is in most cases above the real point margin. On the other hand, logistic and exponential models are in the middle of the data points.

Analyzing Table 3, the Logistic model^3 has the lowest RMSE and the highest R^2, in addition to having the shortest time. This analysis and the behavior of this model presented in the graph of Fig. 9 confirms the numerical data of Table 3; therefore this model was chosen, within the parametric methods, to be evaluated in the prediction of energy production later on in this work.

4.2. Wind speed prediction

To predict the wind speed by the NAR method 5040 samples were used, 4320 for training and 720 for test. Each sample corresponds to the average wind speed in a ten-minute period. The 5040 samples correspond to a period of thirty-five days, where the 4320 samples used for training correspond to a period of thirty days and the 720 samples used for testing are equivalent to 5 days. The data in this step of the results are shown in Fig. 10.

The topology of the NAR method in these tests is configured by four neurons in the hidden layer and one neuron in the output layer, and one immersion dimension of 144 samples with 2 steps of immersion delay. The Optimization Levenberg–Marquardt method was used in the training of the NAR method. The comparison between the real time series and the estimate by the NAR model, where R^2 and RMSE were 0.4769 and 1.1126, respectively.

4.3. Energy production estimation

The energy productivity of a wind turbine may be estimated by combining the wind speed prediction method with the power curve modeling. From the afore discussed results, one model highlight themselves among the others to approximate the power curve of the wind turbine, which is the Logistic. The wind speed is estimated by the NAR neural networks structure. In order to provide a comparison to real and running system the values of the manufacturer's power curve and the real wind speed will be presented.

Table 4 presents a summary of the average energy production estimate during the testing period, where the actual power generated in the period is taken as the baseline for analysis. The power curve proposed is the Logistic Sigmoid approach and the manufacturer's curve. The wind speed is used for the estimation

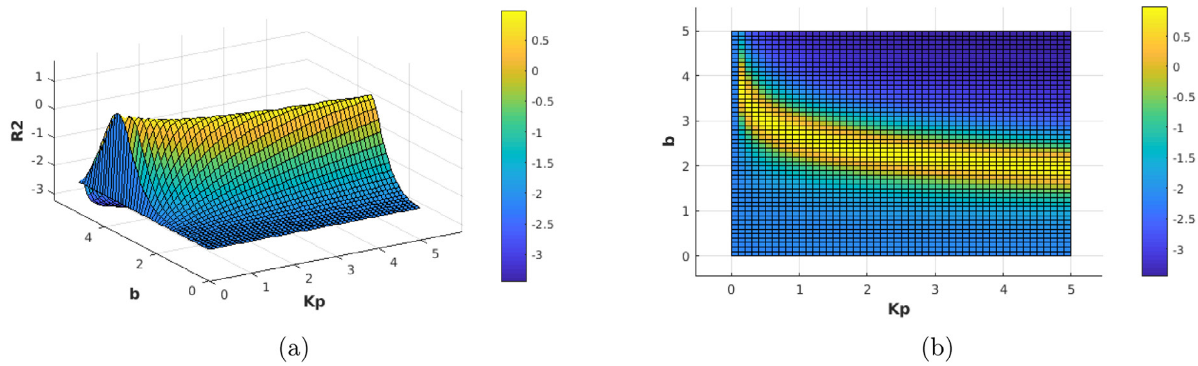


Fig. 7. Similarity analysis for exponential regression ranging K_p and β.

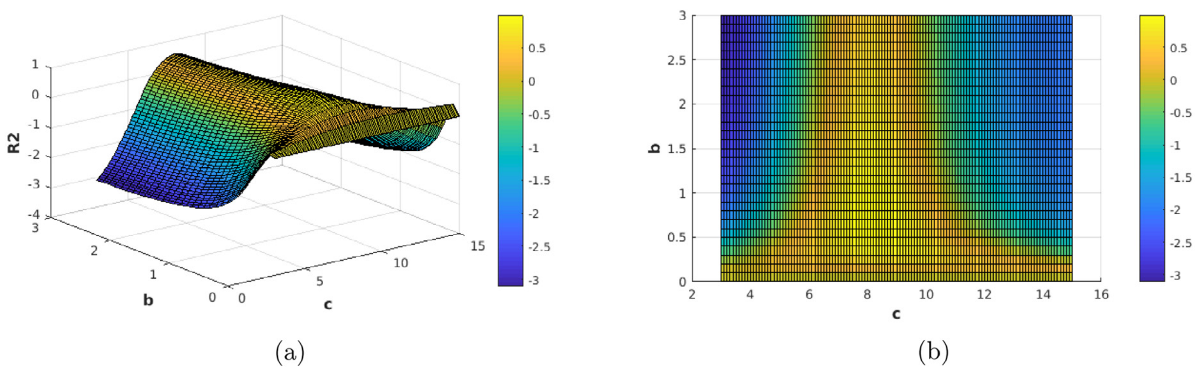


Fig. 8. Similarity analysis for logistic regression with different parameter θ_3.

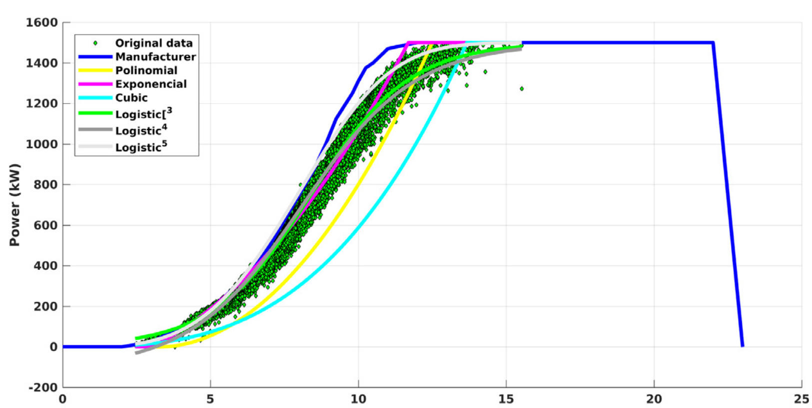


Fig. 9. Approximation of power curve obtained from the parametric models and the manufacturer's curve.

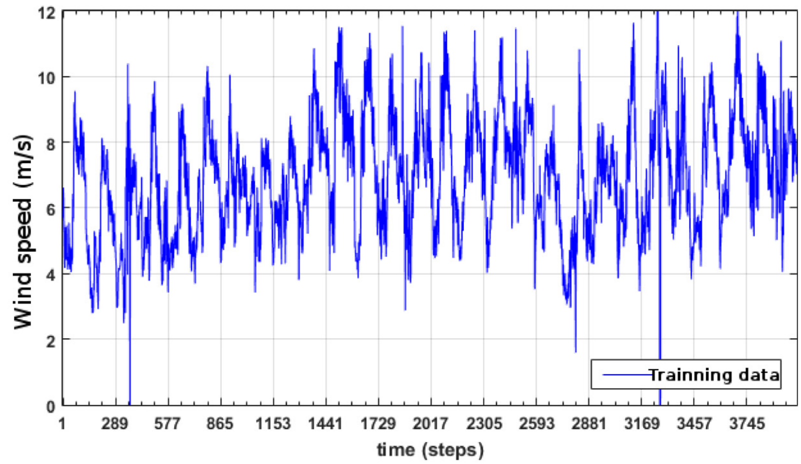
Table 4
Results of the wind energy production estimation, obtained by combining the wind power curve (from both logistic and manufacturer curve) associated with the wind speed (from both NAR method and real wind speed - RWS).

Power curve	Wind speed	RMSE	R^2	Mean (W)
Real Power	–	–	–	526.7872
	NAR	281.9127	0.1409	590.3827
Logistic	RWS	83.9283	0.9239	637.8701
	NAR	309.7881	−0.0374	681.6575
Manufacturer	RWS	123.5668	0.8349	671.6176

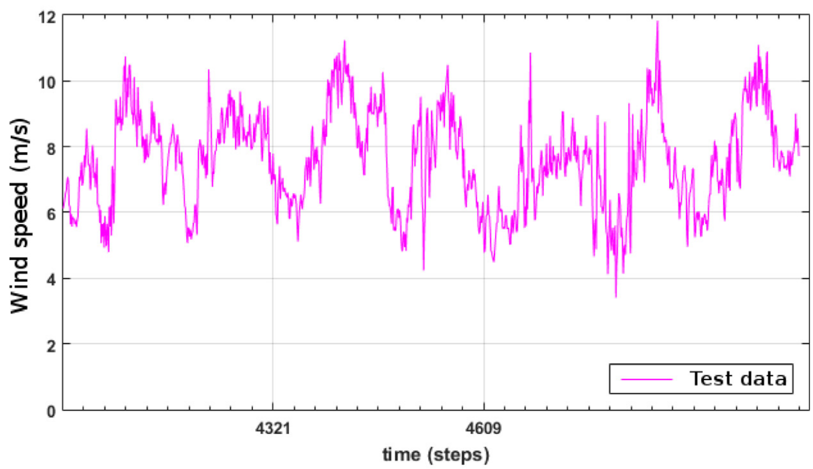
of electricity generation, in which the real speed of wind and the one obtained by the NAR method are presented.

In Table 4 the comparison is shown and it is identified that the logistic power curve is more conservative than the one provided by the manufacturer, *e.g.* around 34 W on average by calculating the potency using the RWS. This shows the manufacturer's curve introduces an error on the system, that might accumulate over time and lead to wrong misalignments between the wind farm and the power grid system. This happens mostly because the power curve provided by the manufacturer was estimated in a controlled environment in a wind tunnel. Others reasons are: the topping between towers, in which a tower can prevent the wind arrives in a second behind the first one; limitation of the high temperature production of some components; partial breakdown of some components of the wind turbine, which limits its efficiency, but not its functionality.

What we would like to emphasize is that using the NAR method we were able to mimic the wind speed pattern, since it provided an average under-estimation of 47 W using the Logistic power curve and a over-estimations of 11 W using the manufacturer's power curve. This error might not be much relevant in a



(a)



(b)

Fig. 10. Data used to analyze the wind speed prediction: (a) training data; (b) testing data.

short-term prediction, up to 7 days. This certainly would serve as a trend to guide management.

The behavior of the wind is exhibit in Fig. 11, in which estimation of energy production versus the manufacturer's data, using the actual wind data, in which it presents an estimate using the Logistic parametric model and the NAR method for wind forecasting.

In the analysis of Fig. 11, the difference of the estimation by the Logistic parametric approximation is on average close to the actual data of the average production of the wind turbine.

4.4. Discussions from a point of view of management

Using the approaches expressed in this experiment, some IoT analyses and functionalities can be used in the management of wind farms. The following sections present three of these analyses: energy production curve, machine production (which are not 100% available) and an analysis of the seasonality of the winds.

4.4.1. Analysis of the energy production curve

An analysis of the results is shown in Fig. 12 which presents the power curve by these approaches and the total non-filtered point margin.

Fig. 12(a) shows that the curve by the methodological approaches, using the Logistic model the wind speed varies speeds from 3 m/s to 9, 5 m/s, and approximately in the middle of the actual data points margin of wind and power generated, different from the curve by the manufacturer. For a better analysis, three regions are highlighted in Fig. 12(b) – (d).

In the first analysis shown in Fig. 12(b), the curve by the manufacturer is optimistic. It predicts the best possible production from the actual data for each wind speed, which generates an estimation error by the manufacturer chart, since most of the real energy produced is below the amount estimated by the manufacturer.

In the second analysis (Fig. 12(c)) the main error in the production estimate in the curve by the manufacturer is that it overestimates the energy output of the 8.5 m/s velocity in the wind data, which generates an even greater error in relation to the optimistic analysis of the manufacturer presented in the analysis of Fig. 12(b). Analyzing the approaches proposed in this study, in this region where wind speed is above 9 m/s, the behavior of the proposed curves is no longer similar, the logistic model is a little lower down with a more pessimistic analysis of production.

The third analysis in Fig. 12(d) presents several real wind data that are well away from the curve, which is due to different situations during the period under analysis. These may be due to a production limitation of the wind turbine, or by a maintenance stop during the same day, among other factors. The points that

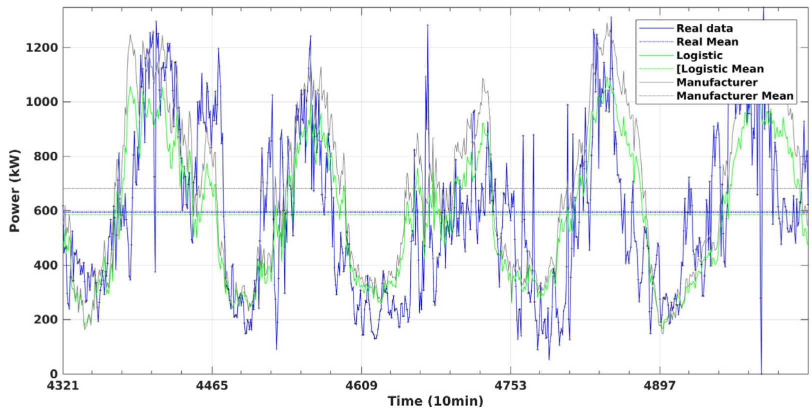
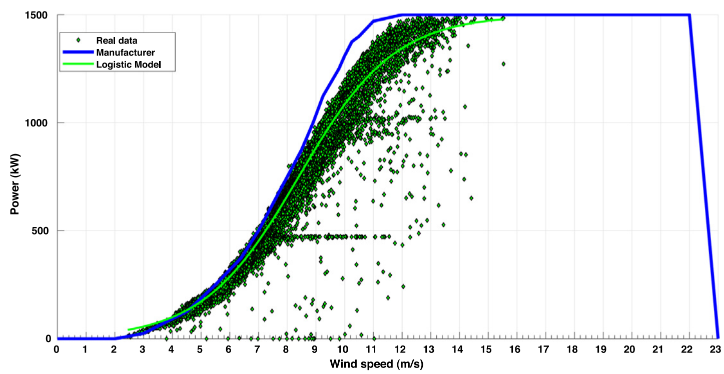
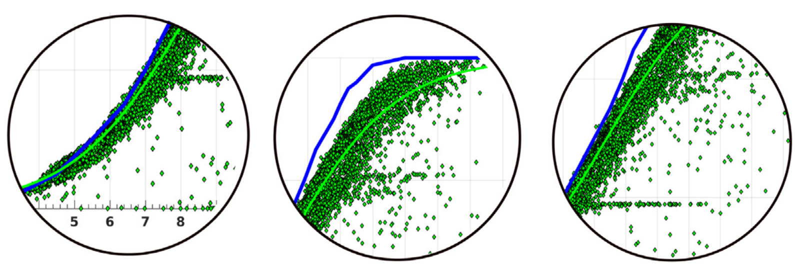


Fig. 11. Results obtained for the estimative of power produced by using the NAR method to forecast the wind speed, and the power curve by the logistic method in (a), versus real data.



(a)



(b) (c) (d)

Fig. 12. Power curves obtained by the proposed methods, in contrast with the power curve provided by the manufacturer.

are away from the curve are not used to estimate the production curve because they are out of phase in the same production range in Watts. This analysis does not tell the cause of the fall in production but allows a more detailed analysis of the wind turbine, and can perhaps improve the maintenance and operation planning of the equipment, mainly based on reports of that period when the aerogenerator was not under normal operations.

4.4.2. Analysis of the production of the period in which the machine was not 100% available

As a second analysis from the results of this experiment, Fig. 13 presents an application of the logistic model to analyze the production of aerogenerators that were not 100% available over a certain period. Fig. 13 shows the daily production of a wind turbine, the information of availability of the aerogenerator and the daily wind speed. From these data and using the curve by the logistic model it is possible to estimate the energy production if the equipment was 100% available throughout the period; data which is extremely useful in the management of a wind farm. For the period in Fig. 13, the VSWT had an availability of 80.16% and produced an average of 6.9 kWh; however, the same VSWT would produce 9.8 kWh if it were 100% available throughout this period.

4.4.3. Seasonality analysis of winds

Because air masses exhibit seasonal behavior a power curve analysis divided one-year samples into four three-month periods, as shown in Fig. 14(a) – (d). An analysis of each quarter cited in Fig. 14, is presented in Table 5, which is a numerical evaluation of the power curves using only the data of each period.

In January, February and March, the wind turbine works most of the time with low wind speeds. As shown in Fig. 14(a), the wind speeds recorded in this period are mainly less than 11 m/s. and the margin of points less thick than the other quarters of the year, Moreover, with lower speeds the oscillation is also less. In this period, the logistic wind prediction methods are centered on the velocity range from 3 m/s to 7 m/s, at the lower edge of the

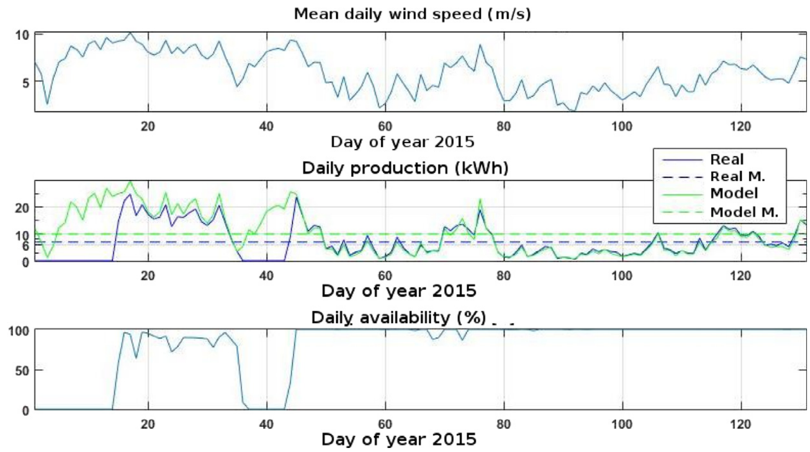


Fig. 13. Application of the logistic model in energy production of logistic model from a real period when the wind turbine has no work in some period.

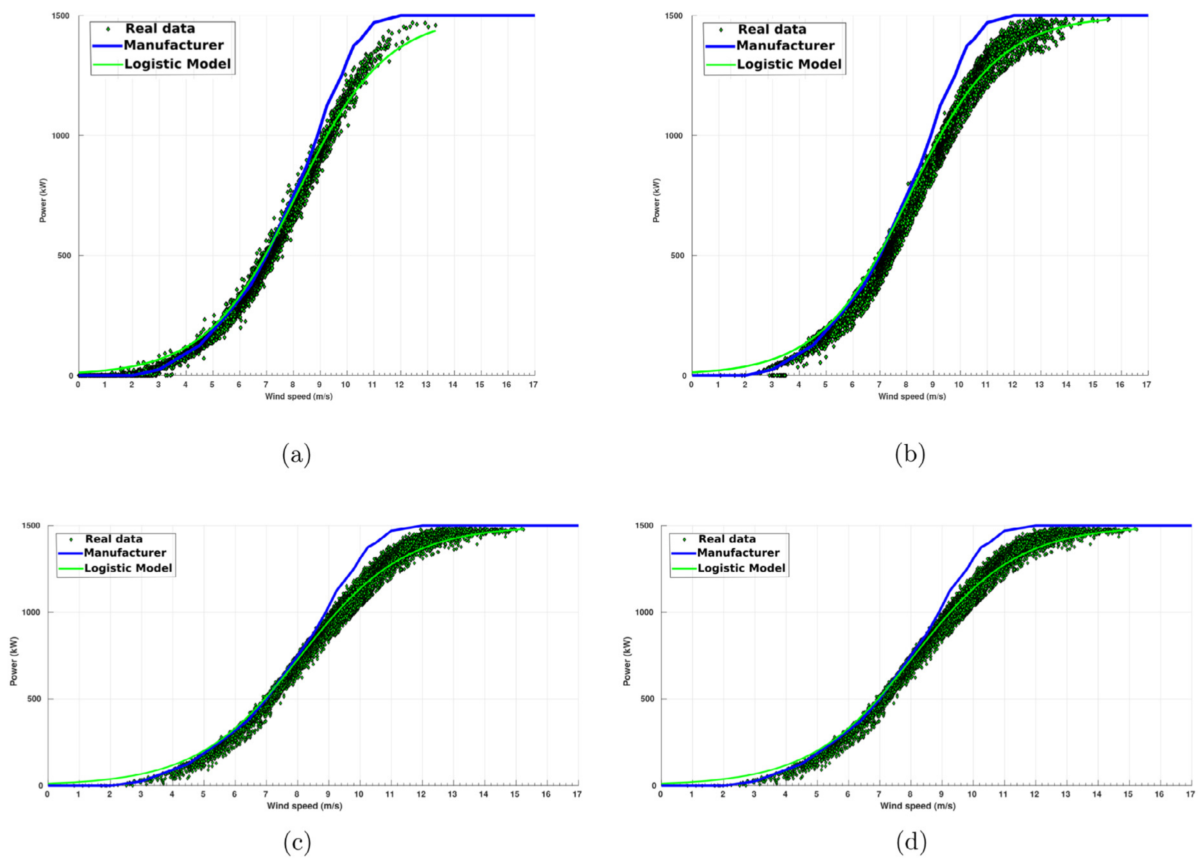


Fig. 14. Analysis of a seasonal production, considering the following months: (a) January, February and March; (b) April, May and June; (c) July, August and September; (d) October, November, December.

Table 5
Analysis of the sigmoid models for each quarter of the year.

Quarter	Model	RMSE	R^2
1	Logistic	46.3121	0.9740
2	Logistic	36.4936	0.9908
3	Logistic	54.4094	0.9780
4	Logistic	56.8190	0.9820

velocity points range from 7 m/s to 9 m/s below the curve after this.

Fig. 14(b) presents the data for the second quarter: April, May and June when there is a moderate increase in the wind speed compared with the first quarter, and a small increase in the thickness of the margin of points, especially at speeds above 10 m/s. The logistic model behaves properly in this period, and is at the center of the cloud of points along the curve; consequently, it has the best result among the evaluated curves, obtaining RMSE and R^2 metrics slightly above the period before the small variation of the thickness of the cloud points at speeds above 10 m/s.

In the third quarter, where Fig. 14(c) presents the production data for the months of July, August and September, there are more points in the region above 10 m/s, which makes the error larger due to oscillation of high speeds, as seen in Table 5. This is the period with the largest error in RMSE and R^2 metrics. In the last period, Fig. 14(d), for the months of October, November and

December, there is still a high value in the error represented in the RMSE and R^2 metrics, but lower than the third quarter of the year under evaluation.

According to the [44], the period of the year with the highest wind intensity in the state of Ceará is August and September, as well as a high value in July, which confirms the analysis of the results of Table 5 and Fig. 14, where the third quarter is the period with the highest intensity of winds. Also according to FUNCEME the fourth quarter has high rates similar to the month of July, but lower than the months of August and September, which also confirms the results of the experiment.

4.5. Comparison to related works

Baptista et al. [25] has been able to reduce an error of energy production estimate in 5%, which represents 750 kWh in productions. This is in fact a remarkable milestone, however they only considered a prediction for 1-hour ahead. With our framework we were able estimate the energy production up to a week with a mean error of 29 W of generated Power, which would an error represent 145 kWh for one hour of production, being 5.17 time more accurate than [25].

In what concerns to the wind speed estimations [26] reports promising results of an error of 0.29 m/s but were not clear how much time-ahead is represented by this error, so there are no means for a fair comparison. On the other hand, Huang and Boland [28] achieved and error of 0.99 m/s for a seven day prediction and 0.17 m/s for a 30 min prediction. These results seems promising but the database used by Huang and Kuo [27] is of records of wind speed in a particularly region in Taiwan, in which has lower wind speeds (an average less then 3 m/s) and more constant (and standard deviation less than 1 m/s). This is not likely the behavior at the state of Ceará, Brazil, in which the average wind speed is more than 8 m/s and suffers from fluctuations up to 16 m/s. And this is more evident in different months throughout the year, that is why we proposed a "specialized" power curve for a 4-month period.

5. Conclusion and future work

The results demonstrate that the NAR model is capable of obtaining wind speed predictions for a 5 day horizon. Also the logistic method is the most applicable for the power curve regression, because it was more representative because it decreases the error of the manufacturer in 63%, providing a power curve 2.7 times more realistic than the manufacturer's one.

It is possible and efficient to forecast energy production, since the, together, the power curve regression and wind speed forecast archived an average error of 29 W of Power generation, compared to the real results for a one week period.

An analysis of our proposed approaches indicates that the wind speed forecast and the power curve modeling might be used separately, for instance, (i) using only the wind speed forecast to optimize maintenance planning, according to periods of low wind speed or even serve as a (ii) tuner for the wind turbine controller, since in multiple operations points while the manufacturer curve is unable to give a real value of generated power, the logistic regression supplied a solid approximation. And, (iii) the power curve modeling could also be used to account the amount of lost power while the wind turbine was stopped for maintenance.

A seasonal analysis of energy production made from the power curve regression during the period demonstrated that the error in third and fourth quarters of year are 50% higher than in the second quarter, due to the season behavior in Ceará, Brazil. So it would be better to model a power curve modeled for each quarter of the year. Finally, the proposed approaches are promising, important and novel techniques. In terms of IoT, we made a robust system, based on large amounts of data from both the wind turbines and wind speed sensors, and created a monitoring system, providing metrics for management and evaluation. Our system represents a trade-off analysis, because the wind farm manager is going to have solid information about present energy production and its estimation in the days ahead, making it possible for them to find a better strategic solution for planning a sustainable energy system.

Acknowledgments

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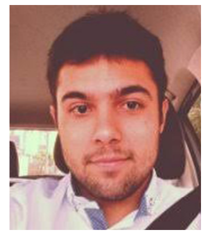

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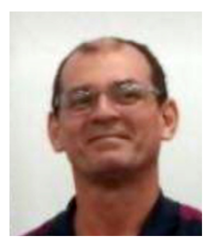

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