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Review

A Review on Wind Turbine Deterministic Power Curve Models †

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† This work aims to be useful for all those researchers who look for accurate tools for modeling wind turbine power curves that, additionally, can be easy to implement in calculation algorithms.

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Abstract: Over the last decades, wind energy has been arising as one of the most promising sources for the future of energy supply, and this trend should be reinforced in the future due to the foreseeable environmental and climatological catastrophe. Therefore, all technologies and issues regarding its development are relevant. Among them, research on wind turbine power curve modeling is of importance for stakeholders and researchers because it allows them to easily obtain information about the amount of power and energy that can be captured from the primary resource, i.e., the wind. The task can be simplified by means of the use of wind turbine power curve models, and many researchers have been presenting their contributions on the topic in parallel with such a development. In this paper, a review on the formulation of wind turbine deterministic power curve models is presented.

Keywords: wind turbine; wind turbine power curve; wind farm; spline model; sigmoid model; logistic curve

1. Introduction

Energy consumption has only just been growing since the beginning of humankind history, but this use has been expedited during the last decades [1]. The future trend, in a world that is immersed in a globalized economy, seems to follow the same path [2]. This fact is crucial when talking about greenhouse gas emissions and, therefore, when dealing with the problem of atmosphere composition change and its consequence on climate, which is observable in global warming and other aspects [3]. The main reason is that a very important part of this energy demand has been traditionally satisfied by means of the use of fossil fuels [4].

There is no doubt about the relationship between energy and economy [5]. Both concepts will predicate an important change in their uses for the future, and renewables will have to be part—and in fact an important part—of the solution. Moreover, there does not seem to be any doubt that all issues regarding wind energy technologies can be considered among the most promising ones for facing such a challenge in the context of renewables. Wind energy is being implemented successfully in most of the electrical energy systems across the world [6]. However, this implementation of new sources and technologies need to be supported by a background of knowledge, and this must be achieved with the help of research. Strictly speaking, it cannot be said that wind energy constitutes a new energy resource, as it has been experiencing an important development since the beginning of the 20th century and, in the case of electrical uses, since the middle of the century [7]. This results in the fact that there is some accumulated knowledge and experience, treasured over the last decades.

As part of the research in wind energy, wind turbine (WT) and wind farm (WF) power curves have been attracting more and more attention in recent years. This paper focuses on reviewing some amount of work developed about WT power curves (WTPC).

It is a well-known fact that WTPCs show the relationship between wind speed and the electrical power supplied by a WT. They are provided by the manufacturers and as a first option; moreover, they can be given in tabular format by means of pairs of values. In a horizontal axis WT (HAWT), it is generally assumed by the researchers the fact that the WT will generate a given value of power for its corresponding value of wind speed when this value of wind speed is the one that can be measured immediately in front of its hub. Alternatively, the manufacturers can simply deliver a graph in which such pairs of values can be derived by observation. In any case, these values can be used by stakeholders and promoters to infer not only the amount of power to be expected in a given location but also the value of energy a given WT can capture from the wind, for which the only additional information needed is the wind speed probability distribution at the given location.

That said, the manufacturers are encouraged to provide their curves in a particular way. There is a standardized procedure to establish them, and it has been given by the International Electrotechnical Commission (IEC) in its document IEC-61400-12-1 [8]. In this way, the measured WTPC is generally determined by applying the so-called method of bins for the normalized data sets. This method uses intervals of 0.5 m/s in the whole range of possible wind speeds, and then it establishes the calculation of the mean values of the normalized wind speed and the normalized power output for each wind speed bin. Therefore, as only a finite number of measurements can be taken, the WTPCs obtained in such experiments are discrete functions.

The above constitutes an idealistic analysis of what actually happens. In a real life case, WTs and, hence, WFs, suffer operating conditions that oust them from the ideal ones experienced in manufacturer laboratories and wind tunnels where the WTPCs are measured. In a WF, WTs are usually subjected to different conditions depending on the air temperature, moisture, turbulence created by several reasons such as wake effect and shear effect, presence of ice, loss of efficiency due to aging, and other possible ones [9].

Regarding the topic of this paper, what is actually of interest is how to tackle WTPCs from an analytical or numerical point of view. In many analysis applications and in many research and software tools, it is important to deal with such curves, and this fact reveals the importance of WTPC modeling. Henceforward, the paper focuses on the analysis and discussion of different WTPC models of three-bladed HAWTs. These kind of machines, with different internal layouts regarding their electrical devices (not analyzed here), are among the most used in the electricity networks across the world.

There are some interesting surveys in the literature, where different models of WTPCs are presented. Although some of them are explained along this paper and this section does not pretend to introduce them all, some studies can be mentioned at this point because they have used several models with different goals. An example is the work by Goudarzi and Ahmadi [10], where the authors proposed a comparative analysis of different techniques for the modeling of WTPCs and applied them to the cases of three different commercial WTs. A similar proposal can be found in the work by Teyabeen et al. [11], a study where the authors modeled WTPCs on the basis of the data collected from 32 different WTs that cover a wide range of powers. Chang et al. [12] applied four kinds of power curve models, i.e., linear, quadratic, cubic, and a general one, used for the first time in their work, to estimate the capacity factor of a pitch-controlled WT with the help of the Weibull distribution, which has generally been accepted as an accurate statistical description of the cumulative wind speed behavior. Carrillo et al. studied WTPC models applied to the different types of WTs on the experimental WF called Sotavento, in Galicia, which is the autonomous region located on the northwestern part of Spain [13]. Lydia et al. presented a study that included a wide overview of WTPC models and a description on the methods for obtaining them [14]. It also evaluated some parametric and nonparametric techniques for the analysis from a critical point of view. Parametric and nonparametric models have also been analyzed in [15], where the parameters of the models were studied with the help of genetic algorithms, evolutionary programming, particle swarm optimization, and differential evolution. Bokde et al. presented a WTPC model based on the expression of the cumulative distribution function of the Weibull distribution [16]. A wide review on the models for WTPCs can be found in Sohoni et al., including a detailed classification of different approaches to the problem [17].

Regarding different techniques that have been proposed for the analysis of WTPCs, some other interesting works can be mentioned, such as [18], which used an artificial neural network (ANN) with two layers of neurons to improve the accuracy of the WTPC modeling, reducing errors. In [19], an ANN was also employed, including a previous filtering of data by means of the Gaussian process modeling, thereby getting improved results with respect to those obtained by means of the conventional ANN process and also by other methods. Machine learning techniques (ML) can also be found in the literature, for instance in [20], where three different ML were used for estimating the relationship between the wind speed and the wind power, although the authors focused on WFs rather than on WTs. A hybrid technique was used in [21], where different extreme learning machines were trained with data obtained by means of a previous fuzzy c-means clustering and with the help of support vector regression. The authors claimed that the technique could be used for obtaining accurate WTPCs in the presence of outliers. Outliers can be excluded by means of probabilistic methods, as shown in [22], a work where such an exclusion was achieved with the help of a copula-based joint probability model. A copula model was also presented in [23] as a proposal for getting the joint probability of power and wind speed. The problem of having inconsistent data was also dealt with in [24], where the heteroscedastic spline regression model and the robust spline regression model were used for improving the accuracy of the obtained WTPCs even in the presence of bad unsuitable data. Some of the authors of the mentioned work also presented a comprehensive review and discussion on WTPC modeling [25], along with a broad analysis of different methodologies. Data mining has also been used in the analysis of WTPCs, and Ouyang et al. proposed an approach based on centers of data partitions and data mining to build such curves by means of a support vector machine algorithm [26]. Hybrid approaches were also studied in [27], a work that employed clustering, filtering, and modeling for achieving accurate WTPCs by means of the k-means-based smoothing spline hybrid model. Additional work on hybrid models can be found in [28].

The applications of the WTPC models are wide and varied. They can be used in the process of assessing wind energy [29,30] or in monitoring and adjusting the operation conditions of a WF [31–33]. WTPC models can also be a tool for choosing the proper location and layout of a WF [34,35], for analyzing the influence of external factors [36,37], or for assessing the reliability in power systems [38,39]. These types of models are helpful when dealing with wind power prediction [40,41] or in economic studies [42] as well.

Some other literature, where more specific models have been detailed, is mentioned and discussed along the rest of the paper, which is organized as follows. Models are introduced in Section 2, with a brief comment about probabilistic models. However, deterministic models are classified into polynomial ones and are analyzed in Section 3, while sigmoids are presented in Section 4. A discussion can be read in Section 5, and the conclusions of the work appear in Section 6.

2. Wind Turbine Deterministic Power Curve Models

According to the related literature, two types of WTPC models have been generally used in wind energy studies: deterministic and probabilistic models. The focus of this paper is exclusively on deterministic models, with the aim of establishing connections among them and, additionally, analyzing a possible reduction of their number. In addition, there is a relationship between the parameters of a WT and those involved in its WTPC model. Hence, the proposal consists of deriving a general model for each case in order to study such a relationship.

As stated in the previous paragraph, it is not the aim of this paper to analyze probabilistic models. However, for those readers who may be interested in deepening their study, some papers can be of interest, such as [43–47].

Coming back to the deterministic approach, it must be reminded that an important objective of these models is to represent WTPCs by means of functions. On a given terrain, i.e., out of laboratory conditions, the same value of wind speed can give rise to different values of power, depending on a survey of conditions, such as those mentioned earlier. However, the mathematical meaning of a function is involved in giving a single output value for a given input one, and this is in part what is pursued with the use of these models.

It can be considered there are two main types of WTPC deterministic models, i.e., those described by means of polynomial functions and those other described by means of sigmoids. In both cases, the models can be used for studying the whole operating range of the WT or only a certain wind speed interval or intervals of it. Additionally, all of these models can be described by means of continuous nonpiecewise functions or by means of piecewise ones, which in general are not continuous. The reason for this is explained in the following paragraph. This last circumstance means that, in most cases, the derivability of the whole function is not guaranteed by the model.

In general, in the case of three-bladed HAWTs, the whole range of possible wind speeds is divided into four intervals. The first one covers from a wind speed equal 0 up to the cut-in wind speed. The cut-in wind speed is the value for which a WT starts operating. Below this wind speed, the WT does not generate any power. The second interval covers the range between the cut-in and the rated wind speeds, and in this interval, the WT increases its generated power as wind speed increases. The third interval depends on the type of WT. In old stall-regulated WTs, due to aerodynamic losses, WT power output decreases as wind speed increases. However, most of the WTs currently used are of the type called pitch-regulated, and in this interval the power output keeps constant as wind speed increases. In both types of WTs, this operating mode happens up to the so-called cut-out wind speed, which is the limit between this third interval and the fourth one, in which the WT is forced to finish its operation due to safety reasons. A typical graphical representation of a WTPC reveals that in the real case, there are two points where the curve is not continuous. The first one corresponds to the cut-in wind speed, where there is a step from power 0, at a point when the wind is below the cut-in wind speed, to a small amount close to but greater than 0 for wind speeds greater than the cut-in one. The second one corresponds to the cut-out wind speed. There is a value of power for wind speeds close to but below this wind speed, and then there is a negative step down to 0 for wind speeds greater than the cut-out one, in this case due to safety reasons as mentioned.

The power generated by a WT P not only depends on the wind speed v but also on the air density ρ; the area swept by the rotor A; and the power coefficient $c_p(\lambda, \beta)$, where λ is the tip speed ratio and β the WT blade angle of attack, according to the well-known Equation (1).

$$P = \frac{1}{2}\rho A v c_p(\lambda, \beta) \tag{1}$$

Polynomial models and sigmoid ones are explained in the following sections.

3. Polynomial Models

Henceforth, the description given about the different intervals of a WTPC is assumed. Polynomial WTPC models describe, for all those intervals, the value of the wind power as a function of the wind speed by means of general Equation (2):

$$P = \sum_{i=0}^{nj} a_{ij} \cdot v^i \quad v_j \leq v < v_{j+1} \tag{2}$$

where a_{ij} is the parameter of order i for the interval j, v_j and v_{j+1} are the lower and upper limits of such an interval respectively, and n_j is the order of the polynomial ($0 \leq n_j$). This notation simplifies the implementation of several of these models simultaneously. Depending on the values of the constants a_{ij}, a classification can be established, such as the one given in the following sections.

3.1. Linear Models

Polynomial models where n_j is equal to or lower than 1 for all the intervals are called linear models (LM). The classic one is based on three intervals such as expressed in Equation (3) [12]:

$$P = \begin{cases} a_{01} & v_1 \leq v < v_2 \\ a_{02} + a_{12} \cdot v & v_2 \leq v < v_3 \\ a_{03} & v_3 \leq v < v_4 \end{cases} \tag{3}$$

where the generally accepted assignation of parameters is that given in Table 1.

Table 1. Relationship among parameters of the linear models and the parameters of the wind turbine (WT).

j	n_j	a_{0j}	a_{1j}	v_j
1	0	0	0	0
2	1	$-v_{ci} \cdot P_r/(v_r - v_{ci})$	$P_r/(v_r - v_{ci})$	v_{ci}
3	0	P_r	0	v_r
(4)	-	-	-	v_{co}

The parameters of the WT used in Table 1 are as follows: P_r is rated power, and v_{ci}, v_r, and v_{co} represent the cut-in, rated, and cut-out wind speeds, respectively. For $j = 4$, there is no interval, but $v_4 = v_{co}$. In this case, the model loses accuracy in the interval between the cut-in and the rated wind speed.

There is a second option for the simulation as a LM. It consists of dividing the wind speed range into five intervals, and in this case there is no relationship between the parameters of the model and the parameters of the WT [14]. Its mathematical expression is given by Equation (4):

$$P = \begin{cases} a_{01} & v_1 \leq v < v_2 \\ a_{02} + a_{12} \cdot v & v_2 \leq v < v_3 \\ a_{03} + a_{13} \cdot v & v_3 \leq v < v_4 \\ a_{04} + a_{14} \cdot v & v_4 \leq v < v_5 \\ a_{05} & v_5 \leq v < v_6 \end{cases} \tag{4}$$

where $a_{01} = 0$, $a_{05} = P_r$, $v_1 = 0$, $v_5 = v_r$, and $v_6 = v_{co}$. The rest of the parameters of this model are not directly related with the parameters of the WT.

3.2. Quadratic Models

Quadratic models (QM) are polynomial ones with values of n_j equal to or lower than 2, for all intervals. The most used one is that which is based on three intervals according to Equation (5) [12].

$$P = \begin{cases} a_{01} & v_1 \leq v < v_2 \\ a_{02} + a_{22} \cdot v^2 & v_2 \leq v < v_3 \\ a_{03} & v_3 \leq v < v_4 \end{cases} \tag{5}$$

A typical assignation of parameters in this model is shown in Table 2.

For $j = 4$, there is no interval, but $v_4 = v_{co}$. The main drawback of this model is its accuracy in the area of the rated wind speed; in other words, the power values corresponding to wind speeds around the rated one are far from the expected ones.

Table 2. Relationship among parameters of the quadratic models and the parameters of the WT.

j	n_j	a_{0j}	a_{1j}	a_{2j}	v_j
1	0	0	0	0	0
2	2	$-v_{ci}^2 \cdot P_r / \left(v_r^2 - v_{ci}^2\right)$	0	$P_r / \left(v_r^2 - v_{ci}^2\right)$	v_{ci}
3	0	P_r	0	0	v_r
(4)	-	-	-	-	v_{co}

A second option for the QM was proposed in [48], and it uses a more complex expression, as shown in Equation (6):

$$P = \begin{cases} a_{01} & v_1 \leq v < v_2 \\ a_{02} + a_{12} \cdot v + a_{22} \cdot v^2 & v_2 \leq v < v_3 \\ a_{03} & v_3 \leq v < v_4 \end{cases} \quad (6)$$

where $a_{01} = 0$; $v_1 = 0$; $v_2 = v_{ci}$; $v_3 = v_r$; $v_4 = v_{co}$; $a_{03} = P_r$; and the values of a_{02}, a_{12}, and a_{22} are given in Equations (7)–(9), respectively.

$$a_{02} = \frac{1}{(v_{ci} - v_r)^2} \left[v_{ci}(v_{ci} + v_r) - 4 v_{ci} v_r \left(\frac{v_{ci} + v_r}{2 v_r} \right)^3 \right] \quad (7)$$

$$a_{12} = \frac{1}{(v_{ci} - v_r)^2} \left[4(v_{ci} + v_r) \left(\frac{v_{ci} + v_r}{2 v_r} \right)^3 - 3 v_{ci} - v_r \right] \quad (8)$$

$$a_{22} = \frac{1}{(v_{ci} - v_r)^2} \left[2 - 4 \left(\frac{v_{ci} + v_r}{2 v_r} \right)^3 \right] \quad (9)$$

A QM with five intervals was also proposed, with three of these intervals expressed through 2-degree polynomials, as shown in Equation (10) [14].

$$P = \begin{cases} a_{01} & v_1 \leq v < v_2 \\ a_{02} + a_{22} \cdot v^2 & v_2 \leq v < v_3 \\ a_{03} + a_{23} \cdot v^2 & v_3 \leq v < v_4 \\ a_{04} + a_{24} \cdot v^2 & v_4 \leq v < v_5 \\ a_{05} & v_5 \leq v < v_6 \end{cases} \quad (10)$$

where a_{01}=0, a_{05}=P_r, $v_1 = 0$, $v_5 = v_r$, and $v_6 = v_{co}$. The other parameters of the model are not related with the parameters of the WT.

3.3. Cubic Models

Among the polynomial models, cubic ones (CM) are those with values of n_j equal to or lower than 3, for all intervals. The most used one is that which is based on three intervals according to Equation (11) [14].

$$P = \begin{cases} a_{01} & v_1 \leq v < v_2 \\ a_{02} + a_{32} \cdot v^3 & v_2 \leq v < v_3 \\ a_{03} & v_3 \leq v < v_4 \end{cases} \quad (11)$$

Table 3 shows the right assignation of parameters.

For $j = 4$, there is no interval, but $v_4 = v_{co}$. The errors in the accuracy of this model in the area of the rated wind speed are very important.

A second option consists of using the CM with $a_{02} = 0$ as shown in [12], but it operates without avoiding the errors of the previous one, and it involves some other errors in the area of the cut-in wind speed.

Table 3. Relationship among parameters of the cubic ones and the parameters of the WT.

j	n_j	a_{0j}	a_{1j}	a_{2j}	a_{3j}	v_j
1	0	0	0	0	0	0
2	3	$-v_{ci}^3 \cdot P_r / \left(v_r^3 - v_{ci}^3\right)$	0	0	$P_r / \left(v_r^3 - v_{ci}^3\right)$	v_{ci}
3	0	P_r	0	0	0	v_r
(4)	-	-	-	-	-	v_{co}

One of the most used CMs for WTPCs that can be considered the most accurate is the spline model (SP) of order three. It consists of using as many intervals as the double of the value of its v_{co} in m/s. For instance, if $v_{co} = 25$ m/s, the model has 50 intervals, i.e., one interval every 5 m/s. On each interval, the model is as expressed in Equation (12) [49]. Therefore, this model establishes a difference with respect to all those commented above, which only considered the four intervals described earlier.

$$P = \quad a_{0j} + a_{1j} \cdot v + a_{2j} \cdot v^2 + a_{3j} \cdot v^3 \quad \frac{j}{2} - 0.5 \le v < \frac{j}{2} \tag{12}$$

Notice that the systematization in the implementation of the model is related with the interval limits $j/2 - 0.5$ and $j/2$. In addition, this model assures the continuity and derivability of the function in all its range of applicability. The continuity of the model provides accuracy in the limits of the intervals. Its derivability facilitates the combination of the model with other functions, i.e., the wind speed probability density function. In this case, there is no relationship between both types of parameters.

The SP can be simplified if polynomials of order three are just used in the interval $[v_{ci}, v_r]$, according to Equation (13), which is a proposal of this paper:

$$P = \begin{cases} a_{01} & v_1 \le v < v_2 \\ \cdots & \cdots \\ a_{0k} + a_{1k} \cdot v + a_{2k} \cdot v^2 + a_{3k} \cdot v^3 & v_k \le v < v_k + 0.5 \\ \cdots & \cdots \\ a_{0m} & v_m \le v < v_{m+1} \end{cases} \tag{13}$$

where the range of k is from 2 to $2 \cdot (v_r - v_{ci}) + 1$ and m equals $2 \cdot (v_r - v_{ci}) + 2$.

For a better understanding of the model, several lines are given in Table 4 with related information. The only drawback of this model is that the derivability of the function is not guaranteed in two points, i.e., v_{ci} and v_r, but it is continuous in the full range $[0, v_{co}]$. The main advantage of this model over the traditional SP is the number of parameters; in the latter case, this number is reduced to $8 \cdot (v_r - v_{ci}) + 2$, which is around the half for most WTs.

Table 4. Relationship among parameters of the CM and the parameters of the WT.

j	n_j	a_{0j}	a_{1j}	a_{2j}	a_{3j}	v_j
1	0	0	0	0	0	0
2	3	a_{02}	a_{12}	a_{22}	a_{32}	v_{ci}
3	3	a_{03}	a_{13}	a_{23}	a_{33}	$v_{ci}+0.5$
...	...	...	...	...	...	...
$k-1$	3	a_{0k-1}	a_{1k-1}	a_{2k-1}	a_{3k-1}	$v_k-0.5$
k	3	a_{0k}	a_{1k}	a_{2k}	a_{3k}	v_k
$k+1$	3	a_{0k+1}	a_{1k+1}	a_{2k+1}	a_{3k+1}	$v_k+0.5$
...	...	...	...	...	...	
$m-1$	3	a_{0m-1}	a_{1m-1}	a_{2m-1}	a_{3m-1}	$v_r-0.5$
m	0	P_r	0	0	0	v_r
$(m+1)$	-	-	-	-	-	v_{co}

3.4. N-Degree Models

Several tests have been carried out with polynomials of a degree higher than 3. Trying to fit the curve to one continuous polynomial function (NM) provides successful results in the case of a degree equal to 6 [12] and 9 [14]. Therefore, the model can be expressed as shown in Equations (14) and (15), respectively:

$$P = a_{01} + a_{11}\cdot v + a_{21}\cdot v^2 + a_{31}\cdot v^3 + a_{41}\cdot v^4 + a_{51}\cdot v^5 + a_{61}\cdot v^6 \quad (14)$$

$$P = a_{01} + a_{11}\cdot v + a_{21}\cdot v^2 + a_{31}\cdot v^3 + a_{41}\cdot v^4 + a_{51}\cdot v^5 + a_{61}\cdot v^6 + a_{71}\cdot v^7 + a_{81}\cdot v^8 + a_{91}\cdot v^9 \quad (15)$$

where there is no relationship between the parameters of the model and those of the WT. However, this model does not fit properly for all types of WTs.

Other options consist of the generalized n-degree models, which deal with values of n_j equal to or lower than N, for all intervals. An example of this is the one based on three intervals according to Equation (16) [12].

$$P = \begin{cases} a_{01} & v_1 \le v < v_2 \\ a_{02} + a_{N2}\cdot v^N & v_2 \le v < v_3 \\ a_{03} & v_3 \le v < v_4 \end{cases} \quad (16)$$

Table 5 shows the proper assignation of parameters.

Table 5. Relationship among parameters of the CM and the parameters of the WT.

j	n_j	a_{0j}		a_{kj}		a_{Nj}	v_j
1	0	0	...	0	...	0	0
2	N	$-v_{ci}^N\cdot P_r/\left(v_r^N - v_{ci}^N\right)$	...	0	...	$P_r/\left(v_r^N - v_{ci}^N\right)$	v_{ci}
3	0	P_r	...	0	...	0	v_r
(4)	-	-	-	-	-	-	v_{co}

However, this model is rarely used due to its performance in the whole second interval, thus making it not suitable for any value of N.

4. Sigmoid Models

Sigmoid models are described by means of the general expression given by Equation (17) [32,50–53].

$$P = b_5 + (b_2 - b_5)\frac{(1 + b_6 f(v, b_0, b_1))}{(b_3 + f(v, b_0, b_1))^{1/b_4}} \quad (17)$$

where all the values b_i are parameters, and $f(v, b_0,\ b_1)$ is a function that can be expressed in two different ways, each of them including the parameters b_0 and b_1. The notation used in Equation (17) allows for the simplification of the implementation of several sigmoid models.

The model expressed in Equation (17) includes five parameters plus those included in $f(v, b_0,\ b_1)$. However, there is not a seven-parameter model. As long as the model needs to be simplified, the values of the parameters that have traditionally been used are as follows, in this order: $b_5 = 0$, $b_4 = 1$, $b_3 = 1$, and $b_2 = P_r$. Moreover, it must be noted that any number of parameters can be used. More than seven involves more accuracy while a lower number means the model is easier to deal with. Applied to WTPCs, just two types of models are currently used, i.e., exponential models (EM) and algebraic models (AM).

4.1. Exponential Models

EMs are sigmoids where $f(v, b_0,\ b_1) = \mathrm{c}^{-b_1(v-b_0)}$, being c, b_0, and b_1 as three constants. A classical value for c is the base of the natural logarithms e, although different values could be used instead. However, the fact of assuming $c = e$ is generally accepted, and other values are seldom considered. Traditionally, EMs have used between three and six parameters. Modeling them with fewer than three parameters means very low accuracy, and using the six parameters makes the model clearly valid.

The traditional EM with six parameters, also known as 6PLE, can be expressed as in Equation (18). It is the result of the combination of Equation (17), where $b_6 = 0$ and the function $f(v, b_0,\ b_1) = \mathrm{c}^{-b_1(v-b_0)}$, where $c = e$.

$$P = b_5 + (b_2 - b_5)\frac{1}{\left(b_3 + \mathrm{e}^{-b_1(v-b_0)}\right)^{1/b_4}} \tag{18}$$

The 5PLE model is given by Equation (19). It corresponds to the EM with five parameters, and it can be obtained from the 6PLE, by doing $b_5 = 0$:

$$P = \frac{b_2}{\left(b_3 + \mathrm{e}^{-b_1(v-b_0)}\right)^{1/b_4}} \tag{19}$$

A further simplification of the model converts it into the 4PLE and is one of the two options for the EM with four parameters. It is obtained from the 5PLE with $b_4 = 1$. Its expression is given in Equation (20).

$$P = \frac{b_2}{b_3 + \mathrm{e}^{-b_1(v-b_0)}} \tag{20}$$

The alternative EM with four parameters, denoted as 4PLEE, is the one that corresponds to Equation (21) and is the result of the combination of Equation (17) with $b_5 = 0$, $b_4 = 1$, and $b_3 = 1$; the function $f(v, b_0,\ b_1) = \mathrm{c}^{-b_1(v-b_0)}$; and $c = e$.

$$P = b_2\frac{1 + b_6\mathrm{e}^{-b_1(v-b_0)}}{1 + \mathrm{e}^{-b_1(v-b_0)}} \tag{21}$$

The simplest EM is the one based on the 4PLE with $b_3 = 1$. It is known as 3PLE, and its mathematical expression is given by Equation (22).

$$P = \frac{b_2}{1 + \mathrm{e}^{-b_1(v-b_0)}} \tag{22}$$

In Table 6, the relationships among the parameters of the models and the parameters of the WT are shown. Some of the models do not have a strong relationship with the parameters of the WT, i.e., those denoted as 6PLE, 5PLE, and 4PLE. However, these relationships can be found in the other two, and these models are recommended due to their good balance between performance and the number of parameters [52], specially the 3PLE.

Table 6. Relationship among parameters of the exponential models and the parameters of the WT.

Model	b_0	b_1	b_2	b_3	b_4	b_5	b_6
4PLEE	v_{ip}	$2s/(P_r - P_{ip})$	P_r	-	-	-	$Log(2P_{ip}/P_r - 1)$
3PLE	v_{ip}	$2s/(P_r - P_{ip})$	P_r	-	-	-	-
3PLE	v_{ip}	$4s/Pr$	P_r	-	-	-	-

The parameters of the WT used in Table 6 are as follows: s as the slope of the WTPC, and v_{ip} and P_{ip} as the wind speed and power at the inflection point of the WTPC, respectively. The 3PLE model may depend on three or four parameters of the WT. Both are included in Table 6, and the simplest option is under the consideration of $P_{ip} = P_r/2$. In addition to this, the conversion from the 4PLEE model into the 3PLE one is simply achieved by making $b_6 = 0$. Notice that some of these models, i.e., the 4PLE and the 3PLE, are known as logistic models because they are generally used in the field of logistics.

4.2. Algebraic Models

AMs are those where $f(v, b_0,\ b_1) = (v/\mathrm{b}_0)^{-b_1}$, with b_0 and b_1 as two constants. In general, $b_6 = 0$ in AMs, and they use between three and six parameters. Using fewer than three parameters means very low accuracy, and the accuracy actually needed is reached with the six parameter model.

The known six parameter AM, i.e., 6PL, is given by Equation (23). It is the result of the combination of Equation (17), where $b_6 = 0$ and the function $f(v, b_0,\ b_1) = (v/\mathrm{b}_0)^{-b_1}$.

$$P = b_5 + (b_2 - b_5)\frac{1}{\left(b_3 + (v/\mathrm{b}_0)^{-b_1}\right)^{1/b_4}} \tag{23}$$

As it is very frequent that $b_5 = 0$, the 5PL is formed as shown in Equation (24).

$$P = \frac{b_2}{\left(b_3 + (v/\mathrm{b}_0)^{-b_1}\right)^{1/b_4}} \tag{24}$$

As a further simplification, the 4PL model is expressed in Equation (25) by doing $b_4 = 1$ in the 5PL model.

$$P = \frac{b_2}{b_3 + (v/\mathrm{b}_0)^{-b_1}} \tag{25}$$

In this case, the simplest AM is the 3PL, which, following the trend of the 3PLE, consists of the 4PL model with $b_3 = 1$. It is shown in Equation (26).

$$P = \frac{b_2}{1 + (v/\mathrm{b}_0)^{-b_1}} \tag{26}$$

However, 4PL and 3PL models are normally discarded due to their accuracy when applying to WTPCs. Moreover, in the case of AMs, there is no specific relationship among their parameters and the parameters of the WT.

5. Discussion

Several aspects must be considered when assessing WTPC models. Table 7 shows a summary of different features of the studied models. For a given model, the analyzed aspects include how to apply it, how many parameters it needs, how easy it is to implement, whether or not it has a direct relationship with the parameters of the WT, and how accurate it is. As some of these features are subjective and thus it is very difficult to establish an appropriate metric to quantify them, a previous legend is shown as a guide for the interpretation of such a table.

Table 7. Assessment of the WT power curves models.

Model	Number of Parameters	Ease to Use	WT Parameters	Accuracy
LM1	4	Very high	Yes	Very low
LM2	8	Medium	No [2]	Medium
QM1	4	Very high	Yes	Low
QM2	5	High	Yes	Medium
QM3	8	Medium	No [2]	Medium
CM1	4	Very high	Yes	Low
CM2	3	Very high	Yes	Very low
SP1	200 [1]	Very low	No	Very high
SP2	80 [1]	Very low	No	Very high
NM1	7	Low	No	Medium
NM2	10	Low	No	Medium
NM3	4	Very high	Yes	Very low
6PLE	6	Low	No	Very high
5PLE	5	Low	No	Very high
4PLEE	4	Very high	Yes	High
4PLE	4	Low	No	High
3PLE	3	Very high	Yes [3]	High
6PL	6	Low	No	High
5PL	5	Low	No	High
4PL	4	Low	No	Low
3PL	3	Low	No	Low

The following observations, given as notes in Table 7, can be mentioned: [1] The number of parameters is around that value, [2] Some parameters can be expressed as a function of the WT parameters, but not all, [3] There are two possible relationships.

The meaning of the different qualifiers in the column "ease to use" is as follows:

- Very high: There is a simple and direct relationship between the WT parameters and those of the model.
- High: There is a complex but direct relationship between both groups of parameters.
- Medium: Some parameters of the model can be obtained directly from the WT parameters, but not all.
- Low: In order to obtain the parameters of the model, an unconstrained optimization procedure is needed.
- Very low: In this case, a constrained optimization procedure is needed.

In the case of the column entitled "accuracy", the meaning of the different qualifiers is:

- Very high: The error made when applying it is completely negligible. In some cases, mean absolute percentage error (MAPE) values lower or equal to 0.005 can be found in the related literature [52].
- High: Depending on the application of the model, the error made can be negligible. The MAPE values, when available, range from 0.005 to 0.025 [51,52].
- Medium: In this case, the error level depends on the WT and/or varies with the values of wind speed. MAPE values are estimated to range from 0.025 to 0.1 by comparison with the rest of the models.
- Low: The error corresponding to some values of wind speed is high. In some cases, MAPE values from 0.1 to 0.15 and/or normalized root mean square error (NRMSE) values from 0.13 to 0.21 can be found in the related literature [11,51].
- Very low: For some ranges of wind speed the error is very high. The MAPE or NRMSE values are not representative here due to some specific unsuitable values.

In order to make a suitable use of Table 7, the application of the model has to be considered. For example, if the model is going to be combined with other expressions in order to simplify more complex problems, i.e., probabilistic load flow or economic load dispatch, it is more recommendable to choose a model with a very low number of parameters and, if possible, with relationships with the parameters of the WT (4PLEE or 3PLE).

A different scenario appears when the accuracy is a priority, i.e., when assessing the exact power provided by the model is critical. In that case, the use of one of the SPs (SP1 or SP2) is strongly recommended.

More options can be, for example, if the user's intention is to deal with a model that is similar to the WTPC and is related with the WT parameters, i.e., for learning objectives. In that case, models as LM1, QM1, and CM1 can be of interest.

6. Conclusions

In this paper, deterministic WTPC models found in the related literature were listed, classified, related to each other with the WT parameters, and qualitatively assessed. They can be used for a wide range of applications. Therefore, the model chosen can vary depending on the objective. As a conclusion, the recommendations can depend on the main feature of the model. When minimizing the number of parameters used is critical, then the best models are CM2, 3PLE, or 3PL. When the ease of use is the most important point, the recommendation is to use some of the models among LM1, QM1, CM1, CM2, NM3, 4PLEE, and 3PLE. When the relationship with WT parameters is the main objective, LM1, QM1, CM1, CM2, 4PLEE, and 3PLE are the best choices. Finally, in case of priority of the accuracy, SP1 and SP2 are the best models for achieving the objective. Moreover, if some features need to be considered simultaneously, two models can be recommended, i.e., the 5PLE, which is more accurate and has with more parameters but not related with those of the WT, and the 3PLE, which is of relatively good accuracy, using the minimum number of parameters needed, and is indeed related with the ones of the WT.

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Nomenclature

AM	Algebraic model
ANN	Artificial neural network
CM	Cubic model
EM	Exponential model
HAWT	Horizontal axis wind turbine
LM	Linear model
MAPE	Mean absolute percentage error
ML	Machine learning technique
NM	Polynomial model of order N
nPL	n-parameter logistic model
nPLE	n-parameter logistic exponential model
nPLEE	n-parameter logistic double exponential model
NRMSE	Normalized root mean square error
QM	Quadratic model
SP	Spline model
WF	Wind farm
WT	Wind turbine
WTPC	Wind turbine power curve

A	Area swept by a wind turbine rotor
a_{ij}	Parameter of order i and interval j of a polynomial function
n_j	Order of a polynomial in an interval j of a polynomial function
b_i	i-th parameter of a sigmoid function
c_p	Power coefficient
P	Power extracted from the wind
P_{ip}	Power at the inflection point
P_r	Rated power
v	Wind speed
v_{ci}	Cut-in wind speed
v_{co}	Cut-out wind speed
v_{ip}	Wind speed at the inflection point
$v_j,\ v_{j+1}$	Lower and upper values of an interval j of wind speeds
v_r	Rated wind speed
β	Blade angle of attack
λ	Tip speed ratio
ρ	Air density

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