Wind Turbine

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Wind Turbine Power Curve models establish a simplified way to apply the relationship between the wind speed at hub height and the output power of the wind turbine. When dealing with deterministic models, two main types appear: polynomial and sigmoid.

Keywords: Wind power ; Power curve ; Wind Turbine Power Curve ; Wind Turbine ; Wind Energy ; Logistc model ; Sigmoid model

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.

2. Application

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].

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][32][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.

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