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Wind Turbines Power Coefficient Estimation Using Manufacturer's Information and Real Data

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ABSTRACT

Dynamic modelling of wind turbines and their simulation is a very useful tool for studying their behaviour. One of the key elements concerning the physical models of wind turbines is the power coefficient *Cp*, which acts as an efficiency in the extraction of power from the wind. Unfortunately, this coefficient is often unknown a priori, as it does not usually appear in the information provided by manufacturers. This paper first describes a methodology for obtaining the power coefficient parameters of a commercial wind turbine model using the power curve provided by the manufacturer, which indicates the theoretical power that the wind turbine can produce at each wind speed. To achieve this, a parameter estimation problem is formulated and solved to determine the power coefficient parameters. Nevertheless, this information is often insufficient, requiring additional knowledge, such as operational data, to improve the fit. Finally, a new parameter estimation is performed using only real data measured from the process, validating the proposed methodology. The operational dataset was obtained from the SMARTEOLE project in France and corresponds to the pitch-controlled variable-speed Senvion MM82/2050 wind turbine.

Keywords: Modelling, Optimization, Wind, Renewable and Sustainable Energy, Pyomo.

INTRODUCTION

As the world shifts towards renewable energy production, wind power has become a key player in reducing our dependence on fossil fuels. Wind turbines and their control systems are now more sophisticated than ever; however, they still face challenges such as wind fluctuations, maintenance costs, and the integration of wind power into the electricity market. To address these issues, digital twin technology is emerging as a promising solution, offering real-time virtual models that optimise wind turbine performance and reliability. This approach aligns with the WindEurope [1] roadmap for the digital wind sector in 2030, which defines the digital technologies to be implemented and aims to develop a comprehensive digital twin. A digital twin is essentially a virtual replica of a physical wind turbine (or a wind farm), continuously updated with real-world data [2]. This technology allows operators to monitor performance in real-time, predict failures before they occur, and adjust operations for maximum efficiency. This study explores a methodology on how to use the measured data to improve wind turbine models for dynamic simulation, which is the basis of a digital twin, specifically the power coefficient behaviour in different scenarios of wind speed, rotor speed, and blade pitch angles for a commercial wind turbine model. One of the most significant variables in the development of a macroscopic mathematical model of a wind turbine is its power coefficient. This coefficient, which will be described later, is crucial for calculating the electrical power supplied by the turbine; nonetheless, it is not typically provided by turbine manufacturers.

This study first describes the methodology for estimating the wind turbine power coefficient using data typically provided by turbine manufacturers, followed by the fitting procedure used when real data are available. The fitting results are then presented for three cases: (Fit 1) based only on real manufacturer data, (Fit 2) using manufacturer data corrected with certain knowledge from process measurements, and (Fit 3) relying solely on real process measurements, which improves the accuracy of the power estimations and validate the proposed methodology. Finally, the results are discussed, followed by the conclusions and suggestions for future work.

C_P ESTIMATION WITH MANUFACTURER'S DATA

In the majority of cases, the information we can obtain from the wind turbine manufacturer's data is limited. Usually, we only have the power curve and some design characteristics of the turbine, such as the length of the blades, the wind speed range in which the wind turbine operates, the type of control system used to limit the generated power or regulate the rotor speed, the mechanical and electrical efficiency, or the air density. The power curve in Figure 1 relates the evolution of the electrical power generated by the turbine to the different wind speeds between the cut-in wind speed (the one from which the turbine starts to generate power) and the cut-out speed (the one from which the turbine is braked to preserve the integrity of its elements).

Even so, with this limited information, a family of power coefficient curves *Cp*() can be obtained for implementation in our models to perform dynamic simulations of wind turbines and wind farms. The power coefficient can be understood as the efficiency of the turbine in extracting the power contained in the wind and depends, among other variables, on the commercial model of the turbine or the characteristics of the wind in the area where the turbine is installed.

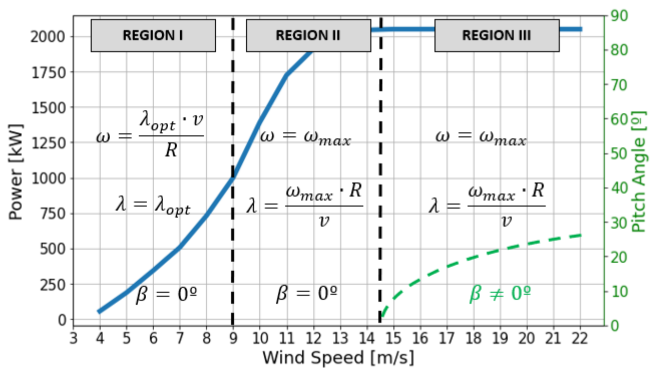

Figure 1. Power curve for the Senvion MM82/2050 turbine model [3].

However, the variables that affect the power coefficient can be reduced to two: the specific speed coefficient (or tip-speed ratio) λ, which is the quotient between the linear speed at the tip of the blades and the speed of the wind speed upstream of the turbine rotor, and the pitch angle β (in the case that the turbine has a pitch control system), which is the angle formed by the blades with their rotation plane. This angle can be modified to reduce or increase the blades' resistance to the wind (and therefore, reduce or increase the power generated).

$$\lambda = \omega_r \cdot R/v \tag{1}$$

where ω_r is the rotor speed in rad/s, *R* is the rotor radius in meters, and *v* is the wind speed upstream of the rotor in m/s.

The theoretical limit for the power coefficient, known as the Betz limit, is 0.59 [4]. That is, for an ideal turbine, it is possible to harness only 59% of the power contained in the wind upstream of the rotor. In real turbines, this amount is always less, as will be shown later. The power coefficient can be modelled in three ways: following a polynomial equation, a sinusoidal equation, or an exponential one. The exponential equation has been found to work well for turbines with variable pitch and speed control [5], which is the type of turbine that is the focus of this study [6-7].

$$C_p(\lambda,\beta) = C_1\left(\frac{C_2}{\lambda_i} - C_3\beta - C_4\beta^{C_5} - C_6\right)e^{\frac{-C_7}{\lambda_i}} \tag{2}$$

$$\frac{1}{\lambda_i} = \left(\frac{1}{\lambda + C_8\beta}\right) - \left(\frac{C_9}{\beta^3+1}\right)$$

The generated power can be calculated by Equation (3) in terms of wind speed, power coefficient, and air density ρ in kg/m³.

$$\hat{P} = \frac{1}{2}\rho\pi R^2 v^3 C_P(\lambda,\beta) \tag{3}$$

The idea is to estimate the C_k parameters of power coefficient (2) that make that curve replicate the behaviour of a given turbine for different λ and β values, which in turn will result in the power calculated with (3) replicating the actual power generated. The parameter estimation problem was formulated as a nonlinear optimisation problem, as described below, and solved using Pyomo 6.4.2 [8] in a Python environment using the IPOPT solver.

The aim of the optimisation problem (4) is to minimise, for each wind speed v_i, the error between the theoretical power of the manufacturer's curve P_i and the power calculated using (3).

$$\min_{\{C_k,\beta_j\}} \sum_i \left(P_i - \hat{P}_i(\lambda_i,\beta_i)\right)^2 \tag{4}$$

To establish the constraints, it must be understood how the power curve behaves for each range of wind speeds. As shown in Figure 1, power curves can be divided into at least three regions owing to different operation conditions based on the wind speed value at each moment. Region I extends from the cut-in wind speed to the speed at which the rotor reaches the maximum speed. In region I, the pitch angle equals zero and the tip-speed ratio value is optimal as a consequence of *the maximum power point tracking* system (MPPT) [9]. Region II extends from the wind speed in which the maximum rotor speed is reached to the rated wind speed, when the generated power reaches its rated value. This region is characterised by a constant rotor speed (at its maximum value); therefore, the tip-speed ratio only varies with wind speed, and the pitch angle is still zero.

Region III extends from the rated wind speed to the cut-off wind speed, and between them there is an increase in the pitch angle, with the rotor speed value being constant at its maximum value.

The optimal tip-speed ratio for a pitch angle of β = 0 (with wind speed values below the rated wind speed) is obtained by deriving expression (2) and equalling it to zero. The result is a relationship between the parameters C_k, as shown in (5). Moreover, this value must be equal to that obtained by calculating the tip-speed ratio with the rated rotor speed and the wind speed at which the maximum power coefficient is reached, which can be determined by clearing Cp from expression (3) and substituting P for the value obtained from the theoretical curve (assuming an ideal generator efficiency of 1 and standard air density of 1.225 kg/m^3).

$$\lambda_{opt} = \frac{C_2 * C_7}{C_2 + C_6 * C_7 + C_2 * C_7 * C_9} = \frac{\omega_{max} \cdot R}{v_{C_{p,i,max}}} \quad (5)$$

Pitch angle β is zero for wind speed values less than the rated speed (6) but positive and increasing values with wind speed for wind speed above rated speed.

$$\beta_j = 0 \; \forall \; v_i \leq v_{rated}; \; 0 < \beta_j < \beta_{j+1} \; \; \forall \; v_i > v_{rated} \quad (6)$$

In addition, certain parameters C_k must have positive values (7) to enable equality (5) to be true and to maintain the structure of term β^{C_5} of equation (2).

$$[C_2, C_5, C_6, C_7, C_9] > 0 \quad (7)$$

There is no a priori information on how the pitch angle β grows with wind speed. Only the moment when it starts increasing and the final pitch angle value at the cut-off wind speed are fixed, assuming typical wind turbine values.

C$_P$ ESTIMATION WITH MEASURED DATA

The data used for this study belong to the SMARTEOLE project, which studied a wind farm in France with seven wind turbines [10], whose layout is shown in Figure 2. The manufacturer's data and the power curve of the Senvion MM82/2050 wind turbine model are presented in Table 1 and Figure 1, respectively. The objective of that project was to study the interactions between the different turbines that make up the wind farm in order to develop a wake-steering control system, which consists of misaligning the rotor of the turbines that are first affected by the wind in order to deflect the wakes that appear behind the rotor so that the downstream turbines are affected by them as little as possible, resulting in an overall increase in the available power in the wind farm. Data were recorded between 17 February and 25 May 2020 with a resolution of 1 min.

This study focuses on the SMV1 turbine because it is close enough to the *WindCube V1* measurement system, as will be explained later.

The necessary measured data to perform the calculations are *active power*, *blade pitch angle*, *wind speed*, *wind direction*, *nacelle position*, and *generator speed*. However, the rotor speed, which is the one we are interested in to obtain $\lambda(1)$, is not measured, but the generator rotational speed is measured, and the gear ratio is known. Therefore, under the assumption that the transmission is ideal (without losses), the rotor speed can be obtained as the quotient (8) between the generator speed ω_g and gear ratio N.

$$\omega_r = \omega_g / N \quad (8)$$

Next, the raw data are filtered to ensure that the dataset contains adequate and reliable information using the following criteria: i) The misalignment (*yaw error*) must be less than 0.1, to consider only situations where the turbine is fully aligned with the wind direction. ii) The generator speed must be positive. iii) The measured wind speed must fall within the turbine's operating range ($v_{cut\text{-}in} < v < v_{cut\text{-}off}$). iv) The generated power (active power) should be positive. As a result, the filtered dataset contains 1,131 points instead of the initial 134,661.

In addition to this filter, all negative but near-zero values of the pitch angle β were replaced with zero, considering them as measurement errors, preventing errors in the calculation of the power coefficient.

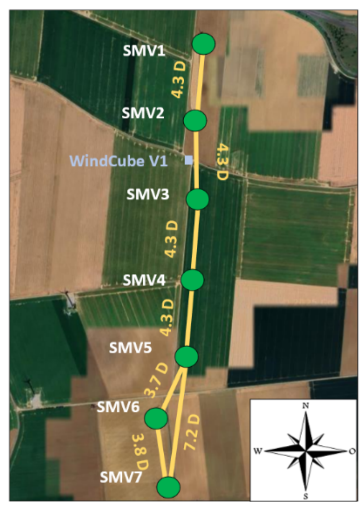

Figure 2. Wind farm layout [11].

An initial hypothesis is that the wind speed measured at the turbine is downstream of the rotor and, therefore, does not correspond to the upstream wind speed (with which the manufacturer's power curves are represented) but to a lower speed resulting from the decrease in wind power as it passes through the rotor.

To discard this initial hypothesis, a new filter is added to the data to have only west wind directions between 250º and 290º, so that the wind speeds measured by the *WindCube V1* system and at the turbine are not affected by the wakes of other turbines. As shown in Figure 3, it is not clear whether one wind speed measurement is higher or lower than the other. Therefore, it is assumed that the wind speed measured at the turbine has been corrected to represent the upstream wind speed values. For calculation purposes, this corrected wind speed was used.

Table 1: Senvion MM82/2050 parameters.

Parameter	Value	Units
Rated Power	2050	kW
Rotor Diameter	82	m
Power Control System	Pitch	
Min. rotor speed	8.5	rpm
Max. rotor speed	17.1	rpm
Cut-in wind speed	4	m/s
Rated wind speed	14.5	m/s
Cut-off wind speed	22	m/s
Gear ratio (*N*)	106	
Generator type	DFIG	
Max. Generator speed	1800	rpm

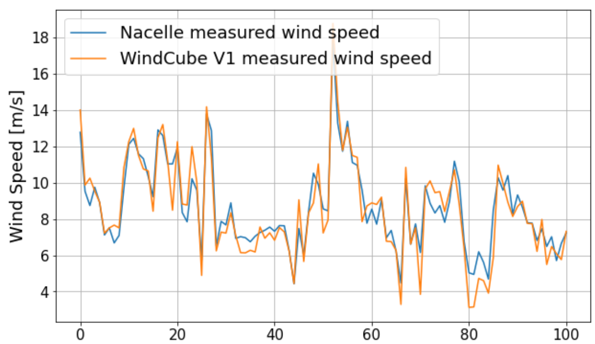

Figure 3. Measured wind speeds between 250º and 290º wind directions.

A crucial difference with respect to the previous estimation problem is the availability of pitch angle β^m and wind generator speed ω_g^m measurements for each wind speed; therefore, it will not be necessary to approximate its behaviour using any of the constraints from Fit 1 and 2. Thus, the estimation problem was formulated as the optimisation problem (9) subject to (10), where the only decision variables are the C_k parameters of the power coefficient curve (2). P_i^m and v_i^m represent the active power and wind speed measurements for each point *i* out of the 1131 points in the dataset, respectively.

$$\min_{\{C_k\}} \sum_i \left(P_i^m - \hat{P}_i(\lambda_i, \beta_i^m)\right)^2 \tag{9}$$

subject to:

Power Coefficient Curve (2)

$$\hat{P}_i = \frac{1}{2}\rho\pi R^2 (v_i^m)^3 C_P(\lambda_i, \beta_i^m)$$

$$\omega_{r,i} = \omega_{g,i}^m / N; \;\; \lambda_i = \omega_{r,i} \cdot R / v_i^m \tag{10}$$

$$[C_2, C_5, C_6, C_7, C_9] > 0$$

As mentioned before, the rotor speed is known at all times and is calculated using (8) so that the tip-speed ratio λ can be calculated directly using (1).

RESULTS

The results of the three parameter estimation problems are shown below: using theoretical manufacturer's data (Fit 1), using theoretical manufacturer's but corrected data (Fit 2), and using measured real data (Fit 3).

Parameter estimation with theoretical manufacturer's data (Fit 1)

Using the data from the theoretical power curve and those in Table 1, optimisation problem (4) was solved. The parameters of the power coefficient are shown in Table 2, and the family of power coefficient curves for different combinations of λ and β is shown in Figure 4. The maximum *Cp* value of 0.578 was reached at λ = 13 for β = 0. It can then be said that for β = 0, the optimal λ is 13. From this maximum, as both λ and β vary, *Cp* decreases. Moreover, if the *Cp* curve is divided into two regions for each pitch angle (to the left of optimal λ, and to the right of optimal λ), the turbine will generally work in the left region, since the opposite would imply that λ is higher than the optimal for wind speeds lower than rated, or that the rotor speed keeps increasing its speed from the rated one for wind speeds equal to or higher than rated (which does not happen, the rotor speed remains constant at its rated value from the moment it reaches it).

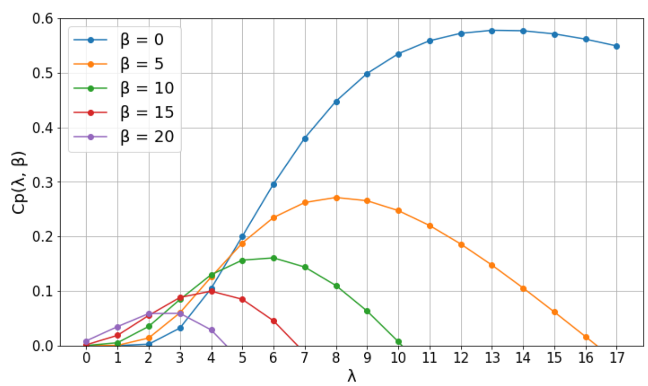

Figure 4. Power coefficient curves for Fit 1.

However, looking at the measured data in Figure 5, it is clear that some of the assumptions made do not correspond to the actual wind turbine behaviour. For example, the pitch angle starts to increase between 11 and 12 m/s, whereas initially this was assumed to occur from 14.5 m/s (rated wind speed v_{rated}). On the other hand, the rotor speed stabilises at its maximum value of 17 rpm for winds above 8 m/s, being the initial assumption that this occurred at 5.5 m/s.

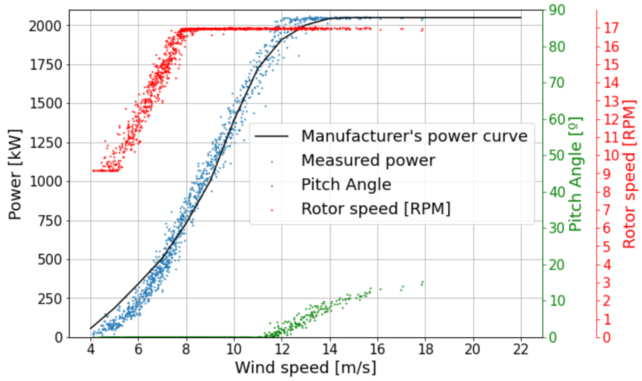

Figure 5. Actual power, pitch angle, and rotor speed data.

Parameter estimation with theoretical manufacturer's corrected data (Fit 2)

Therefore, a second fitting is made by changing to 8 m/s the value of the wind speed at which the rated rotor speed is reached, and indicating that the pitch angle should start to grow from a wind speed of 12 m/s. The new family of power coefficient curves for different combinations of λ and β is shown in Figure 6, and the parameters of the power coefficient are also shown in Table 2.

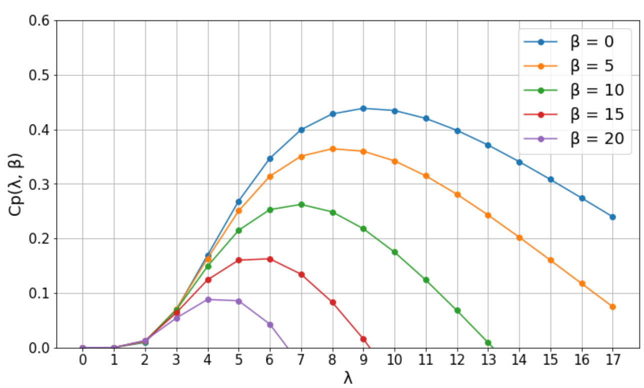

Figure 6. Power coefficient curves for Fit 2.

The solutions of the first problem and the new one are compared in Figure 7. In both cases, the pitch angle for the cut-off wind speed has been forced to be 20º (looking at the measured data, this seems reasonable). It can be observed that the new fitting is better than the first one owing to the incorporation of additional turbine performance information obtained from measured data.

Parameter estimation with measured real data (Fit 3)

Using the measured real data and those in Table 1, the optimisation problem (9) is solved. Table 2 shows the solution for the C_k parameters of the power coefficient curve. Next, Figure 8 shows how the family of power coefficient curves complies with all mentioned in the previous sections and also takes lower values than those of the case with theoretical data (Fit 1). By obtaining the curves from the measured data, all the inefficiencies that occur in the actual operation are included.

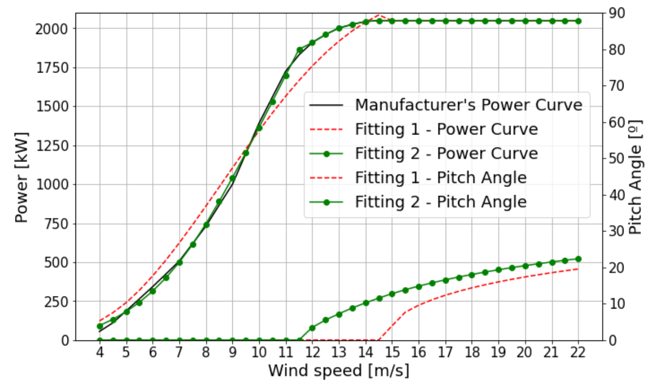

Figure 7. Fit 1 and 2 power curve comparison.

Figure 9 shows a comparison between the measured power, the power calculated with the coefficients of Figure 8, and the manufacturer's power curve, as well as the measured pitch angles. The fit is quite good in general, being worse at the starting zone (between 4 and 7 m/s), caused among other reasons by not having considered the changes in air density (all calculations have been made with a standard density of 1.225 kg/m^3) and by the influence of transient periods during braking of the turbines at low wind speeds or starting the turbines when the wind speed is again above the cut-in speed (v_{in}).

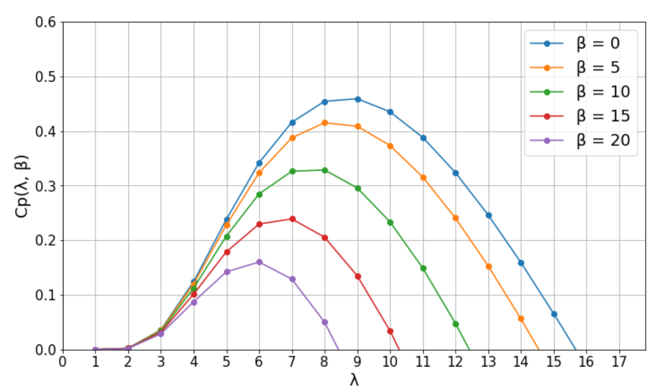

Figure 8. Power coefficient curves for Fit 3.

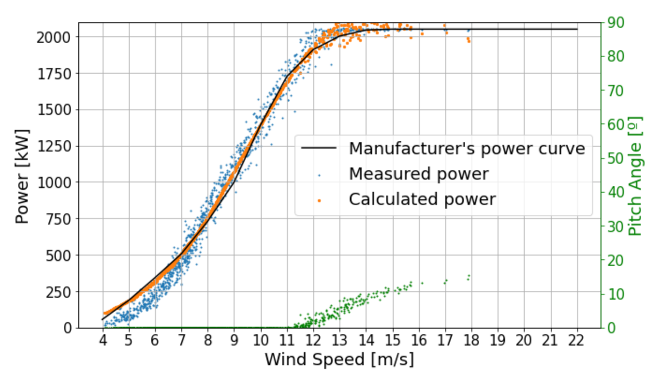

Figure 9. Calculated (fit 3), measured and theoretical power curves, and measured pitch angle.

Table 2: Power coefficient parameters for the three fits

Decision variables	Initial values	Fit 1 values	Fit 2 values	Fit 3 values
C_1	1.0148	0.109	0.077	0.00029
C_2	417.108	345.896	410.740	281927.469
C_3	0.918	1.497	0.436	7.547e-08
C_4	0.0021	3.540	0.071	97.864
C_5	2.569	0.436	2.103	1.689
C_6	37.058	5.702	16.491	17884.972
C_7	28.642	17.868	14.739	19.278
C_8	0.048	0.127	0.0032	0.0
C_9	0.0	0.0024	0.00097	0.00033

CONCLUSIONS AND FUTURE WORK

In this study, a methodology was developed to obtain power coefficients for use in digital twins. The methodology was tested with different levels of available information. After performing the three fits with different information, some conclusions can be drawn.

The first fitting, only with theoretical data from the manufacturer, can be useful to implement in a turbine model for dynamic simulations, since, roughly speaking, the power behaviour is being replicated with more or less accuracy. As for the pitch angle, those are obtained that make all the other constraints met, so they would also be useful, even though they may not be exactly the actual pitch angles. From the discrepancies observed between the initial assumptions and the measured real data of the turbine, the theoretical data are adjusted by correcting the wind speed value at which the rated rotor speed is reached and the wind speed at which the pitch angle starts to grow. It can be seen how the fitting improves, since the information it incorporates is more similar to that obtained from a real operating turbine. It can also be seen in the power coefficient curve families that the values reached for different pitch angles in fit 2 are closer than those in fit 1 curves to those obtained in fit 3, where wind turbine operating data are incorporated into the estimation problem. Finally, the solution to this new estimation problem enables an accurate estimation of the power coefficient *Cp* of a real wind turbine, which can then be included, for example, in a detailed dynamic simulation of a wind farm.

A future line of work is to implement these curves in wind turbine and wind farm models for dynamic simulation, which are intended to be fed with real operating data to update these models with new information. Just as the transition from Fit 1 to Fit 2 has been greatly improved by including more data, the idea is that by gradually incorporating more information into the model, it will become more precise in representing reality. It is also necessary to test this methodology in situations where the measured wind speed that appears in the data is the downstream wind speed without any correction, when the upstream wind speed is unknown, and also when the wind turbines are misaligned to the wind direction.

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