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Parsimonious modeling of wind turbine power curves with explainable parameters

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ABSTRACT

The problem of approximating the shape of wind turbine power curves through analytical formulas has been broadly investigated, resulting in a plethora of alternative expressions of varying complexity, ensuring satisfactory fitting across different curve geometries. However, it seems that minimal attention was paid to the issue of parameter explainability, while most evaluation studies employed so far rely on small samples or specific systems in situ. Taking advantage of a flexible parsimonious relationship from the family of logistic functions, this research aims at investigating whether its two shape parameters depend, and eventually can be inferred, on the grounds of easily retrievable information, in terms of essential properties of commercial wind turbines (rated power, diameter, characteristic wind speed values). This is formalized through a twofold analysis, namely the local calibration of the proposed formula against a large sample of 150 commercial models extending over all available scales, and the global calibration stage, resulting in empirical relationships across three clusters of turbine scales, which allow for direct estimation of reliable parameter values. The derived tools and lessons learned offer several practical implications and future research perspectives, towards the overall goal of improving strategic planning, feasibility assessment and technical design of wind energy systems.

1. Introduction

The wind power sector exhibits systematic growth over last three decades worldwide, while the associated technological advances provide increasingly improved solutions that cover all aspects of wind power exploitation.

Numerous analyses around wind energy rely upon a common modelling task, namely the conversion of the kinetic energy of wind to electricity. These extend from theoretical research exercises, asking for evaluating the wind energy potential over specific areas of interest [1], to site-specific engineering studies, seeking the techno-economic assessment of wind turbines under design [2] or the optimization of a wind farm's layout [3], up to broader energy planning studies aiming at investigating the feasibility of compound schemes (e.g., hybrid renewable energy systems) embedding wind power components [4].

While the input wind power formula is easily retrieved on the grounds of elementary fluid mechanics laws, its transformation to output power (which is, in fact, a sequence of conversions across multiple electro-mechanical components) is subject to significantly complexities, and thus it cannot be expressed via analytical formulas. As made with most energy conversion machines, for any specific model this task is substantially facilitated through graphical means, namely the so-called wind turbine power curves (WTPCs). Focusing on wind turbines, their associated curves depict directly the relationship between the wind speed at the hub height and the electric power supplied. For all commercial wind turbine models, this information is available from the manufacturer's documentation, thus allowing for elaborating all kinds of studies mentioned above. It is also known that for already installed wind turbines or turbine sets (i.e., wind farms), the manufacturers' power curves are adjusted to data in situ, thus accounting for real operational conditions and site-specific peculiarities [5].

For modelling purposes, e.g. in the context of simulation studies asking for converting wind speed data to output power time series, it is strongly preferred to apply continuous relationships that approximate as much as possible the given power curves. A plethora of such approaches are reported in the literature, which are conventionally grouped into two major categories, i.e. parametric and non-parametric. Parametric methods refer to algebraic expressions of pre-defined mathematical structure (linear, polynomial, cubic, sigmoid, logistic, exponential, hyperbolic tangent, etc.), whose parameters are inferred either analytically

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(case of regression models) or through curve-fitting optimization (calibration) [6–8]. On the other hand, non-parametric approaches take advantage of widespread machine learning techniques (neural networks, k-nearest neighbor, support vector machines, spline- regression, random forest, tree-based regression, etc.) to derive the wind-to-power transformation with high accuracy, although in a black-box manner [9]. In general, commercial power curves are handled as deterministic, while real curves are also regarded under a probabilistic context, by adapting statistical distributions, such as Gaussian or beta regression [10,11]. Comprehensive reviews on the multiple approaches to WTPCs modelling over last two decades and associated comparative studies are provided by Thapar et al. [12], Carrillo et al. [13], Lydia et al. [14,15], Chang et al. [16], Sohoni et al. [17], Wang et al. [18,19], Villanueva and Feijóo [20,21], Mehrjoo et al. [22], Al-Quraan et al. [23], Mushtaq et al. [24], and Yesilbudak [25].

It is worth mentioning that less effort is paid so far on modeling the power coefficient, namely the ratio of output electrical power to input wind power, instead of the WTPC per se. This also involves fitting various functional types to actual power coefficient curves, by using as input variables the tip speed ratio and the blade pitch angle. A pioneering work towards this challenging task is attributed to Manyonge et al. [26], while recent reviews of such approaches, which are outside the scope of this research, are provided by Carpintero-Renteria et al. [27] and Castillo et al. [28].

Focusing to WTPC modelling, the review article by Villanueva and Feijóo [21] is of specific interest, since its key target is to assess which of the prevailing mathematical expressions embed parameters that can be directly identified by the characteristic features of the turbine curves. Apart from the three easily retrievable quantities (cut-in and rated wind speed, and rated power capacity), they also consider as known property the inflection point, as defined by the International Electrotechnical Commission (IEC) 61400–1 standard [29]. Eventually, they evaluate several parametric formulas based on three criteria, namely number of parameters, ease to use and accuracy, by concluding that these are rather contradictory, thus suggesting model selection according to each study's objective. Nevertheless, the common experience indicates that as the use of more parameters generally ensures better fitting to the shape of actual power curves, such expressions are preferred by practitioners. For instance, several simulation studies apply polyonymic formulas of high order, e.g. up to six and even nine degrees [9], which are extracted via optimization and do not have any correspondence with the wind turbine characteristics. Wang et al. [18] reproves such practices, stating that "*although some intelligent optimization algorithms get good model parameters via some objective functions, the tuned parameters have no technical meaning*". In a similar perspective, Mushtaq et al. [24] criticize complex approaches (i.e., non-parametric), pointing out that "*despite their inherent flexibility/adaptability, their "black-box" nature often clouds parameter interpretability, raising transparency concerns*". Villanueva and Feijóo [30] attempted to address the so-called issue of "*meaningless [parameter] values*" by reformulating a logistic function to obtain its parameters analytically, based on the features of the power curve (rated power, inflection point coordinates, curve slope at the inflection point).

The issue of parameter explainability remains an open question in the context of WTPC modelling, since, to the authors' knowledge, none of the numerous approaches so far attempted to directly associate the model parameters with commonly available turbine characteristics (rated power, diameter, etc.), thus without requiring any information about the curve geometry. Another shortcoming of known approaches is the lack of evaluation against extended samples, covering all range of commercial turbine models.

To address this gap, a simple yet flexible enough mathematical formula from the broader family of S-type (i.e., logistic) functions is tested, embedding two shape parameters. This parsimonious model was initiated by Zisos et al. [31], within the optimal configuration of a hybrid renewable energy system comprising a mixing of two commercial wind turbines. A more extended use of it was employed in a follow-up study, involving the assessment of the statistically guaranteed wind potential over Greece through the novel concept of spatial reliability [32]. Following a Monte Carlo simulation framework, the proposed parametric expression was applied to describe in analytical means the power curves of 40 commercial wind turbines, which have been randomly distributed over 100 well-documented locations. Motivated by the high accuracy of the two-parameter model across so many diverse turbine models, this study significantly expands the validation dataset to 150 commercial WTPCs across all scales to address a critical gap in the literature, namely parameter explainability. Following a two-stage approach, by means of local and global calibration, the final goal is to establish empirical relationships to estimate the two shape parameters as functions of known turbine data, thus decoupling their extraction from the explicit knowledge of its power curve. As such, a generalized framework is established to construct realistic WTPCs without requiring explicit manufacturer curve data.

The article is organized as follows. Section 2 sets in brief the main theoretical context and provides essential definitions and concepts. Section 3 introduces the new mathematical formula. Section 4 describes the data set of 150 commercial wind turbines, summarizes its statistical characteristics and defines derivative quantities to be used next. Section 5 explains the parameter estimation procedure, which is employed under a two-stage context, namely the local calibration stage, for extracting optimally fitted shape parameters for each individual wind turbine model, and the global stage, resulting in empirical relationships of proven accuracy that make possible inferring the model parameters on the grounds of easily retrievable properties. The conclusions of the overall analysis, with emphasis to practical implications and future research directions, are drawn in Section 6.

2. Overview of wind turbine power curves modelling

2.1. Key principles and definitions

The input wind power received by a turbine rotor of diameter D is expressed in terms of kinetic energy of moving air, and is given by:

$$P_0(v) = \; 1/8\, \rho_\alpha\, \pi\, D^2 v^3 \tag{1}$$

where ρ_α is the air density and v is the wind speed at the hub height. Its transformation to output electricity power is expressed in terms of power coefficient c_p, i.e.:

$$P(v) = c_p(v)\, P_0(v) \tag{2}$$

where the dimensionless quantity c_p (which is more generally called efficiency and symbolized η), is nonlinear function of v. In theory, this function may be retrieved based on turbine blade characteristics (blade design, tip speed ratio and pitch angle), the rotor dimensions and the reference air density, yet such technical information is hardly available by the manufacturers [13].

Instead of theoretical equations, the widely referred to as wind turbine power curves (WTPCs) are applied, illustrating either in tabular format or by means of nomographs, the electrical power output, P, with respect to hub-height wind speed, v. WTPCs are obtained through standardized procedures that are specified by the International Electrotechnical Commission (IEC 61400–12–1 standard) [29]. These follow the so-called method of bins across normalized data sets, thus providing average output power values over wind speed intervals of 0.5 or 1.0 m/s.

In practical applications, two types of WTPCs are utilized. The first are the so-called commercial wind turbine power curves, which are provided by manufacturers and refer to specific industrial products. These are established through laboratory measurements, elaborated under well-controlled conditions to ensure the standard sea level air density of 1.225 kg/m^3, thus for air temperature of 15°C and atmospheric pressure of 1013 hPa.

It is accepted that the use of commercial WTPCs yields to (deterministic) estimations under ideal conditions that dismiss multiple complexities and uncertainties of wind turbines operation in the field. In fact, the actual power coefficient, and eventually the generated electrical power is significantly affected by randomly varying atmospheric processes (turbulence intensity, air density, wind direction, wind shear, wind veer) and other site-specific features affecting the local wind regime, such as the complex terrain [33] and the wake effects produced by adjacent wind turbines [34]. Usually, their combination yields lower output power than the theoretical value expected by the commercial curve. Furthermore, installed wind turbines may also underperform due to numerous other environmental factors, such as pitch and yaw misalignments, blade damage and erosion (more generally, ageing effects), presence of ice, problems with electrical systems (e.g., converters), poor maintenance practices, measurement and control system errors, grid instabilities, etc.

For this reason, in the context of real-time management, monitoring and forecasting purposes, practitioners make use of a second type of power curves, that are refined according to finely resolved (e.g., 10 min) in situ measurements (e.g., by SCADA). Their establishment, either for individual wind turbines or, more generally, wind farms, also follows the IEC 61400 standards, where specific attention is required to filter noise effects and remove outliers under abnormal operating conditions, such as wind curtailment and blade damage. Under this premise, the operational WTPCs (also referred to as site power curves) are also expressed in deterministic means, while more advanced approaches also enable the configuration of probabilistic curves, by fitting suitable statistical models to wind and power data.

2.2. Mathematical modelling of deterministic WTPCs

Under the deterministic setting, and the prevailing case of modern three blade wind turbines (pitch or active-stall controlled), the associated power curves, both commercial and actual, are divided into four regions, based on three characteristic values of wind speed, i.e. cut-in, v_c, rated, v_r, and cut-out, v_s. Until reaching the cut-in speed v_c (region 1), the wind turbine remains idle, and thus no electrical power is generated. Within the range $v_c \leq v < v_r$ (region 2), the generated power increases from zero to the so-called rated power capacity, P_r, following a nonlinear function $P(v)$. Beyond this, and until reaching the cut-out speed, v_s, the output power remains constant due to pitch control (region 3). Finally, when the wind speed exceeds the cut-out value v_s (region 4), the machine is forced to shut down for safety reasons. The above operation is mathematically expressed as:

$$P = \begin{cases} 0 & v < v_c \\ P(v) & v_c \leq v < v_r \\ P_r & v_r \leq v < v_s \\ 0 & v \geq v_s \end{cases} \tag{3}$$

It is important to remark that quite often, at the cut-in wind speed the WTPC is not continuous but makes a small step, since the output power is not exactly zero but exhibits a small value. A similar case refers to the cut-out speed, where the curve is also non-continuous [21].

As mentioned in the introduction, power curve modeling techniques are divided into two groups, i.e. parametric and non-parametric. The first ones often aim to exclusively represent the nonlinear term $P(v)$, as the other three regions are explicitly defined via Eq. (3). There are also some approaches attempting to model the whole WTPC through the so-called integrated power curve fitting schemes, thus making use of unique yet quite complex S-shaped functions. Nevertheless, in all cases the model parameters are inferred through curve fitting techniques, providing either analytical solutions (i.e., via regression, for relatively simple formulas) or empirically derived, through calibration.

In contrast, non-parametric approaches are purely data-driven, and thus they do not need any prior knowledge about the shape of power curve. These are applied to wind turbines or wind farms in situ, by using machine learning methods to capture the complex relationship between wind speed and power output without assuming a fixed mathematical form. This allows better adapting to local conditions and peculiarities, thus offering higher accuracy than traditional parametric methods.

2.3. The principle of parsimony within WTPC parameterization

This research aims providing a generic formula for the nonlinear component $P(v)$, that may describe a wide range of commercial WTPCs, across all scales of rated capacity P_r. In this vein, the principle of parsimony, namely the use of a mathematical expression with minimal number of free parameters, is key requirement, since one of the major challenges is to associate them with easily retrievable technical characteristics of the associated turbine model, thus ensuring at least some kind of physical interpretation. In fact, this stands as one of the major shortcomings of existing approaches, the derived parameters of which do not exhibit any technical meaning [18]. At the same time, regardless of its simplicity, the mathematical formula should easily adapt to all different shapes from the WTPC family. Finally, given that $P(v)$ is a double-bounded function, i.e., for $v = v_c$ and $v = v_r$, the power value is known, the formula should validate the two boundary conditions, thus ensuring mathematical consistency.

All above specifications are met by the following formula, which serves as the basis for next analyses:

$$P(v) = \left[1 - \left(1 - \left(\frac{v - v_c}{v_r - v_c}\right)^a\right)^b\right] P_r \tag{4}$$

where a, b are shape parameters. This parametric expression, which is inspired by the Kumaraswamy distribution model for double-bounded processes [35], falls into the broader family of S-shape, also referred to as logistic functions. Such formulas were introduced within WTPC modelling by Lydia et al. [14], and are recognized as the most promising parametric approaches, since they offer a good compromise between complexity and accuracy [8].

Key advantage of Eq. (4) is its flexibility contrasted to its relatively simple structure. For, by appropriate tuning of its two shape parameters significantly different curve profiles may be represented. Particularly, for $a = b = 1$, Eq. (4) is simplified to a linear model, for $a > 1$ and $b = 1$ or for $a = 1$ and $b > 1$, Eq. (4) yields to a convex and concave polynomic function, respectively, while for $a > 1$ and $b > 1$ a sigmoid function is obtained. These four characteristic cases are shown in the graphical example of Fig. 1. This depicts four WTPCs, where different combinations of shape parameter values are applied to a hypothetical wind turbine with $v_c = 3.0$ m/s, $v_r = 12.0$ m/s, and $P_r = 1000$ kW. An also indicated latter, the most common profile is the sigmoid one, for which the use of two shape parameters usually ensures a quite good approximation of the complex relationship between input wind speed and output power.

The use of only two free parameters (it is highlighted that v_c, v_r, and P_r are not parameters but a priori known technical characteristics) is in line with the key requirement of parsimony. This stands as a fundamental modeling issue, originating from the philosophical grounds of science, which implies choosing the simplest model structure that adequately explains the data over more complex alternatives, thus favoring the use of the less possible number of parameters. This approach allows avoiding overfitting and improves model interpretability and parameter identifiability. To the authors' knowledge, none of the formulas applied so far within WTPC modelling utilize two parameters, except for very simple functions, generally exhibiting poor fitting [21]. In contrast, as mentioned in the introduction, the most common approach in practice is the use of polynomial functions of at least six degrees, thus implying the determination of seven parameters.

It is pointed out that the mathematical structure of (4) does not allow for an explicit derivation of its parameters a and b through regression. Nevertheless, for a given wind turbine machine with known power

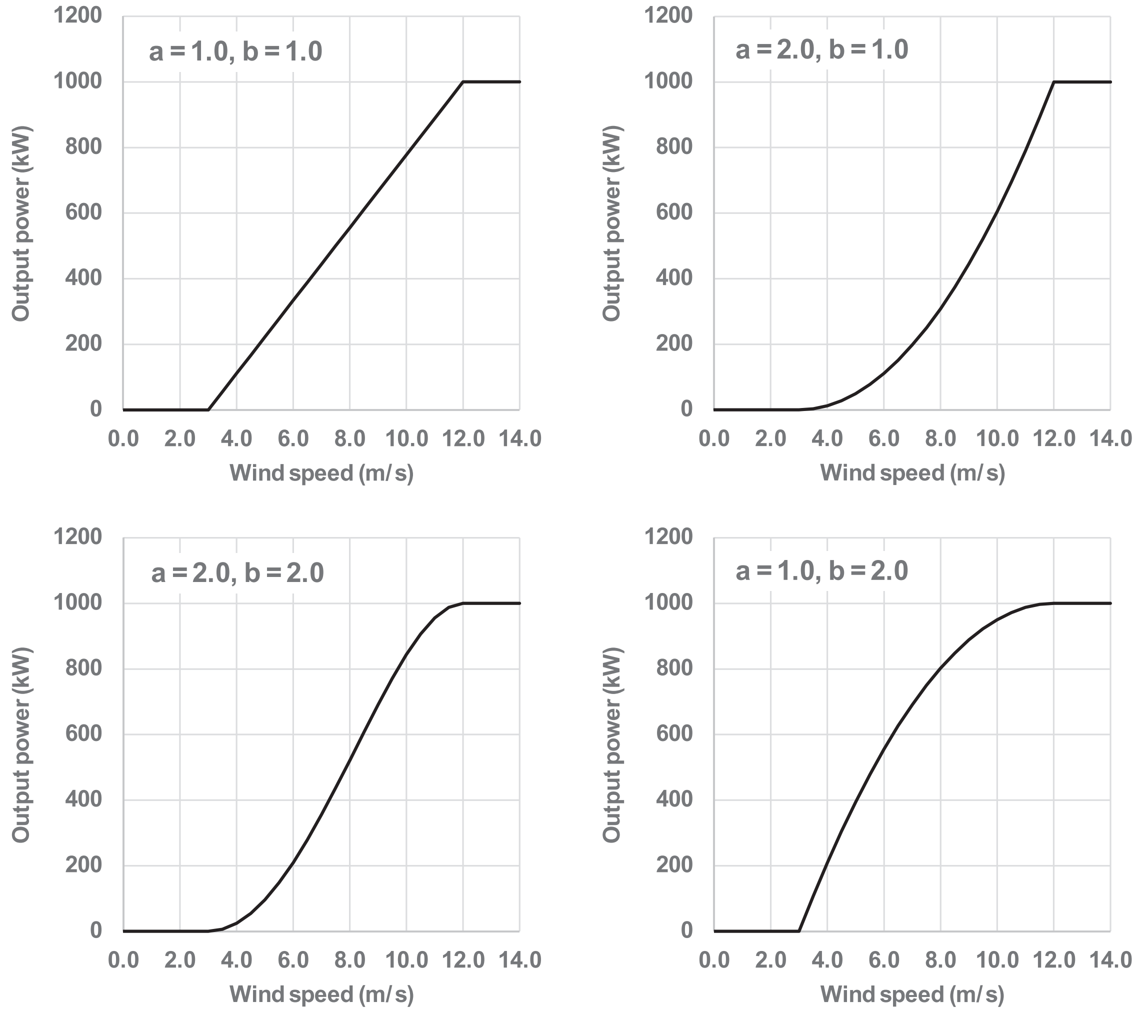

Fig. 1. Representation of four hypothetical WTPCs with $v_c = 3.0$ m/s, $v_r = 12.0$ m/s, and $P_r = 1000$ kW, where region 2 is modelled through Eq. (4), by applying different shape parameter values.

curve, described in terms of paired data (i.e., wind speed vs. output power), this task may be easily formalized as a calibration problem. This implies assigning a suitable error-type objective function (or alternatively, a goodness-of-fitting measure) and employing a nonlinear optimization method (e.g., an evolutionary algorithm) to retrieve the values ensuring the minimized distance of the modelled from the actual curve.

3. Data collection and pre-processing

3.1. Raw data

Essential technical information regarding commercial wind turbines is provided by manufacturers on the web. Typically, this information refers to power-related quantities (rated power and characteristic wind speed limits, i.e., cut-in, rated, cut-out and survival speeds), characteristic dimensions and other properties of the rotor (e.g., diameter, swept area, maximum rotor speed, tip speed, power density), the gear box, the generator (e.g., type, maximum speed, voltage, grid connection and grid frequency), and the tower (e.g., hub height, material), as well as their power curves, also illustrated in terms of wind speed vs. power capacity values.

To evaluate the applicability of the new parameter formula for the WTPC, a data set of 150 commercial wind turbines is configured, spanning over 57 different manufacturers; the most encountered are Enercon (13), W2E Wind to Energy (12), Vestas (10), Leitwind (10), and Hummer (8). All essential information is organized in a spreadsheet (cf. data availability statement), also including processed data. Apart from paired wind speed vs. output power data, the following properties were retrieved:

- Rated power capacity, P_r (kW)
- Rotor diameter, D (m)
- Representative hub height, H (m)
- Cut-in wind speed, v_c (m/s)
- Rated wind speed, v_r (m/s)

In general, the manufacturers suggest three to four alternative hub height values for each turbine model. In that case, their average value was considered as representative.

Table 1 summarizes the statistical characteristics of key technical properties that are accounted for in next analyses. As shown, their range

Table 1
Statistical characteristics of main technical data over the sample of 150 wind turbines.

	Average	St. deviation	Minimum	Maximum
Rated power P_r (kW)	1553	1625	2.0	9000
Rotor diameter D(m)	70.7	43.3	2.0	215.0
Hub height H (m)	65.0	31.9	5.0	170.0
Cut-in speed v_c (m/s)	3.2	0.6	1.0	6.0
Rated speed v_r (m/s)	12.3	1.9	7.5	18.0

is highly extended, thus allowing for capturing all scales of interest, i.e. from very small to very large ones. In particular, the rated power capacity ranges from 2 kW to 9000 kW, and similarly ranges the associated dimensions, in terms of rotor diameter (from 2 to 215 m) and representative hub height (from 5 to 170 m). Quite significant is also the extent of the two characteristic wind speed values. Specifically, the cut-in speed ranges from 1.0 to 6.0 m/s, while the rated speed ranges from 7.5 to 18.0 m/s.

Fig. 2 provides scatter plots among rated power and representative hub height with respect to rotor diameter. As expected, both data pairs are positively correlated. Particularly, the diameter-rated power relationship is well-approximate by a polynomial function, which is reasonable, considering the theoretical wind power law (Eq. 1), while the hub height is practically linear function of diameter. This finding is in accordance with recent scaling analyses employed by Sergiienko et al. [36], based on a small sample of nine non-commercial turbines.

3.2. Adjusted wind speed boundaries

As already mentioned in Section 2.2, commercial power curves usually exhibit a small discontinuity for the cut-in wind speed, v_c, where the generated power, P_c, is little larger than zero. In this respect, and to be consistent with the mathematical structure of Eq. (4), implying no power generation at the lower speed boundary, it is essential to establish a low threshold of the wind speed, symbolized $v_{\min}$, to be employed instead of v_c. A typical example, involving the commercial model Vensys 100/2500, is illustrated in Fig. 3. According to manufacturer's data, this wind turbine starts operating at $v_c = 3.0$ m/s, providing an output power $P_c = 47$ kW. To detect the characteristic velocity $v_{\min}$ at which the output power diminishes to zero, a continuous curve is empirically delineated and extrapolated backwards. As shown in Fig. 4a, the cut-in wind speed adjustment involves 73% of the examined sample (109 out of 150 wind turbines), where $v_{\min}$ is set from 0.25 up to 2.0 m/s less than v_c (the mean deviation is ~0.7 m/s).

A similar issue arises with the rated velocity values, v_r, since for 60% of commercial turbines, the output power differs from the rated one at the given rated speed. This inconsistency is easily remediated, by introducing an adjusted upper low threshold of the wind speed, symbolized $v_{\max}$, where the output power reaches to rated value P_r, and is next used within Eq. (4) instead of v_r. As shown in Fig. 4b, in half of the data sample, $v_{\max}$ exceeds the given rated speed, v_r, while in 10% of it the applied boundary value is lower than the rated one. The mean positive deviation between v_r and $v_{\max}$ is 1.3 m/s, while the mean negative one is −0.9 m/s.

One final remark involves a small yet non negligible number of commercial wind turbines for which the output power is not stabilized after v_r or $v_{\max}$ up to the safety limit v_s (region 3 of WTPWs), but it is either increased or decreased. This condition is non-systematic, depends on the specific turbine model, and thus cannot be embedded within any generalized framework.

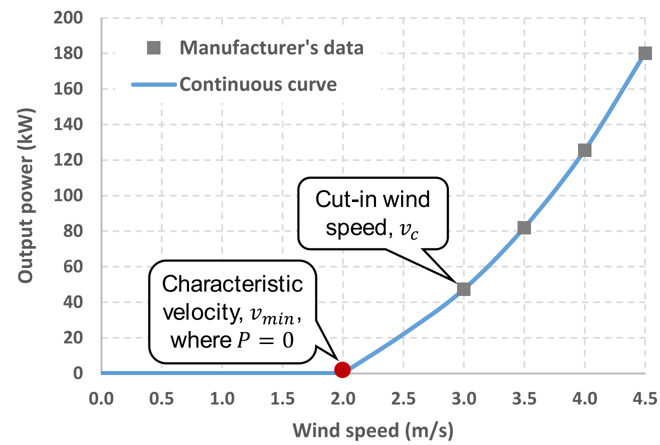

Fig. 3. Delineation of continuous curve to point wind speed vs. output power data provided for model Vensys 100/2500 (https://en.wind-turbine-models.com/turbines/849-vensys-100-2500). The cut-in wind speed is 3.0 m/s, yielding an output power of 47 kW, while the adjusted speed is set to 2.0 m/s.

3.3. Derivative properties

Based on collected raw data, as well as the adjusted wind speed values, the following quantities of interest are calculated, to be later examined whether they could be used as explanatory variables of the proposed parameterization of the power curve. These are:

- the input wind power values $P_0(v_r)$ and $P_0(v_{\max})$ at the rated and maximum wind speed, respectively, which are estimated by the physics-based Eq. (1);
- the power capacities $c_{p,vr} = P_r/P_0(v_r)$ and $c_{p,vmax} = P_r/P_0(v_{\max})$;
- the dimensionless wind speed ranges $1 - v_c/v_r$ and $1 - v_{\min}/v_{\max}$, which is considered as a distance metric of region 2;
- the quantity $\ln(P_r D)$, which stands as an overall metric of the turbine scale.

The statistical characteristics of the derivative wind turbine properties are summarized in Table 2. It is remarked that $c_{p,vmax}$ is the power

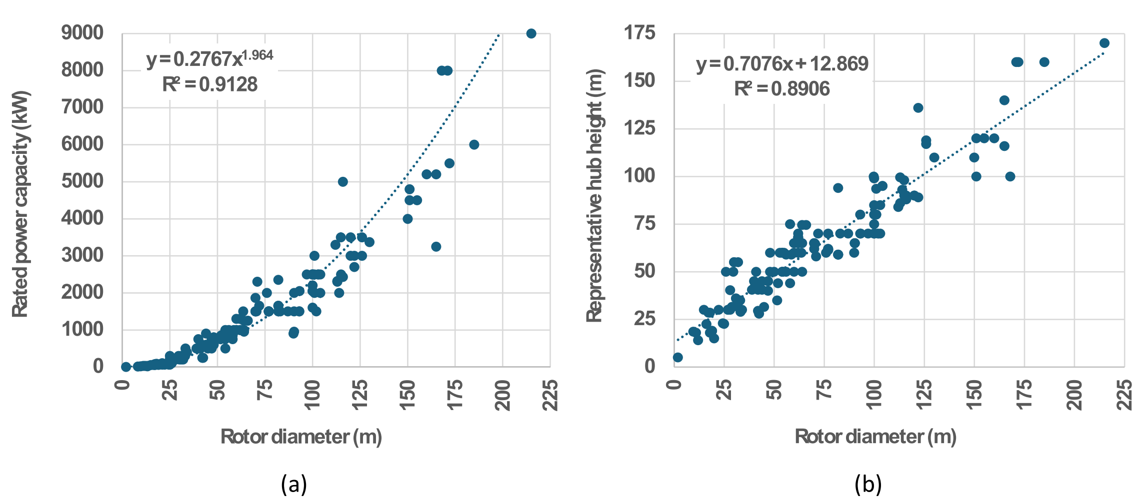

Fig. 2. Scatter plots of (a) rated power capacity, and (b) representative hub height.

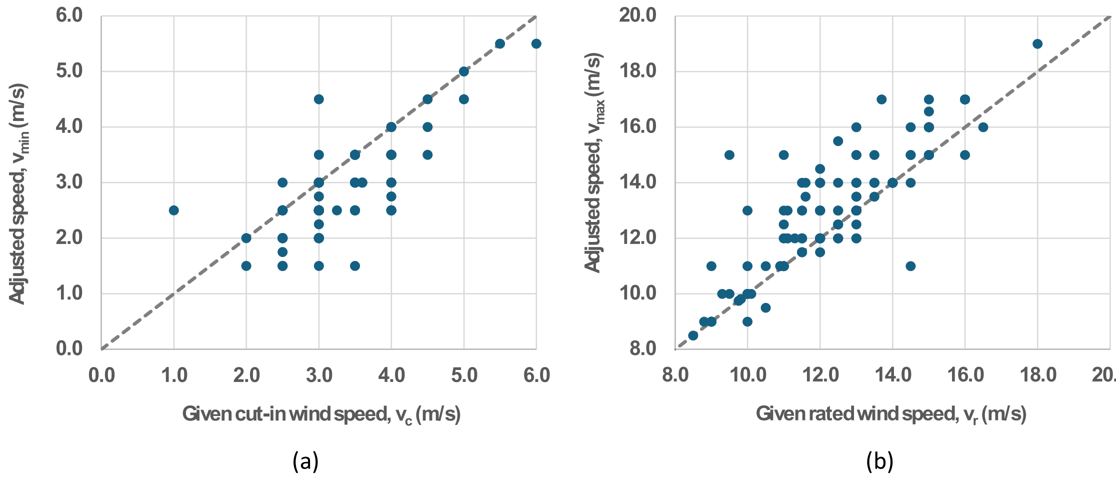

Fig. 4. Scatter plots of given cut-in wind speed, v_c, vs. adjusted lower boundary, $v_{\min}$ (left) and given rated wind speed, v_r, vs. adjusted upper boundary, $v_{\max}$ (right). Dotted line refers to the diagonal, where the corresponding speed values coincide.

Table 2
Statistical characteristics of several quantities of interest over the sample of 150 wind turbines.

	Average	St. deviation	Minimum	Maximum
Input wind power $P_0(v_r)$ (kW)	5980	7417	4.2	48,830
input wind power $P_0(v_{\max})$ (kW)	6642	8051	4.2	48,830
Power coefficient $c_{p,vr} = P_r(v_r)/P_0$	0.291	0.082	0.088	0.473
Power coefficient $c_{p,vmax} = P_r(v_{\max})/P_0$	0.258	0.081	0.075	0.473
Wind speed range $1 - v_c/v_r$	0.735	0.056	0.529	0.909
Wind speed range $1 - v_{\min}/v_{\max}$	0.782	0.051	0.591	0.900
Turbine scale metric $\ln(P_rD)$	10.66	2.25	1.39	14.48

coefficient for $v = v_{\max}$, thus when the turbine reaches its rated capacity, P_r, while $c_{p,vr}$ refers to $v = v_r$. As explained in previous section, the two values do not necessarily coincide, since several commercial turbines do not produce their maximum output power at the rated wind speed, as theoretically expected. Nevertheless, the range of $c_{p,vmax}$ over the sample of 150 wind turbine models is exceptional, since its minimum value is only 7.5%, while the maximum one is 47.3%.

4. Model fitting and investigation of parameter explainability

4.1. Refined power curve formula

By introducing the adjusted wind speed values $v_{\min}$ and $v_{\max}$, the mathematical expression of the entire WTPC must be slightly modified to read:

$$P = \begin{cases} 0 & v < v_c \\ \left[1 - \left(1 - \left(\dfrac{v - v_{\min}}{v_{\max} - v_{\min}}\right)^a\right)^b\right] P_r & v_c \le v < v_{\max} \\ P_r & v_{\max} \le v < v_s \\ 0 & v \ge v_s \end{cases} \tag{5}$$

In this respect, when $v_c > v_{\min}$, the output power at the cut-in wind speed is:

$$P_c = \left[1 - \left(1 - \left(\frac{v_c - v_{\min}}{v_{\max} - v_{\min}}\right)^a\right)^b\right] P_r \tag{6}$$

otherwise $P_c = 0$.

On the other hand, the output power is maximized at $v_{\max}$ instead of v_r, since, as already explained, several times the *reported* rated power of commercial wind turbines, P_r, is not achieved at the *reported* rated speed, as should theoretically be done.

4.2. Calibration protocol

After refining the WTPC formula through Eq. (5), the resulting function can be applied to any commercial wind machine, through appropriate tuning of its shape parameters a and b. This task is implemented by means of a hybrid calibration protocol, employed in two stages, herein referred to as *local* and *generalized*. The first one aims to ensure the best possible fitting against the real (i.e., commercial) WTPC, without paying attention to parameter explainability, while the second one has a twofold objective, i.e. a good fitting of the simulated curve to the real one, by using *explainable* parameters, which are associated with known technical properties of the wind turbines. All calibration tasks are carried out through the evolutionary annealing-simplex algorithm [37], which is a robust global search method allowing handling highly nonlinear objective functions with good accuracy and reasonable computational effort.

Let $i = 1, \ldots, n$ be the index referring to a specific turbine model (where n is the sample size), the power curve of which is described through a paired dataset $[\boldsymbol{v}_i, \boldsymbol{P}_i]$. Vector $\boldsymbol{v}_i$ contains wind speed values between $v_{\min,i}$ and $v_{\max,i}$, whilst vector $\boldsymbol{P}_i$ contains the corresponding output power data, ranging from zero up to the rated capacity, $P_{r,i}$. The locally optimized parameters values, symbolized a_i^* and b_i^*, are derived by minimizing the mean square error between the elements of the actual power vector $\boldsymbol{P}_i$ and the simulated values, $\boldsymbol{P}_{i,sim}$. In this vein, the local calibration procedure is employed n times independently (i.e., for each specific wind turbine), to yield $2n$ optimized parameter values. In the present analysis, given that the number of turbines is $n = 150$, the total number of parameters to optimize is 300. Within the search procedure, the two shape parameters were allowed to range from 0.50 up to 6.0.

It is reminded that similar local calibration exercises, although with much smaller samples, are quite common in the wind industry and the associated literature, where the overall focus is on establishing, assessing or comparing different empirical formulas for modelling WTPCs.

The second, generalized, stage, is conducted by using as basis the sample of already optimized shape parameters. Here the aim is to provide empirical relationships for extracting a^* and b^* against characteristic quantities of the wind turbines, which can be easily retrieved or computed (e.g., rated power, diameter and other raw data and metadata, such as the ones shown in Table 2). In this way, the derivation of

Eq. (5) is decoupled from the knowledge of the power curve, while its two parameters gain at least some macroscopic physical interpretation. As pointed out, this stands as the major novelty of this research.

4.3. Local calibration

As explained, the local calibration stage is employed as a sequence of independent optimization steps. In this vein, an optimized pair of shape parameters a^* and b^* is obtained for each wind turbine model. The values derived exhibit remarkable large variability, as shown in Table 3, as well as in the scatter plot of Fig. 5. This in turn indicates a wide diversity of power curve shapes across region 2, which are generally very well approximated by the proposed two-parametric formula.

As also depicted in Fig. 5, the two parameters are mutually dependent, as indicated by the associated value of the Pearson correlation coefficient ($r = 0.543$). This issue, which is quite common across all aspects of conceptual-empirical modelling, imposes explaining them carefully and makes it difficult to isolate their individual effects. It is also observed that the dependence structure of the two parameters indicates some kind of envelope behavior, by means of linear bounds.

4.4. Correlation analysis and wind turbine clustering

Before establishing empirical relationships between the optimized model parameters and the technical characteristics of the wind turbines, raw and derivative, it is essential to detect and analyze their dependencies. This task is initially formalized by means of estimating the correlation coefficients among each parameter and the technical quantities of interest. In this context, it is considered that a parameter can be adequately explained by a specific technical characteristic only when the resulting Pearson correlation coefficient exceeds 0.50 (in absolute terms). This stands as a typical metric of linear dependency between two variables x and y, and is given by:

$$r = \frac{\sum_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \overline{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \overline{y})^2}} \tag{7}$$

where $\overline{x}$ and $\overline{y}$ are the mean values of x and y, respectively.

However, the correlation analysis yields that this condition is only valid for parameter b^*, while for parameter a^* the correlations are mostly poor, as shown in Tables 4 and 5, respectively. To improve parameter explainability, which is the key objective of this research, the full sample of 150 commercial wind turbine models is classified in three clusters. Specifically, since the rated power values, P_r, extend over four orders of magnitude, i.e. from 2 to 9000 kW, this classification is employed in terms of power scale, thus dividing the initial sample into three clusters as follows:

- $P_r >$ 1000 kW: 82 large-scale turbines, ranging from 1000 to 9000 kW.
- $100 \leq P_r <$ 1000 kW: 48 medium-scale turbines, ranging from 100 to 950 kW.
- $P_r <$ 100 kW: 20 small-scale turbines, ranging from 2 to 83 kW.

By repeating the estimation of Pearson correlation coefficients across the three clusters, much higher dependencies are detected among the

Table 3
Statistical characteristics of optimized shape parameters over the sample of 150 wind turbines.

	Average	St. deviation	Minimum	Maximum
Parameter a^*	2.201	0.365	0.899	3.030
Parameter b^*	2.353	0.988	0.531	5.201

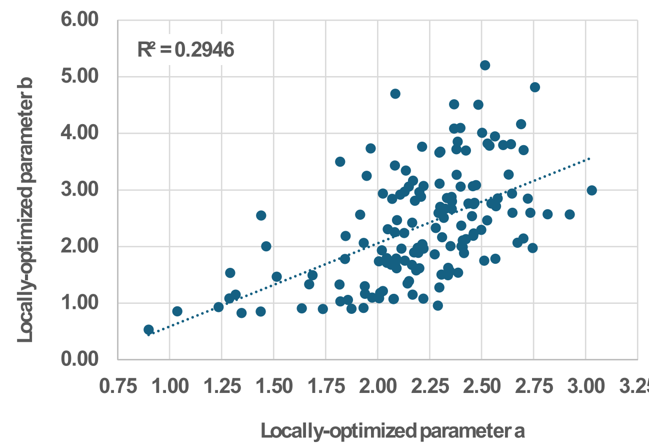

Fig. 5. Scatter plot of locally optimized shape parameters a^* and b^*across the full sample of 150 wind turbines.

optimized parameters per cluster and associated technical quantities (cf. Tables 4 and 5). An interesting observation is that the correlation values very quitter significantly across the three clusters, which means that according to the power scale, different properties of the wind turbines may explain the shape of their power curve over the nonlinear region 2. For instance, both parameters exhibit negligible, weak and marginally satisfactory correlation with rated power, by moving from large, medium and small-scale clusters, respectively.

This preliminary correlation analysis serves as guidance to the most important step of this research, which is the establishment of empirical relationships for direct estimation of parameters a^* and b^*, in the context of the so-called generalized calibration stage, which is applied across the three clusters.

It should be mentioned that in the real-world, small-scale turbines of less than 100 kW are very rarely applied in the field, while most recently constructed onshore wind parks only comprise large-scale turbines, exceeding 1000 kW. In this respect, the forthcoming investigations are of significant practical interest mainly for the first and second clusters. Regarding the last cluster, the associated analyses are presented not only for the sake of completeness, but also for demonstrating the generality of the proposed framework across all available scales.

4.5. Generalized calibration

The generalized calibration procedure is employed as follows. First, for each cluster, an empirical relationship, $\hat{a} = f_1(\lambda)$, is developed that determines the shape parameter a as function of known wind turbine properties (Table 1) and their derivative quantities (Table 3), symbolized λ. The number of independent variables is kept low, i.e., up to four, to allow using as few as possible unknown numerical coefficients (i.e., hyperparameters) within $f_1(\lambda)$. These are specified by maximizing the efficiency metric, given by:

$$E = 1 - \frac{\sum_{i=1}^{n} (a_i^* - \hat{a}_i)^2}{\sum_{i=1}^{n} (a_i^* - a_{mean}^*)^2} \tag{8}$$

where a_{mean}^* is the mean value of the optimized parameters a_i^*, and n is the sample size. The above performance metric, which is analogous (but not identical) to the well-known coefficient of determination, r^2, of regression analysis, compares the variance of the model error to the variance of the data. This goodness-of-fitting metric is quite common, particularly in environmental applications, where the model performance is evaluated by contrasting observed against simulated time series. The value of efficiency ranges between $[-\infty, 1]$. The unit value corresponds to a theoretically perfect model, while a value equal to zero

Table 4
Correlation coefficients of locally optimized shape parameter a with selected technical data and metadata (full sample and clusters of different turbine scales, after removing a small number of outliers). Bold numbers refer to correlation values > 0.50 (either positive or negative).

	Full sample	Large (P_r ≥1000 kW)	Medium (100≤ P_r <1000 kW)	Small (P_r <100 kW)
Rated power P_r (kW)	0.207	0.051	0.253	**0.517**
Diameter D (m)	0.253	-0.017	0.217	0.271
Hub height H (m)	0.143	0.040	0.222	0.045
Cut-in speed v_c (m/s)	-0.323	-0.394	-0.478	-0.330
Rated speed v_r (m/s)	0.163	0.343	-0.173	0.189
Adjusted min. speed $v_{\min}$ (m/s)	-0.362	**-0.526**	**-0.582**	-0.137
Adjusted max. speed $v_{\max}$ (m/s)	0.201	0.347	-0.124	0.371
Input wind power $P_0(v_r)$ (kW)	0.222	0.175	0.072	**0.594**
Input wind power $P_0(v_{\max})$ (kW)	0.223	0.165	0.095	**0.634**
Power coefficient $c_{p,vr}$	-0.105	-0.334	0.173	-0.160
Power coefficient $c_{p,vmax}$	-0.199	-0.392	0.042	-0.391
Wind speed range $1 - v_c/v_r$	0.440	**0.534**	0.408	0.492
Wind speed range $1 - v_{\min}/v_{\max}$	**0.521**	**0.712**	**0.584**	0.429
Scale metric $\ln(P_rD)$	0.392	0.041	0.269	0.203

Table 5
Correlation coefficients of locally optimized shape parameter b with selected technical data and metadata (full sample and clusters of different turbine scales, after removing a small number of outliers). Bold numbers refer to correlation values > 0.50 (either positive or negative).

	Full sample	Large-scale (P_r ≥1000 kW)	Medium-scale (100≤ P_r <1000 kW)	Small-scale (P_r <100 kW)
Rated power P_r (kW)	0.112	0.129	0.334	0.469
Diameter D (m)	0.099	0.064	0.183	0.371
Hub height H (m)	-0.006	0.101	-0.044	-0.084
Cut-in speed v_c (m/s)	-0.060	-0.024	-0.194	0.040
Rated speed v_r (m/s)	0.414	**0.552**	0.344	0.178
Adjusted min. speed $v_{\min}$ (m/s)	0.061	-0.031	0.049	0.139
Adjusted max. speed $v_{\max}$ (m/s)	**0.622**	**0.672**	**0.628**	**0.500**
Input wind power $P_0(v_r)$ (kW)	0.230	0.333	0.441	**0.653**
Input wind power $P_0(v_{\max})$ (kW)	0.287	0.398	**0.670**	**0.852**
Power coefficient $c_{p,vr}$	-0.484	**-0.642**	-0.378	-0.342
Power coefficient $c_{p,vmax}$	**-0.807**	**-0.883**	**-0.799**	**-0.737**
Wind speed range $1 - v_c/v_r$	0.372	0.425	0.435	0.167
Wind speed range $1 - v_{\min}/v_{\max}$	0.373	**0.535**	0.322	0.225
Scale metric $\ln(P_rD)$	0.190	0.096	0.331	0.371

denotes a model of similar predictive capacity with the mean value, which is used as benchmark estimator.

The identification of the most appropriate model structure and associated explanatory variables was quite rigorous, since the combination of technical quantities all exhibiting high correlations against the shape parameter of interest does not necessarily ensure correspondingly good informativeness. In this vein, the outcomes of Tables 4 and 5 were utilized as initial guidance, and then several configurations were explored until reaching an acceptable predictive capacity.

Following this premise, for large-scale turbines, i.e. for $P_r \geq 1000$ kW, the optimized expression of the shape parameter a is:

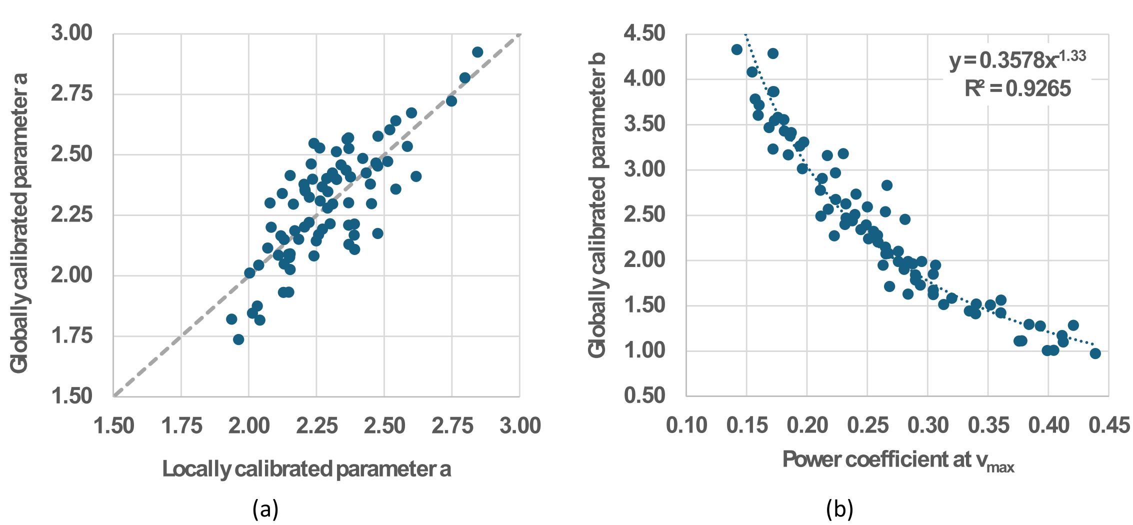

Fig. 6. (a) Scatter plot of locally vs. globally, i.e. through Eq. (9), calibrated shape parameter a; (b) Globally calibrated parameter b as decreasing function of power coefficient at maximum wind speed. The two plots refer to large-scale turbines (P_r ≥1000 kW).

$$\hat{a} = 0.359 + 3.284 \quad {c_{p,vr}}^{0.062}(1 - v_{\min}/v_{\max} \quad)^{1.896} \tag{9}$$

Model (9) fits quite satisfactory the locally calibrated values, as indicated from the resulting efficiency metric (0.630), as well as the scatter plot of Fig. 6a. It is reminded that term $c_{p,vr}$ refers to the power coefficient achieved at the rated speed, v_r, thus it embeds both the rated power, P_r, and the rotor diameter, D. In this respect, the shape parameter a can be determined on the grounds of all key turbine properties, namely the rated power, the diameter, the rated wind speed, and the adjusted wind speed range.

Next, the local calibration procedure is repeated by setting the empirically derived (i.e., globally calibrated) values $\hat{a}$, to extract updated values of the other shape parameter, b. As shown in Fig. 6b, these are very well explained ($r^2 = 0.927$) by the power coefficient achieved at the adjusted maximum wind speed, $v_{\max}$, through the regression function:

$$\hat{b} = 0.358 \quad {c_{p,vmax}}^{-1.330} \tag{10}$$

Eventually, the empirical formulas (9) and (10) can be directly applied to large-scale turbines, to estimate with satisfactory accuracy the two shape parameters of their WTPC expression, on the grounds of easily retrievable information, even if the real curve is not available.

It is noted that within the derivation of Eq. (9) under the global calibration context, only one out of 82 points was detected as outlier, since its deviation from the rest points was distinguishable, thus being removed from the sample (refers to a very large wind turbine of 8000 kW, i.e., aerodyn SCD 8.0/168). On the other hand, for Eq. (10) all data were used to estimate the scale and shape coefficients of the power-type regression formula.

The same procedure is applied for the two other clusters, where the associated fitting performances are depicted in Figs. 7 and 8, respectively. Specifically, for medium-scale turbines, i.e. for $100 \leq P_r < 1000$ kW, the globally optimized expressions of the two shape parameters are:

$$\hat{a} = 1.0 + {c_{p,vr}}^{0.319}(1 - v_{\min}/v_{\max} \quad)^{2.63}[\ln(P_r\, D]^{0.555} \tag{11}$$

$$\hat{b} = 0.480 \quad {c_{p,vmax}}^{-1.102} \tag{12}$$

Finally, for small-scale turbines, i.e. for $P_r < 100$ kW, the globally optimized expressions as much simpler, thus reading:

$$\hat{a} = 0.50 + 0.0015 \quad D^{1.50}\, {v_r}^2 \tag{13}$$

$$\hat{b} = 0.0057 + 0.367 P_0(v_r) \tag{14}$$

All details about the obtained formulas across the three clusters are summarized in Table 6. It appears that across all scales, parameter b is much better approximated than a, by using a single explanatory variable. For shape parameter a, a little more complex relationships are essential to introduce for ensuring acceptable predictability, involving two or three explanatory variables. Another important finding is that the proposed empirical expressions reproduce the locally optimized parameters of the vast majority of the examined wind turbines, with very few exceptions, as indicated by the minimal number of outliers detected.

Table 6 also serves as a guidance for practitioners, since it indicates the appropriate formulas per cluster, for each out of two shape parameters. After specifying their values, the analytical expression of the power curve is retrieved through Eq. (5). It should be remarked that the technical data to be used may slightly differ per cluster.

4.6. Assessment of generalized parametric formula

Fig. 9 illustrates indicative examples of applying the generalized formula with globally optimized parameters per cluster, to approximate the actual WTPCs, across six wind turbines with totally different characteristics. Four of them (Leitwind LTW101 3000, Enercon E-58, Aeolia Windtech D2CF 200, Hummer H25.0–60KW) are already included in the commercial dataset, while the other two concern two independent turbines, namely 10 MW DTU and IEA 15 MW, that lie outside of the examined power capacity ranges. Both are used as reference turbines within offshore wind research [38,39], and here also serve as validation examples. For comparison, the locally optimized curves are also shown. In all cases, the predictive capacity of the global model is very satisfactory, thus indicating its potential to use in an operational context.

5. Conclusions

The well-investigated issue of WTPC modelling via analytical functions has been revisited under the novel perspective of parameter explainability, and by means of a parsimonious parametric formula utilizing only two free parameters. These control the shape of the derived function, thus offering significant flexibility against the wide range of existing curve geometries. The overall methodological framework was established and validated based on a data set of 150 commercial wind turbine models that extend over four orders of magnitude, i.e., from 2 kW up to 9000 kW. To the authors' knowledge, this is the

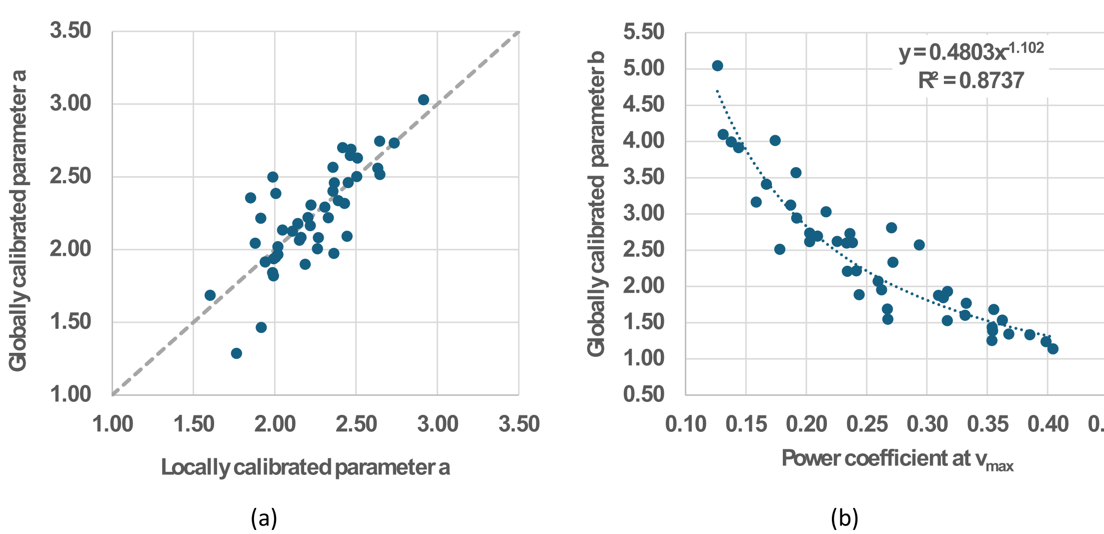

Fig. 7. (a) Scatter plot of locally vs. globally, i.e. through Eq. (11), calibrated shape parameter a; (b) Globally calibrated parameter b as decreasing function of power coefficient at maximum wind speed. The two plots refer to medium-scale turbines ($100 \leq P_r < 1000$ kW).

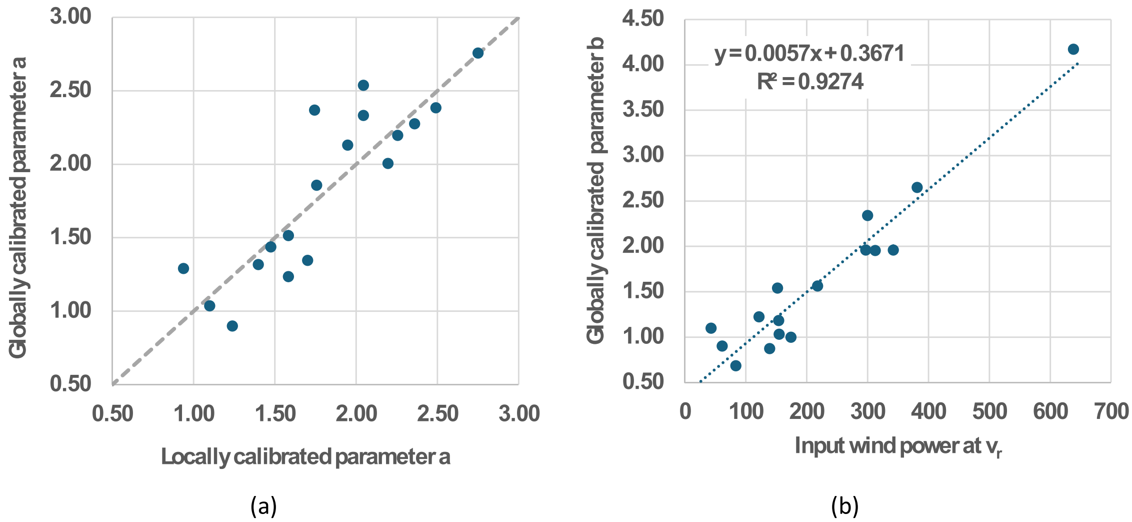

Fig. 8. (a) Scatter plot of locally vs. globally, i.e. through Eq. (13), calibrated shape parameter a; (b) Globally calibrated parameter b as increasing function of input wind power at rated wind speed. The two plots refer to small-scale turbines (P_r <100 kW).

Table 6
Summary information for the global calibration stage across the three wind turbine clusters.

	Large-scale ($P_r \geq 1000$ kW)	Medium-scale ($100 \leq P_r < 1000$ kW)	Small-scale ($P_r < 100$ kW)
Shape parameter *a*			
Empirical formula	Eq. (9)	Eq. (11)	Eq. (13)
Explanatory variables	2	3	2
Sample size	81	46	18
Outliers	1	2	2
Efficiency	0.630	0.617	0.762
Shape parameter *b*			
Empirical formula	Eq. (10)	Eq. (12)	Eq. (14)
Explanatory variables	1	1	1
Sample size	82	44	17
Outliers	0	4	3
Coef. of determination (r^2)	0.927	0.874	0.927

most extended sample used in similar investigations so far.

Initially, the proposed formula was individually fitted to each of 150 commercial curves through the so-called local calibration stage. With very few exceptions, the simulated WTPCs exhibit very satisfactory up to almost perfect representation of the actual ones. The practical product, in terms of locally optimized parameters, is the first contribution of this initiative, to be directly used by scholars and stakeholders in the context of wind power simulations, feasibility studies and related technical analyses.

Yet, the major outcome, and at the same time key innovation of this research is the derivation of empirical relationships that allow for inferring the two shape parameters on the grounds of easily retrievable data, namely rated power, rotor diameter, cut-in speed and rated speed and their adjusted values. To establish them, it was essential to split the whole sample of commercial wind turbines into three clusters, according to their rated power capacity (large-scale, medium-scale, small-scale). The two shape parameters are determined via optimized mathematical expressions comprising different explanatory variables per cluster (cf. Table 6). Although this so-called global calibration approach reasonably ensures slightly lower accuracy with respect to local fitting, it is generally assessed as quite satisfactory, particularly if concerning the multiple complexities governing the conversion of the kinetic energy of wind to electrical power.

Apart from offering an easy-to-use solution to practitioners, thus avoiding the quite laborious task of curve fitting via optimization, the lessons gained reveal several issues for practical implications as well as for future research. For instance, in the context of feasibility, planning and preliminary design studies across specific locations or alternative areas of interest, the commercial machine models to be applied, their key dimensions (i.e. hub height) and their associated power curves must be a priori specified, to allow computing the expected wind power potential. This task may be elaborated in a more elegant manner and under a stochastic setting, by running multiple simulations with hypothetical (e.g., synthetically generated) turbine models, and applying the empirically derived relationships to produce realistic power curves.

Another research idea involves the investigation of parameter variability with respect to scale. The correlation analyses and the established empirical relationships indicate that different mechanisms and processes may determine the shape of commercial WTPCs across scales.

A final research path involves the adaptation of the proposed parametric expression to real-world conditions, which are subject to multiple uncertainties. This option can be offered by expressing either the shape parameters per se or their explanatory relationships in stochastic means.

It should be underlined that the overall methodology, cornerstone of which is the two-stage calibration procedure, may be applicable to any other mathematical expression already proposed in the literature, to derive physically established parameters. In this respect, significant attention must be given to potential parameter dependencies, thus it is strongly encouraged to test as simpler relationships as possible, under the key prisms of *parsimony* and *explainability*.

CRediT authorship contribution statement

Andreas Efstratiadis: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Athanasios Zisos:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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Declaration of Competing Interest

The authors declare that they have no known competing financial

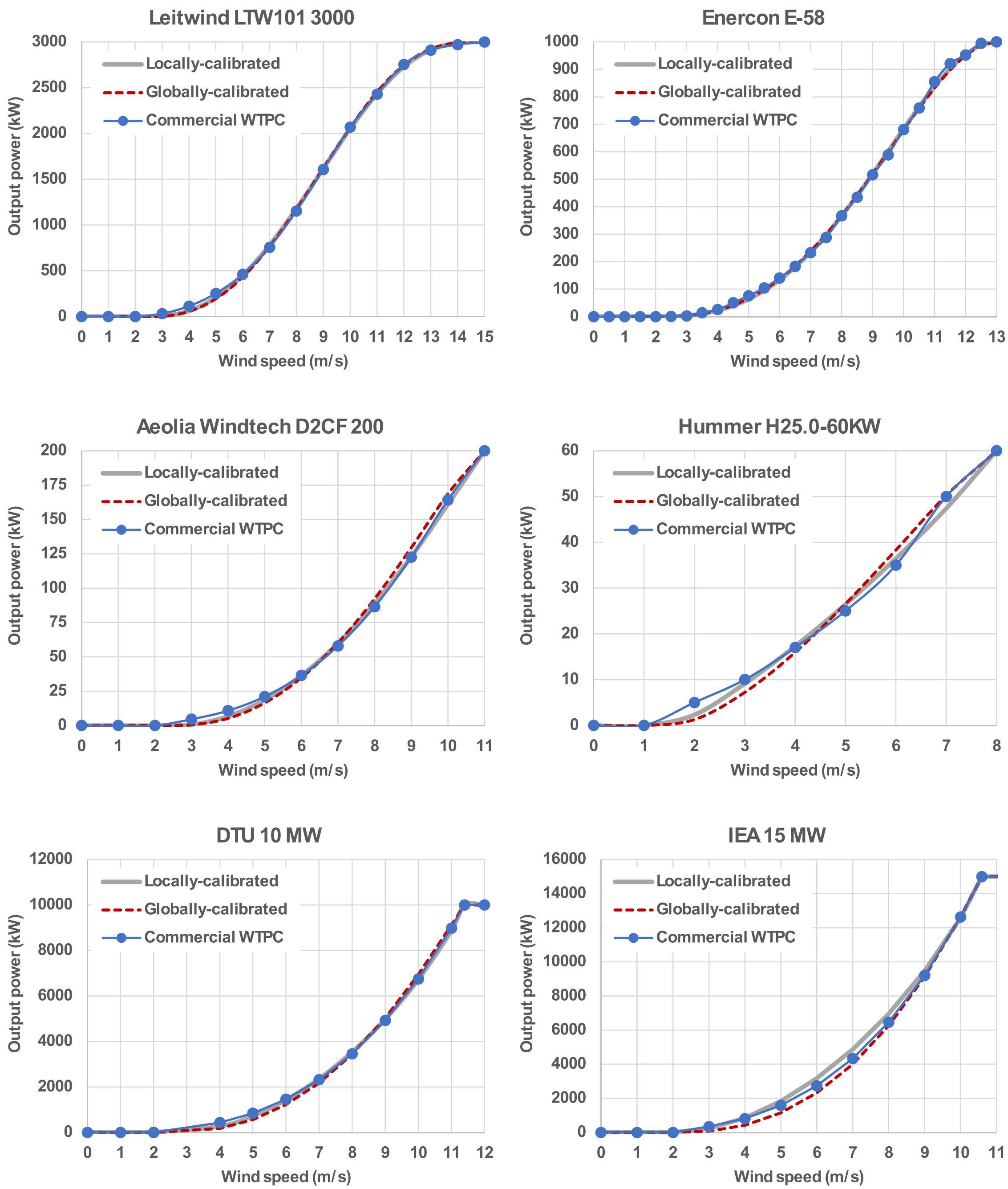

Fig. 9. Comparison of actual and simulated WTPCs through locally and globally optimized shape parameters for six characteristic wind turbine models ranging from 60 kW to 15 MW.

interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data is available in a public repository, provided within the paper (cf. Data Availability Statement).

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