A Modular Framework for Annual Averaged Power Output Generation of Wind Turbines Based on Large Wind Speed Data Sets, Power Curve Modelling and Weibull Distributions

Benjamin Wacker[a,*], Johann V. Seebaß[a,b], Jan Chr. Schlüter[a,c]

[a] *Next Generation Mobility Group, Max-Planck-Institute for Dynamics and Self-Organization, Department of Dynamics of Complex Fluids, Am Fassberg 17, D-37077 Göttingen, Germany*

[b] *Chair of Statistics, Faculty of Business and Economics, Georg-August-University of Göttingen, Humboldtallee 3, D-37073 Göttingen, Germany*

[c] *Institute for Dynamics of Complex Systems, Faculty of Physics, Georg-August-University of Göttingen, Friedrich-Hund-Platz 1, D-37077 Göttingen, Germany*

Abstract

In this article, we develop a flexible method for predicting annual averaged power output generation values of wind turbines. Our adaptable framework relies on power curve data, wind speed data and the easy to replace assumption that wind speeds follow two-parameter Weibull distributions. We thoroughly describe our procedure in this work. At first, we estimate Weibull parameters from given wind speed data. For that purpose, we use a maximum log-likelihood parameter estimation. Afterwards, a least-squares approach is applied to predict a logistic regression function as a power curve function to model the respective power curve data. Additionally, we are able to compare a semi-empirical annual averaged power output generation value and an estimated annual averaged power output generation value based on our computational results. To illustrate our algorithm's usefulness, we demonstrate our procedure with one example of supplied wind speed data from a weather station located at List, Germany and given power curve data from a manufacturer of wind turbines. We finally conclude our work with summarizing statements.

*Corresponding author

Email address: `bewa87@gmx.de` (Benjamin Wacker)

Preprint submitted to Energy Conversion and Management *April 10, 2020*

Keywords: Big Data Analysis, Energy Analysis, Power Curve Modelling, Power Output Generation, Weibull Distribution, Wind Energy

1. Introduction

Motivation. As fossil fuels are limited and reduction of carbon dioxide emissions is indispensable [1], expansion of renewable and sustainable energy sources contributes to sustainable development [2]. One major source represents wind energy [3]. Thus, analysis of wind speed characteristics is significant to predict possible wind power output generation from wind turbines at different locations and perhaps to decide where to locate future sites [4, 5, 6, 7, 8].

Different techniques have been proposed for the purpose of predicting wind power energy output generation [6, 8, 9, 10, 11, 12, 13, 14]. Especially, different sciences have applied various versions of logistic regression functions [15, 16, 17, 18, 19, 20, 21] and these approaches have been modified in wind power curve modeling [9, 10, 22]. As described in [13], we distinguish two classes of wind turbine power curve models - parametric and non-parametric ones. In our study, we restrict ourselves to the case of parametric methods as they predict accurate outcomes [14]. However, we state that those results can also be achieved by machine learning techniques [13].

Contributions. We aim to develop a flexible modular framework to predict annual averaged power output generation values for wind turbines. As we base our analysis on Weibull distributions, we mainly focus on maximum log-likelihood estimation (MLE) to compute parameters for our Weibull distributions [23]. Additionally, we consider a least-squares method with sum of squared differences (SSD) as our cost function to obtain a logistic regression model for power curves of wind turbines [24].

On the base of this literature review, we present our modular method for predicting annual averaged power output generation values of wind turbines based on Weibull distributions and least-squares procedures for logistic regression. At first, we estimate parameters of a two-parameter Weibull distribution for given wind speed data from List, Germany. Afterwards, we have to fit a power curve parametric model with respect to power output data of given wind turbines. Closing these steps, we are able to predict annual averaged power output generation values of a wind turbine placed at List, Germany.

To achieve our goal, we briefly illustrate our work's structure at the beginning of the following Section 2. Especially, we portray our work flow in Figure 1 on which we base our methodology's idea.

2. Methodology

In this section, we thoroughly describe our approach to estimation of an averaged annual power output generation value based on two-parameter Weibull distributions, wind speed data acquired at weather stations across Germany and power curve data from manufacturers of wind turbines.

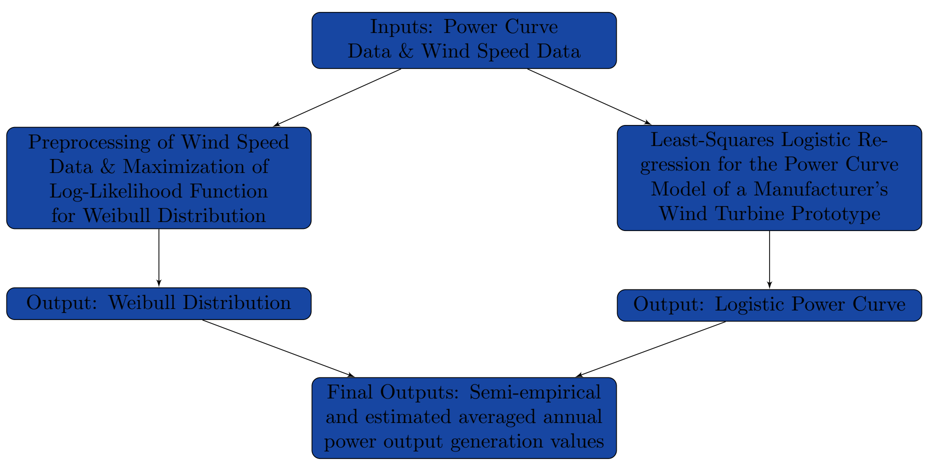

Figure 1: A flow chart of our estimation framework for averaged annual power out generation values based on power curve and wind speed data as inputs.

Let us first present our general procedure. In Figure 1, we portray our work flow. Since log-likelihood functions derived from two-parameter Weibull distributions only allow positive data values, we need to preprocess our wind speed data since . Therefore, we delete zero wind speed values from our data set. We then formulate the log-likelihood function with respect to our preprocessed data and maximize it to obtain our desired scale and shape parameters for our adjusted Weibull distributions. We apply the R package EnvStats for this procedure [25].

After maximizing the respective log-likelihood function, we use R - and GNU Octave for verification and plotting purposes - to implement a logistic regression for given power curve data of a manufacturer's wind turbine [26, 27]. Now, we are able to compute a semi-empirical averaged annual power output generation value and an estimated averaged annual power output generation value based on the calculated logistic regression function and the estimated Weibull distribution.

We illustrate details of these steps in the following paragraphs.

2.1. Two-parameter Weibull distributions and log-likelihood functions

The two-parameter Weibull distribution reads

$$p_{\mathrm{Weibull}}\left(v \,|A, k\,\right) = \frac{k}{A} \cdot \left(\frac{v}{A}\right)^{k-1} \cdot \exp\left(-\left(\frac{v}{A}\right)^{k}\right) \tag{1}$$

for all $v > 0$ where A denotes the scale parameter and k the shape parameter of the corresponding distribution [23]. From (1), we derive the likelihood function

$$l\left(v_j \,|A, k\,\right) = \prod_{j=1}^{N} p_{\mathrm{Weibull}}\left(v_j \,|A, k\,\right) \tag{2}$$

where v_j represents our wind speed data values for all $j \in \{1, \ldots, N\}$. N is the total number of all wind speed values. By applying the natural logarithm on (2), we obtain the log-likelihood function

$$\mathcal{L}\left(A, k\right) = N \cdot \ln\left(k\right) - N \cdot k \cdot \ln\left(A\right) + \left(k-1\right) \cdot \sum_{j=1}^{N} \ln\left(v_j\right) - \sum_{j=1}^{N} \left(\frac{v_j}{A}\right)^{k} \tag{3}$$

where we suppress dependence on our wind speed data values since those are fixed. The maximization approach is called maximum log-likelihood estimation (MLE).

2.2. Preprocessing of acquired wind speed data

Now, we read in the acquired wind speed data from the German Weather Service [28] which are supplied in the following format.

```
STATIONS_ID;MESS_DATUM;  QN_3;       F;     D;eor
       3032;1950010100;     5;     7.4;  -999;eor
       3032;1950010101;     5;     6.6;  -999;eor
       3032;1950010102;     5;     7.4;  -999;eor
       ...
```

We pick this hourly acquired data from location number 3032 and the file PRODUKT_FF_STUNDE_19500101_20181231_03032.TXT of the corresponding ZIP-archive. Additionally, we load meta data from the file with the name METADATEN_GERAETE_WINDGESCHWINDIGKEIT_03032.TXT of the previously mentioned ZIP-archive. We suggest to save those different data files from the German Weather Service within two different directories - one for the hourly acquired data and one for the meta data.

Our algorithmic approach heavily relies on the fourth column of the hourly acquired wind speed data. Finally, we have to eliminate zero values from this chosen column.

2.3. Maximizing log-likelihood functions

Starting from (3), we deduce the necessary conditions for local stationary points. After we differentiate with respect to A or k, those equations read

$$\frac{\partial \mathcal{L}\left(\hat{A}, \hat{k}\right)}{\partial A} = -\frac{N \cdot \hat{k}}{\hat{A}} + \sum_{j=1}^{N} \frac{\hat{k}}{\hat{A}} \cdot \left(\frac{x_j}{\hat{A}}\right)^{k} \overset{!}{=} 0 \tag{4}$$

and

$$\frac{\partial \mathcal{L}\left(\hat{A}, \hat{k}\right)}{\partial k} = \frac{N}{\hat{k}} - N \cdot \ln\left(\hat{A}\right) + \sum_{j=1}^{N} \ln\left(x_j\right) - \sum_{j=1}^{N} \ln\left(\frac{x_j}{\hat{A}}\right) \cdot \left(\frac{x_j}{\hat{A}}\right)^{\hat{k}} \overset{!}{=} 0. \tag{5}$$

Some formal manipulations finally lead to our system of non-linear equations

$$\hat{A} = \left(\frac{1}{N} \cdot \sum_{j=1}^{N} x_j^{\hat{k}}\right)^{\left(\hat{k}\right)^{-1}} \tag{6}$$

and

$$\hat{k} = \left(\frac{1}{N} \cdot \sum_{j=1}^{N} \ln\left(\frac{x_j}{\hat{A}}\right) \cdot \left(\frac{x_j}{\hat{A}}\right)^{\hat{k}} + \ln\left(\hat{A}\right) - \frac{1}{N} \cdot \sum_{j=1}^{N} \ln\left(x_j\right) \right)^{-1} \tag{7}$$

for our necessary conditions. To numerically solve this system by suitable optimization methods [24], we apply the R package EnvStats [25]. Finally, we save the estimated scale and shape parameters A and k associated with our wind speed data set.

2.4. Power curve modelling

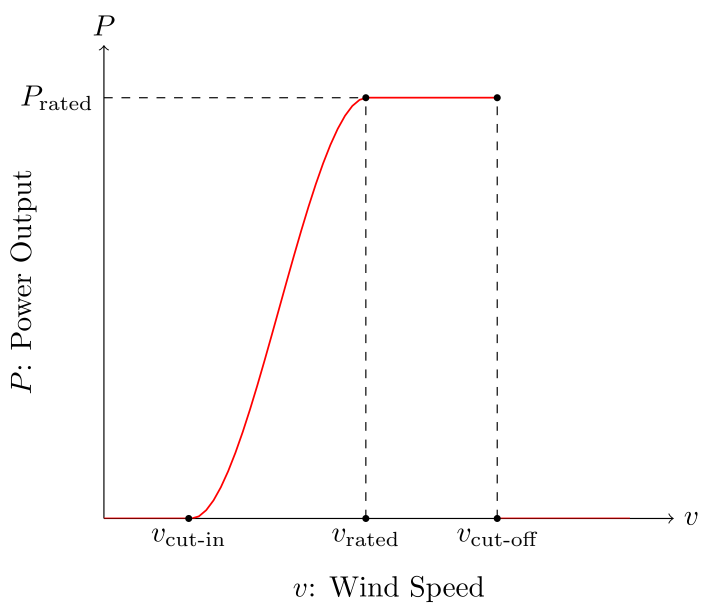

Figure 2: Schematic plot of a general power curve for wind turbines with cut-in wind speed $v_{\text{cut-in}}$, rated wind speed v_{rated}, cut-off wind speed $v_{\text{cut-off}}$ and rated power output P_{rated}.

In Figure 2, we portray the general graph of power curve function for a wind turbine. Since we observe that the power output generation function is only non-constant on the interval $v \in [v_{\text{cut-in}}, v_{\text{rated}}]$, we consider a piecewise defined function

$$P_{\text{Power}}(v) = \begin{cases} 0 & , v \in [0, v_{\text{cut-in}}) \\ q(v) & , v \in [v_{\text{cut-in}}, v_{\text{rated}}] \\ P_{\text{rated}} & , v \in (v_{\text{rated}}, v_{\text{cut-off}}) \\ 0 & , v \in [v_{\text{cut-off}}, \infty) \end{cases} \tag{8}$$

for power output functions as reviewed by Carrillo et al. [9], Sohoni et al. [10] or Pei & Li [13]. Here, we restrict ourselves to the case of parametric models instead of machine learning approaches as presented by Pei & Li [13]. Possible curves may be cubic polynomials

$$q_{\text{cub}}(v \,|a, b, c, d\,) = a \cdot v^3 + b \cdot v^2 + c \cdot v + d \tag{9}$$

or generalized logistic regression functions

$$q_{\text{glog}}(v \,|B, C, D, E, F, G, H\,) = B + \frac{C - B}{\left(D + E \cdot \exp\left(F \cdot (v - G)\right)\right)^{\frac{1}{H}}}, \tag{10}$$

also known as Richards' curves in the literature [15, 16]. As our power curve data seem to be relatively symmetric, we restrict ourselves to logistic regression functions

$$q_{\text{log}}(v \,|B, C, D, E, F\,) = \frac{B}{C + D \cdot \exp\left(-E \cdot v + F\right)}. \tag{11}$$

Equations (9), (10) and (11) are particular cases of functions available for piecewise power curve modeling in (8). By our restriction to (11), we seek for the parameters B, C, D, E and F by a least-squares method which reads

$$\mathcal{J}(B, C, D, E, F) = \sum_{j=1}^{M} \left(q_{\text{log}}(v_j \,|B, C, D, E, F\,) - P_j\right)^2 \tag{12}$$

for our M given power curve data points (v_j, P_j) with $j \in \{1, \ldots, M\}$. We refer to the cost function $\mathcal{J}$ as sum of squared differences (SSD) [29]. Since we want to calculate these unknown parameters, we minimize this cost function $\mathcal{J}$ with respect to the sought parameters for our input power curve data. Regarding implementation, we use R [26] - GNU Octave [27] for verification - and a Nelder-Mead optimization algorithm [30].

Now, all tools are available to predict an averaged annual power output value from our data.

2.5. Calculation of semi-empirical annual averaged power output generation

From our given speed data, we semi-empirically estimate this value by applying one estimated power curve function from Subsection 2.4. We choose a logistic function model to approximate our power curve data. Our averaged annual power output value reads

$$\overline{P_{Hourly,Semi-Emp.}} \approx \sum_{j=1}^{N} \frac{P_{\text{Power}}\left(v_j\right)}{N} \tag{13}$$

for all wind speed data $v_j > 0$ for all $j \in \{1, \ldots, N\}$ with physical unit kWh^{-1} and approximate this integral by a sum of step functions. For more sophisticated numerical integration techniques, we refer the interested reader to the book of Davis and Rabinowitz on this vast topic [31]. This leads to an averaged hourly power output value. We obtain it by

$$\overline{P_{Ann.,Semi-Emp.}} = \frac{365 \cdot 24 \cdot \overline{P_{Hourly,Semi-Emp.}}}{1000000} \tag{14}$$

with physical unit GW per year.

2.6. Calculation of estimated annual averaged power output generation

Since we additionally want to compute the averaged hourly power output value from Weibull distributions by modifying (13), we approximate this integral by step functions. Then, we have to calculate

$$\begin{aligned} \overline{P_{Hourly,Th.}} &= \int_0^\infty P_{\text{Power}}\left(v\right) \cdot p_{\text{Weibull}}\left(v \,|A, k\,\right) \,\mathrm{d}v \\ &\approx \int_0^{25} P_{\text{Power}}\left(v\right) \cdot p_{\text{Weibull}}\left(v \,|A, k\,\right) \,\mathrm{d}v \\ &\approx \sum_{m=0}^{250} p_{\text{Weibull}}\left(\frac{1}{10} \cdot m \,|A, k\right) \cdot P_{\text{Power}}\left(\frac{1}{10} \cdot m\right) \cdot \frac{1}{10} \end{aligned} \tag{15}$$

because 25 is cut-off wind speed of many wind turbines. This yields our hourly averaged power output generation value with physical unit kWh^{-1}. In this case, we evaluate

$$\overline{P_{Ann.,Th.}} = \frac{365 \cdot 24 \cdot \overline{P_{Hourly,Th}}}{1000000} \tag{16}$$

and this yields the annual averaged power output generation value with physical unit GW per year.

3. Results

We briefly want to start with the presentation of both supplied data sets.

3.1. Given power curve data

From the wind turbine manufacturer Vestas [32], we got power curve data of its wind turbine that we present in Table 1. Velocities and hourly power outputs are measured in units $\frac{\mathrm{m}}{\mathrm{s}}$ and $\frac{\mathrm{kW}}{\mathrm{h}}$ respectively.

Table 1: Hourly Power Output Data For Wind Turbine Vestas V112

Velocity	Power Output	Velocity	Power Output	Velocity	Power Output
0.0	0	13.5	3075	27.0	0
0.5	0	14.0	3075	27.5	0
1.0	0	14.5	3075	28.0	0
1.5	0	15.0	3075	28.5	0
2.0	0	15.5	3075	29.0	0
2.5	0	16.0	3075	29.5	0
3.0	26	16.5	3075	30.0	0
3.5	73	17.0	3075	30.5	0
4.0	133	17.5	3075	31.0	0
4.5	207	18.0	3075	31.5	0
5.0	302	18.5	3075	32.0	0
5.5	416	19.0	3075	32.5	0
6.0	554	19.5	3075	33.0	0

6.5	717	20.0	3075	33.5	0
7.0	907	20.5	3075	34.0	0
7.5	1126	21.0	3075	34.5	0
8.0	1375	21.5	3075	35.0	0
8.5	1652	22.0	3075	35.5	0
9.0	1985	22.5	3075	36.0	0
9.5	2282	23.0	3075	36.5	0
10.0	2585	23.5	3075	37.0	0
10.5	2821	24.0	3075	37.5	0
11.0	2997	24.5	3075	38.0	0
11.5	3050	25.0	3075	38.5	0
12.0	3067	25.5	0	39.0	0
12.5	3074	26.0	0	39.5	0
13.0	3075	26.5	0	40.0	0

3.2. Given wind speed data

As mentioned in Subsection 2.2, we use data supplied by DWD Climate Data Center (DWD-CDC) [28]. We concentrate on location number 3032, located at List, Germany. Data was hourly acquired from 01.01.1950 until 31.12.2018 and it is taken from PRODUKT_FF_STUNDE_19500101_20181231_03032.TXT of the corresponding ZIP-archive. Measuring devices and exact geographical positions can be extracted from the corresponding ZIP-archive as well. At first, we eliminate the header of our data file. The interesting column has F as its header and values are measured in $\frac{m}{s}$. From the second column, we can conclude exact time data. As depicted in the fifth column, missing values are given by numerical values of -999. Later, we delete these values from the fourth column of our data vector of interest by R [26] or GNU Octave [27] because these missing values also appear in this fourth column.

3.3. *Weibull distribution from maximum log-likelihood estimation*

The resulting scale and shape parameters for MLE are given by $k \approx 2.23$ and $A \approx 8.07$. A comparison can be drawn from Figure 3 in which relative frequencies of our wind speed data and its approximated Weibull distribution by MLE with $k = 2.23$ and $A = 8.07$ are plotted. While the piecewise linear plot represents the relative frequencies of our given wind speed data, our estimated Weibull distribution, scaled with bin size, is portrayed by the smooth graph.

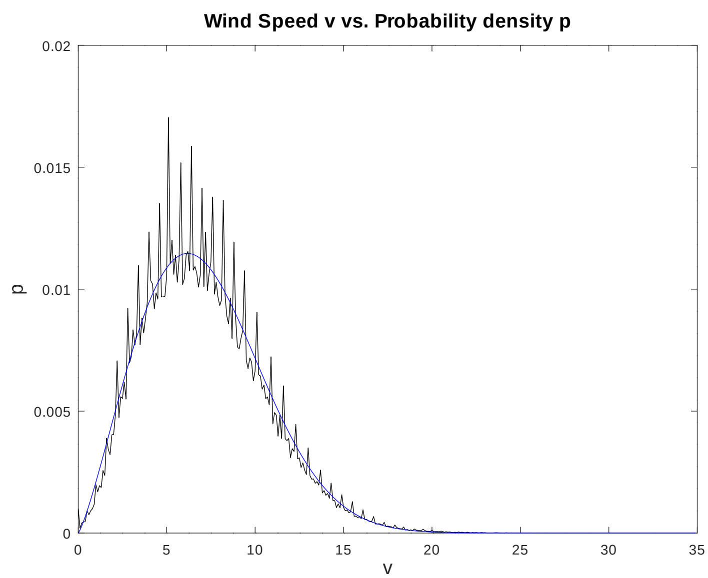

Figure 3: Comparison of relative frequencies of wind speed data (black) with MLE Weibull distribution (blue).

3.4. *Power curve modelling*

Results for cubic and logistic regression functions for given power curve data can be seen in Figure 4. On contrary to the real power curve data, which values are zero for wind speeds smaller than the cut-in wind speed, the cubic as well as the logistic regression function are positive for the cut-in wind speed. This discontinuity with respect to the cut-in wind speed can be fixed by adding certain equality constraints to our minimization process of the cost function in

Subsection 2.4 [24]. However, cubic regression leads to functions that might not be monotonically increasing. For this reason, we prefer logistic regression.

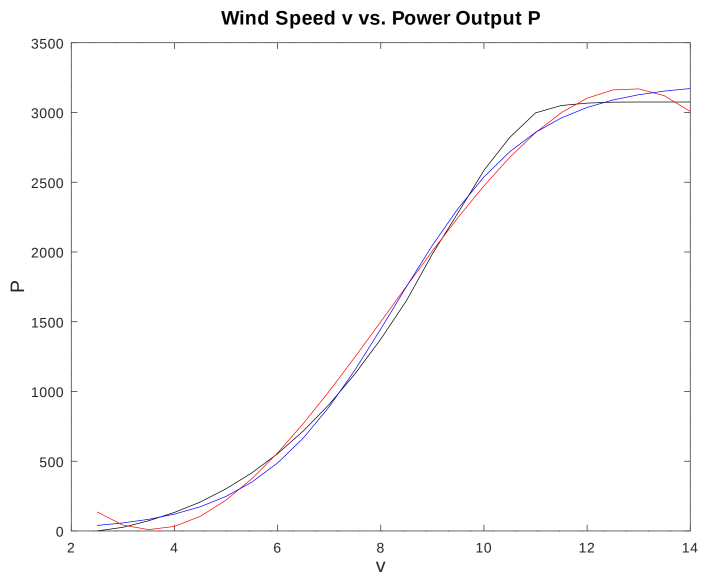

Figure 4: Comparison of given power curve data (black) with cubic (red) and logistic (blue) regression functions.

3.5. Annual averaged power output generation values

Finally, we can compare our semi-empirical and our estimated annual averaged power output generation values. The one predicted from semi-empirical calculation leads us to $\overline{P_{Ann.,Semi-Emp.}} \approx 10.41\,\mathrm{GW}$ while our annual averaged power output generation value from MLE Weibull prediction is approximately given by $\overline{P_{Ann.,Th.}} \approx 10.56\,\mathrm{GW}$. We conclude that these values agree well in this example of List, Germany.

3.6. General prediction of averaged power output generation values

A plot of annual averaged power output generation predicted by Weibull distributions with logistic regression functions for power outputs is presented in Figure 5.

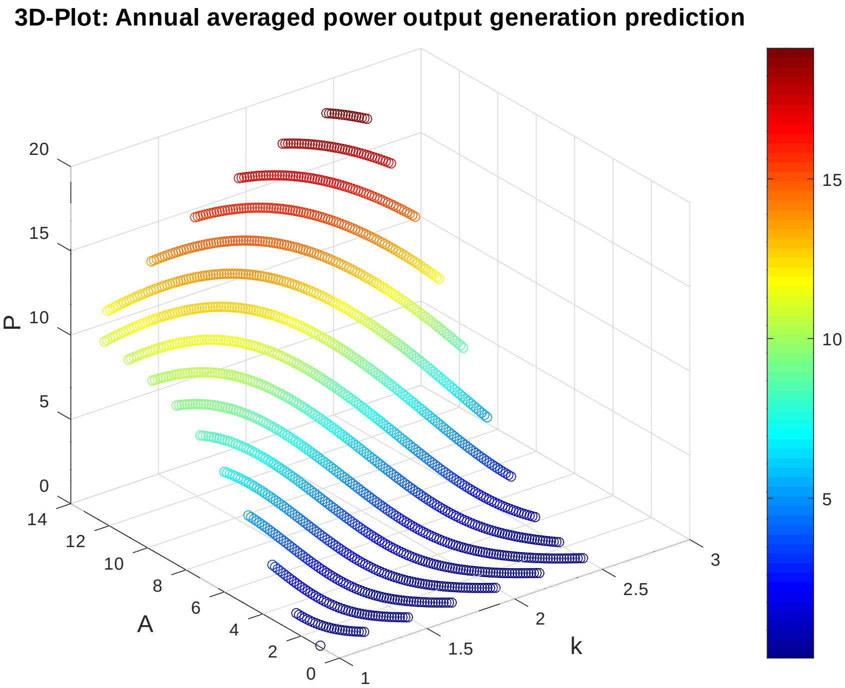

Figure 5: Annual averaged power output generation values based on Weibull distributions and logistic regression functions.

In general, we see for either increasing scale or shape parameters that the predicted annual averaged power output generation value grows as well.

4. Conclusions and outlook

Conclusions. We sketched thoroughly our flexible framework for prediction of averaged annual power generation values for wind turbines. It relies on the combination of maximum log-likelihood parameter estimation of two-parameter Weibull distributions and least-squares approaches of logistic regression functions for power curve modelling. As seen in Section 3, we obtain good wind speed distributions and acceptable power curves from both procedures. Finally, as depicted in Subsection 3.6, our estimations for semi-empirical and estimated averaged annual power output generation values agree well.

Outlook. Since we can easily change our probability distributions [33, 34, 35, 36], our method is flexible with respect to this first major step. Further, we can easily apply different optimization methods and different cost functions for our minimization approach to get our power curve model [24]. Thus, we can easily adapt to different distributions or optimization method and for that reasons, our method becomes applicable in prediction of wind energy potential of different sites. Our algorithm might therefore be a valuable tool for deciding where to locate future wind turbines. To summarize our thoughts, we are convinced that analysis (e.g. error analysis) and extension (e.g. different probability distributions) of our invented algorithm are interesting future research directions in wind energy.

Code availability, data availability and further results

Our R and GNU OCTAVE codes can be downloaded from `https://github.com/bewa87/2020-Energy-AAPOGFWT`. Data for the presented wind turbine from Vestas can be obtained from `https://www.wind-turbine-models.com/turbines/7-vestas-v112-onshore#datasheet`. Wind speed data for all German weather stations are available under [28]. Our appendix contains supplementary computational results for 190 different German weather stations.

Declaration of interest

The authors declare that they have no potential conflict of interest.

References

[1] Gielen, D., Boshell, F., Saygin, D., Bazilian, M.D., Wagner, N., Gorini, R. (2019). *The Role of Renewable Energy in the Global Energy Transformation*, Energy Strategy Reviews, 24: 38–50, DOI: `https://doi.org/10.1016/j.esr.2019.01.006`.

[2] Akella, A.K., Saini, R.P., Sharma, M.P. (2009). *Social, Economical and Environmental Impacts of Renewable Energy Systems*, Renewable Energy, 34(2): 390–396, DOI: https://doi.org/10.1016/j.renene.2008.05.002.

[3] Kumar, Y., Ringenberg, J., Shekara Depuru, S., Devabhaktuni, V.K., Lee, J.W., Nikolaidis, E., Andersen, B., Afjeh, A. (2016). *Wind Energy: Trends and Enabling Technologies*, Renewable and Sustainable Energy Reviews, 53: 209–224, DOI: https://doi.org/10.1016/j.rser.2015.07.200.

[4] Valsaraj, P., Thumba, D.A., Asokan, K., Satheesh Kumar, K. (2020). *Symbolic Regression-Based Improved Method for Wind Speed Extrapolation from Lower to Higher Altitudes for Wind Energy Applications*, Applied Energy, 260: 114270, DOI: https://doi.org/10.1016/j.apenergy.2019.114270.

[5] Katinas, V., Gecevicius, G., Marciukaitis M. (2018). *An Investigation of Wind Power Density Distribution at Location with Low and High Wind Speeds Using Statistical Model*, Applied Energy, 2018: 442–451, DOI: https://doi.org/10.1016/j.apenergy.2018.02.163.

[6] Mahmood, F.H., Resen, A.K., Khamees, A.B. (2019). *Wind Characteristic Analysis Based on Weibull Distribution of Al-Salman site, Iraq*, Energy Reports, DOI: https://dx.doi.org/10.1016/j.egyr.2019.10.021.

[7] Aries, N., Boudia, S.M., Ounis, H. (2018). *Deep assessment of wind speed distribution models: A case study of four sites in Algeria*, Energy Conversion and Management, 155, 78–90, DOI: https://dx.doi.org/10.1016/j.enconman.2017.10.082.

[8] Carrillo, C., Cidrás J, Díaz-Dorado, E., Obando-Montaño, A.F. (2014). *An Approach to Determine the Weibull Parameters for Wind Energy Analysis: The Case of Galicia (Spain)*, Energies, 7:2676–2700, DOI: https://dx.doi.org/10.3390/en7042676.

[9] Carrillo, C., Obando-Montaño, A.F., Cidrás, J. (2013). *Review of Power Curve Modelling for Wind Turbines*, Renewable and Sustainable Energy Reviews, 21: 572–581, DOI: https://dx.doi.org/10.1016/j.rser.2013.01.012.

[10] Sohoni, V., Gupta, S.C., Nema, R.K. (2016). *A Critical Review on Wind Turbine Power Curve Modelling Techniques and Their Applications in Wind Based Energy Systems*, Journal of Energy, DOI: https://dx.doi.org/10.1155/2016/8519785.

[11] Collins, J., Parkes, J., Tindal, A. (2009). *Short Term Forecasting for Utility-Scale Wind Farms - The Power Model Challenge*, Wind Engineering, 33(3): 247–257, DOI: https://dx.doi.org/10.1260/0309-524X.33.3.247.

[12] Dahmouni, A., Ben Salah, M., Askri, F., Kerkeni, C., Ben Nasrallah, S. (2011). *Assessment of Wind Energy Potential and Optimal Electricity Generation in Borj-Cedria, Tunisia*, Renewable and Sustainable Energy Reviews, 15(1): 815–820, DOI: https://doi.org/10.1016/j.rser.2010.07.020.

[13] Pei, S., Li, Y. (2019). *Wind Turbine Power Curve Modeling with a Hybrid Machine Learning Technique*, Applied Sciences, 9(22): 4930, DOI: https://doi.org/10.3390/app9224930.

[14] Lydia, M., Suresh Kumar, S., Immanuel Selvakumar, A., Edwin Prem Kumar, G. (2014). *A Comprehensive Review on Wind Turbine Power Curve Modeling Techniques*, Renewable and Sustainable Energy Reviews, 30: 452–460, DOI: https://dx.doi.org/10.1016/j.rser.2013.10.030.

[15] Richards, F.J. (1959). *A Flexible Growth Function for Empirical Use*, Journal of Experimental Botany, 10(2): 290–301, DOI: https://doi.org/10.1093/jxb/10.2.290.

[16] Lei, Y.C., Zhang, S.Y. (2004). *Features and Partial Derivatives of Bertalanffy-Richards Growth Model in Forestry*, Nonlinear Analysis: Mod-

elling and Control, 9(1): 65–73, DOI: https://doi.org/10.15388/NA.2004.9.1.15171.

[17] Bock, C., Graham, J., Gottwald, T., Cook, A.Z., Parker, P. (2010). *Wind speed and wind associated injury affect severity of citrus canker on Swingle citrumelo*, European Journal of Plant Pathology, 128(1): 21–38, DOI: https://dx.doi.org/10.1007/s10658-010-9624-y.

[18] Cramer, J.S. (2002). *The Origins of Logistic Regression*, Tinbergen Institute Working Paper No. 2002-119/4, DOI: https://dx.doi.org/10.2139/ssrn.360300.

[19] Park, H.-A. (2013). *An Introduction to Logistic Regression: From Basic Concepts to Interpretation with Particular Attention to Nursing Domain*, Journal of Korean Academy of Nursing, 43(2):154, DOI: https://dx.doi.org/10.4040/jkan.2013.43.2.154.

[20] Peng, C.-Y.J., Lee, K.L., Ingersoll, G.M. (2002). *An Introduction to Logistic Regression Analysis and Reporting*, The Journal of Educational Research, 96(1): 3–14, DOI: https://dx.doi.org/10.1080/00220670209598786.

[21] Pyke, S.W., Sheridan, P.M. (1993). *Logistic Regression Analysis of Graduate Student Retention*, Canadian Journal of Higher Education, 23(2): 44–64.

[22] Hennessey, J.P. (1977). *Some Aspects of Wind Power Statistics*, Journal of Applied Meteorology, 16(2): 119–128.

[23] Rinne, H. (2009). **The Weibull Distribution: A Handbook**, CRC Press, Boca Raton.

[24] Nocedal, J., Wright, S.J. (2006). **Numerical Optimization**, Springer Verlag, New York.

[25] Millard, S.P. (2013). *EnvStats - An R Package for Environmental Statistics*. New York: Springer. https://dx.doi.org/10.1007/978-1-4614-8456-1.

[26] R Core Team. (2019). *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

[27] Eaton, J.W., Bateman, D., Hauberg, S. & Wehbring, R. (2019). GNU OCTAVE *Version 5.1.0 Manual - A High-Level Interactive Language for Numerical Computations*, https://www.gnu.org/software/octave/doc/v5.1.0/.

[28] DWD Climate Data Center (CDC). (2018). *Historical Hourly Station Observations of Wind Speed and Wind Direction for Germany*, version006, URL: https://opendata.dwd.de/climate_environment/CDC/observations_germany/climate/hourly/wind/historical/, accessed: 18.02.2020, 17:37.

[29] Modersitzki, J. (2009). **FAIR - Flexible Algorithms for Image Registration**, SIAM, Philadelphia.

[30] Nelder, J.A., Mead, R. (1965). *A Simplex Method for Function Minimization*, The Computer Journal, 7(4): 308–313, DOI: https://doi.org/10.1093/comjnl/7.4.308.

[31] Davis, P.J., Rabinowitz, P. (1984). **Methods of Numerical Integration**, Dover Publications, Mineola (New York).

[32] Vestas: *Vestas V112 Onshore: Datasheet*, URL: https://www.wind-turbine-models.com/turbines/7-vestas-v112-onshore#datasheet, accessed: 18.02.2020, 17:05.

[33] Akpinar, S., Akpinar, E.K. (2009). *Estimation of wind energy potential using finite mixture distribution models*, Energy Conversion and Management, 50:4, 877–884, DOI: https://dx.doi.org/10.1016/j.enconman.2009.01.007.

[34] Akgül, F.G., Şenoğlu, B., Arslan, T. (2016). *An alternative distribution to Weibull for modeling the wind speed data: Inverse Weibull distribution*,

Energy Conversion and Management, 114, 234–240, DOI: https://dx.doi.org/10.1016/j.enconman.2016.02.026.

[35] Calif, R., Emilion, R., Soubdhan, T. (2011). *Classification of wind speed distributions using a mixture of Dirichlet distributions*, Renewable Energy, 36:11, 3091–3097, DOI: https://dx.doi.org/10.1016/j.renene.2011.03.024.

[36] Akdağ, S.A., Güler, Ö. (2015). *A novel energy pattern factor method for wind speed distribution parameter estimation*, Energy Conversion and Management, 106, 1124–1133, DOI: https://dx.doi.org/10.1016/j.enconman.2015.10.042.

Appendix A. German weather stations

All German weather stations under our appendix' consideration can be seen in the German map in Figure A.1.

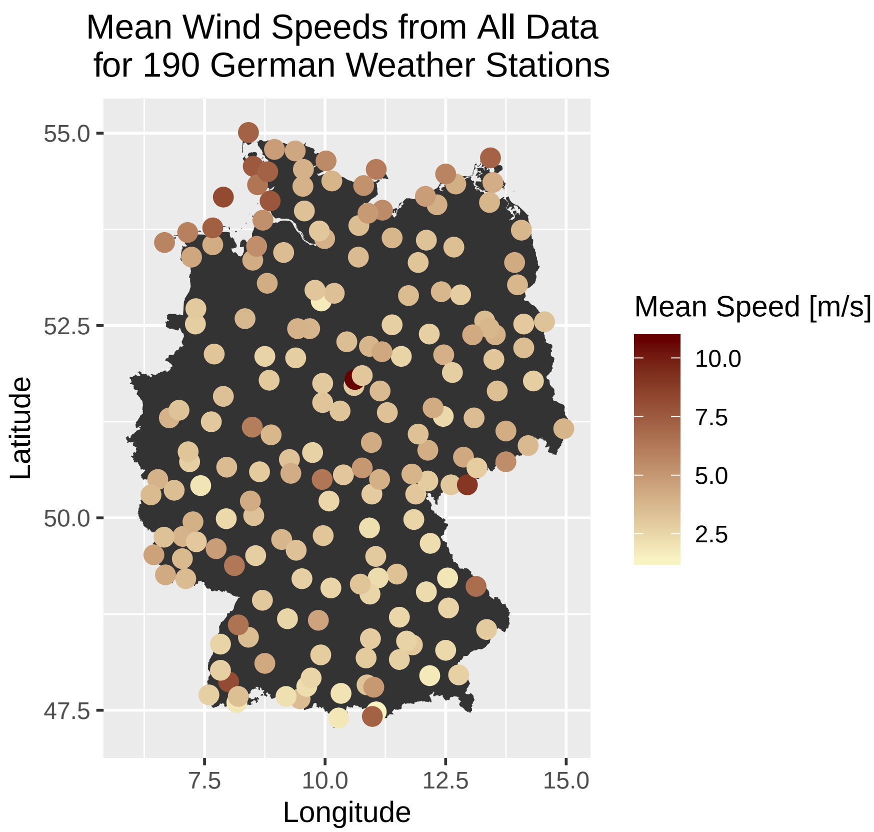

Figure A.1: Map of all German weather stations under consideration.

Here, List is the most northern weather station depicted in Figure A.1. All weather stations with location numbers, mean values

$$\overline{v} = \frac{1}{N} \cdot \sum_{j=1}^{N} v_j \tag{A.1}$$

and standard deviations

$$\sigma = \sqrt{\frac{1}{N-1} \cdot \sum_{j=1}^{N} \left(v_j - \overline{v}\right)^2} \tag{A.2}$$

based on all N data points $v_j > 0.0$ for a considered site are given in the following Table A1.

Table A1: Primitive data from all 190 German weather stations with location numbers (Loc. No.), number of data values (No. of V.), mean wind speed $\overline{v}$ and standard deviation σ.

No.	Loc. No.	Time Fr.	No. of V.	$\overline{v}\ [\mathrm{ms}^{-1}]$	$\sigma\ [\mathrm{ms}^{-1}]$
1	00090	1988/02/19 – 2018/12/31	236506	3.34	2.18
2	00125	1974/03/01 – 2018/12/31	213703	3.45	2.94
3	00161	1980/12/01 – 2018/12/31	250259	1.92	1.39
4	00164	1979/01/01 – 2018/12/31	341858	3.93	2.26
5	00183	1973/01/01 – 2018/12/31	396424	7.44	3.86
6	00198	1961/01/01 – 2018/12/31	471240	3.76	2.56
7	00232	1961/01/01 – 2018/12/31	499480	2.92	2.03
8	00282	1971/08/01 – 2018/12/31	407517	2.09	1.44
9	00298	1981/01/01 – 2018/12/31	318665	4.23	2.67
10	00303	1993/09/06 – 2018/12/31	215005	3.26	2.18
11	00368	1973/01/01 – 2018/12/31	380223	2.39	1.73
12	00427	1973/01/01 – 2018/12/31	393047	4.00	2.27
13	00430	1987/01/01 – 2018/12/31	278388	3.63	2.04
14	00433	1974/01/01 – 2018/12/31	390888	3.89	2.04
15	00460	1969/01/01 – 2018/12/31	433625	4.25	2.50
16	00591	1973/01/01 – 2018/12/31	335545	3.84	1.98
17	00596	1973/01/01 – 2018/12/31	394855	5.68	2.96
18	00603	1986/08/01 – 2018/12/31	256293	2.84	1.55
19	00619	1987/05/01 – 2018/12/31	271861	6.54	3.33
20	00642	1981/01/01 – 2018/12/31	326875	4.38	2.18
21	00656	1937/01/01 – 2018/12/31	484973	3.09	1.78
22	00662	1966/01/01 – 2018/12/31	460427	3.53	1.92
23	00691	1926/01/01 – 2018/12/31	636722	4.37	2.42
24	00701	1952/01/01 – 2018/12/31	585356	5.42	2.95
25	00704	1979/04/01 – 2018/12/31	339269	3.38	2.08

26	00722	1956/01/01 – 2018/12/31	543703	11.19	5.87
27	00788	2007/10/26 – 2018/12/31	97800	7.69	3.77
28	00840	1990/05/01 – 2018/12/31	245777	3.17	1.71
29	00853	1961/01/01 – 2018/12/31	491849	4.53	2.93
30	00867	1972/01/01 – 2018/12/31	398648	2.36	1.70
31	00880	1983/01/01 – 2018/12/31	305377	2.98	1.78
32	00891	1969/01/01 – 2018/12/31	436848	5.52	2.69
33	00953	1969/01/01 – 2018/12/31	428940	3.91	2.49
34	00963	1974/01/01 – 2018/12/31	364291	3.75	2.34
35	01001	1981/01/01 – 2018/12/31	319580	3.79	2.21
36	01011	1990/10/11 – 2018/12/27	182919	4.76	2.58
37	01013	1980/04/01 – 2018/12/31	307868	1.99	1.71
38	01048	1973/01/01 – 2018/12/31	382293	4.00	2.26
39	01078	1952/01/01 – 2018/12/31	580671	3.90	2.20
40	01262	1992/05/19 – 2018/12/31	231640	3.03	2.27
41	01270	1973/01/01 – 2018/12/31	379462	3.98	2.41
42	01303	1963/01/01 – 2018/12/31	488980	3.64	1.95
43	01339	1971/01/01 – 2018/12/31	403378	3.50	2.07
44	01346	1969/01/01 – 2018/12/31	433406	7.96	4.75
45	01357	1993/12/15 – 2018/12/31	212783	2.63	1.67
46	01358	1955/01/01 – 2018/12/31	553672	8.72	4.56
47	01379	1982/12/01 – 2018/12/31	311160	4.48	2.44
48	01420	1967/01/01 – 2018/12/31	440390	3.26	2.07
49	01443	1955/01/01 – 2018/12/31	550162	2.89	2.24
50	01468	1970/10/01 – 2018/12/31	402740	2.94	1.82
51	01490	1965/01/01 – 2018/12/31	353734	3.23	2.31
52	01544	1959/01/01 – 2018/12/31	463450	3.44	2.42
53	01550	1969/01/01 – 2018/12/31	396225	1.20	1.02
54	01580	1951/01/01 – 2018/12/31	573049	2.47	1.74
55	01605	1982/01/01 – 2018/12/31	298768	3.07	1.81

56	01612	1973/01/01 – 2018/12/31	386099	4.13	2.29
57	01639	1939/01/01 – 2018/12/31	664678	2.65	1.79
58	01684	1963/01/01 – 2018/12/31	476398	4.43	2.82
59	01691	1969/01/01 – 2018/12/31	414465	2.77	1.88
60	01694	1981/09/21 – 2018/12/31	315943	3.58	2.27
61	01757	1978/01/01 – 2018/12/31	341733	3.87	2.12
62	01766	1989/10/01 – 2018/12/31	255425	3.31	2.12
63	01803	1991/01/01 – 2018/12/31	94054	4.06	2.35
64	01832	1982/11/01 – 2018/12/31	284471	6.71	3.85
65	01869	1981/01/01 – 2018/12/31	325616	4.63	2.44
66	01963	1969/01/01 – 2018/12/31	394573	7.52	3.67
67	01975	1950/01/01 – 2018/12/31	598635	4.06	2.25
68	01993	1976/12/01 – 2018/12/31	301670	2.77	1.95
69	02014	1950/01/01 – 2018/12/31	600978	3.86	2.19
70	02044	1981/01/01 – 2018/12/31	321095	3.73	2.15
71	02115	1959/01/01 – 2018/11/28	523727	7.72	3.74
72	02171	1976/04/01 – 2018/12/31	364050	2.53	1.78
73	02261	1948/01/01 – 2018/12/31	619782	3.56	2.11
74	02290	1939/01/01 – 2018/12/31	696090	4.74	3.26
75	02303	1969/01/01 – 2018/12/31	431157	4.10	2.49
76	02349	1989/10/30 – 2018/12/31	110482	6.13	3.57
77	02377	1981/01/01 – 2018/12/31	261362	2.86	1.81
78	02385	1974/04/01 – 2018/12/31	382334	3.51	2.57
79	02410	1974/01/01 – 2018/12/31	370396	2.61	1.89
80	02429	1988/03/01 – 2018/12/31	260599	3.44	2.09
81	02483	1969/01/01 – 2018/12/31	437570	6.03	2.55
82	02497	1979/01/01 – 2018/12/31	331627	4.11	2.34
83	02559	1966/01/01 – 2018/12/31	456820	1.89	1.16
84	02564	1974/01/01 – 2018/12/31	344467	3.99	2.21
85	02573	1987/06/10 – 2018/12/31	235596	2.93	2.31

86	02597	1972/12/01 – 2018/12/31	397454	2.11	1.53
87	02601	1966/01/01 – 2018/12/31	459760	4.55	2.03
88	02638	1969/01/01 – 2018/12/31	434390	4.03	2.39
89	02667	1957/07/01 – 2018/12/31	534876	3.23	1.82
90	02712	1959/07/01 – 2018/12/31	509243	2.07	1.54
91	02794	1989/01/01 – 2018/12/31	258551	3.93	2.17
92	02812	1977/01/27 – 2018/12/31	328801	2.60	1.88
93	02886	1970/01/01 – 2018/12/31	412230	2.88	2.05
94	02897	1990/08/30 – 2018/12/31	218041	4.23	2.73
95	02905	1969/01/01 – 2018/12/31	407283	3.05	1.98
96	02907	1974/12/01 – 2018/12/31	377085	4.75	2.72
97	02925	1973/01/01 – 2018/12/31	351323	3.47	2.21
98	02928	1958/01/01 – 2018/12/31	313549	3.16	1.98
99	02932	1972/05/01 – 2018/12/31	401100	4.35	2.41
100	02985	1991/11/01 – 2018/12/31	232483	3.81	2.26
101	03015	1951/01/01 – 2018/12/31	586374	3.60	1.94
102	03023	1970/02/01 – 2018/12/31	426364	3.16	1.73
103	03028	1971/04/01 – 2018/12/31	412482	3.05	1.96
104	03032	1950/01/01 – 2018/12/31	603085	7.14	3.38
105	03086	1985/12/15 – 2018/12/31	284882	3.36	2.00
106	03098	1994/01/01 – 2018/12/31	218509	3.06	1.88
107	03126	1957/08/01 – 2018/12/31	521672	3.16	1.96
108	03158	1989/01/01 – 2018/12/31	254237	3.50	2.10
109	03166	1982/01/01 – 2018/12/31	306764	3.20	1.95
110	03167	1969/01/01 – 2018/12/31	436868	3.56	1.85
111	03196	1981/01/01 – 2018/12/31	312789	3.42	1.91
112	03231	1979/01/01 – 2018/12/31	310939	3.31	1.92
113	03254	1973/01/01 – 2018/12/31	394131	3.01	1.79
114	03287	1987/10/01 – 2018/12/31	268129	3.71	1.89
115	03366	1955/01/01 – 2018/12/31	539928	2.21	1.82

116	03376	1991/01/01 – 2018/12/31	218374	2.89	1.65
117	03379	1985/01/01 – 2018/12/31	292780	2.53	1.61
118	03513	1989/05/01 – 2018/12/31	255455	3.96	1.69
119	03534	1981/03/01 – 2018/12/31	283251	3.44	1.80
120	03552	1973/01/01 – 2018/12/31	370761	3.20	1.91
121	03631	1969/01/01 – 2018/12/31	436983	6.30	3.17
122	03651	1992/04/02 – 2018/12/31	214448	3.07	2.11
123	03660	1995/03/01 – 2018/11/29	207235	3.50	1.83
124	03668	1949/01/01 – 2018/12/31	600053	2.81	1.92
125	03730	1951/01/01 – 2018/12/31	565590	1.37	1.08
126	03761	1952/01/01 – 2018/12/31	554877	2.43	1.70
127	03811	1983/01/01 – 2018/12/31	303267	3.74	2.44
128	03821	1986/01/01 – 2018/12/31	279029	3.97	2.51
129	03905	1990/08/29 – 2018/12/31	219869	4.69	2.39
130	03925	1989/04/06 – 2018/12/31	201301	3.09	2.05
131	03946	1973/01/01 – 2018/12/31	336341	3.27	1.93
132	03987	1893/01/01 – 2018/12/31	1054614	4.74	2.23
133	04024	1982/01/01 – 2018/12/31	313881	4.41	2.42
134	04039	1982/12/01 – 2018/12/31	230094	3.26	1.97
135	04094	1997/12/09 – 2018/12/31	179994	2.26	1.46
136	04104	1949/01/01 – 2018/12/31	595790	2.35	1.63
137	04225	1979/06/01 – 2018/12/31	270436	2.12	1.58
138	04271	1954/01/01 – 2018/12/31	559719	4.94	3.01
139	04279	1989/04/18 – 2018/12/31	245952	3.77	2.07
140	04280	1971/01/01 – 2018/12/31	387133	2.45	1.75
141	04336	1956/01/01 – 2018/12/31	536726	3.47	2.05
142	04371	1969/01/01 – 2018/12/31	432859	2.58	1.61
143	04393	1969/01/01 – 2018/12/31	395836	6.69	3.57
144	04464	1989/08/01 – 2018/12/31	247816	3.90	2.21
145	04466	1958/02/01 – 2018/12/31	532548	4.13	2.11

146	04501	1978/07/01 – 2018/12/31	338023	5.11	2.77
147	04625	1954/01/01 – 2018/12/31	560326	4.05	2.29
148	04642	1976/10/01 – 2018/12/31	352937	3.73	2.12
149	04745	1958/06/01 – 2018/12/31	526486	3.18	1.81
150	04880	1984/12/01 – 2018/12/31	262636	2.71	1.95
151	04887	1952/01/01 – 2018/12/31	581423	4.54	2.64
152	04911	1974/01/01 – 2018/12/31	389048	2.66	1.85
153	04919	1977/10/01 – 2018/12/31	338582	7.30	3.80
154	04931	1953/01/01 – 2018/12/31	557821	2.63	2.01
155	04947	1988/08/17 – 2018/12/31	224098	3.92	2.27
156	05029	1975/06/01 – 2018/12/31	374772	3.64	2.13
157	05078	1971/01/01 – 2018/12/31	408776	4.85	2.51
158	05100	1937/01/01 – 2018/12/31	584439	3.41	2.37
159	05142	1982/01/01 – 2018/12/31	314722	3.88	2.13
160	05158	1989/01/01 – 2018/12/31	256285	4.62	2.82
161	05319	1981/08/01 – 2018/12/31	307038	2.62	1.83
162	05327	1981/07/14 – 2018/12/31	234537	3.42	2.35
163	05349	1981/01/01 – 2018/12/31	307162	3.53	1.92
164	05371	1959/01/01 – 2018/12/31	490329	6.07	3.20
165	05397	1952/01/01 – 2018/12/31	555181	2.30	1.67
166	05404	1972/01/01 – 2018/12/31	255465	2.61	2.12
167	05412	1991/05/31 – 2018/12/31	172608	3.51	2.20
168	05426	1973/12/01 – 2018/12/31	322380	6.25	3.37
169	05440	1969/01/01 – 2018/12/31	424796	2.56	1.85
170	05480	2003/09/10 – 2018/12/31	133109	3.39	2.11
171	05490	1953/01/01 – 2018/12/31	483234	3.69	2.77
172	05516	1957/07/01 – 2018/12/31	535324	6.42	3.35
173	05546	1986/07/01 – 2018/12/31	280480	4.19	2.01
174	05629	1961/01/01 – 2018/12/31	457257	3.18	1.88
175	05640	1969/01/01 – 2018/12/31	420199	4.53	2.68

176	05705	1966/01/01 – 2018/12/31	457331	3.12	2.22
177	05715	1974/01/01 – 2018/12/31	386632	4.06	2.24
178	05779	1976/04/01 – 2018/12/31	338471	5.35	2.55
179	05792	1976/01/01 – 2018/12/31	374447	7.27	4.57
180	05839	1997/07/01 – 2018/12/31	186232	4.41	2.28
181	05851	1997/03/12 – 2018/12/31	177668	3.72	2.19
182	05856	1997/01/03 – 2018/12/31	191969	2.97	1.88
183	05871	1998/11/01 – 2018/12/31	173324	4.05	2.00
184	05877	1997/03/10 – 2018/12/31	171805	5.28	2.94
185	05906	1969/01/01 – 2018/12/31	426654	2.76	1.62
186	05930	1981/08/01 – 2018/12/31	311665	5.76	3.00
187	06091	1997/10/08 – 2018/12/31	181883	7.31	3.53
188	06096	1998/07/17 – 2018/12/31	173405	3.20	2.21
189	06097	1998/11/04 – 2018/12/31	173981	5.80	3.42
190	06211	1987/06/10 – 2018/12/31	231849	1.84	1.47

Appendix B. Semi-empirical and estimated averaged annual power output generation values

Here, we summarize our different averaged annual power output generation values for all 190 mentioned German weather stations in Table B2.

Table B2: Shape parameters k, scale parameters A, semi-empirical averaged annual power output generation values $\overline{P_{\text{semi-emp.}}}$ and estimated averaged annual power output generation values $\overline{P_{\text{th.}}}$.

No.	Location No.	k	A	$\overline{P_{Ann.,Semi-Emp.}}$ [GW]	$\overline{P_{Ann.,Th.}}$ [GW]
1	00090	1.62	3.75	1.90	1.82
2	00125	1.26	3.73	2.82	2.67
3	00161	1.44	2.13	0.34	0.31
4	00164	1.82	4.43	2.62	2.61
5	00183	2.03	8.41	11.00	11.28
6	00198	1.51	4.17	2.82	2.78

7	00232	1.51	3.25	1.37	1.31
8	00282	1.46	2.30	0.39	0.41
9	00298	1.61	4.71	3.61	3.57
10	00303	1.54	3.62	1.80	1.78
11	00368	1.45	2.64	0.77	0.70
12	00427	1.86	4.52	2.73	2.71
13	00430	1.86	4.09	1.97	1.97
14	00433	1.99	4.39	2.26	2.28
15	00460	1.79	4.79	3.30	3.36
16	00591	2.05	4.34	2.14	2.13
17	00596	2.03	6.42	6.50	6.65
18	00603	1.93	3.21	0.82	0.78
19	00619	2.07	7.40	8.64	8.97
20	00642	2.13	4.95	3.10	3.14
21	00656	1.81	3.48	1.20	1.18
22	00662	1.91	3.98	1.73	1.73
23	00691	1.89	4.93	3.42	3.47
24	00701	1.94	6.13	5.84	6.06
25	00704	1.68	3.78	1.77	1.77
26	00722	2.00	12.64	17.46	17.45
27	00788	2.16	8.69	11.91	11.94
28	00840	1.94	3.58	1.19	1.17
29	00853	1.64	5.10	4.29	4.30
30	00867	1.39	2.59	0.71	0.72
31	00880	1.77	3.35	1.14	1.07
32	00891	2.17	6.24	5.85	6.04
33	00953	1.58	4.35	2.91	2.94
34	00963	1.67	4.21	2.52	2.49
35	01001	1.78	4.26	2.38	2.38
36	01011	1.96	5.39	4.23	4.33

37	01013	1.22	2.13	0.60	0.53
38	01048	1.87	4.52	2.72	2.69
39	01078	1.84	4.40	2.49	2.51
40	01262	1.43	3.36	1.73	1.59
41	01270	1.75	4.49	2.87	2.84
42	01303	1.98	4.12	1.89	1.86
43	01339	1.74	3.93	1.87	1.89
44	01346	1.74	8.94	11.90	12.06
45	01357	1.62	2.94	0.79	0.79
46	01358	2.00	9.84	14.01	14.00
47	01379	1.91	5.05	3.67	3.68
48	01420	1.65	3.66	1.68	1.63
49	01443	1.35	3.16	1.63	1.50
50	01468	1.69	3.30	1.14	1.10
51	01490	1.48	3.59	1.93	1.85
52	01544	1.47	3.80	2.24	2.23
53	01550	1.20	1.28	0.08	0.08
54	01580	1.49	2.74	0.80	0.74
55	01605	1.74	3.44	1.21	1.21
56	01612	1.90	4.66	2.93	2.92
57	01639	1.51	2.93	0.91	0.91
58	01684	1.64	4.97	4.02	4.02
59	01691	1.51	3.07	1.08	1.08
60	01694	1.65	4.02	2.24	2.19
61	01757	1.92	4.37	2.36	2.36
62	01766	1.63	3.71	1.77	1.74
63	01803	1.80	4.57	2.93	2.91
64	01832	1.82	7.56	9.36	9.44
65	01869	1.99	5.23	3.83	3.93
66	01963	2.16	8.50	11.45	11.54

67	01975	1.86	4.56	2.76	2.80
68	01993	1.48	3.07	1.17	1.13
69	02014	1.85	4.35	2.44	2.43
70	02044	1.83	4.21	2.26	2.21
71	02115	2.18	8.72	11.91	12.02
72	02171	1.42	2.78	0.81	0.87
73	02261	1.75	3.99	1.99	1.98
74	02290	1.55	5.30	4.68	4.92
75	02303	1.71	4.60	3.14	3.15
76	02349	1.81	6.92	7.82	8.05
77	02377	1.69	3.22	1.09	1.01
78	02385	1.42	3.87	2.54	2.45
79	02410	1.47	2.89	1.04	0.93
80	02429	1.71	3.86	1.83	1.83
81	02483	2.51	6.80	6.89	7.17
82	02497	1.81	4.62	2.97	2.99
83	02559	1.72	2.13	0.22	0.19
84	02564	1.90	4.51	2.62	2.62
85	02573	1.40	3.24	1.58	1.48
86	02597	1.44	2.33	0.49	0.45
87	02601	2.37	5.13	3.19	3.22
88	02638	1.78	4.54	2.91	2.91
89	02667	1.86	3.64	1.34	1.32
90	02712	1.44	2.29	0.51	0.42
91	02794	1.89	4.43	2.49	2.50
92	02812	1.45	2.87	1.01	0.94
93	02886	1.48	3.19	1.36	1.28
94	02897	1.63	4.74	3.69	3.59
95	02905	1.63	3.42	1.41	1.33
96	02907	1.81	5.34	4.51	4.49

97	02925	1.62	3.88	2.03	2.03
98	02928	1.70	3.56	1.51	1.42
99	02932	1.92	4.92	3.35	3.40
100	02985	1.74	4.27	2.48	2.47
101	03015	1.97	4.07	1.86	1.80
102	03023	1.91	3.56	1.20	1.17
103	03028	1.60	3.40	1.34	1.36
104	03032	2.23	8.07	10.41	10.56
105	03086	1.72	3.77	1.66	1.68
106	03098	1.70	3.44	1.28	1.26
107	03126	1.72	3.56	1.47	1.39
108	03158	1.74	3.93	1.91	1.89
109	03166	1.70	3.59	1.48	1.45
110	03167	2.02	4.02	1.69	1.67
111	03196	1.85	3.84	1.59	1.61
112	03231	1.79	3.73	1.52	1.52
113	03254	1.73	3.38	1.15	1.15
114	03287	2.07	4.20	1.90	1.87
115	03366	1.27	2.38	0.77	0.70
116	03376	1.80	3.24	0.92	0.92
117	03379	1.66	2.84	0.75	0.66
118	03513	2.48	4.47	1.95	1.93
119	03534	2.03	3.90	1.53	1.48
120	03552	1.74	3.60	1.44	1.41
121	03631	2.11	7.13	7.84	8.32
122	03651	1.49	3.40	1.55	1.55
123	03660	2.01	3.95	1.59	1.57
124	03668	1.51	3.12	1.16	1.14
125	03730	1.30	1.49	0.11	0.11
126	03761	1.47	2.69	0.75	0.72

127	03811	1.60	4.18	2.67	2.59
128	03821	1.67	4.45	2.89	2.95
129	03905	2.08	5.30	3.89	3.96
130	03925	1.60	3.47	1.52	1.43
131	03946	1.75	3.67	1.49	1.49
132	03987	2.24	5.35	3.71	3.84
133	04024	1.92	4.98	3.47	3.53
134	04039	1.69	3.65	1.53	1.55
135	04094	1.65	2.54	0.50	0.43
136	04104	1.51	2.61	0.67	0.60
137	04225	1.41	2.34	0.54	0.48
138	04271	1.75	5.58	4.84	5.12
139	04279	1.91	4.25	2.17	2.16
140	04280	1.47	2.72	0.82	0.74
141	04336	1.74	3.89	1.81	1.83
142	04371	1.65	2.88	0.71	0.71
143	04393	1.98	7.56	9.10	9.40
144	04464	1.83	4.39	2.52	2.52
145	04466	2.07	4.68	2.71	2.70
146	04501	1.95	5.78	5.06	5.22
147	04625	1.87	4.58	2.80	2.80
148	04642	1.82	4.19	2.19	2.20
149	04745	1.83	3.58	1.30	1.28
150	04880	1.41	2.98	1.12	1.12
151	04887	1.83	5.13	3.83	3.99
152	04911	1.54	2.97	1.03	0.92
153	04919	2.03	8.25	10.77	10.94
154	04931	1.34	2.87	1.16	1.11
155	04947	1.81	4.42	2.62	2.60
156	05029	1.76	4.09	2.12	2.12

157	05078	2.03	5.48	4.31	4.43
158	05100	1.49	3.78	2.16	2.13
159	05142	1.92	4.38	2.40	2.37
160	05158	1.71	5.19	4.29	4.35
161	05319	1.51	2.91	0.96	0.89
162	05327	1.45	3.77	2.14	2.21
163	05349	1.93	3.98	1.74	1.71
164	05371	2.00	6.86	7.44	7.75
165	05397	1.39	2.51	0.64	0.65
166	05404	1.24	2.80	1.25	1.24
167	05412	1.67	3.94	2.08	2.03
168	05426	1.96	7.06	7.67	8.25
169	05440	1.38	2.79	0.92	0.96
170	05480	1.70	3.82	1.85	1.78
171	05490	1.40	4.06	2.89	2.87
172	05516	2.02	7.25	8.52	8.66
173	05546	2.20	4.74	2.64	2.64
174	05629	1.77	3.58	1.39	1.34
175	05640	1.77	5.10	3.98	4.04
176	05705	1.46	3.45	1.72	1.68
177	05715	1.89	4.58	2.76	2.77
178	05779	2.22	6.04	5.30	5.50
179	05792	1.69	8.17	9.96	10.65
180	05839	2.04	4.98	3.30	3.34
181	05851	1.76	4.18	2.27	2.28
182	05856	1.72	3.36	1.27	1.14
183	05871	2.15	4.59	2.44	2.43
184	05877	1.90	5.97	5.53	5.75
185	05906	1.78	3.11	0.83	0.81
186	05930	2.03	6.51	6.67	6.88

187	06091	2.20	8.28	10.56	11.04
188	06096	1.54	3.58	1.80	1.72
189	06097	1.80	6.55	7.07	7.23
190	06211	1.39	2.04	0.43	0.30

Our computed results strengthen the usefulness of our algorithm because semi-empirical and predicted annual averaged annual power output generation values agree well in almost every case.