Weibull Analysis of Wind Data in Ireland *

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Abstract

Human-induced climate change has made the production of energy from renewable sources an urgent requirement. Wind power is the primary source of renewable energy in the Republic of Ireland due to its climate. However, wind turbines are less reliable in producing electricity than fossil fuels, and identifying an appropriate location for a wind turbine remains a challenging task. This is particularly true in the Republic of Ireland where the wind speed is intermittently too high to keep wind turbines operational. In this paper, we present an approach to determine the most suitable locations for the installation of wind turbines, based on Weibull Analysis of historical wind data and our proposed evaluation method. The method is evaluated on five sites across Ireland, highlighting its ability to identify the optimal location and showcase substantial seasonal variability in expected wind speeds.

***Index Terms*—** Renewable Energy, Wind Turbines, Weibull distribution, Location evaluation

1 Introduction

1.1 Motivation

With human-caused climate change and its severe impact on the lives of people around the world, the Paris Agreement (United Nations, 2015) challenges countries around the world to produce more energy from renewable sources. Particularly in the current energy crisis, which has significantly increased the cost of living in most European countries (Guan et al., 2023), the need for non-fossil energy sources that guarantee national energy independence is strongly emphasised. However, each country - or even region within a country - has different climatic conditions that make the use of a particular type of renewable energy more or less compelling.

Due to the relatively low average daily hours of sunshine and the lack of large rivers, the majority of renewable energy generated in the Republic of Ireland comes from wind power (Sustainable Energy Authority Of Ireland, 2023).

*Code for the analysis is provided at https://github.com/amitamola/Weibull_Project/tree/main

1.2 Problem Statement

However, identifying the best form of renewable energy still leaves an important question unanswered: How to find the best location for a wind power plant?

One could naively assume that the best location for a wind turbine is the one with the highest average wind speed, but this oversimplifies the problem. For instance, one of the most important factors in choosing a location for a wind turbine is consistent wind speed, because the energy produced cannot currently be stored efficiently, and a consistent power supply is important for maintaining the stability of the energy system (Sun et al., 2019; Coppez et al., 2010). Especially in a country like Ireland with wind power as its main renewable energy resource, consistent power output is an important consideration point for finding an optimal location for a wind turbine (Foley et al., 2013).

In addition, it is important to note that wind turbines are only capable of safely operating up to a maximum wind speed of approximately $21\frac{m}{s}$ and must be shut down at higher wind speeds (Lumbreras et al., 2015). Furthermore, wind speeds below $5\frac{m}{s}$ are typically insufficient to produce any significant amount of energy (DAERA, 2016; Enerpower, 2021). The highest average wind speed is therefore a poor criterion for selecting the best location for a wind turbine. To address these challenges, the generalised Weibull distribution has been demonstrated to be suitable for modelling wind speed data and identifying optimal locations for wind turbines based on various attributes of the distribution (Al-Hasan and Nigmatullin, 2003; Brano et al., 2011; Lai et al., 2006; Ajayi et al., 2011).

1.3 Research Questions

With the successful application of the Weibull distribution to evaluate the suitability of a wind power turbine, we can formulate the following research questions:

a. Is it possible to determine with high certainty if one five proposed locations are better suited for a wind turbine than the other ones?

b. To what extent plays the season of the year a role in whether or not a location is better suited for a wind turbine?

In this work, we first outline the relevant literature on the Weibull distribution and its application to wind data in Section 2. Based on this literature, we then develop the methods used to answer the research questions in Section 3. These methods are then applied to real-life wind data collected over a time interval of 10 years for five different weather stations located in the Republic of Ireland; the results for which are presented under Section 5. We then discuss these results (5), draw a conclusion and give an outlook on possible future work under Section 6.

2 Related Work

A considerable amount of research has been carried out in the field of wind speed analysis which focuses on finding the optimal location for placing a wind turbine. In the following section, we first outline the use of the Weibull distribution in previous work, and secondly discuss common approaches to estimating the parameters of the distribution from wind speed data. Finally, we outline methods used to compare possible locations for wind turbines based on their respective estimated Weibull distributions.

2.1 The Weibull Distribution and its application to Wind data

A common approach evaluating if a proposed location for a wind turbine is fitting a Weibull distribution to historical wind speed data (Al-Hasan and Nigmatullin, 2003; Brano et al., 2011; Ajayi et al., 2011; Lun and Lam, 2000). Traditionally the two-parameter Weibull distribution with the scale parameter α and the shape parameter β (Wais, 2017a) is fitted on historical wind data (Lun and Lam, 2000; Seguro and Lambert, 2000; Rocha et al., 2012). However, more recent studies investigate the application of the three-parameter Weibull distribution, with an additional location parameter $\gamma > 0$ to model wind speed data. (Wais, 2017b) investigates the differences between the application of two and three-parameter Weibull distributions fitted on windspeed datasets and concludes that the three-parameter Weibull distribution is better suited for data containing a high amount of zero windspeed data points.

The Weibull distribution to estimate wind speed has been applied to various locations all over the world such as Palermo in Italy (Brano et al., 2011), Jordan (Al-Hasan and Nigmatullin, 2003), Brazil (Rocha et al., 2012), and Nigeria (Ajayi et al., 2011). This demonstrates the wide application and good modelling capabilities of the Weibull distribution applied to wind speed data and further justifies its application to wind speed data at different locations in Ireland.

Some studies utilize hourly wind speed data, which is a commonly used frequency in related research on the application of Weibull distributions to wind data (Carta and Ramirez, 2007; Al-Hasan and Nigmatullin, 2003). On the other hand, some studies even employ higher sampled twice hourly data (Brano et al., 2011).

Furthermore, though some related papers identified seasonal differences in the wind speed for certain locations (Al-Hasan and Nigmatullin, 2003), none of these studies seems to investigate if the wind speed differs significantly from one season to another.

2.2 Parameter Estimation for the Weibull Distribution

As it is not possible to derive the parameters of the Weibull distribution analytically, various numerical methods are employed to estimate their values. The most commonly used technique for fitting a distribution to data is the maximum likelihood estimate (MLE) (Seguro and Lambert, 2000; Ikbal et al., 2022). Another frequently used approach is the ordinary least squared (OLS) method (Wais, 2017b; Carta and Ramirez, 2007). Although some researchers advocate for the maximum likelihood estimate (MLE) as the better method for finding the best fitting parameters of the Weibull distribution (Arslan et al., 2014; Ikbal et al., 2022) others argue that the ordinary least squares (OLS) method is more suitable (Carta and Ramirez, 2007; Rocha et al., 2012).

There are also other – not widely used – methods used for parameter estimation. Al-Hasan and Nigmatullin (2003) use the Eigen-coordinates technique to find the best parameters, which involves reducing the dimensionality of the data by analysing eigenvectors of the correlation matrix and extracting important features (Al-Hasan and Nigmatullin, 2003). In addition, Arslan et al. (2014) also compares the use of Monte Carlo simulation and the L-moment-based method, which is an estimation method based on the linear combination of order statistics (Arslan et al., 2014).

However, neither of these methods is widely used for the Weibull distribution, resulting in MLE and OLS being the most commonly used parameter estimation techniques for the Weibull distribution on wind data. In line with Carta and Ramirez (2007) and Rocha et al. (2012), we decide to use the ordinary least square approach to fit the distribution to the data, as this approach seems to result in good distribution fits while being less computationally expensive than MLE.

2.3 Evaluation of the output of the fitted Weibull distribution

After determining the best parameters for the Weibull distribution based on historical wind data, it is still necessary to assess if a given location is suitable for wind turbine installation. This is because consistent power supply is critical for wind turbine placement (Sun et al., 2019; Coppez et al., 2010), and wind turbines cannot operate safely at wind speeds exceeding $21\frac{m}{s}$ (Lumbreras et al., 2015); both of these facts are something that evaluation metrics need to take into account. Additionally, the power generation of a wind turbine can be modeled using a power curve, which includes a cut-in value where the turbine begins generating power, a maximum power output value that is not exceeded even with higher wind speeds, and a cut-out value after which the turbine must be turned off (Schlechtingen et al., 2013; Carrillo et al., 2013).

Some studies evaluate the best location by calculating the expected power output by plugging in the expected wind speed data in the wind profile power law formula (Islam et al., 2011; Ajayi et al., 2011; Bilir et al., 2015), while others comment on the suitability of the distribution based on attributes of the probability density function (PDF), like mean, variance, skewness and kurtosis(Brano et al., 2011). However, none of these papers seems to take into account that most wind turbines cannot be operated over $21\frac{m}{s}$.

In line with previous work, the three-parameter Weibull distribution seems to be the more accurate approach to modelling wind data, so we prefer this distribution to the two-parameter Weibull. Furthermore, we use hourly data as previous literature has shown that this is an appropriate frequency of data points in the context of wind speed modelling. Based on the advantages outlined above, we decide to use the OLS to find the best parameter for the 3-parameter Weibull distribution. As we assume that for our locations in Ireland values over $21\frac{m}{s}$ wind speed occur quite often, we incorporate this fact to develop a new method to assess the suitability of a possible location for a wind power turbine compared to other locations.

3 Methods

3.1 Generalised Weibull Distribution with three parameters

In line with previous literature, we model wind data using a Weibull Distribution. The propabilty density function of the generalized weibull distribution with three parameter is given by

$$f(x;\beta,\alpha,\gamma) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1} e^{-\left(\frac{x-\gamma}{\alpha}\right)^{\beta}}, \tag{1}$$

where x is the random variable representing the wind speed. Moreover, α, β and γ are the parameters corresponding to the Weibull Distribution. In particular, α is the scale parameter, while β defines the shape. The third parameter γ reflects the location and its inclusion has empirically shown to benefit the goal of modelling wind data (Wais, 2017b).

3.2 Ordinary Least Squares for parameter estimation

As discussed in Section 2.2, we use Ordinary Least Squares (OLS) to estimate the three parameters in the Weibull distribution. Suppose that we have wind speed samples $x_1, x_2, ..., x_n$. Then location parameter γ is estimated as the minimum observed wind speed, i.e, $\hat{\gamma} = min(x_1, x_2, ..., x_n)$. The estimates $\hat{\alpha}$ and $\hat{\beta}$ cannot be found analytically and are therefore obtained using computational methods as discussed in Björck (1996).

3.3 Performance Measure

As suggested by Lumbreras et al. (2015), wind turbines can not operate safely at wind speeds over $21\frac{m}{s}$. Moreover, they also do not work when the wind speed is lower than $5\frac{m}{s}$. In order to determine whether a location l is suitable for a wind turbine, we investigate the probability that the wind speed is between these two critical values. We can quantify this probability by taking the area under the curve of the fitted Weibull distribution for each location per season. In other words, we are calculating

$$AUC_{l,s} = P(5 \leq X_{l,s} \leq 21) = \int_{5}^{21} f(x;\beta_{l,s},\alpha_{l,s},\gamma_{l,s})dx, \tag{2}$$

for every location l during a specific season s. It is of interest to compare the performance of different stations l given a season s. Intuitively, this implies that during season s the best location l for a wind turbine would be the one with the largest $AUC_{l,s}$ value.

3.4 Smirnov Kolmogorov Testing Framework

However, simply comparing these $AUC_{l,s}$ does not lead to robust results that we can use to advise a site, e.g. to government agencies. Therefore, we set up a testing framework, which allows us to assess whether the suitability of a location l significantly differs from the suitability of another location during season s.

This testing framework is built upon the methodology of the Smirnov-Kolmogorov test (Kolmogorov, 1933), which is used to compare an empirical cumulative distribution function (CDF) with its hypothesized theoretical counterpart.

Let us define the variable $y_{l,s,i}$, which is defined as

$$y_{l,s,i} = \begin{cases} x_{l,s,i} & \text{if } 5 \leq y_{l,s,i} \leq 21 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Then, we use the Smirnov Kolmogorov test to compare the CDF of station l_k, $F(Y_{l_k,s})$ to the CDF of station l_j, $F(Y_{l_j,s})$, where $k \neq j$. Using the traditional terminology of the Smirnov Kolmogorov test, the first CDF now reflects the empirical cumulative distribution, while the second CDF characterizes its hypothesized theoretical counterpart. If the maximum distance between $F(Y_{l_i,s})$ and $F(Y_{l_j,s})$ is large enough, the null hypothesis that the sample comes from the hypothesized distribution is rejected, suggesting that the two distributions (and therefore the suitability of stations l_i and l_j for season s) are significantly different.

Combined with the computed $AUC_{l,s}$ statistics, we can then directly compare the suitability of two stations for a given season s. In particular, if $AUC_{l_k,s} > AUC_{l_j,s}$ and the Smirnov Kolmogorov yields that the two distributions are significantly different, then we can conclude that station l_k is more suitable than station l_j for generating wind energy during season s.

4 Real Live Data

We gathered data for five weather stations(Dublin Airport, Roches point Cork, Athenry Galway, Malin Head Donegal, Mt. Dillon Roscommon) in Ireland distributed over the whole country as shown in Figure 1 from MET Ireland [2]. As mentioned in the literature review, hourly data proves to be the optimal frequency when modelling Weibull distribution.

Figure 1: Locations of the five selected weather stations

The granularity of hourly data further provides us with an enhanced level of detail, which facilitates greater accuracy in modelling and predicting wind behaviour. To ensure a robust analysis, we

[2] can be accessed under https://www.met.ie/climate/available-data/historical-data

employed data from the last decade(2013-2022), given its availability for all stations. This approach guarantees a sufficiently sizeable sample size while also enabling the inclusion of longer-term trends and patterns. This is particularly important since wind patterns are prone to significant fluctuations over time, which could exert a substantial impact on the functionality and output of wind turbines.

5 Results and Discussion

In the following we will comment on our results after applying our approach as outlined in 3.

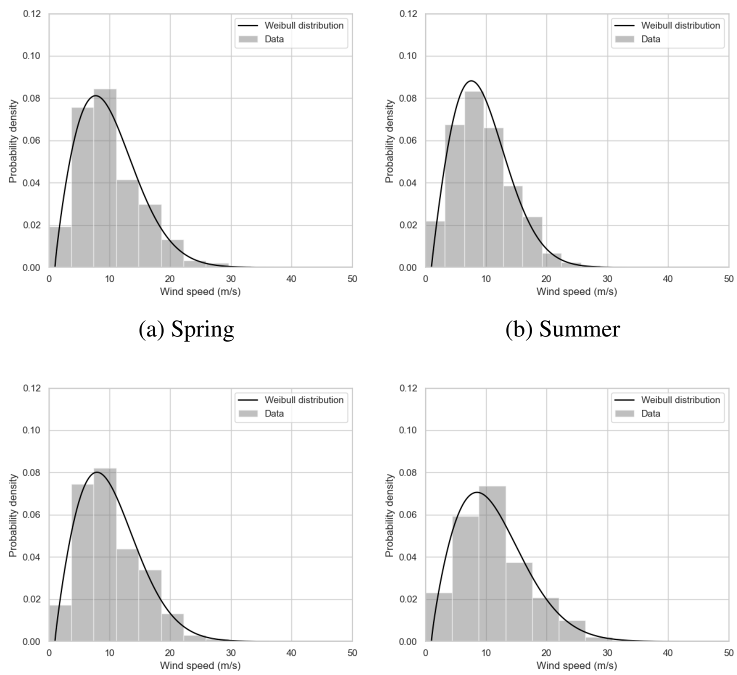
The values presented in Table 1 describe the parameters of the Weibull Distribution fitted on the data for all five stations along with the mean, median and the standard deviation of the metrics calculated. Also, as mentioned in 3.3, in order for a wind turbine to perform optimally and provide adequate throughput, the wind speeds recorded in a given region should be between $5\frac{m}{s}$ and $21\frac{m}{s}$. Hence, for every station, we have also reported the probability of the wind speed getting recorded within the range mentioned across all the four seasons to get a holistic view and enable effective decision making.

Table 1: Atributtes of Weibull distribution fitted on the whole dataset for different seasons

Location	season	α	β	γ	mean	median	σ^2	$p(5 \leq x \leq 21)$
Athenry Galway	winter	8.0827	1.6149	0.7181	7.9588	7.1597	21.1065	0.6867
	spring	7.5386	1.7328	0.6227	7.3406	6.7240	15.9805	0.6734
	summer	7.5265	1.8391	0.3103	6.9970	6.4769	14.2127	0.6561
	autumn	7.7082	1.7449	0.3570	7.2232	6.6048	16.4845	0.6579
Dublin Airport	winter	11.5273	1.8358	0.9990	11.2409	10.4401	33.4514	**0.8026**
	spring	10.1235	1.8662	0.9990	9.9878	9.3173	25.0143	0.8096
	summer	9.5450	1.9415	0.9990	9.4636	8.9020	20.6521	**0.8163**
	autumn	10.3288	1.8884	0.9990	10.1663	9.5057	25.4669	**0.8157**
Malin Head Donnegal	winter	18.7190	2.2648	0.0000	16.5808	15.9220	60.0889	0.6777
	spring	16.1877	2.0966	0.0000	14.3375	13.5915	51.5987	0.7403
	summer	14.8780	2.0697	0.0411	13.2200	12.5045	44.6216	0.7712
	autumn	17.4276	2.2884	0.0000	15.4385	14.8484	51.1349	0.7281
Mt. Dillon Roscommon	winter	8.1005	1.7908	0.2285	7.4340	6.8298	17.3183	0.6742
	spring	7.1103	1.6978	0.6260	6.9706	6.3557	14.7917	0.6426
	summer	6.7800	1.8349	0.4657	6.4898	6.0181	11.5833	0.6195
	autumn	6.9585	1.6963	0.3582	6.5678	5.9646	14.1913	0.6028
Roches point cork	winter	14.0068	1.8130	0.9990	13.4508	12.4420	50.5763	0.7536
	spring	12.4622	1.9987	0.6358	11.6803	11.0100	33.3695	**0.8151**
	summer	11.8635	1.9370	0.8568	11.3780	10.6751	32.0415	**0.8163**
	autumn	12.7781	1.8157	0.9990	12.3578	11.4414	41.9752	0.7809

From the values presented in Table 1, we can see that in general, for all the stations considered for this analysis, the scale parameter α is higher in the winter and autumn seasons, suggesting that the distribution is probably shifted to the right, with a higher probability of intense wind speeds getting recorded in these seasons across all stations. A similar observation can be made regarding the mean and median values for the stations across four seasons and it can be concluded that the average wind speeds in winter and autumn are higher in comparison to summer and spring seasons. We can also observe that the scale parameter α controls the height of the distribution. From the Weibull Distribution that is fit on the wind data captured from 'Dublin Airport' Station (Figure 2), and the one that captures 'Mt. Dillon Roscommon' station (Figure A.3), we can see that the higher the value of α is observed, we see more shift on the final curve towards the right which in turn leads to a higher average wind speed but a reduced peak frequency. The scale parameter α for all four seasons at 'Dublin Airport' region is adequate for a wind turbine to function optimally, suggesting suitable throughput. Additionally, if we consider the shape parameter β, we can see that the Weibull parameter is not high (in any season) rejecting the possibility of gusty winds which is not suitable for the functioning of the wind turbine.

In order to achieve optimal throughput, the region should have wind speeds getting recorded within the range of $5\frac{m}{s}$ and $21\frac{m}{s}$ consistently throughout the year. From the values presented in the table above, we can see that the probability of recording wind speed within the desired range at 'Dublin Airport' station across all seasons is approximately 80%. A similar kind of conclusion can be made for the 'Roches Point Cork' station wherein the probability of recording wind speed within the desired range is close to 81% in spring and summer, but a bit lower for autumn and winter seasons. For all the other stations, the probability of recording wind speeds within the desired range is quite low and varies erratically within seasons. Such a variation is highly unreliable and would not be the right choice for installing a wind turbine.



(a) Spring (b) Summer

(c) Autumn (d) Winter

Figure 2: Output of the Weibull distribution fit on the whole data set for Dublin airport

In order to determine which station is better, we also have to check if the values recorded in one station are different when compared to the other station. From the values presented in B.1, we can see that the highest Kolmogorov–Smirnov statistic observed is for comparing the stations 'Malin Head Donegal' and 'Mt. Dillon Roscommon' for the autumn season, suggesting that the wind speeds recorded from both these stations are the most different during that time of the year. One common observation is that the Kolmogorov–Smirnov statistic is higher for the stations which are geographically farther from each other. If we consider the Kolmogorov–Smirnov statistic for 'Dublin Airport' station compared to all the other four stations, we can see that the magnitude of the statistic value is significantly high and the wind speed recorded is notably different from other stations. In terms of the statistical significance of the values, we can observe that the p-values for all the recordings are particularly low (less than 0.05), suggesting that the distributions of the samples being compared are different.

Considering all these attributes of the wind stations analysed for this use-case, we can fairly conclude that the 'Dublin Airport' station is the best choice to install a wind turbine, which from a statistical point of view, is expected to provide maximum throughput when compared to all the other stations.

This helps us answer the first research question where we are trying to identify whether a given location is better suited for installing a wind turbine when compared to all other locations.

Additionally, if we consider the Kolmogorov–Smirnov test to determine the difference of wind speeds in a station between seasons, we can observe that the KS Statistic is significantly lower for consecutive seasons (Table B.3). For example, the difference in wind speeds between winter and autumn would be significantly lower than the difference in wind speeds between winter and summer. This observation is true for all the stations. In general, the magnitude of the KS statistic observed between winter and summer is the highest. Additionally, if we consider the wind speed probability values reported in Table 1, we can see that the probability of wind speeds getting recorded in the range of $5\frac{m}{s}$ and $21\frac{m}{s}$ in summer season is significantly higher for almost all stations. For 'Dublin Airport' station, we can see that there is 81.6% probability of wind speeds hitting the specified range in summer with considerable scale parameter α and shape parameter β, which is the principle requirement for a wind turbine to function optimally. This suggests that the most throughput can be obtained from a given station from a wind turbine in the summer season. A similar probability value is observed for the 'Roches Point Cork' station in the summer. But when other seasons are considered, 'Dublin Airport' station has greater reliability across all seasons of a given calendar year. Hence, based on the arguments presented above, we can fairly conclude that the 'Dublin Airport' region can be best suited for installing wind turbines with the maximum throughput expected. For the said region, maximum throughput is expected in the summer season. This helps us answer our second research question where we see the influence of the season of a year to determine whether the region is best suited to install a wind turbine.

6 Conclusion

To assist in the transition from fossil fuels to renewable energy, this study provides a comparative analysis of five potential wind turbine sites in Ireland (Dublin Airport, Roches Point Cork, Athenry Galway, Malin Head Donegal, Mt. Dillon Roscommon).

Our results indicate that Dublin Airport is the most appropriate location for constructing a wind power station for the five stations analysed. Using historical data, we find reliable wind patterns at this location, which ensure that potential wind turbines can be operative for a large majority of the time for every season. A second choice location with interesting attributes would be Roches Point, Cork. Even though the performance of wind turbines would not be as consistent across seasons as in the case of Dublin Airport, Roches Point empirically shows to be an attractive location for wind turbines, which would especially be productive during the spring and summer seasons. We advise decision-makers to consider these specific locations when determining the most suitable place for a wind turbine.

We can further demonstrate that there are significant differences between each season at each location, which should be taken into account by decision-makers to ensure the stability of the electricity grid throughout the year.

Further research should aim to extend our statistical framework by constructing a more sophisticated performance measure, which is subsequently used to compare the suitability of the different stations. A suggestion would be to transform the wind speeds directly to power usage, using insights from engineering.

In conclusion, our work can be seen as a valuable step towards identifying suitable locations for wind turbines, taking into account inter-seasonal variability and thus the stability of the electricity grid. We sincerely hope that our work will contribute to the transition to renewable energy and the fight against human-made climate change.

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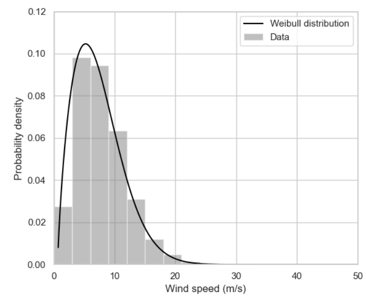
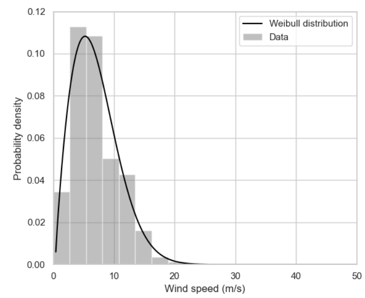
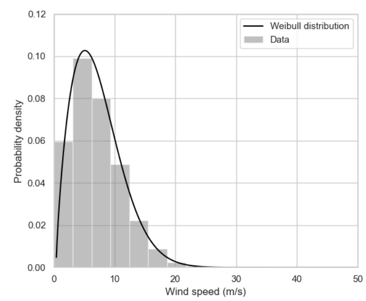
A Visual Outputs of the Weibull Distribution fits



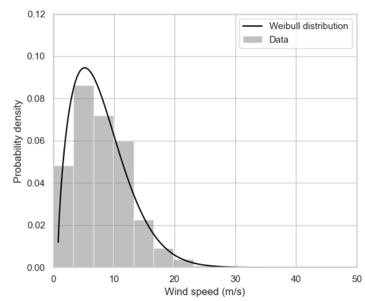
(a) Spring



(b) Summer

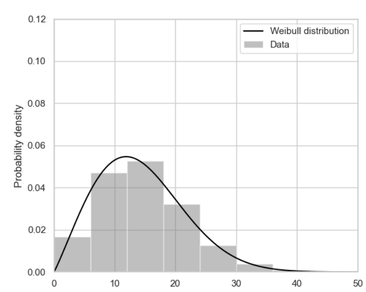


(c) Autumn

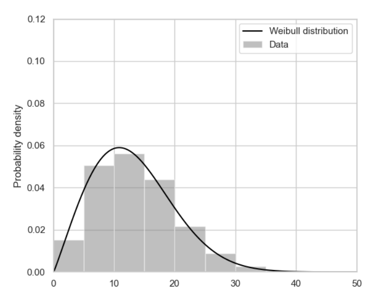


(d) Winter

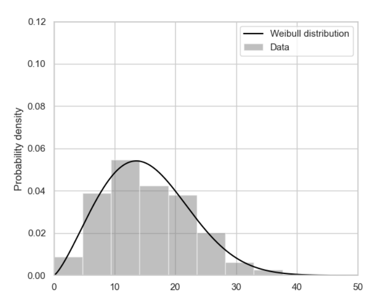
Figure A.1: Output of the Weibull distribution fit on the whole data set for Athenry Galway



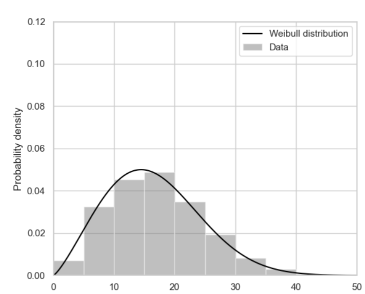
(a) Spring



(b) Summer

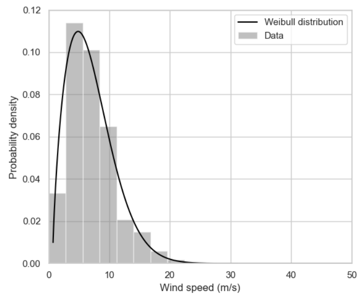


(c) Autumn

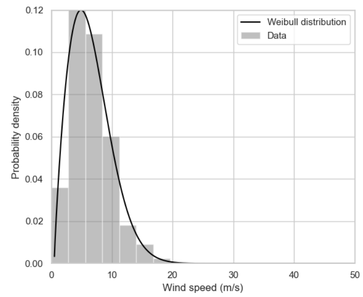


(d) Winter

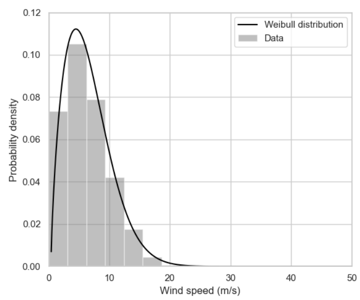
Figure A.2: Output of the Weibull distribution fit on the whole data set for Malin Head Donnegal



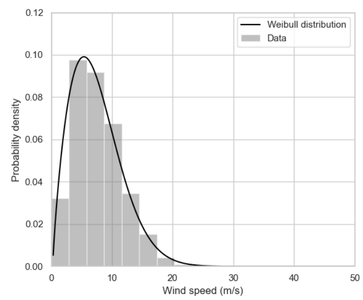
(a) Spring



(b) Summer

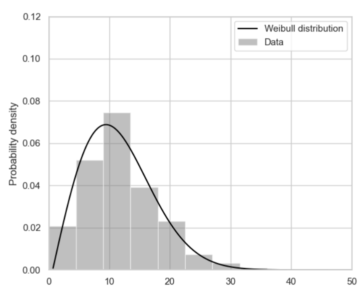


(c) Autumn

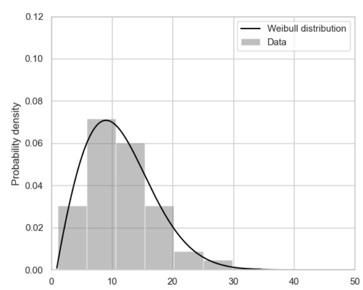


(d) Winter

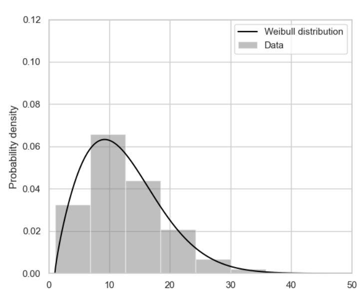
Figure A.3: Output of the Weibull distribution fit on the whole data set for Mt. Dillon Roscommon



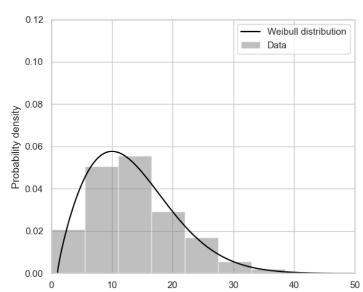
(a) Spring



(b) Summer



(c) Autumn



(d) Winter

Figure A.4: Output of the Weibull distribution fit on the whole data set for Roches point cork

B Kolmogorov–Smirnov test

B.1 Between Stations

Table B.1: Results of pairwise Kolmogorov–Smirnov test on whole distribution

location1	location2	season	ks statistics	p value
athenry galway	dublin airport dublin	winter	0.2441	0.0000e+0
		spring	0.2231	0.0000e+0
		summer	0.2237	0.0000e+0
		autumn	0.2467	0.0000e+0
	malin head donegal	winter	0.5158	0.0000e+0
		spring	0.4704	0.0000e+0
		summer	0.4429	0.0000e+0
		autumn	0.5288	0.0000e+0
	mt dillon roscommon	winter	0.0444	9.6857e-22
		spring	0.0356	2.1198e-14
		summer	0.0586	2.7156e-38
		autumn	0.0622	1.1596e-42
	roches point cork	winter	0.3488	0.0000e+0
		spring	0.3430	0.0000e+0
		summer	0.3491	0.0000e+0
		autumn	0.3668	0.0000e+0
dublin airport dublin	malin head donegal	winter	0.3130	0.0000e+0
		spring	0.2822	0.0000e+0
		summer	0.2675	0.0000e+0
		autumn	0.3365	0.0000e+0
	mt dillon roscommon	winter	0.2850	0.0000e+0
		spring	0.2586	0.0000e+0
		summer	0.2824	0.0000e+0
		autumn	0.3046	0.0000e+0
	roches point cork	winter	0.1279	1.2451e-177
		spring	0.1329	1.1067e-195
		summer	0.1470	2.3676e-239
		autumn	0.1383	1.4855e-209
malin head donegal	mt dillon roscommon	winter	0.5567	0.0000e+0
		spring	0.5012	0.0000e+0
		summer	0.4902	0.0000e+0
		autumn	0.5801	0.0000e+0
	roches point cork	winter	0.1854	0.0000e+0
		spring	0.1662	2.7816e-306
		summer	0.1246	4.6011e-172
		autumn	0.1993	0.0000e+0
mt dillon roscommon	roches point cork	winter	0.3932	0.0000e+0
		spring	0.3748	0.0000e+0
		summer	0.4018	0.0000e+0
		autumn	0.4240	0.0000e+0

Table B.2: Results of pairwise Kolmogorov–Smirnov test between 5 and 21

location1	location2	season	ks statistics	p value
athenry galway	dublin airport dublin	winter	0.1231	7.3893e-120
		spring	0.1128	7.2765e-101
		summer	0.1177	1.2571e-108
		autumn	0.1393	3.0142e-151
	malin head donegal	winter	0.1586	8.5262e-184
		spring	0.1790	1.4069e-245
		summer	0.1338	1.7182e-137
		autumn	0.1648	2.1370e-201
	mt dillon roscommon	winter	0.1426	7.7978e-139
		spring	0.1682	3.7990e-188
		summer	0.1753	7.3411e-197
		autumn	0.1637	6.0543e-168
	roches point cork	winter	0.1382	8.9075e-141
		spring	0.1515	5.4368e-175
		summer	0.1645	6.0365e-205
		autumn	0.1453	2.3311e-154
dublin airport dublin	malin head donegal	winter	0.1303	7.8158e-136
		spring	0.1361	3.1572e-158
		summer	0.1338	6.7056e-157
		autumn	0.1135	1.4060e-108
dublin airport dublin	mt dillon roscommon	winter	0.1217	5.3268e-110
		spring	0.1430	1.9758e-149
		summer	0.1462	1.5561e-152
		autumn	0.1287	1.6191e-115
	roches point cork	winter	0.0721	3.6926e-42
		spring	0.1113	2.3788e-105
		summer	0.1095	2.2947e-103
		autumn	0.0942	1.0461e-73
malin head donegal	mt dillon roscommon	winter	0.1754	1.9220e-212
		spring	0.1790	4.1376e-227
		summer	0.2060	3.6333e-298
		autumn	0.1620	3.3742e-175
	roches point cork	winter	0.1009	6.4965e-76
		spring	0.1053	7.7291e-91
		summer	0.0981	4.4601e-81
		autumn	0.1007	7.6471e-80
mt dillon roscommon	roches point cork	winter	0.1382	9.9480e-133
		spring	0.1515	6.8440e-162
		summer	0.1645	5.4357e-187
		autumn	0.1453	3.4783e-139

B.2 Between seasons

Table B.3: K-S test between seasons

location	season1	season2	ks statistic	p value
athenry galway	winter	spring	0.0571	1.2214e-37
	winter	summer	0.0849	1.0502e-82
	winter	autumn	0.0618	8.3438e-44
	spring	summer	0.0309	1.8562e-11
	spring	autumn	0.0177	5.0000e-4
	summer	autumn	0.0259	4.4133e-8
dublin airport dublin	winter	spring	0.0891	4.3752e-91
	winter	summer	0.1314	4.6732e-198
	winter	autumn	0.0752	1.3160e-64
	spring	summer	0.0425	2.8978e-21
	spring	autumn	0.0185	2.0000e-4
	summer	autumn	0.0597	3.1341e-41
malin head donegal	winter	spring	0.1296	9.4887e-193
	winter	summer	0.1851	0.0000e+0
	winter	autumn	0.0588	1.3397e-39
	spring	summer	0.0573	3.0719e-38
	spring	autumn	0.0712	1.6598e-58
	summer	autumn	0.1285	4.5312e-190
mt dillon roscommon	winter	spring	0.0522	5.7532e-29
	winter	summer	0.1033	2.8302e-112
	winter	autumn	0.0877	1.9396e-80
	spring	summer	0.0512	3.9719e-28
	spring	autumn	0.0441	7.5886e-21
	summer	autumn	0.0245	9.9105e-7
roches point cork	winter	spring	0.1086	4.9457e-124
	winter	summer	0.1241	5.1689e-162
	winter	autumn	0.0655	5.0068e-45
	spring	summer	0.0275	2.0555e-8
	spring	autumn	0.0460	1.2803e-22
	summer	autumn	0.0619	1.2601e-40