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Wellington Wind Climate: Observation Using Synthetic Wind Data

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ABSTRACT

Half a million years of synthetic wind data is generated using the autocorrelation function of the von Karman model and for the Weibull probability distribution for Wellington (New Zealand). The shapes of typical models for the extremes are compared. The penultimate model with a Weibull shape parameter higher than that for the parent data is shown to closely follow the shape of the synthetic data. The Offset Ellipse Normal model for the annual period is tentatively used to help with the separation of the wind mechanisms and to generate synthetic data for individual mechanism separately. The periodic components of diurnal frequency feature in two mechanisms (ellipse), for the northerly winds of relative high speeds, high Weibull parameter and low integral time scale, having a significant impact on the extreme distribution. Additional OEN fit for all hours and month of the years is needed to better separate the mechanisms and re-evaluate the distribution of the extremes.

1. Introduction

One of the noticeable changes introduced in the recent revision of the Australian and New Zealand Standard for Wind Loading is the change in slope of the curve for the design wind speed V. Return Period in New Zealand, meaning that the ratio of the ULS over SLS design wind speeds has reduced, and is now lower than in other regions of similar wind climate affected by extra tropical storms. This result was obtained through a detailed wind climate data and Extreme Value Analysis using GEV models (Pirooz, 2021). A similar result was obtained using a penultimate method (Verhaeghe, 2021), although this ratio was shown to be potentially even lower. This paper continues investigation of the wind climate in Wellington using a method to generate synthetic wind data. It uses the synthetic data to compare the shape of the different statistical models. It reviews the autocorrelation function (ACF) for the entire time-history and identifies diurnal mechanisms. An initial attempt is made to use the Offset Elliptical Normal (OEN) mixture model to discuss wind mechanisms further and generate time-histories for individual mechanism. This study is an initial work in progress largely based on recent publications by RI Harris and NJ Cook and makes use of open-source scripts[1] modified by the author for the purpose of this study and using his own wind speed dataset.

Wellington Wind Climate

Wellington is located in the Cook Strait, a sea channel separating the north and south islands of New Zealand. The wind climate is influenced by the topography located either side of the Strait as approaching winds are forced and accelerated in between the two islands. Strong winds are generally generated by low-pressure weather systems and blow from the two prevailing north and south wind

[1] Wind Engineering Cookbook: Recipes in R www.njcook.uk

directions depending on the location of the depressions in relation with New Zealand. The approach of cold fronts from the south also tends to create strong southerly winds. (Chappell, 2014) also mentions the occurrence of diurnal winds. The data used in the analysis below are the time-histories of the mean wind speeds recorded at Wellington Airport over a 25-year period acquired from MetService. The data was checked for general homogeneity. Before any analysis, the wind speed data were corrected for roughness exposure using the ESDU (1974), to be consistent with Open-Country terrain (z_0=0.02) exposure and at 10m height.

Overview of Method to Generate Synthetic Time Series of Wind Data

The method used to generate time series is that provided in (Harris, 2017) for a parent data of Weibull probability distribution and a given ACF. Only a summary is provided below. The procedure consists in producing two independent series normally distributed using a suitable Random Number Generator. These two series will ultimately be series of coordinates of the wind speed vector in the cartesian axis system. The ACF of the two vectorial components is calculated from the target ACF function of the wind speed vector with the required Weibull form. A set of autoregressive model coefficients is calculated based on the ACF and applied to the two vectorial components to convert them into correlated series. The two components are then squared and added to provide the time series of the wind speeds of a given Weibull index and auto-correlation function. The scripts used in (Cook,2018) for a Rayleigh distribution are adapted for the Weibull k-shape parameter of Wellington. It uses the von Karman (vK) ACF as the target function for the closest integral time scale.

Autocorrelation Function for Wellington

The ACF for Wellington and for the entire time-histories is shown in Figure 1 below for the different time lags. The presence of sinusoidal forms in the observed ACF indicates seasonal and diurnal deterministic period components. As the ACF needed above is that for the macro meteorological random component, it needs to be stripped from the deterministic components. This filtering operation is completed using the method of (Harris, 2008) and extended as in the available R scripts to remove the sidebands, by identifying the harmonics and subtracting them from the observed ACF. The ACF of the von Karman model is then fitted to match the ACF for Wellington by adjusting the integral time scale. The von Karman ACF with the corresponding integral time scale is that used as the target ACF for the generation of synthetic data. The integral timescale was found to be equal to 14 hours, which is relatively short compared to other comparable climates.

Weibull Distribution for Wellington

The cumulative probability distribution was derived from the observed dataset and fitted to a Weibull cumulative distribution function. The Weibull fit revealed a relatively high Weibull k-shape parameter equal to 2.35. The Weibull fit departs from the observed distribution at low wind speeds but improve for higher wind speeds.

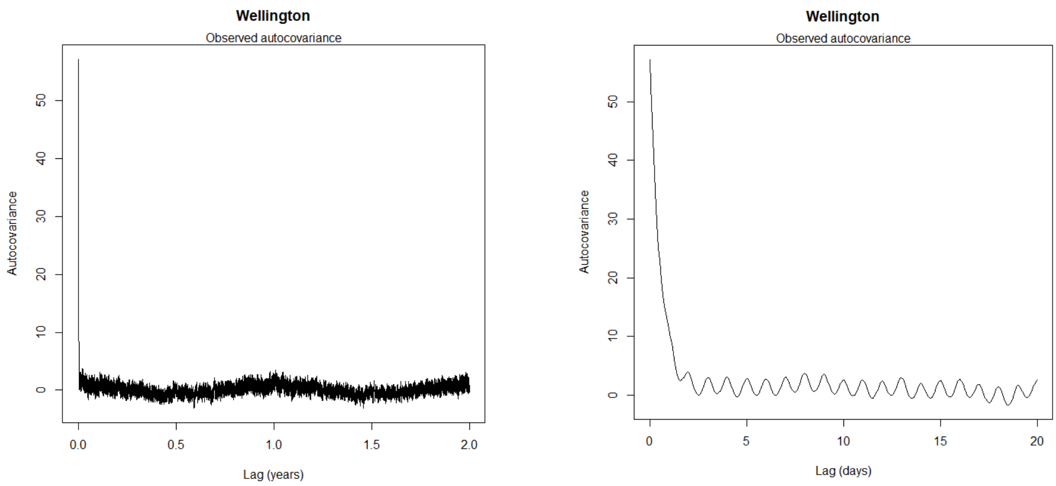

Figure 1. Observed ACF for Wellington (Extract from Cook Software)

Synthetic Parent Wind Data

Based on the ACF of the Von Karman model and the Weibull k-shape parameter above, half a million years of wind data were generated. These data are accumulated in the form of histograms for the analysis. The cumulative probability distribution of the parent synthetic data is shown in Figure 2(a) and confirms a Weibull distribution of shape parameter equal to 2.35.

Shape of the Curve Formed by Extreme Wind Speeds

Annual maxima were extracted from the synthetic data as well as the storm maxima using the Method of Independent Storms (MIS). The plotting positions of the wind speeds were derived using the XIMIS method (Harris,2009) in black, and the annual maxima using (Gringorten,1963), in green. Note that for the purpose of the study, and to highlight the difference in shape of the distribution, all data points are normalized using the corresponding mode, i.e. wind speed at y = 0.

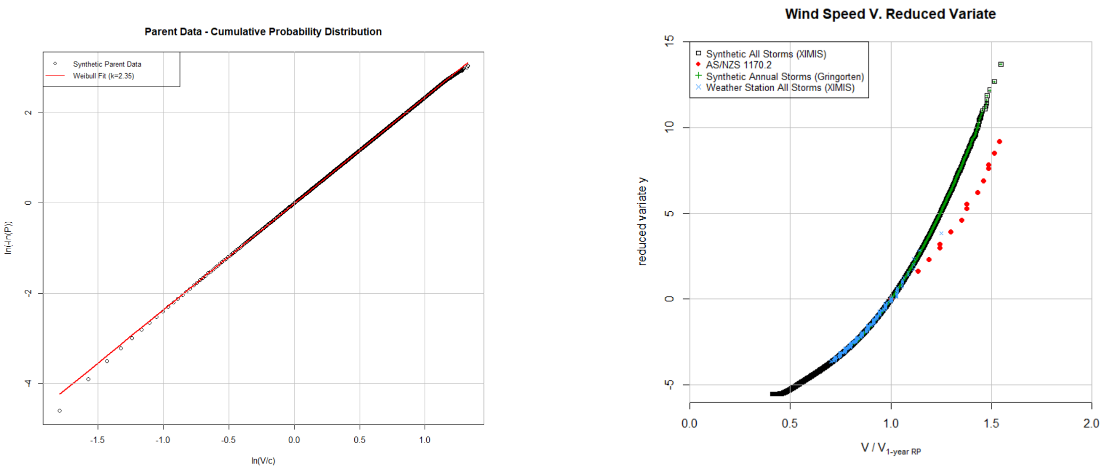

Figure 2 (a) Weibull Fit to Synthetic Parent Data (500,000 years). (b) Synthetic and Observed Storm Data

As highlighted in (Cook,2018) but repeated here, the plotting positions from XIMIS and Gringorten are indistinguishable, but XIMIS includes more data points in the lower tail. The storm data extracted from the observed dataset are also plotted in blue using the XIMIS plotting positions, as obtained from a previous study (Verhaeghe,2021), noting the set was left-censored. As shown in Figure 2(b), the shape of the curve formed by the synthetic storms matches that of that of the observed dataset and is as expected.

Models of Extreme Value Distributions

The typical models for Extreme Value (EV) Distributions are shown in Figure 3. The Fisher-Tippett Type I (FT1), i.e. penultimate V^2-fit, and penultimate $V^{2.55}$ - fit for the observed storm data (in blue in Figure 2, but not repeated in Figure 3), as previously obtained from (Verhaeghe,2021). The shape of the Type 3 EV model is that of AS/NZS 1170.2:2021 shown in red and is generally ''flatter'' than the others, before curving upward more significantly for very high Return Period. The shape of the FT1 model is steeper but tends to gradually depart from the synthetic storms. The penultimate $V^{2.55}$-fit model tends to follow more closely the shape of the curve formed by the synthetic storms, although it is not quite exact neither for very high return period. Also note the difference in the Weibull k-shape parameter (=2.35) between the parent synthetic data and that for that penultimate fit (=2.55). This might be a result of the slight difference in shape between the synthetic and observed data, itself a result of the presence of different mechanisms (See below), and / or the dependence on the wind speed of the annual rate of independent event as in (Cook, 2018). More analysis is needed as detailed below.

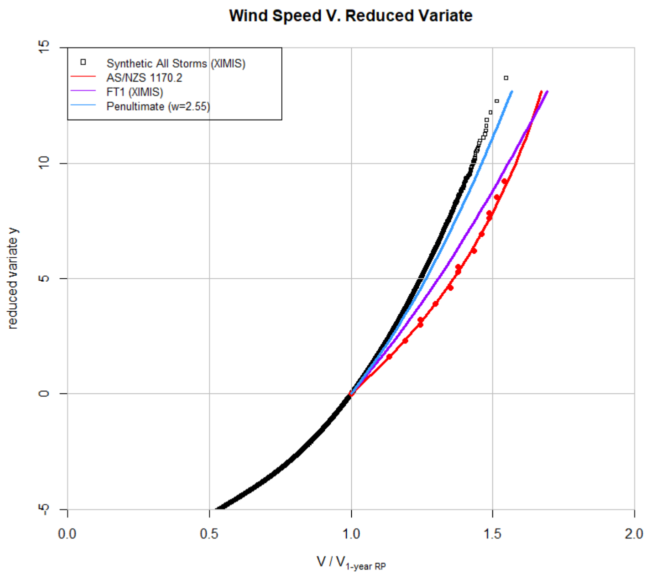

Figure 3. Synthetic Storms & Extreme Wind Speed Models (Normalised by Mode)

Use of the OEN model

The relatively recent methodology by Harris and Cook (2014) using the Offset Elliptical Normal (OEN) model was applied to Wellington. The OEN mixture model for a mixed climate of n disjoints wind mechanism is given as follows:

$$p(x,y) = \sum_{i=1}^{n} f_i \times p_i(x,y) \tag{1}$$

Each distribution p_i can be represented in the x-y cartesian plan by an ellipse rotated and offset from the origin by the mean wind vector. The results below summarize an initial attempt by the author to use the procedure and differs slightly from the procedure outlined by Cook. The result for the annual period is shown in Figure 4.

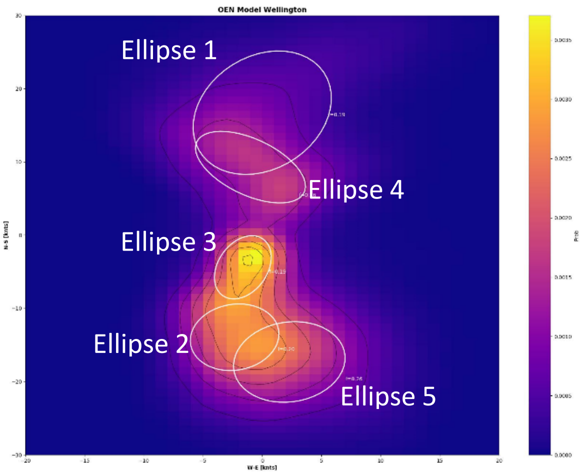

Figure 4. Annual OEN Model

Individual or groups of ellipses were analyzed separately. All observations in the time-history of the observed dataset were weighted by the probability to belong to each ellipse, as in (Cook, 2021). For each ellipse or group of ellipses of interest, the ACF was then computed again using these weighted observations. In parallel, the OEN probability distribution for the selected ellipses were marginalized and fitted to a new Weibull form, hence allowing the derivation of synthetic data for individual or group of ellipses, exactly as for the entire observed dataset. This was tentatively done for the ellipses in Table 1, noting there is no certainty yet over the relevance of the groups of ellipses until a more detailed OEN analysis is done as mentioned below.

Table 1. Integral Time Scale & Weibull Parameters for Groups of Ellipses

Ellipses	**vK Integral Timescale [Hr]**	**Weibull k**	**Weibull c [m/s]**
2,5	9.7	3.1	9.45
1,4	16.6	2.3	9.04

As shown in Table 1, the ACF for the group "Ellipse 2,5" for the strong northerly winds has a relatively low integral timescale and features the periodic components although these are more marked than for the full dataset. Individual Ellipse 2 and 5 feature broadly the same level of periodic components, indicating that the OEN annual fit may not have been entirely successful at separating the diurnal wind component. The periodic components are not shown to be included in Ellipse 3, which would tend to capture lighter winds, potentially more consistent with a sea breeze. An annual analysis is not sufficient in this case and a more detailed OEN analysis by Month and Hour is needed, similar to (Cook, 2021). It is also possible the topography would tend to bias the distributions directionally, making it harder for the OEN fit to separate the different mechanisms. Also note the relatively high Weibull k-shape parameter for the northerly winds, which is also confirmed by doing a simple directional Weibull fit on the observed data. This value is reasonably high and may be the result of the occurrence of more mechanisms than highlighted in Figure 4. Synthetic wind series for the group "Ellipses 2, 5" were generated. The resulting curve was found to be significantly steeper than that shown in Figure 2, having a substantial impact on the shape of the distribution of the extremes. Separating the wind mechanisms more clearly than in Figure 4 and analyzing the various mechanism separately is needed for Wellington.

Conclusions

The shape of the curve for New Zealand extreme wind speeds has changed in the recent revision of the Australian and New Zealand Standard. This study used a method to generate long-term synthetic data and compare the shape of typical models for the extremes. It was shown that the penultimate model with a relatively high Weibull parameter matches relatively well the synthetic storm data. The OEN model for the annual was tentatively used to help with the separation of the wind mechanisms and generate synthetic data for individual mechanism. The periodic components were included in two ellipses of relative high speed, high Weibull parameter and low time scale, having a significant impact on the extreme distribution for these mechanisms. Additional OEN fit for all hours and month of the years is needed to separate the mechanisms and evaluate the distribution of the extremes.

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