Machine learning methods for predicting wind generation

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Version control

Version	Date amended	Comments
1	23/5/2022	First draft
2	25/5/2022	reviewed
3	30/05/2022	Reviewed EC
4	2/6/2022	Removed coverage metric
5	11/7/2022	Accepted all changes

Executive summary

We use the Gluon Time-Series Toolkit (GluonTS), a Python library for deep learning time series modelling, to forecast wind generation.[1] Specifically, we built a model that considers any number of explanatory variables to forecast the wind generation in each trading period. This work was motivated by the rather poor wind generation forecasts that contributed to the grid emergency on 9 Aug 2021. We focus on the windfarms located in Wellington (Meridian) and Tararua (Mercury – formerly Tilt). We find that weather observations (such as wind speed and direction) close to the wind farm are the greatest factors that determine generation. Our results show that this is a promising method for capturing the overall trends, if not the actual generation of these wind farms.

1 (i) A. Alexandrov et al., GluonTS: Probabilistic and Neural Time Series Modeling in Python, J. Mach. Learn. Res. 21(116), 2020. (ii) A. Alexandrov et al., arXiv:1906.05264, 2019.

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1 Introduction

1.1 GluonTS (Gluon Time-Series Toolkit) is the first ever dedicated toolkit for building time series models based on deep learning and probabilistic modelling techniques.[2] It bundles components, models and tools for time series applications like forecasting and anomaly detection. Well-established open-source packages like TensorFlow and PyTorch can perform time-series forecasting, but they require a comparatively large amount of coding and therefore great proficiency in the area of machine learning.

1.2 Given a probabilistic model, the goal of forecasting is to predict the probability distribution of future values given the past values, the associated covariates to the time-series data (i.e. data features), and the model's hyperparameters.

1.3 GluonTS can parse sequences of large collections of time series. The package provides a wide variety of algorithms to build neural network-based models. For example, the DeepAR[3] algorithm uses a recurrent neural network (RNN) to generate a probabilistic forecast using parametric distribution and providing quantiles of the distribution.

1.4 For more details on the algorithm and an overview on neural networks, refer to chapter 7 of the October-December 2021 Quarterly Review.[4]

2 Data inputs and output

2.1 We want to feed inputs into the GluonTS algorithm to see how they affect the wind generation in Wellington and Tararua. Figure 1 shows a schematic of how we train and use the model.

2.2 Inputs are the wind speed (kph), wind direction, and air pressure (hPa). The output is wind generation (MW)[5].

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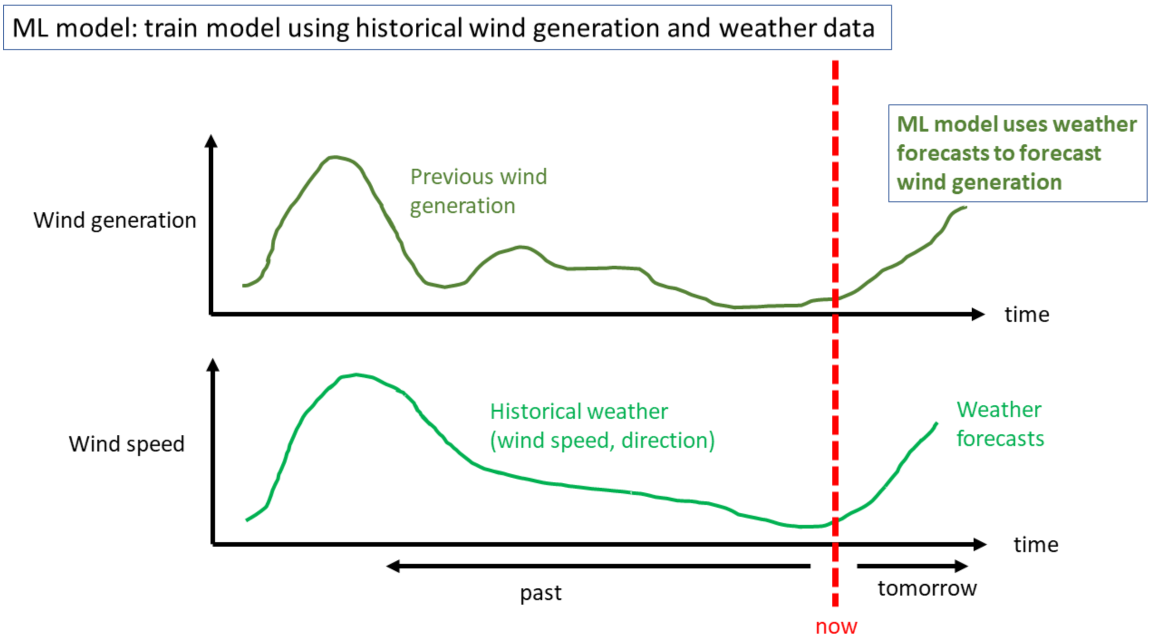
2 A. Alexandrov *et al.*, GluonTS: Probabilistic and Neural Time Series Modeling in Python, *J. Mach. Learn. Res.* **21**(116), 2020.

3 D. Salinas *et al.*, DeepAR: Probabilistic forecasting with autoregressive recurrent networks, *Int. J. Forecast.* **36**(3):1181-1191, 2020.

4 https://www.ea.govt.nz/monitoring/enquiries-reviews-and-investigations/2021/market/

5 Source: Electricity Authority.

Figure 1: Schematic of wind forecasting process



Source: Electricity Authority

2.3 We use equally spaced timesteps of 30 minutes, starting from 1 Jan 2016 00:00:00. We choose 8 Apr 2022 23:59:59 as the end date, which gives us over 100,000 consecutive timesteps (i.e. trading periods) to sufficiently train and test the model.

2.4 For the Wellington site, we consider Meridian's wind farms where the grid injection points (GIPs) are

(a) West Wind: WWD1102, WWD1103

(b) Wilton: WIL0331.

2.5 For the Tararua site, we consider Mercury's (formerly Tilt's) wind farms where the GIPs are

(a) Bunnythorpe: BPE0331,

(b) Linton: LTN0331,

(c) Tararua Wind Central: TWC2201.

2.6 We take the average wind speed and wind direction of the following weather stations:

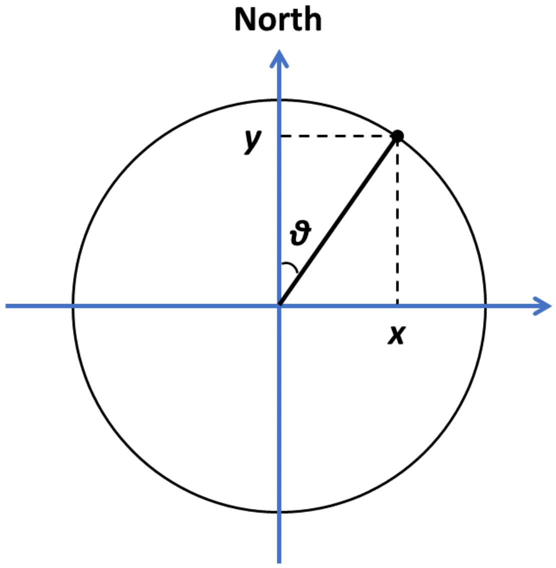
(a) Wellington: Kelburn, Wellington Airport, Aotea Quay

(b) Tararua: Palmerston North Airport.

2.7 Wind direction is given in degrees ϑ where North is 0° and East is 90°. This cyclical feature means that even though 0° and 359° point in nearly the same direction, the model may interpret the values as something physically different. Hence it is important to convert these features into a representation that preserves information such as 0° and 359° being close to each other.

2.8 The best way to handle this is to calculate the sine and cosine component to represent the cyclical feature as (*x*, *y*) coordinates of a circle. In this representation, 0° and 359° are next to each other numerically, as they should be (Figure 2).

Figure 2: Wind direction given as angle ϑ. We convert this into Cartesian (*x*, *y*) coordinates



2.9 Table 1 shows examples of the conversion from direction in degrees to its (*x*, *y*) coordinates.

Table 1: Example of converting wind direction in degrees to its *x* and *y* component

Wind direction (ϑ)	$x = \sin \vartheta$	$y = \cos \vartheta$
North (0)	0	1
East (90)	1	0
South (180)	0	-1
West (270)	-1	0

2.10 We shall assume that today is 7 Apr 2022 and predict tomorrow's wind generation using weather forecasts[6].

6 Source: Weather Underground.

Table 2: Correlation matrix showing relationships between wind generation and weather features for Wellington

	Wind speed, kph	Wind direction, x	Wind direction, y	Pressure, hPa	**Wind generation, MW**
Wind speed, kph	1	-0.0879	0.1050	-0.2261	**0.8045**
Wind direction, x	-0.0879	1	-0.1734	0.2301	**-0.0651**
Wind direction, y	0.1050	-0.1734	1	-0.2206	**0.2982**
Pressure, hPa	-0.2261	0.2301	-0.2206	1	**-0.2346**
Wind generation, MW	**0.8045**	**-0.0651**	**0.2982**	**-0.2346**	**1**

Source: Electricity Authority

2.11 The correlation matrices show a positive relationship between wind generation and wind speed in Wellington (Table 2) and Tararua (Table 3). In Wellington, there is a positive correlation of 0.3 between generation and wind along the North-South direction (y component). This suggests that wind coming from the north is weakly correlated with linearly increasing wind generation. Similarly, in Tararua, there is a negative correlation of -0.31 between generation and wind along the East-West direction (x component). This means wind coming from the west is weakly correlated with linearly increasing generation.

Table 3: Correlation matrix showing relationships between wind generation and weather features for Tararua

	Wind speed, kph	Wind direction, x	Wind direction, y	Pressure, hPa	**Wind generation, MW**
Wind speed, kph	1	-0.1761	-0.2095	-0.1379	**0.6579**
Wind direction, x	-0.1761	1	-0.3635	0.1712	**-0.3121**
Wind direction, y	-0.2095	-0.3635	1	-0.0885	**0.1296**
Pressure, hPa	-0.1379	0.1712	-0.0885	1	**-0.1483**
Wind generation, MW	**0.6579**	**-0.3121**	**0.1296**	**-0.1483**	**1**

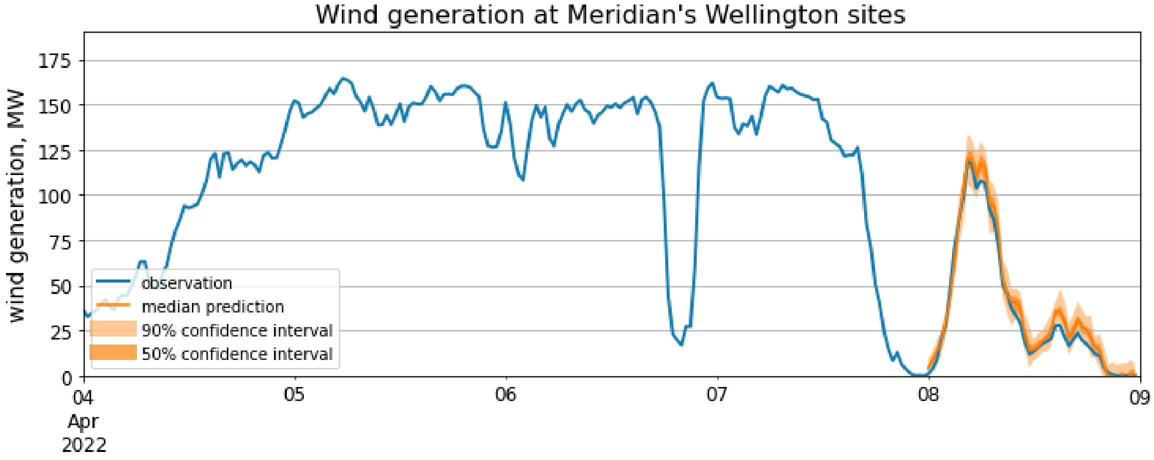
Source: Electricity Authority

3 Results

3.1 Here we show our forecasts for wind generation at Meridian's Wellington windfarms at West Wind and Wilton (Figure 3:), and Trustpower's windfarms in Tararua, Linton and Bunnythorpe (Figure 4:). There was large variation in wind generation on 8 Apr 2022, which gives us an excellent opportunity to test the GluonTS model.

Figure 3: Wellington wind generation forecast for 8 Apr 2022

Model trained model using 40 epochs.

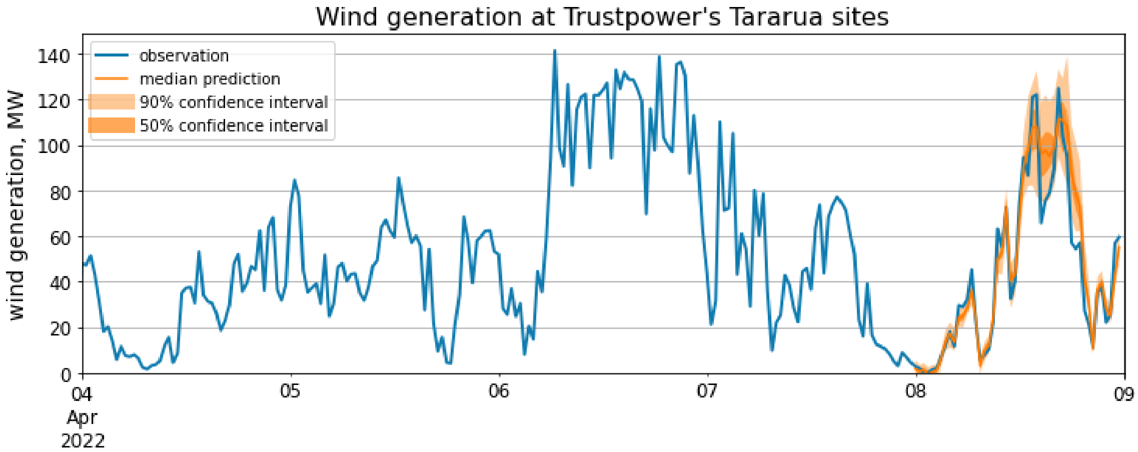


Source: Electricity Authority

3.2 Probabilistic forecasting requires that we learn the distribution of future values, so we need to specify the type of distribution of future values. GluonTS comes with many different distributions like Gaussian, Student-t, and Uniform. By default, the model assumes a Student-t distribution and long short-term memory cells (LSTM) cells. As a first test, we use these parameters to build our model.

Figure 4: Tararua wind generation forecast for 8 Apr 2022

Model trained using 20 epochs



Source: Electricity Authority

3.3 The blue line depicts observed generation. The orange line is the median of the model prediction. The orange shaded areas are the confidence intervals surrounding each prediction, in which 90% and 50% of predictions are expected to fall. Smaller intervals imply greater confidence in the prediction, so we should not be alarmed if the interval increases as we predict generation further into the future.

3.4 These results show the model can adequately predict wind generation in Wellington and Tararua. Even though the forecasts do not precisely match the observations, they provide a decent prediction of the overall trend on 8 Apr 2022.

3.5 To build the forecast model for Wellington, we use 40 training iterations (epochs) over the entire dataset. For Tararua, we use 20 epochs to avoid overfitting and having confidence intervals that are too small.

3.6 To numerically evaluate the quality of our forecasts, we can compute many aggregate performance metrics[7], such as:

mean absolute percentage error

$$\mathrm{MAPE} = \mathrm{mean}\left(\frac{|Y - \hat{Y}|}{|Y|}\right) \tag{1}$$

mean absolute scaled error

$$\mathrm{MASE} = \frac{\mathrm{mean}|Y - \hat{Y}|}{\mathrm{SE}} \tag{2}$$

with scaled error $\mathrm{SE} = |Y_t - Y_{t-m}|$,

and symmetric mean absolute percentage error

$$\mathrm{sMAPE} = 2\ \mathrm{mean}\left(\frac{|Y - \hat{Y}|}{|Y| + |\hat{Y}|}\right) \tag{3}$$

3.7 Table 4 shows the metrics of the model's forecast.

Table 4: Metrics of 8 Apr 2022 forecast

Metrics	Figure 3: Wellington	Figure 4: Tararua
MAPE	21.64	0.2476
MASE	0.0977	0.2418
sMAPE	0.5088	0.3791
Seasonal error	64.06	25.66

Source: Electricity Authority

3.8 From inspecting the above figures, the 90% confidence interval for Wellington's forecast covered all true values.

3.9 In comparison, the confidence intervals for Tararua's forecast are too narrow when predicting generation under 80 MW so fail to cover the true values. This could be due to overfitting the data and deserves further investigation. However, the forecast generation still closely follows the observed trends.

3.10 We now predict wind generation on 9-10 Aug 2021.

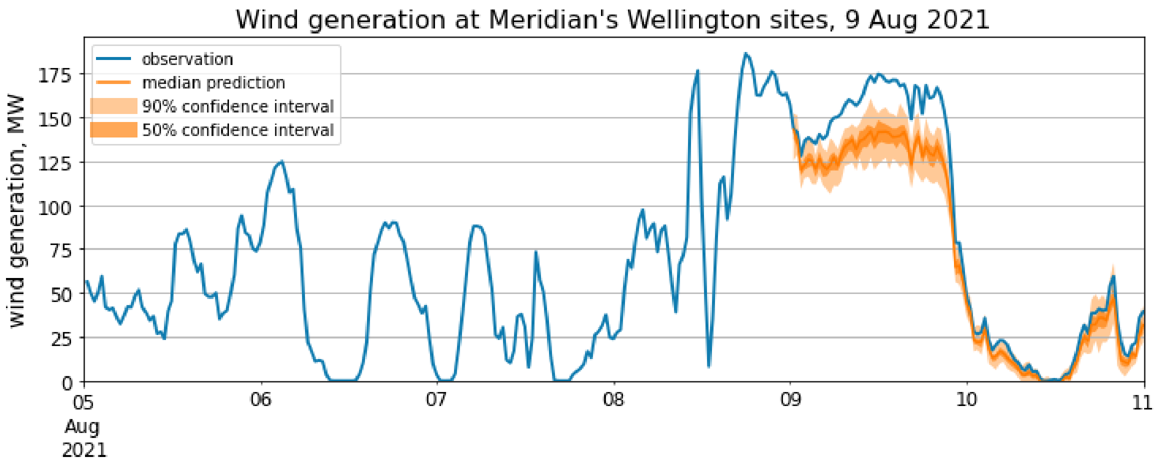
3.11 The model underestimates the generation at Meridian's Wellington stations for much of 9 Aug 2021 (Figure 5), although the predictions follow the same trends as the

7 R. J. Hyndman and G. Athanasopoulos, *Forecasting: principles and practice*, OTexts (3rd ed.), 2021.

observations. The predictions for 10 Aug 2021 are better, as the confidence intervals surrounding each prediction largely cover the observed values.

Figure 5: Wellington forecast for 9-10 Aug 2021

Model trained using 40 epochs.

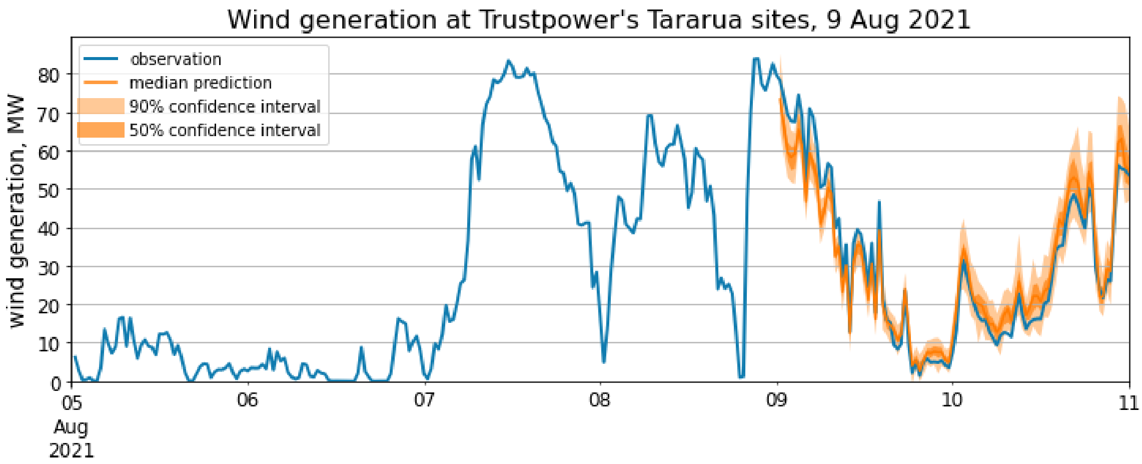


Source: Electricity Authority

3.12 Further north, Trustpower's stations showed a decreasing trend on 9 Aug 2021 and slowly increased the next day (Figure 6). These trends and fluctuations are captured well by the model.

Figure 6: Tararua forecast for 9-10 Aug 2021

Model trained using 40 epochs.



Source: Electricity Authority

4 Conclusions

4.1 We used GluonTS, a specialised machine learning framework, to predict wind generation at Meridian's Wellington and Mercury's Tararua wind farms. We considered weather features such as wind speed and direction to forecast generation on 8 Apr 2022 and 9-10 Aug 2021.

4.2 Our results show that this is a promising method for capturing the overall trends, if not the actual generation of these wind farms.

5 Future work

5.1 Reconfigure the model to predict tomorrow's generation.

5.2 Explore wind generation of other wind farms, such as Turitea and Meridian's future Harapaki project.