Firm Power from Renewables: aiding the transition through stochastic modelling

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Acknowledgement of Country

Figure : Sleepy Lizard - Coulta

Firm Power

- In the International Energy Agency (IEA) Task 16 on Solar resource for high penetration and large scale applications, one of the sub-tasks focuses on Firm Power.
- **Firm power generation represents the capability for a resource or an ensemble of resources to meet electrical demand 24x365, i.e., embodying both baseload and dispatchable generation capabilities.**
- Disclaimer. I believe the goal should be to get as close as possible to this.

How do we do it?

1. Energy storage, absorbing variable renewable energy (VRE) generation when it exceeds demand and releasing it when it falls short of demand.
2. Optimum blending of different VREs that often exhibit complementary diurnal or seasonal generation profiles, reducing the intermittency of the VRE bundle, hence reducing the required amount (i.e., cost) of energy storage.
3. Geographic dispersion that reduces VREs inherent variability.
4. Demand flexibility achieved either via customer-side demand response, or by keeping a fraction of supply-side dispatchable thermal generation, thus modulating the demand seen by the VREs.

Remarks

- I suggest one could go further with 2 and 3 above, and go for overbuilding. Both the IEA report and Rey-Costa et al (2023) come to the conclusion that this is the way forward.
- This may entail convincing the nay-sayers that this is a good way to go.
- One specific point in the IEA report is that overbuilding is much cheaper than batteries.
- I would like to point specifically to 4 above, where I think there is a common problem. When demand is mentioned, only moving it is up for discussion, not lowering demand.

Tools 1 - finding Dunkelflaute

- I will show a toy experiment of how to estimate the probabilities of a number of days with combined solar and wind farm output less than some threshold.
- I use output from Clement's Gap wind farm in SA and Broken Hill solar farm in NSW.
- The first step is to take the 30 minute power output, aggregate it to daily over 12 years, and devise a model for it.
- Note that there are not 12 contemporaneous years for these two installations, so I duplicated some data for this toy experiment.

The time series model

- Define the power output of the combined set as $P(t)$.
- Find a Fourier series representation of the seasonality of $P(t)$, called $S(t)$.
- Define the residual data set $R(t) = P(t) - S(t)$.
- Use the Box-Jenkins methodology to find a one step ahead forecast model for $R(t)$.
- Add the Box-Jenkins model to the seasonal model to get the final representation.

Seasonality

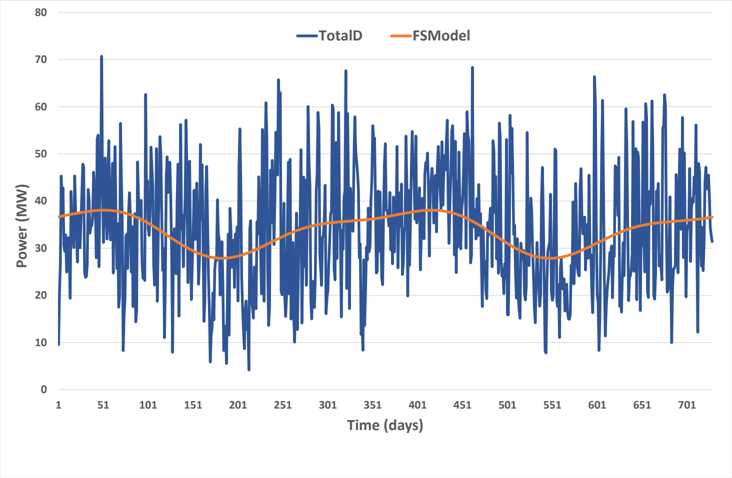


Figure : Data plus seasonal fit

Model description

$$
\begin{aligned}
S(t) &= 33.75 + 4.39\cos(\frac{2\pi t}{365}) + 1.03\sin(\frac{2\pi t}{365}) && (1)\\
&- 1.50\cos(\frac{4\pi t}{365}) + 0.46\sin(\frac{4\pi t}{365}) && (2)
\end{aligned}
$$

$$
R(t) = 0.387R(t-1) - 0.083R(t-2) + Z(t) \qquad (3)
$$

Final model

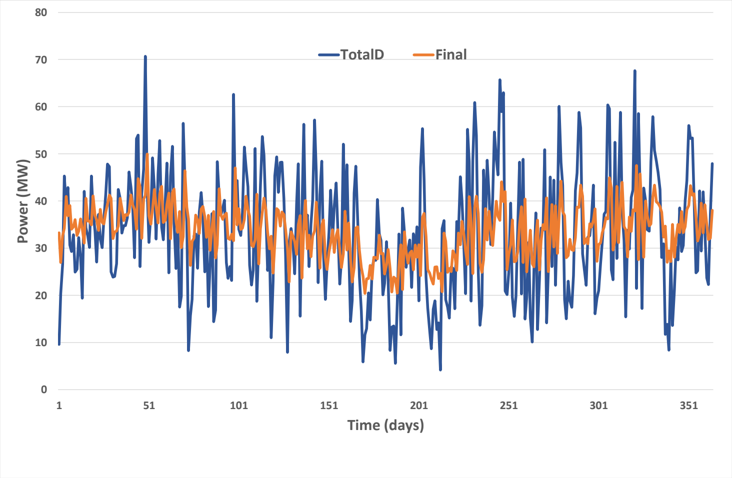


Figure : Data plus final model

Limitations

- In Box-Jenkins modelling, it is hoped that $Z(t)$ is independent and identically distributed (i.i.d.).
- In the best of all possible worlds, it also follows a Normal distribution.
- For systems impacted by climate variables, none of these are true.

Refuting one of these - the others are more complicated

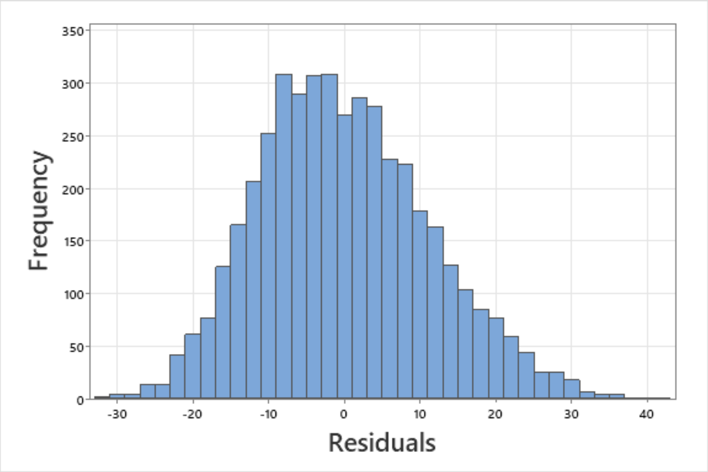
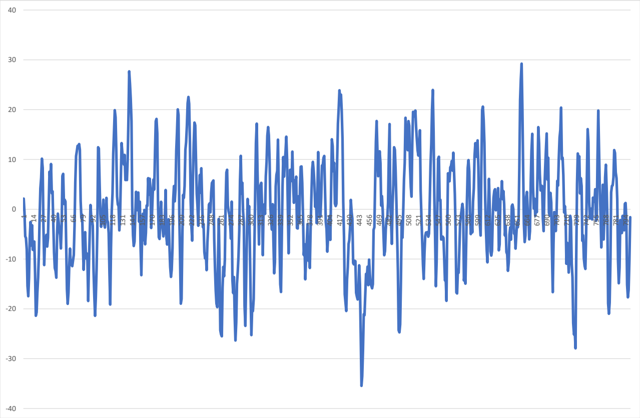


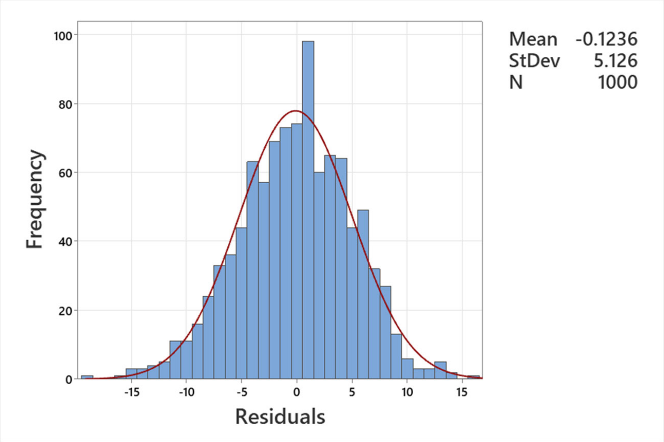
Figure : Histogram of the noise - skewed, and fat tailed

Digression - how we would set error bounds in a perfect case



Showing all is perfect

We fit an autoregressive model to the data and the noise terms are normal.



Calculating the prediction intervals

- Recall that a confidence interval is the mean value plus and minus a value from the standard normal distribution (for the level of confidence you want) times the standard distribution of the data.
- For a prediction interval we take the forecasted value from the AR model, and add and subtract the standard normal value times the standard deviation of the noise.
- We check that it works. How?
- If we want a 95% prediction interval, then 95% of the observed data should fall within the intervals.

Prediction Intervals

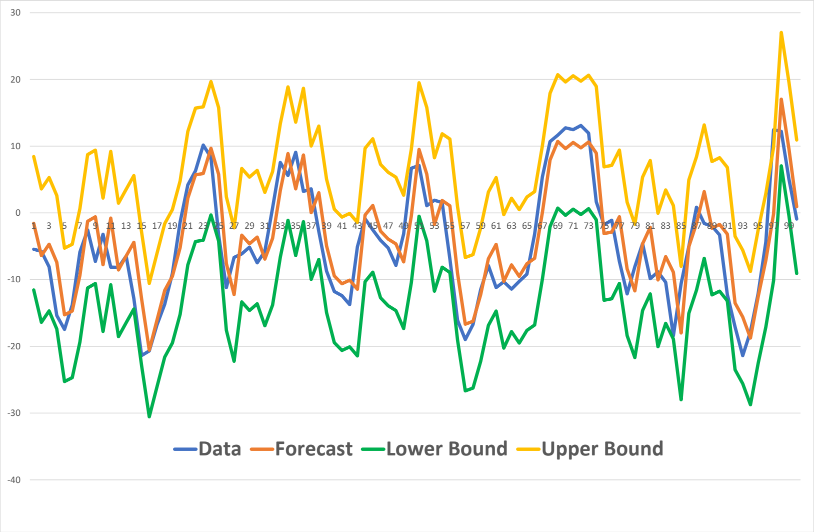


Figure : The perfect picture

The way forward

- We have 12 years of data and a model for it.
- To estimate the probability of sequences of days below a prescribed threshold, we need more data.
- Specifically, this may well not be enough years to fully represent the possibility of long sequences of low output.
- We will use a method to generate any number of years of synthetic data that is statistically indistinguishable from the 12 years, but will contain sequences not seen in the original data.

Bootstrapping

The algorithm for generating synthetic sequences follows the modelling process but sequentially in reverse order. The steps are given below.

1. We start at time step 3 as the autoregressive model is an $AR(2)$. Generate a random number a from a Uniform distribution on $(0, 1)$. This is a probability.
2. Find $g = G^{-1}(a)$, where $G^{-1}(z)$ is the inverse cumulative probability distribution of the noise terms.
3. Add this to $\hat{R}(3)$, the forecast from the $AR(2)$ model for time $t = 3$.
4. Then add this result to the seasonal component $S(3)$.
5. Continue on through whatever number of years is required.

Illustration of the generation of random noise values

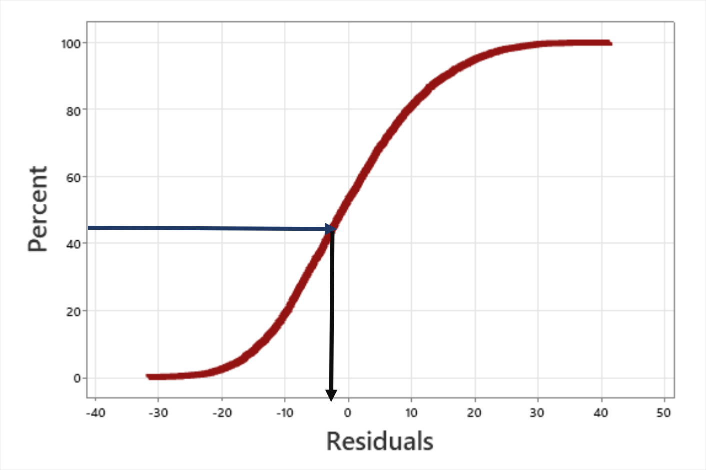


Figure : Synthetic noise for $a = 0.44$

What is the threshold for the low output?

Let's as an example take the $10th$ percentile of the original data set.

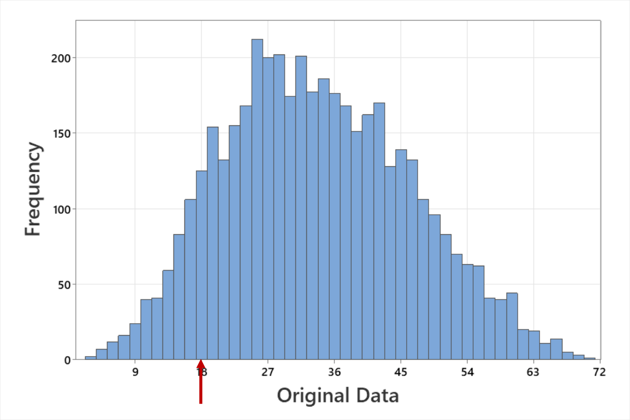


Figure : The threshold

The procedure

- The threshold is 18 MW.
- I have written code to find sequences of days with $2, 3, \ldots, 7$ days in a row below the threshold in the synthetic data.
- I then calculated the probability of occurrence of these sequences, and what time of year they occurred.

Results

Table : The return periods for the tenth percentile

Consecutive Days	1000 years
2	5 yearly
3	1.5 yearly
4	2.5 years
5	8 years
6	20 years
7	40 years

The sequences mainly occurred in autumn and winter.

Forecasting - Why do we need it?

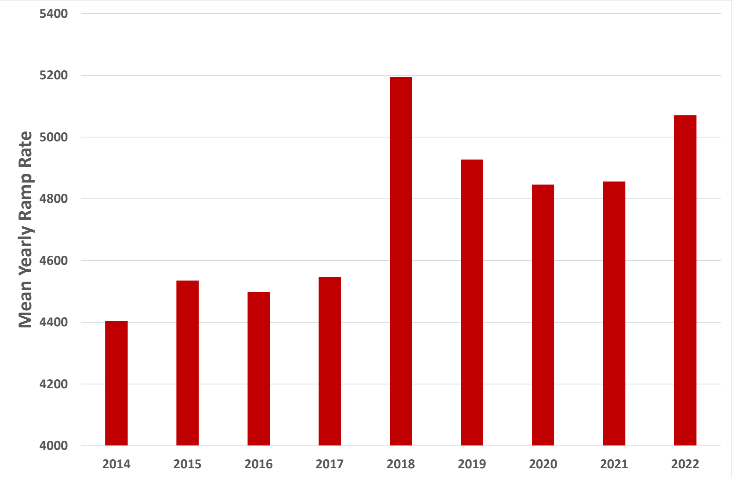


Figure : Mean daily aggregated 5 minute ramp rates of demand

Probabilistic forecasting

Any one step ahead statistical forecasting method can be encapsulated by the structure

$$Y_t = f(F; Y_{t-1}, \ldots, Y_{t-p}; X_{i,t-1}, \ldots, X_{i,t-q}) + Z_t \qquad (4)$$

This contains the seasonality F and any autoregressive qualities, plus any connection with exogenous variables, if applicable. Knowledge of the statistical qualities of Z_t is necessary in order to construct the error bounds of the forecast. In this formulation, it is hoped, and sometimes assumed that Z_t is independent and identically distributed (i.i.d.), and more so normally distributed. But, for solar irradiation, as well as solar and wind farm output, none of these assumptions hold.

Dealing with the noise

- I will outline two methods.
- The first is quantile regression, applied to the noise terms.
- The second involves applying a normalising transformation to the noise terms, then using tools to forecast the conditional variance of them, setting error bounds and back transforming these bounds.

Linear Regression 101

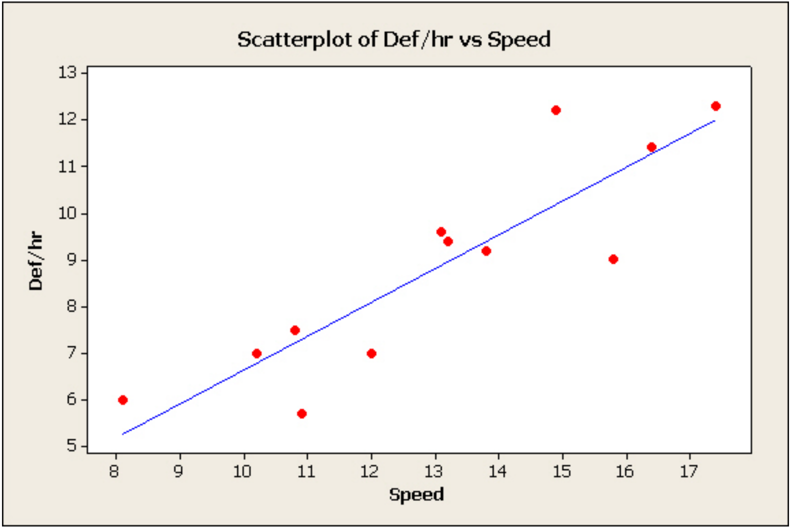


Figure : Line of Best Fit

Linear Regression 101

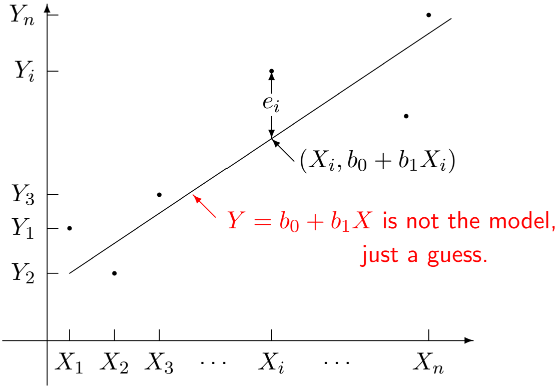


Figure : How do we get the line?

Ordinary Least Squares

By the principle of least squares, we choose those values which make the sum of squares of the residuals least. That is, we minimize

$$S = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (Y_i - b_0 - b_1 X_i)^2$$

with respect to b_0, b_1.

Quantile Regression

For quantile level τ of the response, the goal is to

$$\min_{\beta_0(\tau),\beta_1(\tau),\ldots,\beta_p(\tau)} \sum_{i=1}^{n} \rho_\tau(y_i - \beta_0(\tau) - \sum_{j=1}^{p} z_{ij}\beta_j(\tau))^2. \tag{5}$$

$$\rho = \tau \max(r, 0) + (1-\tau) \max(-r, 0) \tag{6}$$

is the check function. If the error in the regression in a single period, r, is positive, then the check function multiplies the error by τ and by $1-\tau$ if negative. In this study, the predictor variables are the previous 5 lagged values of the noise. Note that when performing the optimisation for the one step ahead forecast for time $t+1$ at time t, we are regressing Z_{t+1} on $Z_t, Z_{t-1}, \ldots, Z_{t-5}$.

Transforming the noise

- Find $F(Z_t, i)$, the cumulative probability distribution (CDF) of Z_t for time of day i;
- Transform z_t according to $\gamma_t = F^{-1}(z_t, i)$, with $\gamma_t \sim N(0, 1)$.
- Form γ_t^2 for every 15 minutes over the year.
- Find the forecast model for γ_t^2.
- Use the model to estimate the variance for each 15 minutes, and then calculate the standard deviation σ_t.

Transform Step 1

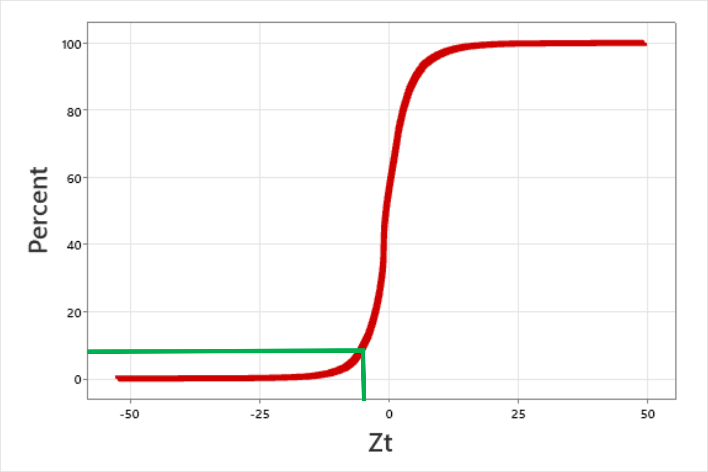


Figure : Find the probability of occurrence of z_t

Transform Step 2

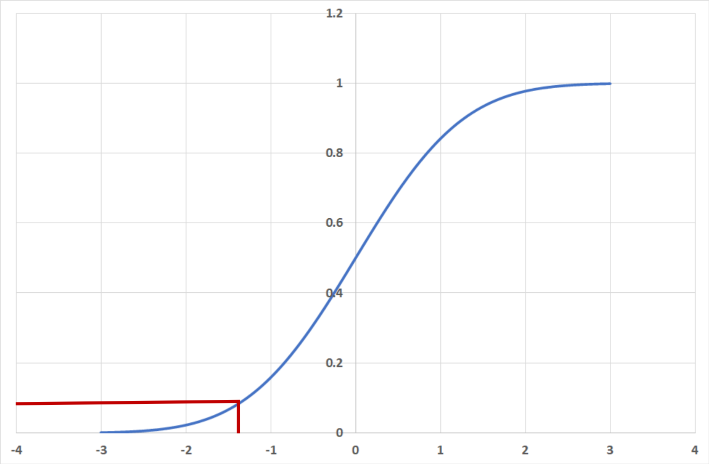


Figure : Find the equivalent value of the standard normal distribution

Continued

- Form the lower and upper bounds for the prediction interval (PI), for instance for a 95% PI, they are $\pm 1.96 \times \sigma_t$.
- Find the corresponding probabilities from the cumulative distribution function of the standard normal distribution p_L, p_U.
- Find the values of $F(Z_t, i)$ corresponding to p_L, p_U, using the suitable CDF in each case.
- Add these bounds to the deterministic forecast, to form the final prediction intervals.

Example results

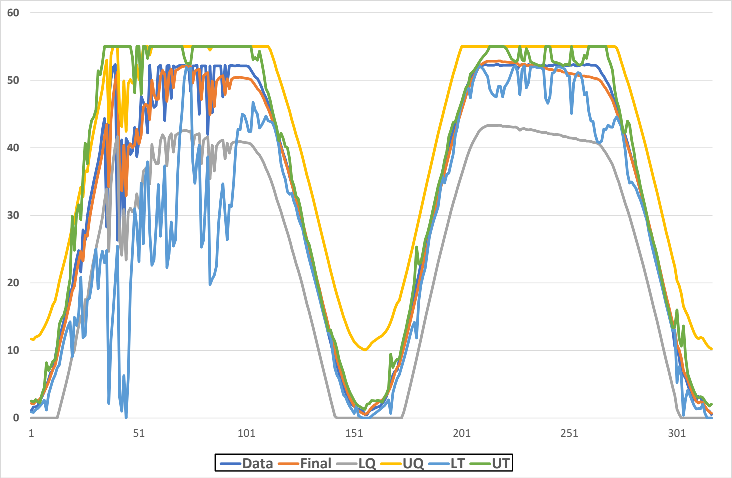


Figure : Comparing prediction intervals for Broken Hill Solar Farm

The elephant in the room - Demand

An article in ABC online on 26 January had these hints on how to beat the heat, while saving money.

- Avoid too low setpoints for aircon - remember Fanger (my addition).
- Added to that, if you want the effect of a 24^o setpoint, use fans and a 27^o setpoint.
- Close gaps and cracks.
- Insulate if possible. It is unimaginable to me that some people still do not insulate ceilings.

Simple steps continued

- Open house for ventilation when cool and close when hot.
- I would add look ahead a few days and plan your actions.
- Use plants for shading. I go further and say for general climate control - cut hot winds in summer and cold winds in winter. See reference later.
- Awnings placed strategically. Not roller blinds. Not in article but my addition.

Why this list frightens me

- It is not the list itself - very good advice.
- What frightens me is that these things have to be mentioned.
- They should be intuitively obvious.

What else needs mentioning?

- Minimum glazing on west side. Shaded when existing.
- No black roofs.
- Precinct design, not block design.
- Mandated permeable surface minimums.
- More later.

Bad example

Figure : Newly constructed house

Why does this matter?

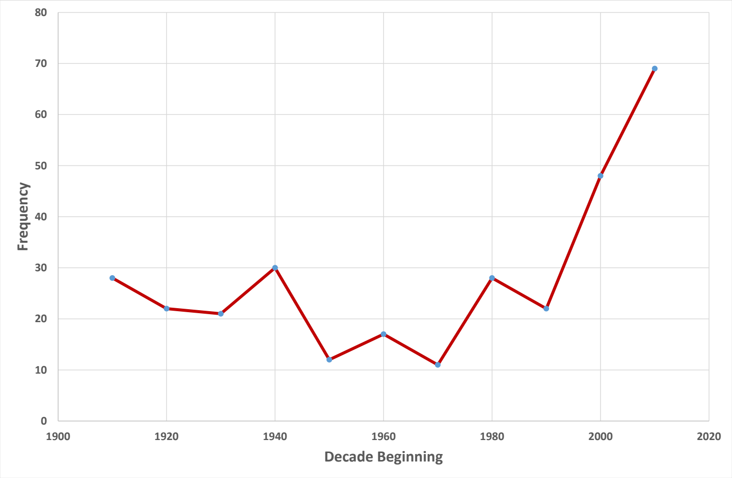


Figure : Number of days per decade over 40 degrees in Adelaide

Good one

Figure : Back of our house - facing west

Good one

Figure : Front of our house - with air conditioners

Monitoring

Figure : Sensors for effects of garden

Remarks

- Overbuilding will benefit firm power.
- To do so, one must get the community on board.
- The increasing demand ramp rate may mean that batteries are part of the mix.
- Community ones would be better.
- The increase in numbers of extreme hot days means we can't just think of supply alone.
- Lowering, rather than just shifting demand is imperative.
- EV charging adds to the complexity.

Extra Resources

- Mediterranean mindset - Gardening Australia
- https://www.abc.net.au/gardening/how-to/mediterranean-mindset/101640868
- Channel 9 News recently - https://twitter.com/9NewsAdel/status/1739922704088596601

References and upcoming conference

- Mina Rouhollahi, Monica Behrend, John Boland, Optimising tree arrangement policy in Australian small-scale residential settings, Sustainable Cities and Society, Volume 102, 2024, 105232, ISSN 2210-6707, https://doi.org/10.1016/j.scs.2024.105232.
- Boland, J and Farah, S 2021, 'Probabilistic forecasting of wind and solar farm output', Energies, vol. 14, no. 16, article no. 5154, pp. 1-14.
- Sleiman Farah, David Whaley, Wasim Saman, John Boland (2019) Integrating climate change into meteorological weather data for building energy simulation, Renewable Energy, 183, pp. 749-760, doi:10.1016/j.enbuild.2018.11.045

- The International Environmetrics Society Conference, UniSA Mawson Lakes, Dec 2-5, 2024.