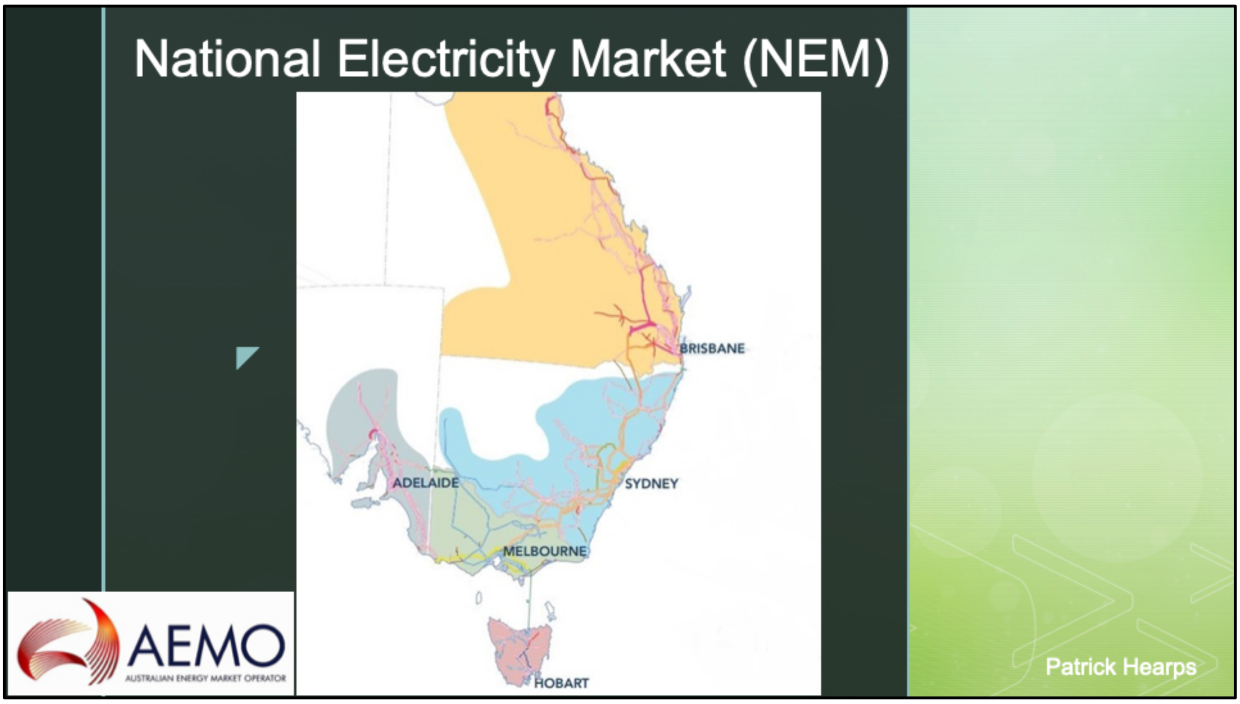
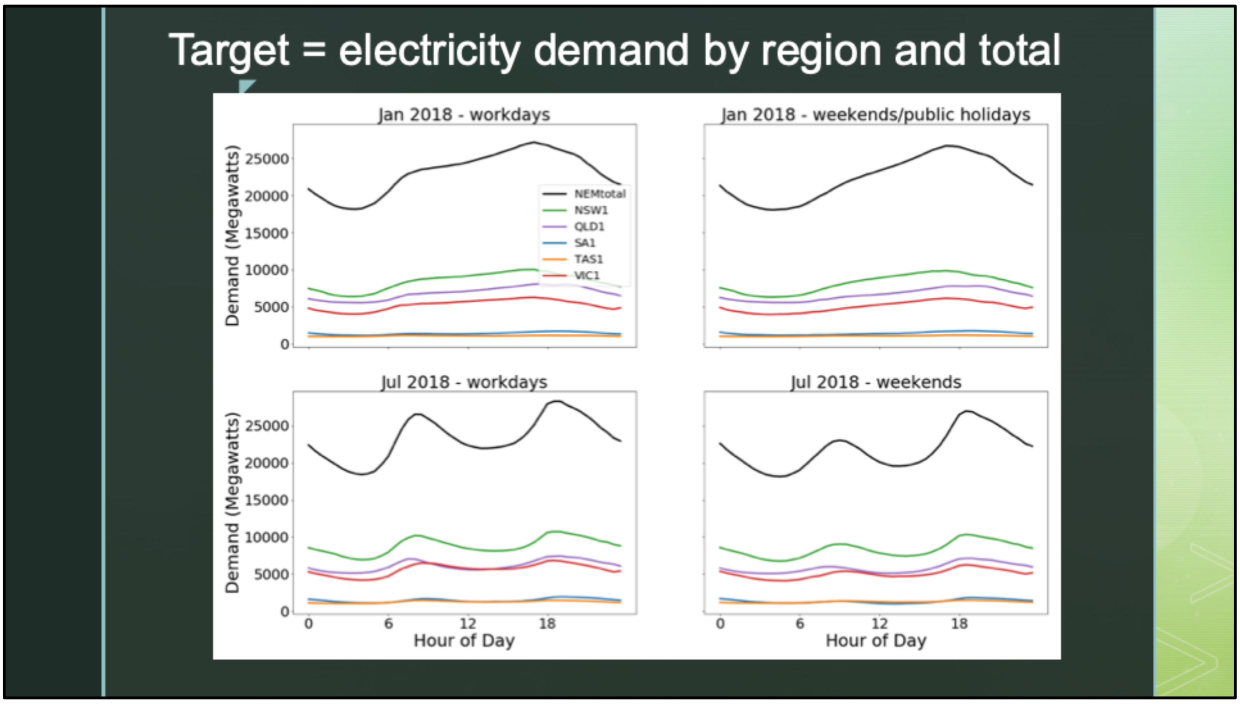


Technical presentation on modelling electricity demand in the Australian National Electricity Market, Patrick Hearps, April 2019

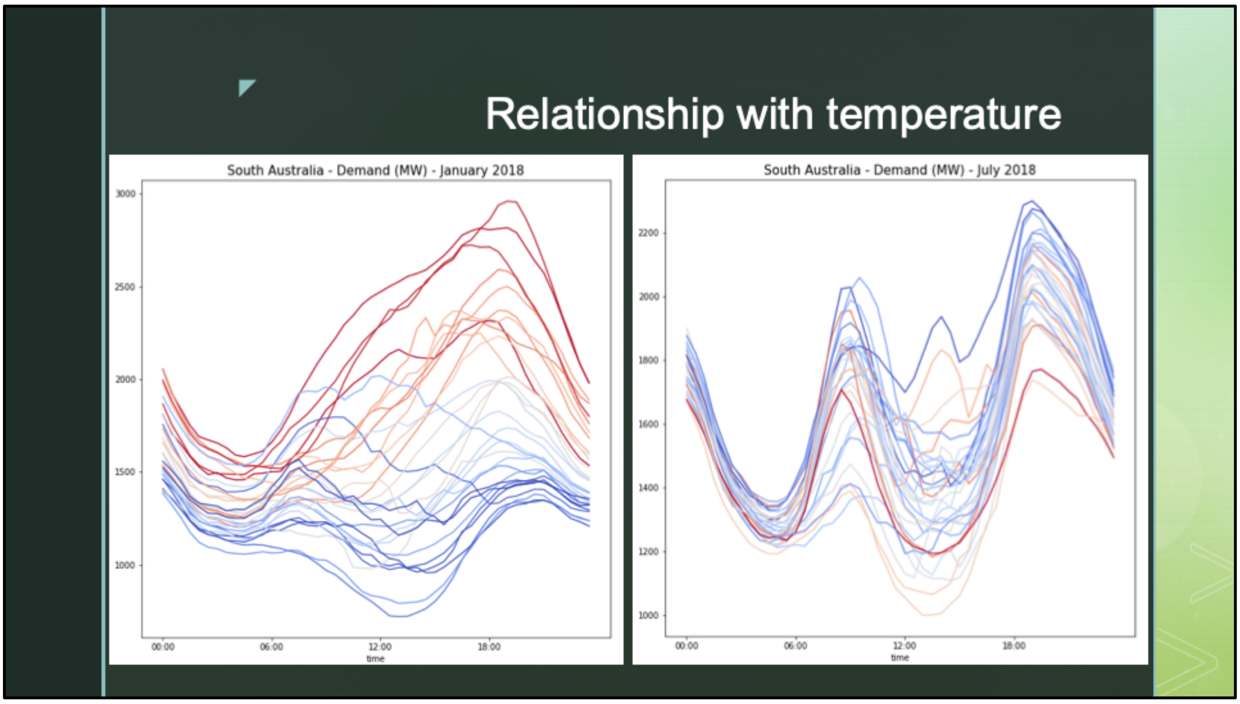


Electricity demand is the aggregate result of millions of people's behavior controlling tens of millions of machines.

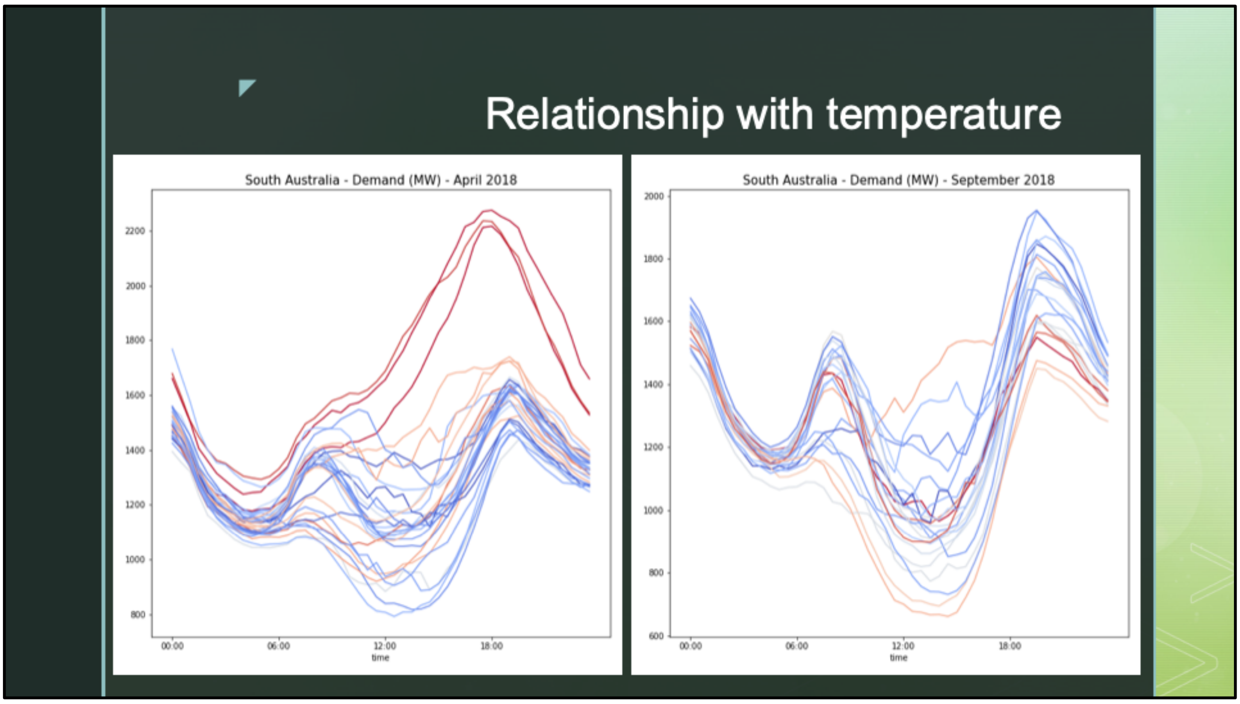
Large factors affecting demand considered in this project include

- temperature, both at the daily/hourly and seasonal timescale,
- weekends/holidays affecting work behavior

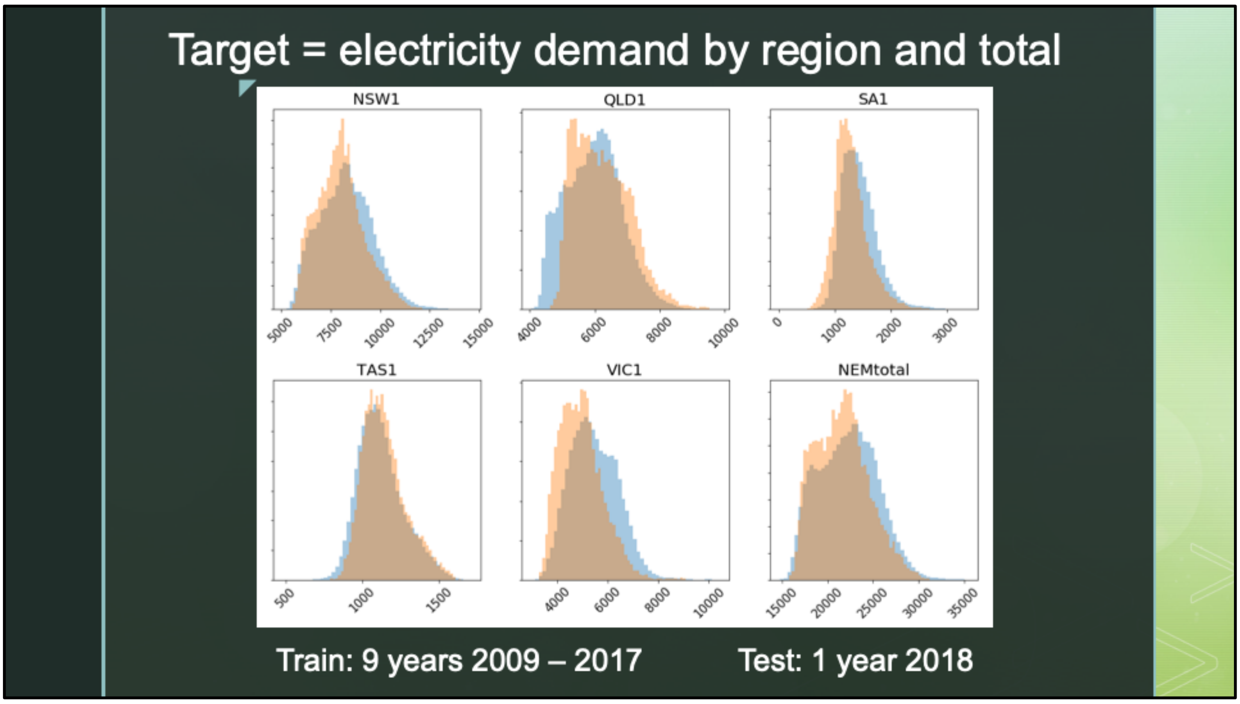
Graph shown displays average demand for each hour over one month (month labelled), filtered by workdays, for all 5 NEM regions and sum



Graphs displays actual demand profiles for each day in a single month for SA1 (South Australian NEM region), month as labelled. Colour-coded cool to warm by max temperature for Adelaide on each day. Relationship is clearest for hot summer days, and some relationship with colder days in winter.

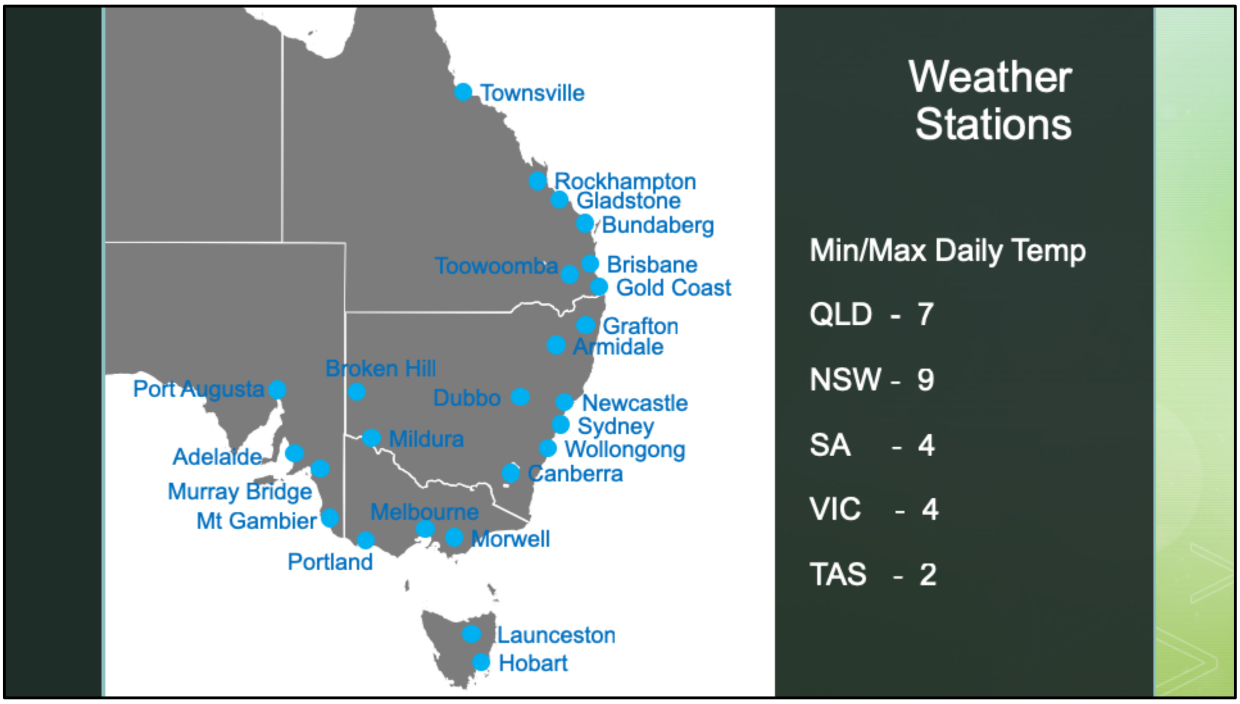


Same graphs as previous page but for different months. Still noticeable relationship with temperature in shoulder seasons (autumn/spring) but less clear.



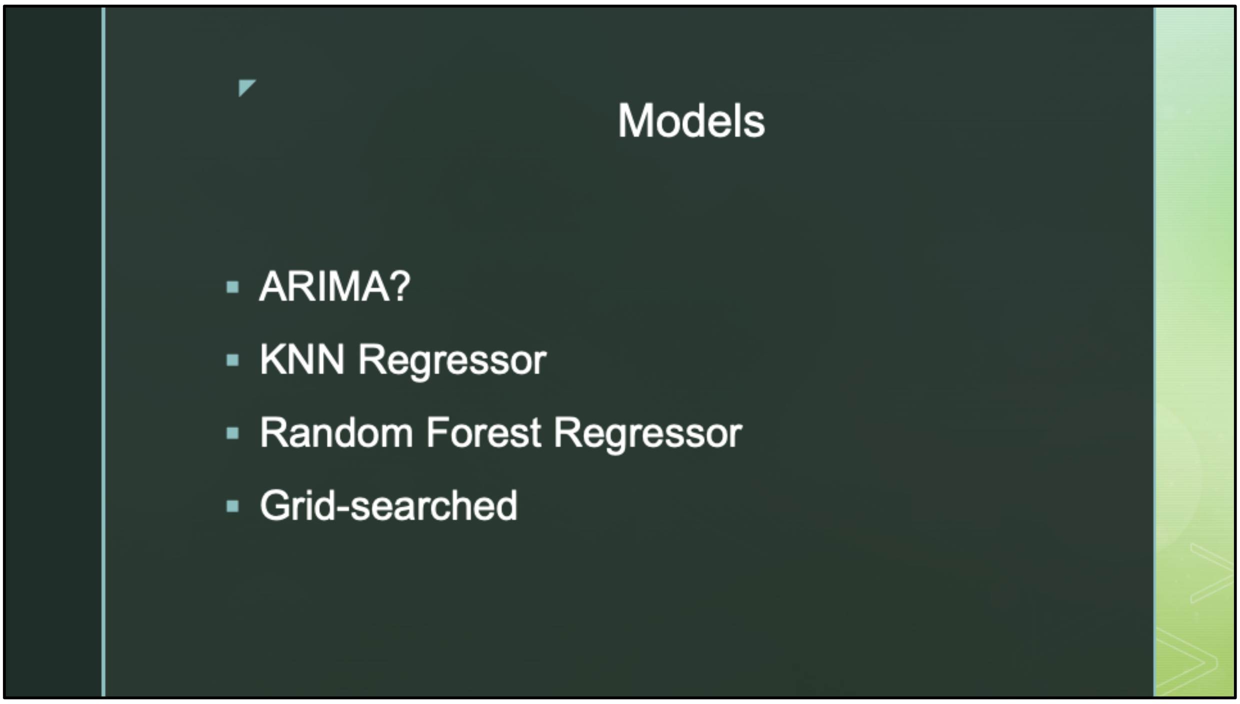
Target was to model and predict half-hourly electricity demand for each of the 5 NEM regions (and summed total by summing outputs of 5 region models), training and cross-validating on 9 years of data, final testing on hold-out dataset for 2018. Histograms show distribution for training set in blue, test set (2018) in orange. Note somewhat different distributions, but overall similar range between training/test.

Input features, public holidays were defined for each NEM region.

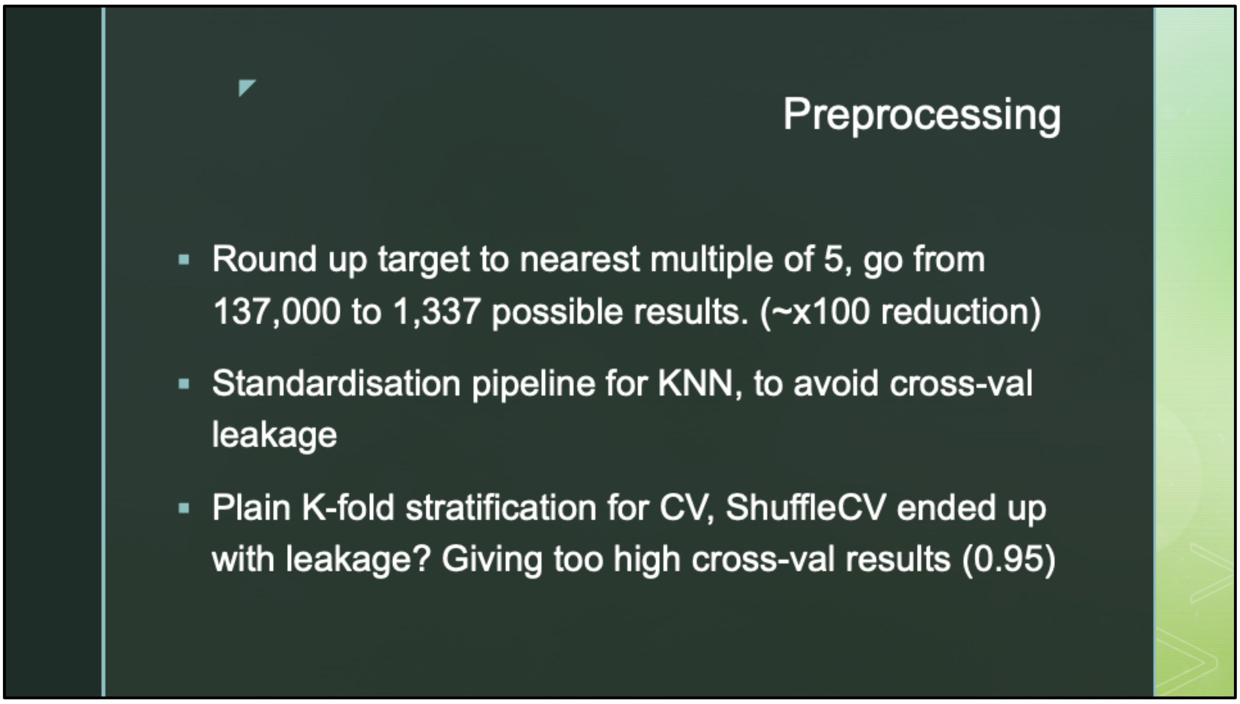


Daily min/max temperature historical observation data from BoM for each of these 26 locations, hand chosen for population/industrial centres and geographical dispersion.
Daily min/max (as opposed to finer timescale) was used for ease of applying to actual daily forecasts in practical applications. Historical forecast data was requested from BoM but would have been expensive ($5K) to obtain, whereas observation history was free.

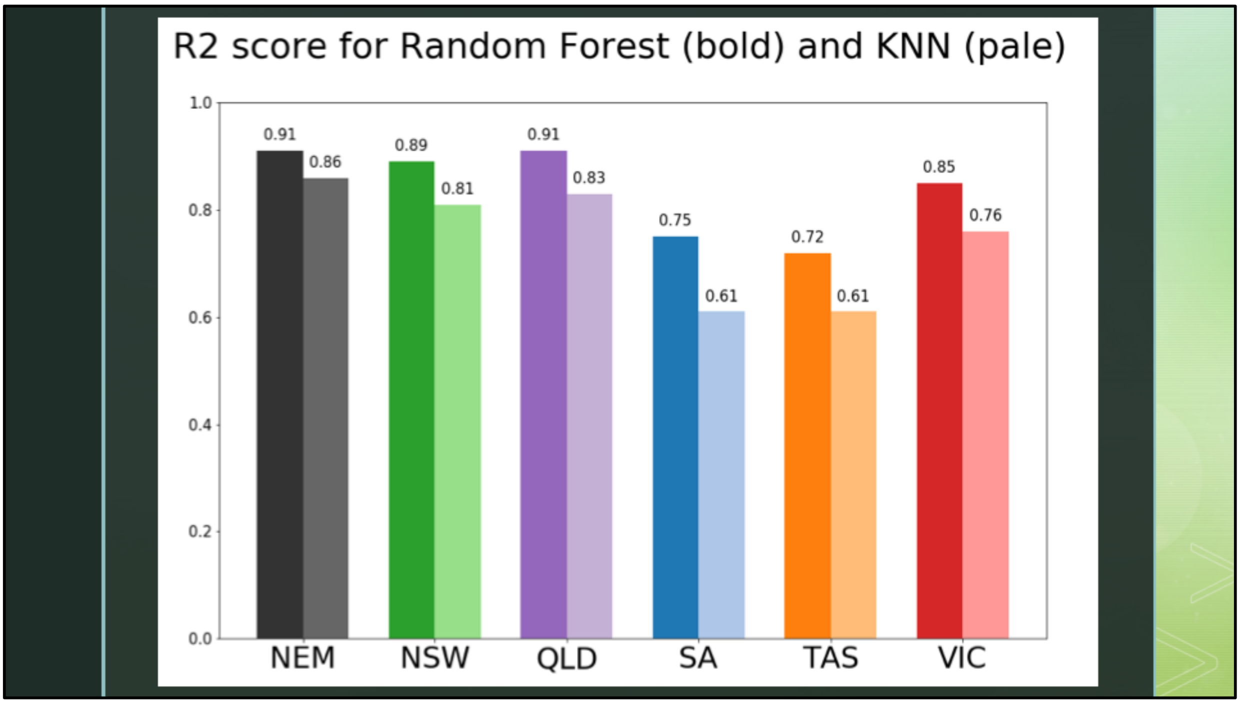
Base map from https://simplemaps.com/resources/svg-au



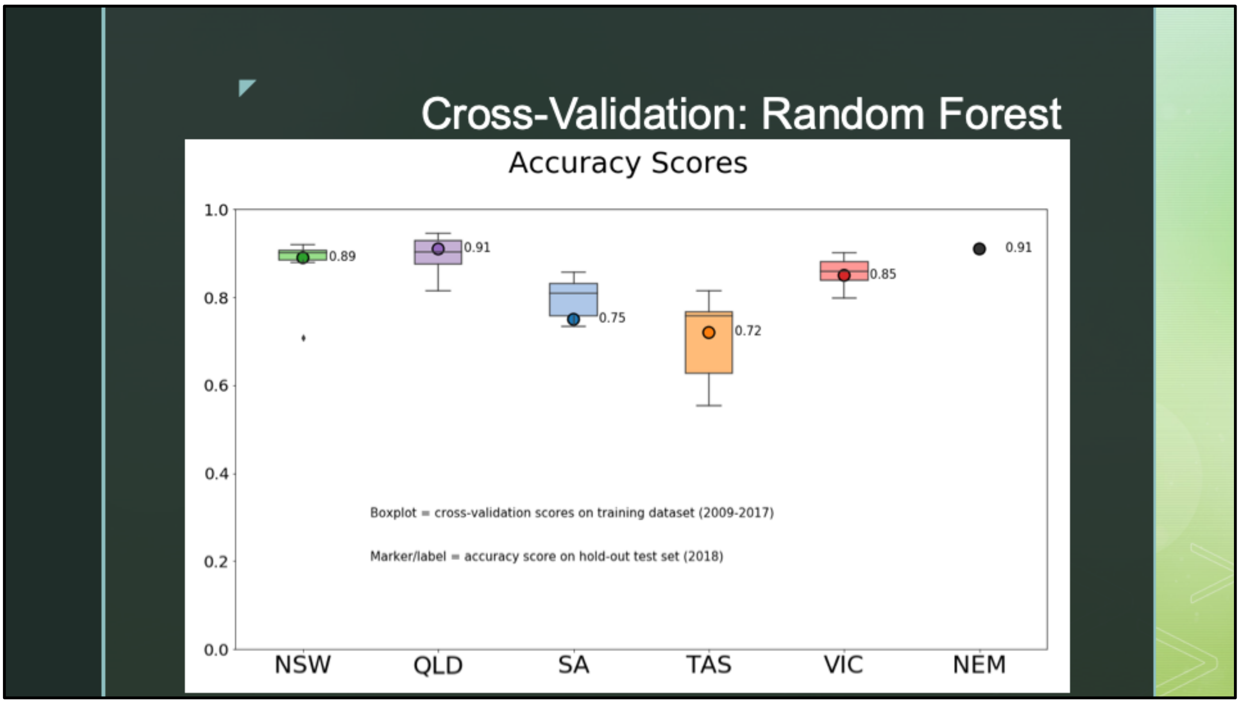
ARIMA was not used but will be explored in future.
KNN and Random Forest applied to explore comparisons of complex past behavior to current patterns of temperature and other factors– Decision Tree was also included in early stages but found to consistently underperform versus Random Forest.
Due to number of branches and leaf nodes of trees in DT/RF regressors, visualization of even one Decision Tree is impractical, unfortunately, but further options exist for interactive web-based visualisations allowing easy zooming in/out that could be explored in future.
Due to time required for grid-search (particularly for RF), grid-searching was mainly done for one NEM region model (VIC1) and same parameters applied to rest of regions. Not ideal, but grid-search solution space was fairly flat, not expecting that this would significantly affect results.



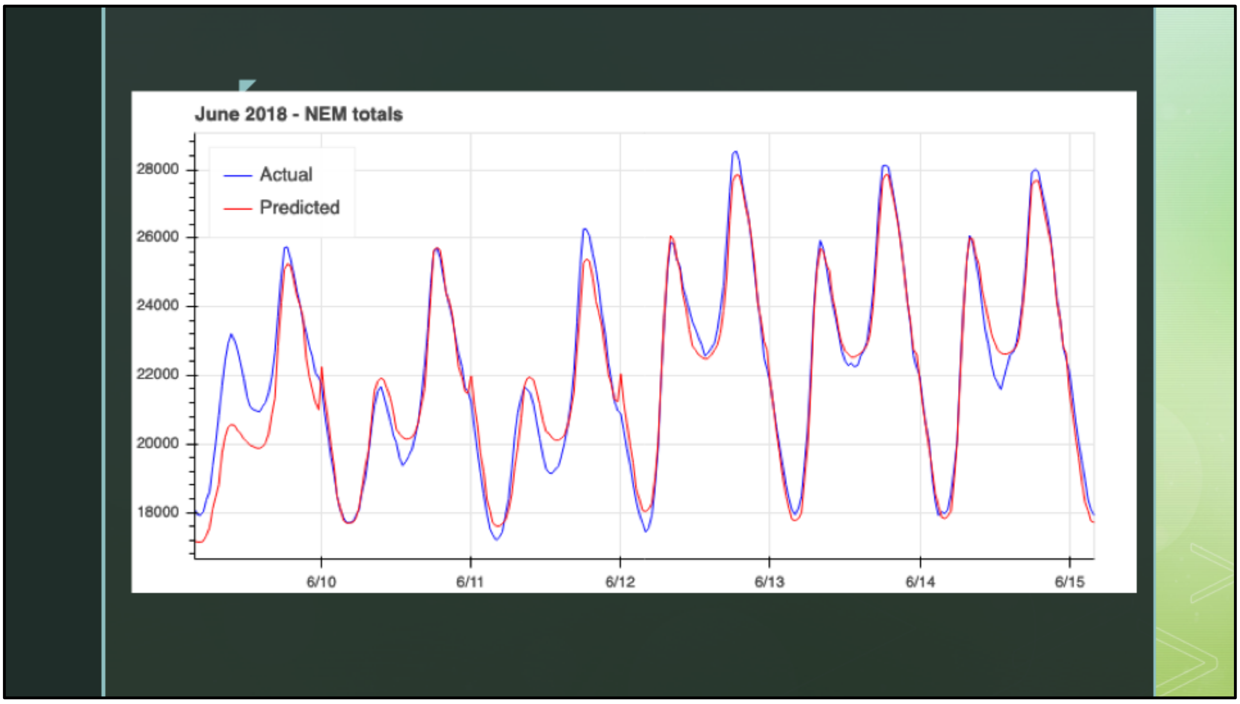
Cross-validation and testing in early stages found multiple steps of data leakage causing results far too good – consistently ~0.95 with essentially zero variance. Good learning.



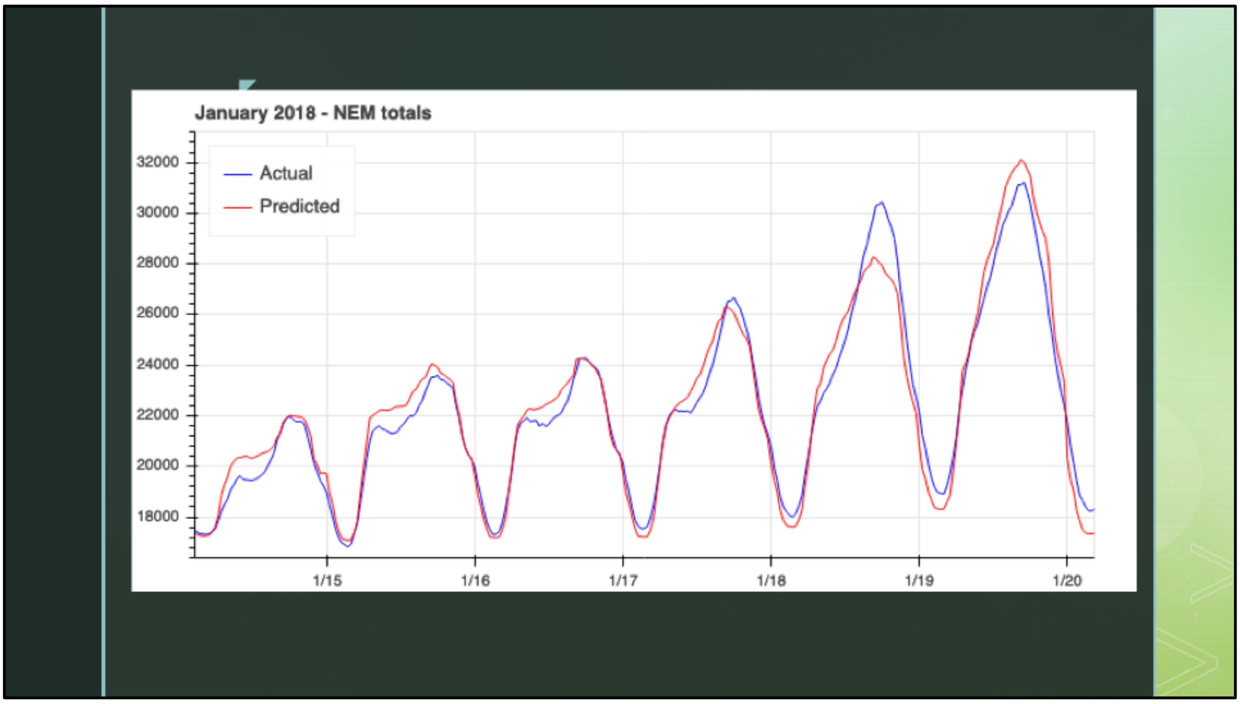
- R-squared accuracy score for 2018 hold-out test data set.
- Random Forest consistently better than KNN.
- Satisfying results for NSW, QLD & VIC.
- Note high score for NEM total – which is not a sixth model but simply the sum of the 5 region models, compared against sum of actual data for 5 NEM regions. Errors averaging/cancelling out?
- Further investigation to be done on why lower scores for SA & TAS. Some ideas include:
    - These two states have much lower demand than other 3, could introduce more variability in actual data as less scale for smoothing random behavior
    - SA having highest penetration of wind and solar power in the NEM
    - TAS having quite different climate patterns from rest of Australia
    - EDA to look for whether low accuracy is concentrated on particular periods or spread across 2018 data set



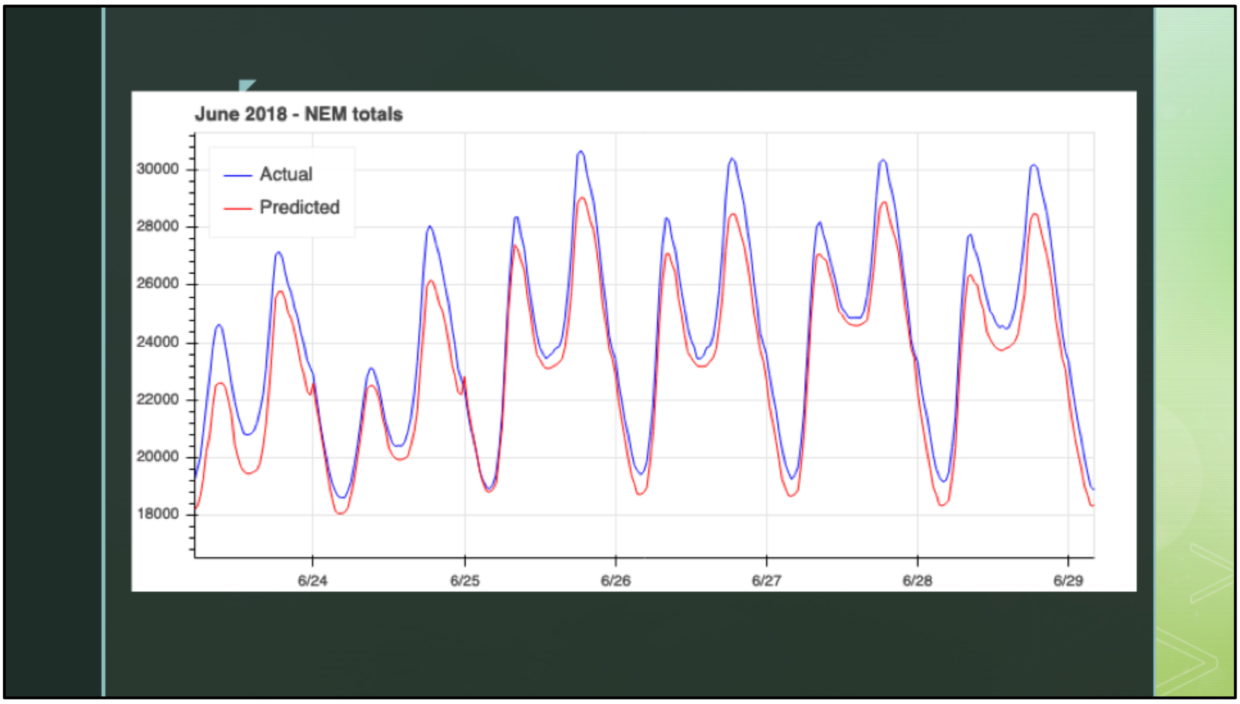
Further dive into accuracy of Random Forest – boxplot shows cross-validation accuracy, CV was done by each year 2009-2017, vs hold-out test accuracy (same as previous page)



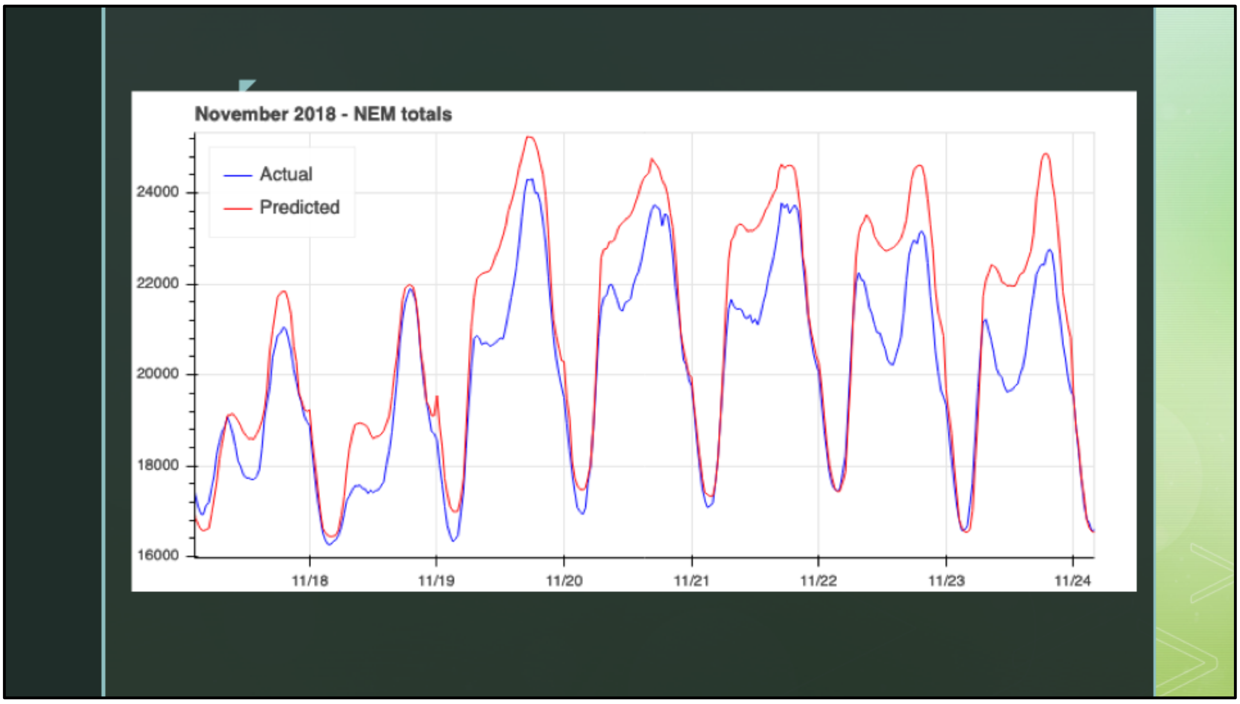
Example of good result period - winter



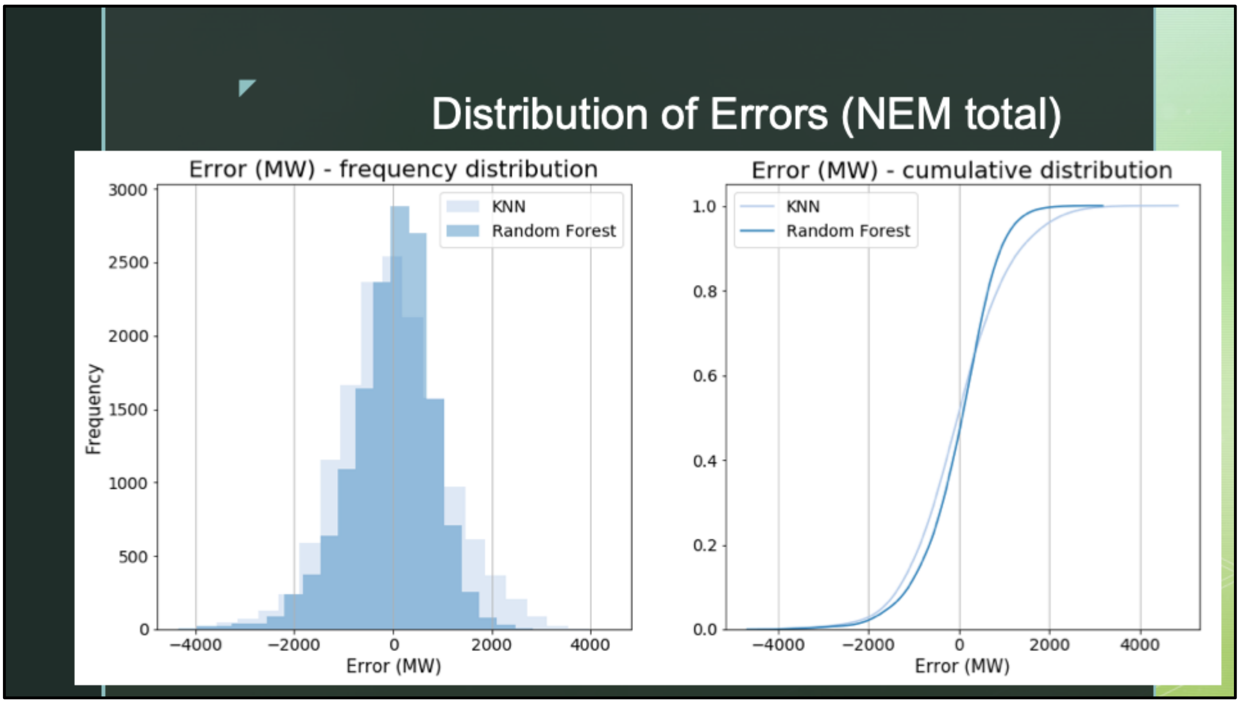
Example of good result period - summer



Example of poor accuracy period - winter



Example of poor accuracy period - spring



Graphs show error values for each half-hour period in 2018 hold-out test set for NEM total sum, frequency and cumulative distribution. Slight tendency to underestimate more than overestimate but is close to normal distribution.

Further work

- Focus on periods of greatest error
- More weather stations? Other weather data (pressure, humidity etc)?
- Solar power production?
- LSTM Neural Network
- Improve time-dependent variables
- ARIMA (SARIMAX) model