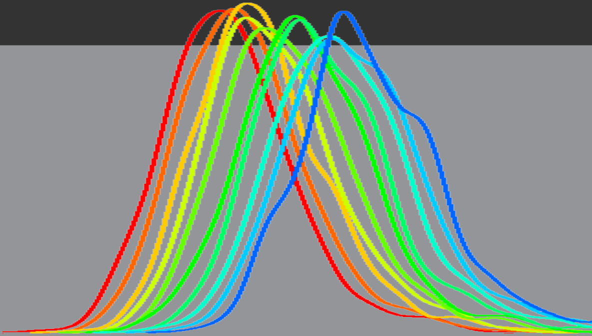
Challenges in forecasting peak electricity demand

Part 1



Rob J Hyndman

Outline

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The problem

- We want to forecast the peak electricity demand in a half-hour period in twenty years time.
- We have fifteen years of half-hourly electricity data, temperature data and some economic and demographic data.
- The location is South Australia: home to the most volatile electricity demand in the world.

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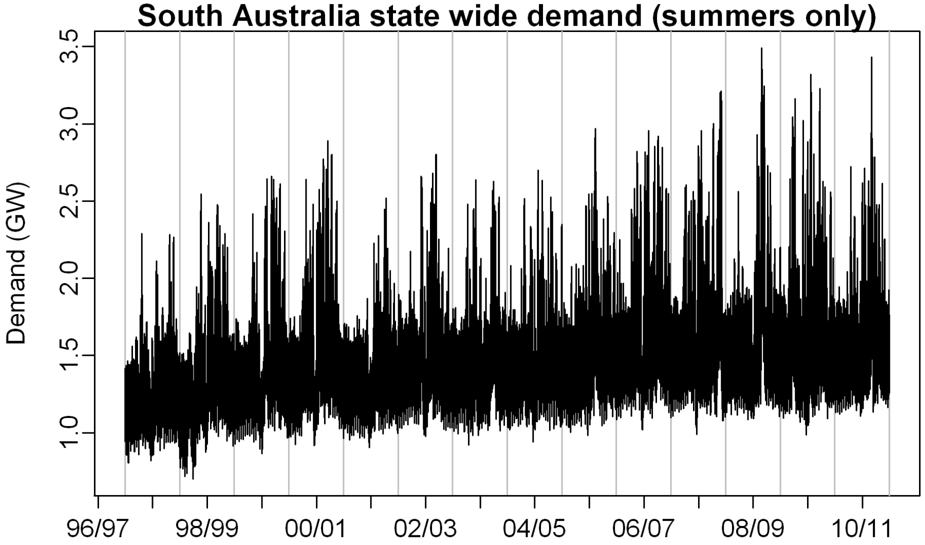
South Australian demand data



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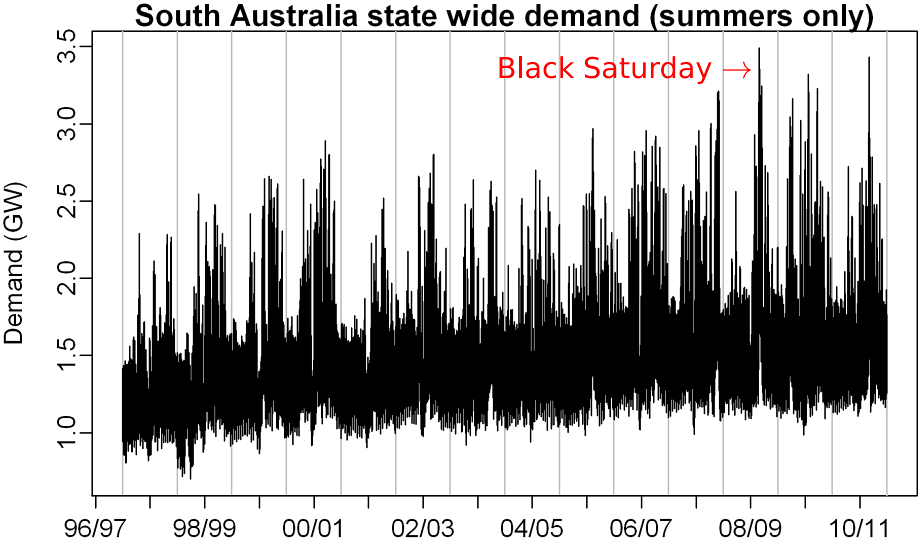

The heatwave

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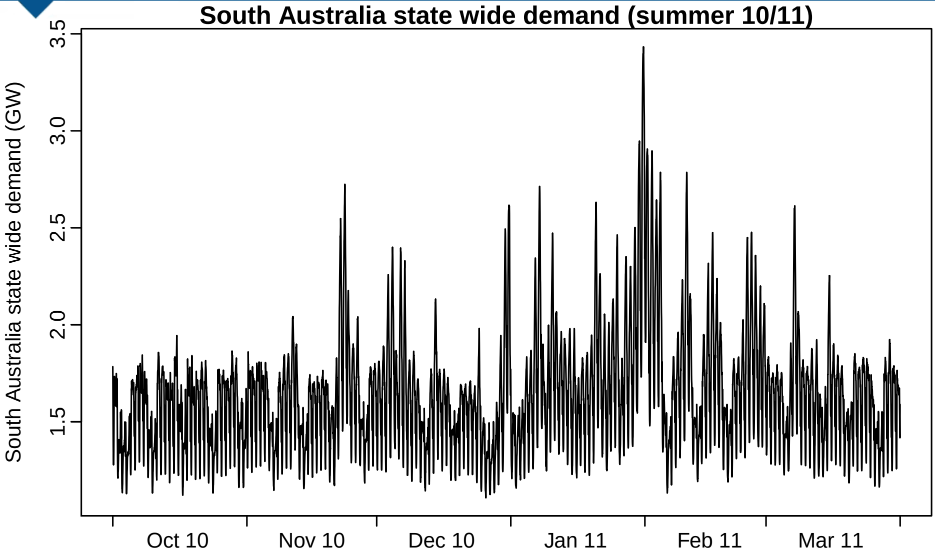

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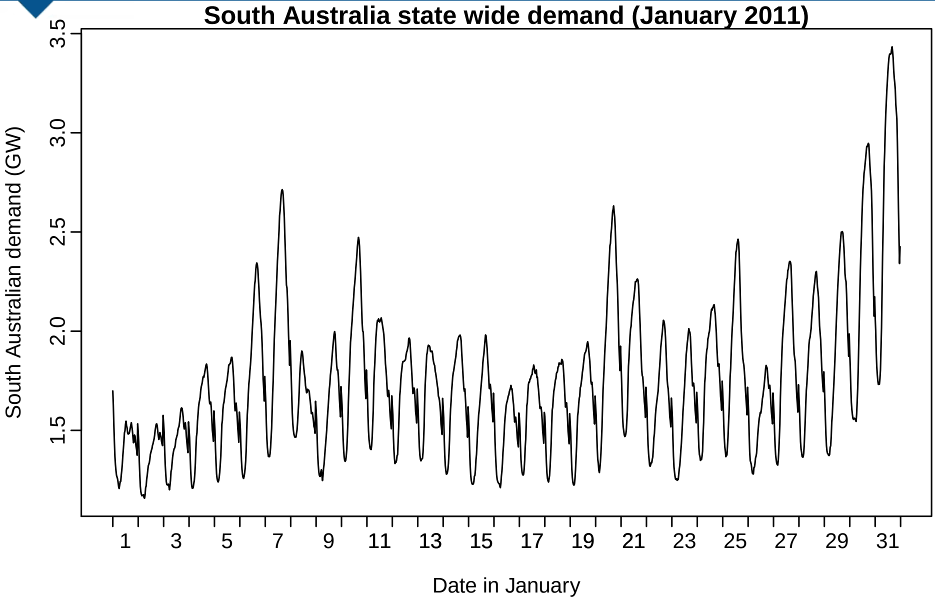
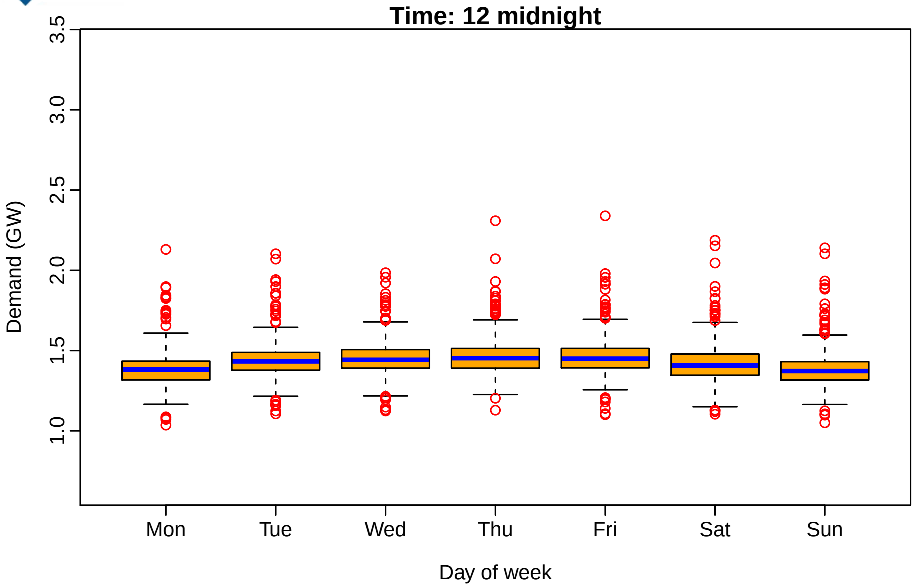
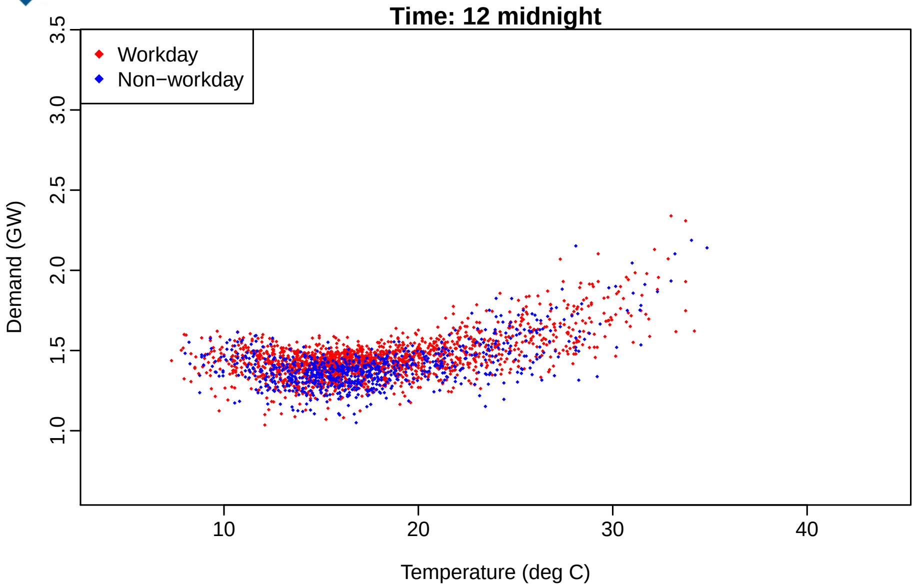


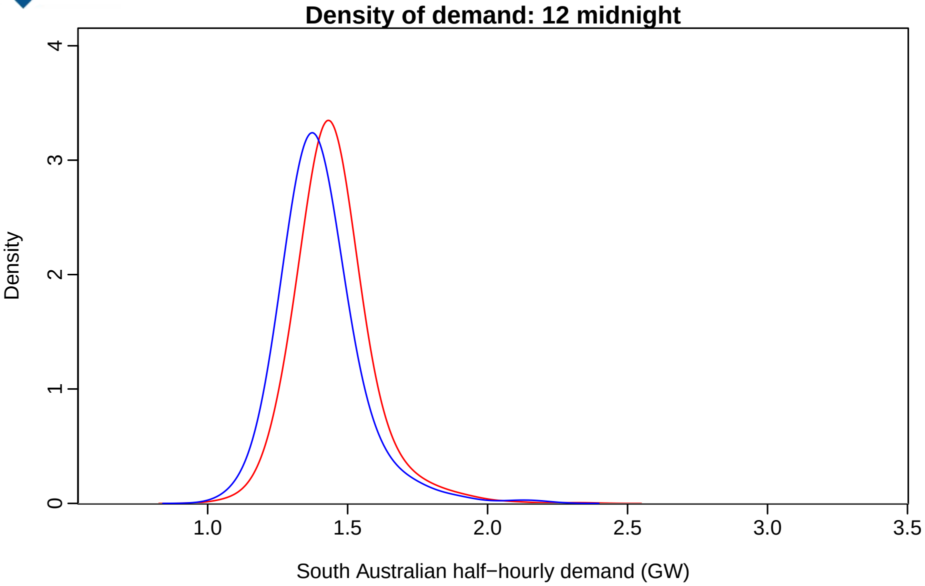
Demand boxplots (Sth Aust)



Temperature data (Sth Aust)



Demand densities (Sth Aust)



Outline

Predictors

- calendar effects
- prevailing and recent weather conditions
- climate changes
- economic and demographic changes
- changing technology

Modelling framework

- **Semi-parametric additive models** with correlated errors.
- Each half-hour period modelled separately for each season.
- Variables selected to provide best out-of-sample predictions using cross-validation on each summer.

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Monash Electricity Forecasting Model

$$y_t = \bar{y}_i \times y_t^*$$

- y_t denotes per capita demand (minus offset) at time t (measured in half-hourly intervals);
- $\bar{y}_i$ is the average demand for year i where t is in year i.
- y_t^* is the standardized demand for time t.

$$\log(y_t) = \log(\bar{y}_i) + \log(y_t^*)$$
$$\log(\bar{y}_i) = f(\text{GSP, price, HDD, CDD}) + \varepsilon_i$$
$$\log(y_t^*) = f(\text{calendar effects, temperatures}) + e_t$$

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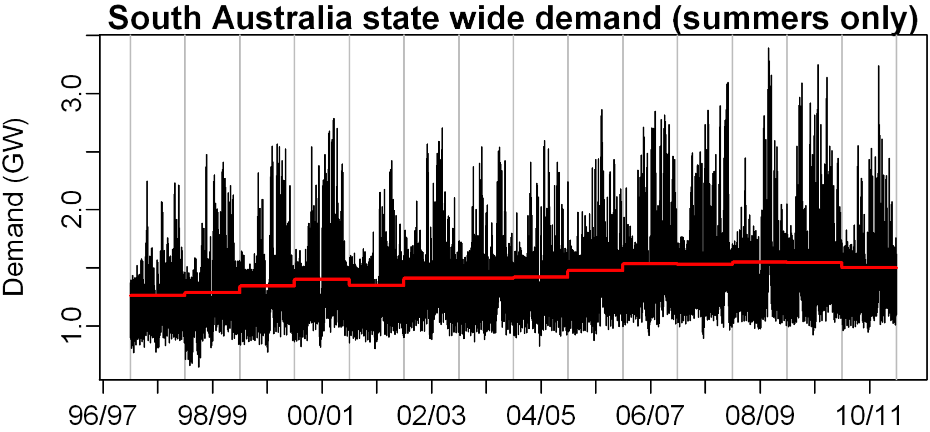

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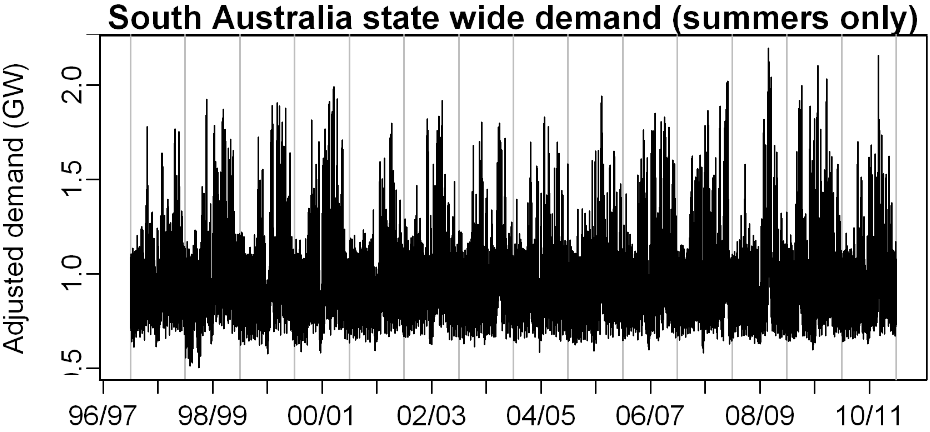

Annual model

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$$\log(\bar{y}_i) = \log(\bar{y}_{i-1}) + \sum_j c_j(z_{j,i} - z_{j,i-1}) + \varepsilon_i$$

- First differences modelled to avoid non-stationary variables.
- Predictors: Per-capita GSP, Price, Summer CDD, Winter HDD.

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Variable	Coefficient	Std. Error	t value	P value
Δgsp.pc	2.02	5.05	0.38	0.711
Δprice	−1.67	0.68	−2.46	0.026
Δscdd	1.11	0.25	4.49	0.000
Δwhdd	2.07	0.33	0.63	0.537

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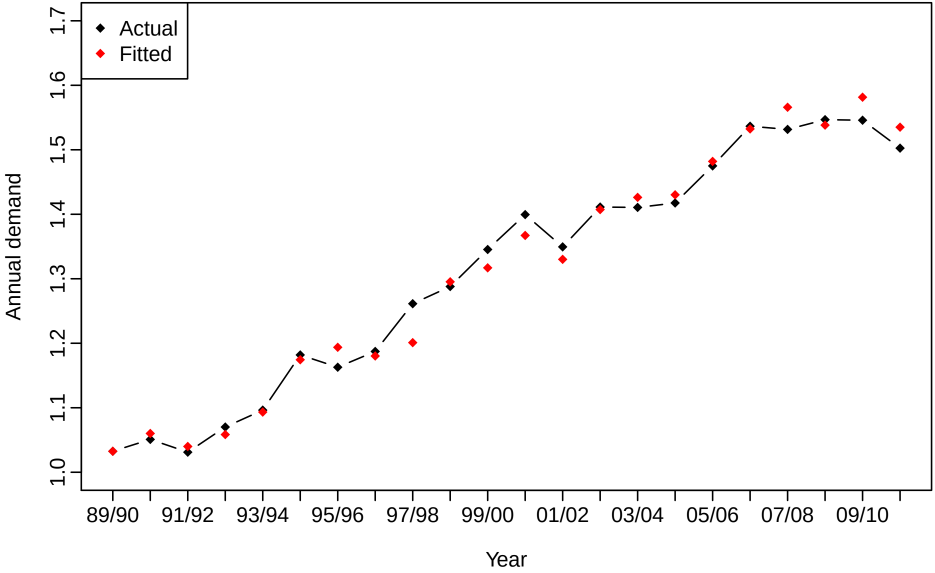

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Calendar effects

- "Time of summer" effect (a regression spline)
- Day of week factor (7 levels)
- Public holiday factor (4 levels)
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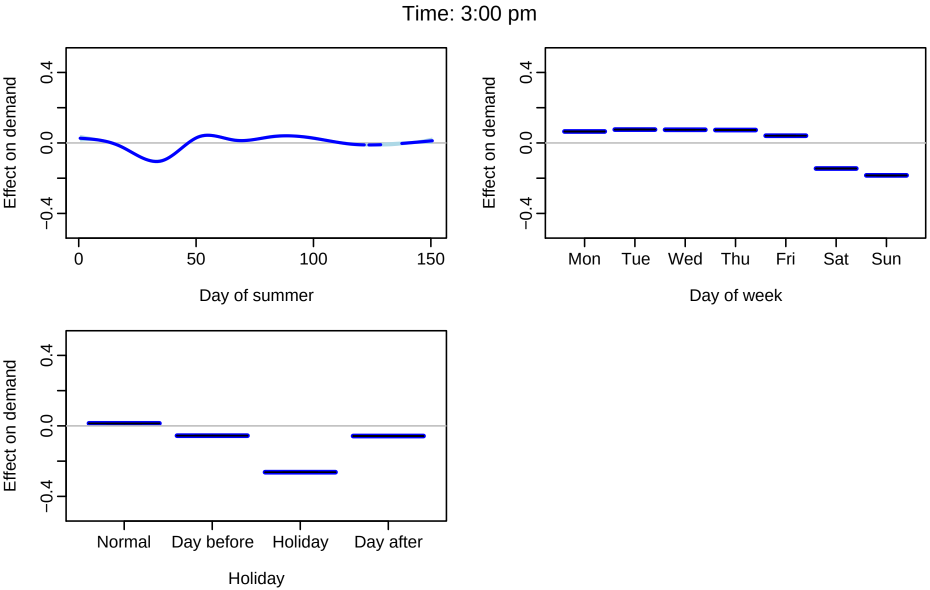
Fitted results (Summer 3pm)



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Temperature effects

- Ave temp across two sites, plus lags for previous 3 hours and previous 3 days.
- Temp difference between two sites, plus lags for previous 3 hours and previous 3 days.
- Max ave temp in past 24 hours.
- Min ave temp in past 24 hours.
- Ave temp in past seven days.

Each function is smooth & estimated using regression splines.

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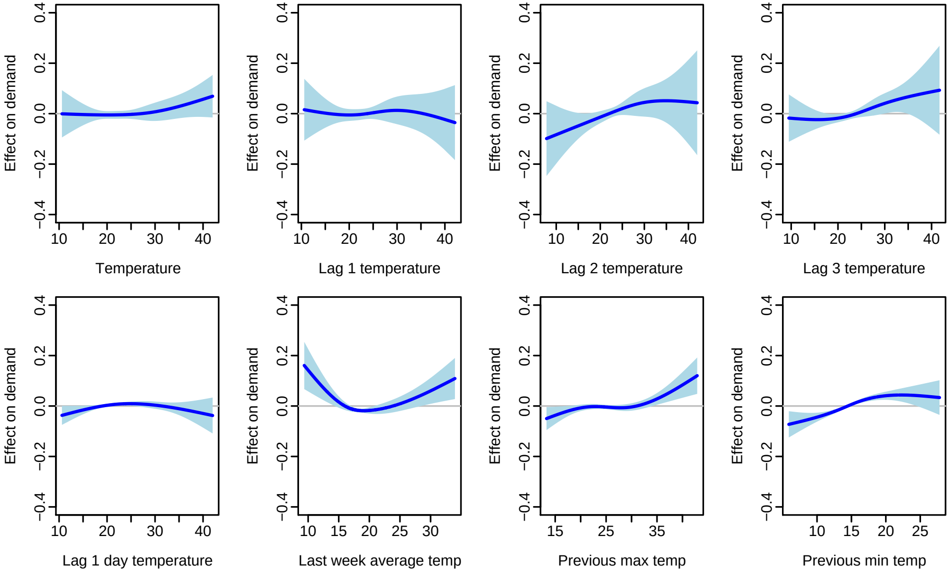

Half-hourly models

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- Separate model for each half-hour.
- Same predictors used for all models.
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	x	x_1	x_2	x_3	x_4	x_5	x_6	x_{48}	x_{96}	x_{144}	x_{192}	x_{240}	x_{288}	d	d_1	d_2	d_3	d_4	d_5	d_6	d_{48}	d_{96}	d_{144}	d_{192}	d_{240}	d_{288}	x^+	x^-	$\bar{x}$	dow	hol	dos	**MSE**
1	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	1.037
2	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●		●	●	●	●	●	●	1.034
3	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●			●	●	●	●	●	●	1.031
4	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●				●	●	●	●	●	●	1.027
5	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●					●	●	●	●	●	●	1.025
6	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●						●	●	●	●	●	●	**1.020**
7	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●							●	●	●	●	●	●	1.025
8	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●		●						●	●	●	●	●	●	1.026
9	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●			●						●	●	●	●	●	●	1.035
10	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●				●						●	●	●	●	●	●	1.044
11	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●					●						●	●	●	●	●	●	1.057
12	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●						●						●	●	●	●	●	●	1.076
13	●	●	●	●	●	●	●	●	●	●	●	●	●	●							●						●	●	●	●	●	●	1.102
14	●	●	●	●	●	●	●	●	●	●	●	●		●	●	●	●	●	●	●	●						●	●	●	●	●	●	**1.018**
15	●	●	●	●	●	●	●	●	●	●	●			●	●	●	●	●	●	●	●						●	●	●	●	●	●	1.021
16	●	●	●	●	●	●	●	●	●	●				●	●	●	●	●	●	●	●						●	●	●	●	●	●	1.037
17	●	●	●	●	●	●	●	●	●					●	●	●	●	●	●	●	●						●	●	●	●	●	●	1.074
18	●	●	●	●	●	●	●	●						●	●	●	●	●	●	●	●						●	●	●	●	●	●	1.152
19	●	●	●	●	●	●	●							●	●	●	●	●	●	●	●						●	●	●	●	●	●	1.180
20	●	●	●	●	●	●		●	●	●	●	●		●	●	●	●	●	●	●	●						●	●	●	●	●	●	1.021
21	●	●	●	●	●			●	●	●	●	●		●	●	●	●	●	●	●	●						●	●	●	●	●	●	1.027
22	●	●	●	●				●	●	●	●	●		●	●	●	●	●	●	●	●						●	●	●	●	●	●	1.038
23	●	●	●					●	●	●	●	●		●	●	●	●	●	●	●	●						●	●	●	●	●	●	1.056
24	●	●						●	●	●	●	●		●	●	●	●	●	●	●	●						●	●	●	●	●	●	1.086
25	●							●	●	●	●	●		●	●	●	●	●	●	●	●						●	●	●	●	●	●	1.135
26	●	●	●	●	●	●	●	●	●	●	●	●		●	●	●	●	●	●	●	●							●	●	●	●	●	**1.009**
27	●	●	●	●	●	●	●	●	●	●	●	●		●	●	●	●	●	●	●	●						●		●	●	●	●	1.063
28	●	●	●	●	●	●	●	●	●	●	●	●		●	●	●	●	●	●	●	●						●	●		●	●	●	1.028
29	●	●	●	●	●	●	●	●	●	●	●	●		●	●	●	●	●	●	●	●						●	●	●		●	●	3.523
30	●	●	●	●	●	●	●	●	●	●	●	●		●	●	●	●	●	●	●	●						●	●	●	●		●	2.143
31	●	●	●	●	●	●	●	●	●	●	●	●		●	●	●	●	●	●	●	●						●	●	●	●	●		1.523

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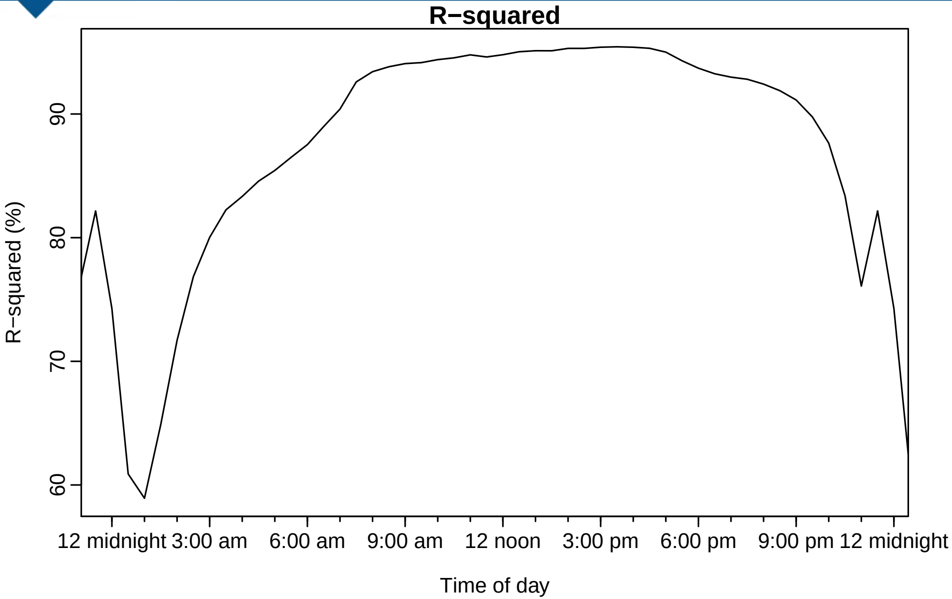

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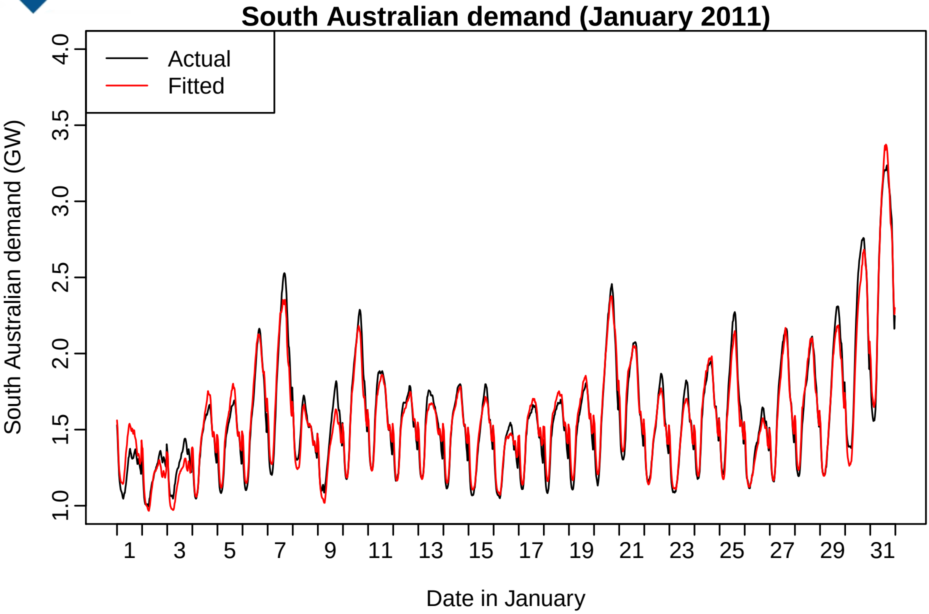

Outline

Peak demand forecasting

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$$\log(\bar{y}_i) = f(\text{GSP, price, HDD, CDD}) + \varepsilon_i$$
$$\log(y_t^*) = f(\text{calendar effects, temperatures}) + e_t$$

Multiple alternative futures created:

- Calendar effects known;
- Future temperatures simulated (taking account of climate change);
- Assumed values for GSP, population and price;
- Residuals simulated

Peak demand backcasting

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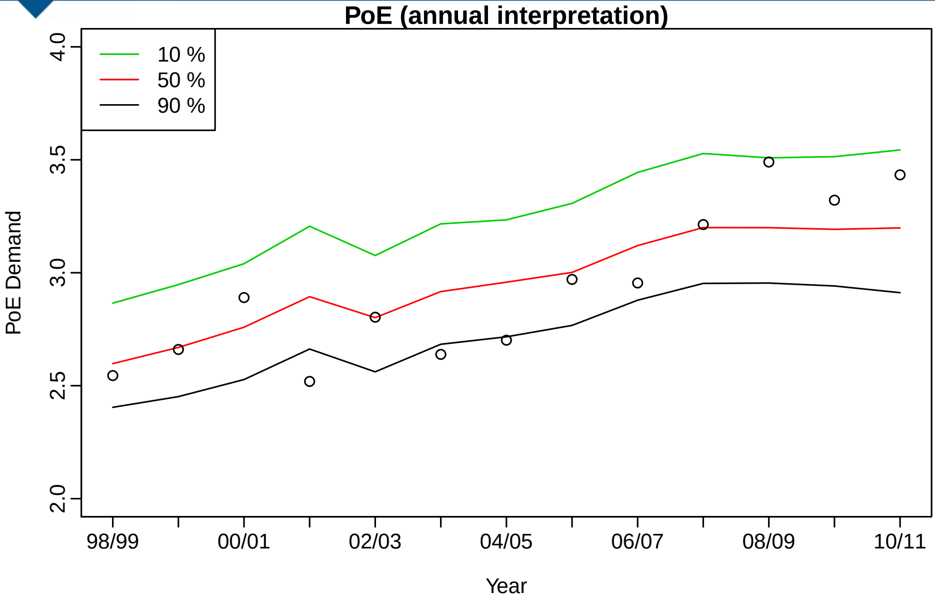
$$\log(y_t^*) = f(\text{calendar effects}, \text{temperatures}) + e_t$$

Multiple alternative pasts created:

- Calendar effects known;
- Past temperatures simulated;
- Actual values for GSP, population and price;
- Residuals simulated

Peak demand backcasting



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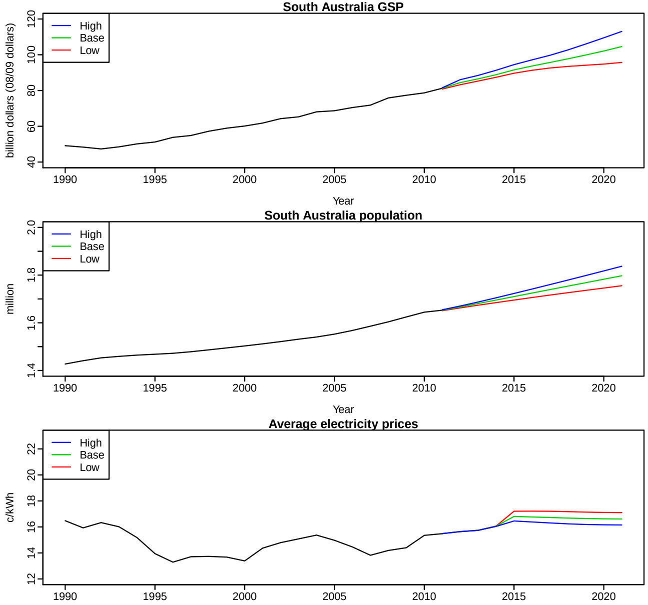
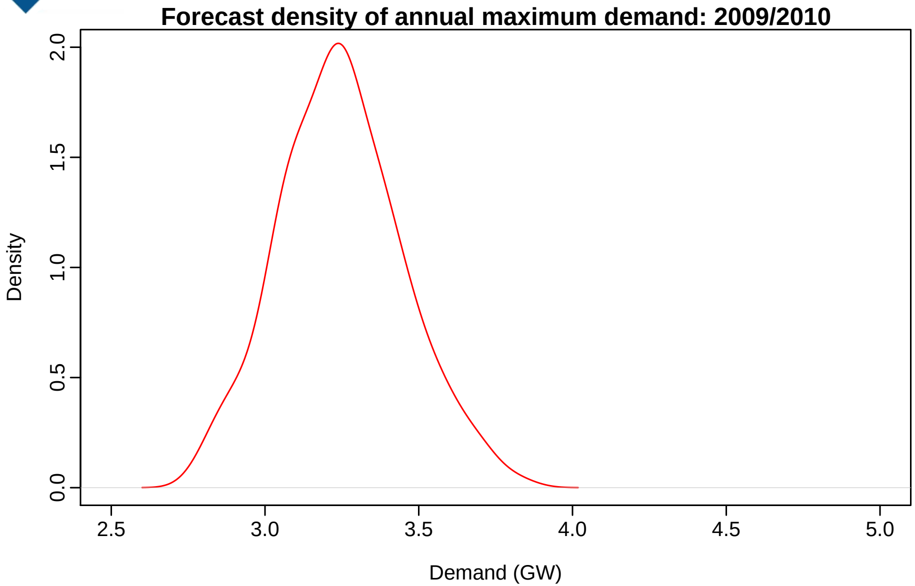


Peak demand distribution



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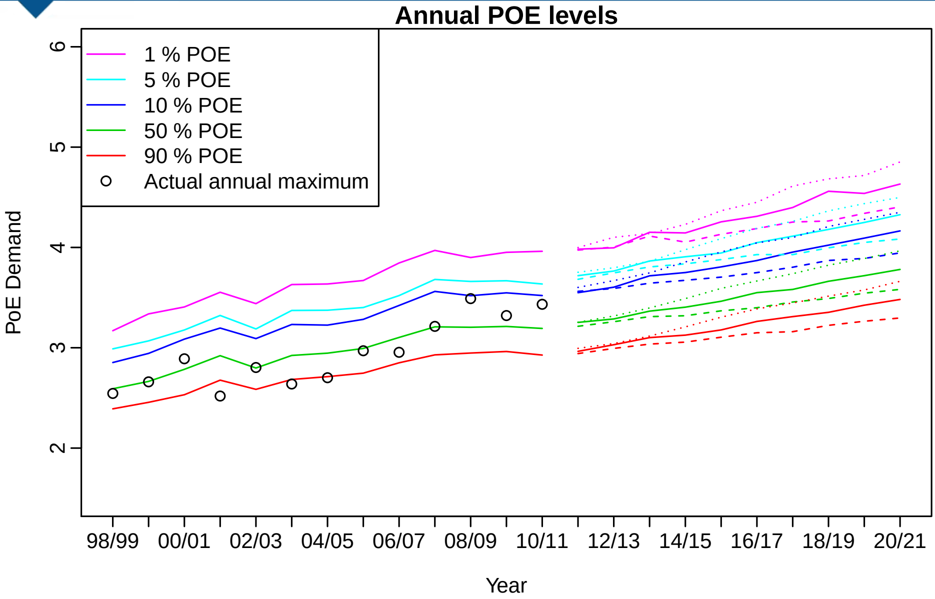

Outline

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Weakest assumptions

- Temperature effects independent of day of week.
- Historical demand response to temperature will continue into the future.
- Climate change will have only a small additive increase in temperature levels.

Further improvements

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- Victoria's Vision 2030 energy plan;
- all regions of the National Energy Market;
- South Western Interconnected System (WA);
- some local distributors.

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IMO INDEPENDENT MARKET OPERATOR

AEMO AUSTRALIAN ENERGY MARKET OPERATOR

Our model is used for long-term forecasting in:

- Victoria’s Vision 2030 energy plan;
- all regions of the National Energy Market;
- South Western Interconnected System (WA);
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It is also used for short-term forecasting comparisons in:

- all regions of the National Energy Market.

UNITED ENERGY

Outline

References

Main papers

- Hyndman, R.J. and Fan, S. (2010) “Density forecasting for long-term peak electricity demand”, *IEEE Transactions on Power Systems*, **25**(2), 1142–1153.
- Fan, S. and Hyndman, R.J. (2012) “Short-term load forecasting based on a semi-parametric additive model”. *IEEE Transactions on Power Systems*, **27**(1), 134–141.
- Ben Taieb, S. and Hyndman, R.J. (2014) “A gradient boosting approach to the Kaggle load forecasting competition”, *International Journal of Forecasting*, **30**(2), 382–394.