Forecasting medium- and long-term peak electricity demand

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Business & Economic Forecasting Unit

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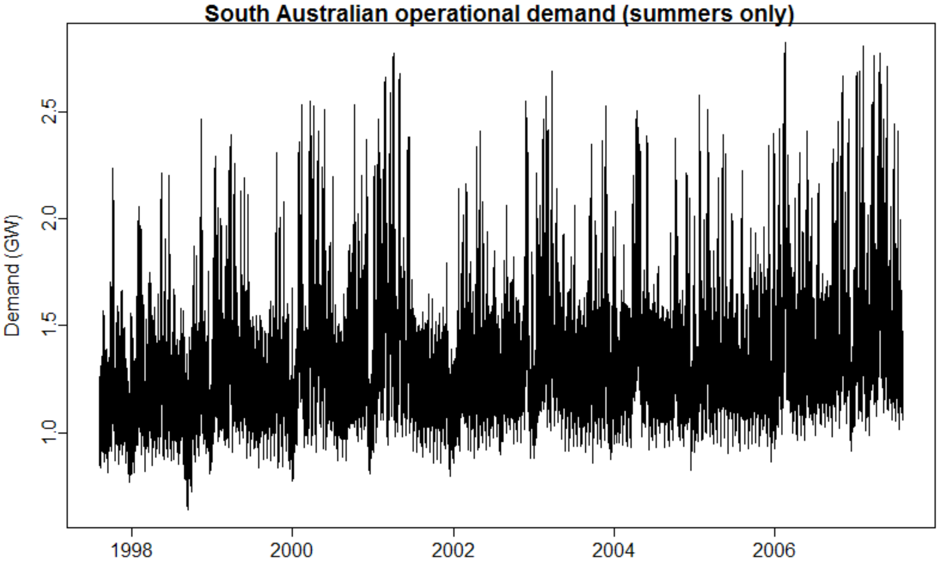
Sounds impossible?

Demand data



Half-hourly demand data for South Australia from 1 July 1997 to 31 March 2007. Only data from November–March are shown.

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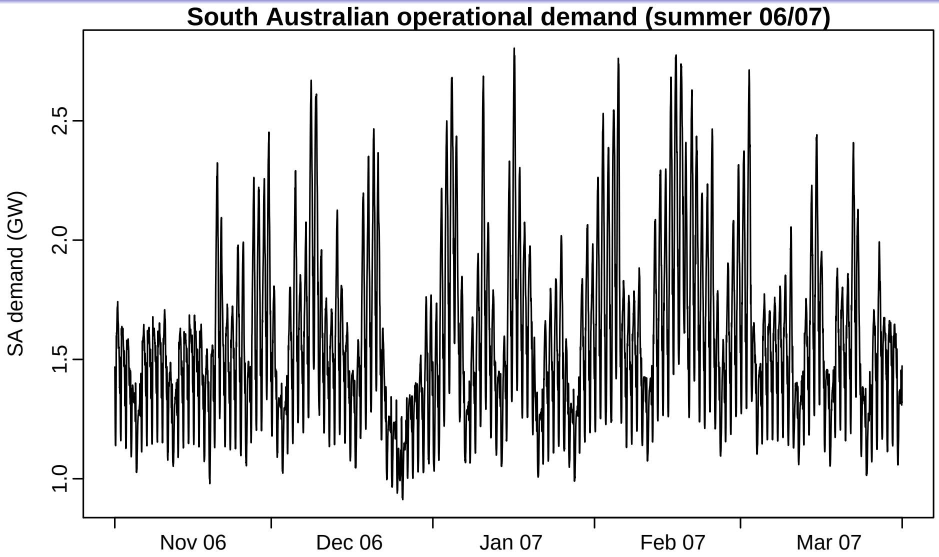

Half-hourly demand data for South Australia from 1 November 2006 to 31 March 2007.

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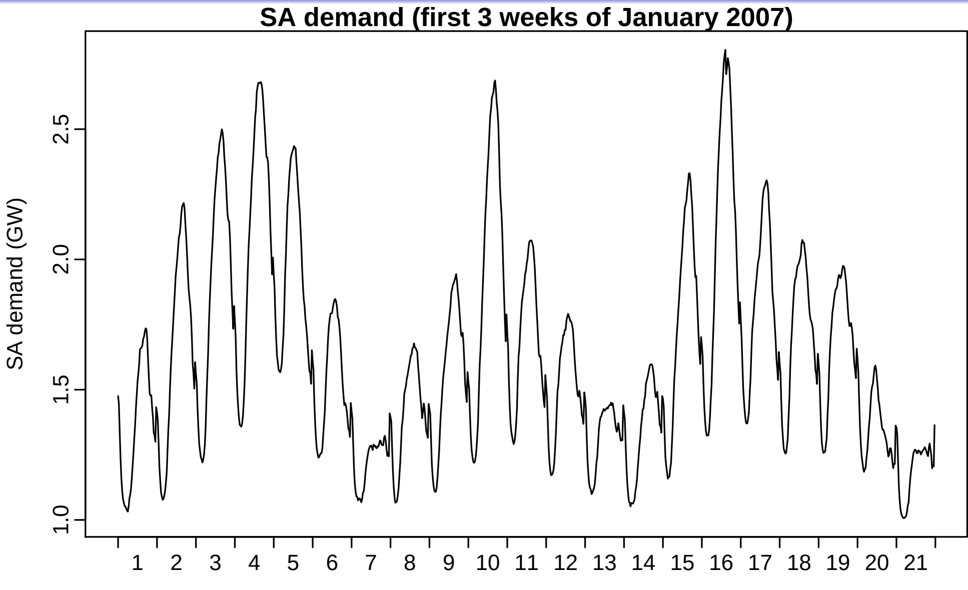

Half-hourly demand data for South Australia from 1–21 January 2007.

Demand boxplots

Temperature data

Demand drivers

- calendar effects

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Modelling framework

- **Semi-parametric additive models** with correlated errors.

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- Each half-hour period modelled separately.

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Modelling framework

- **Semi-parametric additive models** with correlated errors.
- Each half-hour period modelled separately.
- Variables selected to provide best out-of-sample predictions for 2005/06 summer.

Equations

$$\log(y_{t,p}) = h_p(t) + f_p(\mathbf{w}_{1,t}, \mathbf{w}_{2,t}) + \sum_{j=1}^{J} c_j z_{j,t} + n_t$$

- $y_{t,p}$ denotes demand at time t (measured in half-hourly intervals) during period p, $p = 1, \dots, 48$;

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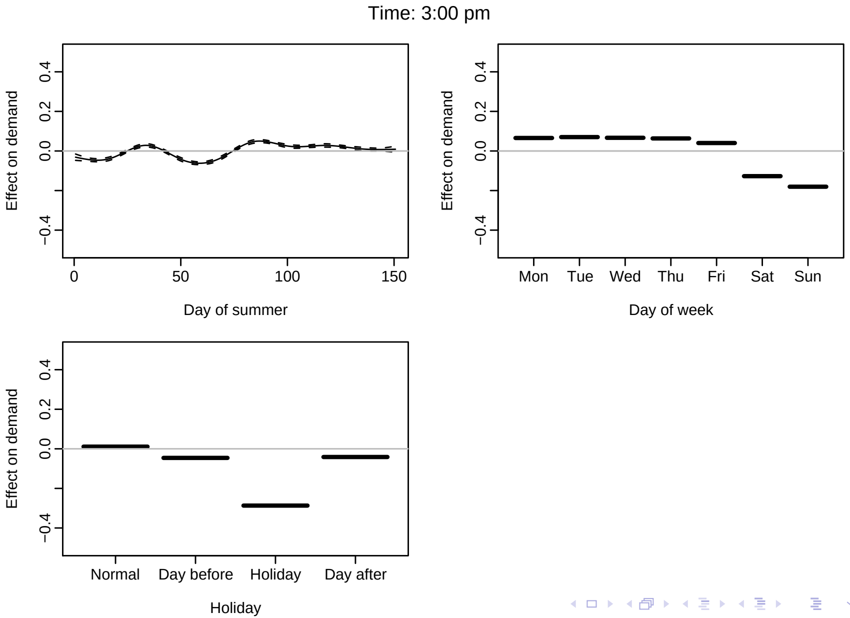
- $\delta_{t,p}$ is millennium effect;

Fitted results (3pm)



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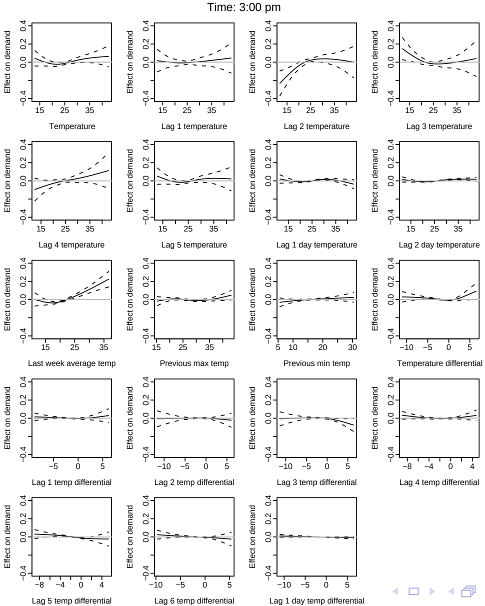
Each function is smooth and estimated using regression splines.

Fitted results (3pm)



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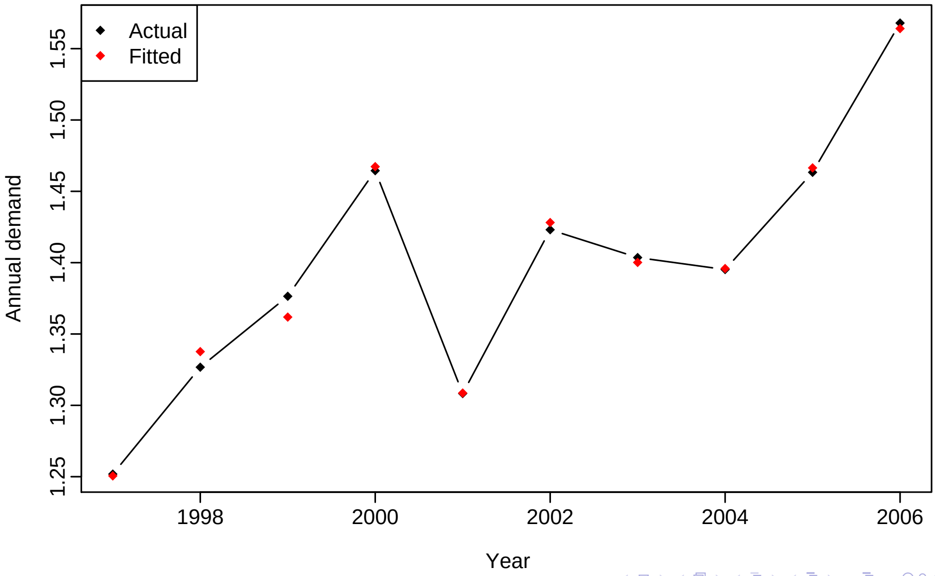
Variable	Coefficient	Std. Error	t value	P value
Intercept	-0.13981	0.04338	-3.222	0.018094
Gross State Product	0.01684	0.00108	15.649	0.000004
Lag Price	-0.04957	0.00727	-6.818	0.000488
Cooling Degree Days	0.36300	0.01716	21.157	0.000001

Predictions



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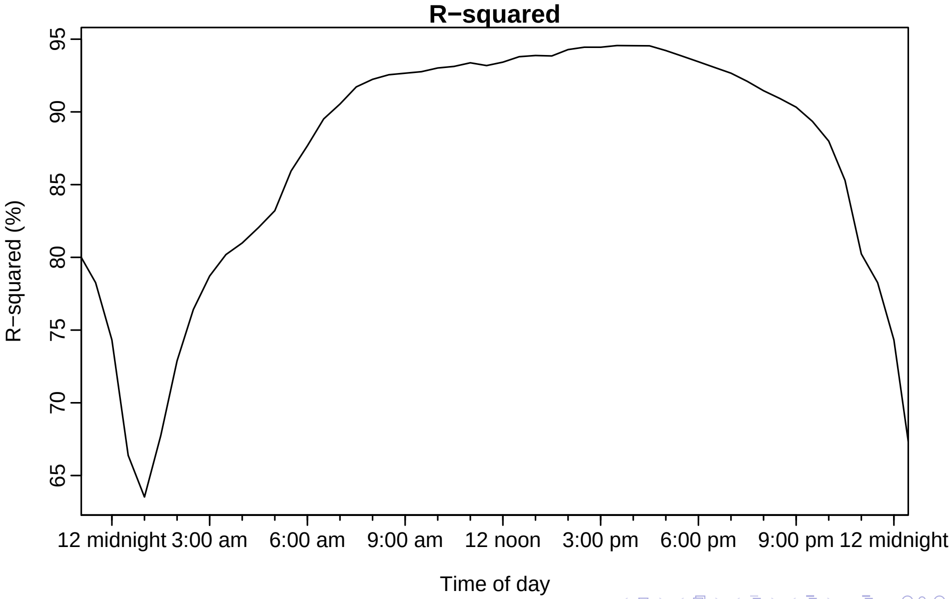

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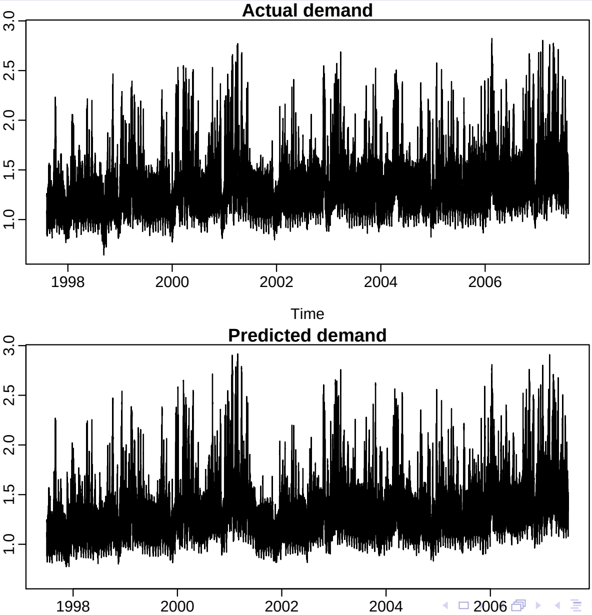

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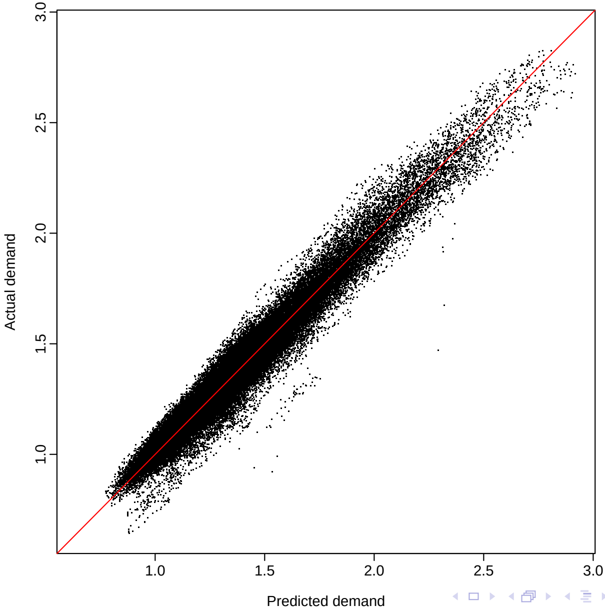

Peak demand forecasting

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Multiple alternative futures created by

- resampling residuals using a seasonal bootstrap;

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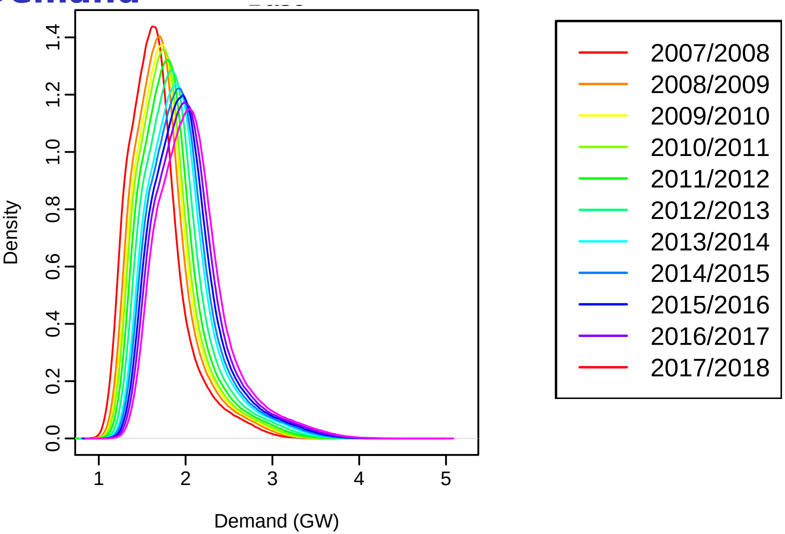
- using assumed values for GSP and Price.

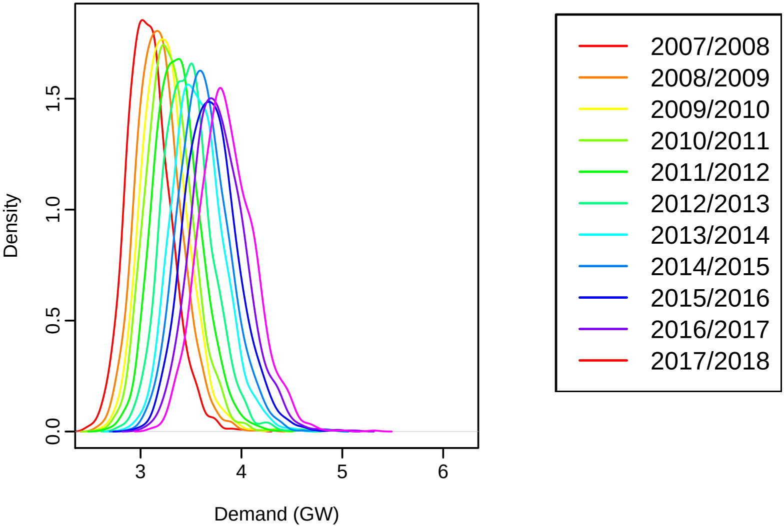
Peak demand distribution

Demand



Peak demand distribution

Annual maximum demand



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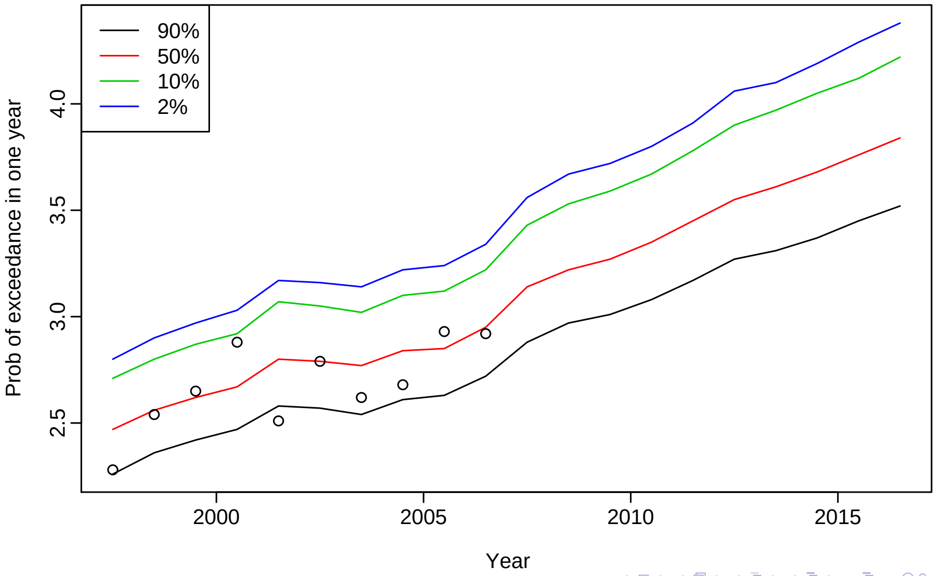

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- Provides way to analyse probability of coincident peaks across different interconnected markets.
- Could be extended to whole year, providing probabilistic forecasts of total energy requirements.
- An R package and a paper will (eventually) appear at **www.robhyndman.info**