Forecasting electricity demand distributions using a semiparametric additive model

Rob J Hyndman
Joint work with Shu Fan
Outline

1. The problem
2. The model
3. Long-term forecasts
4. Short term forecasts
5. References and R implementation
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.
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.
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Sounds impossible?
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Sounds impossible?
South Australian demand data

Forecasting electricity demand distributions

The problem
South Australian demand data

South Australia state wide demand (summers only)

Black Saturday →

Demand (GW)

96/97 98/99 00/01 02/03 04/05 06/07 08/09 10/11

Forecasting electricity demand distributions
The problem 4
South Australian demand data

South Australia state wide demand (summer 10/11)

South Australia state wide demand (GW)

1.5 2.0 2.5 3.0 3.5

Oct 10 Nov 10 Dec 10 Jan 11 Feb 11 Mar 11
South Australian demand data

South Australia state wide demand (January 2011)

Date in January
South Australian demand (GW)
1.5 2.0 2.5 3.0 3.5
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31

The problem
Demand boxplots (Sth Aust)

Time: 12 midnight

Day of week

Forecasting electricity demand distributions
The problem
Temperature data (Sth Aust)

Time: 12 midnight

- Workday
- Non-workday
Demand densities (Sth Aust)

Density of demand: 12 midnight

South Australian half-hourly demand (GW)
Industrial offset demand

Forecasting electricity demand distributions

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

Modelling framework

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- 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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- Each half-hour period modelled separately for each season.
- Variables selected to provide best out-of-sample predictions using cross-validation on each summer.
\[
\log(y_t) = h_p(t) + f_p(\mathbf{w}_{1,t}, \mathbf{w}_{2,t}) + \sum_{j=1}^{J} c_j Z_{j,t} + n_t
\]

- \(y_t\) denotes per capita demand (minus offset) at time \(t\) (measured in half-hourly intervals) and \(p\) denotes the time of day \(p = 1, \ldots, 48;\)
- \(h_p(t)\) models all calendar effects;
- \(f_p(\mathbf{w}_{1,t}, \mathbf{w}_{2,t})\) models all temperature effects where \(\mathbf{w}_{1,t}\) is a vector of recent temperatures at location 1 and \(\mathbf{w}_{2,t}\) is a vector of recent temperatures at location 2;
- \(Z_{j,t}\) is a demographic or economic variable at time \(t;\)
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Monash Electricity Forecasting Model

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\(h_p(t)\) includes handle annual, weekly and daily seasonal patterns as well as public holidays:

\[ h_p(t) = \ell_p(t) + \alpha_{t,p} + \beta_{t,p} + \gamma_{t,p} + \delta_{t,p} \]

- \(\ell_p(t)\) is “time of summer” effect (a regression spline);
- \(\alpha_{t,p}\) is day of week effect;
- \(\beta_{t,p}\) is “holiday” effect;
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Fitted results (Summer 3pm)

Time: 3:00 pm

The model

Forecasting electricity demand distributions
**Monash Electricity Forecasting Model**

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f_p(w_{1,t}, w_{2,t}) = \sum_{k=0}^{6} \left[ f_{k,p}(x_{t-k}) + g_{k,p}(d_{t-k}) \right] + q_p(x_t^+) + r_p(x_t^-) + s_p(\bar{x}_t)
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\[
+ \sum_{j=1}^{6} \left[ F_{j,p}(x_{t-48j}) + G_{j,p}(d_{t-48j}) \right]
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- \(x_t\) is ave temp across two sites (Kent Town and Adelaide Airport) at time \(t\);
- \(d_t\) is the temp difference between two sites at time \(t\);
- \(x_t^+\) is max of \(x_t\) values in past 24 hours;
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- \(\bar{x}_t\) is ave temp in past seven days.

Each function is smooth & estimated using regression splines.
Monash Electricity Forecasting Model

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Fitted results (Summer 3pm)

Forecasting electricity demand distributions

The model
\[ \log(y_t) = h_p(t) + f_p(w_{1,t}, w_{2,t}) + \sum_{j=1}^{J} c_j Z_{j,t} + n_t \]

- Other variables described by linear relationships with coefficients \(c_1, \ldots, c_J\).
- Estimation based on annual data.
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\[
\log(y_t) = \log(y^*_t) + \log(\bar{y}_i)
\]

\[
\log(y^*_t) = h_p(t) + f_p(w_{1,t}, w_{2,t}) + e_t
\]

\[
\log(\bar{y}_i) = \sum_{j=1}^{J} c_j z_{j,i} + \varepsilon_i
\]

- \(\bar{y}_i\) is the average demand for year \(i\) where \(t\) is in year \(i\).
- \(y^*_t\) is the standardized demand for time \(t\).
South Australia state wide demand (summers only)
Monash Electricity Forecasting Model

South Australia state wide demand (summers only)

Adjusted demand (GW)

96/97  98/99  00/01  02/03  04/05  06/07  08/09  10/11
Annual model

\[
\log(\bar{y}_i) = \sum_j c_j z_{j,i} + \varepsilon_i
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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^*
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- First differences modelled to avoid non-stationary variables.
- Predictors: Per-capita GSP, Price, Summer CDD, Winter HDD.
Annual model

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\[
Z_{\text{CDD}} = \sum_{\text{summer}} \max(0, \bar{T} - 18.5)
\]

\(\bar{T} = \text{daily mean}\)
Forecasting electricity demand distributions

The model

Annual model

Cooling and Heating Degree Days

Cooling and Heating degree days

Forecasting electricity demand distributions

The model
<table>
<thead>
<tr>
<th>Variable</th>
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<th>Std. Error</th>
<th>t value</th>
<th>P value</th>
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<tbody>
<tr>
<td>$\Delta gsp.pc$</td>
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<td>$\Delta scdd$</td>
<td>$1.11 \times 10^{-10}$</td>
<td>$2.48 \times 10^{-11}$</td>
<td>4.49</td>
<td>0.000</td>
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<td>$\Delta whdd$</td>
<td>$2.07 \times 10^{-11}$</td>
<td>$3.28 \times 10^{-11}$</td>
<td>0.63</td>
<td>0.537</td>
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- GSP needed to stay in the model to allow scenario forecasting.
- All other variables led to improved AICc.
### Annual model

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</tr>
<tr>
<td>(\Delta scdd)</td>
<td>1.11 \times 10^{-10}</td>
<td>2.48 \times 10^{-11}</td>
<td>4.49</td>
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</tr>
<tr>
<td>(\Delta whdd)</td>
<td>2.07 \times 10^{-11}</td>
<td>3.28 \times 10^{-11}</td>
<td>0.63</td>
<td>0.537</td>
</tr>
</tbody>
</table>

- GSP needed to stay in the model to allow scenario forecasting.
- All other variables led to improved AIC\(_C\).
## Annual model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t value</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta gsp.pc$</td>
<td>$2.02 \times 10^{-6}$</td>
<td>$5.05 \times 10^{-6}$</td>
<td>0.38</td>
<td>0.711</td>
</tr>
<tr>
<td>$\Delta price$</td>
<td>$-1.67 \times 10^{-8}$</td>
<td>$6.76 \times 10^{-9}$</td>
<td>-2.46</td>
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### Forecasting electricity demand distributions

The model
Forecasting electricity demand distributions

The model
Half-hourly models

\[
\log(y_t) = \log(y^*_t) + \log(\bar{y}_i) \\
\log(y^*_t) = h_p(t) + f_p(w_{1,t}, w_{2,t}) + e_t
\]

- Separate model for each half-hour.
- Same predictors used for all models.
- Each model is fitted to the data twice, first excluding the summer of 2009/2010 and then excluding the summer of 2010/2011. The average out-of-sample MSE is calculated from the omitted data for the time periods 12noon–8.30pm.
Half-hourly models

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|   | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $x_5$ | $x_6$ | $x_{48}$ | $x_{96}$ | $x_{144}$ | $x_{192}$ | $x_{240}$ | $x_{288}$ | $d_{d_1}$ | $d_{d_2}$ | $d_{d_3}$ | $d_{d_4}$ | $d_{d_5}$ | $d_{d_6}$ | $d_{d_{48}}$ | $d_{d_{96}}$ | $d_{d_{144}}$ | $d_{d_{192}}$ | $d_{d_{240}}$ | $d_{d_{288}}$ | $x^+$ | $x^-$ | $\bar{x}$ | 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 |

**Forecasting electricity demand distributions**

**The model**

24
Half-hourly models

Forecasting electricity demand distributions

The model

<table>
<thead>
<tr>
<th>Time of day</th>
<th>R-squared (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>12 midnight</td>
<td>60</td>
</tr>
<tr>
<td>3:00 am</td>
<td>70</td>
</tr>
<tr>
<td>6:00 am</td>
<td>80</td>
</tr>
<tr>
<td>9:00 am</td>
<td>90</td>
</tr>
<tr>
<td>12 noon</td>
<td>70</td>
</tr>
<tr>
<td>3:00 pm</td>
<td>90</td>
</tr>
<tr>
<td>6:00 pm</td>
<td>80</td>
</tr>
<tr>
<td>9:00 pm</td>
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</tr>
<tr>
<td>12 midnight</td>
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</tr>
</tbody>
</table>
Half-hourly models

South Australian demand (January 2011)

<table>
<thead>
<tr>
<th>Date in January</th>
<th>South Australian demand (GW)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual</td>
</tr>
<tr>
<td></td>
<td>Fitted</td>
</tr>
</tbody>
</table>

Temperatures (January 2011)

<table>
<thead>
<tr>
<th>Date in January</th>
<th>Temperature (deg C)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>20</td>
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<tr>
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<tr>
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<td>30</td>
</tr>
<tr>
<td></td>
<td>35</td>
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<td></td>
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</tbody>
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South Australian demand (January 2011)

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Kent Town Airport

South Australian demand (January 2011)

Temperatures (January 2011)

<table>
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<tr>
<th>Date in January</th>
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<tr>
<td></td>
<td>10</td>
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</table>

Forecasting electricity demand distributions
Half-hourly models
Half-hourly models
Adjusted model

**Original model**

\[
\log(y_t) = h_p(t) + f_p(w_{1,t}, w_{2,t}) + \sum_{j=1}^{J} c_j z_{j,t} + n_t
\]

**Model allowing saturated usage**

\[
q_t = h_p(t) + f_p(w_{1,t}, w_{2,t}) + \sum_{j=1}^{J} c_j z_{j,t} + n_t
\]

\[
\log(y_t) = \begin{cases} 
q_t & \text{if } q_t \leq \tau; \\
\tau + k(q_t - \tau) & \text{if } q_t > \tau.
\end{cases}
\]

Forecasting electricity demand distributions
### Adjusted model

#### Original model

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Peak demand forecasting

\[ q_{t,p} = h_p(t) + f_p(w_{1,t}, w_{2,t}) + \sum_{j=1}^{J} c_j z_{j,t} + n_t \]

Multiple alternative futures created:

- \( h_p(t) \) known;
- simulate future temperatures using double seasonal block bootstrap with variable blocks (with adjustment for climate change);
- use assumed values for GSP, population and price;
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Seasonal block bootstrapping

Conventional seasonal block bootstrap

- Same as block bootstrap but with whole years as the blocks to preserve seasonality.
- But we only have about 10–15 years of data, so there is a limited number of possible bootstrap samples.

Double seasonal block bootstrap

- Suitable when there are two seasonal periods (here we have years of 151 days and days of 48 half-hours).
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Double seasonal block bootstrap

- Suitable when there are two seasonal periods (here we have years of 151 days and days of 48 half-hours).
- Divide each year into blocks of length 48m.
- Block 1 consists of the first m days of the year, block 2 consists of the next m days, and so on.
- Bootstrap sample consists of a sample of blocks where each block may come from a different randomly selected year but must be at the correct time of year.
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Seasonal block bootstrapping

Actual temperatures

Days

Bootstrap temperatures (fixed blocks)

Days

Bootstrap temperatures (variable blocks)

Days

Forecasting electricity demand distributions

Long-term forecasts
Problems with the double seasonal bootstrap

- Boundaries between blocks can introduce large jumps. However, only at midnight.
- Number of values that any given time in year is still limited to the number of years in the data set.
Seasonal block bootstrapping

Problems with the double seasonal bootstrap

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Variable length double seasonal block bootstrap

- Blocks allowed to vary in length between \( m - \Delta \) and \( m + \Delta \) days where \( 0 \leq \Delta < m \).
- Blocks allowed to move up to \( \Delta \) days from their original position.
- Has little effect on the overall time series patterns provided \( \Delta \) is relatively small.
- Use uniform distribution on \((m - \Delta, m + \Delta)\) to select block length, and independent uniform distribution on \((-\Delta, \Delta)\) to select variation on starting position for each block.
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Seasonal block bootstrapping

Forecasting electricity demand distributions
Seasonal block bootstrapping

Forecasting electricity demand distributions

Bootstrap temperatures (fixed blocks)

Bootstrap temperatures (variable blocks)
Climate change adjustments

- CSIRO estimates for 2030:
  - 0.3°C for 10th percentile
  - 0.9°C for 50th percentile
  - 1.5°C for 90th percentile

- We implement these shifts linearly from 2010.
- No change in the variation in temperature.
- Thousands of “futures” generated using a seasonal bootstrap.
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  - 1.5°C for 90th percentile

- We implement these shifts linearly from 2010.
- No change in the variation in temperature.
- Thousands of “futures” generated using a seasonal bootstrap.
**Climate change adjustments**

- CSIRO estimates for 2030:
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Peak demand forecasting

\[q_{t,p} = h_p(t) + f_p(w_{1,t}, w_{2,t}) + \sum_{j=1}^{J} c_j z_{j,t} + n_t\]

**Multiple alternative futures created:**

- \(h_p(t)\) known;
- simulate **future** temperatures using double seasonal block bootstrap with variable blocks (with adjustment for climate change);
- use **assumed** values for GSP, population and price;
- resample residuals using double seasonal block bootstrap with variable blocks.
Peak demand backcasting

\[ q_{t,p} = h_p(t) + f_p(w_{1,t}, w_{2,t}) + \sum_{j=1}^{J} c_j z_{j,t} + n_t \]

Multiple alternative pasts created:
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- simulate past temperatures using double seasonal block bootstrap with variable blocks;
- use actual values for GSP, population and price;
- resample residuals using double seasonal block bootstrap with variable blocks.
Peak demand backcasting

Forecasting electricity demand distributions

<table>
<thead>
<tr>
<th>Year</th>
<th>PoE Demand</th>
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<tr>
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<td>06/07</td>
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</table>

PoE (annual interpretation)

- **10 %**
- **50 %**
- **90 %**

Year range: 98/99 to 10/11
Peak demand forecasting

\[ q_{t,p} = h_p(t) + f_p(w_{1,t}, w_{2,t}) + \sum_{j=1}^{J} c_j z_{j,t} + n_t \]

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Peak demand forecasting

South Australia GSP

- High
- Base
- Low

South Australia population

- High
- Base
- Low

Average electricity prices

- High
- Base
- Low

Forecasting electricity demand distributions

Long-term forecasts
Forecast density of annual maximum demand: 2009/2010
Peak demand distribution

**Annual POE levels**

- 1 % POE
- 5 % POE
- 10 % POE
- 50 % POE
- 90 % POE
- Actual annual maximum

<table>
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<tbody>
<tr>
<td>98/99</td>
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Forecasting electricity demand distributions

Long-term forecasts
Peak demand forecasting

### Long-term forecasts

#### Base Demand (GW)

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#### Low Demand (GW)

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#### High Demand (GW)

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Forecasting electricity demand distributions
Peak demand forecasting

Forecasting electricity demand distributions

Long-term forecasts
Short term forecasts

\[ q_{t,p} = h_p(t) + f_p(w_{1,t}, w_{2,t}) + \sum_{j=1}^{J} c_j z_{j,t} + n_t \]

- Bootstrapping temperatures and residuals is ok for long-term forecasts because short-term dynamics wash out after a few weeks.
- But short-term forecasts need to take account of recent temperatures and recent residuals due to serial correlation.
- Short-term temperature forecasts are available.
- Building a separate model for \( n_t \) is possible, but there is a simpler approach.
Short term forecasts

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Short-term forecasting model

\[
\log(y_{t,p}) = h_p(t) + f_p(w_{1,t}, w_{2,t}) + a_p(y_{t-1}) + \sum_{j=1}^{J} c_j z_{j,t} + n_t
\]

- \(y_{t,p}\) denotes per capita demand (minus offset) at time \(t\) (measured in half-hourly intervals) during period \(p\), \(p = 1, \ldots, 48\);
- \(h_p(t)\) models all calendar effects;
- \(f_p(w_{1,t}, w_{2,t})\) models all temperature effects where \(w_{1,t}\) is a vector of recent temperatures at location 1 and \(w_{2,t}\) is a vector of recent temperatures at location 2;
- \(z_{j,t}\) is a demographic or economic variable at time \(t\);
- \(n_t\) denotes the model error at time \(t\);
- \(y_t = [y_t, y_{t-1}, y_{t-2}, \ldots]\);
- \(a_p(y_{t-1})\) models effects of recent demands.
Short-term forecasting model

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Short-term forecasting model

\[ a_p(y_{t-1}) = \sum_{k=1}^{n} b_{k,p}(y_{t-k}) + \sum_{j=1}^{m} B_{j,p}(y_{t-48j}) \]
\[ + Q_p(y_t^+) + R_p(y_t^-) + S_p(\bar{y}_t) \]

where

- \( y_t^+ \) is maximum of \( y_t \) values in past 24 hours;
- \( y_t^- \) is minimum of \( y_t \) values in past 24 hours;
- \( \bar{y}_t \) is average demand in past 7 days
- \( b_{k,p}, B_{j,p}, Q_p, R_p \) and \( S_p \) are estimated using cubic splines.
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\[ + Q_p(y_t^+) + R_p(y_t^-) + S_p(\bar{y}_t) \]

where

- \( y_t^+ \) is maximum of \( y_t \) values in past 24 hours;
- \( y_t^- \) is minimum of \( y_t \) values in past 24 hours;
- \( \bar{y}_t \) is average demand in past 7 days
- \( b_{k,p}, B_{j,p}, Q_p, R_p \) and \( S_p \) are estimated using cubic splines.
Weakest assumptions

- Temperature effects are independent of day of week effects.
- Historical demand response to temperature will continue into the future.
- Climate change will have only a small additive increase in temperature levels.
- Locally generated electricity (e.g., PV generation) is not captured in demand data.
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Outline

1. The problem
2. The model
3. Long-term forecasts
4. Short term forecasts
5. References and R implementation
Main papers


R package

We have an R package that implements all methods, but it is not yet publicly available.
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