Emerging Issues in Forecasting Energy Consumption

PRESENTED TO
CRRI Western Conference 2016

PRESENTED BY
Zhen Wang, Ph.D.
Josephine Duh, Ph.D.
Ahmad Faruqui, Ph.D.

June 24, 2016
Agenda

- Growth in energy sales has slowed down and its driving forces
- Emerging issues in forecasting energy sales
- Key lessons learned from case studies
In the United States, growth in energy sales has slowed down since the mid-1950s.

Reasons for the slowdown in US electricity sales

Based on an audience poll from a major energy conference that was held last year by the PJM Interconnection

Similar trends in Australia have been observed over the past decade.
There are several reasons for the decline in energy sales in National Energy Market.

Saddler (13/2015) shows that the largest contributors to the 37 TWh “reduction” in electricity consumption were:

1. Energy efficiency programs (36%)
2. Structural change in the economy away from energy-intensive industries (24%)
3. Consumer response to rising prices (14%)
In light of recent trends, difficult issues arise for forecasters

1. Impending changes will not be reflected in historical data

2. Unobserved structural shifts in electricity consumption may be obscured

3. Forecasts, particularly in recent years, can contain a high degree of uncertainty
In light of recent trends, difficult issues arise for forecasters

1. Impending changes will not be reflected in historical data

2. Unobserved structural shifts in electricity consumption may be obscured

3. Forecasts, particularly in recent years, can contain a high degree of uncertainty.
# Difficult issues warrant creative approaches

<table>
<thead>
<tr>
<th></th>
<th><strong>Collaborate across teams and coordinate resources</strong></th>
<th><strong>Leverage on econometric techniques</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Impending changes will not</td>
<td>Work with other teams to develop forecasts for pieces with high uncertainty</td>
<td>• Use time-series models for short-term forecasts</td>
</tr>
<tr>
<td>be reflected in historical data</td>
<td></td>
<td>• Use microdata to estimate program impacts</td>
</tr>
<tr>
<td>Unobserved structural shifts</td>
<td>Incorporate insights from discussions with stakeholders or customers survey</td>
<td>• Perform “descriptive” analysis to understand drivers</td>
</tr>
<tr>
<td>in electricity consumption</td>
<td></td>
<td>• Analyze residuals for systematic patterns</td>
</tr>
<tr>
<td>may be obscured</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Difficult issues warrant creative approaches

<table>
<thead>
<tr>
<th></th>
<th>Collaborate across teams and coordinate resources</th>
<th>Leverage on econometric techniques</th>
</tr>
</thead>
</table>
| Impending changes will not be reflected in historical data | Work with other teams to develop forecasts for pieces with high uncertainty | • Use time-series models for short-term forecasts  
• Use microdata to estimate program impacts |
| Unobserved structural shifts in electricity consumption may be obscured | Incorporate insights from discussions with stakeholders or customers survey | • Perform “descriptive” analysis to understand drivers  
• Analyze residuals for systematic patterns |
"It takes a village to raise a child"

<table>
<thead>
<tr>
<th>Econometric Model</th>
<th>Post-Estimation Adjustments</th>
</tr>
</thead>
<tbody>
<tr>
<td>• The Brattle Group</td>
<td></td>
</tr>
<tr>
<td>• PNM Forecasting Team</td>
<td></td>
</tr>
<tr>
<td>• UNM BBER</td>
<td></td>
</tr>
<tr>
<td>• Applied Energy Group</td>
<td></td>
</tr>
<tr>
<td>• PNM Energy Efficiency Team</td>
<td></td>
</tr>
<tr>
<td>• PNM Distributed Generation Team</td>
<td></td>
</tr>
</tbody>
</table>

- **PNM sales representatives**
- **Large Industrial Customers Forecast**
- **Final Forecast**
# Difficult issues warrant creative approaches

<table>
<thead>
<tr>
<th></th>
<th>Collaborate across teams and coordinate resources</th>
<th>Leverage on econometric techniques</th>
</tr>
</thead>
</table>
| Impending changes will not be reflected in historical data | Work with other teams to develop forecasts for pieces with high uncertainty | • Use time-series models for short-term forecasts  
• Use microdata to estimate program impacts |
| Unobserved structural shifts in electricity consumption may be obscured | Incorporate insights from discussions with stakeholders or customers survey | • Perform “descriptive” analysis to understand drivers  
• Analyze residuals for systematic patterns |
Example of ARIMA forecasting model

The out-of-sample predictions from a simple ARIMA model and actual monthly energy consumption for New South Wales are shown below:

- ARIMA model was estimated using half-hourly data from January 2002 to June 2013.
- Out-of-sample MAPE = 6.0 percent.
End-Use Model predicts that fuel-switching and take-up of EE appliances and light bulbs drive decrease in energy consumption.
## Comparison of strategies to estimate impact of an impending program

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Advantage</th>
<th>Disadvantage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Econometric program-evaluation approaches</td>
<td>If done properly, estimate is scientifically sound</td>
<td>Data may not be available</td>
</tr>
<tr>
<td>2. End-use modeling</td>
<td>Flexibility to calculate impact of very specific changes</td>
<td>Can be highly data intensive or requires “heroic” assumptions</td>
</tr>
</tbody>
</table>
## Difficult issues warrant creative approaches

<table>
<thead>
<tr>
<th></th>
<th>Collaborate across teams and coordinate resources</th>
<th>Leverage on econometric techniques</th>
</tr>
</thead>
</table>
| Impending changes will not be reflected in historical data | Work with other teams to develop forecasts for pieces with high uncertainty | • Use time-series models for short-term forecasts  
• Use microdata to estimate program impacts |
| Unobserved structural shifts in electricity consumption may be obscured | **Incorporate insights from discussions with stakeholders or customer surveys** | • Perform “descriptive” analysis to understand drivers  
• Analyze residuals for systematic patterns |
## Difficult issues warrant creative approaches

<table>
<thead>
<tr>
<th></th>
<th>Collaborate across teams and coordinate resources</th>
<th>Leverage on econometric techniques</th>
</tr>
</thead>
</table>
| **Impending changes will not be reflected in historical data** | Work with other teams to develop forecasts for pieces with high uncertainty | • Use time-series models for short-term forecasts  
• Use microdata to estimate program impacts |
| **Unobserved structural shifts in electricity consumption may be obscured** | Incorporate insights from discussions with stakeholders or customers survey | • Perform “descriptive” analysis to understand drivers  
• Analyze residuals for systematic patterns |
A “decomposition analysis” can be a useful tool to identify key driver(s)

| Decomposition Analysis of Decline in UPC for Rate Class 2.0 between 2013 and 2017 |
|--------------------------------------------------|---------------------|--------------------------|
| RATE CLASS 2.0                                    | Annual UPC (kwh per customer) | % Decline relative to Predicted UPC in 2013 | Share of overall forecasted decline from 2013 to 2017 |
| Predicted UPC in 2013                            | 18,894               | -5.43%                   |                                                        |
| Forecasted UPC in 2017                           | 17,867               |                          |                                                        |
| UPC in 2013 with 2017 Price levels               | 18,828               | -0.35%                   | 6.4%                                                   |
| UPC in 2013 with 2017 Income* levels             | 18,938               | 0.24%                    | -4.3%                                                  |
| UPC in 2013 with 2017 CDD levels                 | 18,896               | 0.01%                    | -0.2%                                                  |
| UPC in 2013 with 2017 HDD levels                 | 18,825               | -0.36%                   | 6.7%                                                   |
| UPC in 2013 with 2017 "Time" value               | 17,928               | -5.11%                   | 94.1%                                                  |

UPC: usage per customer
Check for systematic patterns in the prediction errors

<table>
<thead>
<tr>
<th>year</th>
<th>month</th>
<th>% Error with ARIMA</th>
<th>% Error with GLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>2014</td>
<td>1</td>
<td>0.7%</td>
<td>0.8%</td>
</tr>
<tr>
<td>2014</td>
<td>2</td>
<td>-0.6%</td>
<td>1.6%</td>
</tr>
<tr>
<td>2014</td>
<td>3</td>
<td>5.4%</td>
<td>6.7%</td>
</tr>
<tr>
<td>2014</td>
<td>4</td>
<td>3.2%</td>
<td>-0.2%</td>
</tr>
<tr>
<td>2014</td>
<td>5</td>
<td>3.0%</td>
<td>1.2%</td>
</tr>
<tr>
<td>2014</td>
<td>6</td>
<td>2.3%</td>
<td>4.9%</td>
</tr>
<tr>
<td>2014</td>
<td>7</td>
<td>-1.1%</td>
<td>0.4%</td>
</tr>
<tr>
<td>2014</td>
<td>8</td>
<td>-0.5%</td>
<td>5.0%</td>
</tr>
<tr>
<td>2014</td>
<td>9</td>
<td>-1.1%</td>
<td>5.1%</td>
</tr>
<tr>
<td>2014</td>
<td>10</td>
<td>0.6%</td>
<td>2.0%</td>
</tr>
<tr>
<td>2014</td>
<td>11</td>
<td>1.7%</td>
<td>3.1%</td>
</tr>
<tr>
<td>2014</td>
<td>12</td>
<td>1.1%</td>
<td>1.5%</td>
</tr>
<tr>
<td>2015</td>
<td>1</td>
<td>-2.2%</td>
<td>-0.3%</td>
</tr>
<tr>
<td>2015</td>
<td>2</td>
<td>2.7%</td>
<td>3.1%</td>
</tr>
<tr>
<td>2015</td>
<td>3</td>
<td>-1.0%</td>
<td>1.1%</td>
</tr>
<tr>
<td>2015</td>
<td>4</td>
<td>5.4%</td>
<td>6.9%</td>
</tr>
<tr>
<td>2015</td>
<td>5</td>
<td>3.7%</td>
<td>1.6%</td>
</tr>
</tbody>
</table>

Example from PNM’s Residential Class

- Prediction errors from GLS model were higher in most of the cases
- PNM ended up using an ARIMA model
In light of recent trends, difficult issues arise for forecasters

1. Impending changes will not be reflected in historical data

2. Unobserved structural shifts in electricity consumption may be obscured

3. Forecasts, particularly in recent years, can contain a high degree of uncertainty.
To deal with uncertainty in the forecast, we need to quantify the sources.

In general, three types can be distinguished (EPRI, 1992):

1. **Parameters**
   - Standard errors for parameters can be used to construct bands of uncertainty around the forecast; these are conditional on explanatory variables being fixed.

2. **Projections of explanatory variables**
   - Monte Carlo simulation can be used to arrive at probability distributions that allow for uncertainty in parameter estimates and explanatory variable projections.
   - Or scenario analysis can be used to construct low, medium and high cases in a deterministic fashion.
Sources of forecast uncertainty (concluded)

3. Model structure

- Multiple models can be estimated to bracket the possibilities and bound the forecast
- The following options should be considered
  - Structural econometric model
  - Time series model, *e.g.*, ARIMA
  - End-use model
  - Statistically-adjusted end use (SAE) model (Train, 1985; Train, 1992)
  - Qualitative consumer panel surveys
Conclusions

Growth in energy sales has slowed down in the U.S. and other regions

Three difficult issues arise for forecasters

- New programs and policies are not reflected in historical data
- Unobserved structural shifts are taking place at the micro level
- Forecasts are increasingly uncertain

Key lessons Learned

- Collaborate across teams and coordinate resources
- Leverage econometric techniques with end-use models and other techniques
- Identify sources of uncertainty and apply feasible strategies
Dr. Zhen Wang is an Associate at The Brattle Group where she focuses on litigation, demand forecasting, and marketing modeling. She has worked closely with utility companies to critically review and develop demand forecasting models. Dr. Wang also works with law firms, government agencies and corporate firms on a variety of legal, regulatory and policy issues. She has performed damages analyses in several high-stake environmental lawsuits and conducted econometric analyses in antitrust/competition related matters. She has also worked on liability determination and damage calculations for commercial arbitrations.

Dr. Wang holds a Ph.D. in Economics from North Carolina State University and a B.S. in Finance from Shanghai Jiao Tong University (Shanghai, China).

The views expressed in this presentation are strictly those of the presenter(s) and do not necessarily state or reflect the views of The Brattle Group.
Additional Resources


Saddler, Hugh. 2015 "Power Down II, the Continuing Decline in Australia's Electricity Demand?."
About Brattle

The Brattle Group provides consulting and expert testimony in economics, finance, and regulation to corporations, law firms, and governments around the world. We aim for the highest level of client service and quality in our industry.

We are distinguished by our credibility and the clarity of our insights, which arise from the stature of our experts, affiliations with leading international academics and industry specialists, and thoughtful, timely, and transparent work. Our clients value our commitment to providing clear, independent results that withstand critical review.
Our Practices

PRACTICES
- Antitrust/Competition
- Bankruptcy and Restructuring Analysis
- Commercial Damages
- Data Analytics
- Environmental Litigation and Regulation
- Intellectual Property
- International Arbitration
- International Trade
- Mergers & Acquisitions Litigation
- Product Liability
- Regulatory Finance and Accounting
- Risk Management
- Securities
- Tax
- Utility Regulatory Policy and Ratemaking
- Valuation

INDUSTRIES
- Electric Power
- Financial Institutions
- Health Care Products and Services
- Natural Gas and Petroleum
- Telecommunications and Media
- Transportation
Offices

CAMBRIDGE

NEW YORK

SAN FRANCISCO

WASHINGTON, DC

TORONTO

LONDON

MADRID

ROME

SYDNEY