Forecasting and the importance of being uncertain

Rob J Hyndman

MONASH University
Speaker introduction

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News report on 16 August 2006
A Russian woman is suing weather forecasters for wrecking her holiday. A court in Uljanovsk heard that Alyona Gabitova had been promised 28 degrees and sunshine when she planned a camping trip to a local nature reserve, newspaper Nowyje Iswestija said. But it did nothing but pour with rain the whole time, leaving her with a cold. Gabitova has asked the court to order the weather service to pay the cost of her travel.
What is it?
What is it?

Clay model of sheep’s liver

Used by Babylonian forecasters approximately 600 B.C.

Now in British Museum.
Delphic oracle
Delphic oracle
Forecasting and the importance of being uncertain

Temple of Apollo

Delphi
Forecasting and the importance of being uncertain

A brief history of forecasting

Temple of Apollo
Vagrant forecasters

The British Vagrancy Act (1736) made it an offence to defraud by charging money for predictions.
Vagrant forecasters

The British Vagrancy Act (1736) made it an offence to defraud by charging money for predictions.

**Punishment:** a fine or three months’ imprisonment with hard labour.
Reputations can be made and lost

“Tell us what the future holds, so we may know that you are gods.” (Isaiah 41:23, 700 B.C.)
Reputations can be made and lost

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“I think there is a world market for maybe five computers.”  
(Chairman of IBM, 1943)
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- “There is no reason anyone would want a computer in their home.” (President, DEC, 1977)
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“There are four ways economists can lose their reputation. Gambling is the quickest, sex is the most pleasurable and drink the slowest. But forecasting is the surest.” (Max Walsh, The Age, 1993)
Those “unforeseen events”

*Precautions should be taken against running into unforeseen occurrences or events.*  
(Horoscope, New York Times)
Those “unforeseen events”

Precautions should be taken against running into unforeseen occurrences or events. (Horoscope, New York Times)

We are ready for any unforeseen event which may or may not occur. (Dan Quayle)
Graphic Forecaster

Create forecasts visually with a "drag and drop" graphic forecaster. The Graphic Forecaster is a simple and powerful tool to streamline the forecasting process. You can change your sales and expenses estimates by simply clicking your mouse button to move the line on your forecast chart or apply a specific growth rate to the whole year. Build forecasts using visual common sense.
Standard business practice today

Crystal Xcelsius Showcase
Examples of what you can build with Crystal Xcelsius.

If you cannot open these demos, download the latest version of Macromedia's Flash Player.

Featured Example: Profitability Analysis

Profitability Analysis
This profitability model allows you to create "what-if" scenarios by modifying sales growth rate and all other relevant accounts measured as a percentage of total sales. This example, built with fictitious data, depicts the most relevant accounts of a profit and loss statement, and shows the impact of changes on net income. The results change immediately, allowing you to create endless what-if scenarios.

Download as PowerPoint
Download as PDF
Download as Word
Download as Flash
Download Source Files
Budget Maestro by Centage
Click here for a free demo

Application: Business Intelligence and Analytics

Price Range: Solutions start at $5K

A huge advance over spreadsheet-based systems, Budget Maestro is a complete solution for budgeting, forecasting, what-if scenario planning, reporting and analysis. Budget Maestro takes the pain out of the budgeting process (no tedious data entry and formula verification) while providing you a tool to more accurately analyze and measure business performance and profitability. Budget Maestro's capabilities include:

**Budgeting and Forecasting:** Budget Maestro utilizes database technology for real-time data collection and reporting. A common interface for all users fosters collaboration and increases the accuracy of data entry. There are no formulas or macros to create, no tedious re-keying of data and no mystery links to chase down and fix. Budget Maestro's built-in “financial intelligence and business rules” builds the formulas for you ensuring 100% accuracy.
Standard business practice today

“What-if scenarios” based on assumed and fixed future conditions.
Standard business practice today

- “What-if scenarios” based on assumed and fixed future conditions.
- Highly subjective.
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Is this any better than a sheep’s liver or hallucinogens?
The rise of stochastic models

1959 exponential smoothing (Brown)
1970 ARIMA models (Box, Jenkins)
1980 VAR models (Sims, Granger)
1980 non-linear models (Granger, Tong, Hamilton, Teräsvirta, . . . )
1982 ARCH/GARCH (Engle, Bollerslev)
1986 neural networks (Rumelhart)
1989 state space models (Harvey, West, Harrison)
1994 nonparametric forecasting (Tjøstheim, Härdle, Tsay, . . . )
Advantages of stochastic models

- Based on empirical data
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- Based on empirical data
- Computable
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- Based on empirical data
- Computable
- Replicable
Advantages of stochastic models

- Based on empirical data
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Advantages of stochastic models

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- **Objective measure of uncertainty**
Advantages of stochastic models

- Based on empirical data
- Computable
- Replicable
- Testable
- Objective measure of uncertainty
- Able to compute prediction intervals
Outline

1. A brief history of forecasting
2. Forecasting the PBS
3. Forecasting CO₂ emissions
4. Forecasting Australia’s population
5. Forecasting peak electricity demand
6. Forecast evaluation
7. Conclusions
Opp demands drug price restriction after PBS budget blow-out

The Federal Opposition has called for tighter controls on drug prices after the Pharmaceutical Benefits Scheme (PBS) budget blew out by almost $800 million.

The money was spent on two new drugs including the controversial anti-smoking aid Zyban, which dropped in price from $220 to $22 after it was listed on the PBS.
Forecasting the PBS

Estimation of forward estimates for the Pharmaceutical Benefit Scheme
Department of Health and Aging

Forecasting the PBS

Estimation of forward estimates for the Pharmaceutical Benefit Scheme
Department of Health and Aging

- Thousands of products. Seasonal demand.
Forecasting the PBS

Estimation of forward estimates for the Pharmaceutical Benefit Scheme

Department of Health and Aging


- Thousands of products. Seasonal demand.

- Subject to covert marketing, volatile products, uncontrollable expenditure.
Forecasting the PBS

Estimation of forward estimates for the Pharmaceutical Benefit Scheme

Department of Health and Aging

- Thousands of products. Seasonal demand.
- Subject to covert marketing, volatile products, uncontrollable expenditure.
- All forecasts being done with the FORECAST function in MS-Excel applied to 10 year old data!
Forecasting the PBS

Estimation of forward estimates for the Pharmaceutical Benefit Scheme
Department of Health and Aging

- We used **time series models** — automated exponential smoothing state space modelling applied to about 100 product groups.
Forecasting the PBS

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Department of Health and Aging

- We used **time series models** — automated exponential smoothing state space modelling applied to about 100 product groups.

- Methodological tools developed in 2002 and published in the *International Journal of Forecasting*.
Forecasting the PBS

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Department of Health and Aging

- We used **time series models** — automated exponential smoothing state space modelling applied to about 100 product groups.

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- Forecast error now a few $million per year.
Forecasting and the importance of being uncertain

Forecasting the PBS

Total monthly scripts: concession copayments
Cardiovascular system drugs

Year
1995 2000 2005

20 40 60 80 100 120 140

80% prediction intervals

x 1000

20 40 60 80 100 120 140
Forecasting the PBS

- Used stochastic models to describe evolution of sales over time.
Forecasting the PBS

- Used stochastic models to describe evolution of sales over time.
- Models allowed for time-changing trend and seasonal patterns.
Forecasting the PBS

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- Stochastic models provide prediction intervals which give a sense of uncertainty.
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- Class of models was based on exponential smoothing.
Forecasting the PBS

- Used stochastic models to describe evolution of sales over time.
- Models allowed for time-changing trend and seasonal patterns.
- Stochastic models provide prediction intervals which give a sense of uncertainty.
- Class of models was based on exponential smoothing.
- At the time, exponential smoothing methods were not thought to be based on stochastic models.
Exponential smoothing is extremely popular, simple to implement, and performs well in forecasting competitions.
Exponential smoothing is extremely popular, simple to implement, and performs well in forecasting competitions.

“Unfortunately, exponential smoothing methods do not allow easy calculation of prediction intervals.”

Exponential smoothing

Since 2002.

- a general class of state space models proposed underlying all the common exponential smoothing methods.
Exponential smoothing

Since 2002...

- a general class of state space models proposed underlying all the common exponential smoothing methods.
- analytical results for prediction intervals.
Exponential smoothing

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- a general class of state space models proposed underlying all the common exponential smoothing methods.
- analytical results for prediction intervals.
- efficient parameter estimation.
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- an algorithm for automatic forecasting using the new class of models.
Exponential smoothing

Since 2002...

- a general class of state space models proposed underlying all the common exponential smoothing methods.
- analytical results for prediction intervals.
- efficient parameter estimation.
- objective model selection.
- an algorithm for automatic forecasting using the new class of models.
- new results on the admissible parameter space.
# Taxonomy of models

<table>
<thead>
<tr>
<th>Trend Component</th>
<th>Seasonal Component</th>
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<tbody>
<tr>
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<td>N</td>
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<td>N</td>
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<td>A</td>
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<td>M</td>
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<tr>
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- **N** (None)
- **A** (Additive)
- **Ad** (Additive damped)
- **M** (Multiplicative)
- **Md** (Multiplicative damped)

**General notation** \( \text{ETS}(E,T,S) \)
### Taxonomy of models

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**General notation** **ETS** *(Error, Trend, Seasonal)*  
**Exponential Smoothing**
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**General notation**

\[ \text{ETS(Error,Trend,Seasonal)} \]

**Exponential Smoothing**

**ETS(A,N,N):** Simple exponential smoothing with additive errors
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### General notation

**ETS**(*Error*,*Trend*,*Seasonal*)

**Exponential Smoothing**

**ETS(A,A,N):** Holt’s linear method with additive errors
### Taxonomy of models

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**General notation**  
ETS(\textit{Error},\textit{Trend},\textit{Seasonal}) Exponential Smoothing

**ETS(A,A,A):** Additive Holt-Winters’ method with additive errors
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### General notation

**ETS**(Error, Trend, Seasonal)

**Exponential Smoothing**

**ETS**(M,A,M): Multiplicative Holt-Winters’ method with multiplicative errors
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#### General notation

**ETS**(*Error*,*Trend*,*Seasonal*)
**Exponential Smoothing**

**ETS(A,A_d,N):** Damped trend method with additive errors
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**General notation** \textbf{ETS}(\textit{Error,Trend,Seasonal})

**Exponential Smoothing**

There are 30 separate models in the ETS framework.
New book!

Springer Series in Statistics

Rob J. Hyndman · Anne B. Koehler
J. Keith Ord · Ralph D. Snyder

Forecasting with Exponential Smoothing

The State Space Approach

- State space modeling framework
- Prediction intervals
- Model selection
- Maximum likelihood estimation
- All the important research results in one place with consistent notation
- Many new results
- 375 pages but only US$54.95 / £28.50 / €36.95

Exponential smoothing methods have been around since the 1950s, and are the most popular forecasting methods used in business and industry. Recently, exponential smoothing has been revolutionized with the introduction of a complete modeling framework incorporating innovations state space models, likelihood calculation, prediction intervals and procedures for model selection. In this book, all of the important results for this framework are brought together in a coherent manner with consistent notation. In addition, many new results and extensions are introduced and several application areas are examined in detail.

Rob J. Hyndman is a Professor of Statistics and Director of the Business and Economic Forecasting Unit at Monash University, Australia. He is Editor-in-Chief of the International Journal of Forecasting, author of over 100 research papers in statistical science, and received the 2007 Moran medal from the Australian Academy of Science for his contributions to statistical research.

Anne B. Koehler is a Professor of Decision Sciences and the Panuska Professor of Business Administration at Miami University, Ohio. She has numerous publications, many of which are on forecasting models for seasonal time series and exponential smoothing methods.

J. Keith Ord is a Professor in the McDonough School of Business, Georgetown University, Washington DC. He has authored over 100 research papers in statistics and forecasting, and is a co-author of Kendall's Advanced Theory of Statistics.

Ralph D. Snyder is an Associate Professor in the Department of Econometrics and Business Statistics at Monash University, Australia. He has extensive publications on business forecasting and inventory management. He has played a leading role in the establishment of the class of innovations state space models for exponential smoothing.
New book!

State space modeling framework
Prediction intervals
Model selection
Maximum likelihood estimation
All the important research results in one place with consistent notation
Many new results
375 pages but only US$54.95 / £28.50 / €36.95

www.exponentialsmoothing.net
Outline

1. A brief history of forecasting
2. Forecasting the PBS
3. Forecasting CO$_2$ emissions
4. Forecasting Australia’s population
5. Forecasting peak electricity demand
6. Forecast evaluation
7. Conclusions
Forecasting $\text{CO}_2$ emissions

**Australian Greenhouse Office**

- Task: produce multi-year forecasts of Australia’s $\text{CO}_2$ emissions with uncertainty limits.
Australian Greenhouse Office

Task: produce multi-year forecasts of Australia’s CO$_2$ emissions with uncertainty limits.

Problems: very little reliable data. Likely major changes in technology making historical data of little value.
Forecasting CO\textsubscript{2} emissions

Australian Greenhouse Office

- Task: produce multi-year forecasts of Australia’s CO\textsubscript{2} emissions with uncertainty limits.
- Problems: very little reliable data. Likely major changes in technology making historical data of little value.
- Solution: Use judgmental methods
Forecasting CO₂ emissions

Key drivers ‘high’ and ‘low’ scenarios for sector

Expert A
Expert B
Expert C
Expert D
Expert E

Expert A’s best estimate & 95% confidence interval
Expert B’s best estimate & 95% confidence interval
Expert C’s best estimate & 95% confidence interval
Expert D’s best estimate & 95% confidence interval
Expert E’s best estimate & 95% confidence interval

probability
emissions
probability
emissions
probability
emissions
probability
emissions
probability
emissions

Figure 2: Effect of triangular distributions on combined sectoral projection distribution

Monash University Department of Econometrics and Business Statistics

Forecasting CO$_2$ emissions

Australian Greenhouse Office

Key drivers ‘high’ and ‘low’ scenarios for sector

R3 Correlations module

Combined sectoral projection

Actual emissions distribution

Monash University Department of Econometrics and Business Statistics


Forecasting and the importance of being uncertain
Forecasting and the importance of being uncertain

Outline

1. A brief history of forecasting
2. Forecasting the PBS
3. Forecasting CO$_2$ emissions
4. Forecasting Australia’s population
5. Forecasting peak electricity demand
6. Forecast evaluation
7. Conclusions
The Australian Bureau of Statistics provide population “projections”.

“The projections are not intended as predictions or forecasts, but are illustrations of growth and change in the population that would occur if assumptions made about future demographic trends were to prevail over the projection period. While the assumptions are formulated on the basis of an assessment of past demographic trends, both in Australia and overseas, there is no certainty that any of the assumptions will be realised. In addition, no assessment has been made of changes in non-demographic conditions.”

ABS 3222.0 - Population Projections, Australia, 2004 to 2101
ABS population projections

The ABS provides three projection scenarios labelled “High”, “Medium” and “Low”.

- Based on assumed mortality, fertility and migration rates
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- Not prediction intervals.
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- Based on assumed mortality, fertility and migration rates
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- No variation allowed across ages.
- No probabilistic basis.
- Not prediction intervals.

Most users use the “Medium” projection, but it is unrelated to the mean, median or mode of the future distribution.
### ABS population projections

#### Australian total population

<table>
<thead>
<tr>
<th>Year</th>
<th>Millions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1920</td>
<td>5</td>
</tr>
<tr>
<td>1940</td>
<td>10</td>
</tr>
<tr>
<td>1960</td>
<td>15</td>
</tr>
<tr>
<td>1980</td>
<td>20</td>
</tr>
<tr>
<td>2000</td>
<td>25</td>
</tr>
<tr>
<td>2020</td>
<td>30</td>
</tr>
<tr>
<td>2040</td>
<td></td>
</tr>
</tbody>
</table>

- **A**
- **B**
- **C**
Forecasting and the importance of being uncertain

ABS population projections

What do these projections mean?
Annual age-specific population

Australia: male population (1921–2004)
Annual age-specific population

Australia: female population (1921–2004)
Stochastic population forecasts

Key ideas

- Population is a function of mortality, fertility and net migration.
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Stochastic population forecasts

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- Combine the results to get **age-specific stochastic population forecasts**.
Mortality rates

Australia: male mortality (1921)
Mortality rates

Australia: male death rates (1921–2003)
Mortality rates

Australia: male mortality (1921–2003)
Mortality rates

Australia: male mortality forecasts (2004–2023)
Mortality rates

Australia: male death rate forecasts (2004 and 2023)

80% prediction intervals
Forecasting and the importance of being uncertain

Fertility rates

Australia: fertility rates (1921)
Forecasting and the importance of being uncertain

Fertility

Australia: fertility rate forecasts (2004 and 2023)
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Fertility

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80% prediction intervals

Age

Fertility rate

80% prediction intervals
Forecasts of life expectancy at age 0

Forecast female life expectancy

Year
Age
1960 1980 2000 2020
70 75 80 85 90

Forecast male life expectancy

Year
Age
1960 1980 2000 2020
70 75 80 85 90
Forecast population pyramid for 2024, along with 80% prediction intervals. Dashed: actual population pyramid for 2004.
Population forecasts

Population forecasts

Forecasting and the importance of being uncertain

Old-age dependency ratio forecasts

Year | ratio
---|---
1920 | 0.10
1940 | 0.15
1960 | 0.20
1980 | 0.25
2000 | 0.30
2020 | 0.35
Stochastic population forecasts

- Forecasts represent the median of the future distribution.
Stochastic population forecasts

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- Percentiles of distribution allow information about uncertainty.

Economic planning is better based on prediction intervals rather than mean or median forecasts. Stochastic models allow true policy analysis to be carried out.
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The problem

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Sounds impossible?
Demand data
Demand data

South Australian operational demand (summer 06/07)
Demand data

SA demand (first 3 weeks of January 2007)
Demand drivers

- calendar effects
Demand drivers

- calendar effects
- prevailing weather conditions (and the timing of those conditionals)
Demand drivers

- calendar effects
- prevailing weather conditions (and the timing of those conditionals)
- climate changes
Demand drivers

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Modelling framework

- Semi-parametric additive models with correlated errors.
Demand drivers

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Modelling framework

- Semi-parametric additive models with correlated errors.
- Each half-hour period modelled separately.
Demand drivers

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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.
### Predictions

<table>
<thead>
<tr>
<th>Year</th>
<th>Actual</th>
<th>Fitted</th>
</tr>
</thead>
<tbody>
<tr>
<td>1998</td>
<td>1.25</td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>1.30</td>
<td></td>
</tr>
<tr>
<td>2002</td>
<td>1.40</td>
<td></td>
</tr>
<tr>
<td>2004</td>
<td>1.45</td>
<td></td>
</tr>
<tr>
<td>2006</td>
<td>1.55</td>
<td></td>
</tr>
</tbody>
</table>
Forecasting and the importance of being uncertain

Predictions

<table>
<thead>
<tr>
<th>Time of day</th>
<th>R-squared (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>12 midnight</td>
<td>95</td>
</tr>
<tr>
<td>3:00 am</td>
<td>95</td>
</tr>
<tr>
<td>6:00 am</td>
<td>95</td>
</tr>
<tr>
<td>9:00 am</td>
<td>95</td>
</tr>
<tr>
<td>12 noon</td>
<td>95</td>
</tr>
<tr>
<td>3:00 pm</td>
<td>95</td>
</tr>
<tr>
<td>6:00 pm</td>
<td>95</td>
</tr>
<tr>
<td>9:00 pm</td>
<td>95</td>
</tr>
<tr>
<td>12 midnight</td>
<td>65</td>
</tr>
</tbody>
</table>

The graph shows the R-squared values for different times of the day, with the highest values during the evening and early morning hours.
Forecasting and the importance of being uncertain

Predictions

Actual demand

Predicted demand

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual demand</td>
<td>1.0</td>
<td>1.5</td>
<td>2.0</td>
<td>2.5</td>
<td>3.0</td>
</tr>
<tr>
<td>Predicted demand</td>
<td>1.0</td>
<td>1.5</td>
<td>2.0</td>
<td>2.5</td>
<td>3.0</td>
</tr>
</tbody>
</table>

1.0 | 1.5 | 2.0 | 2.5 | 3.0 |

Predictions
Peak demand distribution

Annual maximum demand

Demand (GW)

Density

2007/2008
2008/2009
2009/2010
2010/2011
2011/2012
2012/2013
2013/2014
2014/2015
2015/2016
2016/2017
2017/2018
Forecasting and the importance of being uncertain

Peak demand distribution

<table>
<thead>
<tr>
<th>Year</th>
<th>2000</th>
<th>2005</th>
<th>2010</th>
<th>2015</th>
</tr>
</thead>
<tbody>
<tr>
<td>90%</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
<tr>
<td>50%</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
<tr>
<td>10%</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
<tr>
<td>2%</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
</tr>
</tbody>
</table>

Prob of exceedance in one year

- 90%
- 50%
- 10%
- 2%

Year


Prob of exceedance in one year

- 2.5
- 3.0
- 3.5
- 4.0

Year

Forecasting peak electricity demand

- We have forecast the extreme upper tail in ten years time using only ten years of data!
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This method has now been adopted for the official South Australian, Victorian and Western Australian peak electricity demand forecasts.
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Method could also be used for short-term demand forecasting, if we add a model for correlated residuals.
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Provides way to analyse probability of coincident peaks across different interconnected markets.
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- This method has now been adopted for the official South Australian, Victorian and Western Australian peak electricity demand forecasts.
- Method could also be used for short-term demand forecasting, if we add a model for correlated residuals.
- 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.
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Forecast evaluation

- Ensure you have a systematic evaluation process.
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- Ensure you have a systematic evaluation process.
- Check past forecasts against actuals.

Definitions
- Bias: systematic under- or over-estimating future value. Usually due to the method.
- Variability: random (unpredictable) errors. Usually due to the data.
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Bias and variability

High bias, high variability

High bias, low variability
Bias and variability

Low bias, high variability

Low bias, low variability
Bias and variability
Bias and variability

Low bias, high variability

Low bias, low variability
Bias and variability

**Forecast bias** is due to **problems with the forecasting method:**

- Forecast method inappropriately chosen.
- Data changes around time of forecast the method does not allow for this change.

**Forecast variability** is due to **unexplained variation in the data:**

- There are predictable sources of variation in the data that have not been included in the model.
- There is unpredictable (random) variation in the data.
Bias and variability

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Measure of bias

Average of forecast errors.
Bias and variability

Measure of bias
Average of forecast errors.

Measure of variability
Average of absolute (or squared) forecast errors.
### Bias and variability

<table>
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<th>Measure of bias</th>
</tr>
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<tbody>
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</tr>
</tbody>
</table>

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</tr>
</thead>
<tbody>
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</tr>
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</table>

If you don’t use systematic forecast evaluation, you will never learn from your mistakes!
Useful resources

Organization:

- International Institute of Forecasters.
- Websites:
  - www.forecasters.org
  - www.forecastingprinciples.com
- Conferences:
- Journals:
  - International Journal of Forecasting
  - Foresight
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Slides available from www.robjhyndman.com