Using Probability to Obtain the Best Possible Forecast

Brian Peters – Product Manager
Dr. Devin Kilminster – Senior Scientist
Dr. Meghan Stephens – Research Scientist
Meteorological Service of New Zealand, Ltd. (Metra)
International Conference on Energy & Meteorology 2011

Presentation Outline

- What is “Best”?
- Description of Probability Density Functions
- Examples of “Best”
- Summary

What is the “Best” Forecast?

- Ideally a perfect forecast would be “Best”
- Meteorology has not yet achieved perfection

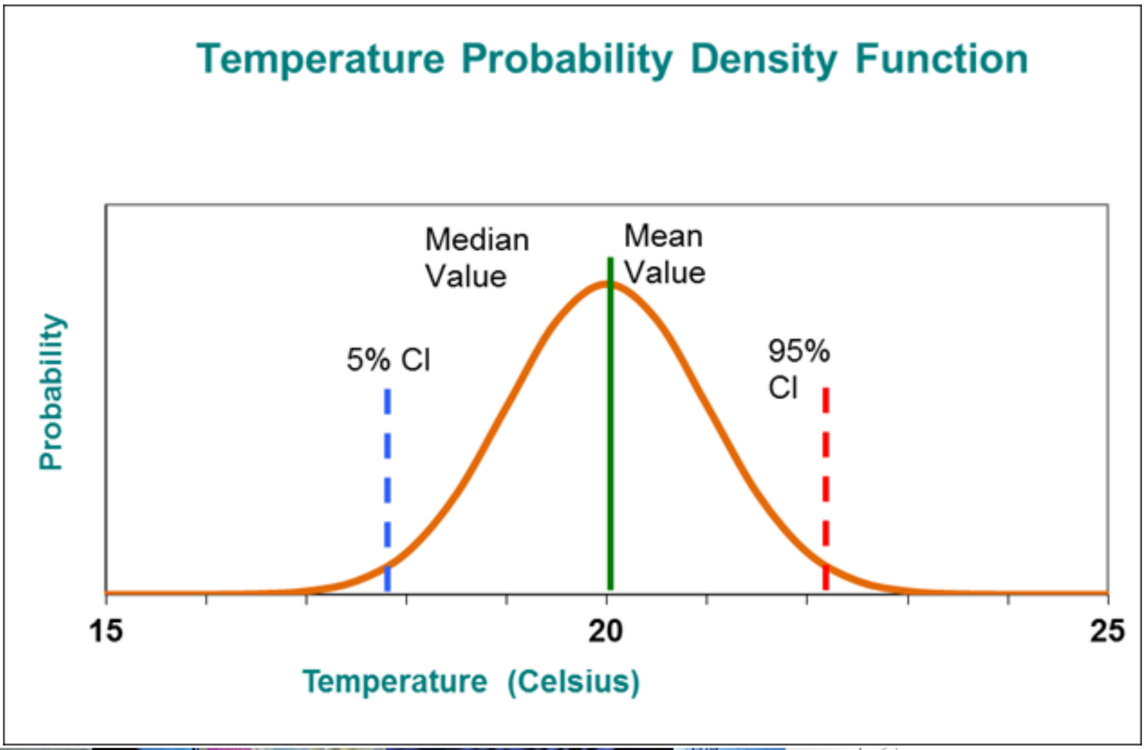
- Each user makes different decisions and has different costs associated with the forecast being wrong.
  – Hurricane approaching city…evacuate?
  – Money & Disruption vs. Lives

Probabilistic Forecasts

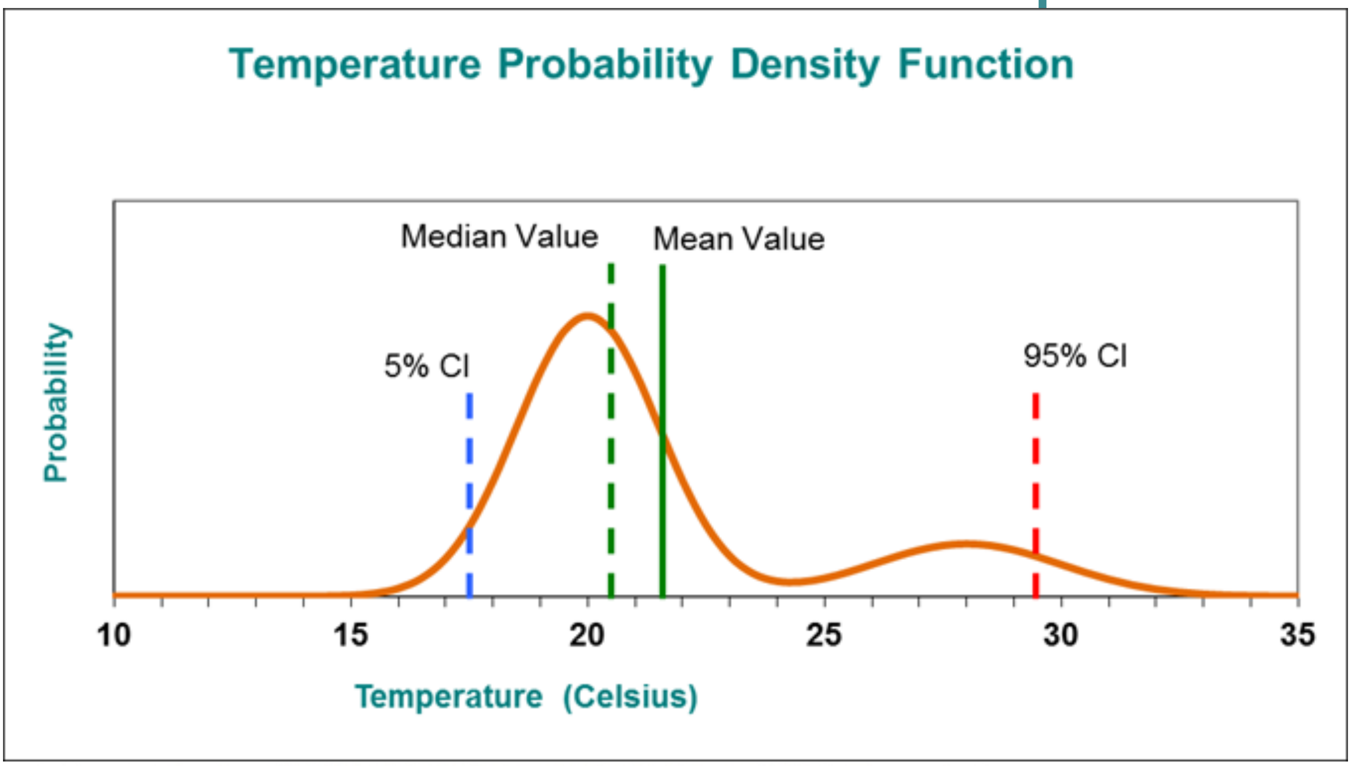
- Temperature, wind speed, etc. (Continuous)
- Many ways to produce and many formats
- **Ultimately all (should) derive from probability density function (pdf)**
  – **real or estimated**
- Recognises that forecasts are not perfect
- Provides entire range of possible outcomes

METRA

Probability Density Functions Confident Example



Probability Density Functions Less Confident Example



What Value Is the “Best”?

- Many possible “single value” forecasts

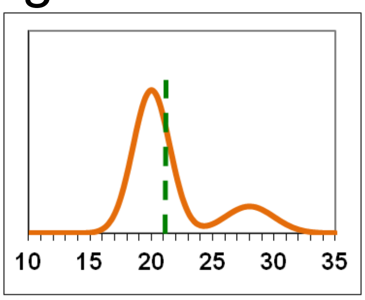
- Entire branch of mathematics to determine “Best” value to use.

<u>What are the costs if the forecast is wrong?</u>

Simple Example

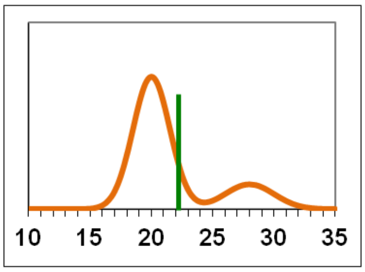
- Costs are symmetric (independent of being too cold or too warm) & linear
  - If forecast out by 1 degree lose $1.
  - if forecast out by 5 degrees lose $5.
- Want best day-to-day performance
- Choose forecast that reduces average error magnitude (MAE)

- “Best”: pdf median (50% CL)



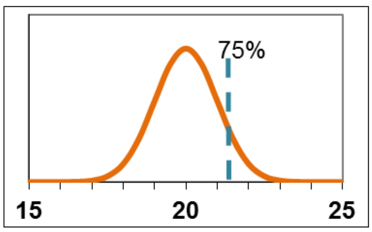
Slightly More Complex Example

- Costs are symmetric & non-linear
  - If forecast out by 1 degree lose $1
  - If forecast out by 5 degrees lose $25.
- Want to reduce large errors
- Choose forecast value that reduces squared error (MSE)
- “Best”: pdf mean value



More Complex Example

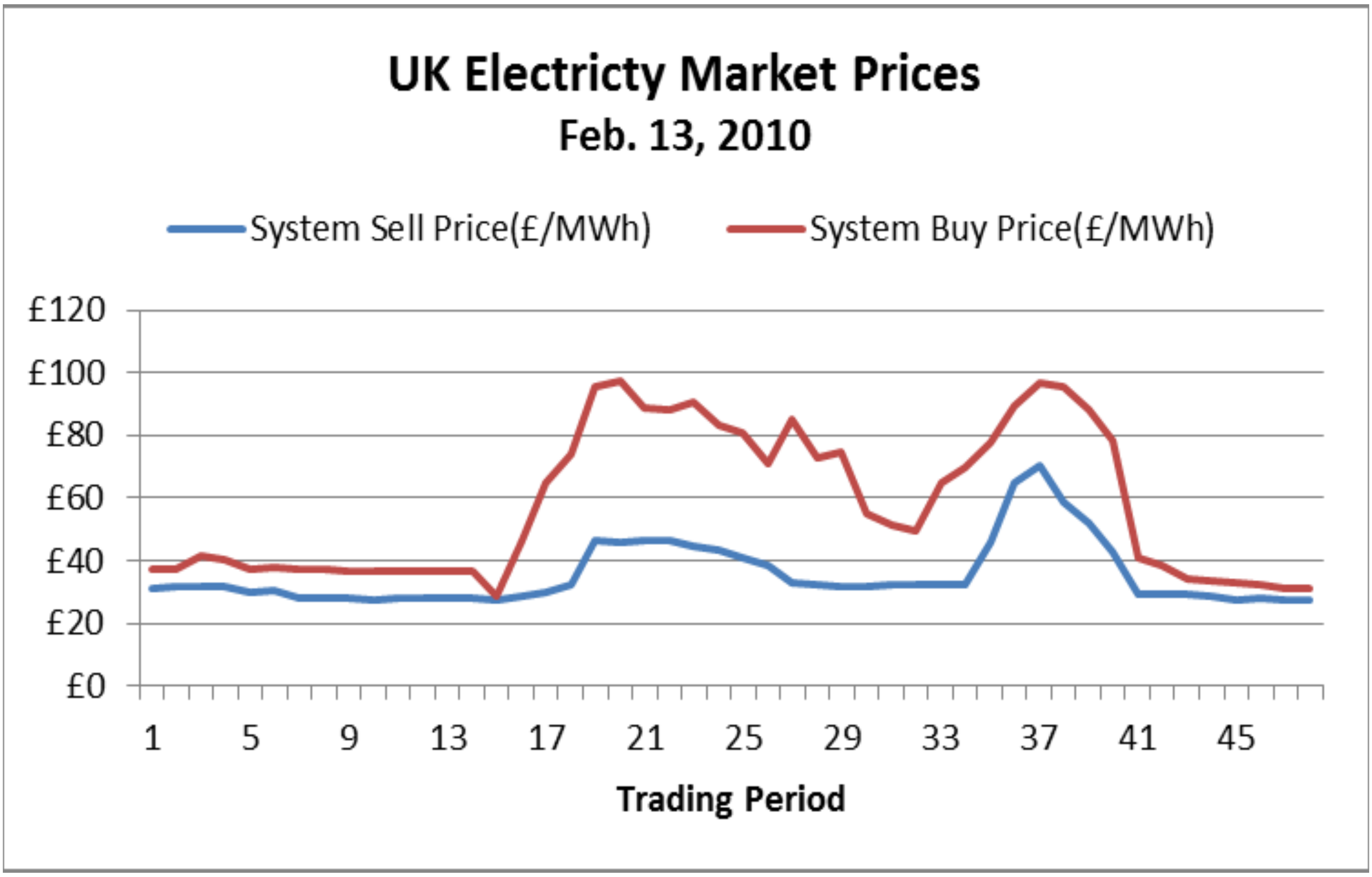
- Costs are asymmetric & linear
  - If forecast too warm by 1 degree lose $1
  - If forecast too cold by 1 degree lose $3
- Want to minimise costs of forecast being too cold and costs of forecast being too warm
- 3:1 ratio prob too warm : prob too cold
- “Best”: 75% CL



Applied Example – CCGT UK

- Power generation efficiency dependent on air density
  - Temperature, Pressure, Relative Humidity
  - Colder temperatures – higher generation
- Must let grid operator know how much power will be provided.
- If forecast too cold…need to buy on spot market
- If forecast too warm…extra generation that could have been sold

METRA



METRA

CCGT UK – The Theory

- **Cost of forecasting too cold is higher than forecasting too warm**
- **Buy and Sell prices (ratio of Buy/Sell) vary**

Buy price > Sell Price.

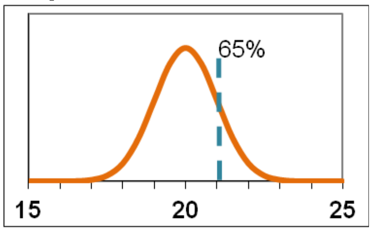
- **Costs**
  - **Electricity which must be purchased**
  - **Electricity which could have been produced, but was not.**
- **What forecast will minimise costs?**

CCGT UK – The Details

- CCGT (450MW) at Heathrow
- 1 year of hourly (pdf) forecasts (issued for 5am to 4am next morning) – Sep 2010 to Aug 2011
- Calculated approximate forecast and actual generation
- 1 year of actual UK wholesale electricity prices

CCGT UK – The Result

- Spring & Summer
  - Electricity prices less volatile
  - Minimal spread between Buy and Sell price
  - Optimal forecast near 55% CL
  - PDF Mean reasonable forecast
- Autumn and Winter
  - Much higher spread between Buy and Sell price
  - Optimal forecast 65% CL
  - Would have saved £14,925 over median
  - But MAE would have been worse



Summary

- Proper use of probabilistic forecasts can save the user money.
- Important to know the true costs of getting the forecast wrong
- Need to work with the forecast provider to help them understand these costs

(Also MAE may be an easy verification number to understand, but its use not always appropriate.)

METRA