MONASH University

MONASH BUSINESS SCHOOL

Probabilistic energy forecasting for smart grids and buildings

Rob J Hyndman

21 March 2017

Demand forecasting

Demand forecasting in the smart grid

Figure: `http://solutions.3m.com`

$$\underbrace{\text{Energy sources (fossil fuel, wind, solar, wave, ...)}}_{\text{Supply}} \longrightarrow \underbrace{\text{Energy consumers}}_{\text{Demand}}$$

Demand forecasting in the smart grid

Need demand forecasts for outage planning, energy trading, demand response, system management, ...

Predictors

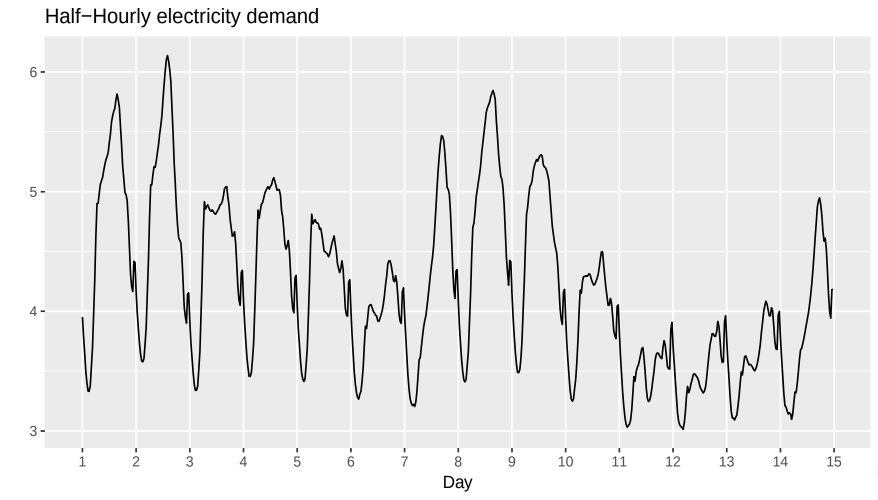
- calendar effects
  - Time of day
  - Day of week
  - Time of year
  - Holidays
- prevailing and recent weather conditions
- demand response incentives
- household characteristics

We build a nonlinear nonparametric stochastic model of demand as a function of these predictors.

Probabilistic forecasting

Probabilistic forecasting

Aim: forecast entire probability distribution of demand, not only the average.



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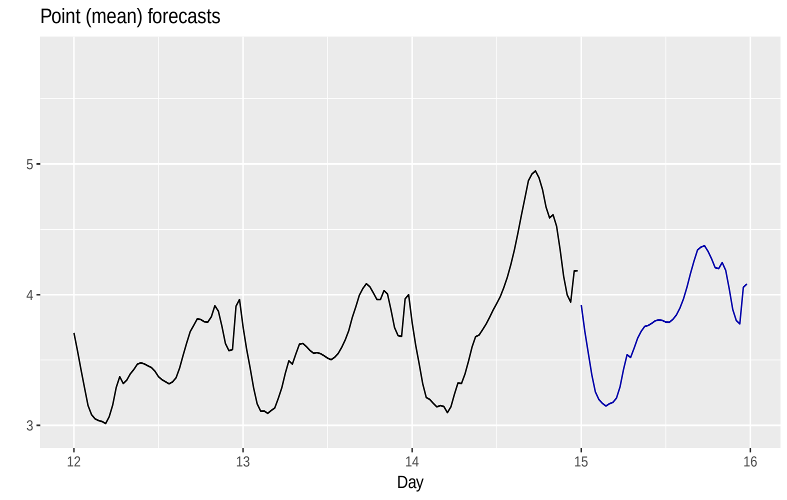

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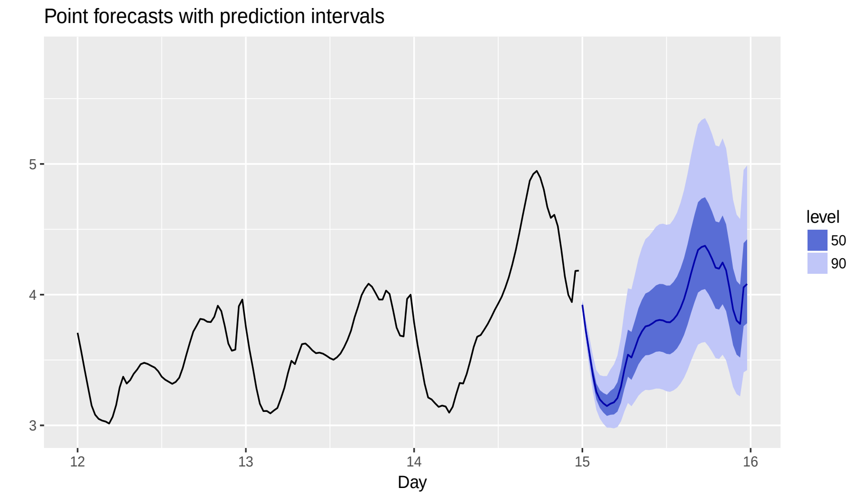

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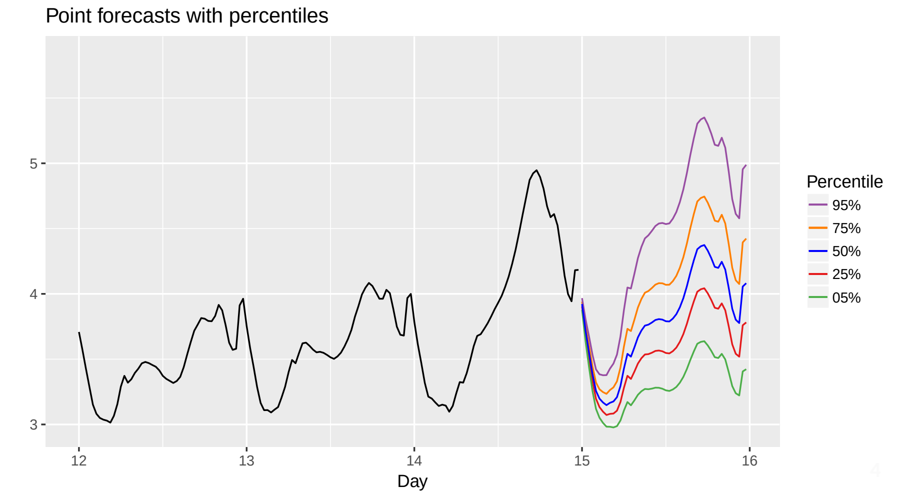

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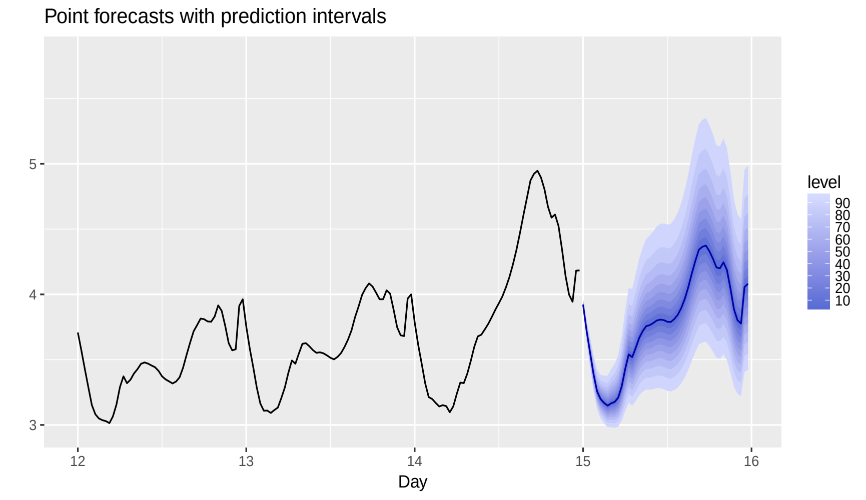

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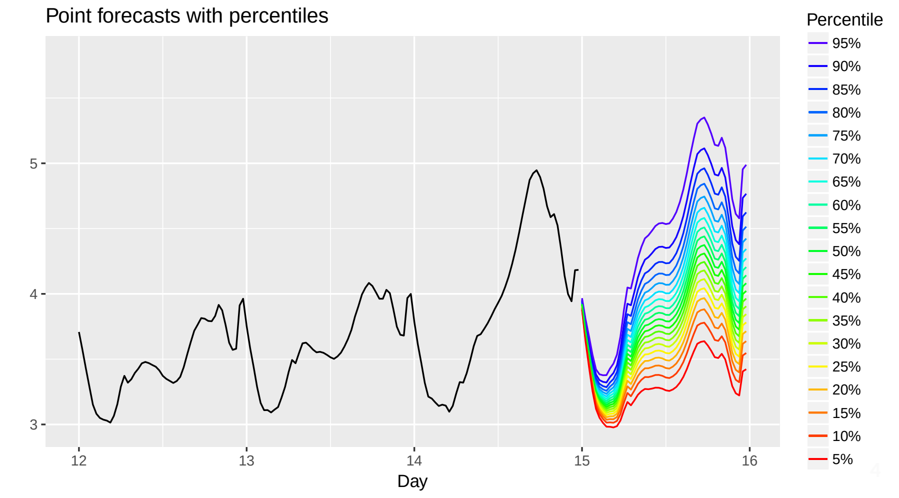

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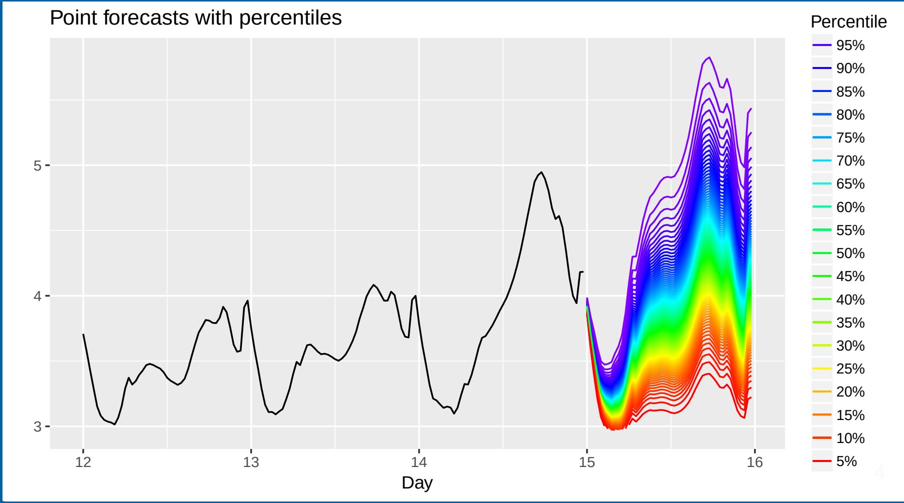

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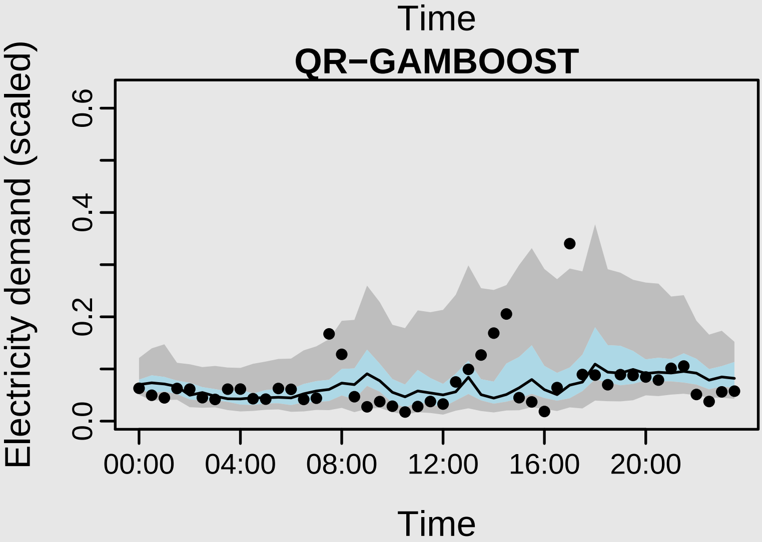

Half-hourly data. Blue: 50% region. Grey: 95% region.

Forecast accuracy measures

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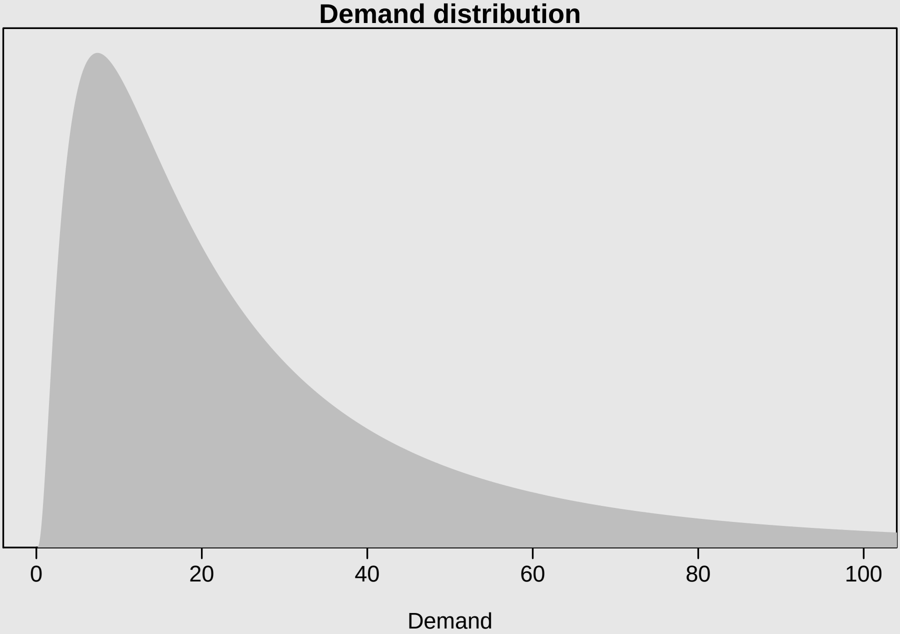
$q_t(p) =$ Percentile forecast of y_t, to be exceeded with probability $1 - p$.

➥ If $q_t(p)$ is accurate, then y_t should be less than $q_t(p)$ about $100p\%$ of the time.

➥ Need to penalize unlikely side more (a “pinball loss” function)

Forecast scoring



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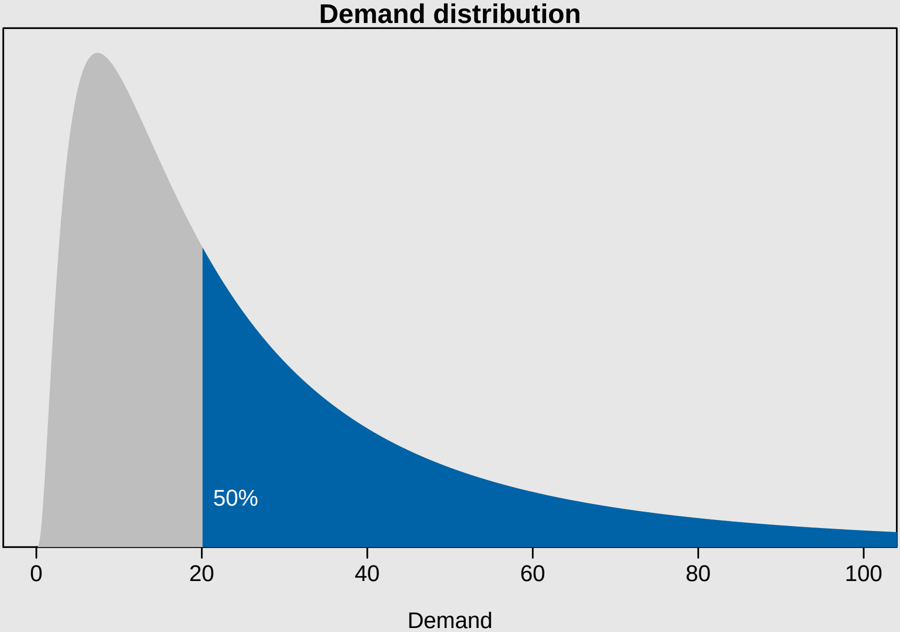

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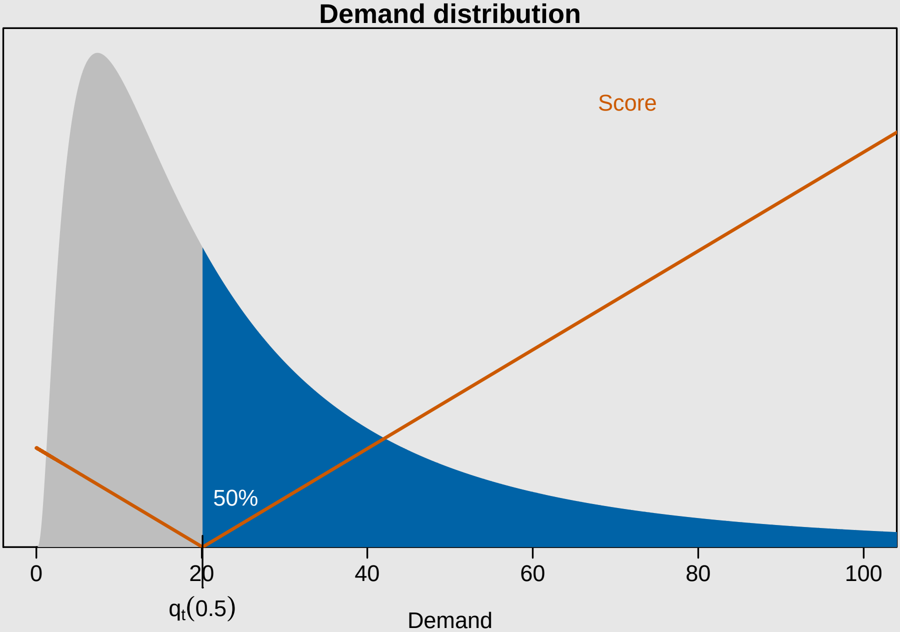

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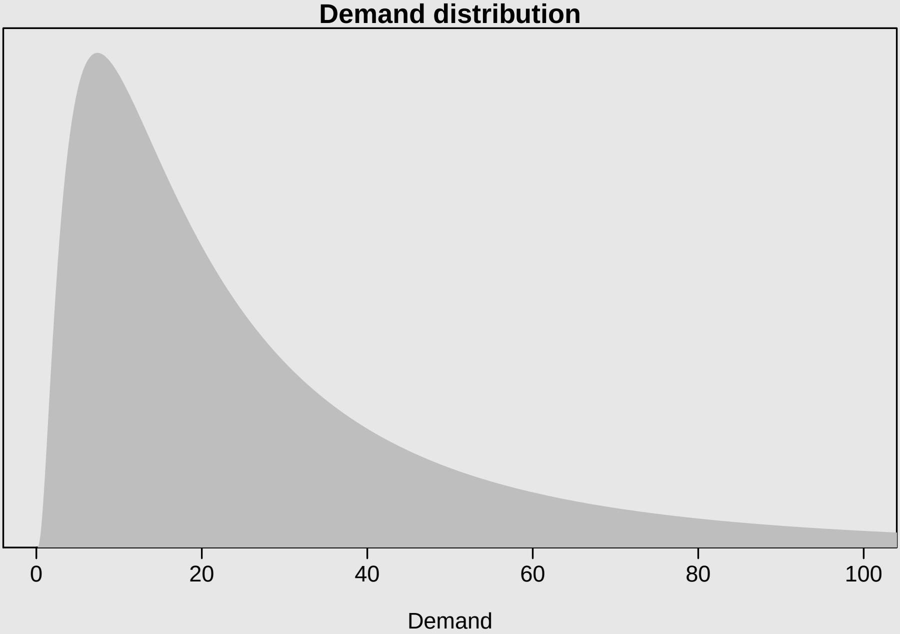

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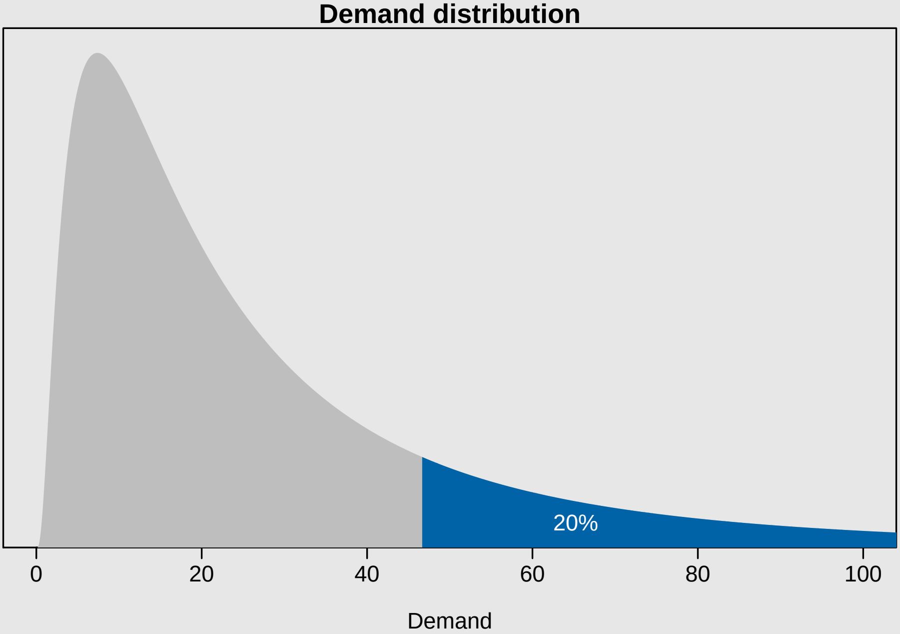

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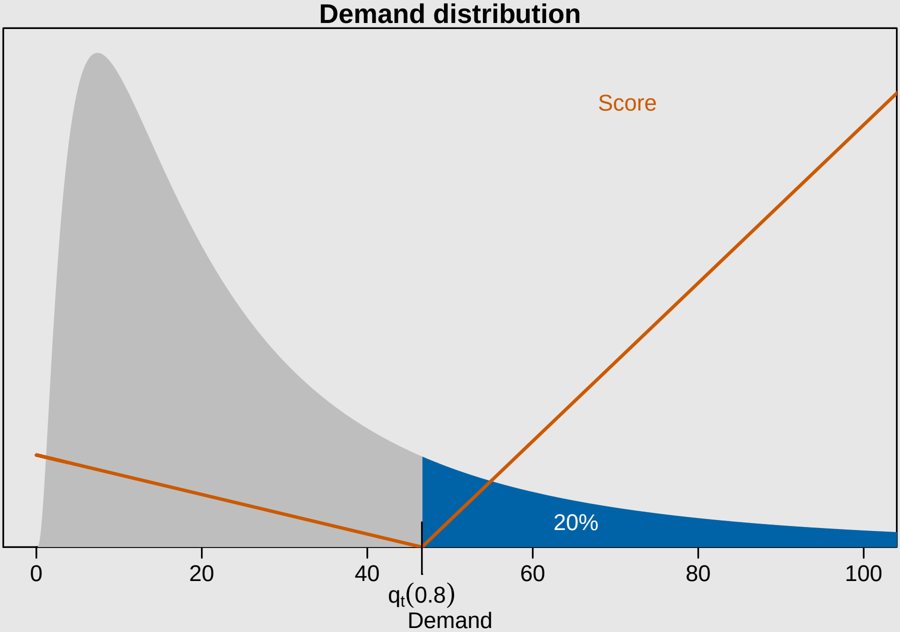

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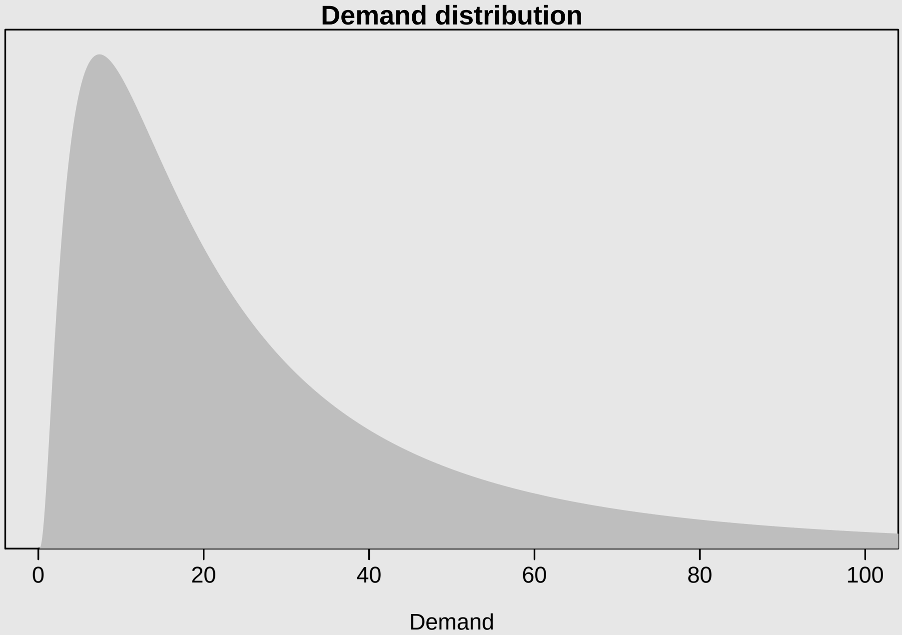

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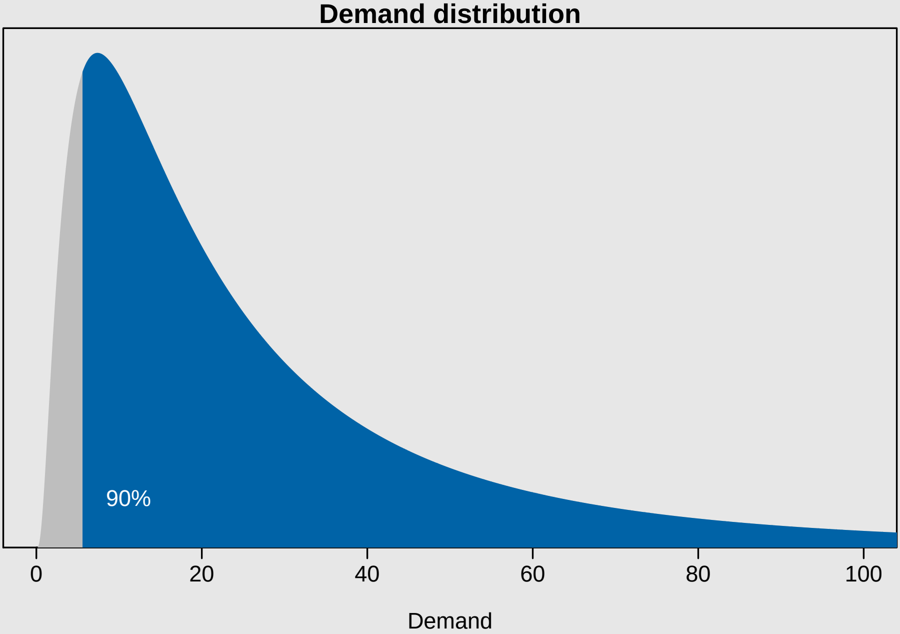

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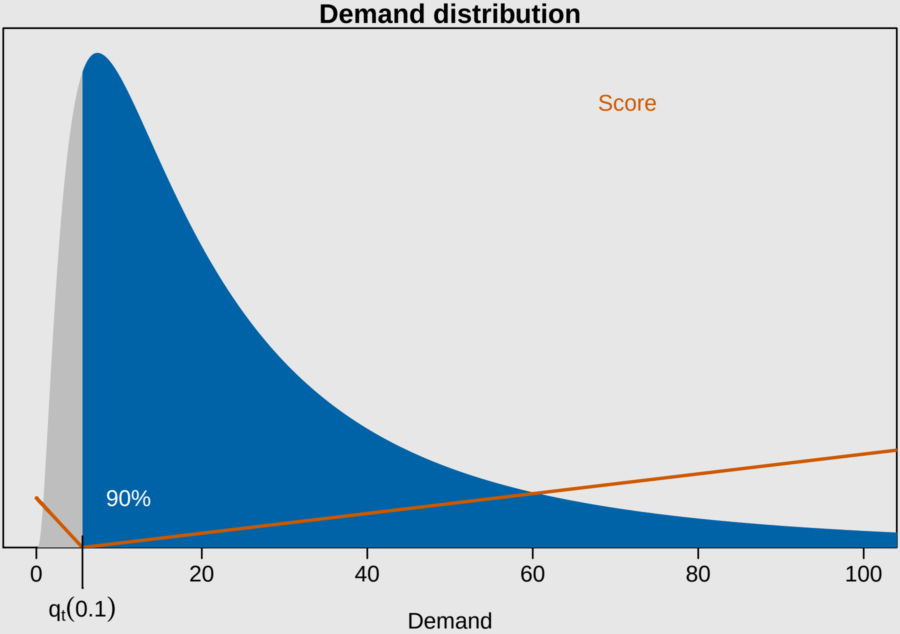


Forecast scoring

Quantile Score for observation y:

For $0 < p < 1$:

$$S(y_t, q_t(p)) = \begin{cases} p(y_t - q_t(p)) & \text{if } y_t \geq q_t(p) \\ (1-p)(q_t(p) - y_t) & \text{if } y_t < q_t(p) \end{cases}$$

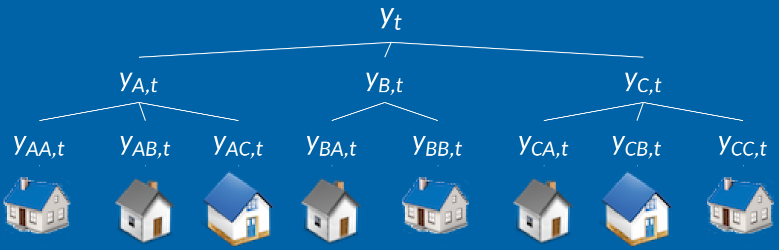
- Scores are averaged over all observed data for each p to measure the accuracy of the forecasts for each percentile.
- Average score over all percentiles gives the best distribution forecast:

$$QS = \frac{1}{99T} \sum_{p=1}^{99} \sum_{t=1}^{T} S(q_t(p), y_t)$$

- Equivalent to CRPS (Continuous Rank Probability Score).
- Reduces to MAE if we are only interested in $p = 0.5$.

Hierarchical forecasting

Hierarchical electricity demand data



$$
\begin{aligned}
y_t &= y_{A,t} + y_{B,t} + y_{C,t} \\
y_{A,t} &= y_{AA,t} + y_{AB,t} + y_{AC,t} \\
y_{B,t} &= y_{BA,t} + y_{BB,t} \\
y_{C,t} &= y_{CA,t} + y_{CB,t} + y_{CC,t}
\end{aligned}
$$

Aggregations may be based on:

- Geography (suburbs, regions, states)
- Demography (number of people in household, age distributions)
- Appliances (air conditioning, electric heating)

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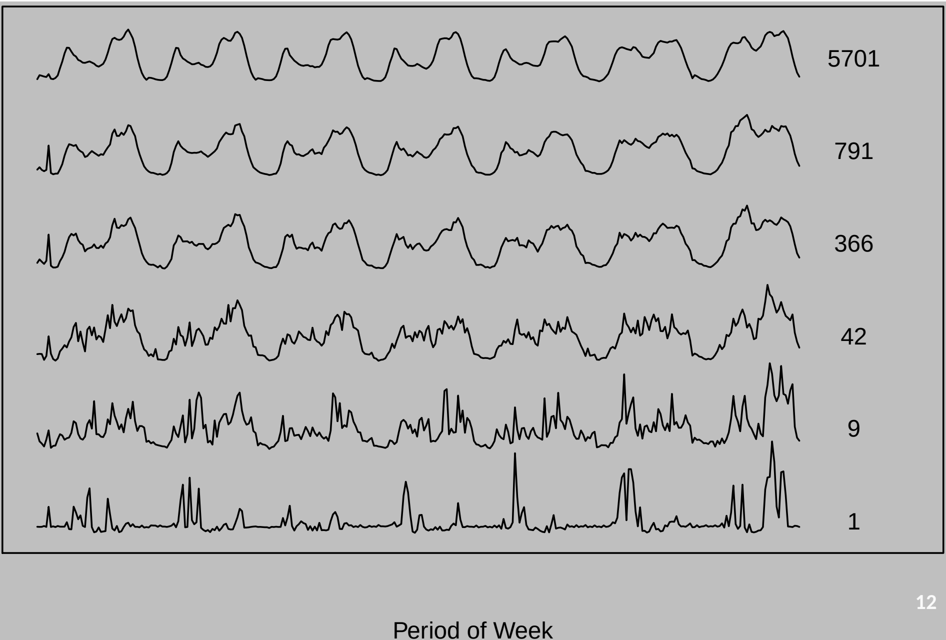

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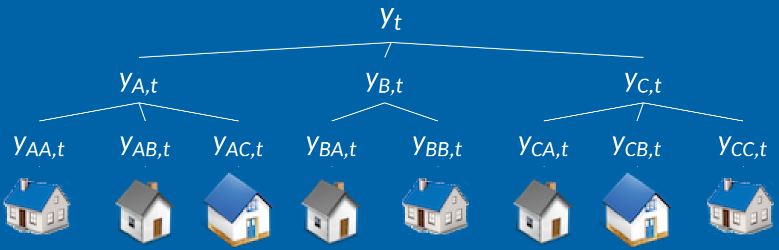


- Easier to forecast at more aggregated levels.
- We forecast at every level and reconcile the forecasts.
- Optimal reconcilation algorithm: Hyndman et al (2011, 2016, 2017)
- Forecast means should add up, but percentiles are more complicated
- **Current research topic:** How to reconcile percentiles at all levels?

Building-level energy forecasting

Managing commercial buildings

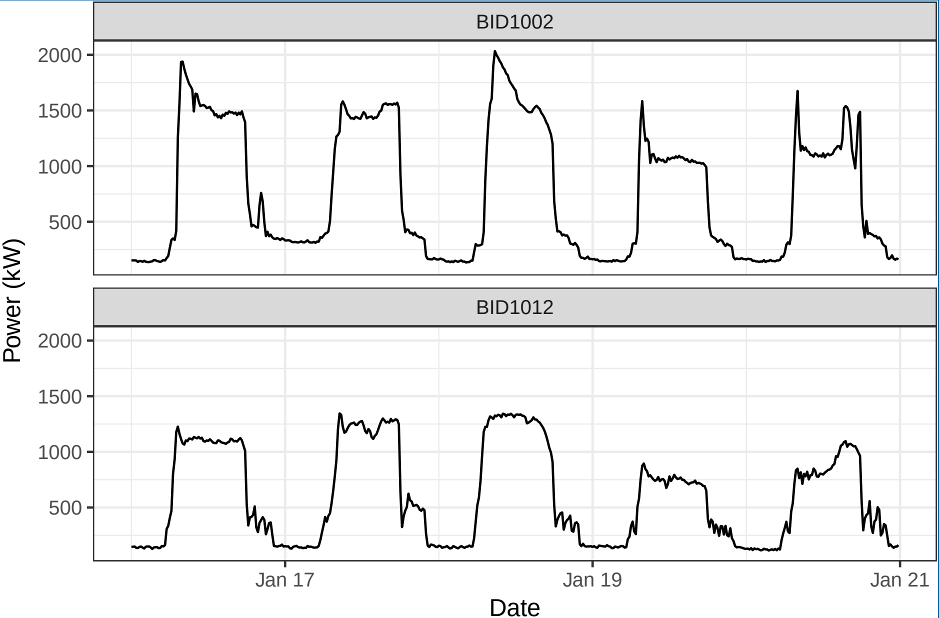
Commercial buildings require energy forecasting to help:

- Manage peak demand.
- Quantify the impacts of building management changes.
- Assess performance and energy efficiency.

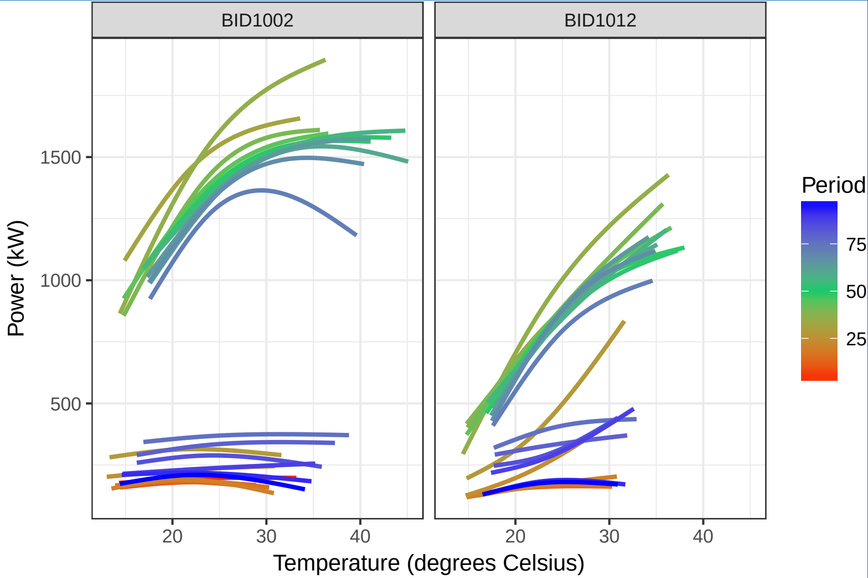
Buildings Alive works with 150+ commercial buildings which include supermarkets, hospitals and office blocks.

Each require daily forecasts to inform facilities managers.

Building Level Data



Building Level Data



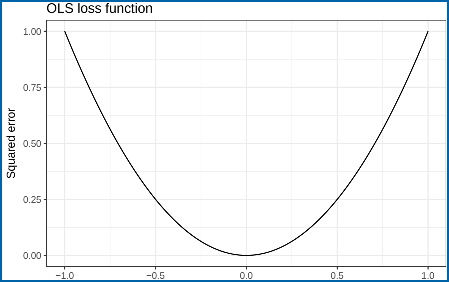
Natural cubic splines for each period of the day (df = 2).

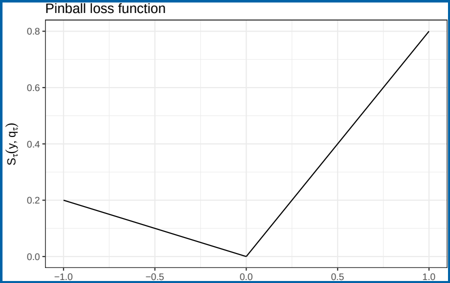
Quantile Regression

Probabilistic forecasts can be produced using quantile regression.

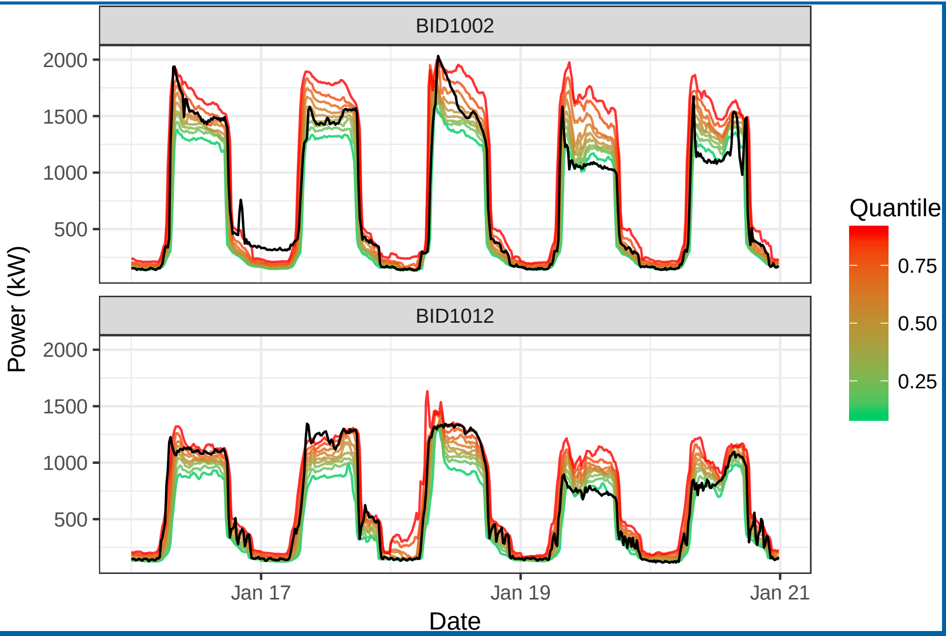
Use the pinball loss function:

$$S_p\left(y, q_p\right) = \begin{cases} p(y - q_p) & \text{for } y \geq q_p, \\ (1-p)(q_p - y) & \text{for } q_p > y. \end{cases}$$





Quantile Regression Forecasting



Assessing performance

- Forecasting a full distribution allows facilities managers to better assess risks and take appropriate actions.
- Allows facilities managers to know the severity **and probability** of demand peaks.
- Can immediately assess if a building's performance was good compared to historical performance under similar conditions.

Competitions, conferences and resources

GEFCom

Global Energy Forecasting Competitions

- Organized by Professor Tao Hong (UNC)
- GEFCom 2012: Load, Wind Forecasting
- GEFCom 2014: Load, Price, Wind, Solar Forecasting
- GEFCom 2017: Hierarchical probabilistic forecasts, real-time, rolling origin.
- **gefcom.org**
- Winning entries published in *International Journal of Forecasting*.
- Huge improvements in forecast accuracy over previously published methods.

International Symposium on Energy Analytics 2017

Predictive Energy Analytics in the Big Data World

Proudly sponsored by International Institute of Forecasters

June 22–23, 2017

Cairns, Australia

Featured speakers

- Yannig Goude, Electricite de France, France
- Rob J Hyndman, Monash University, Australia
- Pierre Pinson, Technical University of Denmark, Denmark
- Richard Povinelli, Marquette University, USA
- Rafal Weron, Wroclaw University of Technology, Poland
- Hamidreza Zareipour, University of Calgary, Canada
- Xun Zhang, Chinese Academy of Sciences, China

International Symposium on Forecasting 2017

Some resources

Blogs

- `robjhyndman.com/hyndsight/`
- `blog.drhongtao.com/`

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Organizations

- International Institute of Forecasters: `forecasters.org`
- IEEE Working Group on Energy Forecasting: `linkedin.com/groups/IEEE-Working-Group-on-Energy-4148276`

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