Thames Valley Vision: LV data analytics and forecasting

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Introduction

Background and Context

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- Electricity Networks are "no longer fit for our changing energy mix"[1].
- Expected electricity Network Investment 2014-2020: £34Billion
- Smart grids could reduce additional reinforcement costs by £2.5B-£12B by 2050[1].
- Low Carbon Network Fund: £500M "support projects…to try out new technology, operating and commercial arrangements"[2]:
  - Battery Storage
  - Demand Response
  - Flexible Networks…
- ***Advanced forecasts and analytical methodologies are needed to optimise such solutions.***

http://www.networkrevolution.co.uk/smart-grid/

[1] Delivering UK Energy Investment: Networks, DECC, January 2015.
[2] https://www.ofgem.gov.uk/electricity/distribution-networks/network-innovation/low-carbon-networks-fund

Thames Valley Vision

- TVV: £30M low carbon network fund (LCNF) project
- How will the DNO need to understand, anticipate and support changes in customer behaviour to develop an efficient network for the low-carbon economy?
- Solutions considered: New network modelling environment, modelling low carbon technologies, testing of monitoring and storage devices, …

TVV: How will the DNO need to understand, anticipate and support changes in customer behaviour to develop an efficient network for the low-carbon economy?

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Understand

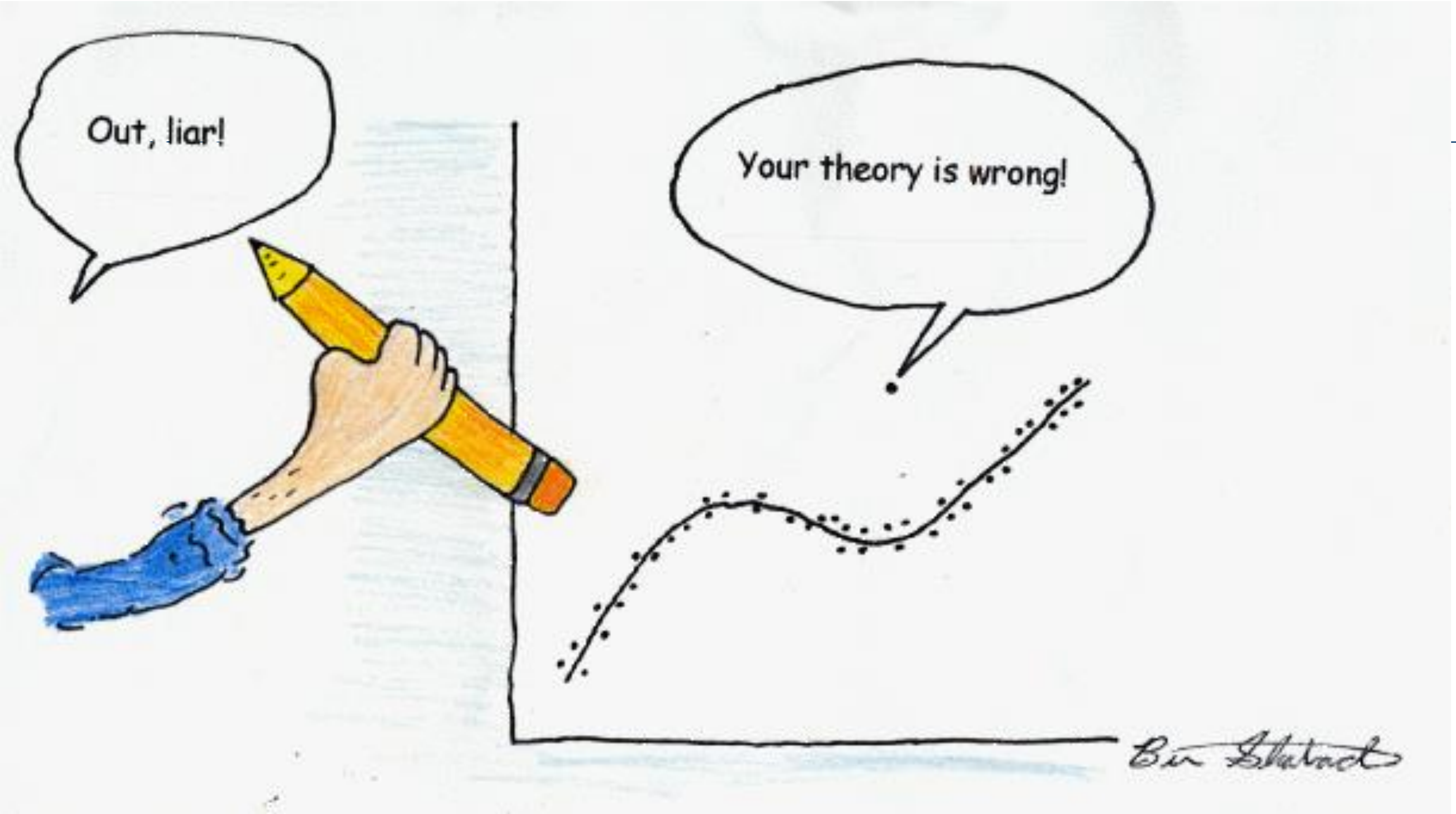
- Customer end-point monitors
- Substation monitors
- Smart Metering
- Categorisation
- Listening

Anticipate

- Network Modelling Environment [Electric Office & Cymdist]
- Distribution Management System [Power On Fusion]
- Aggregation & Forecasting

Support

- Automatic Demand Response
- Electronics & Batteries
- Thermal storage (hot and cold)
- Commercial Models
- Smart Control



http://davidmlane.com/ben/cartoons.html

Data: Analysis & Challenges

Data Resources

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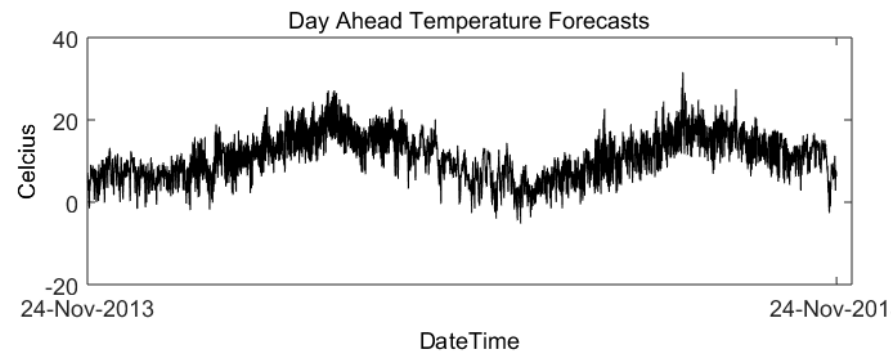
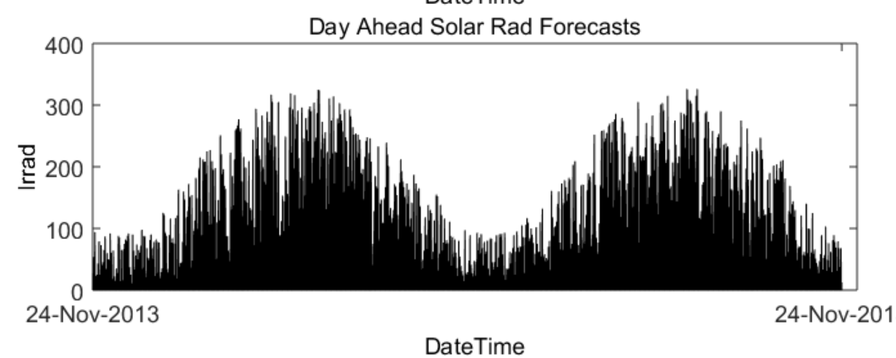
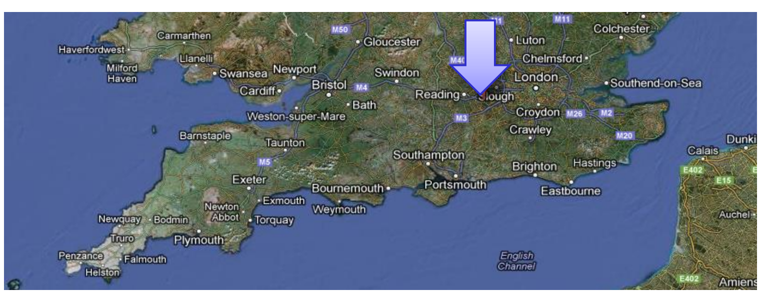
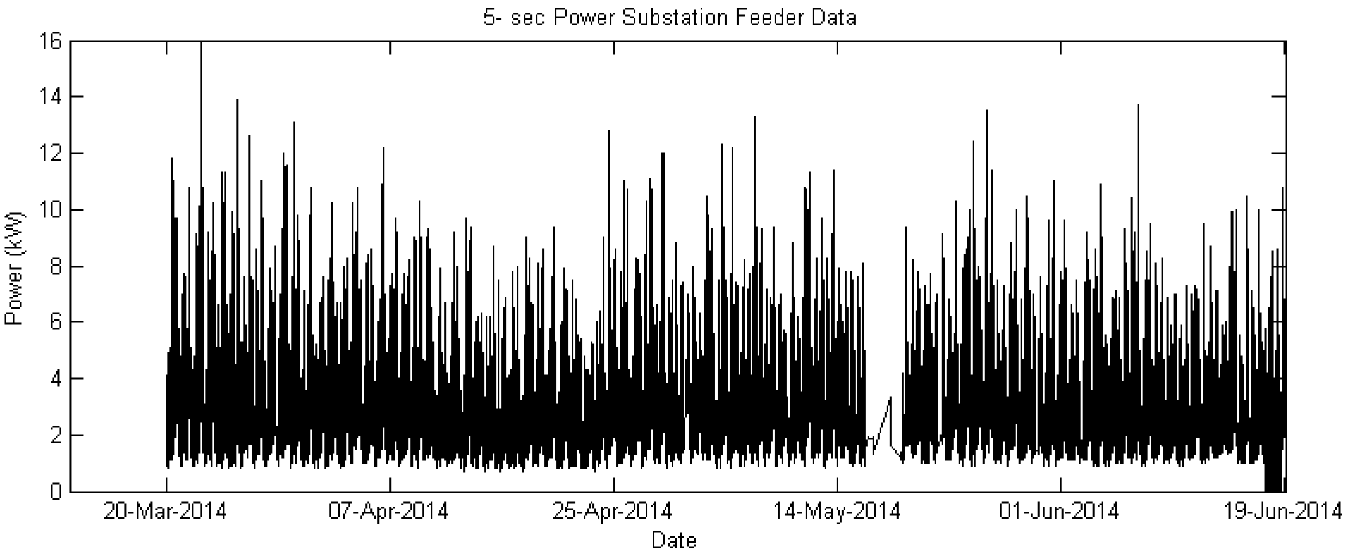
- ~250 End point monitors
- ~300 LV substations monitored
- Meta data:
  - Demographic data
  - Quarterly meter readings
  - Council Tax bands
- Weather data – Forecasts and actuals







Challenges



- Less literature for demand at the Low Voltage (LV) level or low aggregations of customer
- LV demand much more volatile than at HV
- Each feeder has a different number of customers and mixtures of customers (residential and commercial).
- Not everyone monitored, Missing data!
- Little investigation into association of weather effects at LV level.

Understanding and modelling customers

How many types of customers are there?

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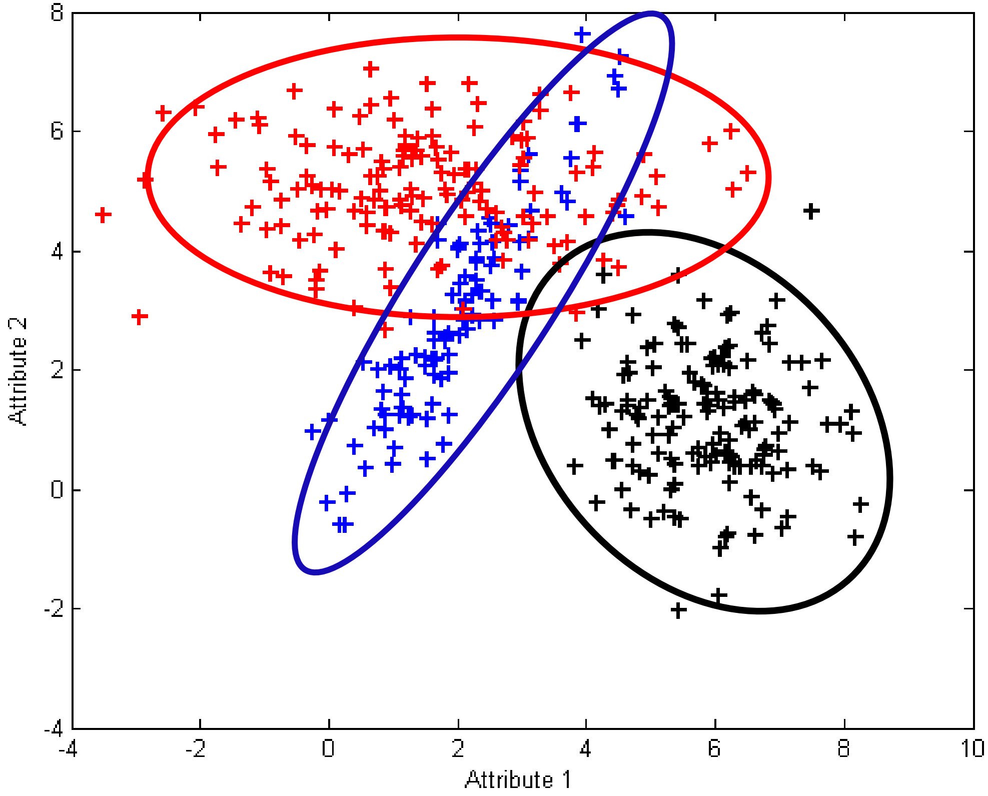
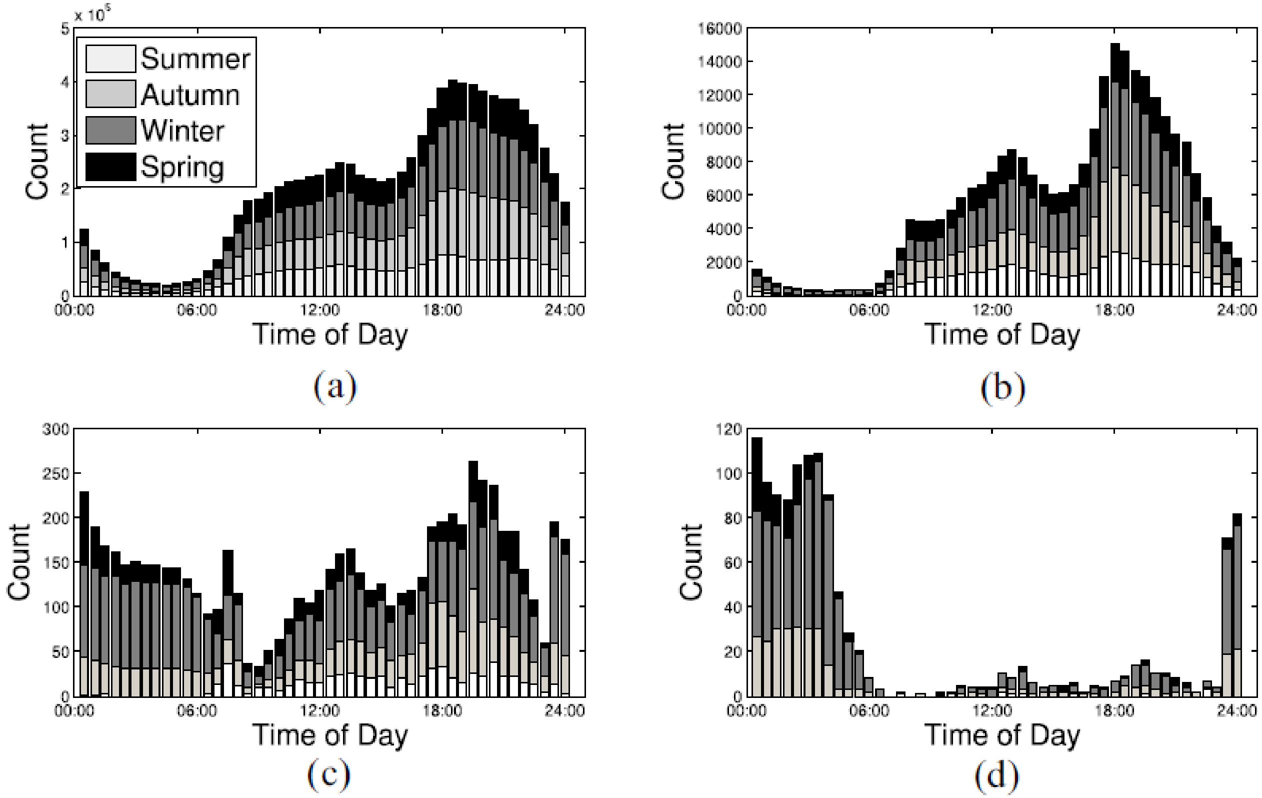
- Large commercial customers already half hourly monitored
- Commercial/SME more regular than domestic
- How many different types of domestic customers are there?
- Can we reduce the amount of information required to model the LV networks?
- What are the important attributes?



When do people use their energy?



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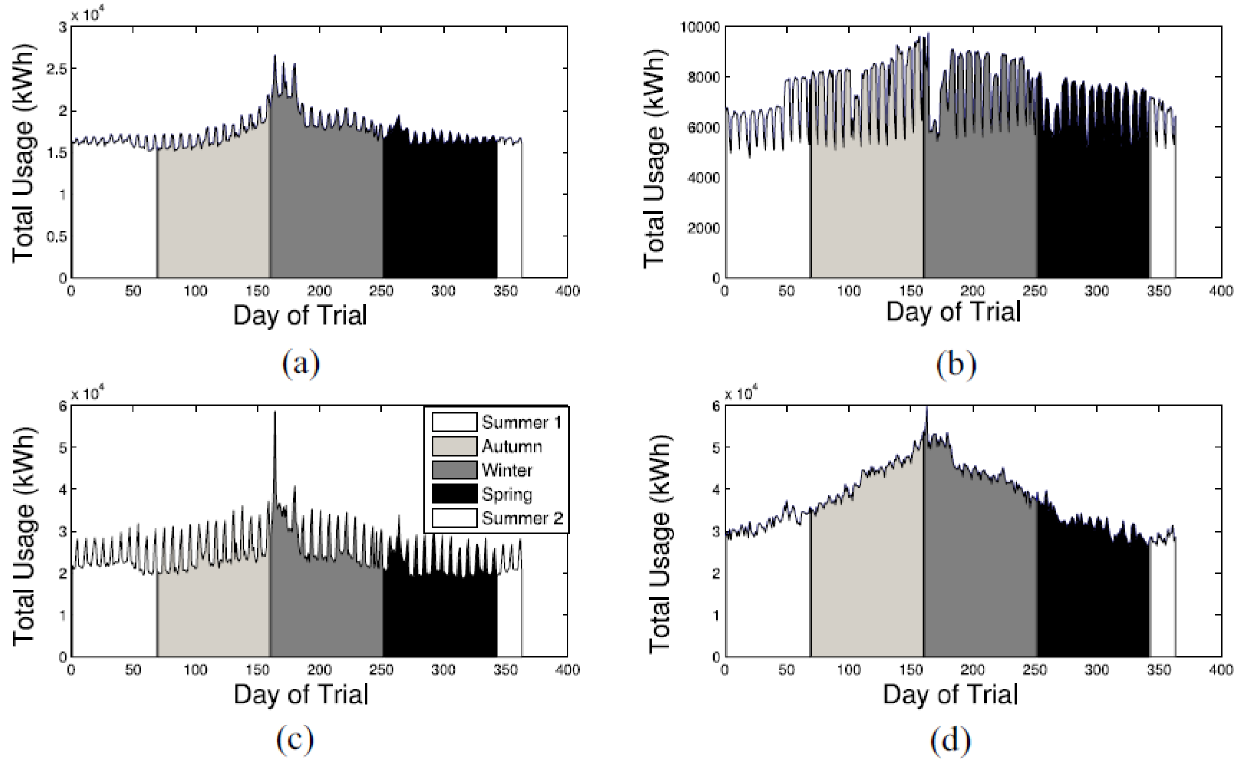

Sum of usage of all customer for each day in time. (a) Period 1 (overnight). (b) Period 2 (breakfast). (c) Period 3 (daytime). (d) Period 4 (evening).

Final attributes for clustering

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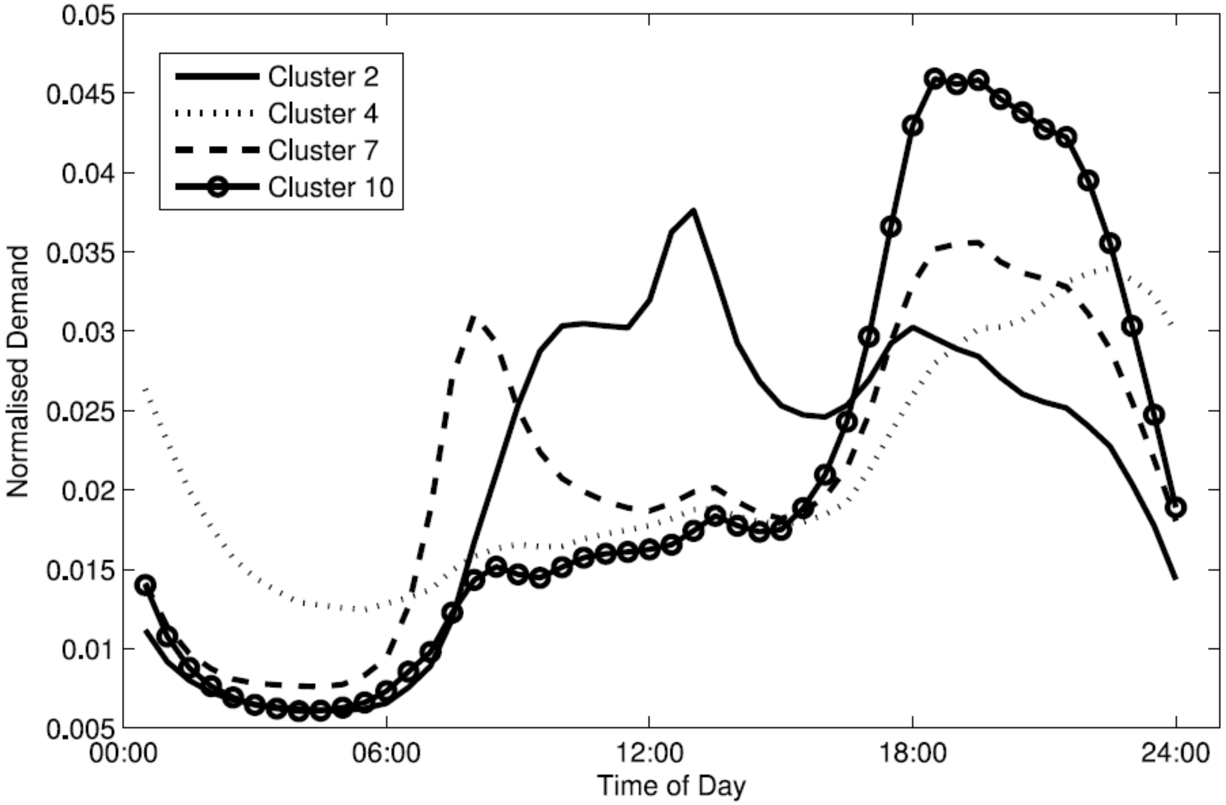
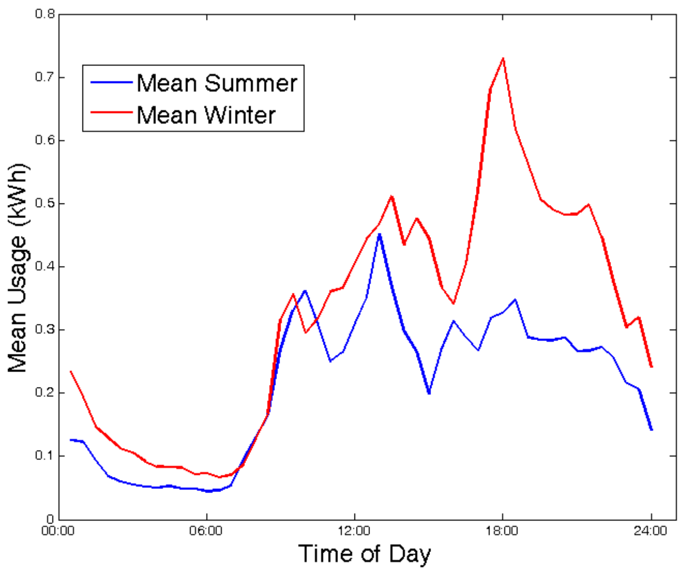
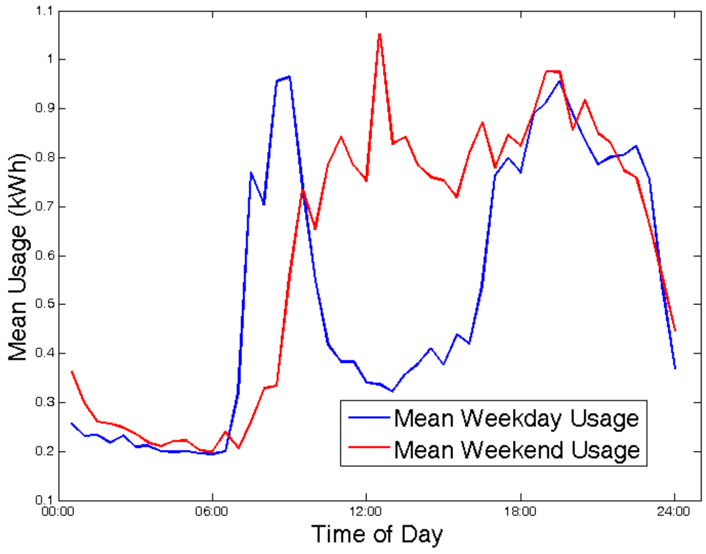
- Distribution of demand in 4 time periods
- Seasonal measure
- Weekend-weekday difference
- General volatility

Clustering residential energy behavioural usage

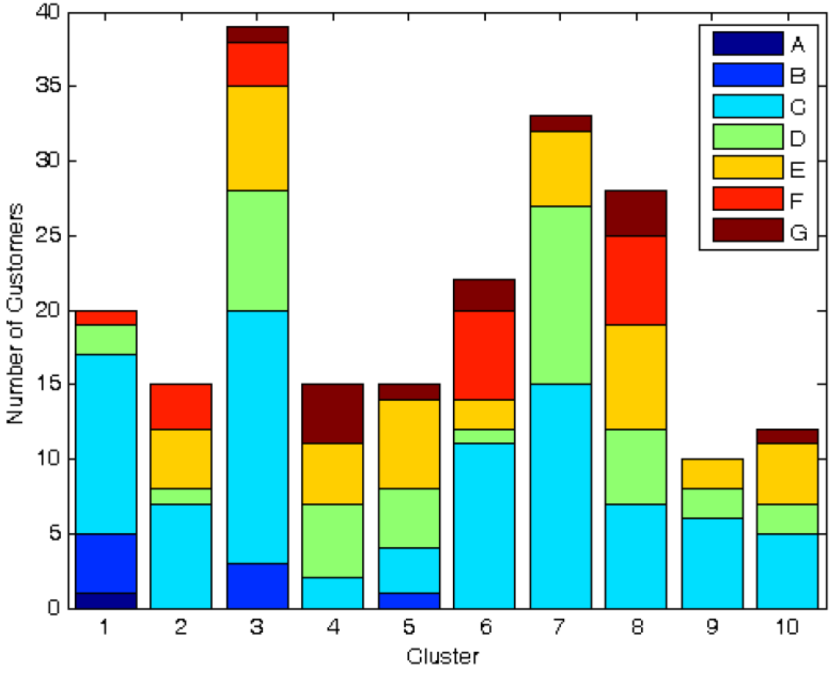


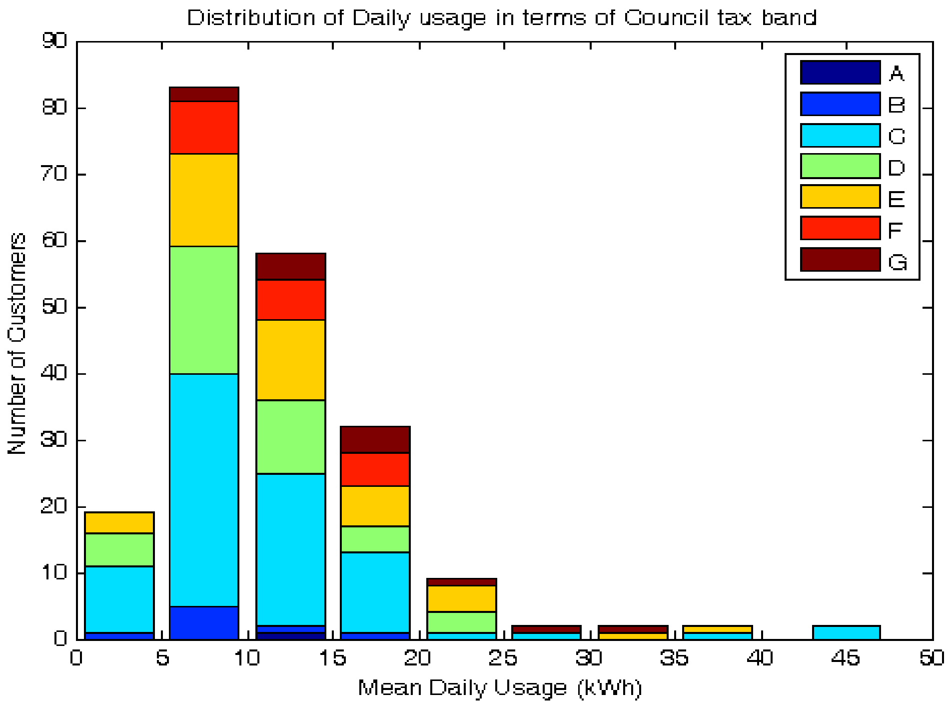
Clusters: different seasonal and weekend behaviour



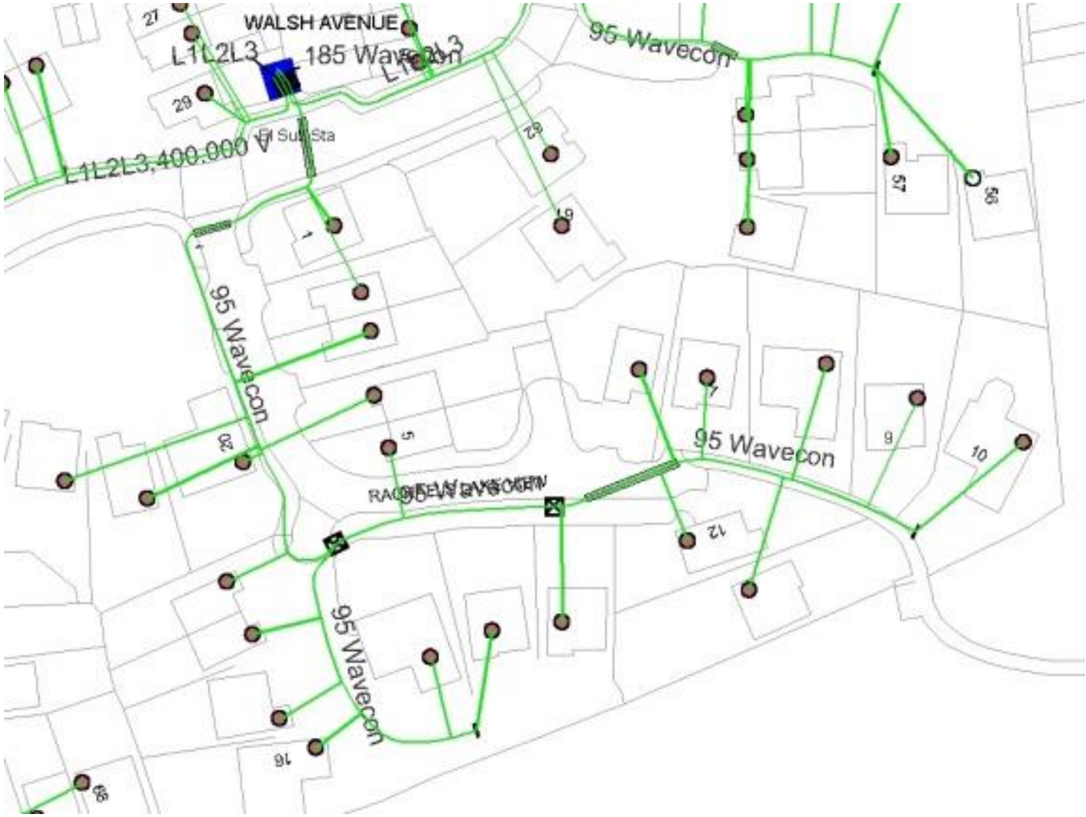


Breakdown of clusters according to Council Tax





How to model unmonitored customers?



Buddying

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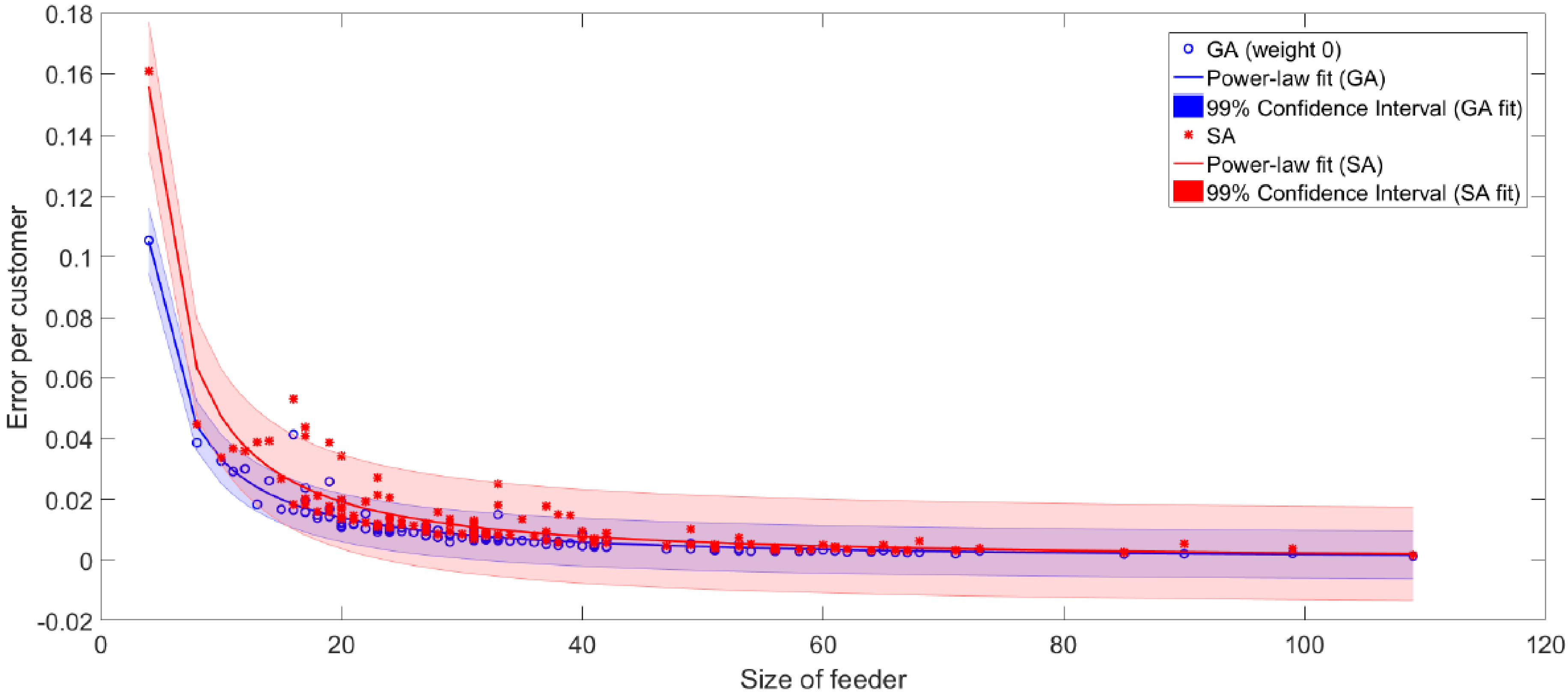
- Limited connections between demographics and energy behavioural usage: use clustering to define broad groups.
- Buddy unmonitored customers to monitored customers from a similar “group”. Minimise the error between the substation total and the individual daily demands.

$$F(\tilde{\mathcal{P}}, \mathbf{c}, \mathbf{s}) = (1-w)\sum_{t=1}^{H} \frac{\|a(t)-s(t)\|}{S} + w\sum_{j=1}^{M} \frac{\|U_j - \hat{U}_{k_j}\|}{D},$$

- Full substation monitored buddy (w=0) to **simple** quarterly meter reading buddy (w=1)
- Use a genetic algorithm to find the optimal buddy
- Serves as baseline to further tools: forecasting, impact of LCTs.

Simple Vs Substation Buddying



Short Term Load Forecasts

Forecasting – some comments

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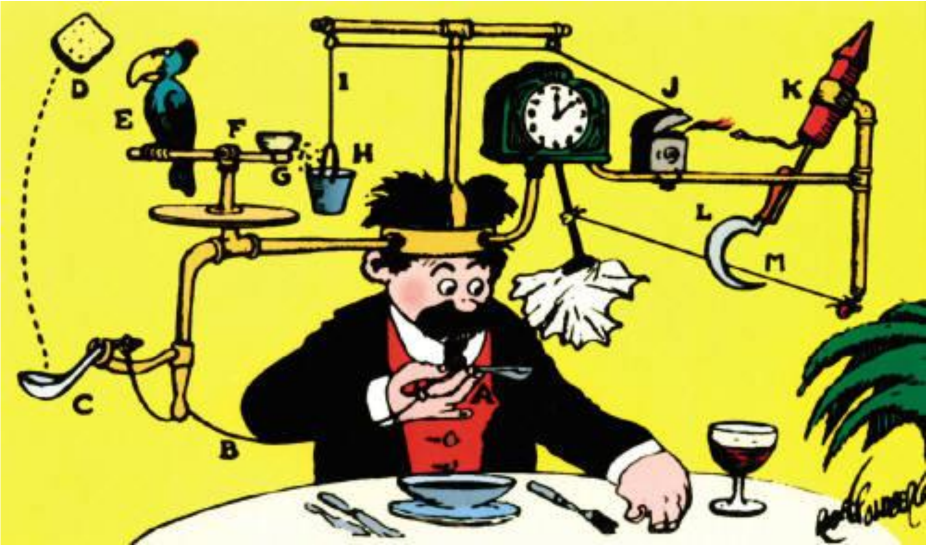
- “All forecasts are wrong but some are useful”
- Enables “smartness”
- Anticipate and plan rather than react
- Facilitate new solutions
- Quantify uncertainty



Forecast models

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- Seasonality: yearly, weekly and daily.
- Trend potential for change points: change in energy efficiency, churn, new technologies.
- Impact of weather minimal in many cases detrimental
- Recent demand most important
- Basic benchmarks very effective! (see later)

Example Forecasts

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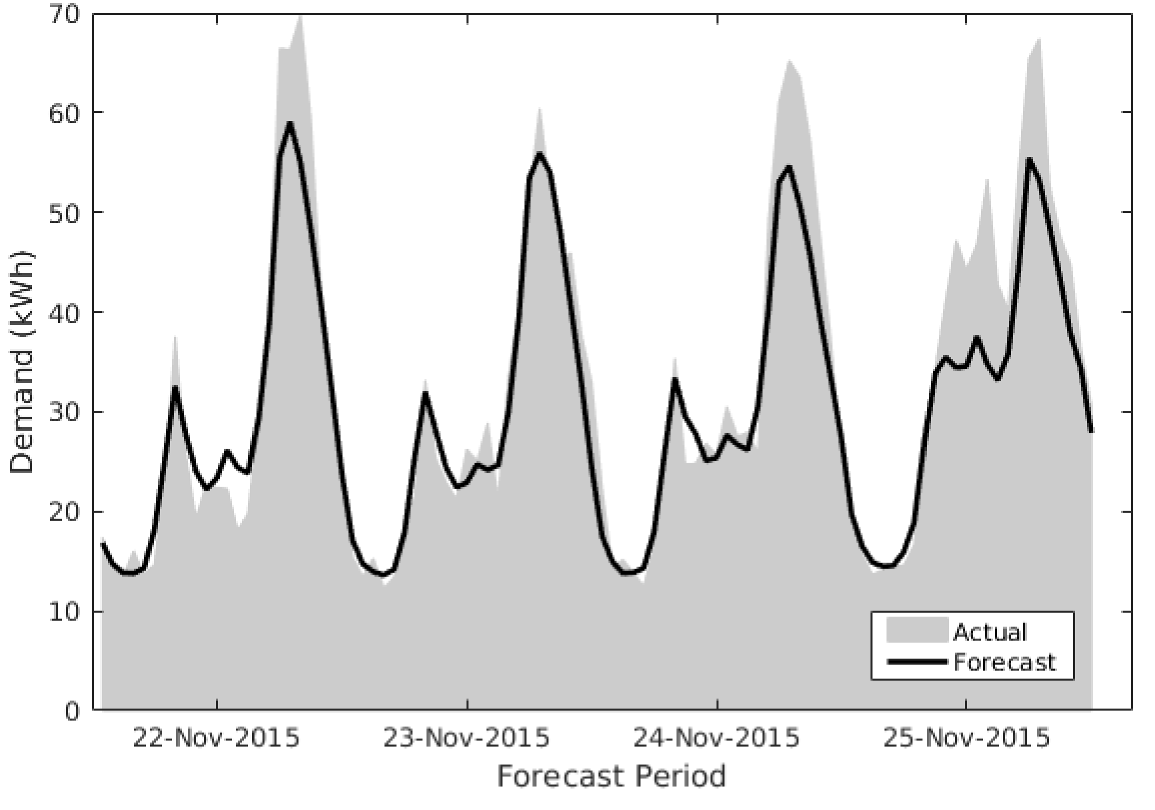

Examples Use in Storage Device

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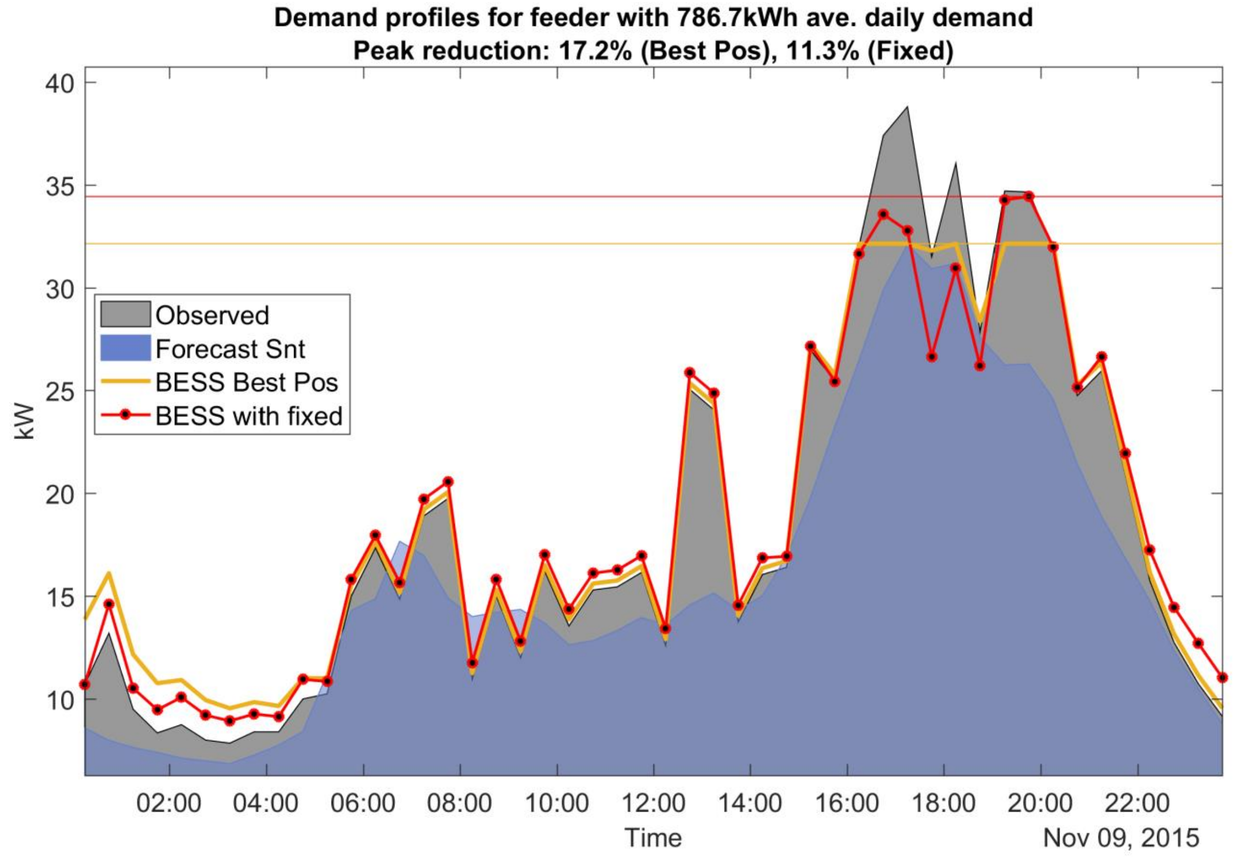
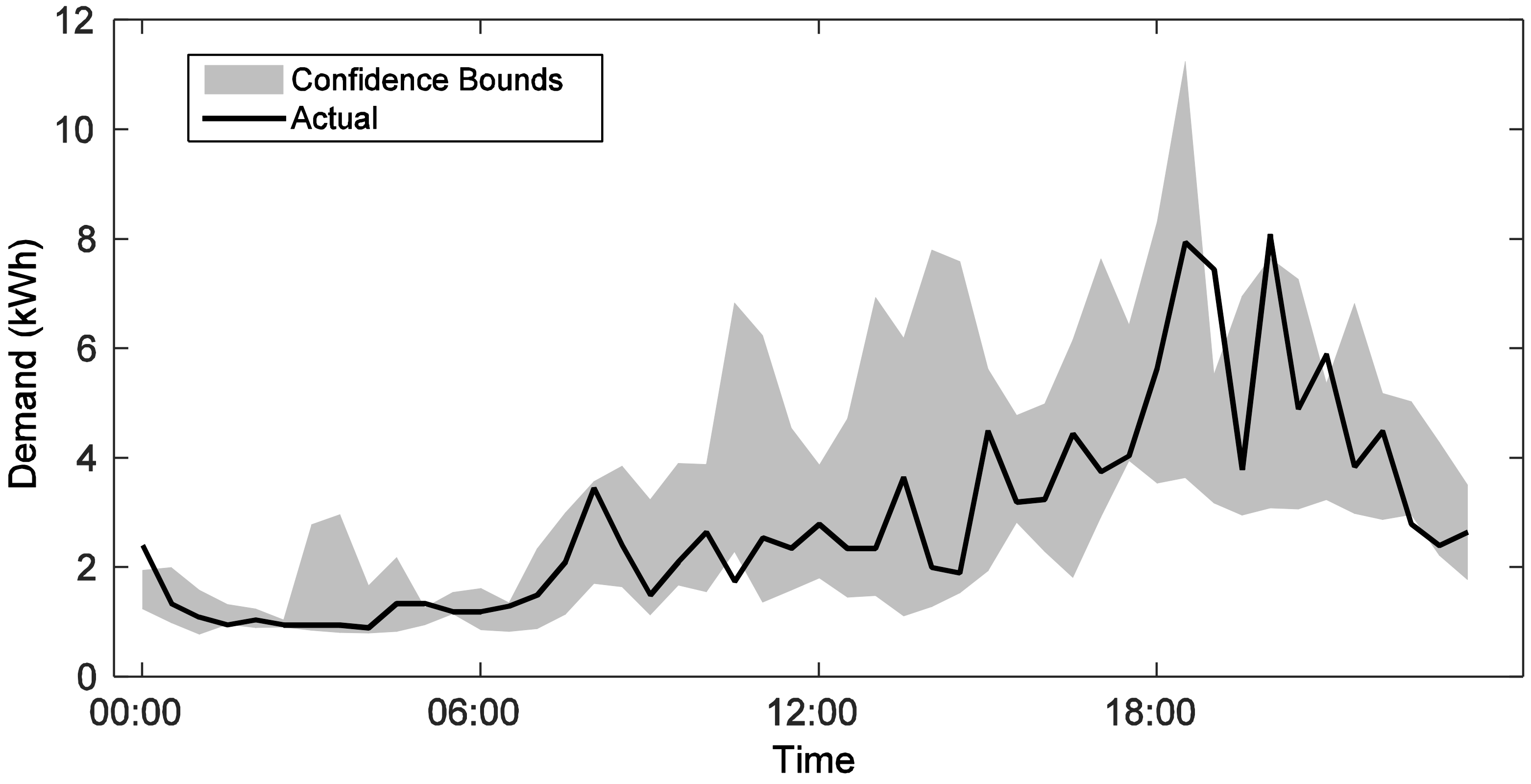


Probabilistic forecasts: Using substation monitoring



Probabilistic forecasts: No substation monitoring

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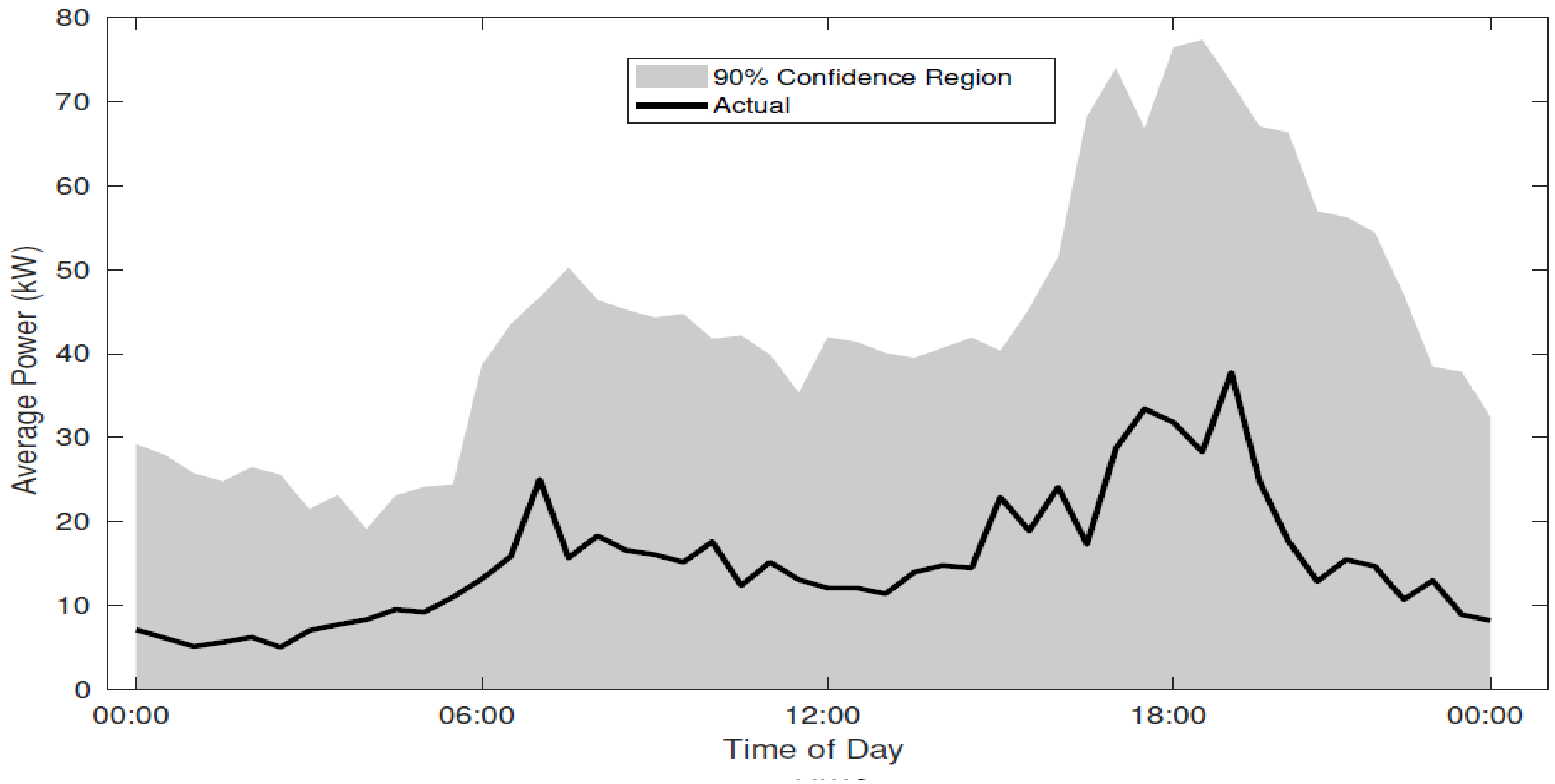
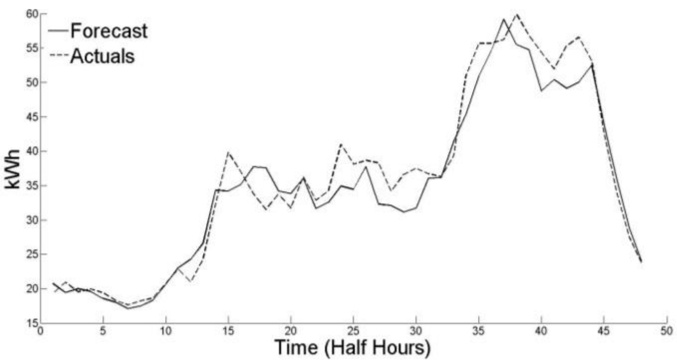


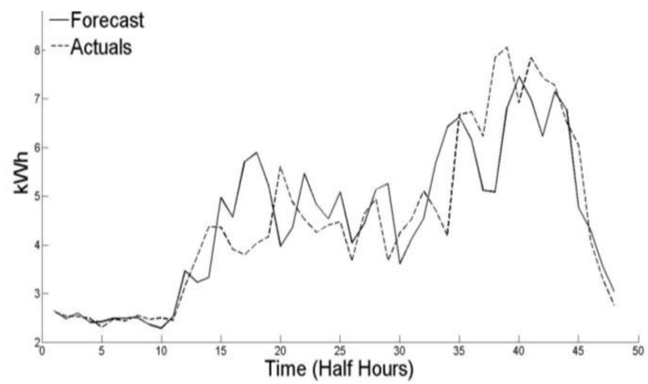
Household level forecasts

Forecasts versus aggregation level

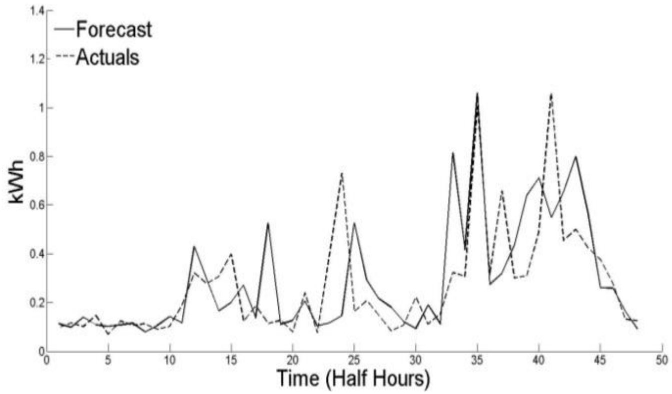
150 household



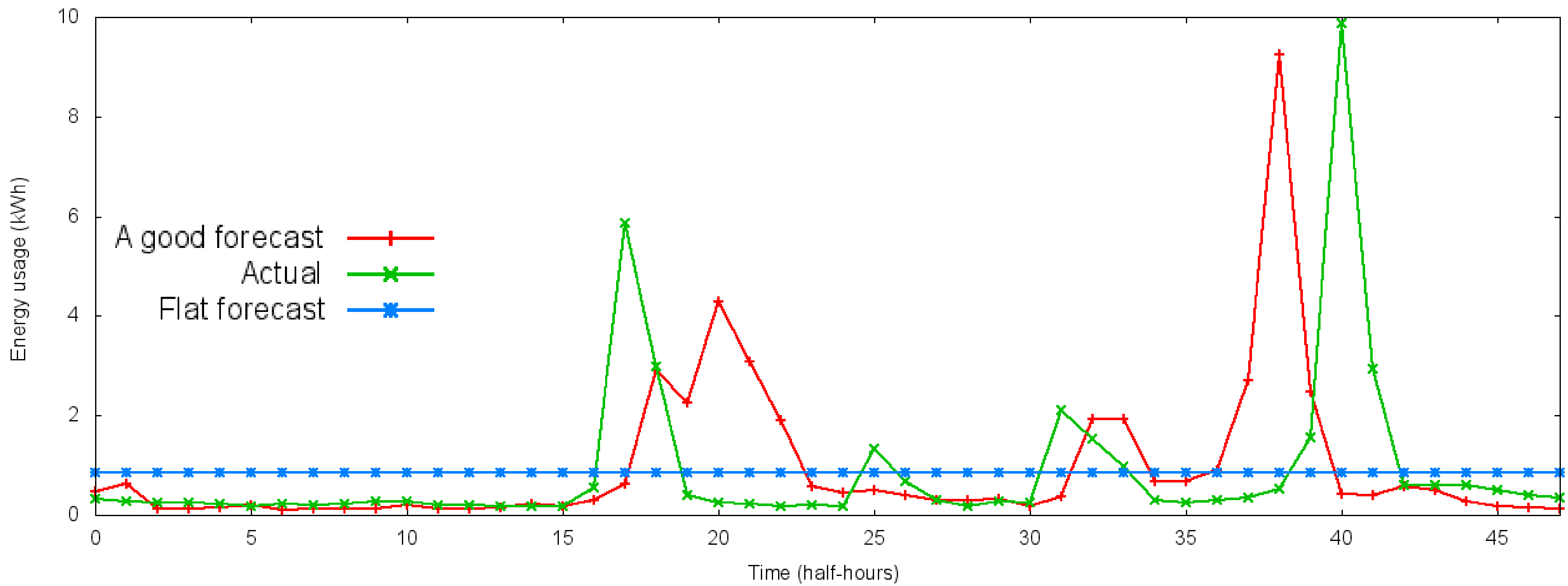
20 household



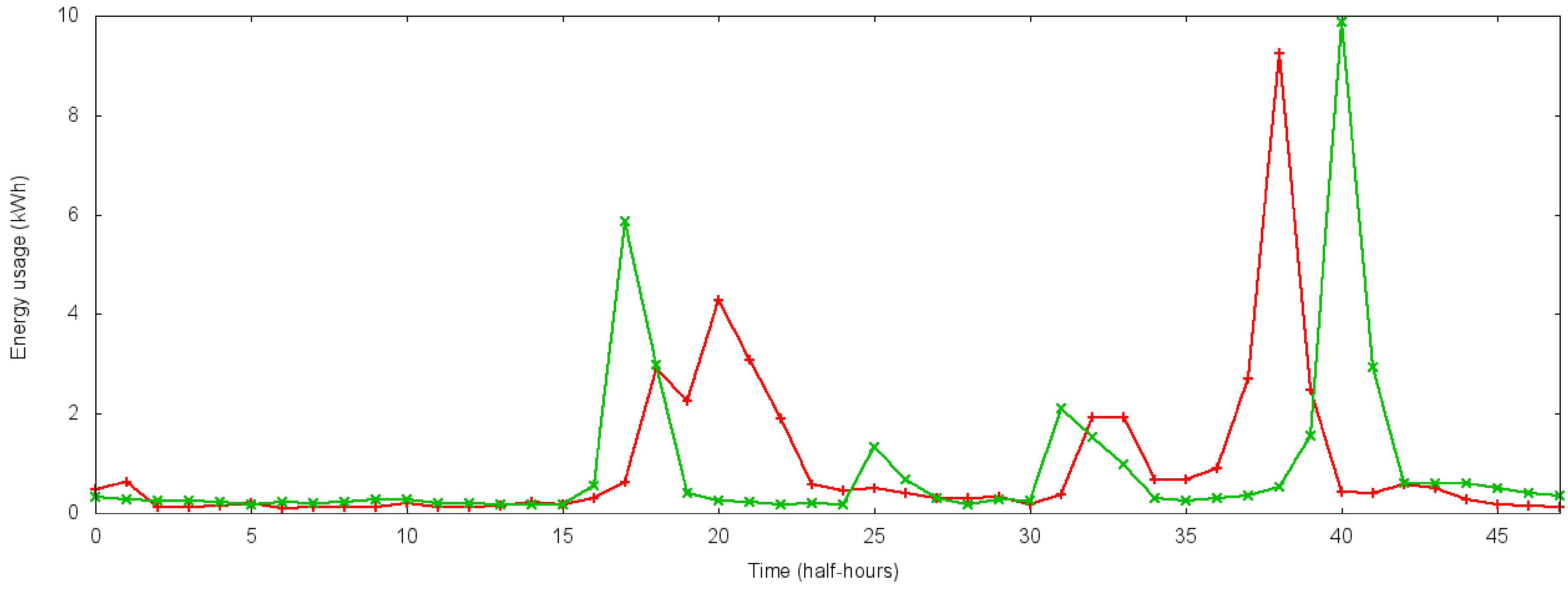
1 household



What is a good forecast?



What is a good forecast?



Summary

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1. Aim: develop low voltage level analytics and forecasting methods to support the current and future low carbon networks
2. Investigated understanding and simulating demands
   a. Types of customers: investigate key features
   b. Links to easily obtained attributes?
   c. How to cope with minimal monitoring
3. Short Term Forecasts
   a. Facilitate storage devices
   b. Quantifying uncertainty: with and without full monitoring

Some Key Learnings

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1. Demographics not enough – you are not like your neighbour
2. Traditional Methods not necessarily appropriate at the LV level: new error measures and forecast techniques particularly **household level**
3. Uncertainty quantification is key – probabilistic techniques in forecasting and control: **Ensemble forecasts**!
4. No one size fits all solution: new and types of customers strongest drivers
5. Back to basics model development:
   a. Weather: Is it relevant?
   b. Change points: new technologies have greater impact at LV level