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Unlocking the long tail of demand response: quantification and control

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Four research themes

- Power systems and energy
- Power electronics
- Control theory and applications
- Smart grids [integration of other activities]

***Maurice Hancock* Smart Energy Lab**

- Reconfigurable 8-node network 2x90kVA programmable voltage supplies
- Rapid prototyping control system (Simulink/Labview)

Outline

1. Introduction

2. Response to dynamic time-of-use tariffs
   - Peak shaving response
   - Household responsiveness

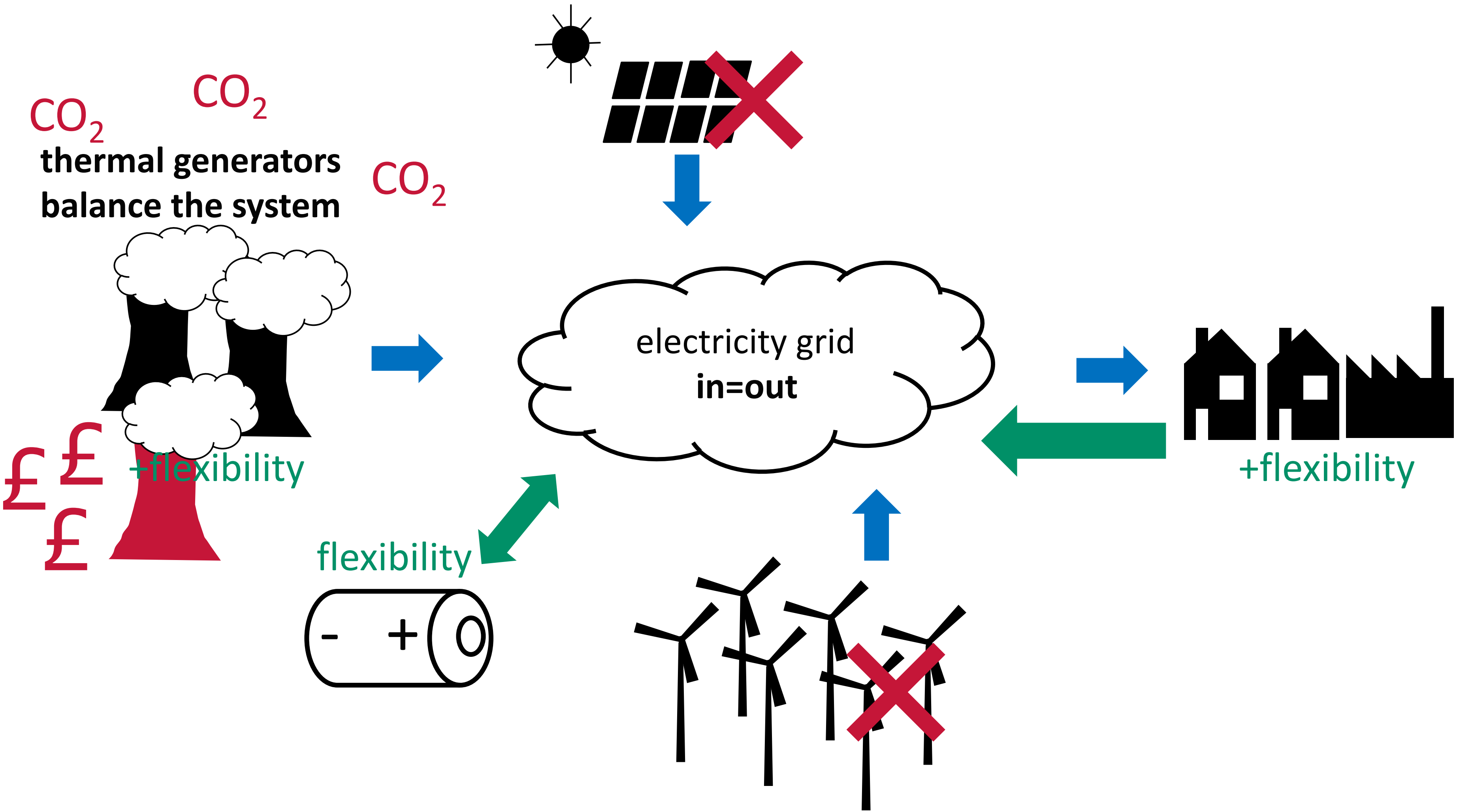
3. Controlling smart refrigerators
   - Stochastic controller
   - Aggregation

4. Final remarks

The case for flexibility

Business as usual approach limits the uptake of renewable generation

To achieve carbon emission and reliability targets in a cost-effective manner we must *increase and exploit flexibility*



Flexibility and the optimal energy mix

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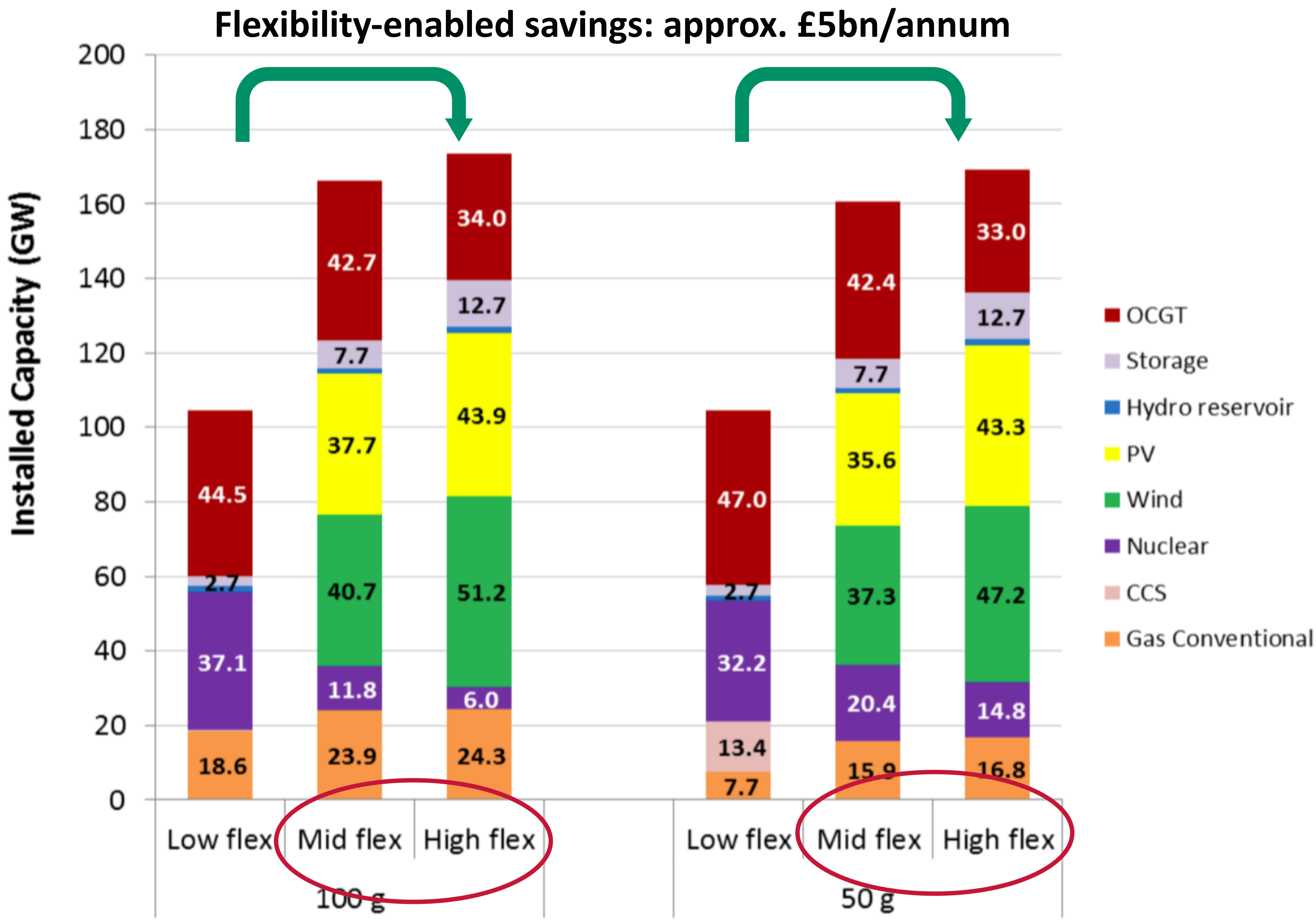
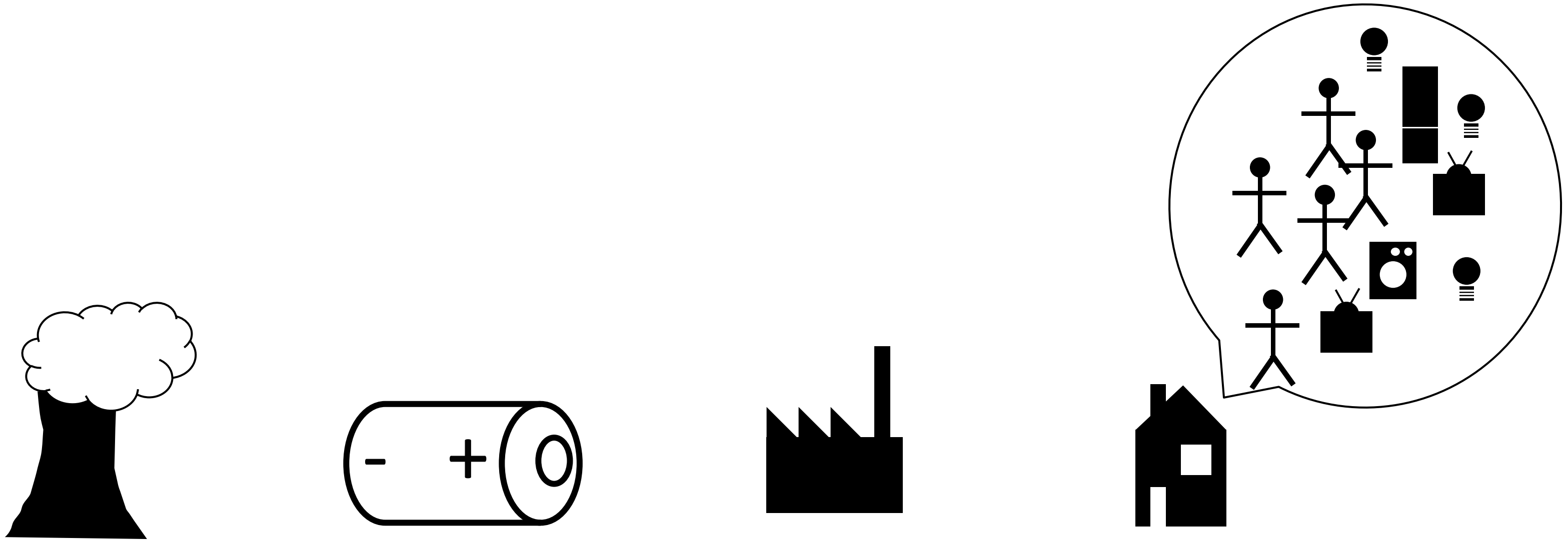


"Value of Flexibility in a Decarbonised Grid and System Externalities of Low-Carbon Generation Technologies"
Report by Imperial College and NERA Consulting for the UK Committee on Climate Change

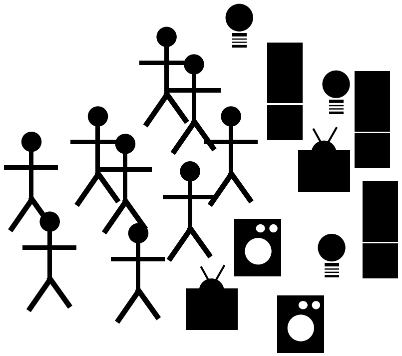
The flexibility spectrum



source	Flexible generators	Grid scale storage	Industrial and commercial DR	residential DR
individual magnitude	10-100MW	1-1000MW	100kW - 1MW	10W – 1kW
number	100	10 - 1000	1000 - 10000	10s of millions

‘Long tail’ of demand response

Unlocking the long tail



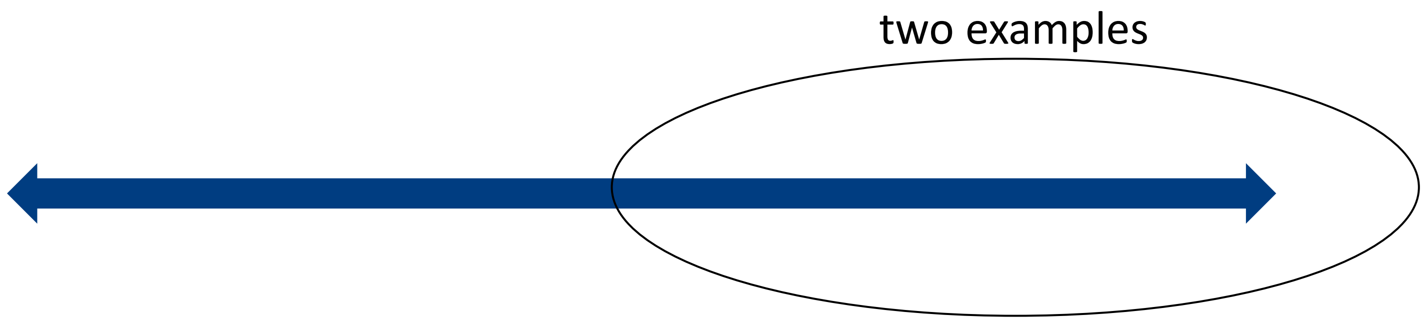
Constraints/challenges

- Flexibility is a by-product of other activities, which will affect service availability.
- Small per-device flexibility contribution, so cost *and* attention budget is small
- Significant heterogeneity

Opportunities

- Very large number of devices (at least at regional/national levels), so large-number statistics apply.
- Regular consumption patterns allow for aggregate prediction.

Control approaches



Direct control

Real time dispatch of resources

V
- Accountability

✕
- Requires real-time communication
- Limited autonomy
- Privacy concerns

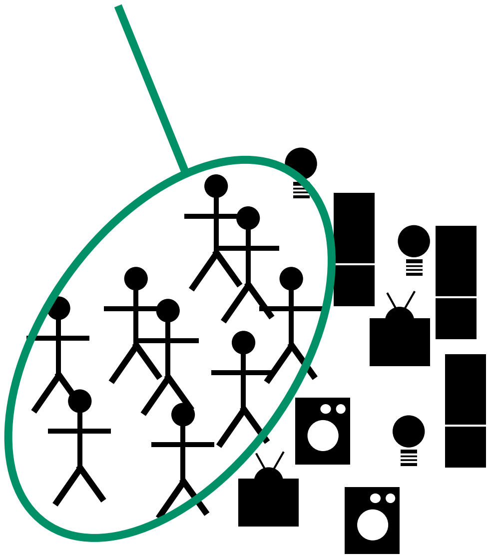
Indirect control

Decentralised response to non-local control signals (e.g. prices)

V
- Autonomy
- Low cost

?
- **Does it work?**

User-mediated
demand response



DYNAMIC TIME-OF-USE TARIFFS

CHARACTERISING RESPONSIVENESS

The Low Carbon London demand response trials (2013)

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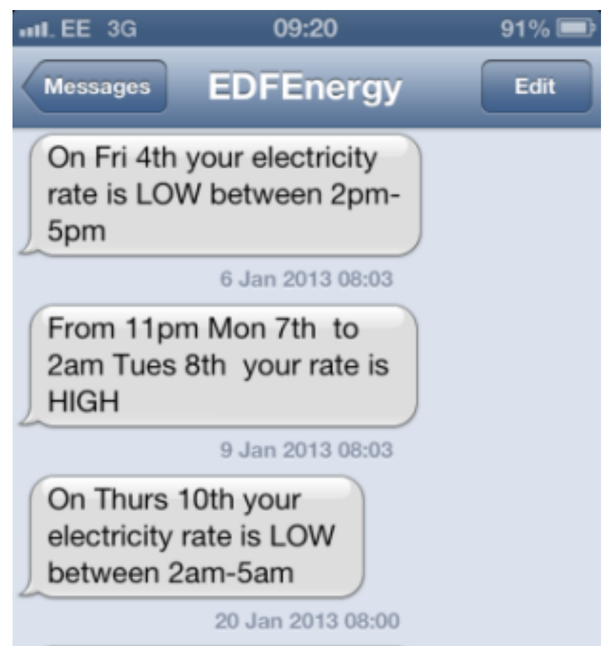
5536 households with smart meters (30-min kWh measurements)

1119 households took part in a **dynamic time of use trial:**

- Day ahead notification of prices via SMS and in-home displays
- Three price levels
    - Default: £0.1176/kWh
    - Low: £0.0399/kWh
    - High: £0.672/kWh



Low carbon LONDON

UK Power Networks

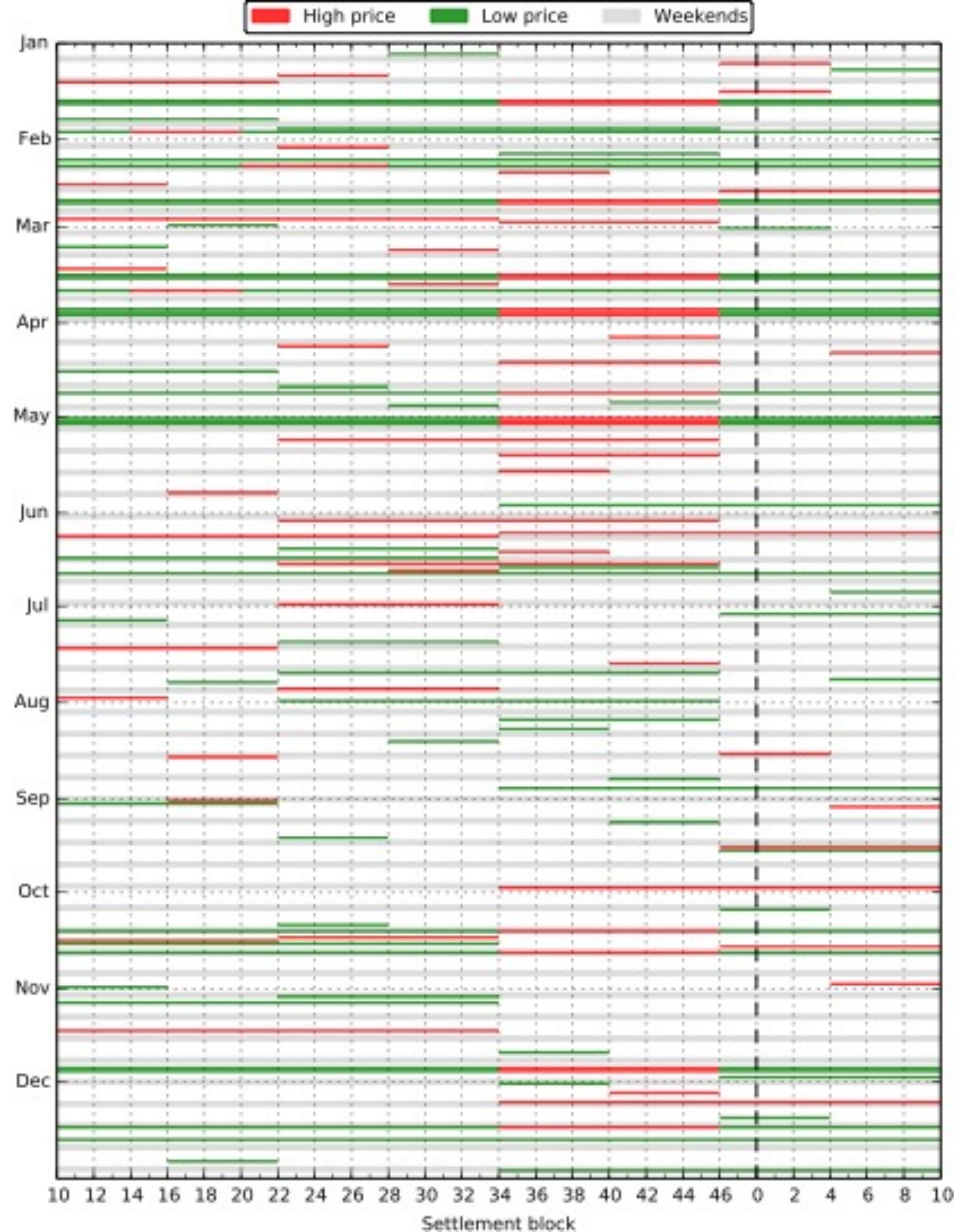
EDF ENERGY

93 supply following events

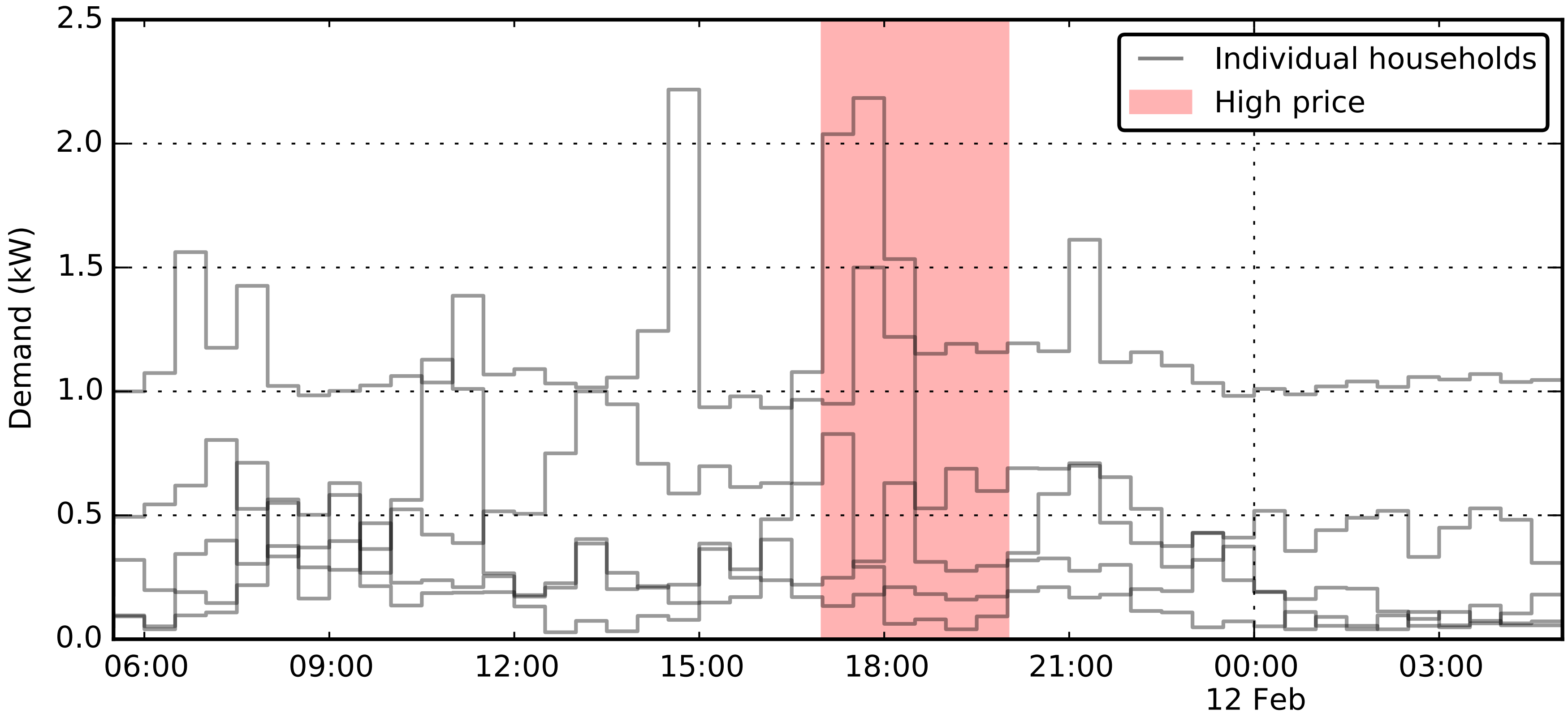
- 45 high price events (3-12 hours)
- 48 low price events (3-24 hours)

13 constraint management events

- high price, flanked by low prices
- primarily targeted at evening peaks
- 1-3 consecutive days (21 days in total)



Measured response to events



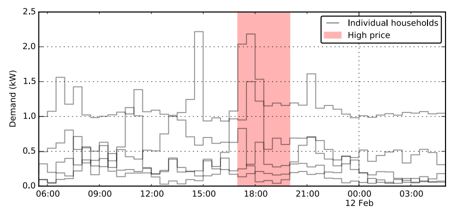
Dataset can be downloaded from UK Data Service
www.ukdataservice.ac.uk ; search for “Low Carbon London”

Analysis through aggregation

single event

many events

single household



Topic 2:
Analysis of household responsiveness

many households

Topic 1:
Analysis of aggregate response

Baselines to measure demand response

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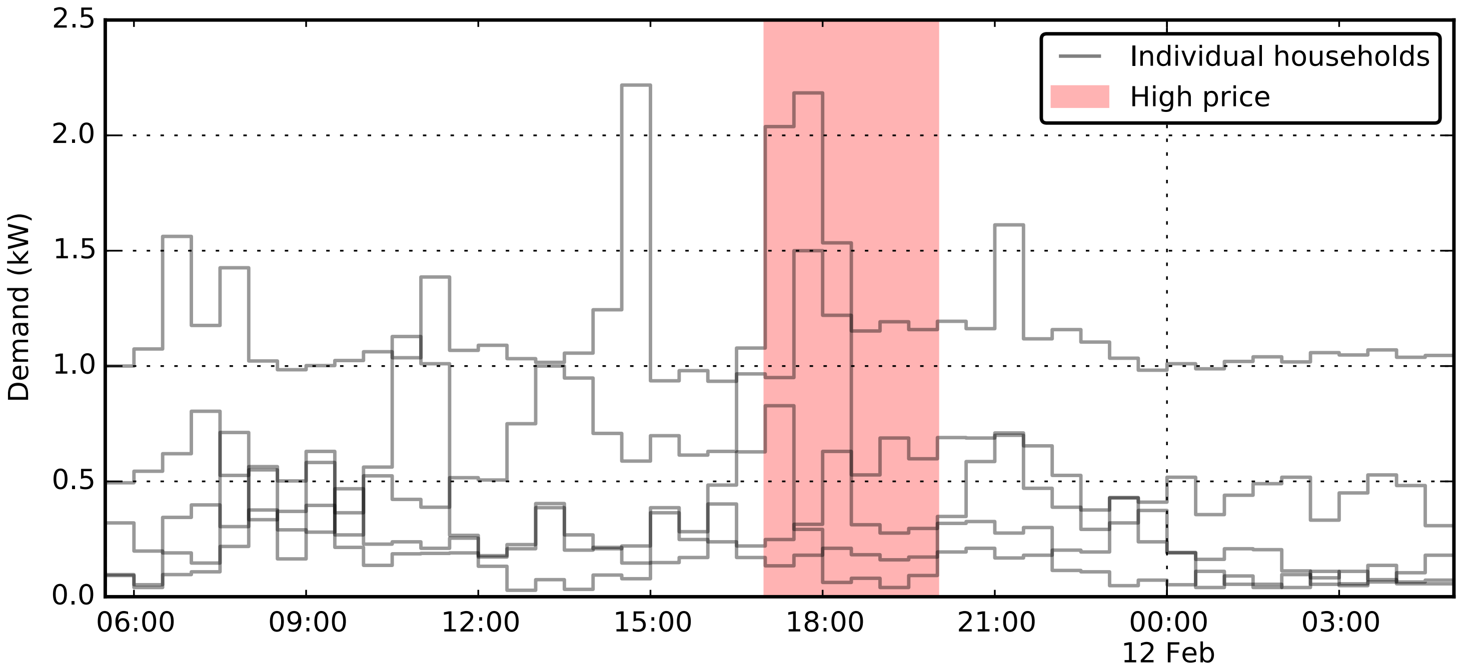


Construct a linear regression model for the baseline, trained on non-event days.

$$B_t = \sum_{w=1}^{W} \left(\alpha_h d_{w,t} + \beta_w A^{\text{non-tou}}{}_t d_{w,t}\right) + \gamma m + \delta T_t$$

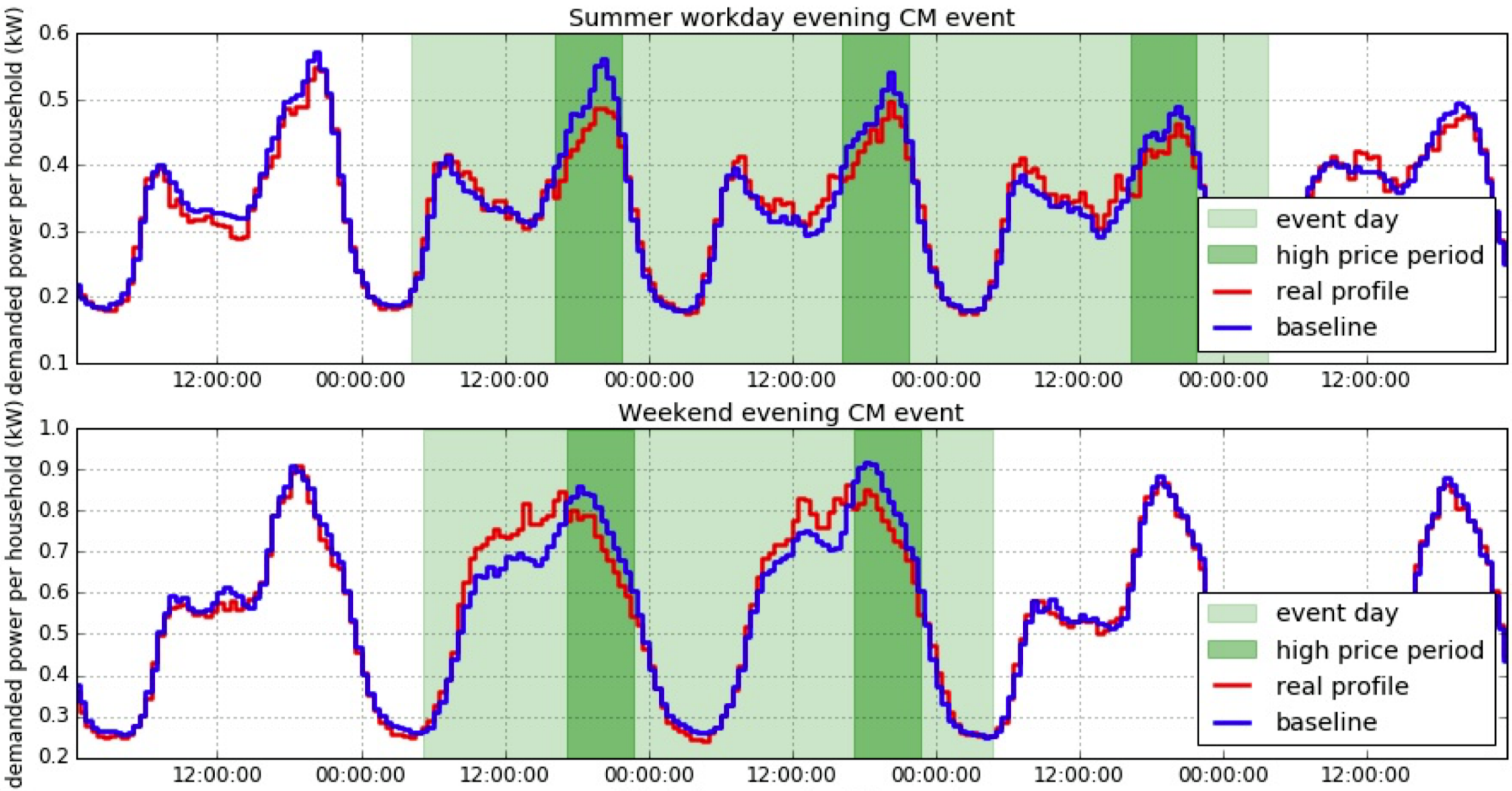
weekly profile

non-ToU group consumption

trend line

temperature factor

Example of measured response

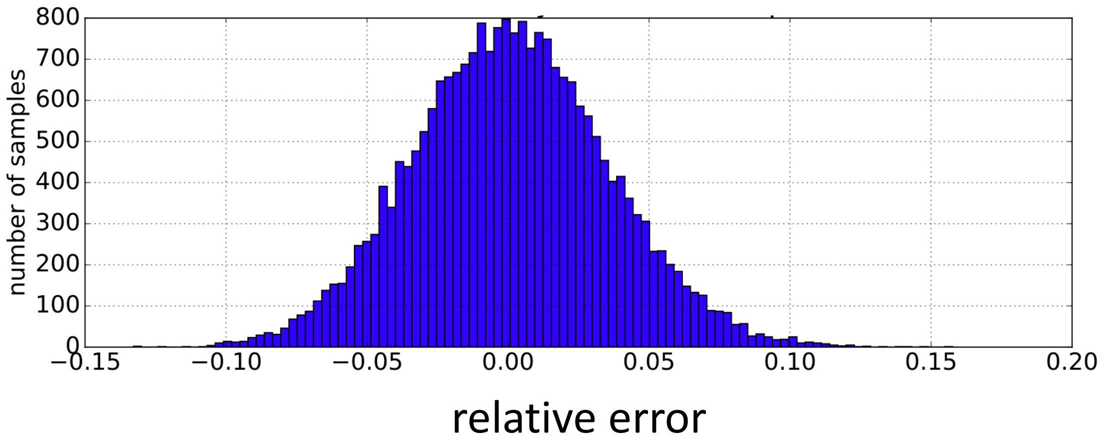


How good is the baseline model?

Bootstrap procedure

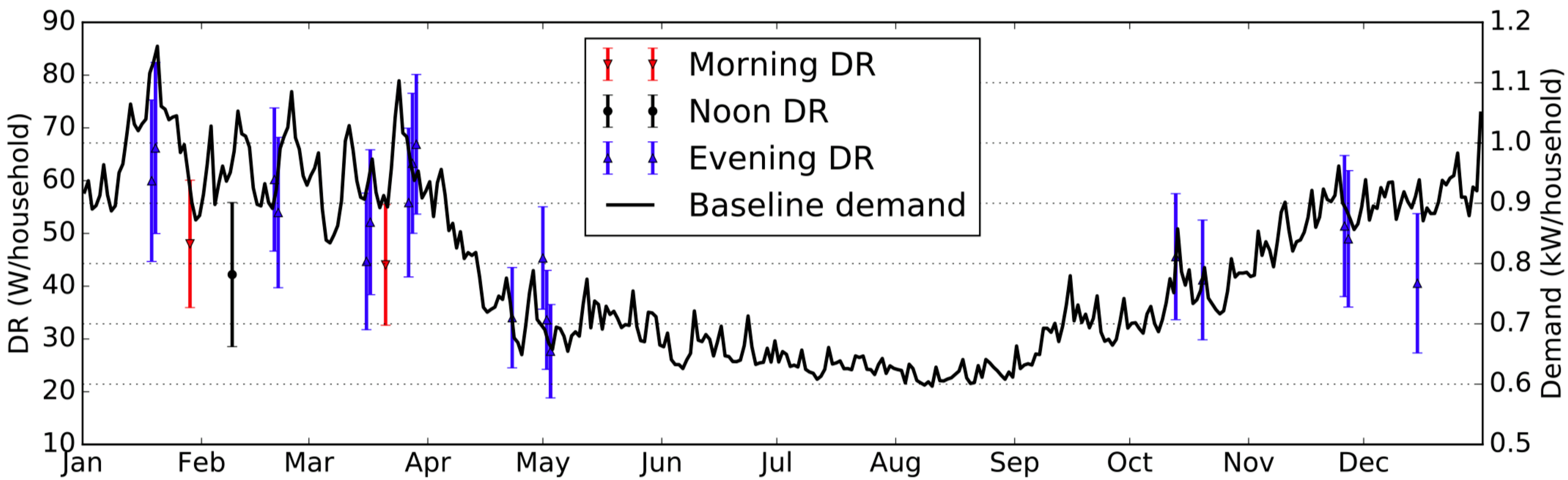
1. Resample the training data $N_{resample}$ times by selecting random days with replacement.
2. Train a baseline model for each resampled data set.
3. Compute the average out-of-bag error for each 30min settlement block.

Result: *Relative* errors are normally distributed



DR block	St Dev
30 mins	3.5%
3 hours	2.5%
6 hours	2.0%

Analysis of peak shaving events



Consider 21 *constraint management* events (peak shaving)

- High price at peak (evening, morning, weekend noon)
- Low price on either side of peak

Procedure

- Estimate DR using baseline model (averaged over block)
- Estimate error using baseline error model

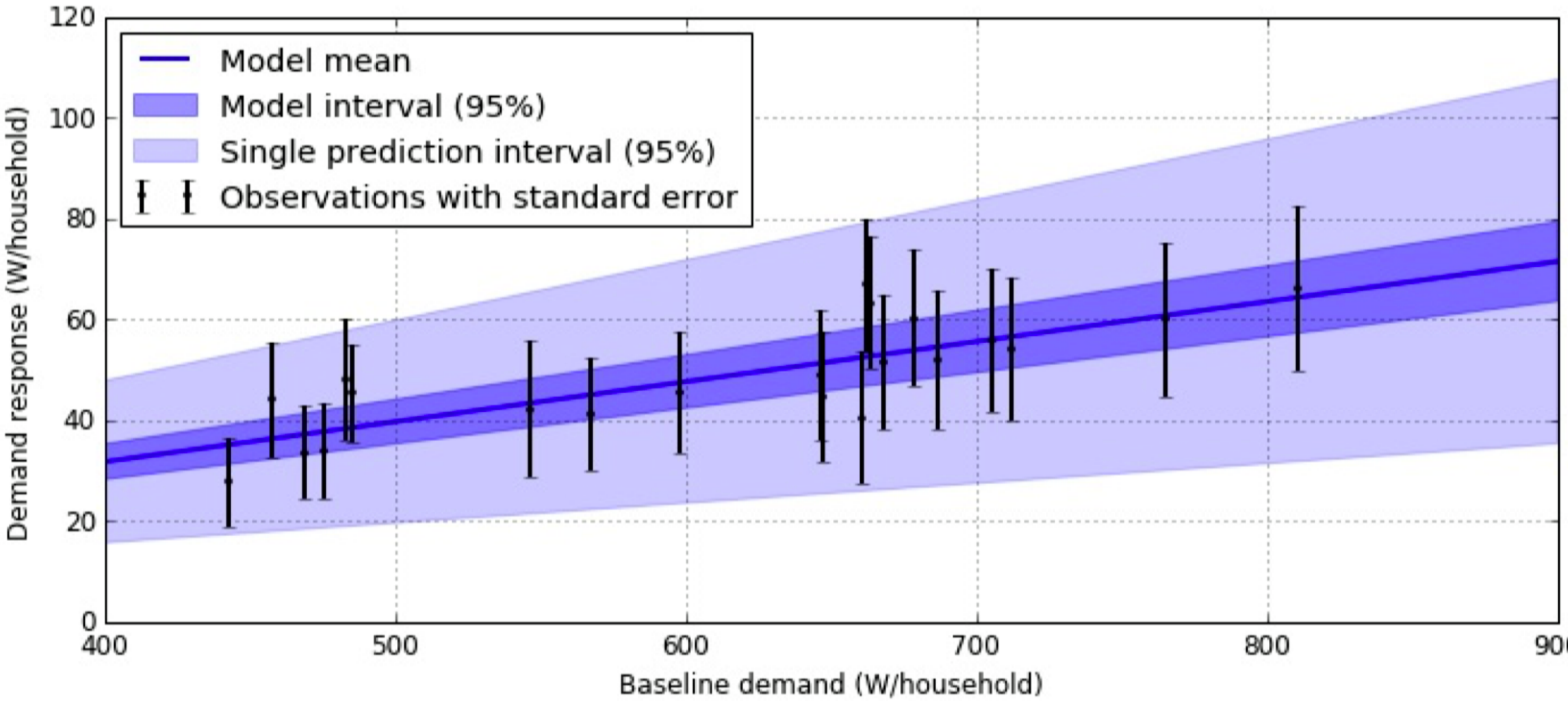
Towards predictive modelling

1. **Select simplest consistent model**

$$R_{CM}^{demand} = -0.079 \times [\text{baseline demand}] + (\text{random variation})$$

2. **Model uncertainty = confidence of parameter fit**
   demand reduction between 7.1-8.8% of baseline demand (95% confidence)

3. **Uncertainty of next measurement = model uncertainty + baseline variability**
   demand reduction between 4-12% of baseline demand (95% confidence)

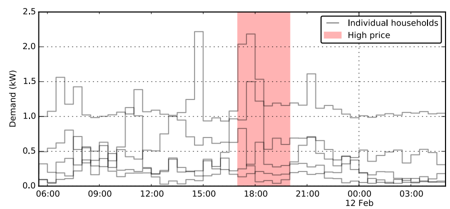


Analysis through aggregation

single event

many events

single household



Topic 2:
Analysis of household responsiveness

many households

Topic 1:
Analysis of aggregate response

How to identify 'responsive' households?

Naive approach: Change in bills

Compare actual bill with hypothetical bill on a flat tariff

- Only measures *success*, but not the intent
- Does not account for natural differences in consumption *magnitude*, *flexibility* and *pattern*

Proposed approach: resampling

1. Compute the actual bill b^* using the actual price signal p_t and consumption c_t:

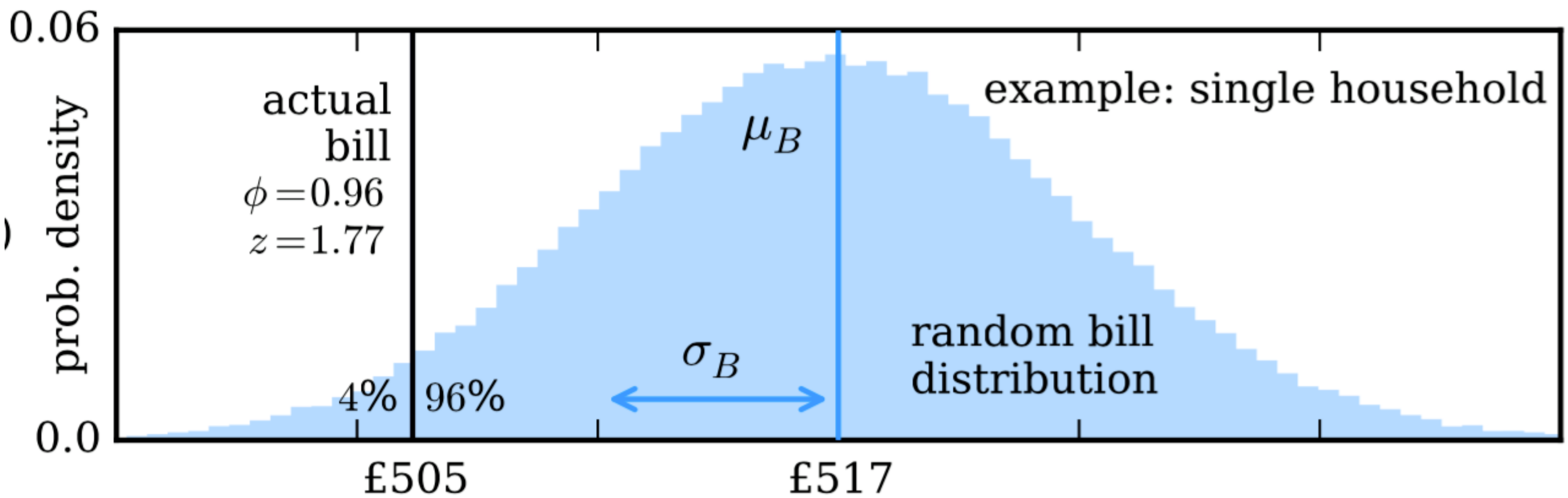
$$b^* = \sum_{t=1}^{T} p_t c_t$$

2. Generate randomised bills tariffs by permuting daily price signals

$$B = \sum_{t=1}^{T} p_{\Pi(t)} c_t$$

3. Compare the true and hypothetical bills

James Schofield, Simon Tindemans, Goran Strbac, arXiv:1605.08078



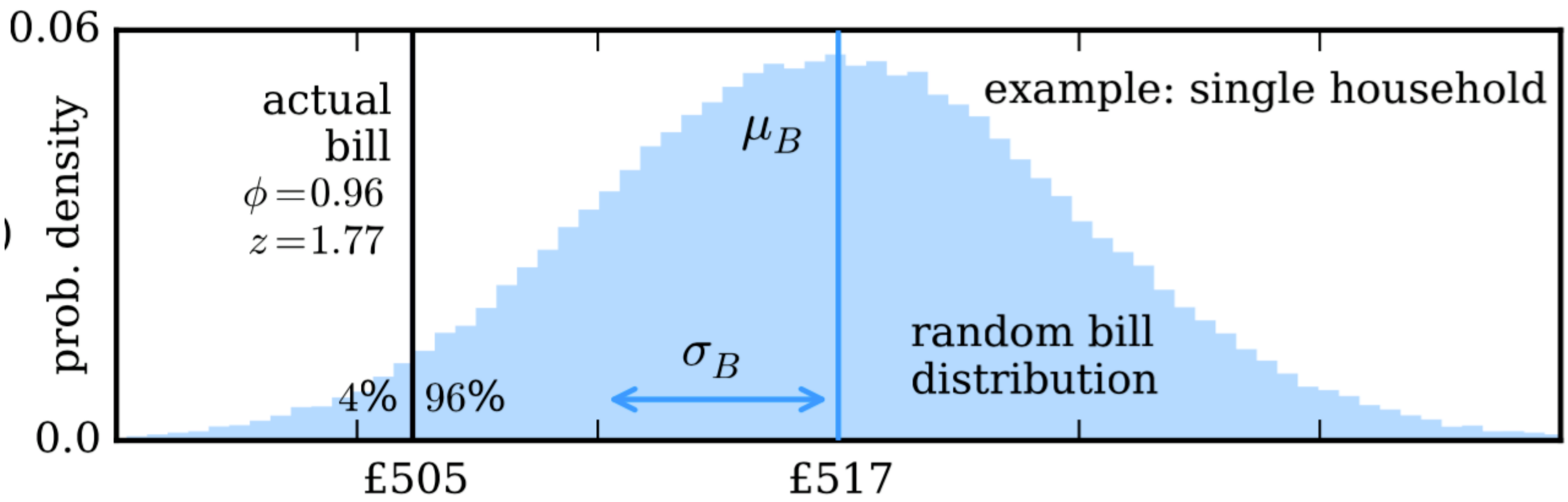
B is approximately normal [combinatorial CLT; Hoeffding, 1951].
Define a measure of responsiveness

$$\varphi = \Pr(B > b^*)$$

$B \sim$ random bill distribution
b^* = actual bill

- **Intuitive interpretation as a signal-to-noise measure.**
- **Provides a *confidence ranking* across households that correlates highly with stated actions (more so than DR measurements).**

Interpreting per-household responsiveness

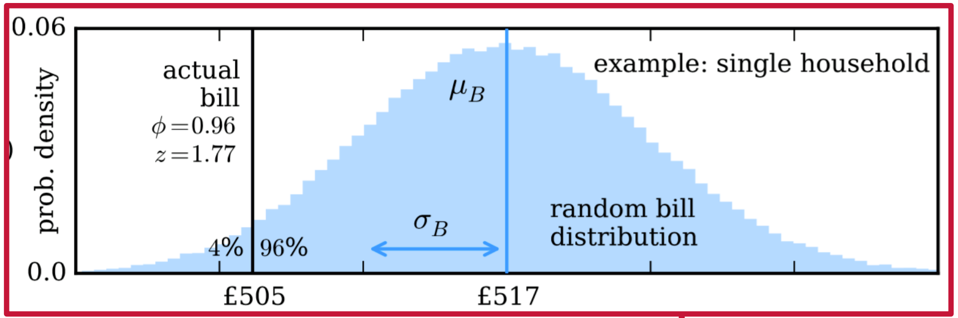


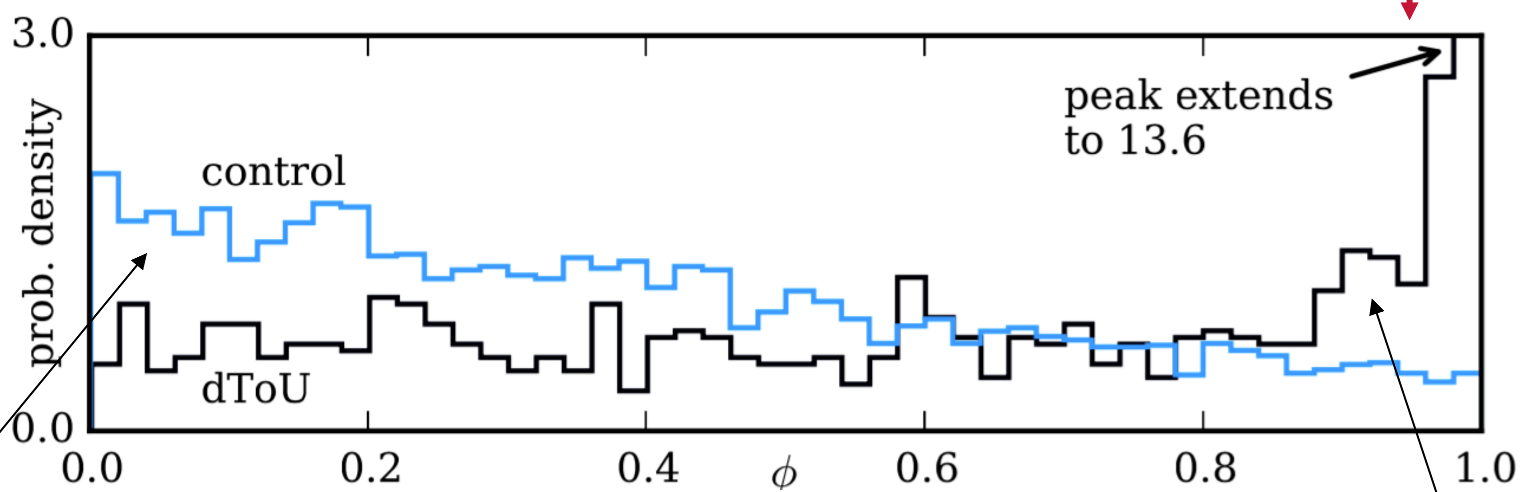
What makes a household 'responsive'?

1. Deliberate demand response
2. 'Accidental' demand response (both variable and constant) ← quantify
3. Price signal bias, relative to the population's consumption pattern (e.g. high prices that target winter peaks) ← eliminate

We can dig deeper using data from a control group

Correcting for price signal bias





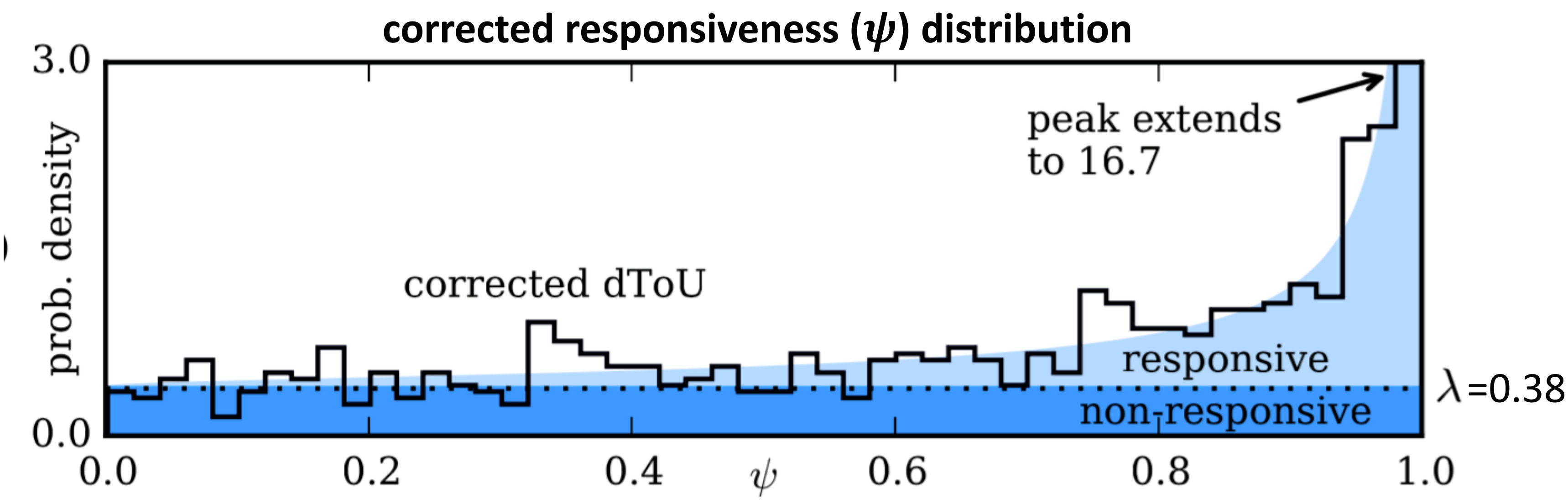
Evidence of price signal bias

Evidence of significant demand response

Use control group to create a new coordinate that corrects for price bias

$$\psi = F_{control}(\varphi)$$

Quantifying household responsiveness



Divide participants into **responsive** and **non-responsive sub-populations**

62% of households are responsive - but there is no need to state which is which.

Basis for a **probabilistic assessment of household responsiveness**:

$$\Pr(responsive|\psi) = \frac{f(\psi;\lambda) - \lambda}{f(\psi;\lambda)}$$

Summary and outlook: dTOU data

Low carbon LONDON

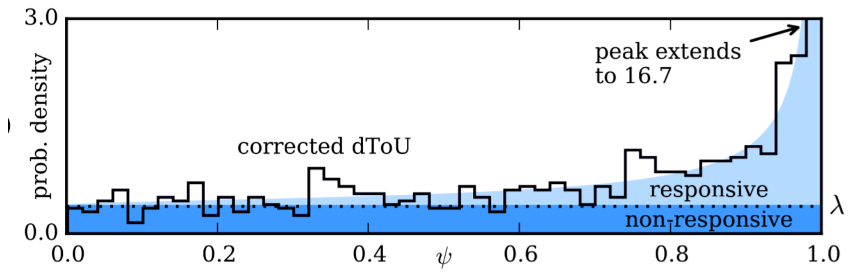
single event

many events

single household

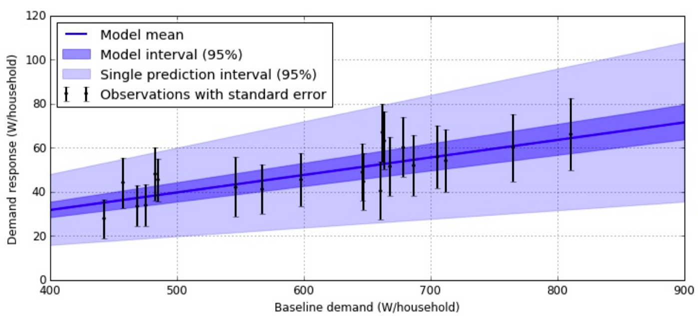
many households

online learning from business as usual data



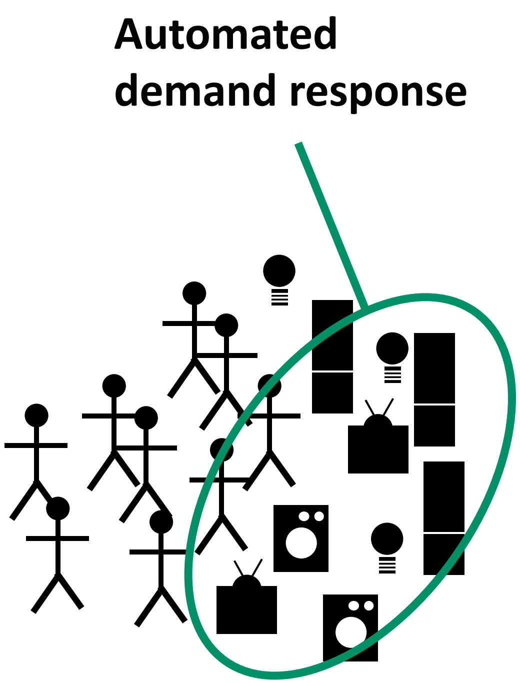
Nonparametric method to quantify responsiveness

62% of participants were responsive



Significant event-to-event variation in DSR peak shaving

4-12% reduction for the next event (95% confidence)



SMART REFRIGERATORS

DESIGNING A DECENTRALISED CONTROLLER

Refrigerator hysteresis controller

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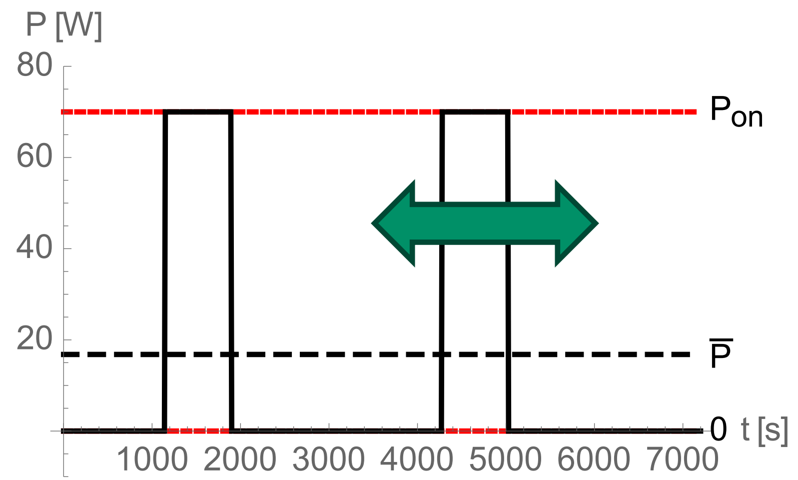
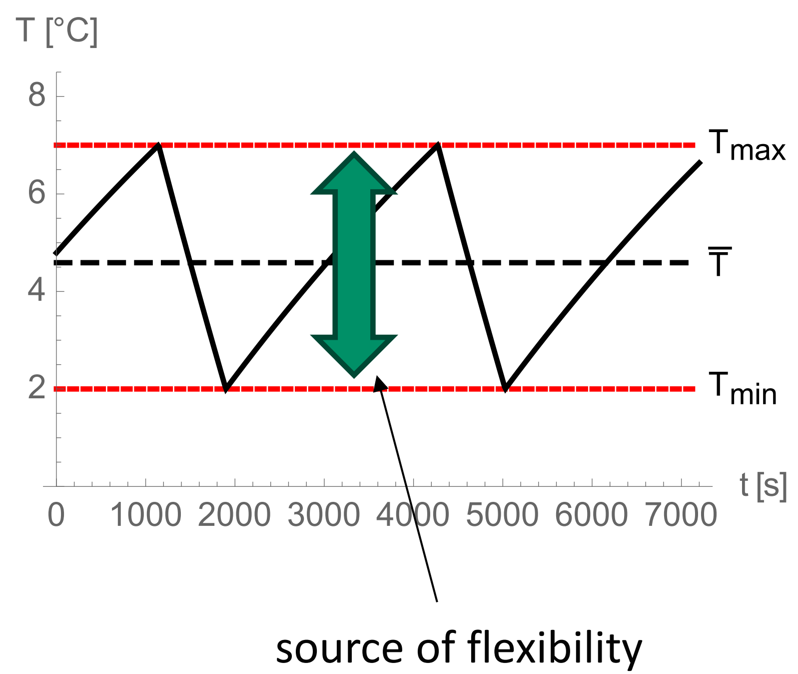
Power consumption



Temperature



Flexible refrigeration: from ‘what’ to ‘how’

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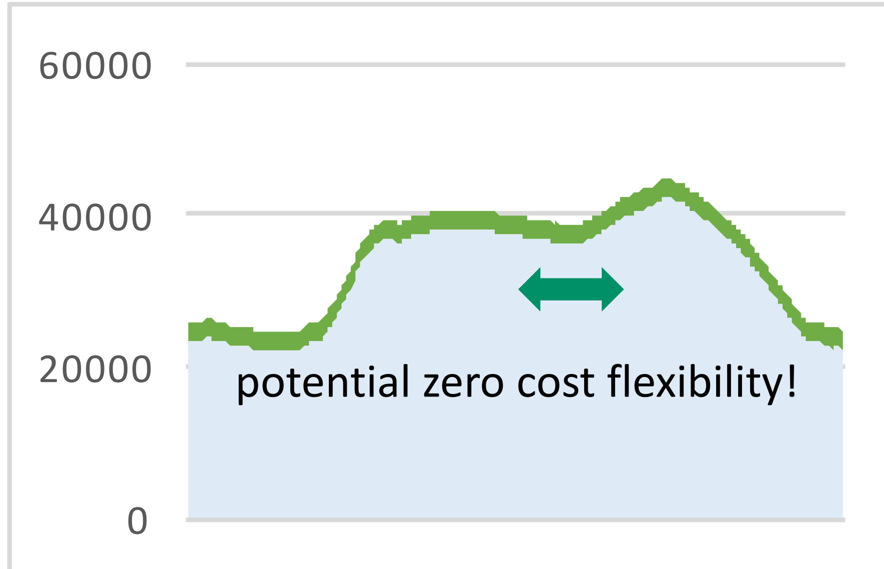
The opportunity

- Refrigerators represent 5-15% of system load (est. 2-3GW in GB)*
- Load shifting for ~30 minutes is free* **secondary use**



The challenge

- **Maintain cooling performance:** Secondary use (flexibility) should not compromise the primary use (cooling) of devices.
- **Robustness and scalability:** Reliance on real-time communication may result in bottlenecks and single points of failure
- **Controllability:** Ensure sufficient control over power consumption, and avoid *unwanted interactions.*

“Semi-autonomous control”

Our approach: **semi-autonomous control**

- *Collective goals* are set centrally
- *Actions* are decided locally, adapted to expected *group behaviour*

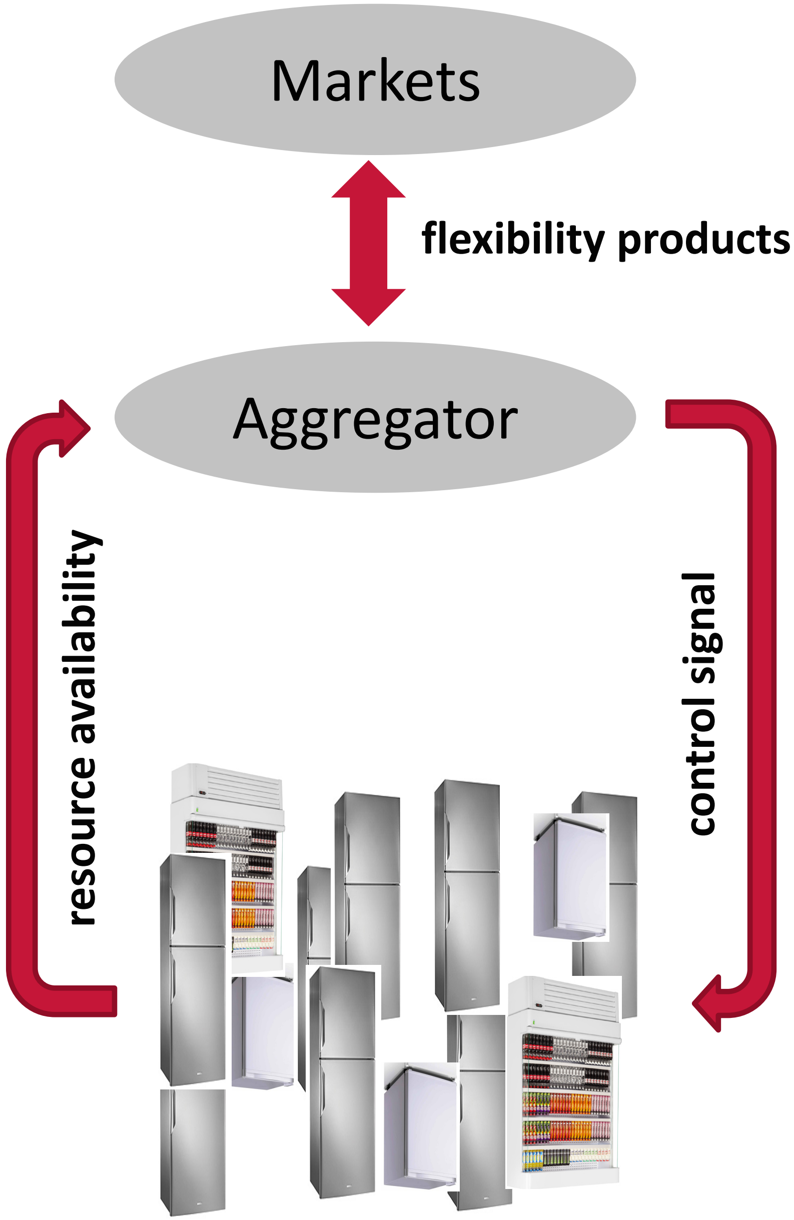
Direct control

Goals and actions are decided centrally, or in a distributed fashion

Indirect control

Decentralised actions on the basis of a non-local control signals

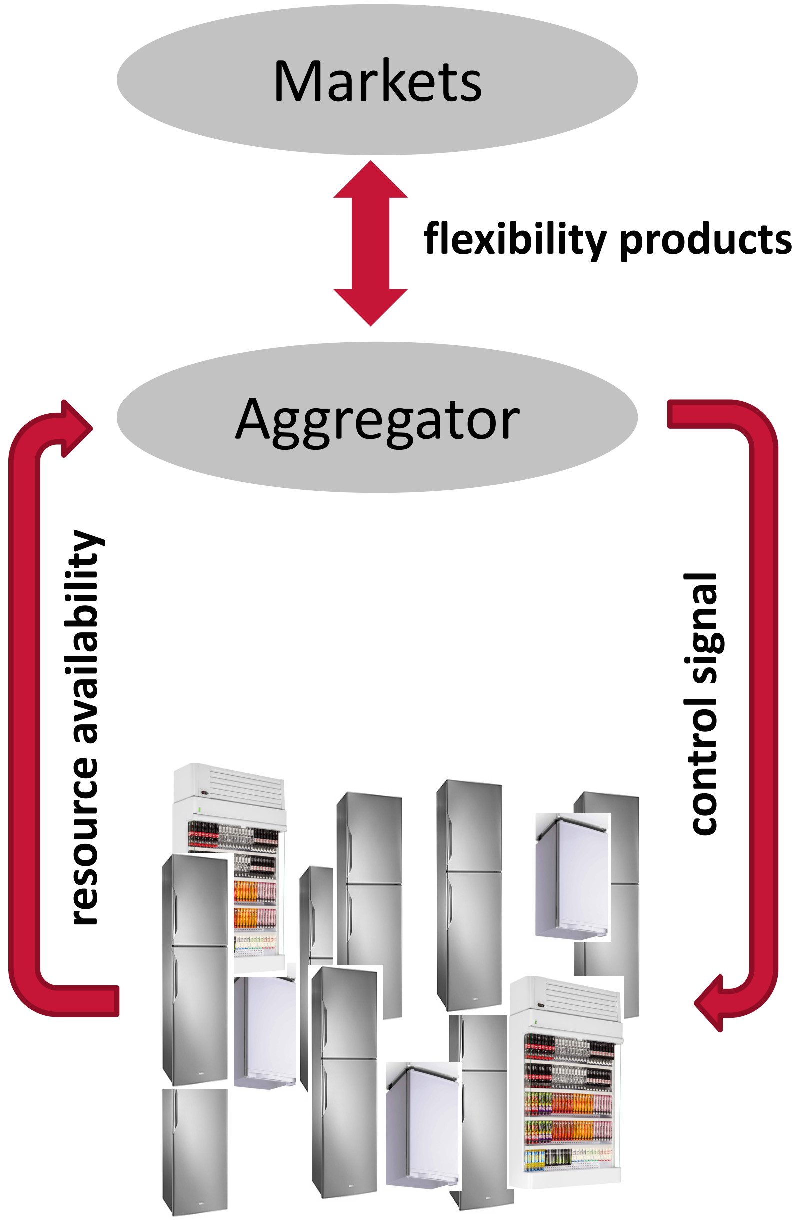
High-level approach



Model of collective flexibility

Aggregate load dispatch

High-level approach



Model of collective flexibility

Aggregate load dispatch

Control through the law of large numbers

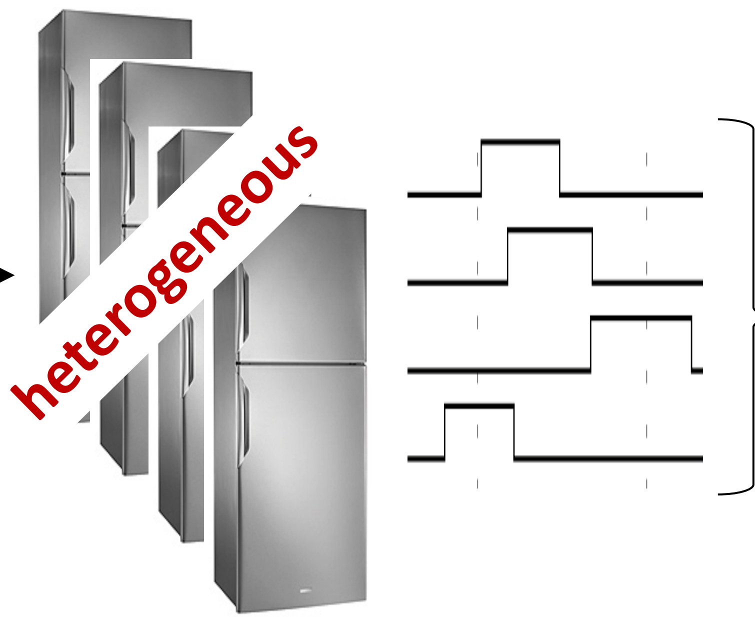
$$E[P^a(t)] = \overline{P_0^a}$$

control intent **modulates power consumption of all appliances**
$\Pi(t) = 1$ for steady state

power consumption
of appliance *a* (a random process)

steady state power consumption
of appliance *a*

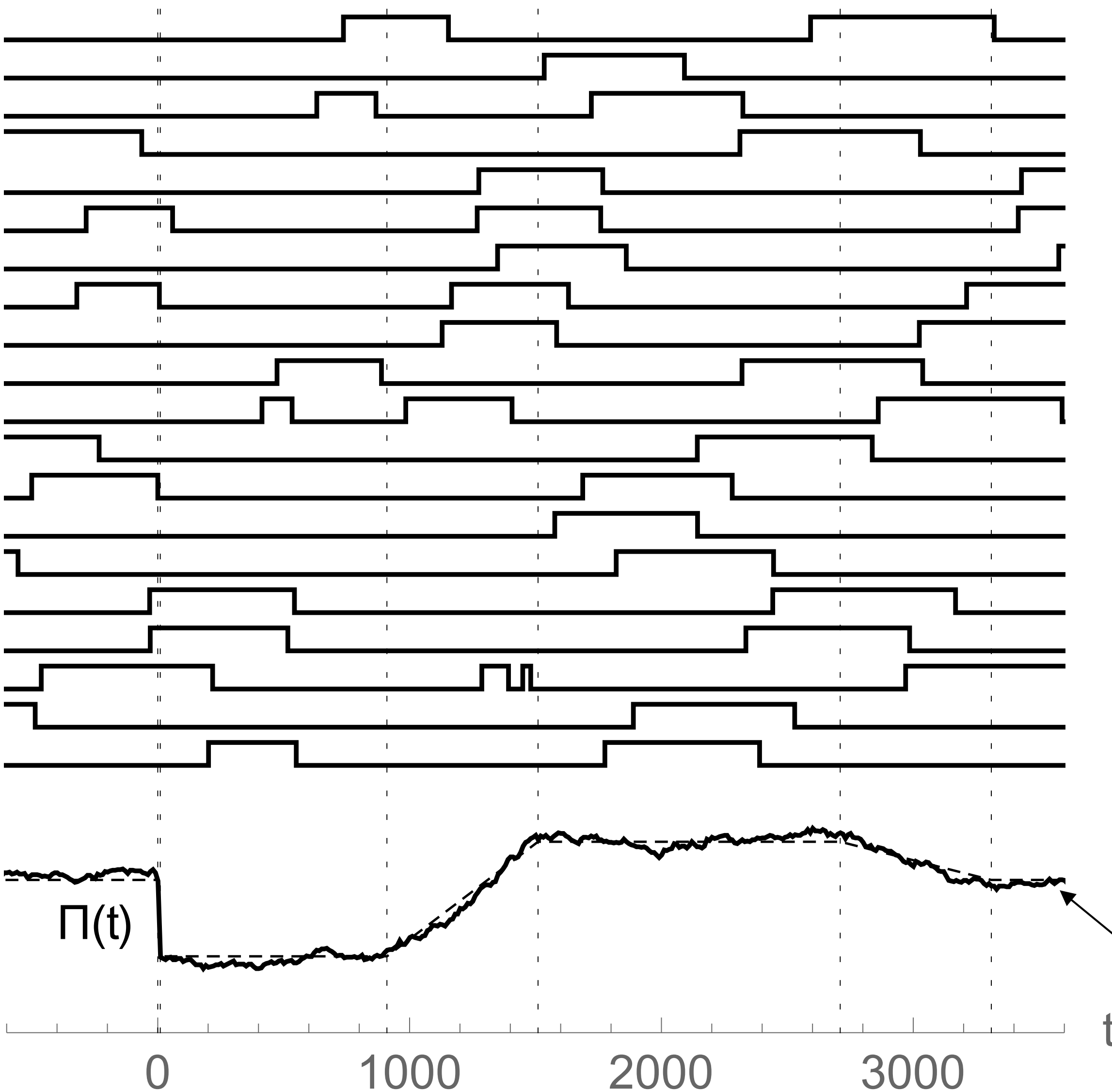
$\Pi(t) \longrightarrow$



$$P^{total} = \sum_a P^a(t) = P_0^{total} \times \Pi(t) + \mathcal{O}(N^{-1/2})$$

Simon Tindemans, Vincenzo Trovato, Goran Strbac, “Decentralised control of thermostatic loads for flexible demand response.”, *IEEE Transactions on Control Systems Technology*, (2015)

Aggregate convergent response



Collectively, **fridges track the reference signal $\Pi(t)$** – even when each appliance is different!

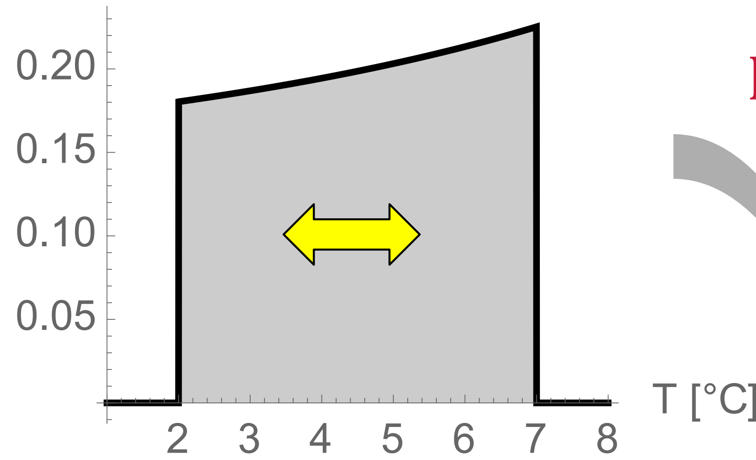
N=1000 domestic refrigerators

Controller implementation

1. Each appliance knows its **state** and **model**

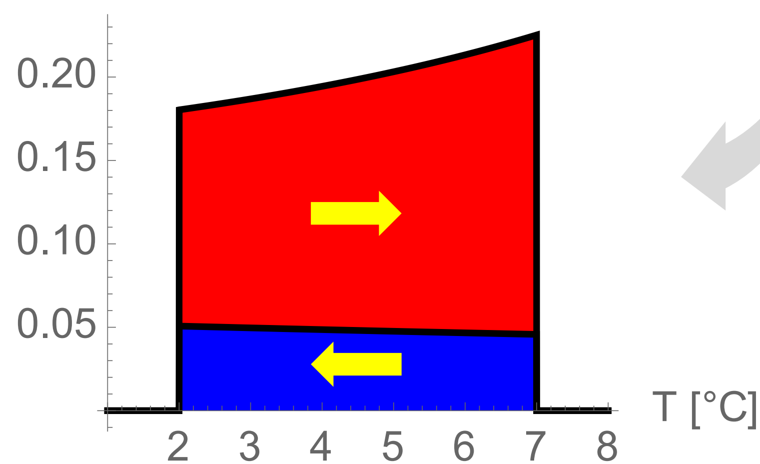
$$\frac{dT(t)}{dt} = \begin{cases} -\alpha(T(t) - T_{on}) & \text{(on)} \\ -\alpha(T(t) - T_{ambient}) & \text{(off)} \end{cases}$$

2. **Construct a *homogeneous* 'virtual population'** with random temperatures.

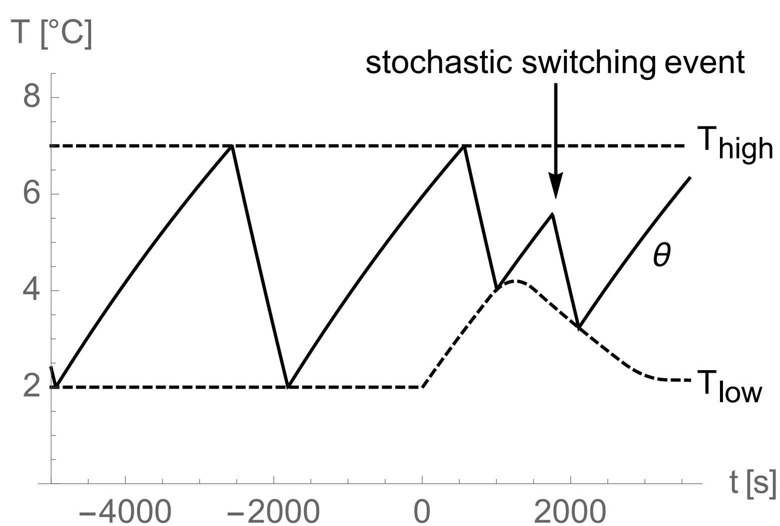


$\Pi(t)$

3. **Manipulate the 'virtual population'** to control its (virtual) power consumption in line with $\Pi(t)$.



4. **Determine device-specific actions,** based on the actual device temperature



Controller implementation

1. Each appliance knows its **state** and **model**

2. **Construct a *homogeneous* 'virtual population'** with random temperatures.

Each appliance considers itself as a random representative of a population...

4. **Determine device-specific actions,** based on the actual device temperature

3. **Manipulate the 'virtual population'** to control its (virtual) power

...and takes individual actions in line with population objectives

Analytical solution

(sub-)population avg temperature

$$\bar{T}(t) = T_{\mathrm{OFF}} - \alpha(T_{\mathrm{OFF}} - \bar{T}_0) \int_{-\infty}^{t} \Pi(t')\mathrm{e}^{-\alpha(t-t')}\, dt'.$$

$$\beta(t) = \frac{\Pi(t)(T_{\mathrm{OFF}} - \bar{T}_0) - (T_{\mathrm{OFF}} - \bar{T}(t))}{T_{\max} - \bar{T}(t)}.$$

rate of heating/cooling

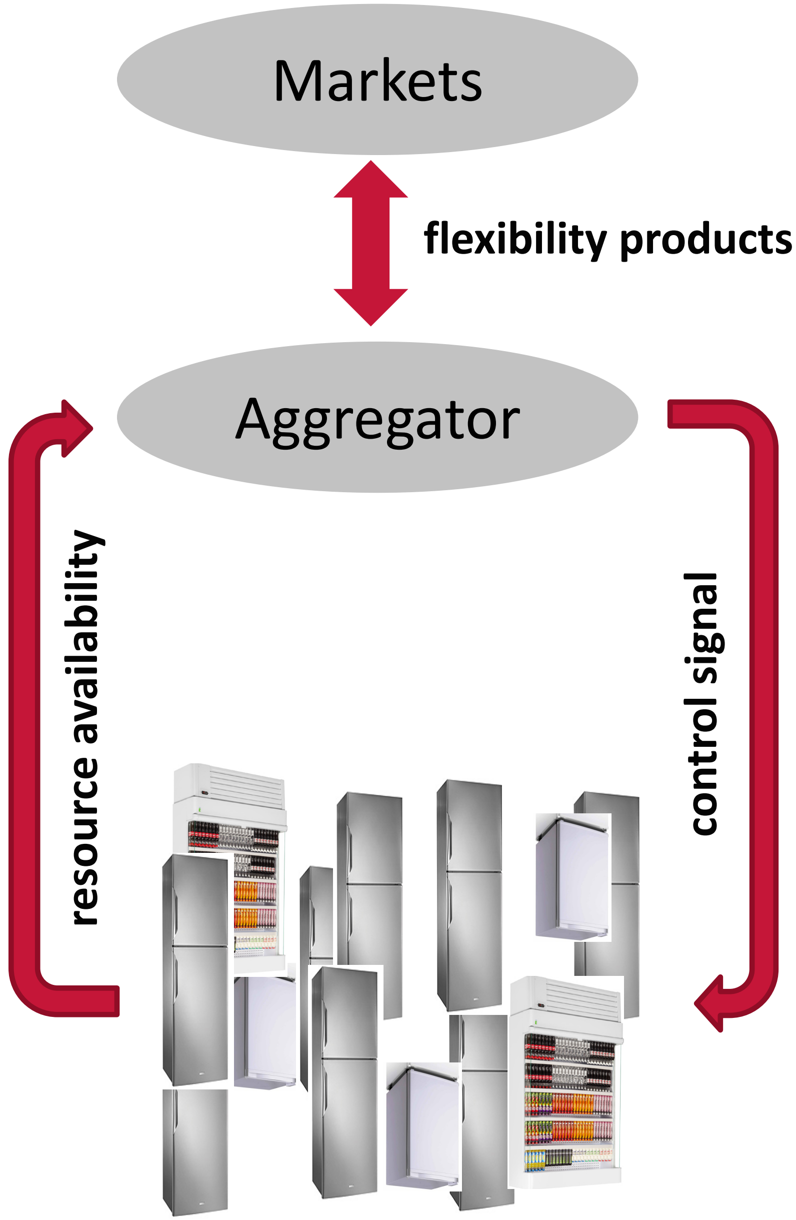
$$v(T,t) = \alpha\beta(t)(T - T_{\max}).$$

switching rates

$$r_{\mathrm{OFF}}^{\mathrm{ON}}(T,t) = \max\left(0, \frac{\Xi(T,t)}{v_{\mathrm{OFF}}(T) - v(T,t)}\right)$$
$$r_{\mathrm{ON}}^{\mathrm{OFF}}(T,t) = \max\left(0, \frac{\Xi(T,t)}{v_{\mathrm{ON}}(T) - v(T,t)}\right).$$

$$\begin{aligned}\Xi(T,t) = {} & \alpha\tau_{\max}\frac{d\beta(t)}{dt} + \alpha^2\left(\frac{\hat{\tau}_{\mathrm{OFF}} + \hat{\tau}_{\mathrm{ON}}}{\hat{\tau}_{\mathrm{OFF}}\hat{\tau}_{\mathrm{ON}}}\right) \\ & \times (\tau_{\mathrm{OFF}} + \beta(t)\tau_{\max})(\tau_{\mathrm{ON}} + \beta(t)\tau_{\max}) \\ & - \alpha^2(1 + \beta(t))(\tau_{\mathrm{OFF}} + \tau_{\mathrm{ON}} + \beta(t)\tau_{\max}).\end{aligned}$$

High-level approach



Model of collective flexibility

Aggregate load dispatch

The leaky storage unit

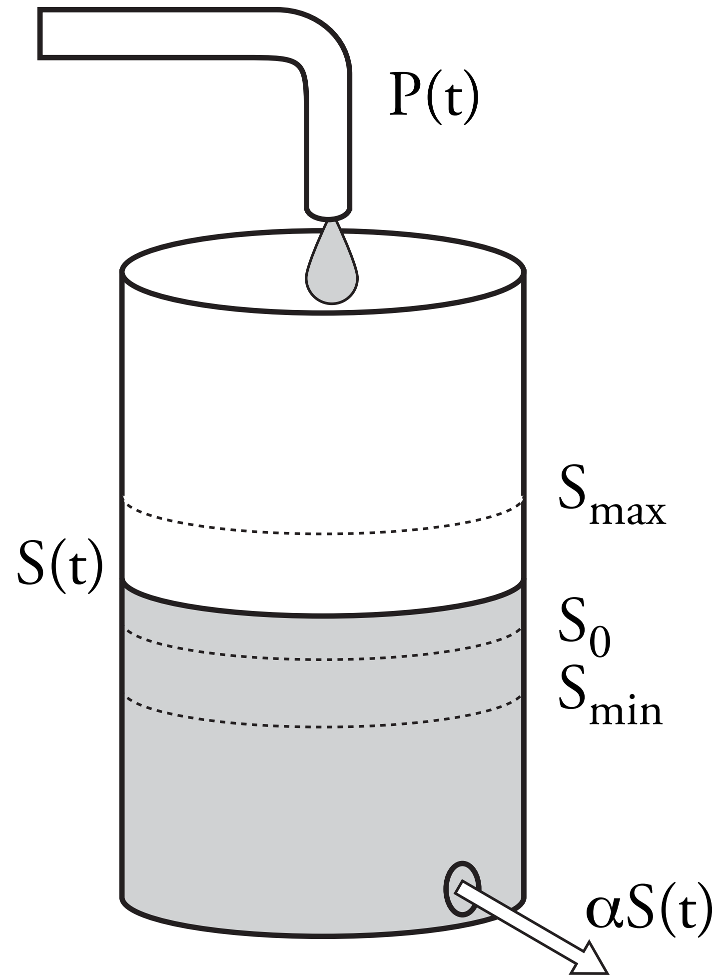
Six-parameter model to describe the flexibility of a homogeneous population

$$\frac{dS(t)}{dt} = P(t) - \alpha S(t)$$

with constraints:

$$P_{min} \leq P(t) \leq P_{max}$$
$$S_{min} \leq S(t) \leq S_{max}$$
$$\int_0^T S(t)dt = S_0$$

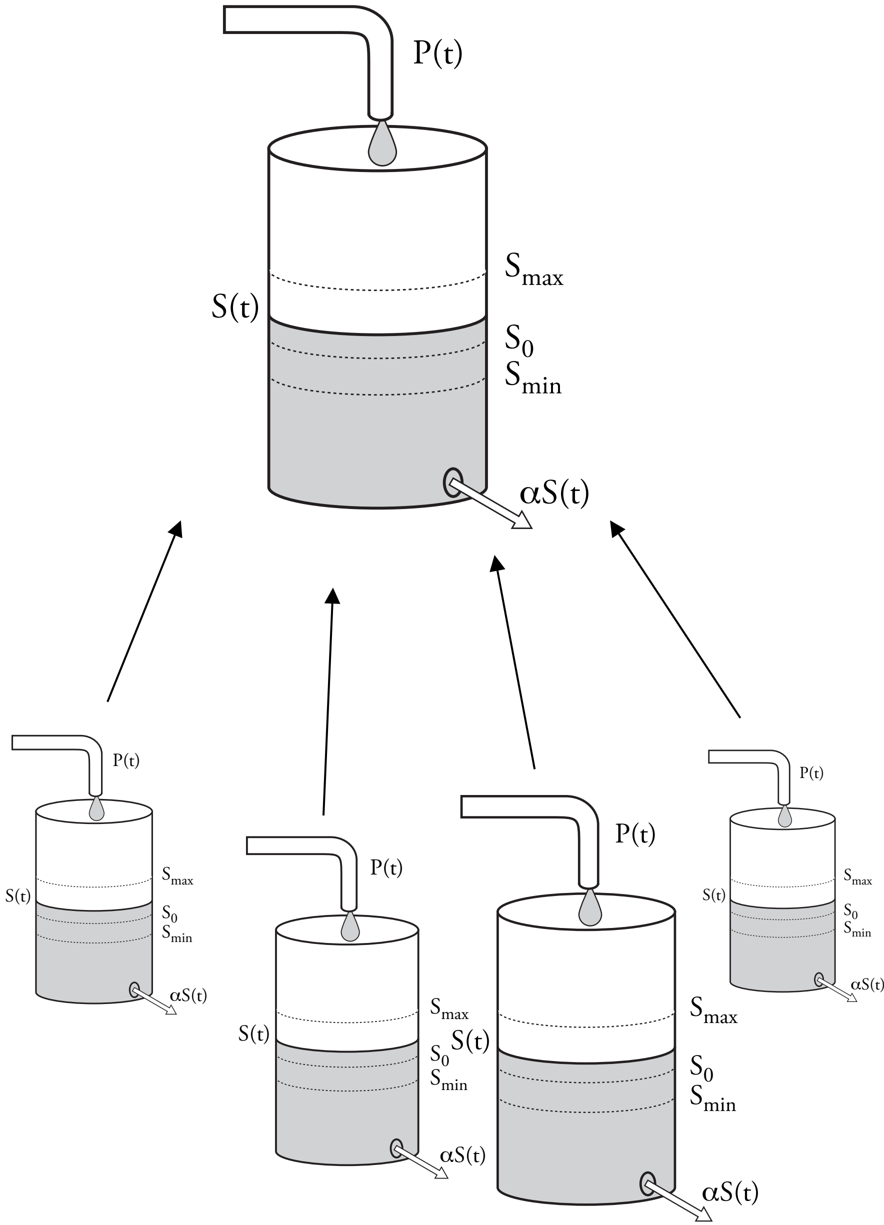
preserve the food!



Vincenzo Trovato, Simon Tindemans, Goran Strbac, *IET Generation, Transmission & Distribution* (2016)

Aggregation of leaky storage units

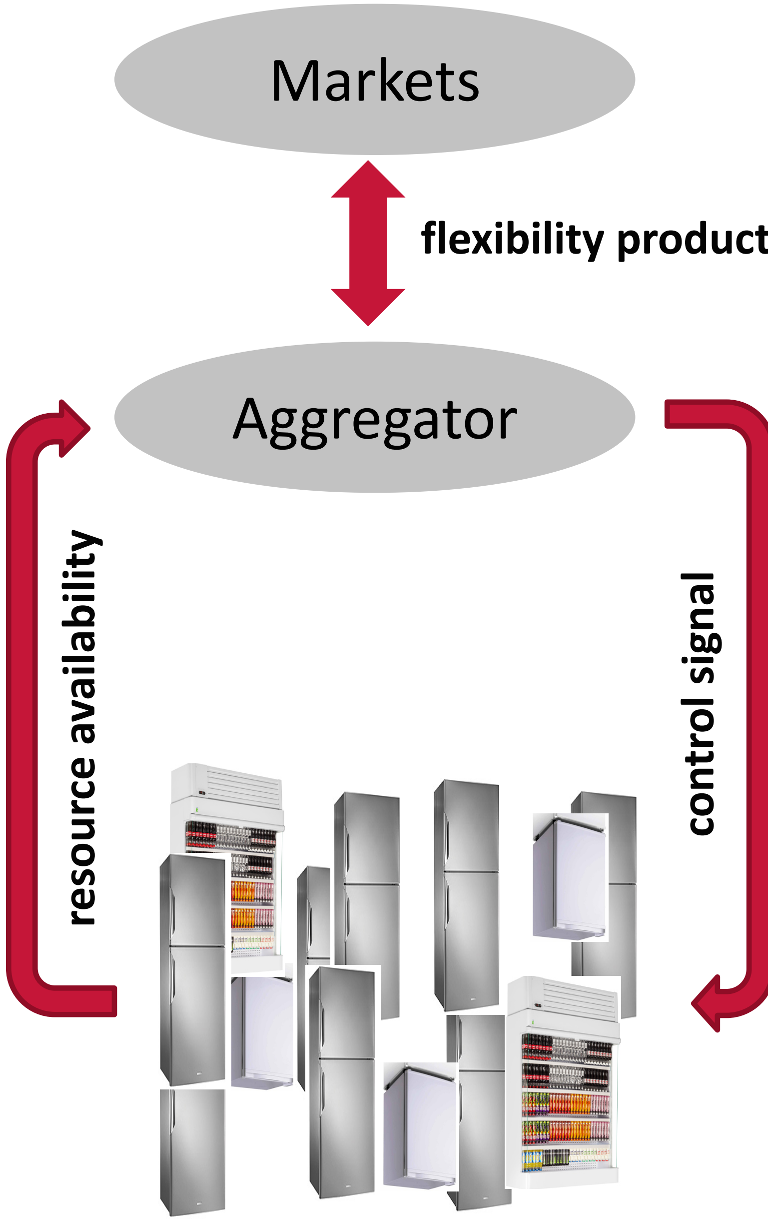
Imperial College London



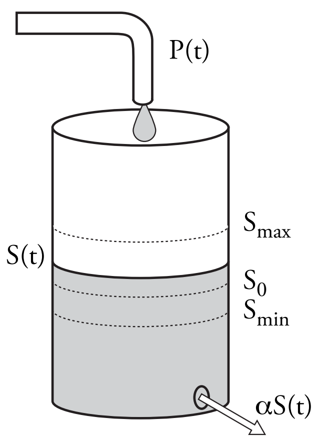
Heterogeneous models are merged into a conservative **envelope flexibility model**.

The model is **sufficient and linear,** for easy embedding in dispatch models.

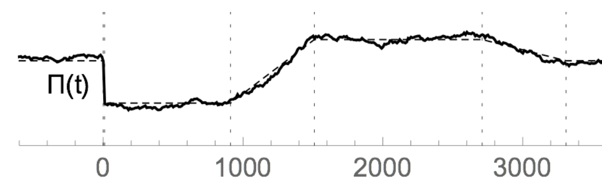
Clustering can be used to match similar appliances.



Model of collective flexibility



Aggregate load dispatch



Communication requirements

Robust ‘semi-autonomous’ operation

aggregator

real-time control signal $\Pi(t)$

or

power response model

ahead of time

Significant changes in:

- thermal model
- constraints

response design cycle

operational cycle

1. Measure temperature
2. Update model
3. Switch on/off

real time

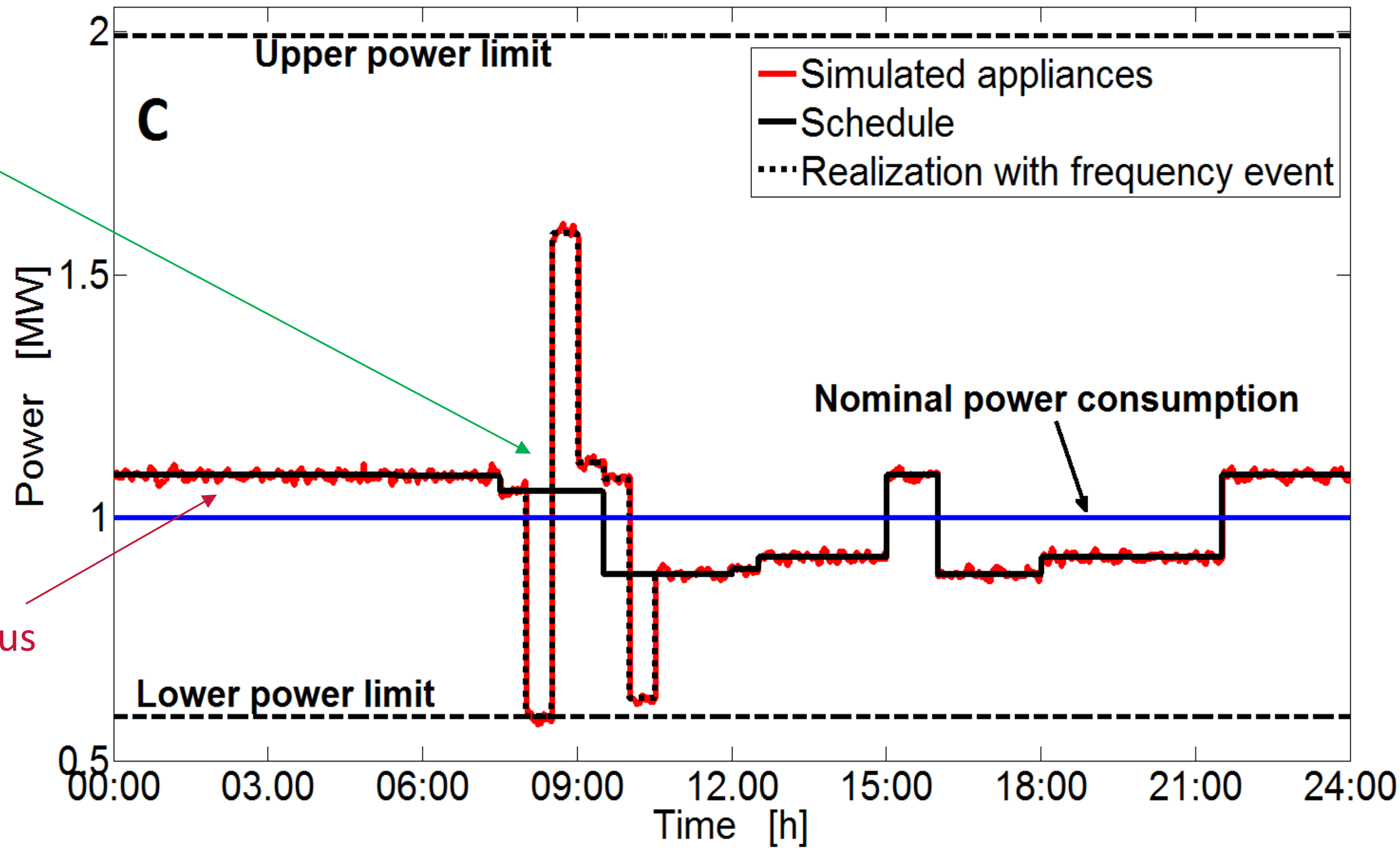
Example: optimal allocation of flexibility

59,524 refrigerators (1MW); 24-hour allocation

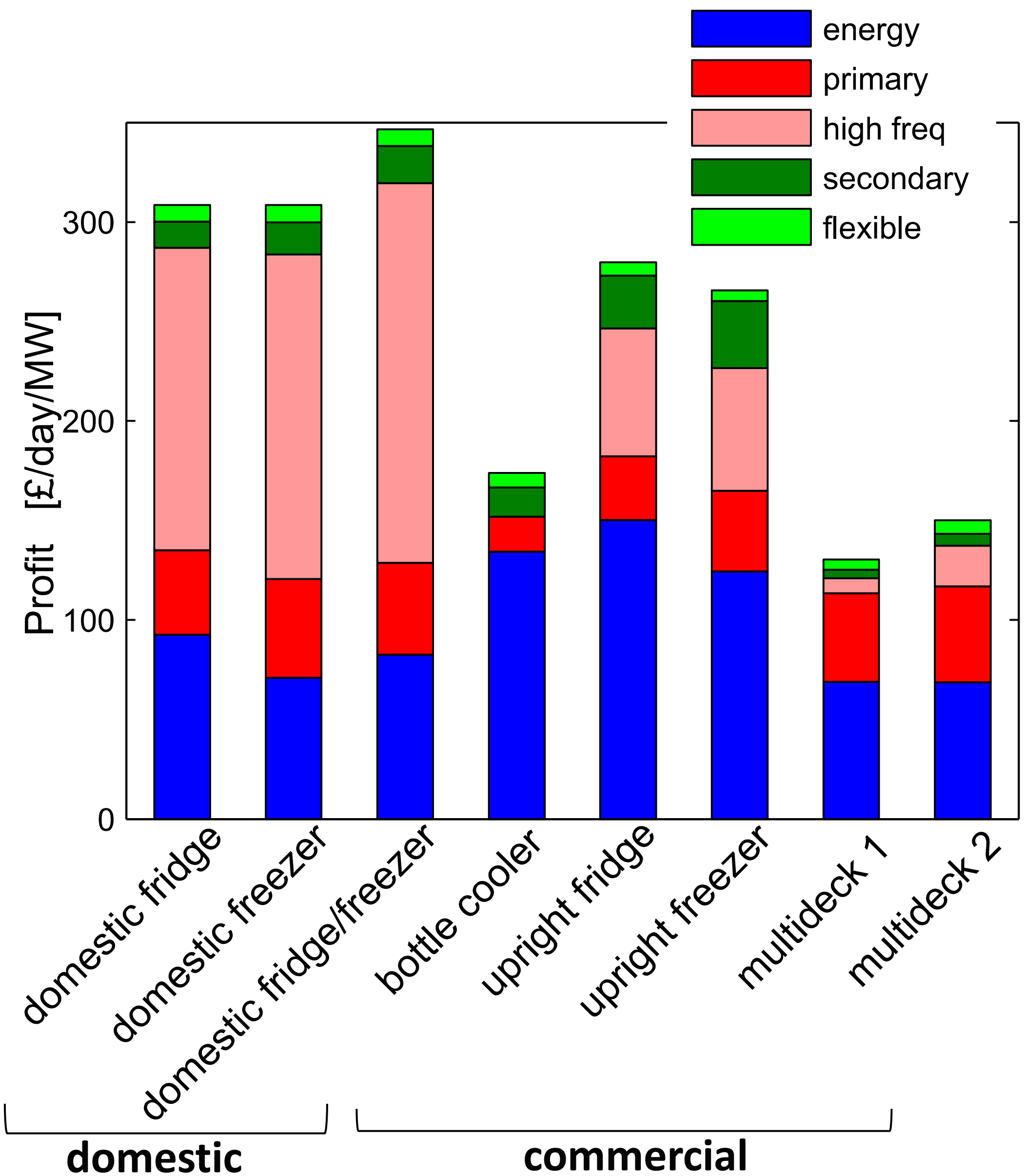
Using refrigerators to provide **energy arbitrage *and* frequency services**, making optimal use of device flexibility

delivery of frequency response

simulation of heterogeneous refrigerators (60,000)



Example: Optimal use of different device classes



Service allocations reflect physical characteristics:

- Slow thermal time constants are good for energy arbitrage
- Low duty cycles in domestic appliances leave headroom for high frequency response.

Summary and outlook: Smart refrigerators

Summary so far

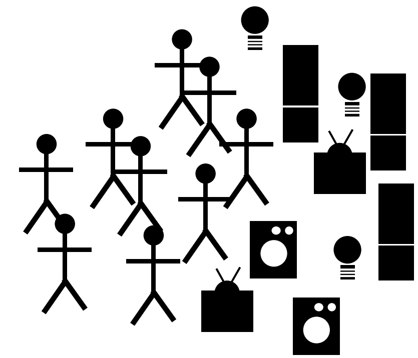
- We have developed a stochastic control scheme that is **nondisruptive, decentralised** and **accurate**.
- **Semi-autonomous control** separates the communication and operation time scales, and is robust to perturbations and heterogeneity.

New developments

- **Implementation** (Lab tests starting soon)
- **Testing and proving robustness** against ‘things going wrong’ (model misspecification, user actions, etc)
- **Optimal control** of ‘leaky storage’ units

FINAL REMARKS

Residential DR: research challenges



- The long tail of demand response is substantial, but there are restrictions on control.
- Modelling and quantification of uncertainty is essential.
- Diversity should be used as an asset, not a hindrance.

Understand response to control signals

- Data-driven modelling to quantify and *predict* response
- Design of experiments for automated model testing and improvement in a business as usual environment

Quantify and mitigate risks

Develop purpose-built decentralised controllers

- *Guarantee* local service quality and *quantify* system service quality
- Ensure fairness of outcomes
- Analyse robustness against disturbances

Design subject to risk and fairness constraints

The (near) future: analysing complexity

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- Peer-to-peer communication (aka 'the energy internet') *will* give rise to unexpected emergent behaviour.

- Do we need to develop 'grid safety certification' for smart energy appliances?
- Lab tests and demonstrators will not be sufficient; we need simulations and basic analysis.

Funders

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Want to know more?

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