Thermal modelling of homes and buildings from minimal sensor deployments

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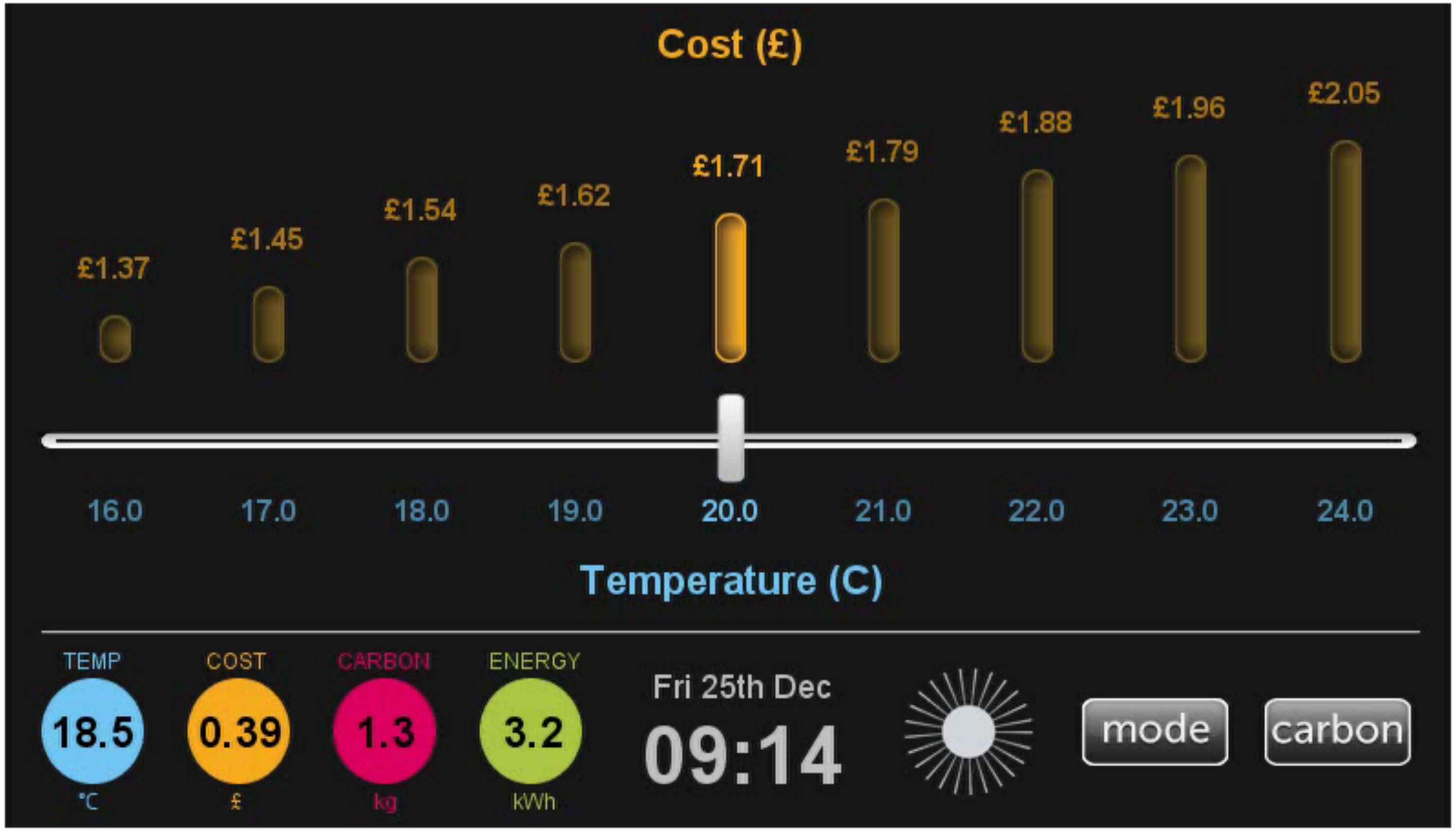
Developing in smart heating controls that understand thermal performance of homes



Developing smart online strategies to store electricity in the form or hot or cold air

The starting point for both applications are accurate thermal models of the building

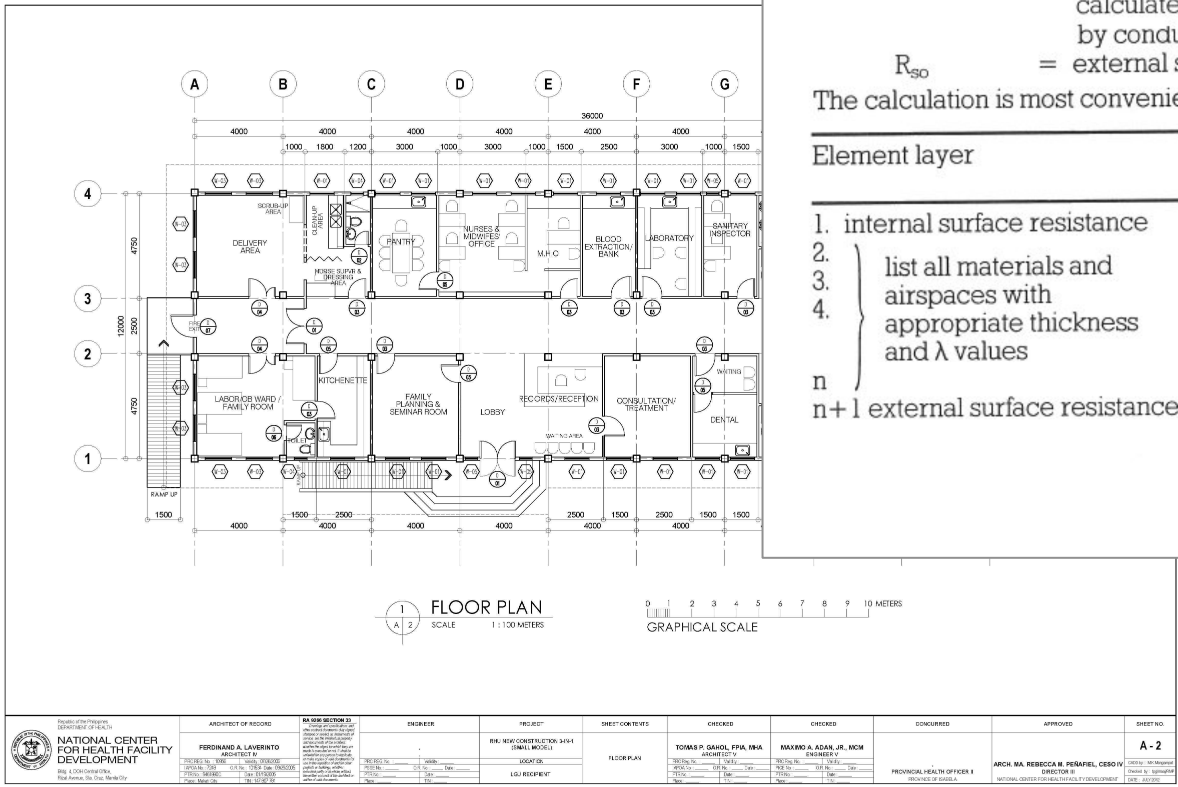


TABLE 3.3 U-value calculation

U-values can be calculated using the following formula:

$$U = \frac{1}{R_{si} + R_{a1} + R_{a2} \ldots R_{an} + R_1 + R_2 \ldots R_n + R_{so}}$$

where R_{si} = internal surface resistance (see Table 3.5)
$R_{a1,\ldots n}$ = any airspace resistance (see Table 3.6)
$R_{1,2\ldots n}$ = resistance of material layer 1, 2 . . . n where resistance is calculated by dividing thickness (L in metres) by conductivity of material (λ) (see Table 3.4)
R_{so} = external surface resistance (see Table 3.5)

The calculation is most conveniently performed in a table form

Element layer	L (m)	λ (W/mK)	R (m^2K/W)
1. internal surface resistance			R_{si}
2. list all materials and		$\frac{L}{\lambda} = R$	R_2
3. airspaces with			R_3
4. appropriate thickness and λ values			R_4
n			R_n
n+1 external surface resistance			R_{s_o}
Sum of all resistances		=	ΣR

$$U = \frac{1}{\Sigma R} = U\ W/m^2K$$

We build an explicit physical model of the thermal properties of a building

- Heat flows from heater and leakage

$$\eta^t = \eta_{on}^t r_h - \phi \left(T_{in}^t - T_{ext}^t \right) + \epsilon^t$$

- Change in internal temperature

$$T_{in}^{t+1} = T_{in}^t + \frac{\eta^t \Delta t}{c_{air} m_{air}}$$

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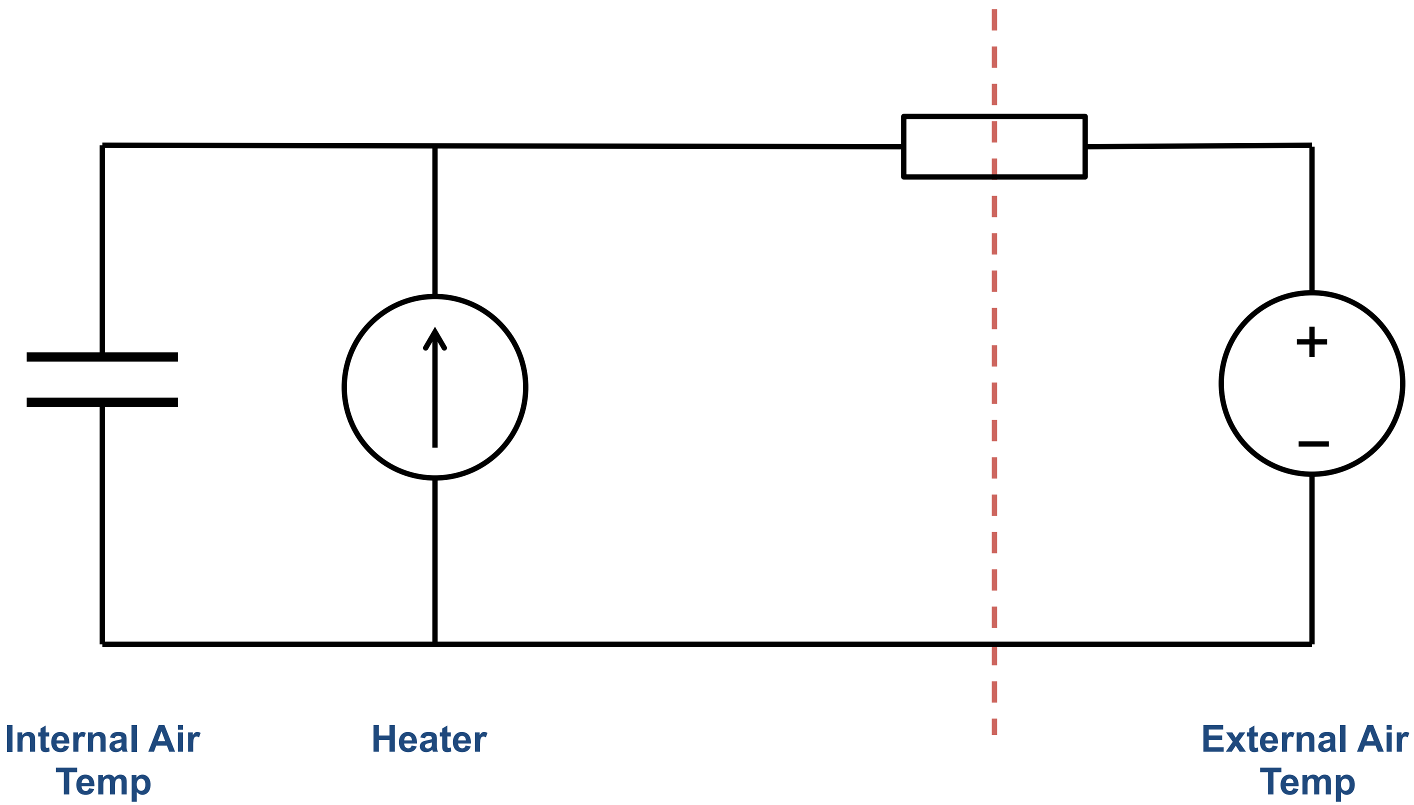

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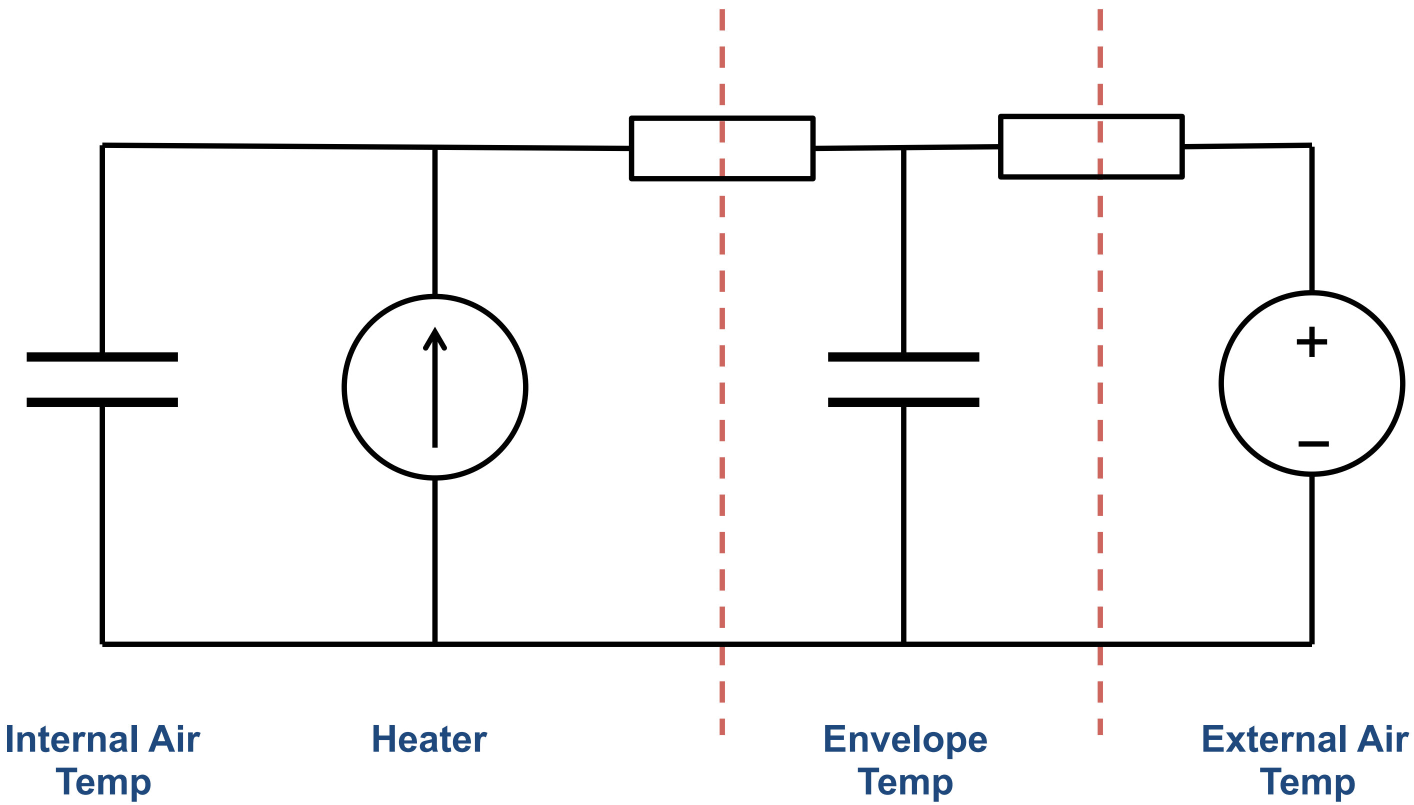

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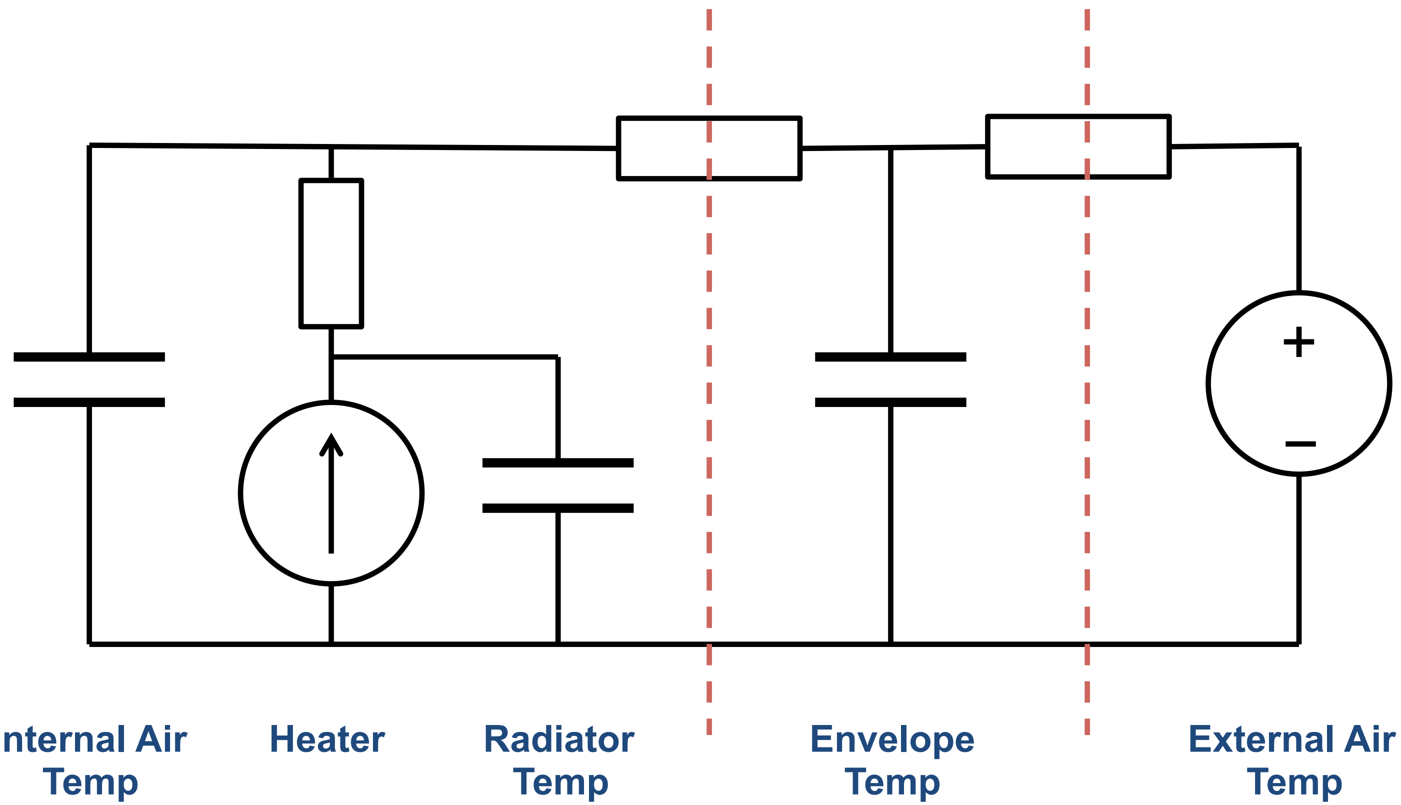

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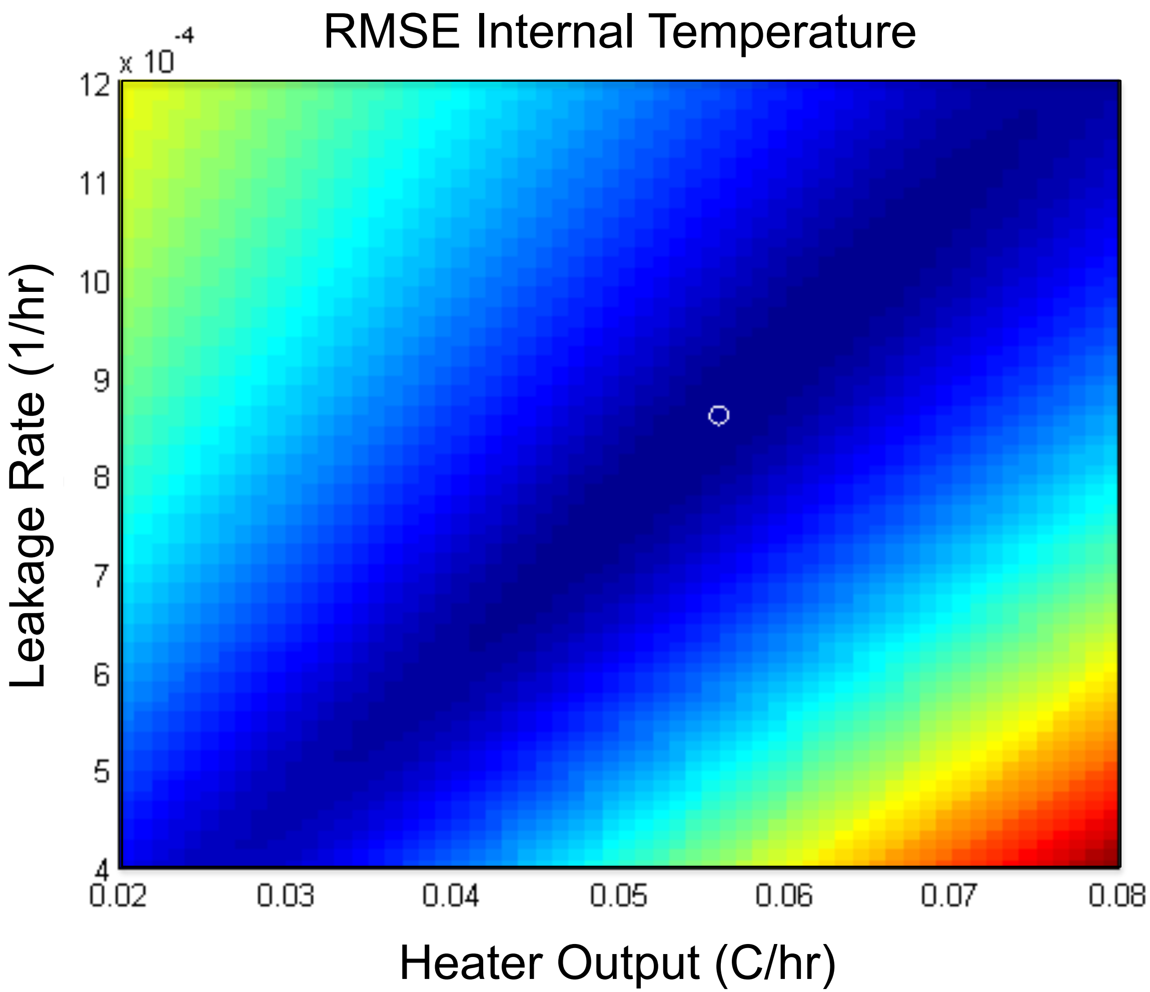
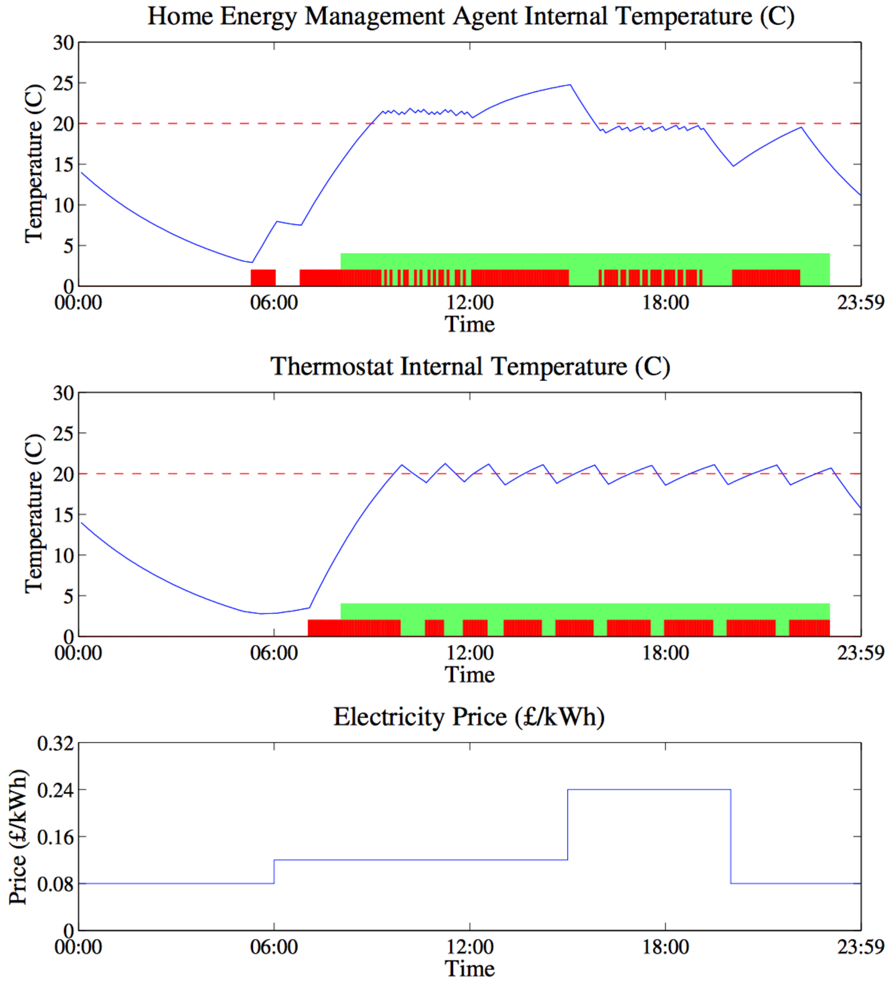
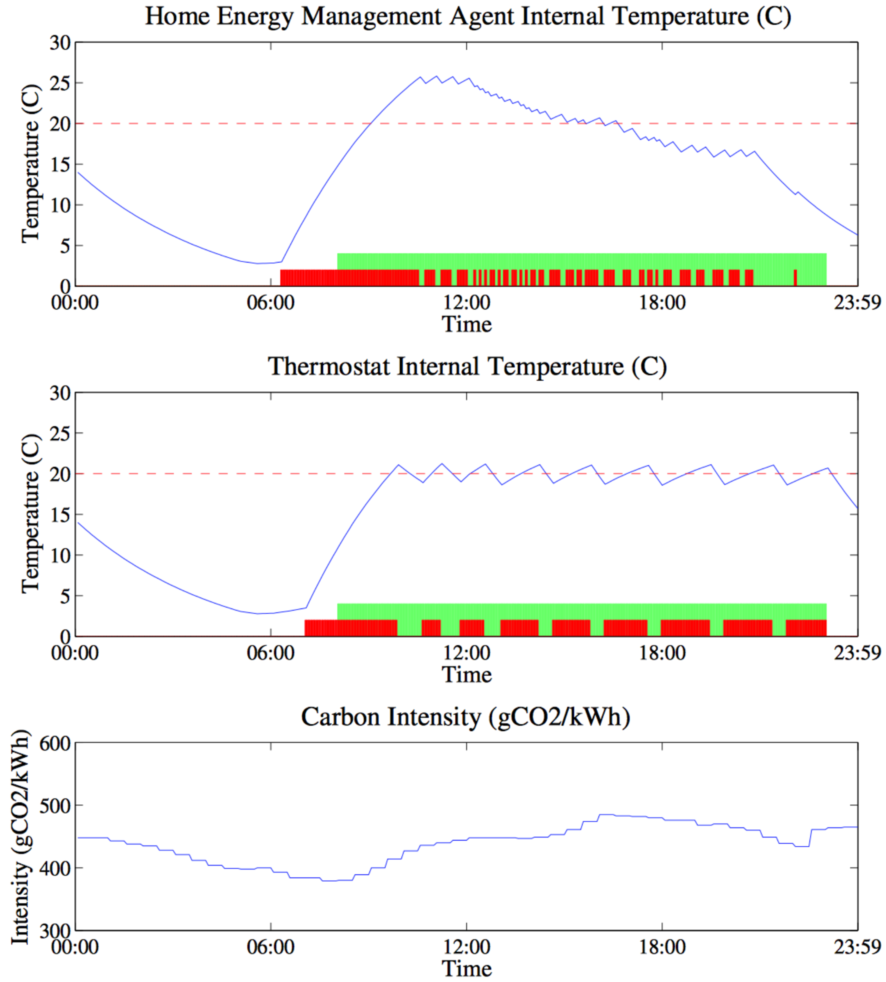
We can use a range of algorithms to fit model parameters to real world observations



With a predictive model we can control the heating system to mininise cost or carbon



Cost

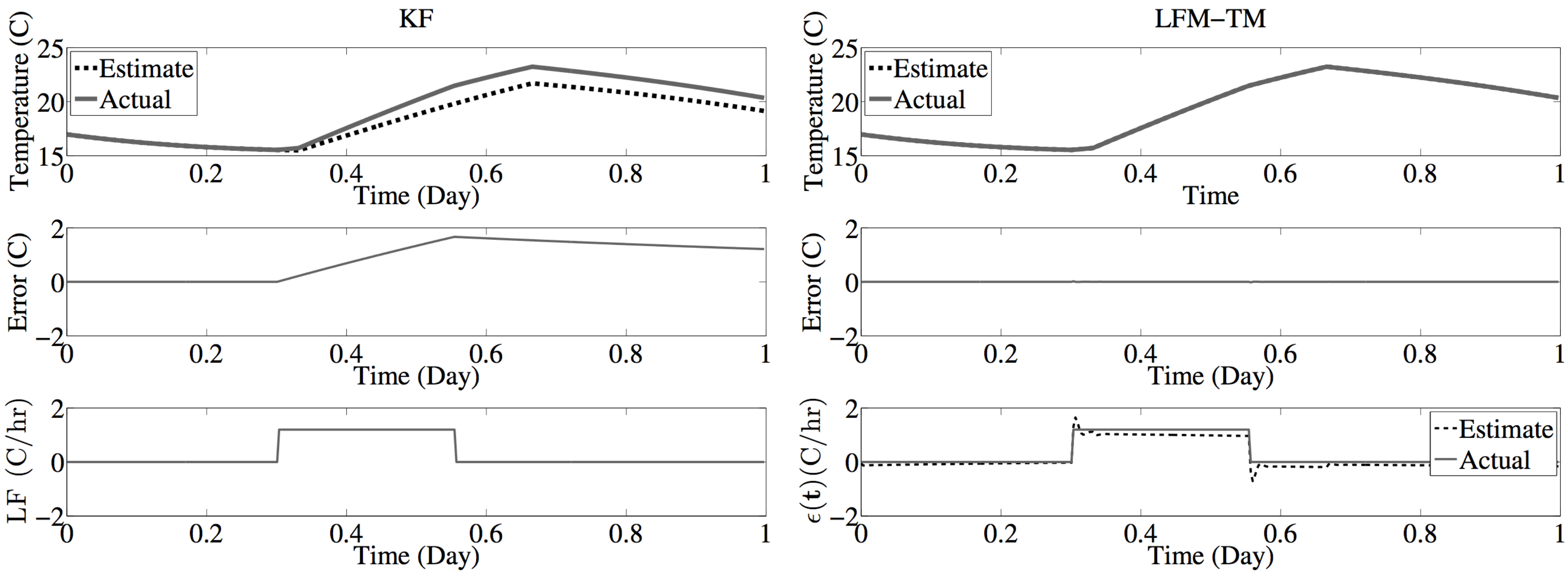


Carbon

We can use a range of algorithms to fit model parameters to real world observations

- Kalman filter
  - Explicit model of uncertainty and process noise
- Latent force Gaussian process model
  - Combine differential equations into GP framework
  - Model latent driving force
    - Failures of our physical model
    - Additional heat from householder activity
  - We can build in 24 hour periodicity

Latent force models minimise effect of additional driving forcing on parameters



Latent force models minimise effect of additional driving forcing on parameters

Reece, S., Roberts, S., Ghosh, S., Rogers, A. and Jennings, N. R. (2014) **Efficient state-space inference of periodic latent force models**. Journal of Machine Learning Research, 1-66. (In Press).

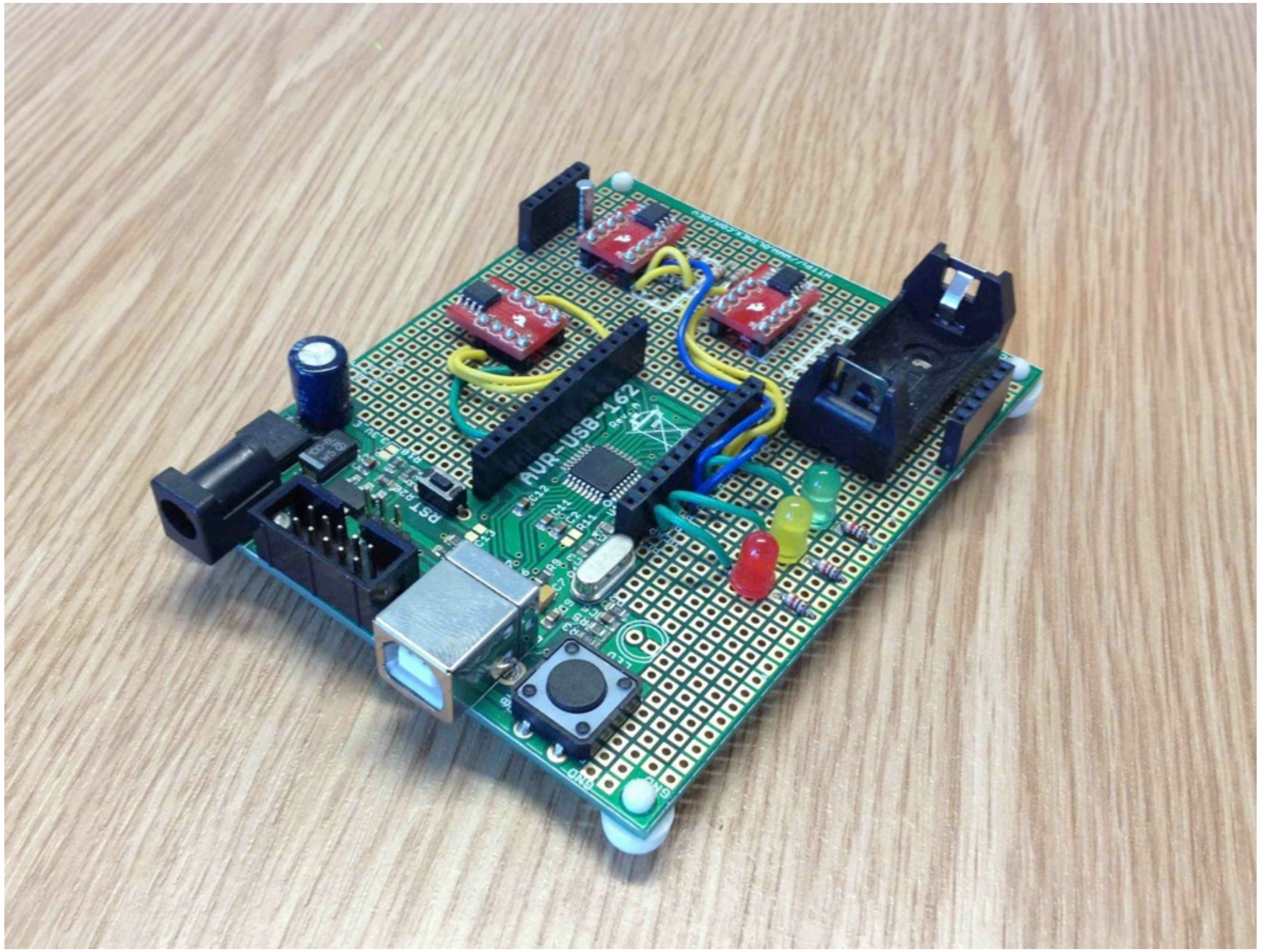
Ghosh, S., Reece, S., Rogers, A., Roberts, S., Malibari, A. and Jennings, N. R. (2014) **Modelling the thermal dynamics of buildings: A latent force model based approach**. ACM Transactions on Intelligent Systems and Technology, A:1-A:28. (In Press).

We evaluated these approaches on typical 1930s homes owned by the University

We explored the use of low-cost temperature loggers to collect data at scale

- Sense the control point of the home
  - Can provide useful energy feedback
- Commercial USB loggers difficult to use
  - Require software to download data
  - Poor user interface

Developed a customer low-cost temperature logger which was easier to configure and use



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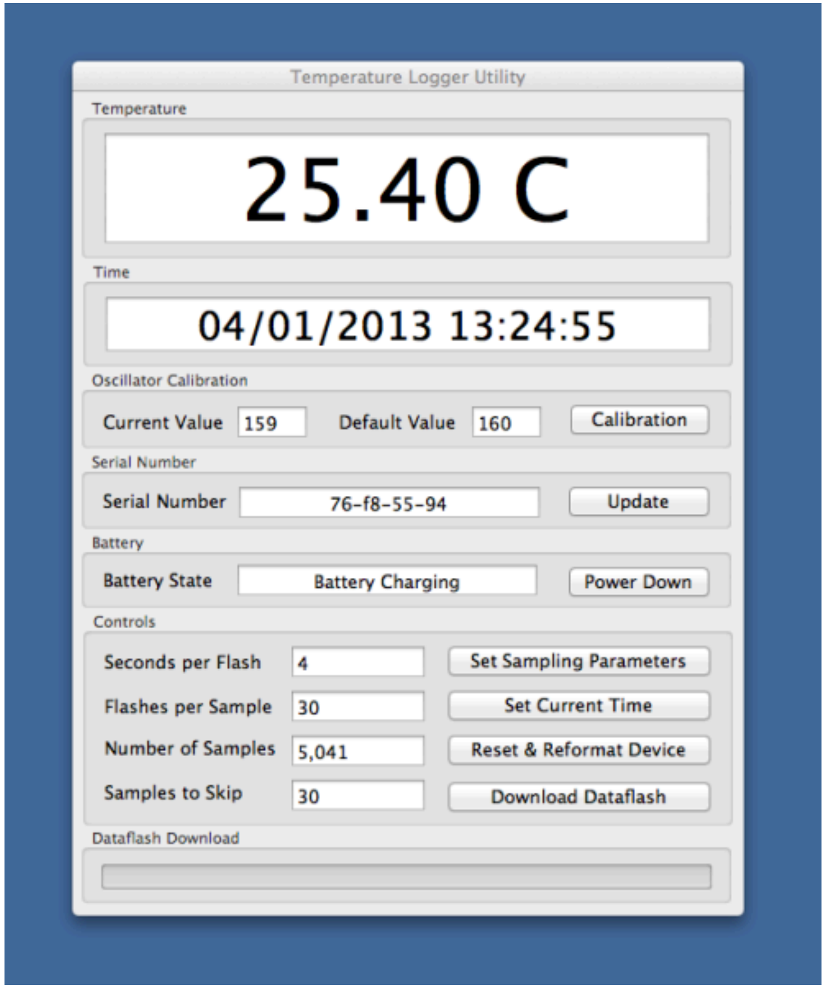

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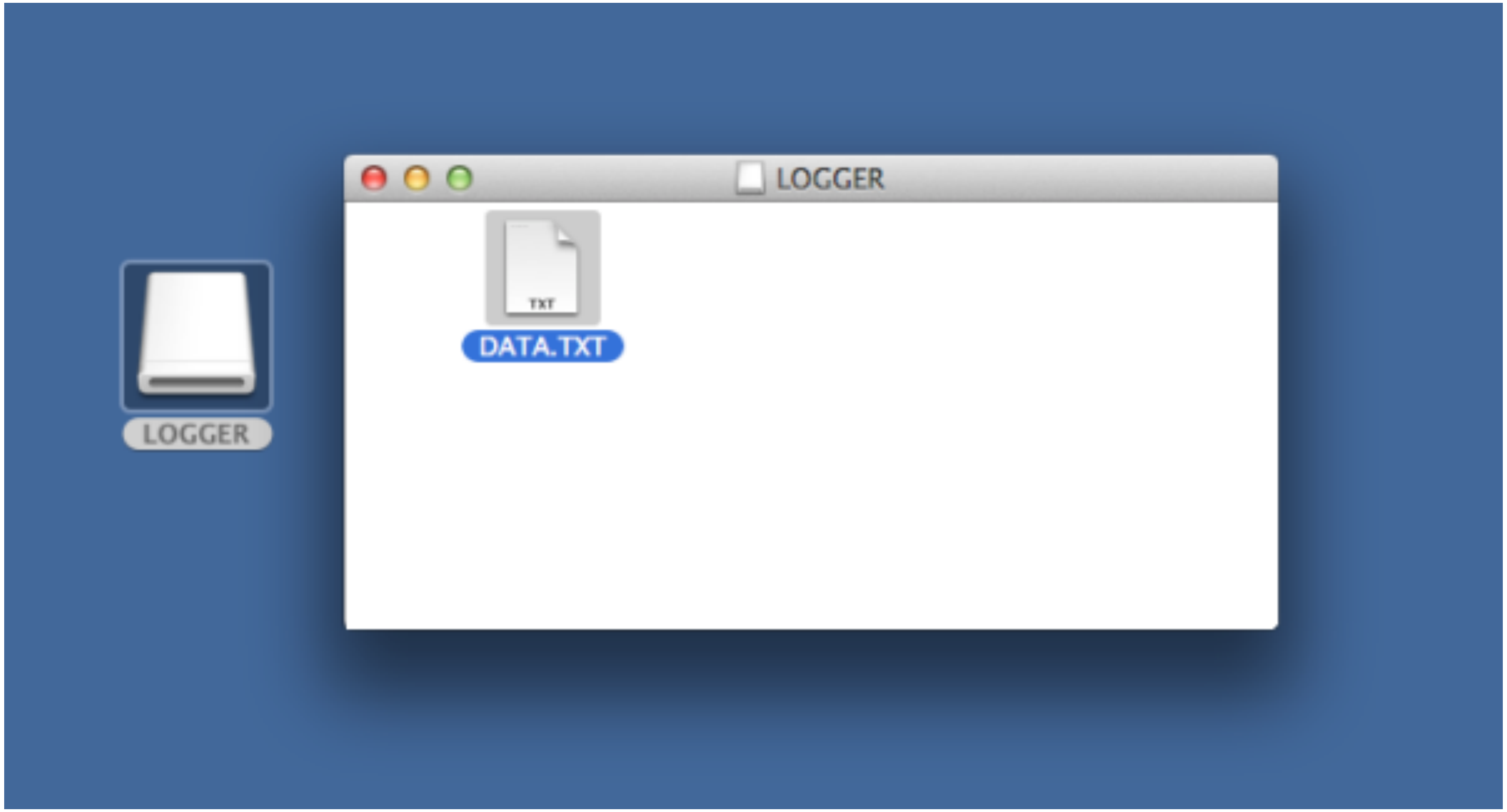

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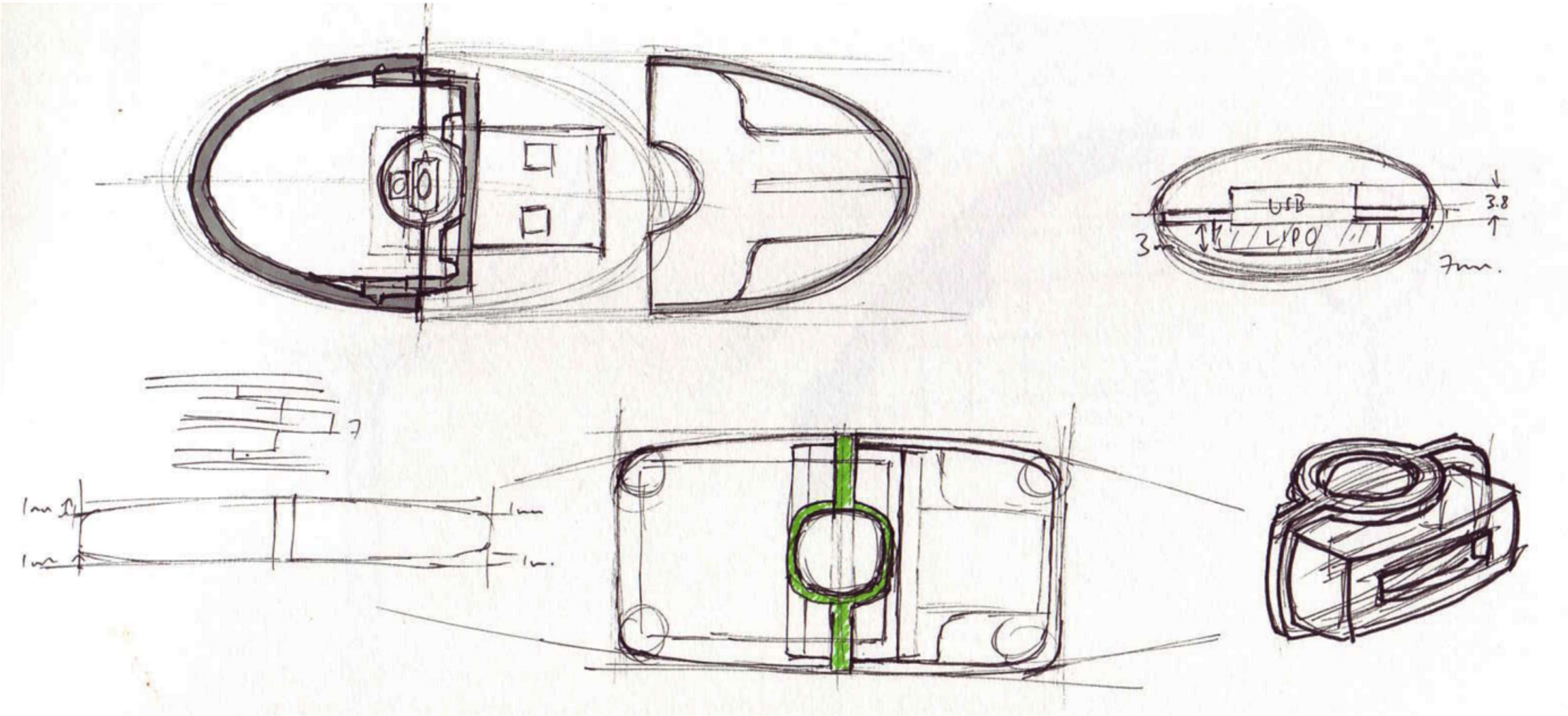

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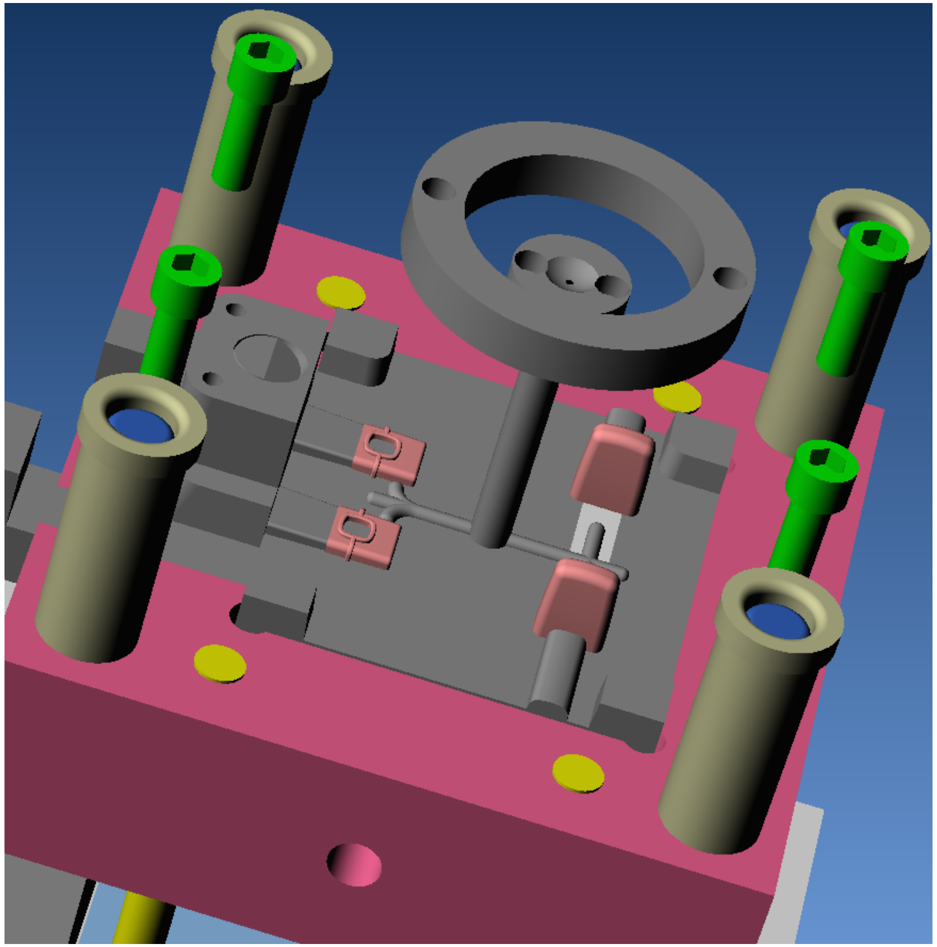

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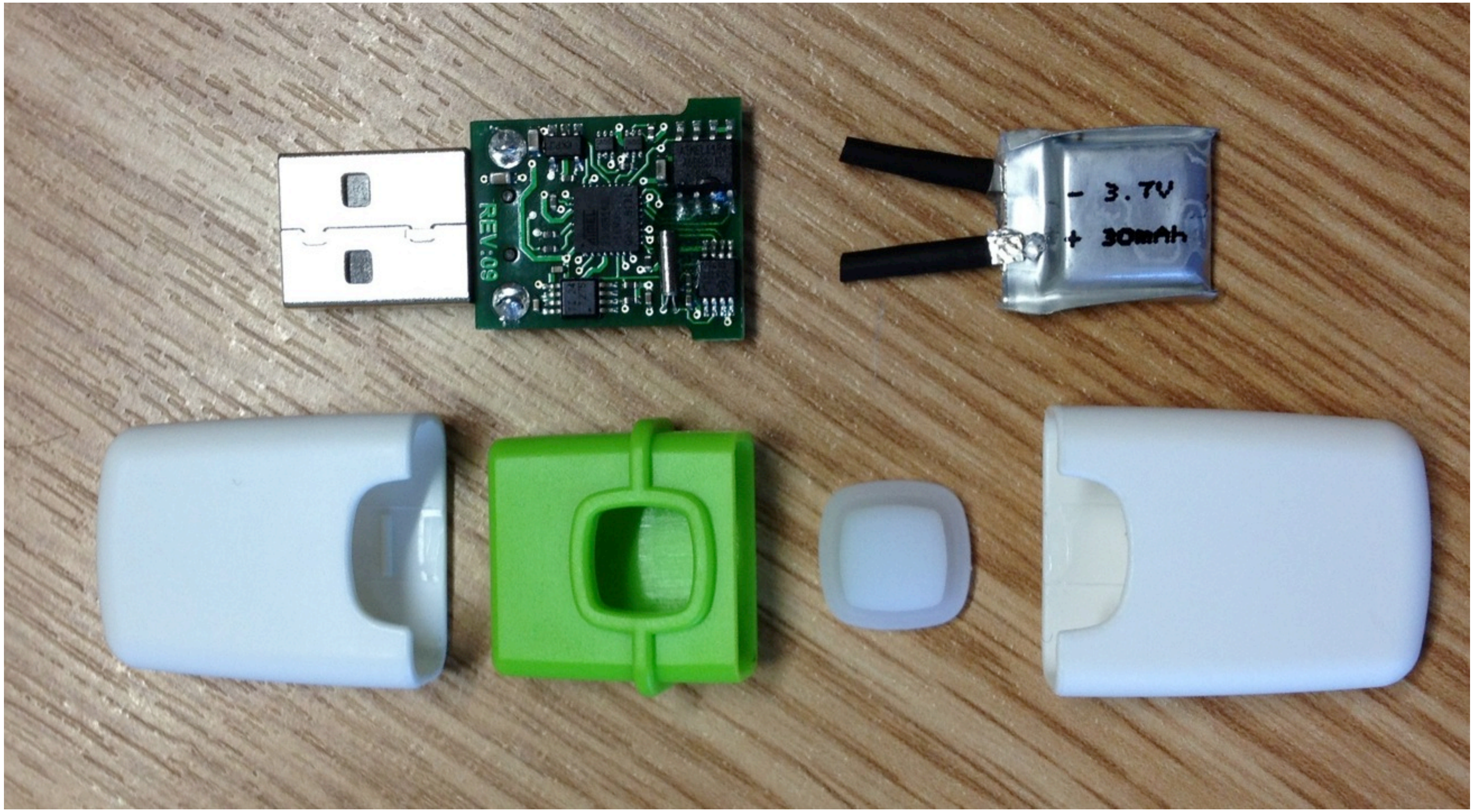
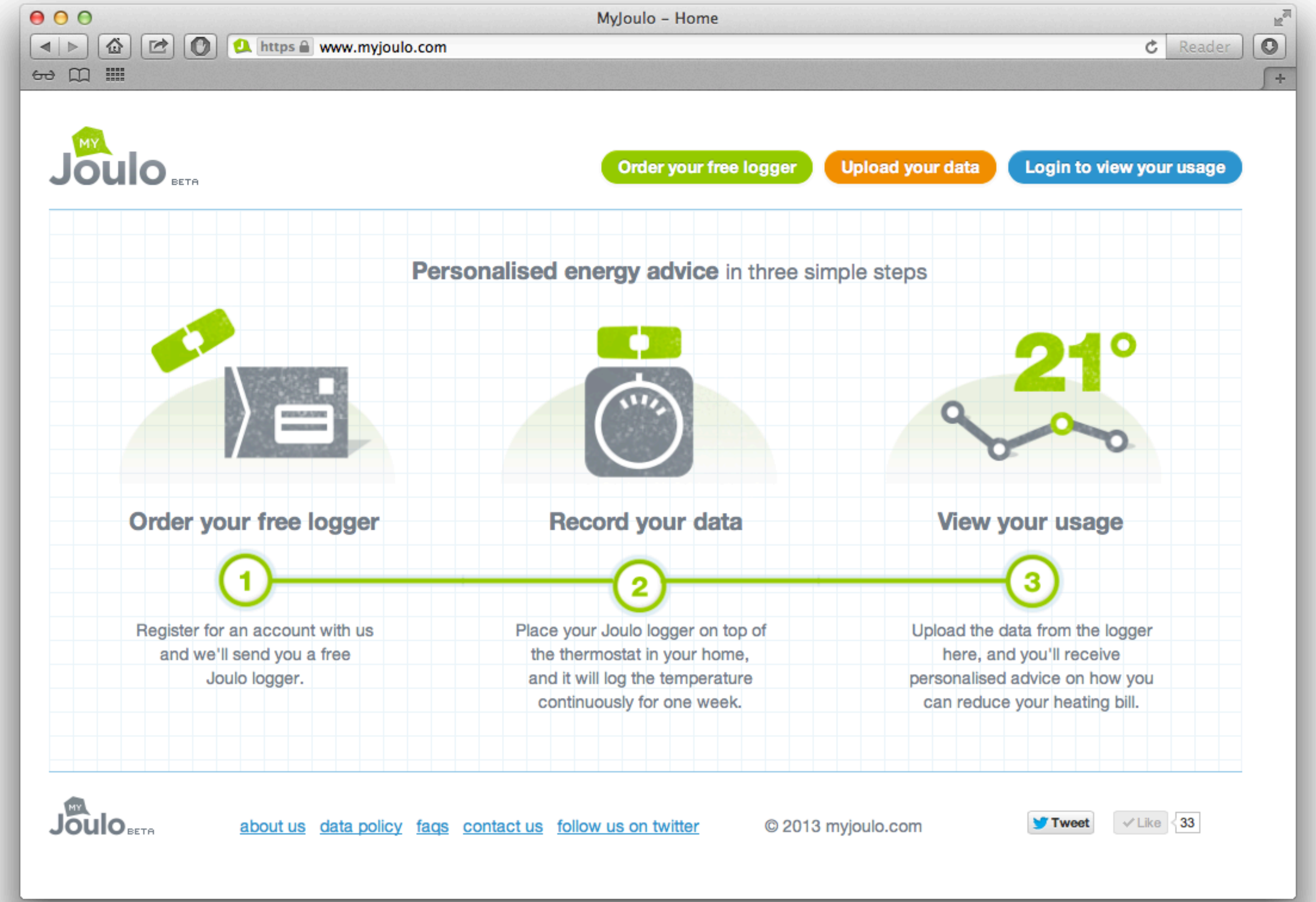


Deployed Joulo as a trial service to over 750 homes during January to March 2013



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Provide feedback on temperatures.

Detect thermostat setpoint

Compare to average
Calculate energy saving on reduction to the average

Used simple parameter search approach to build thermal model of the home

- Leakage is proportional to the difference in temperature (collected from the internet)

$$\hat{T}_{int}^{i+1} = \hat{T}_{int}^{i} + \left[r_p \times r_h^i - \phi \left(\hat{T}_{in}^{i} - T_{ext}^{i} \right) \right] \Delta t + \epsilon^i$$

- We parameterize the operation of the heating system

$$\boldsymbol{\theta} = [r_p, \phi, T_{set}, s_1, e_1, s_2, e_2, m]$$

- Search parameter space for the best fit

$$\boldsymbol{\theta}^* = \arg\min_{\boldsymbol{\theta}} \sum_{i=1}^{n} \left(\hat{T}_{int}^{i} - T_{log}^{i} \right)^2$$

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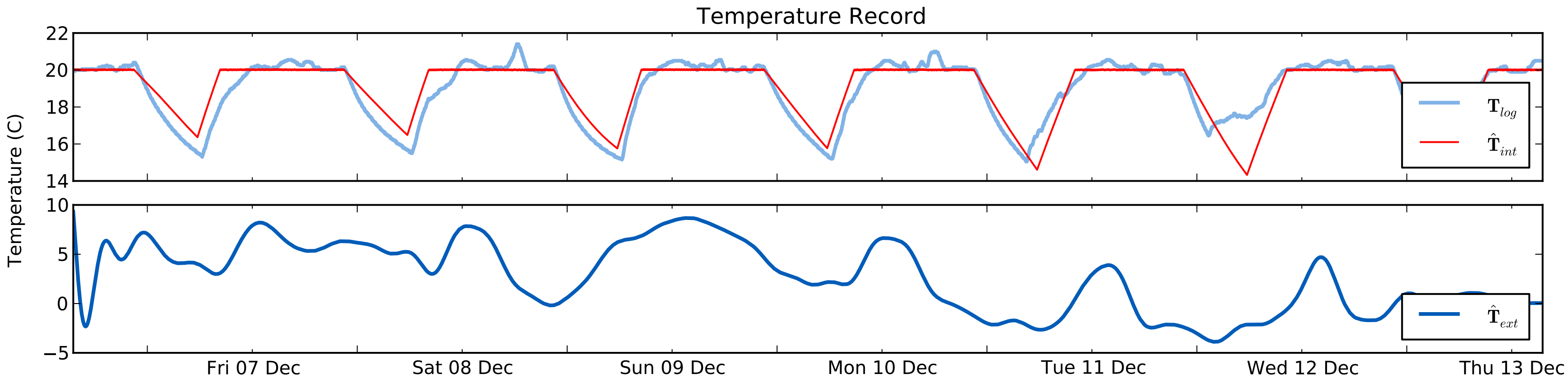
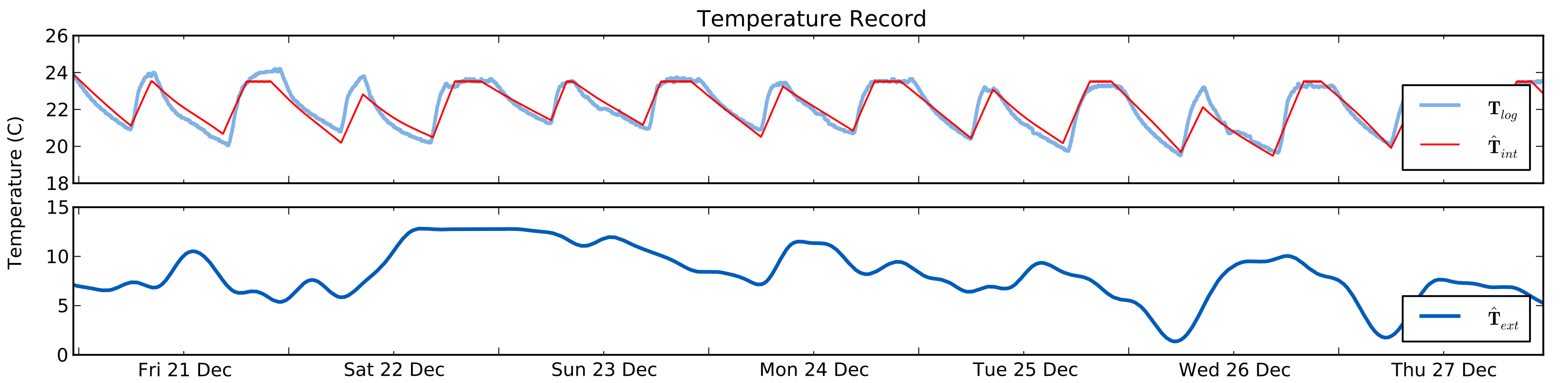
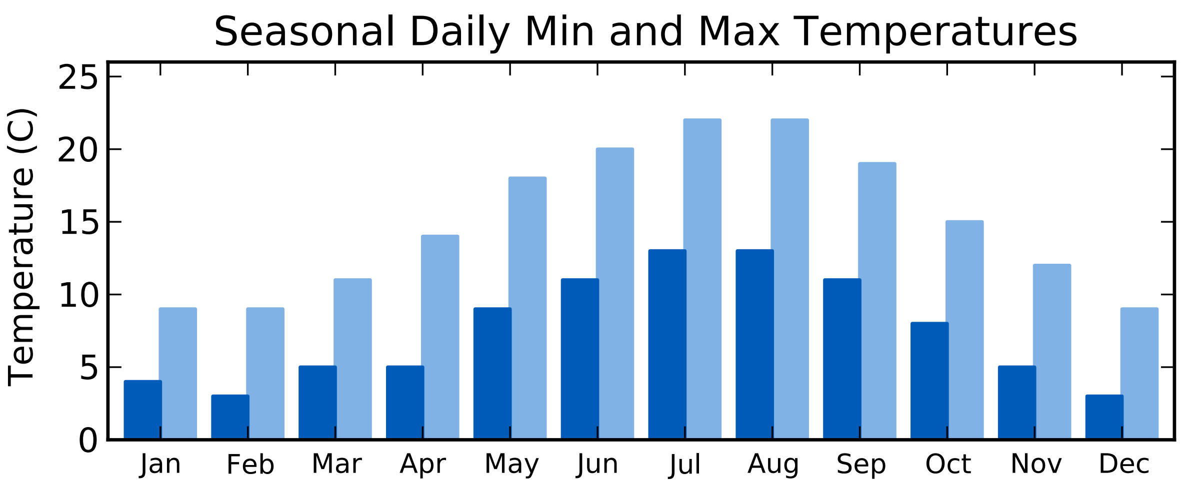




Calculated and provided feedback on energy savings achieved on changing setpoint

- Use seasonable average max and min data to generate synthetic external temperatures



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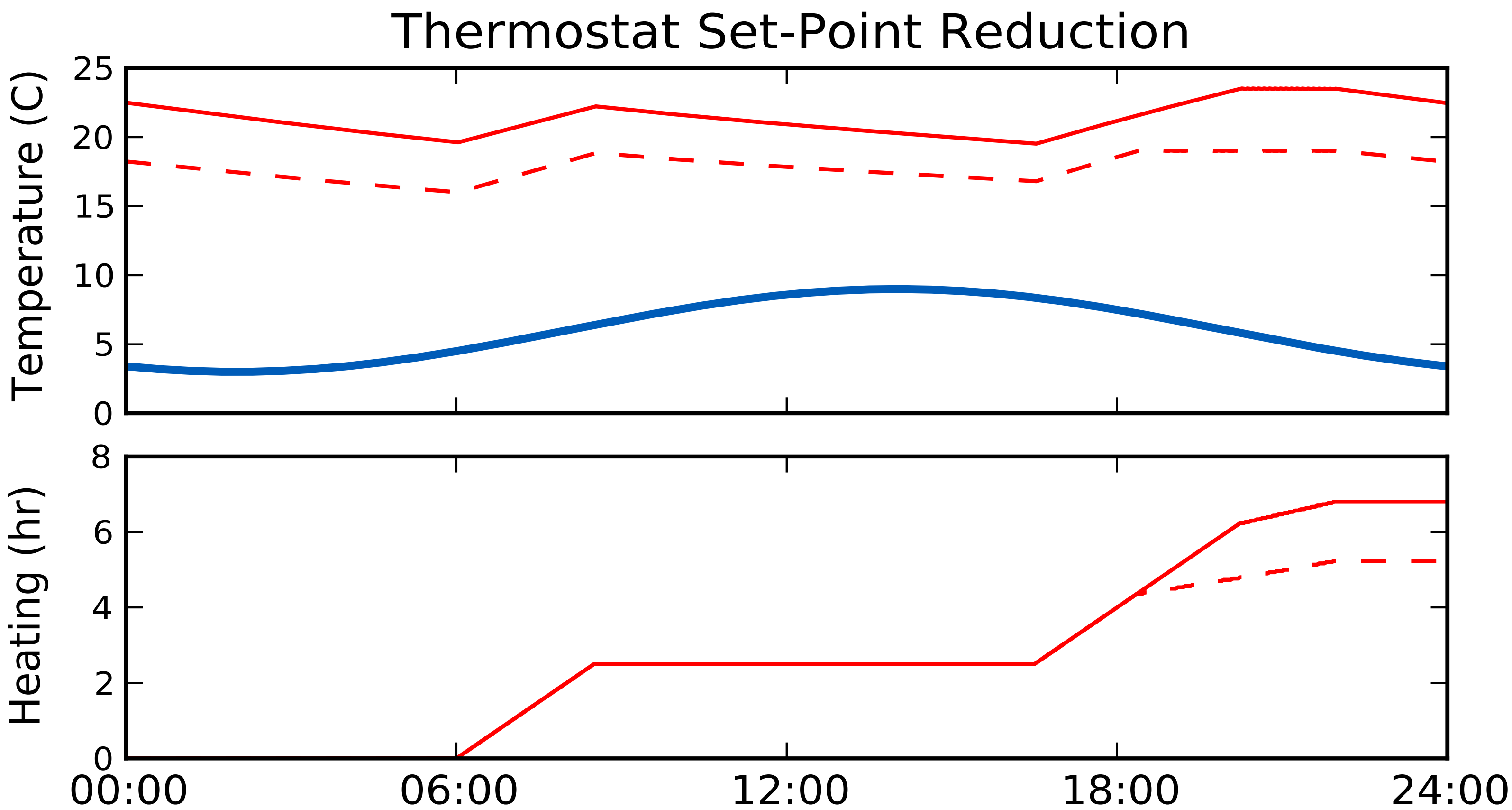
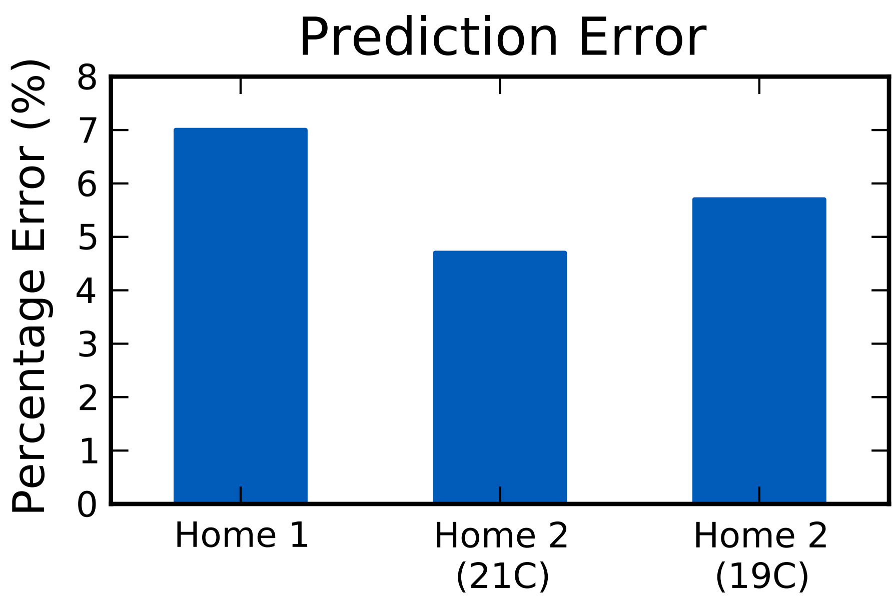
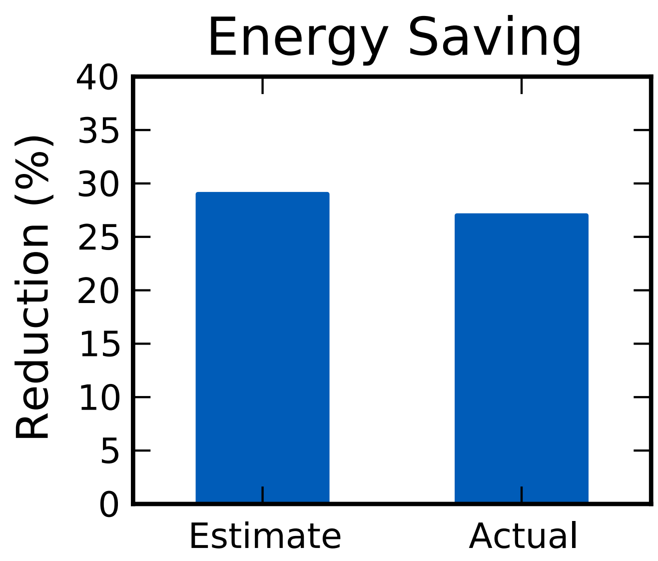


Compared our approach to real data on two benchmark homes

- Real comparison of saving is complicated by seasonal temperature changes and long term nature of the trial





Joulo was used to collect baseline data for DECC Smart Heating Controls survey

In September 2013 we won British Gas Connected Homes Start-up Competition

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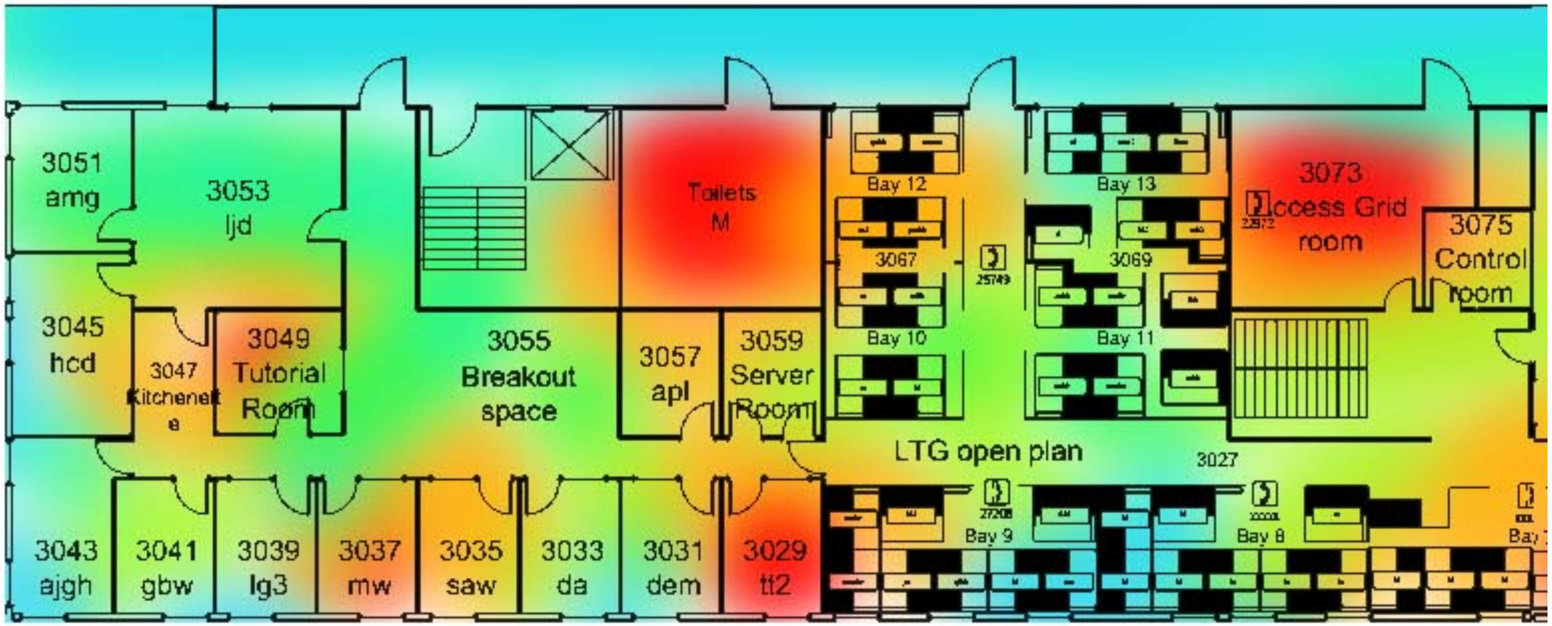
Demo

Joulo Ltd was spun out of the University and acquired by Quby in January 2015

Deploying multiple (200+) loggers in single buildings to understand overheating issues



We are working with KiwiPower to deploy modelling approaches for demand response

KiWiPOWER
demand management

Conclusions

- Machine learning and inference can fill in some of the gaps in what we cannot sense directly
- Deploying sensors at scale requires us to minimise installation complexity
  – Mail-out self-installation kits can be a great way to generate a large user base at low cost
- Low cost manufacturing and prototyping techniques make this possible within research projects