Demo Abstract: A Scalable Low-Cost Solution to Provide Personalized Home Heating Advice to Households

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Abstract

In this demonstration, we present a scalable low-cost solution to provide personalized home heating advice to households. Our solution uses a specially designed USB temperature logger, placed on top of the thermostat, to infer the operation of the heating system indirectly. Using additional external temperature data, available through the internet, it builds a simple thermal model of the home, which is then used to calculate the impact, in terms of percentage reduction in heating costs, of various interventions (such as reducing the thermostat set-point temperature); providing specific actionable advice to the household.

1 Introduction

Recent years have seen significant research into providing households with realtime feedback on their energy consumption in an effort to reduce the carbon emissions from the domestic sector. Much of this work has focused on low cost solutions that use a small number of easily deployed sensors to provide actionable advice, and to date, has typically focused on domestic electricity consumption. For example, non-intrusive load monitoring attempts to disaggregate total electricity consumption into individual appliances using a single clamp-on sensor on the main feed to the home [3].

However, electrical appliances are not the only consumers of energy within the home, and other forms of consumption can be equally or more significant. In particular, home heating typically accounts for 60-70% of domestic energy consumption in northern latitudes, and yet, has received less attention in the research literature. The reasons for this are numerous. Heating in many countries uses gas-fired boilers, and non-invasive metering of gas consumption is not straightforward. Furthermore, there is little quantitative data on how households use their heating systems, and thus, developing actionable advice in this context is problematic [2].

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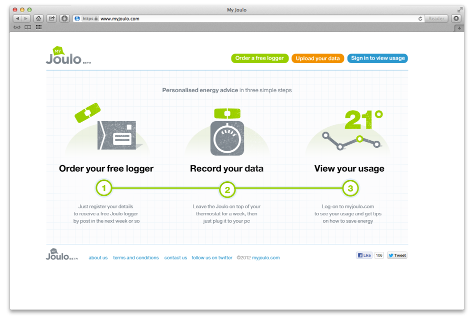

Figure 1. myJoulo website.

Figure 2. USB temperature logger.

To address both these issues, in this demonstration we present a solution that provides personalized home heating advice to households, which can simultaneously be used to collect data on typical heating use across a large number of homes. Rather than attempting to directly measure gas or electricity consumption, we use a specially designed low-cost USB temperature logger, placed on top of the thermostat (the single point of control of most heating systems), to infer the operation of the heating system indirectly. Our solution uses additional external temperature data, available through the internet, to build a simple thermal model of the home, which is then used to calculate the impact (in terms of percentage reduction in heating costs) of various interventions (such as reducing the thermostat set-point temperature); providing specific actionable advice to the household.

2 Solution Components

Our solution consists of three key components: (i) a low-cost USB temperature logger, (ii) a website through which households can sign up to the service, request a temperature logger, and see the results of the analysis, and (iii) algorithms that model and calculate the impact of interventions.

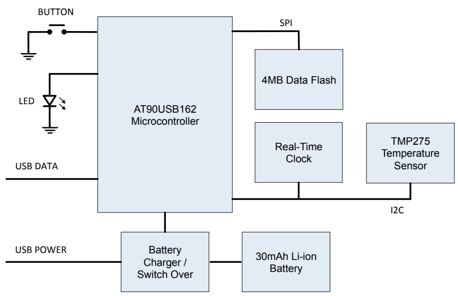

Figure 3. USB temperature logger schematic.

2.1 USB Temperature Logger

Commercially available temperature loggers failed to provide the necessary accuracy and ease of use (typically requiring installed software or additional hardware to access the logger data), and thus, a specially designed temperature logger, based around an Atmel AT90USB162 microcontroller with a TI TMP275 temperature sensor, is used (see Figures 2 and 3). This provides +/- 0.2°C measurement accuracy without requiring additional calibration. The logger is triggered by the single button, and then records temperature at 2 minute intervals for 7 days. The logger firmware supports both USB HID and Mass Storage protocols, such that it can be configured prior to dispatch (setting sampling rates and serial number), and then appear as a conventional flash drive (with the recorded data in a 'DATA.TXT' file), when the householder uploads the recorded data to the website.

2.2 Website

The website (see `www.myjoulo.com` and Figure 1) allows households to request a temperature logger be mailed to them, upload data recorded by the logger, and examine the resulting analysis. Since the temperature logger is returned after use, the marginal cost of providing the service is very low, and the service can operate at scale at low cost.

2.3 Analysis Algorithms

Initial analysis of the temperature data consists of calculating simple metrics such as min, max, and average temperature, and identifying the set-point of the thermostat. For example, Figure 4 shows three homes, all using a thermostat set-point of 22°C, but exhibiting very different dynamics. Feedback is provided to the household by comparing heating periods and thermostat set-points to population averages.

To provide more complex feedback on the impact of making specific interventions (such as reducing the thermostat set-point, or changing heating timing), we build a simple thermal model of the home, using additional external temperature data, for the specific location of the home, from `www.wunderground.com`. We use a standard model, in which internal heat leaks at a rate that is proportional to the difference between internal and external temperatures [1]. This model can be conveniently expressed as a discrete stochastic differential equation given by:

$$T_{in}^{t+1} = T_{in}^{t} + \left[r_h^t - \phi\left(T_{in}^t - T_{ext}^t\right)\right]\Delta t + \varepsilon^t \qquad (1)$$

where T_{in}^t and T_{ext}^t are internal and external temperatures (°C) at time step t, Δt is the time interval (1/30 hr in this case), r_h^t is the heat provided by the heating system (°C/hr), ϕ is the leakage rate of the home (1/hr), and ε^t is Gaussian noise capturing unmodeled effects. We embed this differential equation within a state space model and solve it sequentially using a Kalman filter, infering the unknown parameters r_h^t and ϕ using maximum likelihood. Hence, we can calculate the percentage change in heating costs the household would have experienced over the logged week, had they operated their heating system differently (e.g. using a lower set-point).

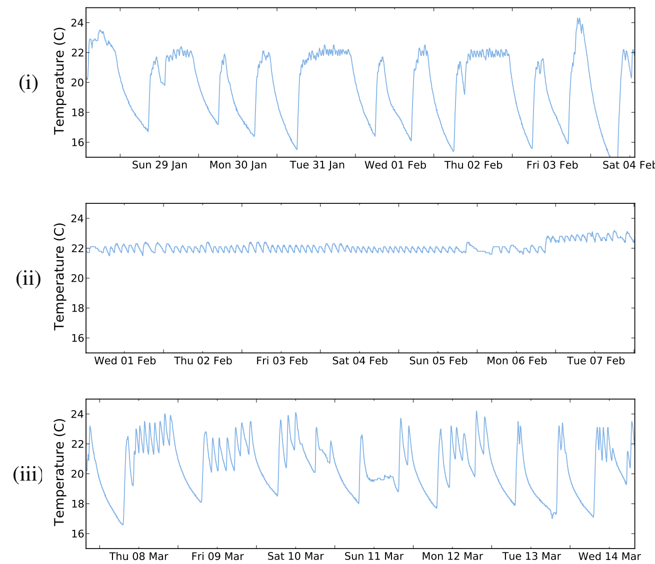

Figure 4. Logger data for three homes, all with set-points of 22°C, with (i) timed heating periods using an electronic proportional control thermostat, (ii) constant heating using an electronic proportional control thermostat, and (iii) timed heating using a mechanical thermostat.

3 Conclusions

In this demonstration, we presented a scalable low-cost solution to provide personalized home heating advice to households. Our system was launched in beta form in the UK in November 2012 with the intention to provide advice to over 1000 households during the winter heating period.

4 Acknowledgments

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5 References

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