Remote energy auditing: Energy efficiency through smart thermostat data and control

Guy R. Newsham
National Research Council Canada (NRC) – Construction Portfolio
1200 Montreal Road, Building M24
Ottawa, ON, K1A 0R6
Canada
guy.newsham@nrc-cnrc.gc.ca

Ajit Pardasani
National Research Council Canada (NRC) – Construction Portfolio
1200 Montreal Road, Building M24
Ottawa, ON, K1A 0R6
Canada
ajit.pardasani@nrc-cnrc.gc.ca

Yuri Grinberg
National Research Council Canada (NRC) – ICT Portfolio
1200 Montreal Road, Building M50
Ottawa, ON, K1A 0R6
Canada
yuri.grinberg@nrc-cnrc.gc.ca

Koby Bar
Energy Management Advisor
Israel
kobybar29@gmail.com

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Abstract

We describe the development of "remote energy audit" techniques using data from a pilot study in 500 dwellings in Ontario, Canada. This pilot study provided a unique combination of data sets: smart thermostat, occupancy events, and smart meter data, combined with basic information on household characteristics and weather data. With knowledge of building physics and occupant energy use behaviours, we deployed a variety of data analytic techniques to derive insights into household energy use characteristics. These included partial end-use disaggregation of electricity, opportunities for energy savings via dynamic thermostat setback, and an estimate of the relative thermal efficiency of the house structure. The results on these metrics emphasize the heterogeneous nature of energy performance even across households in the same region. Such individualized remote audit information may be a relatively inexpensive way for utilities to target energy efficiency programs and messaging towards households more likely to yield benefits.

Introduction

Residential energy use forms a substantial fraction of any country's total secondary energy use, and improving the energy efficiency in dwellings is a key part of the energy policy of most countries. For example, residential energy use in Canada in 2013 comprised 17 % of total secondary energy use, and 14 % of GHG emissions (NRCan, 2016).

On-site audits of the energy performance of houses, as a facilitator of energy efficient upgrades, are supported by numerous jurisdictions worldwide, and can be effective in improving energy efficiency and occupant comfort, specifically because the recommendations are customized to each house (Parekh et al., 2000; Frondel & Vance, 2013; Taylor et al., 2014; Considine & Sapci, 2016). However, such audits, conducted by professionals, are invasive and relatively expensive to deploy at scale. With the availability of new datasets from smart devices and public/existing databases, there is the potential for utilities (or others) to use data analytics to conduct "remote energy audits" without entering the home (Zeifman & Roth, 2016). Remote audits will not be as accurate and detailed as on-site audits, but can be exercised at a fraction of the cost.

Utilities have often advertised the same energy efficiency program to all customers, regardless of circumstance. Theoretically, remote audit information will enable utilities to target energy efficiency programs towards households most likely to accept the offer, and most likely to yield benefits to the householder and the utility. One option may then be to elevate financial incentives to the target households, further increasing likelihood of program participation, and raising the effect of incentive investments. Retailers and their service providers have been using data to target advertising for years, and utilities are now starting to follow their lead (Du Bois, 2014).

Data-driven and innovative approaches to enhance residential energy efficiency began with benchmarking and feedback on social norms: in simple terms making higher users aware of how they compare to others, with the goal of eliciting behavioural change, in some cases supported by incentivized technol-

Table 1. Characteristics of sample dwellings.

Dwelling Type	Total	Number of Bedrooms				Number of Occupants				
		2	3	4	5	1	2	3	4	5
APARTMENT	2		1		1			1		1
ATTACHED	51	1	36	13	1	3	11	12	14	11
DETACHED	201	1	39	127	34	7	35	41	64	54
Grand Total	254	2	76	140	36	10	46	54	78	66

ogy (Ehrhardt-Martinez, 2012). Some approaches have focussed on classifying (or segmenting) households into socio-economic groups, and using survey data to understand which groupings have a greater propensity for energy program uptake and to target programs toward these groupings (Du Bois, 2104; Horizon Utilities Corporation, 2014). Simply targeting customers with pre-existing higher energy use may yield substantial benefits for conservation programs (Taylor et al., 2014). Alternative methods look at patterns of energy use using hourly load profiles, enabling, for example, targeting of air-conditioning demand response (DR) programs to households that tend to have higher usage on summer afternoons (Kwac et al., 2014; Albert & Rajagopal, 2015).

Other approaches come closer to the spirit of auditing, by deriving end-use estimates for appliances or appliance classes (Armel et al., 2013), or identifying particular characteristics of the house, or the behaviours of its occupants, that effect energy use. Importantly, this may identify households that are not among the highest users overall, but which nevertheless could realize substantial savings in certain aspects of energy use. Some of these approaches require the installation of additional hardware (e.g. high sampling rate electricity meters), which might offer higher accuracy or more features (although accuracy is still limited, see St. John, 2013), but somewhat subverts a scalability goal. Others rely on data that is already readily available to utilities, or is easily obtained (Birt et al., 2012; Schmidt, 2012). The rapidly increasing deployment of advanced (or smart) metering infrastructure worldwide (Accenture, 2013), and greater availability of weather, geo-spatial and demographic data generally, offers opportunities to develop more smart audit features. Advanced insights may be enabled particularly when data science is married with a strong understanding of building physics (Zeifman & Roth, 2016).

Connected (or smart) thermostats are undergoing rapid market uptake, and offer the potential for identifying energy efficiency opportunities from the high volume of data that they typically collect, and one such opportunity is support for remote auditing (Rotondo et al., 2016). Data from smart thermostats typically include: setpoint temperatures, actual indoor temperatures, HVAC (heating, ventilating and air conditioning) system runtimes, and, in some cases, motion sensor data.

This paper describes the development of a variety of remote energy audit techniques using data from a pilot study providing a unique combination of data sets: both smart thermostat and smart meter data, combined with weather data, and basic information on household characteristics. These insights highlight the potential to target energy efficiency programs and messaging using relatively straightforward, and scalable, analytical techniques.

Household Sample and Descriptive Data

The pilot project was managed by a Canadian telecom service operator. A typical install of their Home Energy Management System (HEMS) consisted of: a smart thermostat, two wireless motion sensors, two wireless door sensors, and two wireless smart plugs to monitor and control appliances. These devices were connected using a Zigbee wireless mesh network to the telecom service operator's data servers via an internet gateway. We aggregated event-based smart thermostat and motion/door sensor data to hourly values, and merged these with hourly, whole-house smart meter data from the local electrical utility company, and hourly weather data from Environment Canada. The telecom service operator also provided information on household characteristics reported by the home owner when they first engaged with the HEMS (on-boarding).

The Canadian telecom service operator provided data for 564 houses. The dataset contained energy and thermostat data (setpoints, actual temperatures, HVAC run-times) for 527 dwellings, motion/door (occupancy) data for 416 houses, and household characteristics data for 254 houses. Table 1 summarizes the household characteristics; the two dwellings were electrically heated and were removed from further analysis, all other dwellings were gas heated.

There were 515 houses that had energy consumption records for at least 8000 hours from March 2015 to February 2016 (inclusive). Figure 1 shows the distribution of average hourly energy use among those houses[1]; mean=1.05 kWh, median=0.90 kWh, standard deviation (SD)=0.56 kWh.

Furthermore, Table 2 shows the average hourly electricity consumption by number of household occupants. As expected, average total energy use increased systematically with the number of occupants.

These data are consistent with comparable studies, and add to our confidence that this sample is representative. Newsham et al. (2011) examined electricity data from 320 houses in Southern Ontario in 2008, and reported a mean hourly electricity use of 1.0 kWh over a full calendar year. Other studies

1. Ten houses were excluded from this analysis because they were clear outliers (total energy use was three standard deviations above the mean).

conducted in Ontario report typical average hourly household electricity use of 1.0–1.2 kWh (Strapp et al., 2007; Navigant, 2008). Newsham et al. (2011) further reported that electricity use increased linearly with number of household occupants.

Figure 2 shows average hourly load and occupancy activity profiles for winter months, as an example, for weekdays and weekends separately. As expected, higher energy use was associated with a higher frequency of occupancy-related events. On weekends the morning increase in electricity use was later and less pronounced than on weekdays. Average energy use declined during the middle of the day on weekdays because many homes are vacated during these hours, but this decline did not occur on weekends when daytime occupancy is more common; overall, energy use was higher on weekends than weekdays.

Disaggregation of Energy Use

REFRIGERATION AND PHANTOM LOAD USE

Some electrical loads, such as refrigerators and other plugged-in appliances (so called "phantom loads" or "base" or "standby" loads) draw energy continuously (at the hourly level). To estimate these loads in each house we examined electricity use during hours when HVAC was not operating. We then rank-ordered these hourly loads and considered the 10th percentile value; this served to exclude hours with the highest discretionary appliance use, while also eliminating hours with very unusually low consumption. This approach is likely to primarily identify consumption during typical overnight hours. Figure 3 shows estimates for all houses[2]; mean=0.35 kW, median=0.30 kW, SD=0.23 kW.

From 327 Southern Ontario houses from 2008, Birt et al. (2012) reported a result of 0.3 kWh/hour using a similar approach. Nelson (2008) reported results of a similar study of~300 households in British Columbia, Canada, the average base load was 0.30 kW for single-family dwellings, and 0.15 kW for row houses. In 12 highly-instrumented households in British Columbia, Nelson et al. (2014) reported an average baseload of 0.29 kW, the major contributors to which were refrigeration, computing and entertainment, and water heating (if applicable). By comparison, the estimates derived in our study appear credible. Typical average base loads for houses in Europe (based on measurements from >1000 households) are about half these values, consistent with lower electricity use compared to North America generally, with refrigeration comprising about half the total base load in Europe (Grinden & Feilberg, 2008).

AIR CONDITIONING (AC) USE

We considered summer data and hours in which there were no occupancy events (to reduce variation in the energy use due to discretionary appliance usage). The data were plotted (x-axis: fraction AC runtime/hr, y-axis: kWh/hr total household energy use) and a robust regression analysis was performed[3].

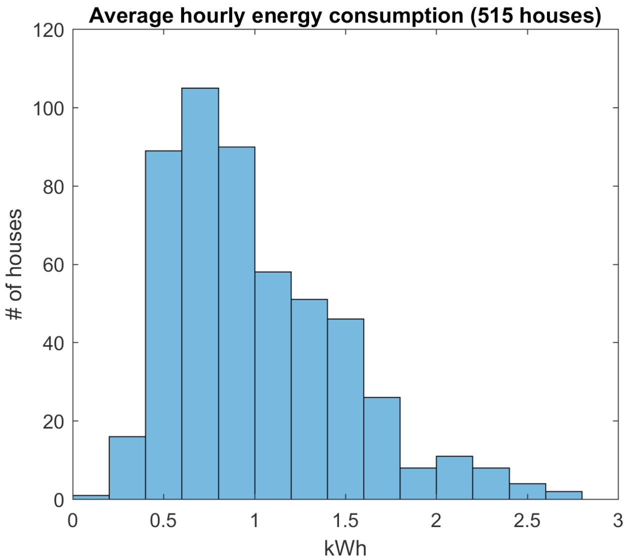


Figure 1. Average hourly electricity consumption for sample dwellings.

Table 2. Average hourly electricity consumption by number of household occupants.

# of occupants	1	2	3	4	5
Mean (kWh)	0.52	0.94	0.98	1.16	1.38

An example from one house is shown in Figure 4. There is considerable scatter in the data, reflecting the variability across all electricity end-uses and all hours. Very low values of electricity use during high run-time hours might reflect data communication errors, or times when the thermostat called for cooling but when the AC unit was disconnected. Nevertheless, the regression trend is obvious. Subtracting the regression fit at value "0" (AC was not running) from the fit at value "1" (AC was running all hour) gives an estimate of the size of the central AC unit controlled by the thermostat, in kW.

There were 122 houses with applicable data for which the R^2 value of the regression was above 0.6, and for these the estimated AC size (kWh per hour/hour=kW) is shown[4] in Figure 5; mean=2.63 kW, median=2.45 kW, SD=0.90 kW.

Direct measurement of 390 residential AC units in Ontario showed an average power draw of 1.93 kW (min. 0.99 kW; max. 5.01 kW) (KEMA, 2009), whereas Toronto Hydro (2016) guidance on energy use suggests 3.5 kW for a central air-conditioner. The mean value of 2.63 kW that we derived lies within this range, and by comparison, the estimates derived in our study appear credible. We can calculate the annual energy use for AC in each house by multiplying the estimated AC size by the total hours and partial hours of AC runtime[5]. Figure 6 shows the estimated annual energy used for AC cooling for houses with suitable data; mean=952 kWh, median=752 kWh, SD=792 kWh.

2. We also applied a further filter, removing hours in which there were some occupancy events, to provide extra assurance that there was minimal discretionary appliance use. This reduced the sample size substantially, but produced very similar results to Figure 3.

3. Given that run-time data were available directly from the thermostat, this was the most direct way to estimate AC size. Absent run-time data, AC size might be estimated by plotting electricity use vs. outside temperature, as described in Birt et al. (2012).

4. This includes the power draw of the central circulation fan.

5. We filled in missing data via the nearest-neighbour approach, based on: hour of day, and outside temperature.

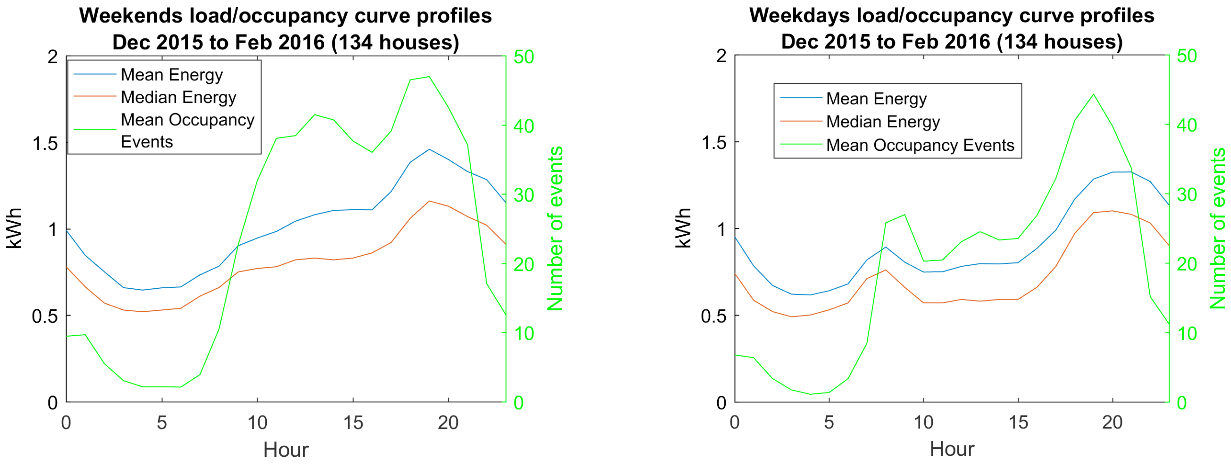


Figure 2. Average load and occupancy event profiles for the winter season (December 2015–February 2016) for the sub-set of houses with suitable data.

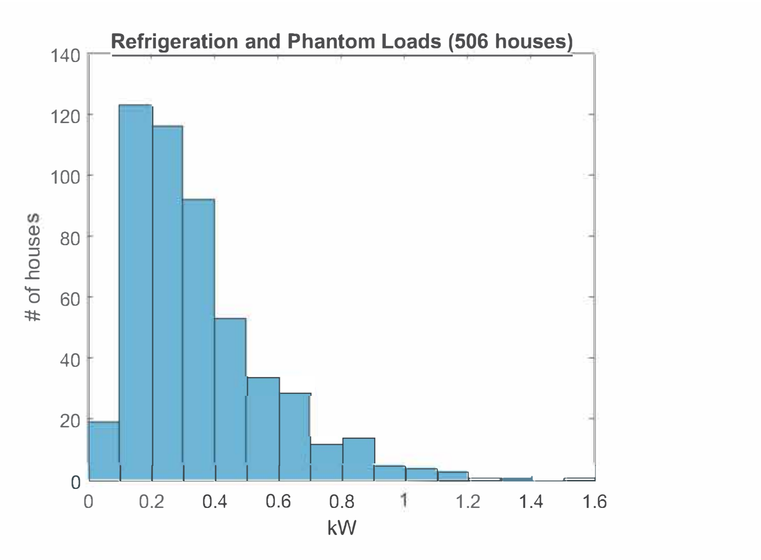


Figure 3. Estimate of refrigeration and phantom loads for all houses.

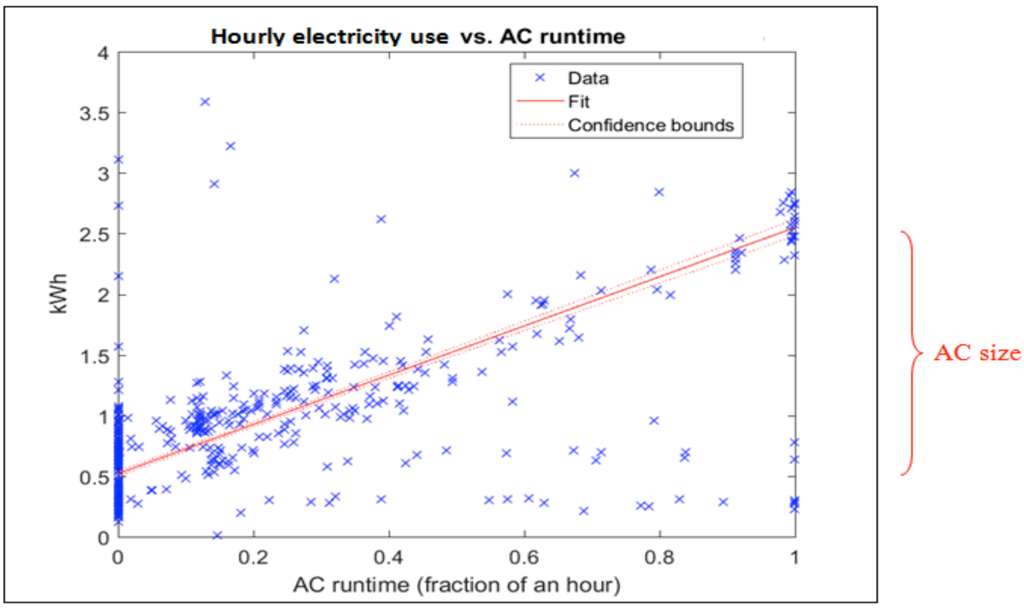


Figure 4. Example of regression used to make an AC size estimation for a single house, regression R^2=0.79.

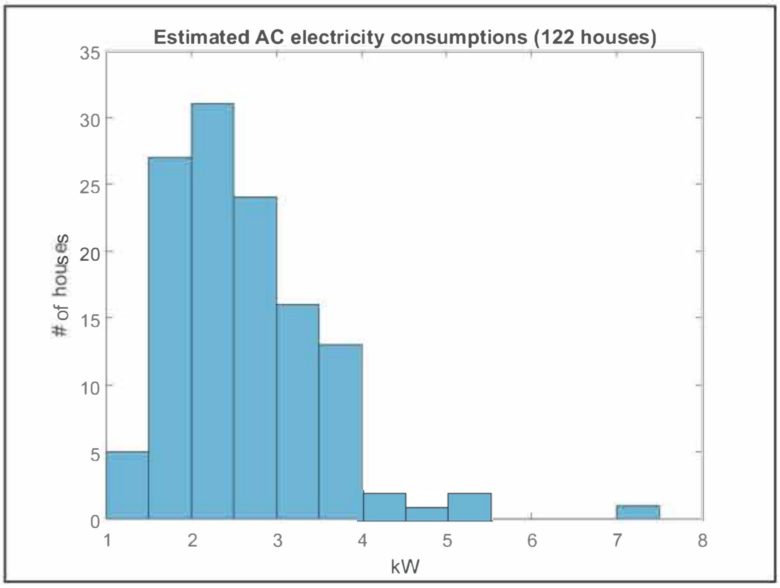


Figure 5. Estimate of AC size for the sub-set of houses with strong regression fits.

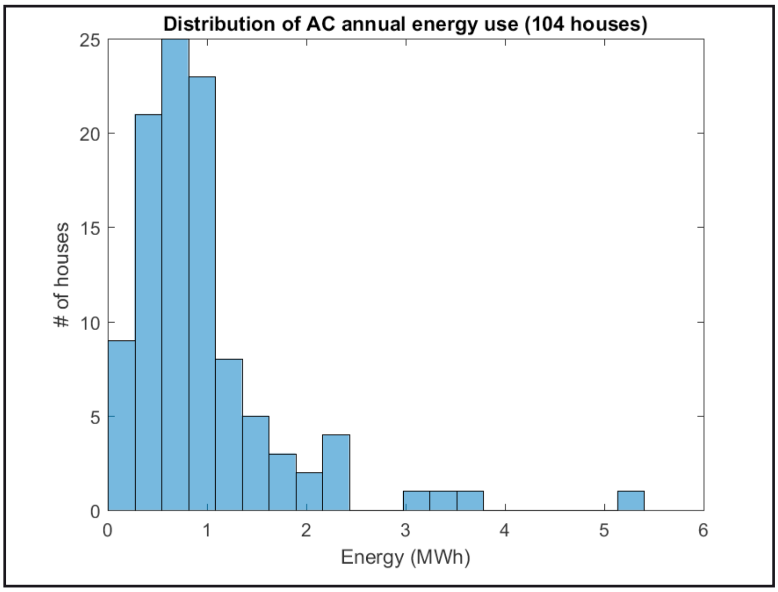


Figure 6. Estimated energy use attributable to the AC for the sub-set of houses with suitable data.

Newsham & Donnelly (2013) generated a statistical model for residential electricity and gas use based on a large sample of households across Canada. Using their coefficient for central cooling, and applying average cooling degree day values for Toronto, yields an estimate of ~700 kWh/yr. Newsham & Donnelly (2013) quote other estimates of residential central AC energy use in Canada, including British Columbia at 346 kWh/yr and 1,963 kWh/yr for Quebec, both of which have a milder summer climate than Southern Ontario. By comparison, the estimates derived in our study appear credible.

FURNACE FAN USE

Dwellings heated by natural gas in this pilot used a central furnace (typically in a basement), with warm air distributed throughout the dwelling using ducts and an electrically-powered circulation fan. To disaggregate the furnace fan electricity use, we employed a similar technique to the AC consumption estimation, considering records from the heating season during which no occupancy events were recorded. Figure 7 shows the estimated furnace fan power draw for all houses with suitable data[6]; mean=0.50 kW, median=0.49 kW, SD=0.22 kW.

The Canadian Centre for Housing Technology (CCHT) comprises full-scale single-family detached research houses built to standards similar to the current Ontario Energy Code. Measurements of the power draw of examples of both Permanent Split Capacitor (PSC) and Electronically Commutated Motor (ECM) type furnace fans at the CCHT showed their full

6. The furnace fan is a smaller load than AC, and thus more difficult to estimate. We tried limiting our estimates to houses where the regression R^2 was >0.6. This reduced the sample size substantially, but produced very similar results to Figure 7.

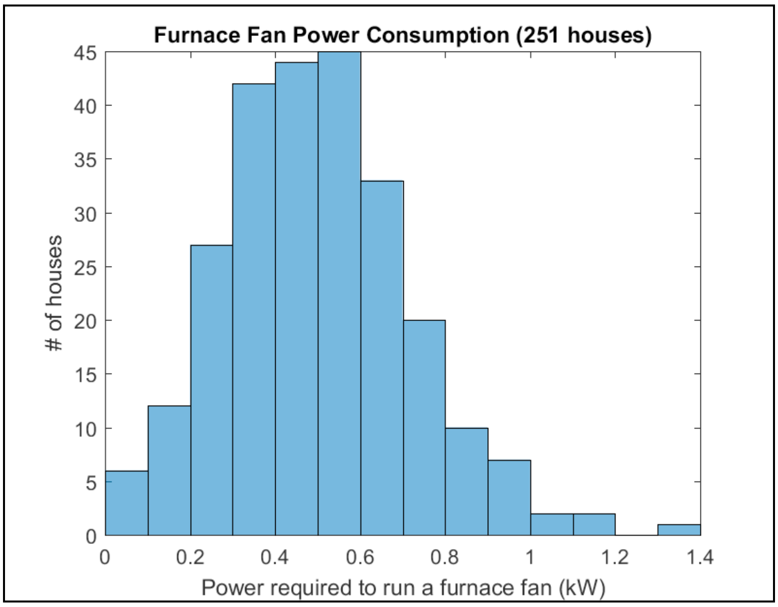


Figure 7. Estimated furnace fan power draw for all houses with suitable data.

output power was 0.49 kW and 0.28 kW, respectively (Gusdorf et al., 2002). The PSC type is the most common in residential applications. Consumer guidance on furnace fan wattage ranges from 0.35–0.75 kW (Toronto Hydro, 2016; Consumer Reports, 2016). By comparison, the estimates derived in our study appear credible.

Potential Energy Savings from Additional Thermostat Setback

More savings can result from additional thermostat setbacks during absence or night-time than those programmed in the houses, either because no setback[7] was programmed at all, or because the programmed setback was not as deep as it potentially could be. A smart thermostat, supported by occupancy information, could engage such setbacks automatically (e.g. Lieb et al., 2016). To estimate the upper limit of these savings for the heating period, we summed all the HVAC runtime hours when the thermostat setpoint was above 18 ˚C, and there were no occupancy-related events in the three previous hours[8]. For the cooling season, we summed the HVAC runtime hours when the thermostat setpoint was below 25.5 ˚C and there were no occupancy related events in the three previous hours[9].

Note, however, our analysis was limited to houses for which reliable occupancy event data were available. Reliability could have been compromised for several reasons, including: the occupancy/door sensors were not installed; the sensors were installed but not in places where activity occurred; the sensor batteries failed; or, there was a wireless data transmission error.

Figure 8(a) shows the estimated additional HVAC runtime savings in the heating season, for houses with suitable data; mean=144.0 hours per house, median=127.5 hours, SD=92.1 hours. Figure 8(b) shows similar data for the cooling season; mean=48.4 hours, median=33.2 hours, SD=56.6 hours.

We consider this analysis an upper estimate of the potential savings in runtime hours for several reasons. First, the suggestion that setback could be deeper than 18/25.5 ˚C might not be acceptable to the occupant. Second, we are suggesting that all run-time hours will be saved with these additional thermostat setbacks. In fact, if the absence is long enough that the internal temperature reaches the setback temperature the HVAC system will resume operation. Finally, when the resident returns there may be additional energy use in HVAC activity to recover to the occupied setpoint. The exact energy impact of these effects depends on occupancy schedules, solar gains and other exterior conditions.

Some consideration needs to be given to how big the automated setback should be, and to house temperature recovery time, given that the occupant may be returning to a temperature they had not programmed. The safest choice is what might be termed a "shallow setback", perhaps only 1 ˚C, which would be unlikely to be noticed by a returning occupant, and is within the deadband and measurement error margin of many thermostats anyway.

Relative House Structure Thermal Characteristics

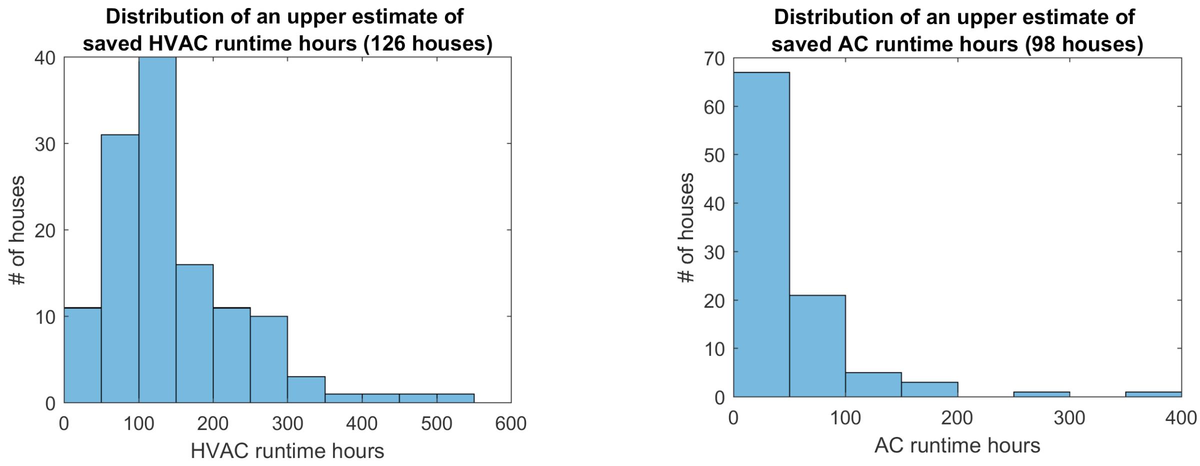
This analysis is based on a variant of the basic heat balance equation for a house, in the absence of solar gains (Eq. 1):

$$\Delta T_i = \frac{UA(T_o - T_i)}{M_t} + \frac{Q_{int}}{M_t} + \frac{Q_f}{M_t}$$

7. We use the generic term "setback" for both heating and cooling seasons. In the heating season, this means lowering the thermostat setpoint during absences or overnight, in the cooling season it means raising the setpoint.

8. Given that the occupancy-related sensors might not capture all occupant activity, we chose three hours as an (arbitrary) safety factor to be confident that the house was indeed unoccupied.

9. 18 and 25.5 ˚C were guided by the setpoints reported in a survey of Canadian households (NRCan, 2010); they were within the range of reported values, but towards the more energy-efficient end of the range.



(a) (b)

Figure 8. Upper estimates of HVAC runtime hours savings due to additional setback in the (a) heating season, and (b) cooling season, for houses with suitable data.

where,

- ΔT_i change in indoor air temperature in one hour
- U integrated envelope heat loss characteristic due to conductive and infiltrative processes
- A exposed area of building
- T_o outdoor air temperature
- T_i indoor air temperature
- Q_{int} internal heat gains (e.g. waste heat from appliances, occupant metabolic heat)
- Q_f heat gains from furnace
- M_t thermal mass characteristic (higher thermal mass means slower change in temperature for a given heat gain)

This can be expressed as a simple linear equation (Eq. 2):

$$y = mx + c$$

where,

$y = \Delta T_i$
$x = (T_o - T_i)$
$m = UA/M_t$
$c = (Q_{int} + Q_f)/M_t$

From the thermostat data we know the indoor air temperature in any given hour and its change during that hour, and we know the outdoor air temperature from Environment Canada data, therefore, we can conduct a regression on these data and estimate the *m* and *c* parameters. A relatively high value of *m*, meaning relatively high heat loss, indicates a relatively poorly insulated envelope, an envelope with relatively high air leakage, a relatively large envelope area[10] or a house with relatively low thermal mass, or a combination of all three.

To estimate these parameters in the heating season, we looked at the time period when the house cooled down at night after the night setback started. Note that in this situation $Q_f = 0$ and *c* represents internal gains (and thermal mass) only. For each house, the cool down time was recorded along with the average inside and outside temperature observed at that time (the cool down period was only recorded if the indoor temperature drop overnight was at least 1 ˚C). Thus, for a single night, ΔT_i is the temperature drop in the cool down period divided by the time that the cool down took, and $(T_o - T_i)$ is the difference between the average outdoor and indoor temperatures during that period.

An example of a single night of time series data is shown in Figure 9. We identified the beginning of the house cool down period at night-time when temperatures started falling consistently, 23:55 in the example in Figure 9. We identified the end of the cool down period when the indoor temperature did not drop anymore and/or the furnace started, 03:37 in the example in Figure 9. The indoor-outdoor temperature difference was ((20.5+17.8)/2)–2.25=16.9 ˚C. The cool down rate was thus 2.7/3:42=0.73 °C per hour. Note that in the Figure 9 example the indoor temperature drop during cool down was very linear.

We did this for all nights with valid data for a single house. Finally, we performed a linear regression on this set of points to find the amount of time it took for the house to cool down as a function of the temperature differences between the inside and the outside. To limit the regression artefacts, we constrained the regression to output models with non-negative intercept[11]. Figure 10 shows the resulting "rate vs. temperature difference" plot for all nights for the same single example house.

The best fit regression line in Figure 10 was: Y=0.07*X+0.28; this generates the *m* (slope=0.07) and *c* (intercept=0.28) parameters in Eq. 2. We then computed these parameters for all houses with suitable data, and the result is shown in Figure 11. Note that the houses with the largest slopes also tend to have the largest intercepts, suggesting common causes that affect both parameters. For example, these could be houses with relatively low thermal mass, or relatively large houses that would tend to have larger envelope areas and higher internal gains. Nevertheless, for houses with low intercept values, there was a range of slopes, and those with larger slopes could be targets for energy efficiency programs designed to improve envelope performance.

10. Note, it might be possible to parse out the effect of envelope area with data on house size, supplied either by the homeowner or from a public database.

11. A negative intercept would mean that the house keeps losing temperature even though the outside temperature is equal to the temperature inside the house, a physical impossibility.

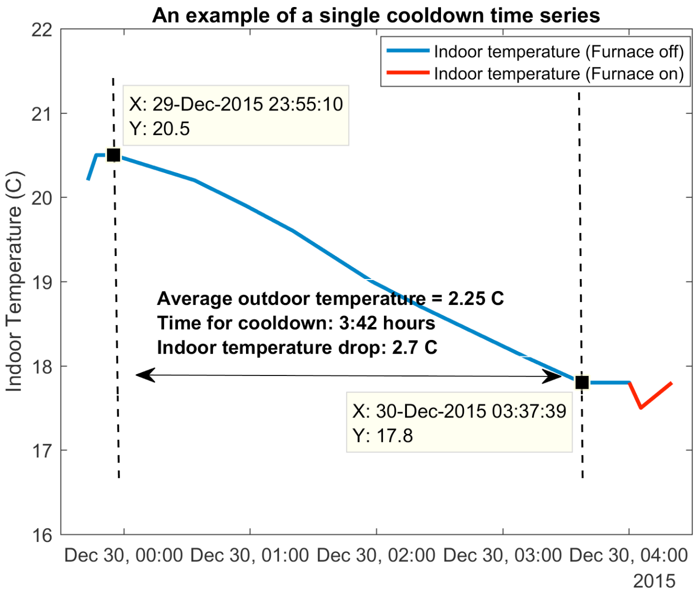


Figure 9. Indoor temperature cool down during night-time setback for a single house on a single night, showing derivation of parameters for our analysis.

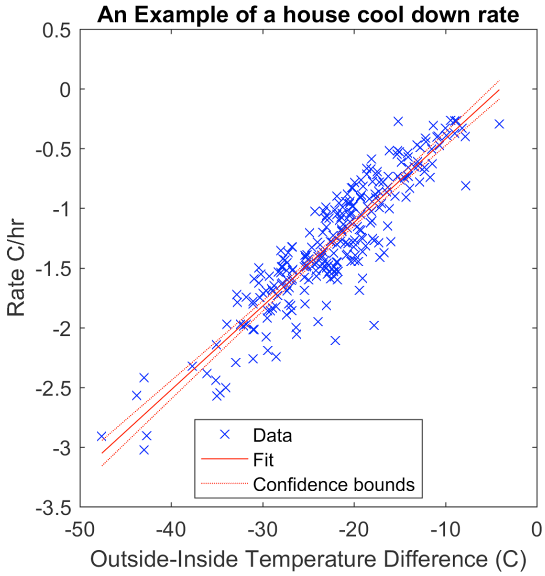


Figure 10. Cool down rate vs. temperature difference for an example house over the heating season. The best fit regression line is shown.

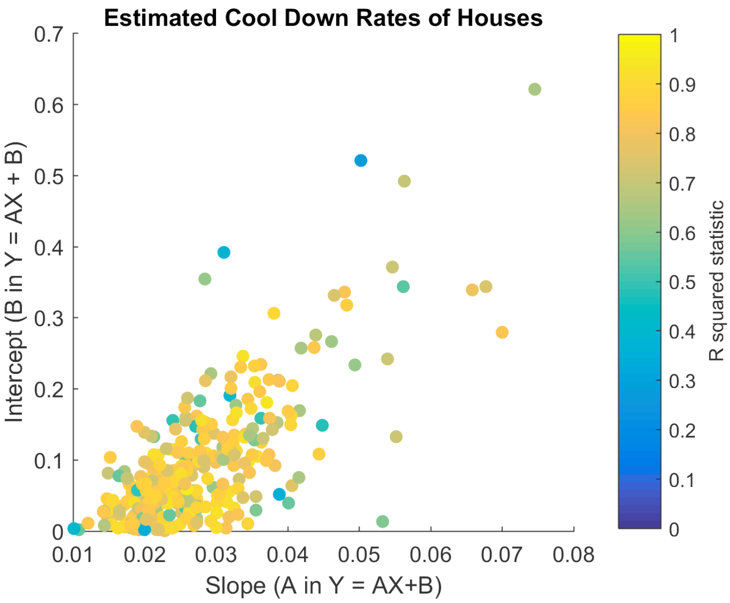


Figure 11. Estimated cool down rates of all houses with suitable data. The colours of each point represent the variability explained (R^2) by the regression fit for each house.

Conclusion

The growing availability of house performance data from smart thermostats, smart meters, and public databases offers many possibilities for estimating various house characteristics and quantifying savings opportunities at the individual house level. Segmentation of household populations based on such estimates may be used to target energy efficiency programs towards houses most likely to benefit. In principle, this may increase program participation, and yield more benefit for a given program investment.

Data from a sample of typical houses in Ontario, Canada demonstrated some viable approaches for deriving such characteristics and opportunities related to end-use disaggregation, automated thermostat setbacks, and thermal characteristics of the houses. The end-use disaggregation estimates were credible compared to other methods on similar house populations: mean refrigeration and phantom loads were estimated as 0.35 kW, the mean central AC size was 2.63 kW, and the mean furnace fan power draw was 0.50 kW. For many houses, a hundred or more of hours of potential HVAC run-time could have been saved by automatically adjusting the thermostat when no occupancy was detected for an extended period. Further, analysing the rate at which a house cools down overnight provides an indicator of relative thermal efficiency. Doubtless, other energy efficiency insights may be gained by further analysis of similar data by researchers with a knowledge of building physics, occupant behaviour, and data science. For example, households whose electricity demand has greater coincidence with the system-wide peak could be identified, and be targeted for demand-response programs.

The next step should be to validate remotely-derived household characteristics by comparison to on-site physical audits. If successful, future market research should test the hypothesis that targeting programs based on these estimates and segmentation does indeed lead to program benefits.

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