The Electricity Journal 30 (2017) 64–70

Contents lists available at ScienceDirect

The Electricity Journal

journal homepage: www.elsevier.com/locate/electr

Using advanced metering infrastructure to characterize residential energy use

Brock Glasgo[a,*], Chris Hendrickson[b], Inês M.L. Azevedo[a]

[a] Engineering and Public Policy, Carnegie Mellon University, 129 Baker Hall, 5000 Forbes Ave., Pittsburgh, PA 15213, United States
[b] Civil and Environmental Engineering, Carnegie Mellon University, 3050 Hamburg Hall, 5000 Forbes Ave., Pittsburgh, PA 15213, United States

ARTICLE INFO

Article history:
Available online 20 April 2017

ABSTRACT

Decades of effort have been dedicated to understanding precisely where energy is consumed in residences to help consumers, device manufacturers, utilities, and policymakers better manage this consumption. We review and classify the three most prevalent methods currently used to build this understanding. We then compare two prominent studies, and make recommendations for how existing datasets can inform estimates of device-level energy consumption in the U.S.

1. Introduction

A transition to sustainable energy systems that address climate change, provide energy services with low environmental and health effects, and are affordable and environmentally just will likely include a broad deployment of energy efficiency and conservation strategies. Many of these strategies and policies to date have focused on the residential sector. This makes strategic sense, as residential buildings in the United States currently account for about 22% of all energy consumption (US Energy Information Administration, 2015a) and 21% of all US greenhouse gas emissions, 71% of which is a result of electricity use in homes (US Environmental Protection Agency, 2013). Despite decades of effort to better understand and reduce the energy consumed by U.S. residences, detailed appliance level data on actual energy consumption is still sparse.

Building this understanding of precisely where energy is consumed in residences is crucial to managing residential energy use and reducing its effect on our environment. Consumers would benefit by knowing what devices most affect their energy bills, allowing them to make behavioral and investment decisions to more effectively reduce those bills. Manufacturers would be better positioned to develop and market efficient appliances and devices. Utilities and grid operators could incorporate these data to better forecast loads. And policymakers and utility program designers could use this information to develop viable energy efficiency, demand response (DR), and demand-side management (DSM) initiatives that deliver sustainable, cost-effective, and verifiable results.

There are a number of technological and analytical methods currently being used to meet this need for more granular data on residential energy use. We break these methods into three classes: (i) direct metering of end-use devices and circuits, (ii) non-intrusive load monitoring, and (iii) statistical methods for disaggregation.

In Section 2 we provide a description of these different methods and review studies that use these approaches in the United States. There are many more studies looking at estimating overall residential electricity consumption, but we focus only on those that have appliance-level estimates. In Section 3, we then focus on using data from a specific circuit level monitoring dataset and provide – to the best of our knowledge – the first ever comparison between circuit-level monitored data and the estimates from the EIA's Residential Energy Consumption Survey. In Section 4 we present the methods used, and in Sections 5 and 6 we present results of the analysis, conclusions reached, and recommendations for future work.

2. Methods for disaggregating residential energy use

2.1. Direct metering methods

Direct metering methods are the most basic means of generating disaggregated energy use data in residences. These methods measure actual power flow at the device or circuit level using distributed sensors, and therefore have the potential to provide the most accurate ground truth data about where energy is being used in a building. In residences installed with direct metering, the generated data can be used to provide direct real-time feedback to occupants about their energy use, DR and DSM opportunities, and the performance and operating characteristics of critical devices and equipment.

* *Corresponding author.
E-mail addresses: bglasgo@andrew.cmu.edu (B. Glasgo), cth@andrew.cmu.edu (C. Hendrickson), iazevedo@cmu.edu (I.M.L. Azevedo).

http://dx.doi.org/10.1016/j.tej.2017.03.004
1040-6190/

The drawbacks of these systems are primarily related to the cost of installing and maintaining extensive networked meter deployments, and of collecting and managing the resulting dataset. In a report for the EIA, Leidos Inc. conducted interviews with submeter suppliers and found the hardware cost alone to submeter a single home ranges from approximately $120 to over $1000 (US Energy Information Administration, 2015b). In large deployments of the type implemented for utility or research purposes, these costs increase due to installation and data management requirements, resulting in final costs estimated to be on the order of $2000 per home. In the same study, Leidos found a complete lack of a regulatory framework for submeter deployments in the U.S. Lacking this regulatory involvement, which was in place prior to the deployment of smartmeters, the authors conclude that submeters will not be widely used by utilities or others in the near future.

Despite these barriers, a number of pilot projects are under way to better understand the benefits and challenges of submeter deployments. A summary of these projects can be found in Table 1.

2.2. Non-intrusive load monitoring methods

Non-intrusive load monitoring (NILM) refers to methods of extracting device-level energy use estimates from a single-point whole-residence sensor measuring voltage and current signals at frequencies up to 500 kHz (Froehlich et al., 2011). NILM methods analyze these signals to observe real power, reactive power, and harmonics in the line, and apply algorithms to extract device-specific features that allow power consumption to be attributed to various devices. The biggest benefit of these methods is the reduced monitoring equipment and installation needs, while maintaining real-time device-level energy disaggregation.

As a result of the reduced monitoring requirements of NILM, there are several drawbacks associated with these methods. These include the need for more advanced sensors and data acquisition, the need for some level of calibration to match observed signals to specific end uses, and energy allocations that depend on the ability of algorithms to detect device consumption. Current research is largely focused on better refining these algorithms and improving

Table 1
Summary of studies using direct metering, NILM, and statistical methods to disaggregate residential energy use.

Method of Disaggregation	Examples	Description	Results/Findings
Direct metering	Pecan Street Dataport (2016)	Funded by a $10.4 M DOE stimulus grant, the Pecan Street Research Institute has installed device- and circuit-level submeters in over 700 volunteer residences in Austin, TX.	Pecan Street has curated the world's largest dataset of appliance- and circuit-level residential electricity data intended for research purposes. These data are made available to volunteer participants, and are also anonymized, licensed, and made available for download to the public.
	Duke Energy (2014–2015)	Implemented submetering in a 61-home pilot project in Charlotte, North Carolina. (US Energy Information Administration, 2015b)	Pilot project was implemented to help better understand how Duke's residential customers consume energy, and "help develop optimization algorithms and strategies for their electric distribution grid operations." Results are not publicly available.
	San Diego Gas and Electric (2013)	Implemented submetering in a 30-home pilot project in San Diego, California. (US Energy Information Administration, 2015b)	Pilot project was implemented to build an understanding of end use energy consumption as a means of improving future utility programs. Results are not publicly available.
	Community Power Partners (2014–2016)	Partnered with the Pecan Street Research Institute to implement submetering in 48 homes in Boulder, CO. (US Energy Information Administration, 2015b)	The pilot is intended to research how residences consume energy and what tools and information occupants need to better manage their energy use. Results are not publicly available.
Non-intrusive load monitoring	Berges et al. (2008)	Tested the ability of four disaggregation algorithms to classify features of a monitored dataset generated using a laboratory setup of common appliances connected to a single electrical outlet.	Machine-learning classification with the 1-nearest-neighbor algorithm was found to be the most successful at identifying features. 90% of lab-generated events were successfully identified.
	Kolter et al., (2016)	Used a sparse coding algorithm to learn devices' power signals, and then apply the learned information to disaggregate power consumption from a single meter.	The algorithm is able to correctly estimate up to 55% of energy consumed over one week. Discriminative training is found to improve algorithm performance in nearly all cases.
Statistical methods	RECS (2009) EIA (2013)	Collected monthly energy bills and administered a survey to a nationally representative sample of over 12,000 US residences.	Collected data are combined in a nonlinear regression model to estimate end-use energy consumption for five fuel types and five end uses of energy. Results are released to the public and serve as a primary data source for other EIA publications and residential sector research.
	Torres et al. (2015)	Tested the RECS disaggregation models used to estimate air conditioning loads. Used the RECS data, and submetered air conditioning use data and energy audit records from the Pecan Street Research Institute to test different model forms and independent variables.	Found statistically significant differences between the RECS and Pecan Street datasets, and found that cooling energy might be underestimated in RECS. The authors recommend including several predictors not currently collected in the RECS survey, and makes recommendations on how to improve end-use disaggregation estimates.
	Borgeson (2013)	Explores various applications of smart-meter data to improve efficiency program targeting. Part of this analysis includes a disaggregation of heating and cooling loads from 30,000 PG&E customers into base and thermal loads.	Two methods are proposed for disaggregation: a simple linear regression of utility use on heating and cooling degree days, and simply taking the difference between observed base load and actual consumption. Findings are used to draw conclusions about targeting of homes for space heating and cooling initiatives from utilities or PUCs.
	Birt et al. (2012)	Uses a submeter dataset to estimate segmented regression models that disaggregate smart-meter data into five load categories based on activity level and space conditioning loads. The resulting model is then applied to hourly smart-meter data for a sample of 327 homes which underwent a utility survey.	The model is able to disaggregate base loads, activity loads, temperatures at which AC is used, cooling season gradients, and heating season gradients in most of the sampled homes. The authors find limitations to the model, but argue that this type of analysis provides insight into end use consumption data that is already being collected that can help direct DSM and efficiency initiatives.

methods for disaggregation. A number of these studies are summarized in Table 1.

2.3. Statistical methods

Statistical methods for disaggregation refer to a broad range of analytical approaches to estimating device-level energy use from detailed residence descriptions and existing aggregate energy use data. Without the need for additional on-site monitoring, these methods can be applied to large numbers of homes and are therefore often used in national-level analyses of residential energy use. The EIA's Residential Energy Consumption Survey (RECS) is the most prominent example of this type of study. Some common methods used in these analyses include various regression models, engineering methods, and neural network modeling.

The obvious drawback of these methods is the need to collect or otherwise obtain enough information about a large number of residences and their occupants to specify a model. Most commonly, this information gathering takes the form of a survey administered to residents that asks questions about income, occupancy, appliance ownership, building parameters, and other characteristics known to influence energy consumption.

As these methods often rely on utility-provided energy use data, they benefit from increasingly shorter metering intervals. Smart-meter data, collected at 15-min or hourly intervals, has greatly improved the ability of models to attribute energy use to end uses. This ongoing shift towards advanced metering infrastructures (AMI) is seen as support for the increased use of these methods.

2.4. Sample studies

Table 1 summarizes prominent studies using the three methods described above.

3. Data

For this analysis we rely on data from the EIA's RECS and submeter data from the Pecan Street Research Institute. These datasets are described in detail below.

3.1. RECS data

The most comprehensive study of energy use in American homes is the EIA's Residential Energy Consumption Survey (RECS). These surveys are administered to a nationally representative sample of primary housing units from which energy use, physical residence characteristics, and household demographics are assessed (EIA, 2016a). The raw data is released to the public, where it is widely used in the peer-reviewed literature on energy systems, energy policy, energy efficiency, and other topics. The resulting data also serve as inputs to other EIA publications such as the Annual Energy Outlook and the Annual Energy Review.

The first RECS survey was administered starting in 1978, with annual updates until 1982. As the length of the surveys grew, subsequent releases became less frequent and since 1997 have been conducted every four years (EIA, 2016a). The most recent RECS survey, now in its 12th iteration, was conducted in 2009 and became available to the public in 2012.

The 2009 RECS was administered to a sample of homes chosen to represent all 113.6 million primary U.S. residences (EIA, 2011). Homes are selected through a process beginning with the random selection of counties across the country to be surveyed. Each of these counties is then divided into groups of census blocks. A fraction of these census blocks are then chosen at random and the houses within each listed. The final homes to be surveyed are then selected randomly from this list. In the most recent survey conducted in 2009, this method was used to select 19,000 residences to survey. Approximately 15,300 of these were occupied primary residences, and of these approximately 12,083 housing units replied to the survey. In order to present the results of the work at a national scale, each response is assigned a sample weight between approximately 500 and 96,000 that describes how many residences in the U.S. that surveyed residence represents (EIA, 2016a).

Data for the survey is collected in two parts. A team of trained interviewers first conducts extensive in-person interviews of residents and landlords (EIA, 2011). These surveys are known as the Household Survey and Rental Agent Survey. Questions attempt to identify behavioral patterns of residents that impact energy consumption, as well as physical characteristics of the building and its appliances. The only physical measurement taken by the interviewer during this session is the square footage of the residence. All other recorded results are based on the perceptions of the interviewee. For example, the survey asks of homeowners "Would you say that your home is well insulated, adequately insulated, or poorly insulated?", but does not measure the thickness or record the type of insulation present. Once these survey responses have been collected, the Energy Supplier Survey (ESS) is sent to each housing unit's utility providers to quantify, both in energy units and dollars, how much electricity, natural gas, fuel oil, and propane the residence consumed in the past year.

Once validated and edited, the results of these two surveys are input into non-linear regression models that disaggregate the total annual consumption of each utility into five components: space heating, air conditioning, water heating, refrigeration, and other. The models vary by appliance and fuel, but rely on factors such as the size and type of the appliance, building age and size, weather, and number of residents, among others to estimate each load's contribution to annual energy consumption (EIA, 2013).

The results of these surveys and models provide the EIA with not only a static breakdown of how residences in the U.S. consume energy, but observable long-term trends in energy consumption patterns across the residential sector. Findings from these studies are also fed directly into the EIA's Annual Energy Outlook reports. These provide projections of national energy supply, demand, and prices under current policies out to 2040 and provide decision support for government and industry.

3.2. Pecan Street data

Residence- and device-level energy consumption data used in the analysis were obtained from the Pecan Street Research Institute's Dataport (Pecan Street Dataport, 2016). Pecan Street Inc. is a 501(c)(3) not-for-profit corporation and research institute headquartered at the University of Texas at Austin. Volunteers from in and around the city of Austin elect to join the study and work with Pecan Street researchers to decide which circuits and appliances in their home or apartment to monitor.

The first residences in this sample begin reporting data in January 2012, and installations and monitoring continue to date. The resulting dataset includes monitored demand readings for approximately 722 homes and apartments at 1-min and 15-min intervals. For this analysis, we use 15-min interval data to calculate end-use consumption.

In addition to monitored data, results of energy audits and four annual surveys administered to participants are available to provide physical characteristics of the homes and sociodemographic descriptions of the occupants. We also note that as part of their ongoing research, Pecan Street has implemented several interventions in volunteer residents' homes and apartments. These include providing residents access to an online portal to observe their energy use, simulating time-of-use pricing schemes, and providing new appliances to homeowners, among others. We assume that these interventions do not significantly alter the appliance-level energy consumption in the monitored homes.

4. Methods

Using the metadata included in the RECS dataset, we filter the nationally representative sample to include only respondents similar to the Pecan Street residences: single-family homes and apartments in Texas with central cooling. Using the weighting factors provided in the RECS dataset, these 595 homes and 200 apartments are representative of around 5.0 million homes and 1.7 million apartments across Texas.

To filter the Pecan Street dataset, we apply validation criteria requiring at least one year of whole-home or whole-apartment use data with less than one week of missing values. We also require the residence to have completed a survey to ensure the availability of demographic details. From the original 722 homes and apartments, this reduces the sample size to 339 homes and 104 apartments. Monitored appliances vary by residence, resulting in fewer records for each appliance. Energy use values for final comparisons are calculated from the most recent year of data available for each home or apartment.

Lastly, Austin Energy sales data from 2012 show the average residential customer calculated as total billed kWh divided by number of residential customers. It should be noted that the Austin Energy average includes both homes and apartments. This level of consumption is, therefore, likely an underestimate of average home consumption in Austin and an overestimate of average apartment consumption.

5. Results

In Section 5.1 we present summary statistics of the RECS and Pecan Street datasets. In Sections 5.2 and 5.3 we compare whole-residence and device-level consumption estimates from the RECS and Pecan Street datasets.

5.1. Summary statistics of RECS and Pecan Street datasets

Table 2 shows a comparison of the RECS and Pecan Street samples. Pecan Street summary statistics are taken from all homes and apartments in the study meeting minimum data validation criteria. Surveys and energy audits were not administered to every home or apartment in the sample, so not every field is known for every residence in the study.

Table 2
Summary statistics for Pecan Street and RECS homes and apartments.

Residence	Characteristic	RECS		Pecan Street	
		Mean	Std. Dev.	Mean	Std. Dev.
Homes	Sample size[a] (qty)	595	–	339	–
	Age (yrs)	35	20	28	25
	Area (ft^2)	2400	1300	2000	740
	Cooling degree days (qty)	2900	650	2940	30
	Residents (qty)	2.9	1.5	2.6	1.2
	Household income[b] ($/yr)	$60k	$36k	$156k	$135k
Apartments	Sample size[a] (qty)	200	–	104	–
	Age[c] (yrs)	38	15	4	0
	Area (ft^2)	870	290	1100	240
	Cooling degree days (qty)	3000	630	2940	10
	Residents (qty)	2.2	1.4	1.7	0.9
	Household income[b] ($/yr)	$30k	$23k	$52k	$42k

[a] Meeting minimum data validation requirements.
[b] Household incomes were provided as a range. Values above were calculated using the median of this range except for the bottom bracket (<$10k) and top bracket ($1M+).
[c] Ages were only available for (3) of the (104) apartments meeting data validation requirements.

This comparison shows the greatest differences in the two datasets are related to the age, size, and household incomes of the sampled residences. Homes in the RECS sample are only slightly older than those in the Pecan Street study. Only three apartments in the Pecan Street study have a reported age, and all three report being only four years old. Pecan Street homes are smaller, on average, than the RECS homes, but the opposite is true of apartments. Lastly, the largest difference between the samples relates to household income. Both home and apartment occupants in the Pecan Street study report much higher incomes than those in the RECS sample.

5.2. Total residence consumption

Total annual home and apartment electric consumption are shown in Fig. 1. The median of the Pecan Street home consumption data, around 10,100 kWh/yr, is outside of the interquartile range of the RECS sample. The whiskers in all boxplots presented extend to 1.5 times the interquartile range above and below the 75th and 25th percentiles, respectively. Values outside of this range are marked as outliers. Nearly all of the Pecan Street homes fall within this range of the RECS data. Comparing medians, the Pecan Street homes consume around 33% less electricity than the RECS homes and around 13% less than the average Austin Energy residential customer. When separated into income brackets, Pecan Street homes' median consumption is similarly less than that of homes in the RECS across all income ranges.

Looking at apartments, the median of the Pecan Street data, around 4800 kWh/yr, is again outside of the interquartile range of the RECS sample. Comparing medians, the Pecan Street apartments consume around 48% less electricity than the RECS apartments, and nearly 60% less than the average Austin Energy customer.

The reduced energy use in Pecan Street homes and apartments is likely due to selection bias as participants volunteer to be included in the Pecan Street sample. These individuals are likely more energy-conscious, make more energy-aware purchase decisions, and exhibit more energy-aware behavior than average residents in the RECS. A portion of this reduced use is likely also due to the Hawthorne effect, which has been shown to reduce energy use when individuals know they are participating in a study of household energy use (Schwartz et al., 2013).

5.3. Device-level consumption

Next, we show the total annual home and apartment air conditioning, water heater, and refrigerator electric consumption data in Fig. 2. The RECS data present the results of the EIA's statistical models in estimating energy consumed by air conditioner condensing units, electric water heaters, and refrigerators.

Median air conditioning consumption in the Pecan Street homes is within the interquartile range of the RECS data and is around 67% of the RECS median. The use of the RECS model outputs instead of measured data introduces a potential source of error in the RECS estimate. Median AC consumption in the Pecan Street apartments is outside the interquartile range of the RECS data at around 40% of the RECS median.

Total annual home and apartment electric water heater consumption are shown in the middle two boxes of each figure. The RECS data present the results of the EIA's statistical models in estimating energy consumed by all-electric water heaters in homes and apartments. Here, the same filters were applied to the RECS sample, but sample sizes are smaller than previously presented, as

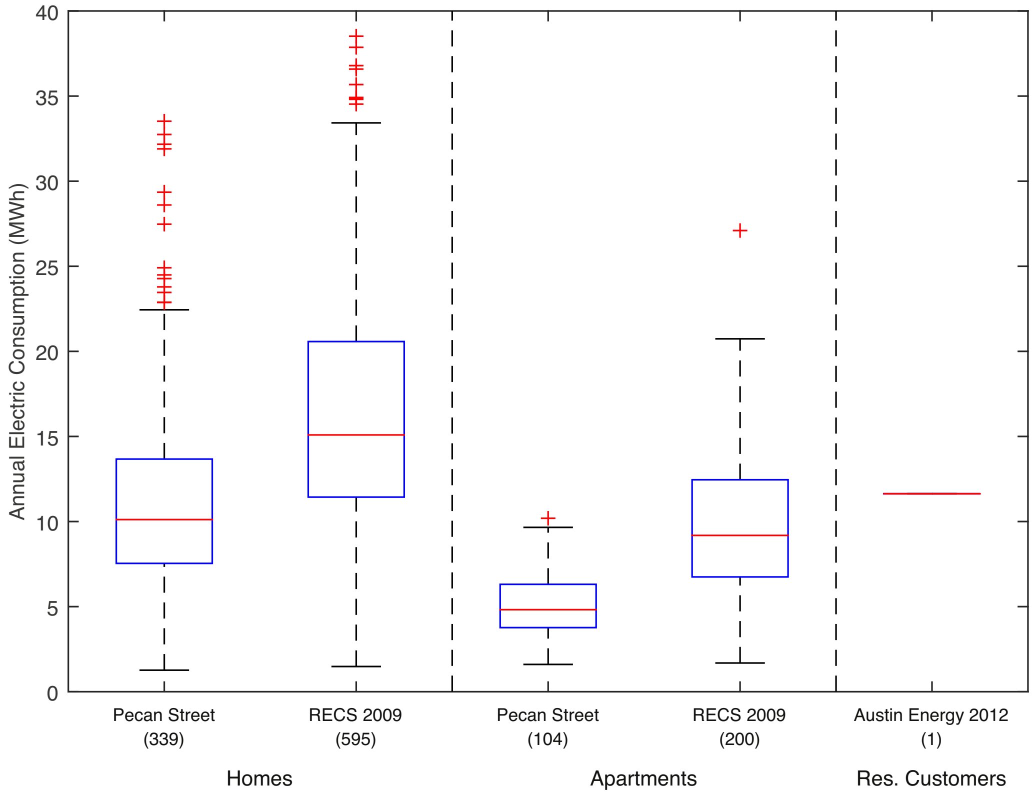

Fig. 1. Comparison of Pecan Street monitored data to RECS 2009 data and Austin Energy 2012 sales data. Box plots show the median, 25% quartile, 75% quartile, maximum, minimum, and outliers. The left box shows Pecan Street data, the middle box shows the RECS reported annual consumption, and the right box shows Austin Energy data. The number of data points represented in each plot is shown below the source.

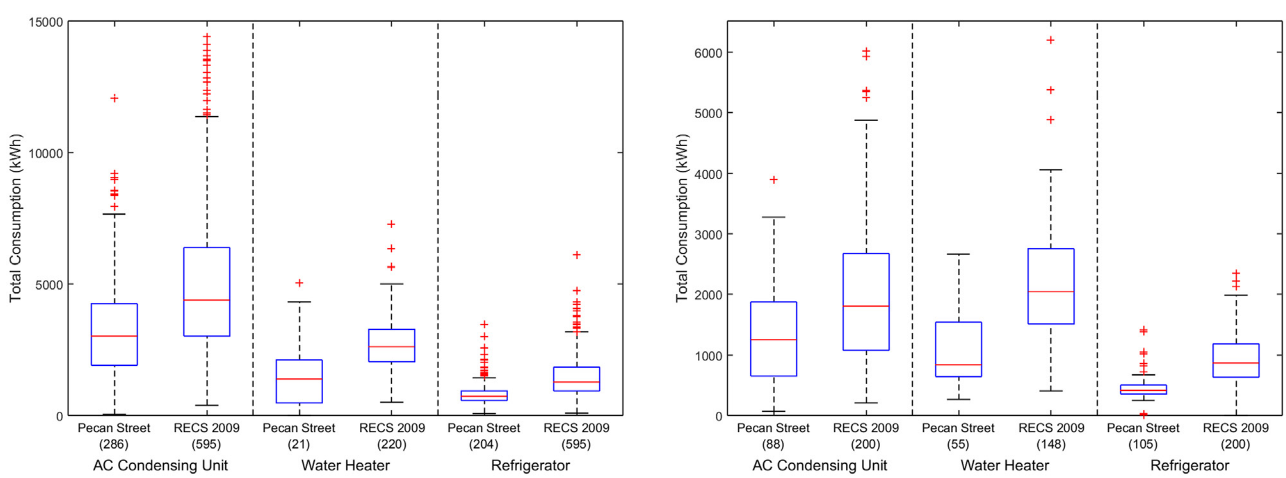

Fig. 2. Device-level energy consumption for homes (left) and apartments (right). Box plots show the median, 25% quartile, 75% quartile, maximum, minimum, and outliers. For each appliance, the left box shows Pecan Street data and the right box shows RECS data. The source and number of data points represented in each plot is shown below each box.

many households use natural gas water heaters. Using the reported weighting factor for each home, these 220 and 148 samples are representative of approximately 1.8 million and 1.2 million American homes and apartments. Despite similar occupancy in both homes and apartments, medians of monitored consumption are around 53% and 41% of RECS reported values, respectively.

Median refrigerator consumption in the monitored homes is outside of the interquartile range of the RECS data, and is around 57% of the RECS median. Median refrigerator consumption in the Pecan Street apartments is also outside of the interquartile range of the RECS data, and is around 48% of the RECS median.

As explained in Section 3.1, the RECS appliance-level consumption estimates are all calculated as a fraction of whole-residence use, so comparing each appliance's contribution to total energy use may be a more appropriate comparison of the two datasets. Fig. 3 shows boxplots of these comparisons.

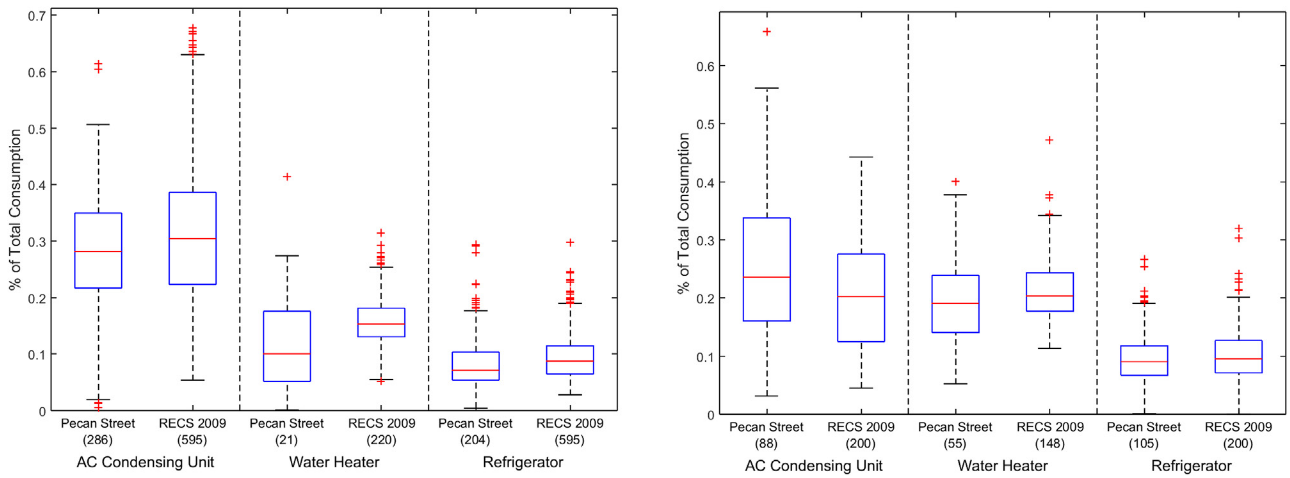

Fig. 3. Device-level energy consumption as a fraction of total residence consumption for homes (left) and apartments (right). Box plots show the median, 25% quartile, 75% quartile, maximum, minimum, and outliers. For each appliance, the left box shows Pecan Street data and the right box shows RECS data. The source and number of data points represented in each plot is shown below each box.

In homes, the largest gap between the RECS and Pecan Street fraction of home load by a single device is around 5 percentage points for water heater consumption. In the RECS sample, models estimated that these devices represent around 15% of total electricity consumption. In the Pecan Street monitored data, median consumption is around 10% of total consumption. In apartments, all appliances are in better agreement. The largest gap between medians is for AC condensing units. RECS models estimate these devices consume 20% of total home energy use, while in the Pecan Street sample this number is around 23%.

6. Discussion and conclusions

In this study, we provide a review of the types of data available to estimate appliance-level electricity consumption in U.S. homes, and a comparison between two specific methods: the survey data collected by the EIA in the Residential Energy Consumption Survey, and detailed submetered data from the Pecan Street Research Institute.

Comparisons of resident demographics, home sizes, and whole-residence energy consumption reveal critical differences between the Pecan Street population from Austin and the RECS' broader sample of Texas residences. These differences mean that the differences between the measured and RECS-estimated appliance-level energy consumption cannot be attributed to problems with the RECS modeling technique.

Overall, we find that Pecan Street homes and apartments consume less energy than comparable residences in the EIA's RECS. The same is true of device-level energy consumption. Submetered Pecan Street appliances consume significantly less energy on average than the RECS device-level consumption estimates. However, the EIA disaggregation model results and the Pecan Street submeter data show similar results in estimating the fraction of total residence energy consumption by air conditioning, refrigeration, and water heating loads in this sample of homes and apartments.

There are several recommendations that arise from this work:

Nationally representative submetered data could help improve a characterization of U.S. residential electricity consumption at the appliance level.

In addition to the Department of Energy's interests in submetering projects, utilities and city governments have already begun to explore the potential of device-level monitoring to improve their understanding of their residential loads. The efforts of Pecan Street, Duke Energy, San Diego Gas and Electric, and the city of Boulder's Community Power Partnership, detailed in Table 1, are evidence of this interest.

In line with recent efforts at EIA, we recommend further consideration of existing submeter installations as a means to continually improve the RECS dataset, and more importantly the understanding of residential electricity consumption. The existing Pecan Street data could be used as a cost-effective way for the EIA to validate end-use disaggregation methods.

Large submetered datasets are becoming more widely available and can be utilized to improve confidence in study findings

At current equipment and labor prices, monitoring the 12,083 housing units included in the most recent RECS would be prohibitively expensive at approximately 20% of the EIA's annual budget (EIA, 2016b). But as the cost of monitoring equipment drops, it may become feasible to monitor a fraction of the residences in the RECS sample. Not all residences and not all loads would need to be included. Fig. 3 above shows that approximately 50% of homes' and apartments' electricity use is consumed by just three devices. Further, Fig. 2 shows relatively little variation in refrigerator energy consumption, so monitoring of these devices could be implemented in only a small number of residences.

Alternatively, given the size and level of detail of the Pecan Street dataset, the existing data could be used as a more cost-effective way for the EIA to validate end-use disaggregation methods. Pecan Street homes could be added to the RECS sample and end-use consumption estimated using the existing disaggregation models. These estimates could then be compared to the homes' and apartments' existing submeter data to validate the standard models, assumptions, and adjustments used by the EIA in these estimates.

Further, the use of these types of datasets should not be considered limited to validating end-use consumption estimates. Monitored device-level data captures a number of factors such as occupant behavior, appliance stock characteristics, and usage patterns, among other things, that have the potential to lend greater confidence to various types of studies. Incorporating these data in place of generic load profiles or aggregate consumption estimates in any type of study or survey can provide a more realistic measure of how energy is actually used in homes, and can serve to better understand and optimize efficiency and conservation methods that will reduce the environmental impacts of residential energy use in the U.S.

Acknowledgments

This work is supported by the Center for Climate and Energy Decision Making (CEDM) through a cooperative agreement between Carnegie Mellon University and the National Science Foundation [grant number SES-1463492]. Additional funding was provided by the Phillips and Huang Family Fellowship in Energy.

References

Berges, M., Goldman, E., Matthews, H.S., Soibelman, L., 2008. Training load monitoring algorithms on highly sub-metered home electricity consumption data. Tsinghua Sci. Technol. 13, 406–411. doi:http://dx.doi.org/10.1016/S1007-0214(08)70182-2.

Birt, B.J., Newsham, G.R., Beausoleil-Morrison, I., Armstrong, M.M., Saldanha, N., Rowlands, I.H., 2012. Disaggregating categories of electrical energy end-use from whole-house hourly data. Energy Build. 50, 93–102. doi:http://dx.doi.org/10.1016/j.enbuild.2012.03.025.

Borgeson, S., 2013. Targeted Efficiency: Using Customer Meter Data to Improve Efficiency Program Outcomes. , pp. 206.

EIA, 2011. How Does EIA Estimate Energy Consumption and End Uses in US Homes? . . (Accessed July 29, 2016) http://www.eia.gov/consumption/residential/reports/2009/methodology-end-use.cfm.

EIA, 2013. Residential Energy Consumption Survey (RECS) End-Use Models. FAQs. http://www.eia.gov/consumption/residential/methodology/2009/pdf/faqs-enduse-models022013.pdf.

EIA, 2016a. Residential Energy Consumption Survey. . (Accessed July 29, 2016) http://www.eia.gov/consumption/residential/index.cfm.

EIA, 2016b. About EIA: Budget and Performance. . (Accessed Jan. 1, 2016) http://www.eia.gov/about/budget_performance.cfm.

Froehlich, J., Larson, E., Gupta, S., Cohn, G., Reynolds, M., Patel, S., 2011. Disaggregated end-use energy sensing for the smart grid. IEEE Pervasive Comput. 10, 28–39. doi:http://dx.doi.org/10.1109/MPRV.2010.74.

Kolter, J.Z., Batra, S., Ng, A.Y., 2016. Energy disaggregation via discriminative sparse coding. Adv. Neural Inf. Process. Syst. 2010, 1153–1161.

Pecan Street Dataport, 2016. Pecan Street Dataport. . https://dataport.pecanstreet.org.

Schwartz, D., Fischhoff, B., Krishnamurti, T., Sowell, F., 2013. The Hawthorne effect and energy awareness. Proc. Natl. Acad. Sci. U. S. A. 110, 15242–15246. doi:http://dx.doi.org/10.1073/pnas.1301687110.

Torres, P., Blackhurst, M., Bouhou, N., 2015. Cross comparison of empirical and simulated models for calculating residential electricity consumption. Energy Build. 102, 163–171. doi:http://dx.doi.org/10.1016/j.enbuild.2015.05.015.

US Energy Information Administration, 2015a. Annual Energy Outlook 2015, vol. 1. DOE/EIA-0383(2013)..

US Energy Information Administration, 2015b. An Assessment of Interval Data and Their Potential Application to Residential Electricity End- Use Modeling. US Energy Information Administration EIA.

US Environmental Protection Agency, 2013. Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2011. EPA 430-R-13–001.Washington DC.

Brock Glasgo is a Ph.D. candidate in Engineering and Public Policy at Carnegie Mellon University. His research with the Climate and Energy Decision Making Center is in developing methods and applications where device-level residential energy use data can be used to inform policy and investment decision-making. Prior to coming to CMU, he worked as a consultant applying data mining tools to develop energy management plans for industrial facilities under utility- and state-sponsored energy efficiency programs. He holds a bachelor's degree in mechanical engineering from the University of Dayton.

Inês Azevedo is an Associate Professor in the Department of Engineering and Public Policy at Carnegie Mellon, where she serves as Principal Investigator and co-director for the Climate and Energy Decision Making (CEDM) Center. Azevedo's research interests lie at the intersection of behavioral and decision-making, environmental, technical and economic issues, such as how to address the challenge of climate change and to move towards a more sustainable energy system. She addresses complex problems in which traditional engineering plays an important role but cannot provide a complete answer. She has participated in several reports from National Research Council and from the U.S. National Academy of Sciences.

Chris Hendrickson is the Hamerschlag University Professor Emeritus, Director of the Traffic 21 Institute at Carnegie Mellon University, member of the National Academy of Engineering and Editor-in-Chief of the ASCE Journal of Transportation Engineering. His research, teaching, and consulting are in the general area of engineering planning and management, including design for the environment, system performance, construction project management, finance and computer applications.