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Using advanced metering infrastructure to characterize residential energy use☆

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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.

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

☆ 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.

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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 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

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.