CADMUS

Southern California Edison Miscellaneous End-Use Loads Methodological Review Final Report

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Cadmus partnered with Relational, Inc., and Fraunhofer Center for Sustainable Energy Systems (the Cadmus team) to conduct this study. Relational, Inc., supported this effort by reaching out to professional contacts to collect information on state-of-the-art disaggregation methods and metering technology. Outreach included one-on-one discussion with professionals at Verlitics, research labs at University Washington, and Home Energy Analytics. Fraunhofer Center for Sustainable Energy Systems worked on a small case study using metered data to provide primary data to support our literature review findings.

Abstract

California investor-owned utilities (IOUs), including Southern California Edison Company (SCE), Pacific Gas and Electric (PG&E), San Diego Gas and Electric (SDG&E), and SoCalGas (SCG), under the guidance of Energy Division, hired Cadmus and subcontractors, Fraunhofer Center for Sustainable Energy Systems (CSE) and Relational, Inc., (the Cadmus team) to conduct a review of the miscellaneous end-use load (MEL) literature, identify gaps in the industry's understanding, and recommend areas for additional research. Individually, miscellaneous end-use loads (e.g., televisions, gaming systems account for small shares of the residential consumption but collectively account for 20% or more. Moreover, their share of residential consumption is growing. As such, California IOUs have an interest in understanding MEL patterns and opportunities for achieving energy and peak demand savings from MELs.

The primary research objective was to determine data, disaggregation methods, and predictive models that would be required to develop residential customer MEL profiles. We performed secondary research that involved a literature review, third-party residential customer databases, and Cadmus team expertise and experience.

Key findings from this research included the following:

- Whole-house energy-use data can be reliably disaggregated into two or three of the largest primary end-use loads using one-hour AMI data.
- Collection of higher frequency data using additional metering technology can enable more accurate disaggregation of large loads and semi-reliable disaggregation of a handful of smaller primary loads.
- Current disaggregation methods and products could be incorporated into energy management technology to allow customers to better understand and manage their electricity use. They could comply with AB-793 if incorporated into user interfaces such that customers could monitor and better understand and monitor large end-use electricity use.
- MELs cannot be reliably estimated through non-intrusive load monitoring (NILM) disaggregation of whole-home power signals or indirectly as a residual after subtracting disaggregated primary end-uses from whole-home loads.

As MEL patterns vary significantly between households, utilities seeking efficiency and demand response savings from MELs could benefit from additional research and development of MELs profiles for different customer types. The Cadmus team recommends that utilities use customer end-use surveys, end-use metering, customer demographic and housing characteristic data, and predictive analytics to develop MEL profiles for various customer segments.

Specifically, the Cadmus team recommends that a future study:

- Compile AMI data and customer demographic and household characteristic data for a representative sample of homes.
- Researchers have applied several approaches to model whole-home or primary end-use loads including statistical regression, stochastic modeling, methods rooted in artificial intelligence, and combinations of these with engineering algorithms. We recommend selecting a few to model MELs.
- Collect appliance saturation data for a sample of homes and directly meter MELs for a subset of the sample.
- Test and compare the accuracy and precision of the selected approaches to estimate MEL patterns.

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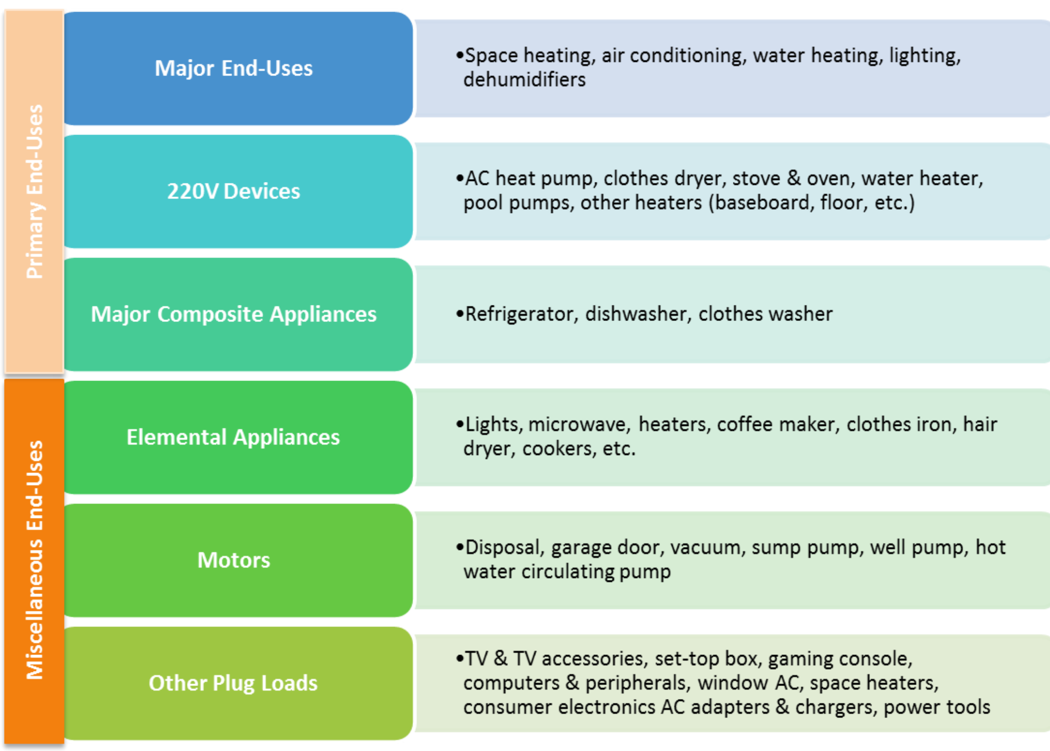
Introduction

The California investor-owned utilities (IOUs), including Southern California Edison Company (SCE), Pacific Gas and Electric (PG&E), San Diego Gas and Electric (SDG&E), and SoCalGas (SCG), under the guidance of Energy Division, hired Cadmus and its subcontractors, Fraunhofer Center for Sustainable Energy Systems (CSE) and Relational, Inc., (the Cadmus team) to research and provide insight on the miscellaneous end-use loads (MELs) patterns in the residential sector. Miscellaneous end-use loads individually account for small shares of the residential load, but collectively account for a substantial portion of the total load. Examples of residential MELs include televisions, gaming systems, home personal computers, and kitchen microwaves.

We grouped residential end uses into six categories according to their load signatures (Figure 1). The top three categories show primary end uses and the bottom three categories show miscellaneous end uses.[1] Primary end uses each account for a substantial portion of the total residential load and include space heating, space cooling, water heating, pool pumps, and refrigerators.

Figure 1. Residential Energy Loads



1 Note that miscellaneous end uses were not consistently defined across the reports and studies Cadmus reviewed for this effort. Where possible, we refer to specific end uses.

A number of studies have demonstrated that MELs are significant, accounting for 20% or more of the residential load.[2] Based on the previous Phase I study, televisions, set-top boxes, desktop computers, and other end uses that can be grouped into entertainment center or home office end-use groups were the most widespread MELs that consumed the greatest amount energy. Given the growth of these MELs, it may be cost-effective for California utilities to continue their efforts to target them for efficiency and peak load savings.[3] Previous research on residential consumer electronics energy consumption has also found dramatic differences in the number of devices per home and in their usage.

Figure 2 illustrates energy consumption in a single home, showing the whole-home load, aggregate primary end-use loads, aggregate MELs, and the single MEL group, home office, which includes desktop computer, printer/scanner/fax, and other office accessories as a component of the whole-home load. Each of the loads presented in Figure 2 can be measured directly using a variety of metering technologies or indirectly using load disaggregation algorithms.[4] In this study, we reviewed the disaggregation technologies and accuracy to determine if disaggregating the primary end-use loads from the whole-house loads and then deriving the MELs would result in a viable option for estimating MELs.

We expect significant variation in MELs between homes.[5] Homes could vary in the types of MELs, the size of individual and total MELs, and when these loads occur during the day. As such, we recommend the utilities collect customer-specific MEL usage data to develop usage profiles and tailor the design, marketing, implementation, and incentives for efficiency and demand response programs. Using the collected data, researchers can conduct analysis to correlate MELs with customer demographics and household characteristics. These data could also be used to develop predictive models that forecast load profiles based on a number of customer and household variables. In this research, we explore the data and methodology that would be required for this research.

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[2] U.S. Energy Information Administration (EIA). *Analysis and Representation of Miscellaneous Electric Loads in NEMS*. December 2013.

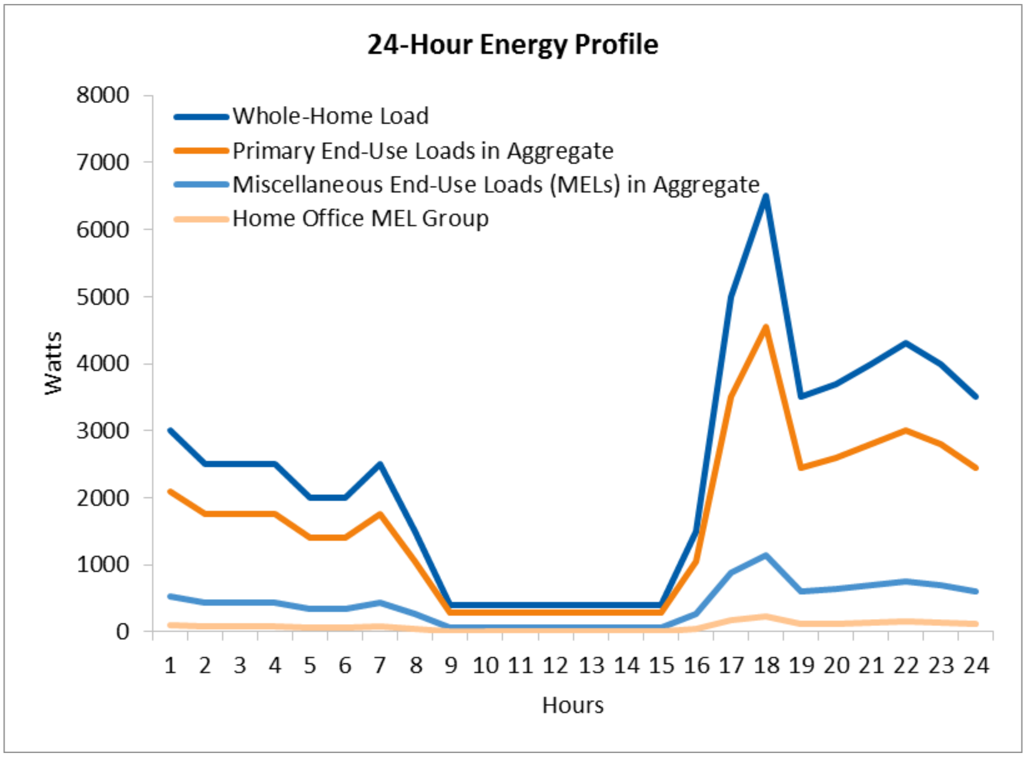
Roth, Kurt. Mckenney, C. Paetsch, and R. Ponoum. *U.S. Residential Miscellaneous Electric Loads Electricity Consumption*. Presented at ACEEE Summer Study on Energy Efficiency in Buildings. 2008.

[3] California Energy Commission, University California Irvine California Plug Load Research Center, Home Energy Analytics, seventhwave, Energy Center of Wisconsin and numerous others have studied efficiency standards and plug load controls as cost effective means to energy savings for years.

[4] Data in Figure 2 are for illustration purposes only and do not represent observed energy consumption.

[5] Urban, Bryan. V. Shmakova, B. Lim, and K. Roth. *Residential Consumer Electronics Energy Consumption*. Presented at ACEEE Summer Study on Energy Efficiency in Buildings. 2013.

Figure 2. Household Energy Consumption



Study Objectives

The objective of this research was to determine the types of data, disaggregation methods, and predictive models that would be required to further study MEL patterns and correlate these loads with customer demographics, housing characteristics, and home energy consumption. We also explored whether or not these methods could be used to provide real-time or near real-time data for load monitoring that would comply with the State of California Assembly Bill Number 793 (AB-793). In the research plan, we developed a number of research questions surrounding disaggregation, demographic data and predictive modeling, in support of planning for a future Phase III study.[6] The Phase III study, should it align with the interests and priorities of California IOUs, will test specific research methodologies and hypotheses determined through this study.

[6] Cadmus. *Southern California Edison Miscellaneous End-Use Research Plan*. Prepared for Southern California Edison. 2015.

The Cadmus team focused its research on identifying data requirements and analytic methods to achieve the following:

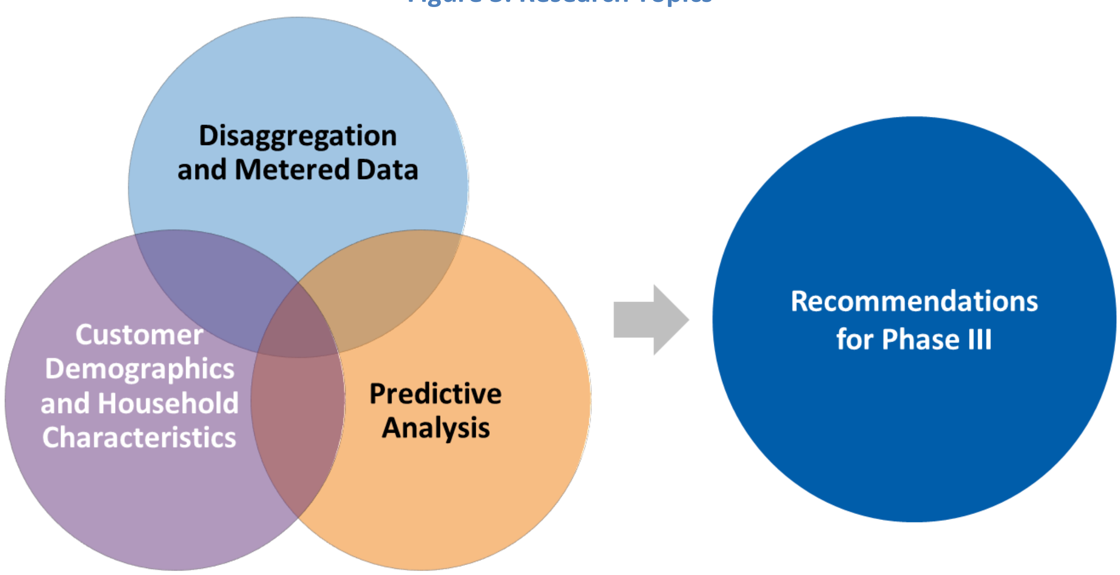
- Determine the volume and quality of existing data and the best disaggregation methods for differentiating end-use loads
- Identify demographic and household characteristics commonly associated with residential MELs[7]
- Predict MELs within distinct residential subpopulations

The Cadmus team reviewed disaggregation methods that utilities can use to identify or estimate end-use loads from whole-house electricity data (e.g., advanced metering infrastructure [AMI] data). We also investigated the availability and accuracy of customer demographic and household characteristic data, and reviewed analytical methods used to study correlations and build predictive models in the Phase III study.

Research Topics and Questions

To guide our research, we developed a set of research questions to investigate three topic areas: disaggregation and metered data, customer demographics and household characteristics, and predictive analytics (Figure 3).

Figure 3. Research Topics



[7] This research will focus on energy profiles in the residential existing homes population. We expect that this research will identify methodology and data requirements that the IOUs can use to guide future studies on new construction, zero net energy housing, multifamily housing, and other sectors.

We designed the research questions listed below to set the foundation for further research in the Phase III study:

- Can disaggregation methods be used to accurately estimate MELs—either directly by disaggregating AMI to estimate MELs or indirectly by subtracting out disaggregated primary end-use loads?
- What is the availability of data on customer demographic and household variables?
- Which methods should be used to identify correlations between MELs and customer and household variables? What methods should be used to cluster or classify customers with similar characteristics and MELs?
- Which methods should be considered for predicting MELs based on customer demographics and household characteristics? What sample sizes would be required to develop a predictive model and subsequent updates?

We have organized our findings by topic area, with each topic area written as a separate chapter. We list the specific research questions used to investigate a particular topic at the beginning of each chapter.

Research Methods

This report summarizes the information that Cadmus team gathered through secondary research for each research topic. Our secondary research relied on the following methods and sources:

- **Literature review:** using online search engines, we reviewed numerous journals and identified over 70 applicable papers and reports published in and outside of the energy industry. We reviewed energy, finance, and statistical journal articles to collect information on recent advances in predictive analytics, clustering, and studies on MELs and disaggregation. While we focused on literature published between 2010 and 2015, we collected a handful of relevant material outside of that date range.
- **Cadmus' expertise and experience:** we assessed technology options for metering and submetering based on our extensive field work and testing. We estimated uncertainty in derived MEls based on subtracting disaggregated primary end-use loads from whole-house loads.
- **Third-party residential customer databases:** using information we received from InfoUSA, we reviewed customer database information to determine the types of data available. We determined its accuracy based on published literature.
- **Third-party industry experts:** using information we collected from disaggregation industry experts, we summarized the current state of nonintrusive load monitoring (NILM) disaggregation technologies.

Findings and Recommendations

Key findings from this research include the following:

- Whole-house AMI energy-use data can be reliably disaggregated into two to three of the largest primary end-use loads when the AMI data are collected at one-hour intervals.

- Higher frequency data (less than one-hour intervals) using additional metering technology (e.g., optical reader) can enable more reliable disaggregation of large end-use loads and semi-reliable disaggregation of a handful of smaller primary end-use loads.
- Current disaggregation methods and products could be incorporated into energy management technology (products, services, or software) that would allow customers to better understand and manage their electricity use. These methods and products would comply with AB-793 if they allowed customers to monitor large energy end uses and to better understand and manage electricity use; however, they would not allow customers to monitor loads associated with individual miscellaneous end uses or miscellaneous end-use groups.
- MELs cannot be reliably estimated either directly through NILM disaggregation of the power signal alone or indirectly as a residual load after subtracting NILM disaggregated primary end-use loads from whole-home loads. Subtracting disaggregated primary end-use loads from the whole-home AMI load will result in imprecisely estimated MELs because of the uncertainty of disaggregated primary end-use loads (i.e., there will only be noise but no signal).
- Utilities can use commercially available products or surveys to collect customer and household data.
- Researchers have applied several approaches to model whole-home or primary end-use loads including statistical regression, stochastic modeling, methods rooted in artificial intelligence, and combinations of these with engineering algorithms.

In the final section of this report, we make recommendations about technology, data, and analytic methods that the IOUs should consider for a Phase III MELs study. In short, the Cadmus team recommends that the study include the following components:

- Compile AMI data for a representative sample of homes
- Compile customer demographic and household characteristic data available from commercial databases (most utilities have already invested in obtaining these data sets)
- Collect appliance data using surveys for a sample of homes
- Collect reliable MEL data using direct metering of MELs in a subset of sampled homes
- Select two to three analytic methods for clustering of homes and prediction of MELs using end-use surveys, customer and household data, AMI whole-home load data, and metered MEL data
- Test and compare the accuracy and precision of MEL predictions that result from each method

Research Topic One: Disaggregation and Miscellaneous End-Use Load Data

The Cadmus team compiled information from our internal experts, reviews of the latest technology and methodology, and industry experts involved with technology research and development to understand costs, hardware options, data frequency, customer burden, advantages, and disadvantages of current primary data collection and disaggregation methods.[8] We developed the research questions outlined in Table 1 to understand current metering technologies, how disaggregation can play a role in detecting MELs, the expected accuracy of disaggregated load profiles, and the size and variability in MELs.

Table 1. Disaggregation and Metered Data Research Questions

#	Research Questions
1	At what intervals are AMI currently collected by each IOU? What is the resolution of the AMI data?
2	What is the catalog of primary end-use load disaggregation methods? What hardware is required to collect the required data? What are the advantages and disadvantages of each method when applied to AMI data? Are other data such as local weather or daylight necessary for AMI load disaggregation available at the required frequency and (geographic) reporting levels?
3	How precise are derived aggregate MELs expected to be for each disaggregation method? Can patterns in aggregate MELs be discerned? What level of accuracy in the derived ME consumption profile based on hourly or 15-minute profiles as compared to daily or monthly average profiles?
4	Which MELs or MEL groups account for the largest consumption? When does energy consumption occur? What is the coincidence of different MELs? How large is variation in MELs between homes?

Findings by Research Question

This section details our findings for the research questions listed in Table 1.

Research Question 1: At what intervals are AMI data currently collected by each IOU? What is the temporal resolution?

[8] Disaggregation in this research is synonymous with nonintrusive load monitoring or nonintrusive appliance load monitoring (NILM or NIALM) which relies on whole-home data collection (e.g., power, current, voltage), feature extraction, and end-use classification.

Findings

The California IOUs collect residential AMI data at hourly intervals.[9] With the installation of a Home Area Network (HAN) gateway, the IOUs can collect 10-second interval data.[10] A number of HAN gateway technologies are compatible with SCE meters.

Research Question 2: How precise are derived aggregate MELs expected to be for each disaggregation method? Can patterns in aggregate MELs be discerned? What level of accuracy in the derived ME consumption profile based on hourly or 15-minute profiles as compared to daily or monthly average profiles?

Findings

Catalog of Primary End-Use Load Disaggregation Methods

A catalog of primary end-use load disaggregation methods is available in a recent technical report from Pacific Northwest National Laboratory (PNNL).[11] We can categorize current disaggregation methods based on a combination of data requirements and detection capabilities. Most rely on appliance-level data that are used to develop and train algorithms to disaggregate appliance loads from the whole-home or circuit loads. Typically, end-use loads are identified based on observed changes in power and patterns in those changes (transitions) over time or based on harmonics and waveform analysis. The frequency of the collected data and the type of data (power, current, voltage, etc.) determine which methods can be used. AMI data alone will not provide sufficient granularity for disaggregation algorithms to be able to detect more than a handful of primary loads.[12]

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[9] Southern California Edison. "Smart Meters FAQ." Accessed online June 20, 2016: https://www.sce.com/wps/portal/home/customer-service/my-account/smart-meters/FAQ/

PG&E. "How the SmartMeter system works and what it can do for you." Accessed online June 20, 2016: http://www.pge.com/en/myhome/customerservice/smartmeter/facts/index.page

San Diego Gas & Electric. "Smart Meter FAQ." Accessed online June 20, 2016: http://www.sdge.com/residential/about-smart-meters/smart-meter-faq

SoCalGas. "Smart Meter FAQ." Accessed online June 20, 2016: https://www.socalgas.com/save-money-and-energy/advanced-meter/about-the-program

[10] Southern California Edison. "Home and Business Area Network." Accessed online March 9, 2016: https://www.sce.com/wps/portal/home/residential/my-account/hanlogin

[11] Mayhorn, E.T., R. Butner, M. Baechler, G. Sullivan, and H. Hao. *Characteristics and Performance of Existing Load Disaggregation Technologies.* Prepared for Pacific Northwest National Laboratories. 2015. Accessed online June 20, 2016: http://www.pnnl.gov/main/publications/external/technical_reports/PNNL-24230.pdf

[12] End-use loads refer to the load associated with specific end-uses or appliances. A number of solutions exist, for example, those provided by Home Energy Analytics and seventhwave that disaggregate five or more end-use groups (e.g., cooling equipment).

Table 2 shows an overview of the data frequencies and detection capabilities. The size of the loads also dictates the number of end uses or appliances that can be disaggregated reliably.[13] A number of statistical approaches have been used to disaggregate end-use loads from aggregate loads. Multivariate regression (also referred to as conditional demand analysis) can identify larger end-use loads and has used household appliance surveys or market saturation estimates in a number of applications.[14] A number of studies have used regression analysis to estimate the effects of different end uses on the whole-home load. In all of these, the space heating and cooling loads were defined as a separate component and modeled either as a function of outside temperature or a related variable (e.g., heating degree day [HDD] or cooling degree day [CDD]). Many included variables indicating the presence or absence of primary end uses (e.g., refrigeration, clothes washers and dryers). Most considered MELs as an aggregate, "other," category and used resident characteristics as a proxy for the combination of factors that could increase or decrease loads attributable to MELS. Most studies applied regression analysis to whole-home energy consumption data at hourly, 30-minute, or 15-minute frequencies. Researchers used home survey data to construct appliance-related variables and often mixed building simulation model results with home survey data on building characteristics (e.g., square footage, insulation) to build the space heating and cooling components of the regression models. In Appendix B, we review multivariate regression approaches that were used in previous studies.

Table 2. Disaggregation Methodology Overview[15]

General Method	Sampling Rate	Identification State	Detection Capabilities	End Uses Detected
Low Sample Rate Statistical Analysis	One hour to 15 minute	Transition (on/off) Patterns over time	About 3 large end-use loads	Temperature and time dependent loads (e.g., HVAC, lighting)
	One minute to 1Hz	Transition (on/off) Patterns over time	Up to 10 large end-use loads	Same as previous and refrigerator, pool pump, washers, dryers, etc.
	1Hz to 60Hz	Transition (on/off) Patterns over time	10 to 20 end-use loads	Same as previous and small electronic devices (e.g., DVD, wireless routers, printers)
	10 kHz to 40kHz	Current and voltage	20 to 40 end-use loads	Same as previous and

13 Armel, K.C., A. Gupta, G. Shrimali, and A. Albert. *Is Disaggregation the Holy Grail of Energy Efficiency? The Case of Electricity.* Precourt Energy Efficiency Center Technical Paper Series. 2012.

Verlitics LLC. Personal communications with Hal Alles, Chief Technical Officer. December 2015.

Home Energy Analytics. Personal communications with Lisa Schmidt, President and CEO. December 2015.

14 Northwest Power and Conservation Council and Northeast Energy Efficiency Partnerships. *End-Use Load Data Update Project Final Report. Phase 1: Cataloguing Available End-Use and Efficiency Measure Load Data*. 2009

15 *Ibid*. (Armel, K.C., et al. 2012)

General Method	Sampling Rate	Identification State	Detection Capabilities	End Uses Detected
Harmonic or Waveform Analysis		Medium order harmonics		smaller appliances (e.g., toasters, computers)
	>1MHz	Current and voltage High order harmonics	40 to 100 end-use loads	Same as previous and separate end uses of the same type (e.g., differentiates between two lights)
Electromagnetic Interference (EMI) Analysis[16]	> 1kHz	High frequency voltage, current, and electromagnetic interference	Up to 30 end-use loads	

Hardware

A variety of options exist to collect and transfer home consumption data to researchers performing end-use studies. The Cadmus team has reviewed and lab- or field-tested most of the following options:

- Optical or pulse readers that attach to the utility meter. Vendors include WattVision, Blue Line Innovations, Efergy, and Northstar. They collect whole-house data.
- Current transformer meters (CT meters) at the electric panel. Options include TED, JetLun, Building 36, eGauge, Brultech Research, CurrentCost, Dent, and Watt Node.
- Collar-based meters installed between the meter socket and the meter. These meters require installation by utility personnel and generally disconnect power for up to one minute. Vendors include Carina and Enetics.
- Home area network gateways to utility-installed smart meters. Vendors, including Rain Forest, offer ZigBee-compatible devices that communicate with smart meters and send consumption data to a user-designated server (i.e., directly to a disaggregation vendor).
- Appliance or plug-load meters. Vendors include Building 36 and JetLun.
- Hybrid meter. Cadmus built a hybrid meter that combines an optical reader with a cellular model and power supply which performed well under very preliminary testing; we did not deploy the technology but could develop a robust solution for future use.[17]

[16] Belkin owns the ElectriSense technology and does not currently offer commercially available EMI sensor products.

[17] Cadmus is in the preliminary stages of developing a meter that combines an optical revenue reader with a cellular modem and long-term power supply. The optical reader provides electric demand (kW) at a predetermined interval and is stored on a flash drive or similar device. An internal modem sends the data once a day to Cadmus' secure server. The meter is enclosed in a waterproof box with power and PV supply. The advantage of this option is that it does not require placing any devices in the home or using the customer's internet connection. It may now be possible to connect the optical/pulse readers to a cellular network, eliminating the need for new meter development and decreasing intrusions to the customer.

- Specialized, very high-frequency data meters that measure the physical properties of waveforms. Not currently available on the market; technology has been developed and undergone limited testing.
- Electromagnetic interference (EMI) meters. Belkin owns ElectriSense, a potential solution for automatically detecting and classifying electronic device usage from a single point of sensing. Modern consumer electronics and fluorescent lighting systems employ switch mode power supplies (SMPS) with higher efficiency. They generate high frequency EMI during operation. The EMI propagates through power wiring.[18]

Table 3 lists the hardware options, in order of increasing cost per device, and typical data frequency, customer burden, advantages, and disadvantages of each option.

Except for the plug meters and the EMI meters, the hardware options listed in Table 3 were not designed to accurately track MELs. Additional research and development will be required to further develop these technologies to enable consistent and accurate data collection for major end uses and MELs, as we discuss in the next section.

18 Microsoft Research. Personal communications with Sidhant Gupta, Research Scientist. December 2015. Gupta showed analytically and using in-home experimentation that EMI signals are stable and predictable based on the device switching frequency characteristics. He asserted that, unlike past transient noise-based solutions, this approach could provide the ability for EMI signatures to be applicable across homes and to differentiate between similar devices in a home. He has evaluated the technology in seven homes, including one six-month deployment. He reported results from that study which indicated that ElectriSense can identify and classify the usage of individual devices with a mean accuracy of almost 94%.

Table 3. Data Hardware Summary

Price*	Hardware Option	Data Frequency	Customer Burden	Advantage	Disadvantage
$	Meter Sensor at Plug Load	Once per 1-15 minutes	High	• Highly accurate for each appliance and no need to disaggregate load	• Portable device metering may not be feasible due to current plug meter technology • High intrusiveness level
$	Home Area Network Gateway	Once per 1-10 seconds	Low	• Where available, technology already is in place • Connects to popular cloud services • Data available for authorized 3rd party analyses	• Only works with ZigBee smart meters • Not every customer will have this installed
$$	Optical/Pulse Readers	Once per 1 minute to 1Hz	Low	• Low intrusiveness level • Good price point • Data capture at sufficient frequency for load disaggregation (large appliances)	• Data frequency limited • Data can be intermittent • Exposed to elements and theft
$$$	CT Meters	0.5Hz to 1Hz	Medium	• Low intrusiveness level • Data capture at sufficient frequency for load disaggregation (large appliances)	• Depending on jurisdiction, requires installation by licensed electrician • The higher price point may be become a barrier for large-scale deployment
$$$$	Hybrid	Once per 1 minute to 1Hz	Very Low	• Least intrusive option • Does not require customer interaction	• Higher costs due to cellular monthly fees; requires its own power supply
$$$$	Collar Meter at Utility Meter	Once per minute	High	• Metering occurs outside of the home; higher frequency possible than with optical readers	• Requires utility electrician to install meter. Power to house must be temporarily cut
$$$$	Specialized	1kHz to 1Hz	Low to Medium	• Data capture at sufficient frequency to enable small plug appliance load disaggregation	• High cost and not commercially available • Controlled laboratory testing only
N/A	Electromagnetic Interference (EMI) Sensing	9kHz to 30MHz	Low	• Automatically detects and classifies use of electronic devices from a single point of sensing • Relies on switch mode power supplies generating high frequency EMI • Capable of differentiating between similar devices	• Not currently commercially available

$** = Less than $150 per unit; ***$$= $150 to $250 per unit; ***$$$*** = $250 to $500 per unit; ***$$$$*** = More than $500 per unit.

Additional Data Requirements

Most algorithms incorporate geographic and weather data to account for dependencies of end-use loads on these factors. Many studies also included appliance survey data, including self-reported end uses in the home, to provide a ground truth for the algorithms.[19]

Summary

High frequency energy data (or direct plug metered data) will be required to detect MELs. Monitoring individual end-use loads in California's residential customer population would require direct plug-load metering of end uses or end-use groups in a sample of home. Disaggregating larger MELs from whole-home data (i.e., smaller electronic devices including DVD players, wireless routers, etc.), will require 1 to 60Hz data. Accordingly, to disaggregate whole-home energy consumption into distinct MEL or MEL group profiles, researchers should consider one of the following solutions:

- Optical or pulse meters installed in each home
- Panel or circuit meters in each home
- Hybrid solution
- Specialized hardware
- EMI meters in each home

There are challenges with using plug meters to record end-use energy consumption. The current state of plug-meter technology requires one meter to be used for one outlet and one end use. This means that plug meters may not be able to collect high-quality data for portable devices. One implication of this on a future study or effort to collect MEL data is that the scope of end uses included in the study will need to be limited to a subset of non-portable end uses or strict guidelines put in place directing study participants to consistently use the same plugs for their set of portable devices. Newer technologies are being developed that claim to track appliances, but they have not been tested independently.[20] Alternatives include developing an energy logger application for smart phones, tablets, and laptops that can monitor energy consumption while the device is plugged in. Development applications exist to track energy consumption in some forms in some operating systems that can be expanded on in future research.[21]

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19 NegaWatt. "Residential Disaggregation." Prepared for San Diego Gas & Electric Company. 2014.

Fraunhofer CSE. Personal Communications with Michael Zeifman. 2015.

20 SafePlug is a technology developed for the dual purpose of increasing safety and monitoring energy use. Accessed online June 20, 2016: http://www.safeplug.com/energy-management.html

21 Instruments application gathers data from a running application and presents it in a graphical timeline. Accessed online June 20, 2016. https://developer.apple.com/library/ios/documentation/Performance/Conceptual/EnergyGuide-iOS/MonitorEnergyWithInstruments.html

Research Question 3: Which MELs or MEL groups account for the largest consumption? What is the timing of consumption? What is the coincidence of different MELs? How large is variation in MELs between homes? What is the distribution of MELs in the population?

Findings

Overview

In our review of the literature, Cadmus did not identify studies that provided estimates of MEL timing, coincidence, variation, or distribution based on representative samples of residential populations similar to the California IOU residential population. In a future study that aims to answer these questions, driving or limiting factors that must be considered in the study design include both the variation in MEL timing and coincidence but also the uncertainty with which MELs are measured. The sampling plan must be developed so that the sampled data can be used to detect patterns and differences in MELs in the population, given the variability and uncertainty. In this research we focused on estimating the uncertainty in derived MELs, estimated by subtracting disaggregated primary end-use loads from whole-house loads, to determine if the derived MELs could be used in a future study to detect patterns. In this section, we summarize our findings on the uncertainty in MEL data that can be expected when MELs are derived by subtracting disaggregated primary end-use loads from whole-home AMI data.

Cadmus estimated the uncertainty of derived aggregate MELs based on the uncertainty of combined disaggregated primary end-use loads. To do this, we set the derived aggregate MELs equal to the difference between the whole-house load and the sum of disaggregated primary end-use loads, as expressed in Equation 1.

Equation 1

$$\boldsymbol{Derived\ Aggregate\ MELs = Household\ Load - \sum_{h=1}^{H} Disaggregated\ Primary\ End\text{-}Use\ Load_h}$$

We expressed the uncertainty of the derived aggregate MELs equal to uncertainty of the difference between the whole-house load and sum of the disaggregated primary end-use loads (i.e., we set the uncertainty of the left hand side of Equation 1 equal to the uncertainty of the right hand side of Equation 1). We assumed that the whole-house load could be measured with 100% accuracy, or 0% uncertainty, and that the uncertainty of each disaggregated primary end-use load is equal to 100% minus the reported accuracy.[22] For example, if the accuracy of disaggregated pool pump loads was reported to be 75%, we set the uncertainty to 100% to 75%, or 25%. Further, we assumed that the uncertainty of the derived aggregate MELs is a function of the uncertainty of the sum of disaggregated primary end-use loads, as expressed in Equation 2, where *h* denotes a single disaggregated load and *H* denotes the total number of disaggregated loads.

22 Accuracy was defined as a function of the relative root mean squared error (RMSE), where accuracy=1-RMSE/average(x) where x represent the ground truth measurements.

Equation 2

$$\boldsymbol{Uncertainty(Derived\ Aggregate\ MELs)} = \boldsymbol{Uncertainty\left(\sum_{h=1}^{H} Disaggregated\ Primary\ End\text{-}Use\ Load_h\right)}$$

We determined the uncertainty of the sum of disaggregated primary end-use loads based on the uncertainty of individual disaggregated loads assuming that the accuracy is a function of size of the disaggregated load because larger loads were generally disaggregated with higher accuracy. When we divide the uncertainty by the size of the load, then we can express uncertainty as a percentage (Δ) in Equation 3.

Equation 3

$$\begin{aligned} &\Delta \boldsymbol{Derived\ Aggregate\ MELs} \\ &= \frac{\boldsymbol{Uncertainty(Derived\ Aggregate\ MELs)}}{\boldsymbol{Derived\ Aggregate\ MELs}} \\ &= \frac{\boldsymbol{Uncertainty\left(\sum_{h=1}^{H} Disaggregated\ Primary\ End\text{-}Use\ Load_h\right)}}{\boldsymbol{\sum_{h=1}^{H} Disaggregated\ Primary\ End\text{-}Use\ Load_h}} \\ &= \Delta \boldsymbol{Disaggregated\ Primary\ End\text{-}Use\ Loads} \end{aligned}$$

We can solve Equation 3 for the uncertainty of derived aggregate MELs (ΔMELs) and/or for the uncertainty of disaggregated primary end-use loads to understand the relationship between the two and then use these equations to calculate and plot the relationship between the size of the loads and the expected uncertainty in derived MELs. We present this relationship in Figure 4 for a number of scenarios that differ depending on the percent of the whole-house load that MELs account for and a range of primary end-use loads and derived MELs uncertainty levels.

We provide details on the data used and resulting uncertainty below.

Accuracy and Uncertainty of Disaggregated End-Use Profiles

In our review of previous studies, we found that the accuracy of disaggregated primary end-use loads varied depending on the granularity of the input data as well as the relative size of the end-use load, in comparison to both the household load and loads of other end uses. End uses that use more energy relative to others are generally estimated with higher accuracy and thus lower uncertainty. Higher frequency data generally results in more accurate and less uncertain primary end-use load estimates.

In Table 4, we summarized the results of a study sponsored by SDG&E. Researchers reported accuracy for a number of disaggregated end-use loads based on NILM algorithms developed by four vendors using data sets of varying frequencies. SDG&E's reported results for each vendor and data source, as noted in the column headings. The disaggregation vendors used home area network data at 10-second,

1-minute, and 15-minute intervals and Green Button[23] AMI data at hourly intervals to develop algorithms based on the electric consumption data alone (pre-survey) and in combination with appliance survey data (post-survey). We translated the accuracy into uncertainty as described above for the purposes of inferring uncertainty in derived MELs in the next section.

Following the same guidelines as in the SDG&E report, we labeled uncertainty as acceptable if ΔPrimary End-Use Load was between 0% to 30%, fair if between 30% to 40% as fair, and poor if 40% or higher. Good is color coded as green, fair as yellow, and poor as red; empty cells indicate that vendors did not report results.[24] Higher accuracy, corresponding to lower uncertainty, is better; the values are unit-less and are a function of the root mean squared error. Accuracy of 1.0 or uncertainty of 0% would represent an algorithm that predicted end-use loads perfectly in 100% of the time intervals, with no variation from the true load.

Overall, two vendors were able to develop algorithms that predicted pool pumps and electric vehicle charging stations with uncertainty lower than ±30%. Including the survey data decreased uncertainty in some cases, had no effect in most cases, and increased uncertainty in one case (Vendor B, home area network, 10-second data). Almost all monthly predictions had very poor uncertainty. Uncertainty ranged from ±12% (good) to ±95% (very poor) across all 10 end uses for daily predictions. From these results, we see that primary end-use loads could be disaggregated from 10-second data with uncertainty between ±12% and ±75%. Hourly Green Button AMI data was disaggregated with uncertainty between ±19% and ±95%. Electric vehicle charging, pool pumps, refrigerators, and dryers were end uses with the most accurate and least uncertain predictions in this study.

The study report did not disclose vendor names, but represented them as vendors A, B, C, and D. Similar results were reported in the PNNL disaggregation review.[25]

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23 Green Button is an initiative offered by numerous utilities to provide energy usage data and analytics. More information is available online: http://www.greenbuttondata.org

24 *Ibid* (NegaWatt 2014).

25 *Ibid* (Mayhorn, E. et al. 2015)

Table 4. Uncertainty of Predicted Daily Primary End-Use Loads

End Use	Home Area Network Pre-Survey (10 second)		Home Area Network Post-Survey (10 second)		Green Button Pre-Survey (1 hour)		Green Button Post-Survey (1 hour)	Home Area Network Improved (10 second)
	Vendor B	Vendor C	Vendor B	Vendor C	Vendor C	Vendor D	Vendor C	Vendor B
Electric vehicle	Acceptable		Acceptable	Acceptable		Poor	Poor	
Pool pumps	Acceptable	Acceptable	Acceptable	Acceptable	Fair	Fair	Acceptable	Acceptable
Refrigerator	Acceptable	Poor	Acceptable	Poor				Acceptable
HVAC	Poor		Poor					Fair
Water heater	Poor		Poor					Fair
HVAC and water heater		Poor		Poor	Poor		Poor	
Dryer		Fair		Fair		Fair		
Oven		Poor		Poor	Poor		Poor	
Cooking and washer/dryer	Poor		Poor					Poor
Solar	Poor							Poor

Table 5. Uncertainty of Predicted Monthly Primary End-Use Loads

End Use	Home Area Network Pre-Survey (10 second)	Home Area Network Pre-Survey (1 minute)	Home Area Network Pre-Survey (15 minute)	Green Button Pre-Survey	Green Button Post-Survey
	Vendor A	Vendor A	Vendor A	Vendor A	Vendor B
Pool pumps					Acceptable
Refrigerator	Poor	Poor	Poor	Poor	
HVAC	Poor	Poor	Poor	Poor	Poor
Microwave	Poor	Poor			
Washer/dryer	Poor	Poor	Poor		
Dishwasher	Poor	Poor	Poor		

Accuracy and Uncertainty of Derived MELs

The Cadmus team used the methods described above to understand the relationships between the uncertainty in derived aggregate MELs and the size and uncertainty of disaggregated primary end-use loads. Our estimates of uncertainty in derived aggregate MELs are represented as curves in the plot in Figure 4. These estimates are based on a range of load sizes (horizontal axis)[26] and a range of uncertainty in the disaggregated primary end-use loads (vertical axis). As previously discussed, we used the results from the SDG&E study[27] to infer the level of uncertainty expected in disaggregated primary end-use loads. We calculated the combine uncertainty of the sum of disaggregated loads based on the variance of the sum of random variables to estimate the resulting uncertainty in the derived MELs.

We considered a range of the portion of the whole-home loads that primary end uses and MELs could account for and a range of expected uncertainty in the disaggregated primary end-use loads. Each curve in the plot represents a level of uncertainty in the derived aggregate MELs load, increasing from 0% toward the bottom of the plot up to 100% toward the top of the plot.

The horizontal axis shows the portion of the household load that the combined MELs could account for. We allowed the aggregate MELs to range from 0% to 80% of household energy consumption but expect them to account for between 20% and 40% of the load, as outlined by the orange box. The vertical axis represents the expected uncertainty in disaggregated primary end-use loads. We inferred the uncertainty in primary end-use loads based on the accuracy, as previously described, and accounted for uncertainty in the sum of disaggregated results. We expect the combined uncertainty of the sum of disaggregated primary end-use loads to range from ±30% to ±80%, outlined by the orange box.

The curves in the figure indicate the level of uncertainty that we expect for derived MELs, estimated by subtracting the disaggregated primary loads from the whole-home load. For example, if MELs are 30% of the load and disaggregated primary end-use loads are estimated with ±30% uncertainty, then we can expect uncertainty around the MEL estimate to be ±70%, illustrated by the orange dot. Clearly, with higher uncertainty in primary end-use loads, we can expect uncertainty in derived MELs to be so high that the resulting estimate is fairly uninformative.

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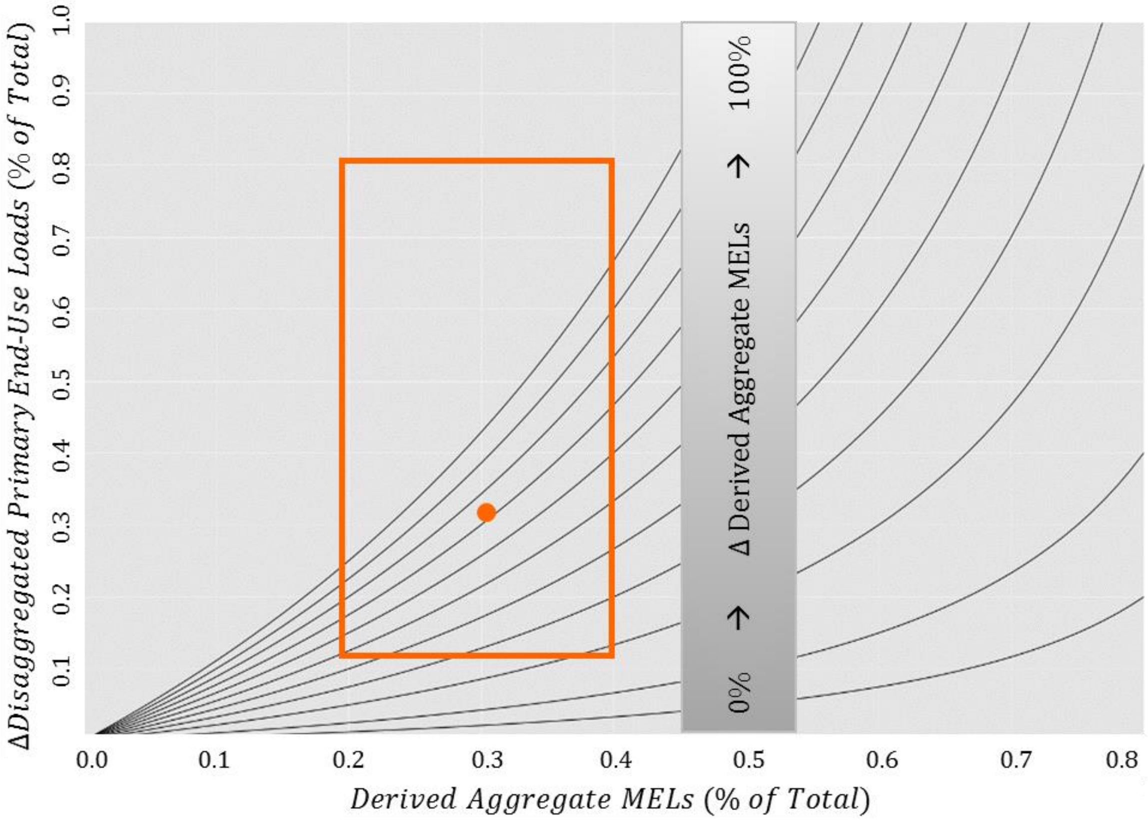
26 Note that the horizontal axis in the plot represents the percentage of the household load that is accounted for by aggregate MELs, ranging from 0% up to 80%. The percentage of household load accounted for by the combined disaggregated primary end use loads is simply the converse of this, ranging from 100% on the left-hand side of the plot, down to 20% on the right-hand side.

27 *Ibid*. (NegaWatt 2014).

Figure 4. Estimated Uncertainty of Derived MELs



Accuracy and Precision in MELs Derived from Low Frequency Data

Based on the results for hourly and sub-hourly data, we expect lower frequency data to result in primary end-use disaggregation with even higher uncertainty, or lower accuracy. In other words, we expect that MELs derived from low frequency data will be estimated with uncertainty high enough to mask any patterns or information at the household level.

Detecting Patterns in Derived Aggregate MELs

It is unlikely that patterns in derived MELs can be detected, even with 10-second data. The box in Figure 4 shows the upper and lower bounds of the expected uncertainty for derived MELs given the uncertainty observed in primary end-use loads in previous studies. In this scenario, the results are based on 10-second data. Even in the case where MELs are 30% of the total load and uncertainty in primary end-use loads is ±30% (which is optimistic, based on the SDG&E study), then uncertainty in the derived MELs would be ±70%. Detecting patterns in derived MELs that have this level of uncertainty is unlikely.

Case Study

The Cadmus team performed a case study to provide a ground-truth from directly observed data for our estimates of uncertainty and conclusions about the feasibility of detecting MELs by subtracting disaggregated primary end-use loads from AMI data. The findings of this case study are presented in

Appendix A and support the findings from our literature review. Low frequency data, even at 5- or 15-minute sampling rates, result in disaggregated loads that do not align definitively with any metered end use.

Research Question 4: Which MELs or MEL groups correspond to the largest consumption? When do MELs occur? Are different MELs independent or correlated? How large is the variation of MELs across homes? What is the distribution of MELs in the population of utility customers?

Findings

In a 2013 U.S. Energy Information Administration (EIA) study,[28] electronics and computers represented the largest groups of MELS among residential utility customers nationally. Among individual end uses, televisions, pool heaters and pumps, desktop personal computers (PCs), set-top boxes, and ceiling fans were among the MELs that used the most energy. Projections showed expected decreases in average energy consumption for most MELs but increases for set-top boxes, rechargeable electronics, security systems, portable electric spas, and audio equipment. In the EIA 2012 Annual Energy Outlook, MELS constituted a substantial portion (roughly over 35%) of the total projected end-use shares of electricity between 2005 and 2035.[29] The end uses in this projection included toasters, blenders, shavers, vacuums, electric toothbrushes, curling irons, and hair dryers in one group and TVs, PCs, set-top boxes, video game consoles, rechargeable devices, DVD players, coffee makers, microwaves, home audio, spas, and security systems in another group.

In Figure 5, we reproduced the 2013 EIA summary various end-use contributions to the residential load, with combined MELs accounting for just over 25% of the total.

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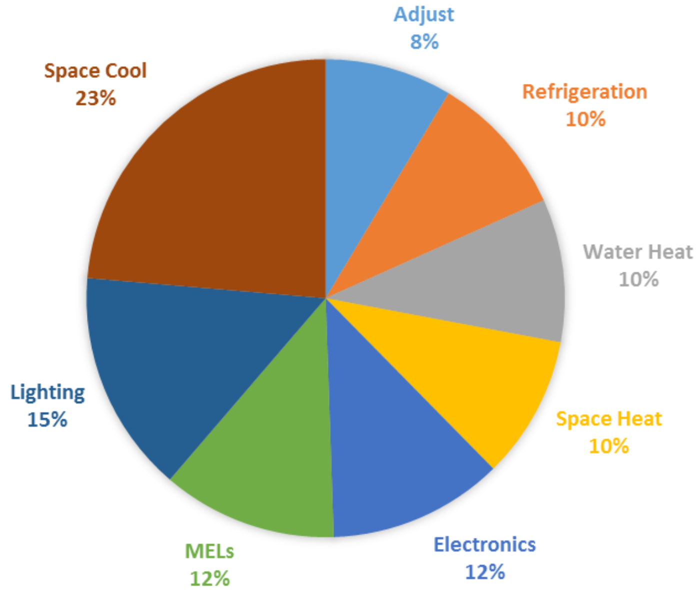
[28] Navigant Consulting, Inc. *Analysis and Representation of Miscellaneous Electric Loads in NEMS.* Prepared for the U.S. Energy Information Administration. December 2013.

[29] U.S. Energy Information Administration. 2012. Annual Energy Outlook 2012 with Projections to 2035. Accessed online June 20, 2016: http://www.eia.gov/forecasts/aeo/pdf/0383(2012).pdf

Figure 5. 2013 EIA Estimate of MEL Contribution to Residential Load



Numerous authors and studies emphasize that the timing of consumption is an important factor and also highlight the differences between measuring idle or standby and active modes of MELs.[30] MELs in idle modes often continue to add to the household's load, despite appearing to be in the off mode to the customer. Detecting or estimating MELs in idle mode is difficult.[31] In a report to the Consumer Electronics Association,[32] hourly load shapes are provided for a number of MELs, including Blu-ray disc players, desktop computers, DVD devices, etc.

Topic One: Summary of Findings

Current disaggregation technologies (both open-source and proprietary) are effective at identifying large primary end-use loads (greater than 1,000 watts) including HVAC and water heating equipment. The number of detectable end uses is dependent on the size of each end-use load and the frequency or sampling rate of energy consumption data. High resolution energy monitoring with sampling rates of 60 observations per second (60Hz) or greater can reliably identify loads above 50 watts. Because most miscellaneous end-use loads are less than 50 watts, with the exception of some televisions and game consoles with loads around 100 watts, higher frequency data will be required to detect MELs, on the order of between 1 kHz and 1MHz. The hardware required to collect these high frequency data are not commercially available at this time. Further, disaggregation technologies typically require a state

30 NRDC. *Plug-in Equipment Efficiency.* Issue Brief. 2015.

31 Nelson, J., A.J. Berrisford, and J. Xu. *MELs: What Have We Found through End-use Metering?* Presented paper. ACEEE Summer Study on Energy Efficiency in Buildings. 2014.

32 Fraunhofer CSE. *Energy Consumption of Consumer Electronics in U.S. Homes in 2010*. Prepared for Consumer Electronics Association. 2011. Available online: http://www.cta.tech/CorporateSite/media/Government-Media/Green/Energy-Consumption-of-CE-in-U-S-Homes-in-2010.pdf]

transition (powering from off to on or vice versa) to occur in order for a device to be reliably identified. Many MELs will not transition frequently throughout the day, making them difficult to detect using data sampled at more than 1-minute intervals.

Our findings do not support the hypothesis that evaluators can derive aggregate MELs by subtracting disaggregated primary end-use consumption from whole-home consumption. The amount of uncertainty in derived MELs is highly dependent on their contribution to the whole-home load and the accuracy and uncertainty of the disaggregation algorithm primary end-use loads. Existing technologies applied to AMI data will not provide accurate disaggregation of MELs.

Optical or pulse meters and panel or circuit meters both provide moderate per-home cost options to collect data at higher frequencies, between once per second (1Hz) to once per minute. They are both moderately intrusive for the customer but increase the number of detectable primary end-use loads (up to 10) using disaggregation methods. The end uses that can be disaggregated include the large, temperature and time-dependent loads such as those of refrigerators, pool pumps, washers, and dryers. Although we could derive an estimate of aggregate MELs as the difference between the whole-home load and disaggregated primary loads, individual MELs or MEL groups likely would not be differentiated from the noise. At a similar price point, however, plug meters offer a solution to increase the number of measured end-use loads and to directly meter the loads rather than disaggregating them. To date, due to challenges with implementation, data collection, and analysis, systematic and objective studies summarizing the performance of different NILM disaggregation technologies have not yet been published.[33] Therefore, the findings presented in this report are based on limited information and are tentative.

Industry benchmarks for uncertainty in individual disaggregated primary end-use loads likely lies between ±20% and ±100%, which would result in derived aggregate MELs uncertainty between ±50% and ±100%. We based the reported uncertainty levels[34] in disaggregated primary end-use loads on studies that utilized 10-second and 5-minute interval data. We found wide variation in reported accuracy and uncertainty, depending on the disaggregation vendor, primary end uses detected, and the number of modifications required to update algorithms to enhance detection capabilities. When we considered subtracting aggregate primary end-use loads from whole-home loads to derive aggregate MELs, we accounted for the uncertainty in the aggregate primary loads and the contribution of both aggregate primary loads and MELs to the whole-home load.

33 Mayhorn, E.T., Butner, R.S., Baechler, M.C., Sullivan, G.P., and H. Hao. "Characteristics and Performance of Existing Load Disaggregation Technologies." Pacific Northwest National Laboratories publication: PNNL-24230. 2015.

Ibid. (NegaWatt 2014).

34 Uncertainty here is equal to 100%-reported accuracy.

Research Topic Two: Customer Demographics and Household Characteristics

The Cadmus team drew on in-house expertise, interviewed industry experts, and reviewed the latest studies and reports in technology research and development to understand the availability and accuracy of customer demographic, household characteristic, and AMI data. Specifically, our team reviewed the Residential Building Stock Assessment (RBSA) Metering Study,[35] California Statewide Lighting and Appliance Efficiency Saturation Study[36] and the most recent Residential Energy Consumption Survey (RECS).[37] We determined the types of residential customer demographic and household characteristic data that are routinely collected by the California IOUs. We then assessed the reliability of that data and identified the demographics and household characteristics most likely to predict MELs in California. Our team also determined whether additional demographic or household data will be required to conduct a Phase III study. Table 6 lists the research questions we used to investigate the availability and quality of customer and household data.

Table 6. Customer Demographics and Household Characteristics Research Questions

#	Research Questions
6	What is the availability of market segmentation data and unprocessed demographic/housing/attitudinal data (from this stakeholder group)? What is the quality/accuracy of these data?

Details on Research Questions

Research Question 6: What is the availability of market segmentation data and unprocessed demographic, housing, and attitudinal data (from this stakeholder group)? What is the quality and accuracy of these data? What is the correlation between aggregate MELs and demographics, household characteristics, whole-home energy, and primary end-use energy profiles? What is the correlation between plug-load MEL or MEL group energy profiles and these variables?

Findings

Availability and Accuracy of Customer Data

We found that California utilities regularly collect customer demographic and household characteristic data for general marketing purposes as well as for targeting marketing, design, and evaluation efforts

[35] Ecotope. *Residential Building Stock Assessment: Metering Study*. 2014. Prepared for Northwest Energy Efficiency Alliance. Available online: http://neea.org/docs/default-source/reports/residential-building-stock-assessment--metering-study.pdf?sfvrsn=6

[36] KEMA, Inc. *WO21: Residential On-site Study: California Lighting and Appliance Saturation Study (CLASS 2012)*. Prepared for the California Public Utilities Commission, Energy Division. 2014. Available online: https://websafe.kemainc.com/projects62/Portals/4/CLASS_Doc/2014.05.02%20WO21%20CLASS%20Webtool%20User%20Guide.pdf

[37] Residential Energy Consumption Survey (RECS). Accessed June 20, 2016: http://www.eia.gov/consumption/residential/

for energy efficiency and demand response programs.[38] Typically, the demographic data include age, income, marriage status, gender, and number of children. The household data include dwelling type, square footage, number of stories, swimming pool indicator, home space heating fuel, building construction style or materials, and year built.

Utilities commonly purchase demographic and household data from commercial database vendors and supplement this information with survey data to segment customers according to self-reported energy-use attitudes and behaviors. However, survey data collected across multiple demand-side management programs may vary by program and may not be comparable as survey responses are subject to a number of biases.

There are commercial databases of varying sizes and costs available; vendors include Experian, Equifax, Acxion, Dun and Bradstreet, Marketing Systems Group, InfoUSA, and others. These vendors populate their databases with data collected in-house or purchased from other vendors. Vendors typically organize the data by a population group or a subset of the population and also provide segmentation data based on algorithms that identify customers with similar characteristics across a number of attributes. For example, Experian categorizes customers as Affluent Suburbia, Upscale America, Small Town Contentment, etc.[39] Data available from large vendors often provide much more information than any single survey can provide, including information on the entire customer base as well as a large number of attributes for each customer.

The accuracy and completeness of commercial databases vary. Vendors collect some data directly from sources such as property tax records and financial or credit reports, collect other data indirectly by matching sources to customers (with some uncertainty), and impute data on some variables based on observed correlations. Numerous sources who purchased commercial data reported missing and inaccurate data for a number of variables—data may be missing for between 5% and 30% of

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38 Opinion Dynamics Corporation. *PG&E Whole House Program: Marketing and Targeting Analysis*. Prepared for the Pacific Gas and Electric Company. 2014. Available online: http://www.calmac.org/publications/PGE_Whole_House_Report_COMBINED_MARKETING_REPORT_FINAL1ES.pdf.

HINER & Partners, Inc. *Low Income Energy Efficiency (LIEE) Household Segmentation Research for Southern California Edison 2009-2011*. Prepared for Southern California Edison. 2011. Available online: http://www.calmac.org/publications/sce_liee_segmentation_report.pdf

Cadmus. *Appliance Recycling Program Process Evaluation and Market Characterization*. Prepared for Southern California Edison and Pacific Gas and Electric. 2013. Available online: http://rtf.nwcouncil.org/subcommittees/fridgerecycle/SCE_PGE_ARP_Final_Report_Vol.1_09-18-13.pdf

Opinion Dynamics. *The Southern California Edison (SCE) Advanced Light Emitting Diode (LED) Ambient Lighting Program Customer Preference and Market Pricing Trial.* Prepared for Southern California Edison. 2012. Available online: http://www.calmac.org/publications/SCE0324.01.pdf

39 Experian Marketing Services. "Mosaic USA Consumer Lifestyle Segmentation." Accessed online March 11, 2016: http://www.experian.com/marketing-services/consumer-segmentation.html

households. Indicators for children and household income were missing least often, while race, ethnicity, and education level were missing most often.[40] However, when these data were available, they were often inaccurate. Table 7 lists data available from common commercial database vendors and our assessment of its expected accuracy based on the publications we reviewed.

Table 7. Customer Data Sources

Accuracy	Variables
High Quality	Home ownership status
	Age*
	Marital status
	Gender
Medium Quality	Race**
	Ethnicity
Low Quality	Number adults per household
	Household income
	Presence of children
	Education level

*Accuracy varies on range of age (i.e., accuracy is higher for 18 to 24 years and over 65 years, but medium quality for between 25 to 65 years of age).
**Accuracy of race and ethnicity vary depending on the category.

The California IOUs tend to use demographic and housing characteristics in combination with energy consumption to define customer segments. Many of the commercial database vendors combine demographic and housing characteristics with attitudinal information about energy use. One vendor in particular, Tendril, aggregates energy consumption data, combining it with demographic data from other vendors to profile individuals accordingly for micro-targeting and customer outreach.[41] Vendors update data as frequently as once per month and up to once per year, depending on the variable.[42] IOUs

40 DiSogra, Charles, J. Michael Dennis, and M. Fahimi. *On the Quality of Ancillary Data Available for Address Based Sampling. Section on Survey Research Methods.* Paper Presented to the Joint Statistical Meetings of the American Statistical Association. 2010.

Valliant, R., F. Hubbard, S. Lee, and C. Chang. “Efficient Use of Commercial Lists in U.S. Household Sampling.” Journal of Survey Statistics and Methodology. 2014: 2, 182–209. 2014.

41 Tendril. “Tendril Brings the Power of Micro Targeting and Personalization to the Energy Industry.” Accessed online March 11, 2016: https://www.tendrilinc.com/newsroom/press-release/tendril-brings-power-micro-targeting-personalization-energy-industry

42 InfoUSA Data Quality summary. Accessed June 20, 2016: https://www.infousa.com/data-quality/

http://support.qas.com/data-update-frequencies

with high customer turnover rates should consider submitting monthly or biannual requests to obtain data for new customers. We did not identify "of the shelf" commercial products that combine customer attitudinal data with customer characteristics or energy consumption data.

Correlations Between MELs and Other Variables

Correlations between MELs and customer characteristics are not well understood.[43] Some information is available about correlations of customer characteristics with MELs in aggregate. For example, larger homes and homes with more rooms tend to have higher plug loads.[44] However, more detailed information about how MEL usage correlates with customer characteristics or on MELs usage over time are not widely published.

A California study[45] developed models of whole-home daily peak and idle load where weather, location, and floor area were the most important variables for predicting energy consumption. Although this study did not specifically examine relationships between whole-house loads and MELs in general, it did collect data on entertainment devices and electric water heaters. The study found that entertainment devices and found high correlations between the number of such devices and whole-house idle loads. It found that the number of occupants and the number of electric water heaters were correlated with peak whole-house consumption but that income levels, home ownership, and building age were not correlated with whole-house energy consumption.

A 2006 NREL study presented energy savings calculation methodologies for different residential MELs. At that time, most previous baseline calculations only included the square footage of finished floor area and the location (state) to calculate baselines. The authors proposed including the number of bedrooms as an additional predictor of miscellaneous end-use energy consumption.[46]

The 2014 RBSA Metering Study[47] collected plug-load data for a number of appliances, including a handful of MELs in two categories: (1) TVs and TV accessories and (2) computers and computer accessories. Although the final report included annual energy consumption of individual end uses and presented those results for the Northwest as a whole and broken out into three sub-regions, the report

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43 Behringer, Alexandra. "Energy-Efficiency Segmentation: Results from the Residential Products and Services Survey," *Intelligent Utility*. 2010. Available online: http://www.intelligentutility.com/article/10/11/energy-efficiency-segmentation-results-residential-products-and-services-survey

44 *Ibid.* (Armel, K. Carrie., et al. 2012).

45 Kavousian, A., R. Rajagopal, and M. Fischer. "Determinants of residential electricity consumption: Using smart meter data to examine the effect of climate, building characteristics, appliance stock, and occupants' behavior." Energy: 55 20123 184-194. 2013.

46 Hendron, R. and M. Eastment. *Development of an Energy-Savings Calculation Methodology for Residential Miscellaneous Electric Loads.* NREL/CP-550-39551 and ACEEE Summer Study on Energy Efficiency in Buildings. 2006.

47 *Ibid.* (Northwest Energy Efficiency Alliance 2014)

did not include details on energy consumption with residential demographics or household characteristics. Similarly, the 2012 RBSA final report did not present results specific to separate demographic groups.

Topic Two: Summary of Findings

The California Public Utilities Commission (CPUC) asserts that the success of policy and infrastructure changes and plans relies heavily on customer participation and behavior and enabling customers in their roles as smart customers and home energy managers.[48] In recent years, there has been a shift from using only demographic predictors like age and income to also include personality characteristics like lifestyle choices, beliefs, and behaviors to characterize customer segments and to understand the motivations and barriers among customers and energy efficiency and demand response program participants. Because of their recent investments in collecting customer data, the California IOUs already have a substantial amount of customer data for a possible Phase III study.

California IOUs regularly collect demographic and household data for a number of purposes including marketing, targeting, design, and evaluation. They sponsor in-house surveys and purchase customer data from third-party vendors. Data available from commercial vendors are often more voluminous than data from any single survey but the accuracy and completeness of commercial databases varies. These databases contain a wealth of demographic, household, and lifestyle characteristics, but often have large amounts of missing or inaccurate data. Despite the potential for low quality customer data, these databases are still a valuable source of information for prediction.

Even if customer data from commercial vendors are inaccurate, they may still be used for prediction of MELs. If correlations between inaccurate customer data and MELs can be quantified, then even these low-quality data could be used in a predictive model, for when the goal is to predict MELs, any variable that does so accurately should be considered, even if the interpretation of the correlations is not meaningful. If the data quality is so poor that correlations with MELs cannot be detected (even when they do exist), then this data will be of little use in future predictive modeling efforts. Future research will be required to determine if accurate customer data (collected directly from customers) is correlated with MELs, inaccurate customer data (from third-party vendors) is correlated with MELs, and if those correlations are similar.

Previous research findings indicate that customer demographics and household characteristics do indeed correlate with whole-house electricity consumption. The results of correlations between these variables and miscellaneous end-use energy consumption have not been published and warrant further research, especially for the population of California IOU customers.

Limited information about which customer characteristics influence MELs and how they are related has limited the extent to which evaluators can use this information in practice to model or predict MELs for different customer groups. Evaluators have traditionally used square footage and the number of

48 *Ibid.* (Douglas, Kristin R., et al. 2013).

bedrooms to predict MELs, but they are also interested in predicting MELs based on other customer characteristics. Researchers have called for studies, evidence, and data to develop an understanding of how customer and housing characteristics correlate with MELs. To date though, industry researchers have completed or published very few studies that can illuminate these differences.[49]

[49] KEMA, Inc. *Building the Business Case Implementing a Comprehensive Pacific Northwest Electric End-Use Data Development Project Executive Summary.* Prepared for the Northwest Power and Conservation Council #181662. 2012.

Research Topic Three: Predictive Analytics and Modeling

MELs represent an increasing proportion of residential energy consumption and will likely become a larger contributor to utilities' peak demands. Due to their increasing importance, utilities may consider targeting MELs for energy efficiency or demand response programs in the future. However, we expect MEL usage to vary significantly between households and within households. The timing and size of MELs likely depend on customer and household characteristics such as the age of the household head, size of the household, presence and ages of children, floor area of the home, and age of the home. Therefore, utilities may be able to improve the cost-effectiveness of any MELs-related energy efficiency or demand response programs by correlating MELs with customer characteristics to develop customer-specific or customer segment-specific marketing and program offerings.

Cadmus has identified two ways utilities can correlate MELs with customer characteristics. The first is to collect metered data on individual MELs for a representative sample of homes in the population of interest (e.g., all residential customers, zero net energy housing customers, etc.). As described in the first chapter, installing plug meters to collect MELs directly will be more costly than using disaggregation of AMI data to estimate MELs, but will result in MEL data with the accuracy required for subsequent analyses. Extensive metering efforts will be required to capture the expected range of MELs in the customer population. Repeated metering will also be required to monitor and update the correlations over time, as MELs are expected to change as new products enter the market and customers' homes.

As an alternative to comprehensive MELs metering, utilities can use customer end-use surveys (or appliance surveys) to determine the correlations between MELs and customer and household characteristics. Using the end-use surveys, utilities can use a number of methods to predict MEL loadshapes, total MEL consumption, and peak MEL consumption based on the presence or absence of end uses in each house. End-use surveys can greatly reduce plug-load metering requirements. Limited metering will be required initially for the development and testing of the predictive models; however, the number of homes will be smaller than that in an end-use metering only approach. As with the end-use metering approach, additional end-use surveys and limited metering will likely be required over time to update the models. New data will be required to update the training and testing of those models.

Cadmus reviewed recent literature and reports to understand possible approaches, data requirements, and analytic methods for predicting MELs. We assessed the advantages and disadvantages of each and provide a summary of the literature and outline additional details associated with both the end-use metering only approach and the end-use survey approach in the remainder of this section.

Table 8. Predictive Analytics Research Questions

#	Research Questions
6	What is the correlation between MELs (either in aggregate, by end use, or in end-use groups) and demographics, household characteristics, whole home energy, and primary end-use load profiles?
7	Which statistical procedures can be used to determine which variables are significantly correlated with MELs? Which methods can be used to cluster or classify MELs into groups with similar characteristics? What are the strengths, weaknesses, and challenges anticipated for MEL applications? What data will be required to test methods?
8	Which statistical methods should be considered for predicting MELs? How should model testing and validation be performed? How frequently would each predictive model need to be updated to reflect changes in MELs over time? What sample sizes would be required to develop a predictive model and subsequent updates?

Details on Research Questions

Research Question 6: What is the correlation between MELs (either in aggregate, by end use, or in end-use groups) and demographics, household characteristics, whole home energy, and primary end-use load profiles?

Findings

There is very little published research that provides insight into the correlations between MELs and customer variables. We found studies that focused on correlations between whole-house or specific end-use energy consumption, customer demographics, and household characteristics but not on MELs specifically.

These studies relied on directly metered energy consumption or data collected from customers through surveys to understand which variables were correlated with energy consumption. Cadmus found that almost all of the studies found significant correlations between household electricity consumption and household size, income, and age of residents. Several studies found significant correlations between dwelling size, employment status, and location (i.e., rural versus urban) and energy consumption but low or nonsignificant correlations with education levels. In one study, researchers modeled the energy consumption of specific temperature dependent end uses (e.g., heat pump space heating and cooling and central air conditioning) as a function of square footage and income levels. They utilized these models as priors in a Bayesian model of whole-house energy consumption and found that smaller square footage and lower income were correlated with flatter heating profiles.[50]

[50] Blaney, J.C., M.R. Inglis, and A.M. Janney. *Hourly Conditional Demand Analysis of Residential Electricity Use*. ACEEE proceedings. 1994.

McLoughlin found that the following explanatory variables had highly significant effects on whole-house electricity consumption: [51]

- Home characteristics including location, value, residence type, floor area, and residence vintage
- Occupant characteristics including income and age, length of residency, social class and socio-economic group, number of people living in home, indicator of working at home
- End-use presence including numbers of televisions, personal computers, digital boxes, portable electric heaters, storage heaters and showers per week. Although these results were based on correlations with whole-home energy consumption, similar correlations may exist with MELs.

Through a meta-analysis of published literature, European researchers identified the following variables that were consistently correlated with whole house energy consumption: number of inhabitants, net income, age of surveyed resident, and employment status. [52] The researchers developed a model of whole-home energy consumption based on generated energy and storage technologies and presented an argument that these factors, in addition to customer characteristics and end-use energy consumption, should be factored into load profile research.

Research Question 7: Which statistical procedures can be used to determine which variables are significantly correlated with MELs? Which methods can be used to cluster or classify MELs into groups with similar characteristics? What are the strengths, weaknesses, and challenges anticipated for MEL applications? What data will be required to test methods?

Findings

Cadmus identified four approaches for correlating MELs with customer characteristics. Each approach requires customer MELs data—either from end-use metering or from disaggregating AMI whole-house loads. Also, each approach requires customer-level demographic and household characteristic data. The approaches are differentiated not just by the method for obtaining miscellaneous end-use data but also by whether customers are clustered before or after correlating their characteristics with MELs. A future study should use one of these approaches to predict MELs or compare two or more of them to test which approach yields the highest prediction accuracy.

In Figure 6, we illustrate two approaches to predicting MELs based on metered end-use data and customer and household characteristics. Approach A employs end-use meter data in a model to predict MELs and then clusters customers according to predicted MELs. The first step in Approach A is to build and estimate a model based on metered MELs and customer and household characteristics from a sample of customers. The second step is to use the model to predict MELs as a function of the customer and household characteristics for the larger utility customer population. Then the third step is to group

[51] McLoughlin, F. *Characterising Domestic Electricity Demand for Customer Load Profile Segmentation.* Ph.D. thesis. Dublin Institute of Technology. 2013.

[52] Hayn, M., V. Bertsch, and W. Fichtner. "Electricity load profiles in Europe: The importance of household segmentation." Energy Research & Social Science: 3 2014 30-45. 2014.

customers into clusters with similar predicted MELs where similarities can be identified based on total miscellaneous end-use load, peak miscellaneous end-use load, etc. In Figure 6, we show customer and household characteristics, in combination with metered end-use load data, being used to classify predicted MELs into three clusters under Approach A. The actual number of clusters will depend on observed similarities and differences between the features of interest in the predicted MELs.

Approach A can be implemented using conditional demand analysis or multivariate regression to model energy consumption as a function of customer and household variables. Although previous studies have applied this approach to model whole-house residential energy consumption, it can likely also be used to model MELs using customer data and then to predict and cluster customers with similar MELs.

Approach B is similar to Approach A but, instead of modeling metered MELs as a function of individual customer and household characteristics, researchers first identify customer segments or clusters and then model MELs as a function of the cluster identifiers. The models will yield an estimate of the average MELs for each cluster. [53]

The figure also illustrates using customer and household characteristics to group customers into three clusters which are then combined with metered end-use data to model average MELs for each cluster. In Approach B, the actual number of clusters will depend on the customer and household characteristics of interest to the utility. As an example of Approach B, researchers assigned each of 75 Norwegian utility customers to one of three clusters according to customer age and number of residents (households with young singles or couples, families with children and more than two inhabitants, households with retired one to two inhabitants) and then predicted hourly whole house energy loads for each cluster. The researchers used one year of whole-house hourly metered data, average hourly consumption of appliances based on four to five weeks of end-use metered data and daily average outdoor temperature.[54] Although this study predicted whole-house loads for customer categories, a future study could use similar methods to predict MELs. In a similar study, customers were clustered based on their daily load profiles, correlated with customer and household characteristics which were then used to predict customer load profiles. [55]

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53 The model can predict average, maximum, or other features of MELs. Future research should include an assessment of the accuracy of each.

54 Morch, Andre, N. Feilberg, H. Saele, and K.B. Lindberg. *Method for development and segmentation of load profiles for different final customers and appliances.* ECEEE SUMMER STUDY proceedings. 2013.

55 *Ibid.* (McLoughlin, F. 2013).

Figure 6. Approaches Using Directly Metered MELs

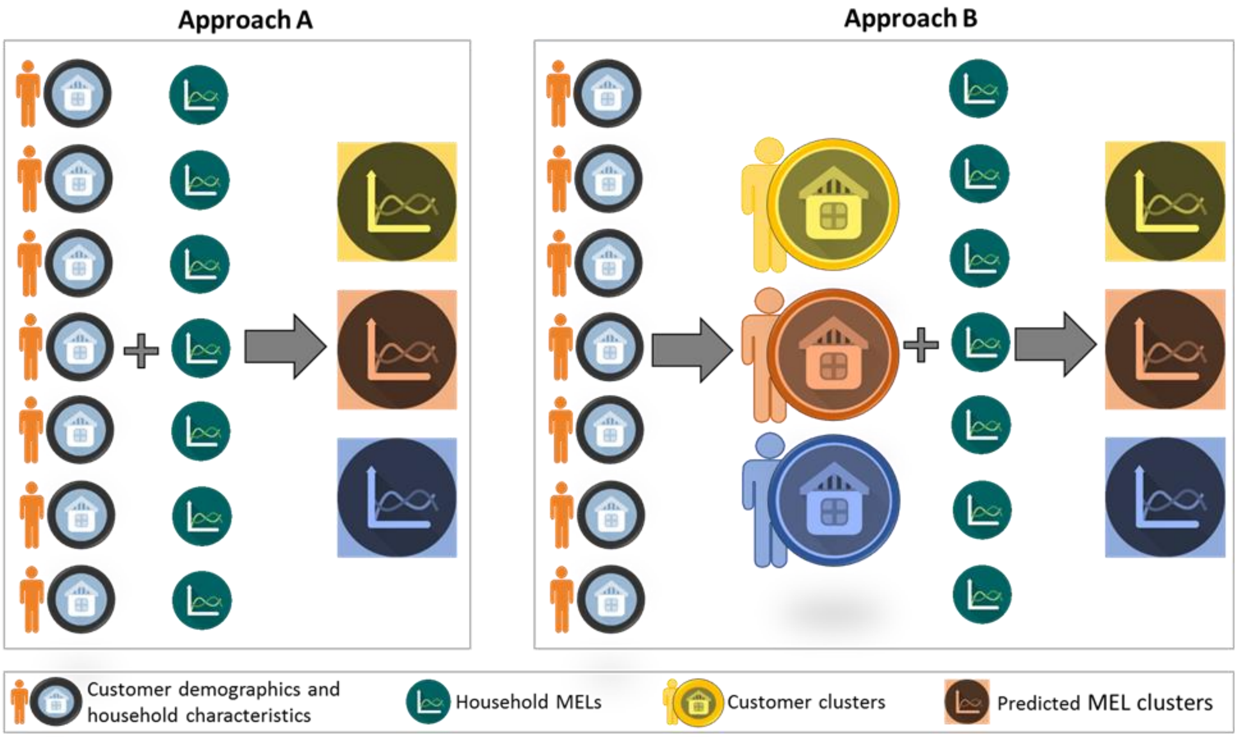

Figure 7 illustrates two approaches to predicting MELs based on end-use survey data in place of metered end-use data. Approaches C and D use end-use survey data in load disaggregation models and then build predictive models to estimate MELs based on customer and household characteristics. In Approach C, disaggregated MELs will be correlated with individual customer and household characteristics and then customers will be clustered based on similarities in their MEL features. In Approach D, disaggregated MELs will be correlated with customer clusters and then average MELs will be predicted for each cluster.

In Approaches C and D, the first step is to estimate MELs by building a model to disaggregate AMI energy use based on end-use presence using data collected in end-use surveys. The disaggregation model will include variables that signal the presence or absence of a number of end-uses, including miscellaneous end uses as well as primary end uses to account for space heating, space cooling, lighting, and water heating loads. The regression coefficients in the disaggregation model will be used to estimate miscellaneous end-use energy consumption which would then be used in a predictive model that correlates MELs with customer and household characteristics. In Approach C, the estimated MELs will be modeled based on individual customer and household characteristics and customers will be clustered based on similarities in their MEL features. In Approach D, customers will be clustered and MELs will be correlated with the cluster identifiers to predict average MELs for each cluster.

Although some end-use metering will be required for a subsample of customers to test the accuracy of the disaggregation models, it will not be required for the entire sample used in model development. The advantage of Approaches C and D is that in the development stage, if indeed disaggregation models result in accurate MELs estimates, then training data sets consisting of end-use survey data will be less costly to collect in comparison to comprehensive end-use metered data sets required for model development and testing in Approaches A and B.

An example of Approach C is to use conditional demand analysis to estimate end-use energy consumption based on end-use survey data. In one collaborative study in eleven European Union countries, household appliance survey data, whole-home metered data, and other demographic and economic data were collected for over 1,000 homes to calculate and publish annual energy demand profiles for individual appliances.[56] This analysis relied on variation in the presence or absence of specific appliances across homes to capture differences in loads attributable to each appliance. Although this study estimated annual load profiles, an additional step can be added to correlate appliance load profiles with customer variables and use those correlations to predict MELs. A second study provides another example of Approaches C,[57] where end-use loads were modeled using information on appliances in combination with national survey data from Residential Services Energy Network (RESNET)[58] and the U.S. Department of Energy Building America Program.[59] The study found that the regression model provided accurate estimates of MEL consumption in the test homes with larger MEL consumption (greater than 2,000 kWh).

Method C takes this one step further to use the regression model coefficients to estimate MELs for a larger group of customers, model those MELs as a function of demographic and household characteristics (data available to the utility for every customer), and cluster MELs based on their predicted MELs.

Approach D is similar to Approach C except that it clusters customers based on customer and household characteristics and then uses the clusters in a predictive MELs model. For example, a Finland study including over 4,000 residential customer households clustered customers based on housing type and

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56 Sæle, Hanne, E. Rosenberg, and N. Feilberg. *State-of-the-art Projects for estimating the electricity end-use demand.* 2010. Available online: https://www.sintef.no/globalassets/project/eldek/publisering/tr-a6999-state-of-the-art-projects-for-estimating-the-electricity-end-use-demand.pdf

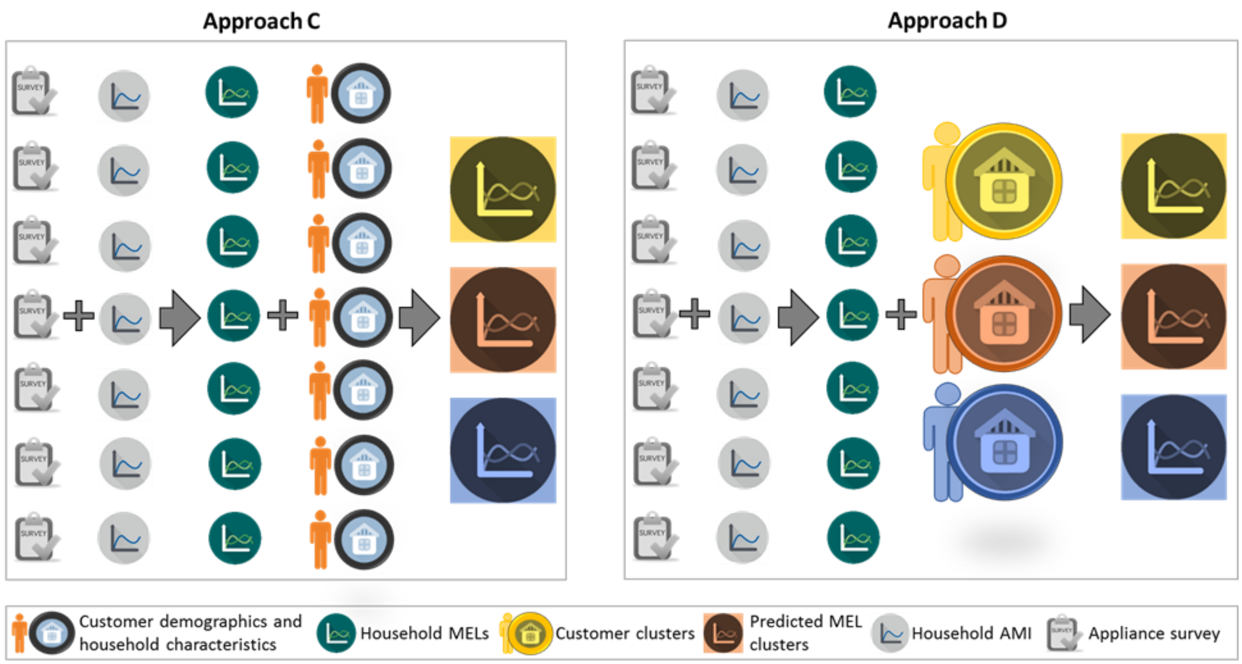
57 Burgett, J. and A. Chini. "Using Building and Occupant Characteristics to Predict Residual Miscellaneous Electrical Loads: A Comparison between an Asset Label and an Operational Model Specifying Residential Retrofit." Journal of Building Performance Simulation. Vol. pg numbers? 2015.

58 RESNET. "Lighting, Appliance, and Miscellaneous Energy Usage Profiles." Accessed online March 11, 2016: http://www.resnet.us/standards/PropStdsRevision-01-11_Revised_FINAL.pdf

59 Office of Energy Efficiency & Renewable Energy. "Building America Research." Accessed online March 11, 2016: http://energy.gov/eere/buildings/building-america-research

heating systems and then estimated typical load profiles within each customer cluster using hourly load data.[60].

Figure 7. Approaches Using AMI and End-Use Survey Data



Data Requirements

Directly metered MEL data, customer demographics and household characteristics, and AMI data will be required in all four approaches outlined above. Utilities can select one or multiple approaches for testing. The accuracy of Approaches A and B can be assessed by reserving a subset of the metered MELs data to test whether or not the methods result in predicted MELs that are similar to the actual MELs. The accuracy of Approaches C and D can be assessed by collecting metered MELs data for a subset of the customers to compare the disaggregated MELs results to the metered data. Methods that predict MELs close to the actual MELs will have higher predictive accuracy and be preferred.

Table 9 shows the data requirements for each approach. Because the IOUs already have the ability to collect AMI data and collect customer data, the bulk of the data collection required to develop and test predictive modeling approaches includes deploying end-use meters or end-use surveys to collect data end-use loads and/or presence.

[60] Mononen, Matti, J. Saarenpaa, M. Johansson, and H. Niska. *Data-driven Method for Providing Feedback to Households on Electricity Consumption*. IEEE Ninth International Conference. 2014.

Table 9. Data Requirements

Approach	Data	Customer Variables	AMI Data	Metered MELs	End-Use Survey
A and B	Population	✓			
	Sample	✓		✓	
C and D	Population	✓	✓		
	Sample	✓	✓	♦	✓

✓ Indicates that data is required for the entire population or sample.

♦ Indicates that the data is only required for a subsample.

Clustering and Classification Methods

Depending on the approach, different variables can used to cluster customers. Approaches B and D rely on customer demographics and household characteristics to cluster customers before building predictive models. Approaches A and C rely on features of predicted MELs in combination with customer demographics and household characteristics to cluster customers after predictive models were used to estimate MELs. In Approaches A and C, algorithms used to cluster customers after predictive modeling would use variables describing predicted miscellaneous end-use peak consumption, time of use, duration of use, etc., along with customer and household variables. In Approaches B and D, algorithms used to cluster customers before making predictions use customer and household variables only and then predict the MELs for each cluster. *A priori*, we cannot know which method would result in more meaningful clusters. However, we do know that clustering before building a prediction model will reduce the number of variables required in the predictive model, potentially simplifying the clustering algorithm and the predictive model.

Cluster definitions can be defined ahead of time where units are assigned, or classified, to clusters and the similarities and differences in the response variable(s) of interest are analyzed. As an example, if we are interested in examining similarities and differences in MELs between households with children and households without children, we can classify homes into one of two clusters ahead of time and then use statistical analysis to identify similarities and differences in MELs between the clusters. We can expand on this to define a number of clusters, based on multiple variables, and then use a model to study correlations between MELs and the cluster characteristics.

Alternately, in cases where we want to explore various cluster definitions, we can perform cluster analysis to define them. This approach can be particularly helpful if we do not know *a priori* how to define clusters and are interested in exploring the possible definitions. The methods used to identify and define clusters include k-means, hierarchical, density-based clustering, and self-organizing maps, among numerous variations on these and other algorithms. Most methods include variations that handle both categorical and continuous data.

Research Question 8: Which statistical models (e.g., regression, machine learning) should be considered for predictions in the absence of ME or ME group plug load data? What model testing and validation procedures are most appropriate for each method? How frequently would each type of model need to be updated to adapt to changes in MELs over time? What sample size would be required to collect the data to fit a model with sufficient confidence and precision? Would subsequent updates require data sets similar in size and scope to initial training data sets or could the updates be made using fewer data points?

Findings

Predictive Models

Predictive modeling is performed with the objective of predicting new observations of a response variable based on data for the predictor variables only. This can be different from traditional statistical modeling, or “explanatory” modeling, where the objective is to explain and quantify important relationships between independent variables and a response. Predictive models and explanatory models can take the same form (e.g., a predictive model could be a standard linear regression model if that model provides accurate prediction). However, more accurate predictions can result from a more complex model, perhaps with numerous higher order interactions, nonlinear form, etc. The divergence between predictive and explanatory modeling occurs when the prediction accuracy increases but the interpretability decreases and the more complex model is preferred for predictive analytics. In addition to traditional statistical models, other models or algorithms based in artificial intelligence, including neural networks, have been found to perform well as predictive models, particularly when relationships between variables are nonlinear. These models, however, tend to be more difficult to interpret than traditional statistical models. In this research, we considered predictive modeling methods that include both traditional statistical modeling approaches as well as those associated with artificial intelligence and machine learning.

Few researchers have predicted MELs based on customer demographics and household characteristics other than home size. Most frequently, researchers have implemented statistical regression and econometric methods to investigate the influence of socioeconomic, dwelling and appliance characteristics on whole-home electricity consumption.[61] However, a handful of studies have investigated the ability to predict whole home energy consumption. In a study utilizing neural networks,[62] researchers used electric appliance (lighting, refrigerator, chest freezer, cooking, dishwasher, washing machine, domestic hot water, cooling and heating systems, TV, VCR/DVD, computers, and electronic entertainment), as well as apartment area and number of occupants to predict energy consumption. Artificial neural network algorithms predicted daily and hourly whole-home energy consumption using hourly energy data for 93 homes over the course of three weeks. This

[61] Jones, R.V., A. Fuertes, and K.J. Lomas. “The Socio-economic, Dwelling and Appliance Related Factors Affecting Electricity Consumption in Domestic Buildings.” Renewable and Sustainable Energy Reviews: 43 2015 901–917. 2015.

[62] Rodrigues, F., C. Cardeira, and J.M.F. Calado. “The Daily and Hourly Energy Consumption and Load Forecasting Using Artificial Neural Network Method: A Case Study Using a Set of 93 Households in Portugal.” Energy Prodecia: 62 2014 220-229. 2014.

study used correlation, R^2, mean absolute percent error (providing relative uncertainty), and standard deviation of the error to assess the accuracy predictions. Correlation and R^2 were generally greater than 90% and relative uncertainty was less than 20% for daily average and maximum energy consumption as well as hourly demand.

A second study predicted energy consumption patterns and totals based on traditional regression analysis, decision trees, and neural network methods.[63] The authors advocate for developing models using each method and comparing the predictive accuracy of each to determine the best approach for a given application. In another study comparing explanatory models with artificial intelligence methods,[64] the authors predicted hourly energy consumption based on occupancy, day type, temperature, irradiance, and interactions between predictors. They reported that, in comparison with time series regression, support vector machine offered slight improvements in predictive accuracy.

One study compared the results from multiple methods through a literature review and primary research.[65] The authors were particularly interested in comparing multivariate regression (conditional demand analysis (CDA)) to other predictive methods. In the primary research, the authors found that CDA engineering models and neural networks produced similar results. Although the studies and results were applied to whole-home energy consumption, similar methods can be considered for predicting MELS. In the authors' review of relevant literature, mixed results were reported on using fixed effects CDA, random effects CDA, and a Bayesian model to predict hourly end-use profiles had mixed results, with accuracy of the predicted loads increasing with model complexity, in comparison to billing data.

Predictive analytic methods are used in many industries. Finance and banking, genetic research, manufacturing and electronics are fields from which substantial research has been performed and is supported by publications in industry journals. In the financial and banking industry, researchers have assessed a number of predictive modeling methods to quantify risk and predict failures. Discriminant analysis, logit and probit modeling, and classification trees have historically been used for predicting business failures or bankruptcy.[66] Artificial intelligence methods including artificial neural networks (ANNs), have been used more recently (since the 1980s) after several studies demonstrated the increased predictive power of these methods. Numerous studies have investigated the power of ANNs for predicting the classification of bankrupt firms into three categories after their failures in banking

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63 Tso, G.K.F and K.K.W. Yau. "Predicting Electricity Energy Consumption: A Comparison of Regression Analysis, Decision Tree and Neural Networks." Energy: 32 9 2007 1761-1768. 2007.

64 Dagnely, P., T. Ruette, E. Tsiporkova, and C. Verhelst. *Predicting Hourly Energy Consumption. Can you Beat an Autoregressive Model?* Arrowhead and Sirris Software Engineering. White Paper. 2013.

65 Aydinalp-Koksal, M., and U.V. Ismet. "Comparison of Neural Network, Conditional Demand Analysis, and Engineering Approaches for Modeling End-use Energy Consumption in the Residential Sector." Applied Energy: 85 4 2008 271-296. 2008.

66 Min, J.H. and Y.C. Lee. "Bankruptcy Prediction Using Support Vector Machine with Optimal Choice of Kernel Function Parameters." Expert Systems with Applications: 28 2005 603-314. 2005.

applications. Findings indicate that ANNs generally result in better predictive accuracy than logistic regression and nonparametric discriminant analysis, although statistical significance of improvements varies depending on training and test samples. Support vector machines have also been studied and shown to out-perform traditional methods including multiple discriminant analysis and logistic regression analysis (statistically significant) as well as back-propagation neural networks (not statistically significant), though performance can depend on the sampled training and test data. Neural network algorithms and related variations, including using ensemble models with combined methods, have been shown to predict accurately in a number of banking industry and credit analysis applications.[67] Because we do not have a benchmark for the performance of these methods in the context of MELs prediction, we recommend that future research tests one or more of these methods to classify MEL features or patterns into discrete categories based on demographic and household characteristics as well as the observed whole-home AMI data.

In cases where the trends in MELs over time are of interest, time-series data mining techniques provide another option. Methods include the aforementioned ANNs and ensemble models, building upon them to identify similarities of patterns and correlations over time.[68]

Genetic and medical research applications have studied probabilistic neural networks and genetic algorithms for classification of patients and biological samples into clusters with similar probabilities of disease. DNA research often uses image processing and classification for these analyses. Healthcare analytics uses predictive analytic methods to mine large datasets, predict patient outcomes, and improve customer experience.[69]

Sample Sizes and Updates

Sufficient sample sizes are necessary to develop predictive models of MELs that satisfy requirements for confidence and prediction accuracy. Required sample sizes will depend on the variation between MELs within different customer clusters and the correlations between MELs, customer variables, and AMI data. However, little is known about variation in MELs between households and customer clusters.

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[67] Becerra, V.M., R.K.H. Galvao, and M. Abou-Seada. “Neural and Wavelet Network Models for Financial Distress Classification.” Data Mining and Knowledge Discovery: 11 2005 35-55. 2005.

Shi, L., L. Xi L., X. Ma., and X. Hu. *Bagging of Artificial Neural Networks for Bankruptcy Prediction.* International Conference on Information and Financial Engineering. 2009.

Kim, M.J. and D.K. Kang. “Ensemble with neural networks for bankruptcy prediction.” Expert Systems with Applications: 37 2010 3373-3379. 2010.

Iturriaga, F.J.L. and I.P. Sanz. “Bankruptcy Visualization and Prediction Using Neural Networks: A study of U.S. Commercial Banks.” Expert Systems with Applications: 42 2015 2857-2869. 2015.

[68] Baydogan, M.G. and G. Runger. “Time Series Representation and Similarity Based on local Autopatterns.” Data Mining Knowledge Discovery: 30 2016 476-509. 2016.

[69] Miner, L., P. Bolding, J. Hilbe, M. Goldstein, T. Hill, R. Nisbet, N. Walton, and G. Miner. *Practical Predictive Analytics and Decisioning Systems for Medicine.* 2015.

Future research should consider a pilot to collect data on MELs and the variation of MELs (in terms of their size, time of use, etc.) and their presence or absence in the population of interest. The results of this type of pilot study will help utilities decide which approach will provide the most valuable information on the population and is optimal for launching a full-scale data collection and model development effort.

During a full-scale data collection and model development effort, utilities will require sufficient data for a training data set and a test data set. Between 20% and 40% of the collected data will be required for the test data set, which is set aside for testing and validating the predictive accuracy of the trained algorithms.[70]

The frequency of required updates to the predictive models will depend on how rapidly miscellaneous end-use technology changes. Introduction of new technologies that use substantial amounts of energy and change energy consumption will require significant updates and new data collection efforts.

Challenges Anticipated in MEL Applications

Challenge #1: There are no proven studies demonstrating methods for, expected accuracy of, or challenges to predicting customer MELs. The next research will serve as a building block for subsequent research efforts.

Some of the challenges of applying predictive models to MELs include the absence of evidence about which methods work, obstacles to model development, and whether some methods show more promise than others for different purposes. The approaches outlined above represent a combination of approaches used for whole-home or population-level predictive modeling that researchers can apply to MELs. However, because of the lack of research in this research area, initial progress in applying predictive modeling approaches to customer MELs may be slow. Future research in this area will break ground, providing invaluable information to the California IOUs, researchers, and other stakeholders interested in identifying customer MELs.

Challenge #2: Which MEL features should be predicted? Can these features be predicted accurately? Can customers be differentiated by these features?

Utilities will need to determine which MELs features are most important to predict to achieve programmatic objectives. Utilities will also need to determine whether it is feasible to make accurate predictions.

Because little information has been published on how customer demographic and household characteristics relate to MELs, utilities will need to put forth substantial effort to tie customer MELs to specific marketing or programmatic goals. Throughout this report, we have mostly referred to MELs

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[70] Variations on handling training and test data set can be used, especially in model averaging or ensemble approaches, where numerous random samples of training and test data sets are used to train and test the predictive models and results are combined to provide optimal results.

without distinguishing between different MELs features or end uses. MELs have multiple dimensions including hourly or peak loads, average loads, energy consumption, etc. In addition, MELs can be measured for particular end uses, a group of related end uses (e.g., entertainment center), or all MELs combined. Depending on the programmatic objectives, the predictive analytic efforts could differ significantly. For example, if the goal of the program is to reduce peak MELs, utilities will need to identify customers with peak-coincident MELs for marketing demand response programs. Or if the programmatic goal is market transformation for a particular end use, then utilities will need to identify customers using energy for that specific end use. It is possible that some methods will be better at predicting certain features of MELs than others.

Challenge #3: Some MELs may not vary between households due to appliance standards or efficiency programs and therefore be harder to detect.

Predictive analytics and cluster methods require a sufficient signal to noise ratio to detect patterns. If that ratio is not high enough, it may be difficult to detect MELs for some end uses. For some end uses, appliance standards and programs like ENERGY STAR® have likely reduced differences in energy consumption between technologies.[71] For example, ENERGY STAR specifications have reduced the total energy consumption of televisions, making it more difficult to detect entertainment center consumption with load disaggregation methods. As another example, differences in the number and types of end uses may not vary substantially between homes. In these cases, researchers will not be able to use between-home variation and instead rely on within-home variation to identify changes in usage.

Challenge #4: Collection of accurate data may be costly.

Data collection could be costly. We recommend installing plug meters to measure MELs directly and administering appliance surveys to a representative sample of homes. Extensive metering efforts would likely be required to capture the variation in MELs expected between households. Further, a limitation of plug meters is that they are not designed to account for portability of devices that are plugged into different outlets over time. Some solutions to the plug meter challenge include limiting the focus of the research to predicting non-portable MELs or, at the risk of jeopardizing the study validity, placing strict guidelines on the use of portable devices. In the latter case, if the guidelines are not adhered to, the collected data could be inaccurate for specific MELs.

We recommend that utilities consider using appliance surveys in combination with AMI data as an alternative to costly submetering efforts. If it can be shown that predictions of MELs based on appliance surveys and AMI data are accurate, utilities may be able to rely on this approach.

[71] Comstock, O. and K. Jarzomski. *Consumption and Saturation Trends of Residential Miscellaneous End-Use Loads.* ACEEE Summer Study on Energy Efficiency in Buildings. 2012.

Recommendations

Based on our review of relevant literature, the Cadmus team summarized its findings and recommendations for future research.

Data Collection: Metering and Customer Data

Finding #1: There is limited availability of hardware and software solutions to collect granular data on individual end uses. Current research is focused on improving the accuracy of primary end-use disaggregation, not on identifying MELs. The EMI option is intriguing and showed promise for directly collecting load data for individual end uses in a case study. It is unfortunate that there is no commercially available solution at this time.

Recommendation: Collect data on both primary and miscellaneous end-use loads as part of a future MEL research effort. Use plug load meters to collect data on individual end uses of interest and perform analyses to understand end-use loads in the population. If the IOUs are interested in contributing to the research and development of disaggregation algorithms, then they should analyze the end-use data along with AMI data.

Finding #2: Utilities will face logistic and cost challenges in metering MELs directly. Directly metering the power draw corresponding to charging portable devices such as cell phones, tablets, and laptops will either require strict guidelines for participating customers, new and improved plug meter technologies, or development of software applications for self-metering of devices. Current plug load meters are not designed to be portable.

Recommendation: Future research should focus on energy consumption associated with a limited number of MELs or MEL groups that remain stationary and can easily be metered using plug meters (e.g., entertainment center).

Finding #3: Currently, disaggregation tools cannot provide real-time or near real-time disaggregation for end-use load monitoring and thus do not comply with AB-793.

Recommendation: California IOUs should continue to monitor advancements in disaggregation technology and performance of methods over time. Research and development in this area is ongoing, and experts expect improvements in accuracy of load disaggregation methods over the next 3-5 years.

Predictive Analytics: Assess the Predictive Power of Customer and AMI Data

Framework

Findings: Researchers have applied several approaches to model whole-home or primary end-use loads using statistical regression, stochastic modeling, artificial intelligence, and combinations of these methods with engineering algorithms. Using statistical analysis, researchers have correlated whole-home and primary end-use loads with the characteristics of utility customers. Utilities could use similar methods in combination with commercially available household data or surveys to correlate MELs with customer characteristics. The dearth of research in this area underscores the need for future research to help the California IOUs plan and design effective energy efficiency programs.

Recommendation: Because MELs cannot be reliably estimated directly using existing disaggregation technologies, California IOUs should consider directly metering MELs or statistical methods to estimate MELs or a combination of these approaches. Prior to designing a research study, the IOUs should develop a research framework with stated objectives and scope.

The Cadmus team recommends that the California IOUs conduct a pilot study focused on one or two significant MELs to test the viability of correlating MELs with customer characteristics using one or more of the approaches and methods outlined in the previous chapter.

Pilot Study

The pilot study should select one or two miscellaneous end uses of particular interest and should deploy end-use meters in a sample of homes to meter the corresponding MELs. It should develop surveys to collect end-use and customer data and also collect commercial customer data for the sampled customers. The pilot should compare the survey data with the commercial data and the correlation of both with MELs. Correlations between the survey data and MELs should be examined in all data sources to determine the feasibility of using AMI data, commercial customer data, and end-use surveys in place of a large number of plug meters for a full-scale study. The pilot should focus on two to three customer segments between which differences in MEL usage are expected.

The following research questions should be addressed in the pilot study:

- How accurate are the third-party customer data in comparison to the self-reported survey data?
- How accurate are the survey data on presence and time of use in comparison to on-site observations and end-use metered data?
- Are MEL usage patterns (in the metered data and the survey data) correlated with patterns observed in AMI data? Which features in the AMI data are most useful for detecting these correlations?
- Are MEL usage patterns (in the metered data and the survey data) correlated with customer characteristics (in the commercial data and the survey data)?
- What is the variation of MELs within customer segments, e.g., do customers in different segments own home entertainment systems at similar rates and is time of use correlated with which segment the customer is in?
- At what resolution do correlations matter, i.e., do hourly, daily, or weekly MELs, on-peak MELs, MEL time or duration data all provide insight into customer MEL usage or is one metric more useful than the others?
- Are MEL usage patterns consistent over time, e.g., do customers tend to use miscellaneous end uses at the same time and for the same duration over the course of the study period?

- Do customers with similar MELs share a set of customer characteristics other than those defined by the segments? Are the combination of characteristics distinct (in both the survey and commercial data)?

Answering these questions will provide the California IOUs with insight into the feasibility and direction of a future full-scale study. Understanding the accuracy of the commercial customer data and survey data will help to determine whether these data should be used in large scale study and how the data collection should be augmented to make them more useful. Understanding correlations between patterns in whole-house AMI and MEL usage will provide insight into whether or not AMI data should be used in a future study. Understanding the variation of MELs within customer segments and if the expected differences in MEL usage between segments exist will impact the scope of a future research study. For example, if predefined customer segments correlate strongly with MEL usage, then a future study will require less research to determine which customer characteristics to include in a predictive model than if other customer characteristics correlate with MELs more strongly. In this case, additional work will be required to define the characteristics to cluster customers with for the purpose of predicting MELs.

The pilot study should sample customers at random in the customer segments of interest. Survey and plug-load metering sample sizes of roughly 30 customers per segment should provide a sufficient number of data points to examine MEL usage patterns in the segments and to determine if they correlate to customer segments and AMI usage patterns. If additional research questions evolve from interesting findings in the preliminary sample, additional customers could be sampled to investigate them further.

Research Design

Future research on predicting MELs should adhere to rigorous study design principles. In particular, future research should:

- Define the MELs characteristic of interest (e.g., household MEL total, MEL on peak, MEL time of use, etc.)
- Collect a reliable data set that can be used to train and test one or more predictive models
- Assess the predictive accuracy of analytic approaches and methods
- Determine the best methods and approaches that the California IOUs can use to develop and efficiently update a model that accurately predicts MELs based on customer characteristics

A future study will require, first and foremost, a highly reliable data set for the study population. Cadmus recommends that any such data include the following:

- **Customer demographic and household characteristic data**. The California IOUs can utilize commercial data sets that they have previously purchased for customer marketing and segmentation. The customer demographic and household characteristic data must be of similar quality as the data expected to be available and used for predictions once an algorithm has been developed.

- **Customer AMI data**. The California IOUs already collect AMI data for most residential customers.
- **End-use meter data**. The California IOUs should collect accurate metered end-use energy consumption data for a representative sample of homes. The sample size should be sufficient to estimate the MELs with the desired confidence and precision.
- **Customer survey data**. The California IOUs should survey a representative sample of customers about the miscellaneous end uses present in their homes and hours of operation of each. We recommend comparing the predictive accuracy of a method that relies on survey data to the accuracy of a method that employs metered end-use data. If the methods yield similar and accurate predictions, researchers may be able to update the predictive models mostly using information obtained from surveys. A limited number of end-use metering may be required to test the accuracy of the survey responses. This approach would be more cost-effective to collect data collection and update the model.

Appendix A. Case Study on Deriving MELs from NIALM Disaggregation

As a member of the Cadmus team, Fraunhofer CSE performed a case study to provide a ground-truth for its estimates of uncertainty and conclusions about the feasibility of detecting MELs by subtracting disaggregated primary end-use loads from whole-home energy consumption data.[72]

Method Overview

Fraunhofer CSE developed and patented a version of an event-based method for nonintrusive appliance load monitoring (NIALM), or disaggregation, of household electric power data sampled at approximately 1Hz.[73] Using this algorithm, events are detected based on significant changes of power corresponding to appliances being turned on, off, or changing status. Raw power signal data are then used to combine subevents corresponding to single events with prolonged durations where events include power surge values (in-rush current, characteristics of several types of appliances) and additional power features. The signal features corresponding to the events are calculated where the features include power change values or deltas. Events with similar features are clustered together where clusters usually correspond to distinct on and off states of appliances used during the observation period, although the appliances do not need be frequently used (e.g., for a coffee maker, there can be several hundred of power cycles during a single use that would produce a cluster). Clusters corresponding to appliance-use starts are matched with clusters corresponding to appliance-use finishes, producing a time series of appliance usage corresponding to events from pairs of matched clusters.

Whereas conventional NIALM methods calculate the power trace of each cluster to disaggregate end-use loads, the Fraunhofer CSE method uses the durations of time that appliances are on or off to better separate overlapping clusters (overlapping occurs when two or more appliances are on at the same time). Additional cluster features including power standard deviations during on and off times are also calculated. Based on the distribution functions of on and off durations, transition probabilities are calculated and the modified Viterbi algorithm is used to optimally reconstruct clusters. Reconstructed clusters can be matched with major end uses on the basis of their power and duration on and off features. The method requires a dataset of household power consumption collected over about two weeks. Figure 8 shows a diagram of the Fraunhofer CSE method.

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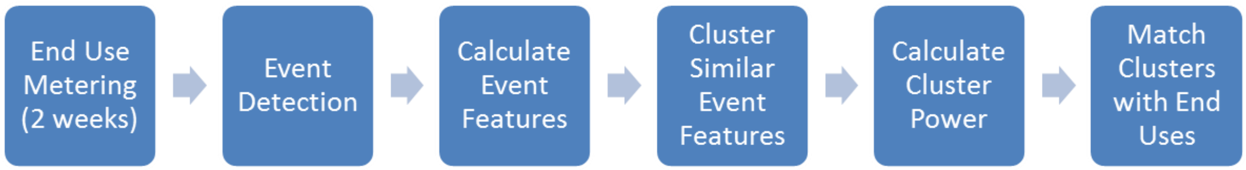
[72] The data used this case study were collected under a separate contract.

[73] Zeifman, M. "Disaggregation of Home Energy Display Data with Probabilistic Approach." IEEE Transactions on Consumer Electronics: 58 2012 23-31. 2012.

Zeifman, M. and K. Roth. "Nonintrusive Appliance Load Monitoring: Review and Outlook." IEEE Transactions on Consumer Electronics: 57 2011 76-84. 2011.

Zeifman, M. and K. Roth. "Viterbi Algorithm with Sparse Transitions (VAST) for Nonintrusive Load Monitoring." IEEE Symposium on Computational Intelligence Applications in Smart Grid (CIASG): 2011 1-8. 2011.

Figure 8. Diagram of Fraunhofer CSE NIALM Disaggregation Method



After implementing this method on the historical dataset of one household, it can be used to perform near real-time disaggregation for the same household. New events can be detected over small time windows (e.g., 10 minutes) and classified using the data collected over large time windows (e.g., one day).

Study Data

The Cadmus team collected aggregate and submetered data for 18 households during August and September 2015. The sampling rate was at 5-minute intervals for the aggregate data and 15-minute intervals for submetered end-use data. Submetered data included both MELS (e.g., computers, entertainment centers, TVs) and other appliances (e.g., refrigerators, washers, dehumidifiers) but did not include major household end uses such as central HVAC, electric dryers, dishwashers, domestic water heaters and lighting. Data cleaning and quality assurance revealed some inconsistencies in the submetered and aggregate data where summed values of submetered data exceeded the aggregate data. Note that that this type of inconsistency tends to persist in publicly available data sets as well (e.g., in the Reference Energy Disaggregation Data Set).[74]

Also, the aggregate power had little variation for several sites. For example, at one site, aggregate data values of 348 watts appeared in 20.7% of the observations. This particular value (348 watts) was frequent at several other sites, appearing 30% to 60% of the time. Observations with this value actually indicated the instrument limitations—the meters could not detect or record lower wattages and, thus, these censored values appeared any time the wattage was lower than 348 watts. Challenges associated with detection limits are also not uncommon; similar resulting data sets have been collected by Fraunhofer CSE and Cadmus as parts of other efforts.

[74] Reference Energy Disaggregation Dataset. Accessed online June 20, 2016: http://redd.csail.mit.edu/

Disaggregation Method

The data posed the following limitations for the patented Fraunhofer CSE disaggregation method:

- **Sampling frequency**: Sampling rates of one observation per five and 15 minutes provide data that are 300 to 900 times coarser than the 1Hz data that the patented method was developed to handle. The coarseness results in numerous overlapping events, with two or more per interval and loss of features including power surges, posing challenges to signal processing.
- **Lack of ground truth**: Partial submetering provided data for major end uses that could be used to semi-automatically optimize algorithm performance. Manual fitting of the algorithm to the data was possible but time consuming and not feasible for this case study.

In light of these challenges, Fraunhofer CSE proceeded using a disaggregation method that matched end-use groups with power deltas observed in the aggregate energy consumption data. Recognizing that the coarseness of the data would likely result in high uncertainty, the team pursued this approach to assess its feasibility when applied to whole-home AMI data. The disaggregation method clustered events in the energy consumption data that had similar on and off signatures, or changes in power. Figure 9 depicts identified event clusters for one home in the case study. In this example, the event clusters are differentiated by the size of the changes in power where the top cluster of events (cluster 1) includes changes in wattage between 300 to700 watts, the middle cluster (cluster 2) are between 1,000 to 3,000 watts, and the bottom cluster (cluster 3) are over 3,000 watts.

After identifying these event clusters, the team used calculated the correlations between each disaggregated load cluster and the submetered end-use loads. Correlations were calculated for between the 5- or 15-minute interval loads within 24-hour intervals. We used average and maximum correlation coefficients across the 24-hour intervals to identify potential matches between disaggregated loads and metered end-use loads. We also calculated correlations between the metered data and disaggregated clusters and residuals. High average or maximum correlation coefficients between disaggregated clusters and submetered end-use loads could be used to identify a disaggregated load as a particular metered end use. We repeated the analysis for 15-minute data to understand how sampling frequency would affect the results.

Results

Figure 9 shows the disaggregated event clusters for one site in this case study (site 5). Three event clusters were detected. We can see that the timing of use is similar but that the size of the power draw differs between clusters.

Figure 9. Example of Disaggregated Clusters of Events at One Site

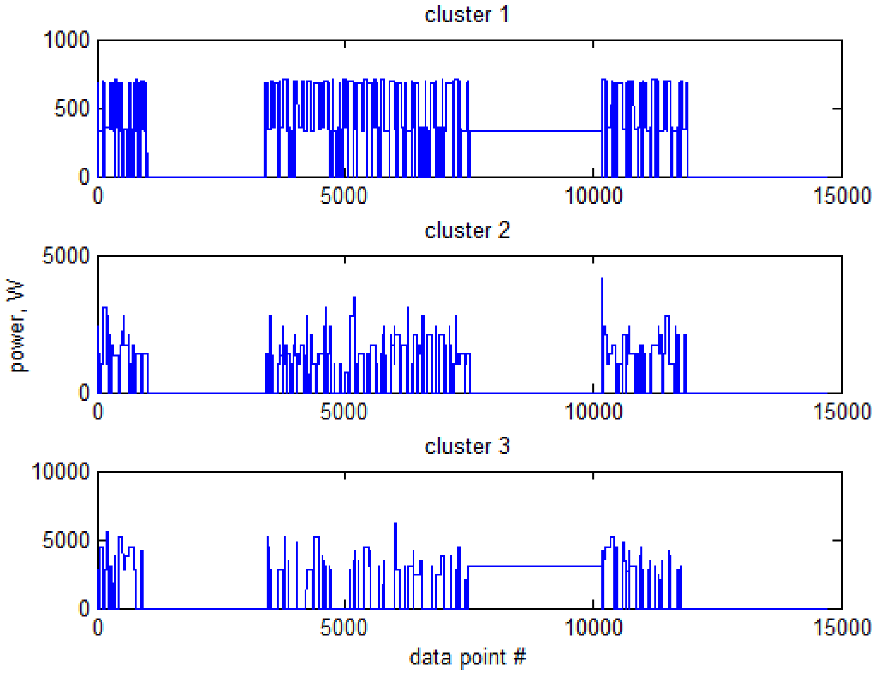


Figure 10 shows the directly submetered data for five end uses at the same site (two refrigerators, a computer, an entertainment center, and a clothes washer). There is no obvious association between the disaggregated clusters and the metered end uses. Two of the three clusters correspond to higher power than most of the metered end uses, indicating that they represent non-metered end uses or combinations of the metered end uses.

Figure 10. Example of Submetered Data for Five End Uses

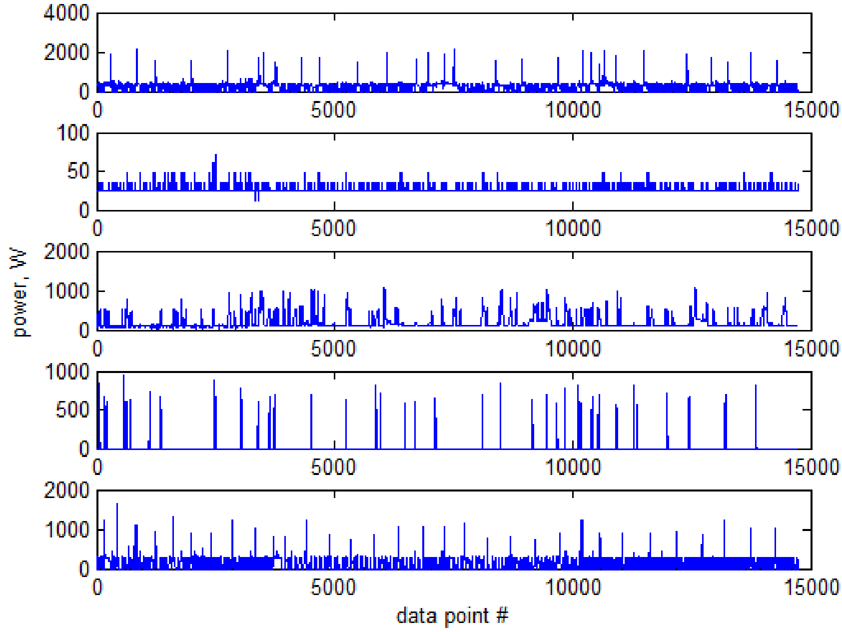
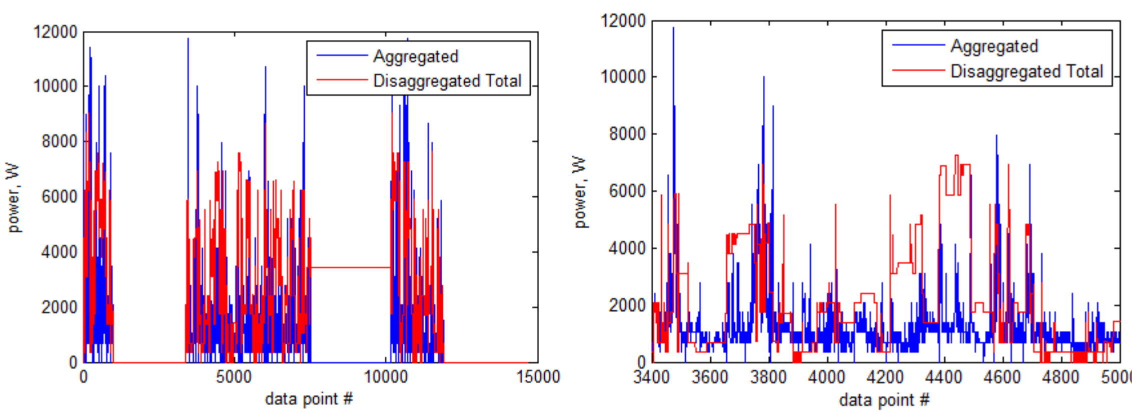


Figure 11 shows the sum of disaggregated loads (red) and the directly metered aggregate load (blue) for the same site in this case study. The plot on the left shows data over the entire two-month study period and the plot on the right shows data for a subset of five days during the period.

Figure 11. Comparison of Disaggregated Total and Aggregate Energy Consumption



The sum of disaggregated loads does not align with the metered aggregate energy consumption except in the timing of peak consumption over the course of the study. It often exceeds the measured aggregate, posing additional challenges to using the residual to estimate aggregate MELs. To address this challenge, the team defined the residual as the absolute value of the difference between the metered aggregate and the sum of disaggregated loads.

Correlation results for the same site based on 5-minute data are presented in Table 10 and

Table 11 show the average and maximum correlation coefficients between disaggregated load clusters, their sum, and the residuals (rows) and submetered end-use loads (columns). Table 12 and Table 13 show the average and maximum correlation coefficients between disaggregated load clusters, their sum, and the residuals (rows) and submetered end-use loads (columns) for results based on 15-minute data. Note that the 5-minute data result in three disaggregated end-use clusters, whereas the 15-minute data result in only one cluster due to more overlap of events in the larger time window where more events can occur.

Table 10. Average Correlation Coefficients (5-minute data)

Cluster	Refrigerator 1	Refrigerator 2	PC	Entertainment Center	Washer	Sum of PC and Entertainment Center
Cluster 1	0.12	0.07	0.15	0.14	0.11	0.15
Cluster 2	0.15	0.07	0.16	0.18	0.13	0.17
Cluster 3	0.15	0.09	0.19	0.12	0.15	0.19
Cluster Sum	0.17	0.08	0.20	0.16	0.15	0.20
Residuals	0.15	0.07	0.15	0.11	0.12	0.15

Table 11. Maximum Correlation Coefficients (5-minute data)

Cluster	Refrigerator 1	Refrigerator 2	PC	Entertainment Center	Washer	Sum of PC and Entertainment Center
Cluster 1	0.35	0.25	0.46	0.65	0.37	0.65
Cluster 2	0.44	0.34	0.47	0.54	0.26	0.71
Cluster 3	0.51	0.43	0.35	0.39	0.47	0.49
Cluster Sum	0.45	0.29	0.48	0.48	0.38	0.67
Residuals	0.46	0.34	0.37	0.45	0.43	0.54

Table 12. Average Correlation Coefficients (15-minute data)

Cluster	Refrigerator 1	Refrigerator 2	PC	Entertainment Center	Washer	Sum of PC and Entertainment Center
Cluster 1	0.17	0.13	0.22	0.22	0.14	0.31
Residuals	0.15	0.13	0.17	0.11	0.11	0.19

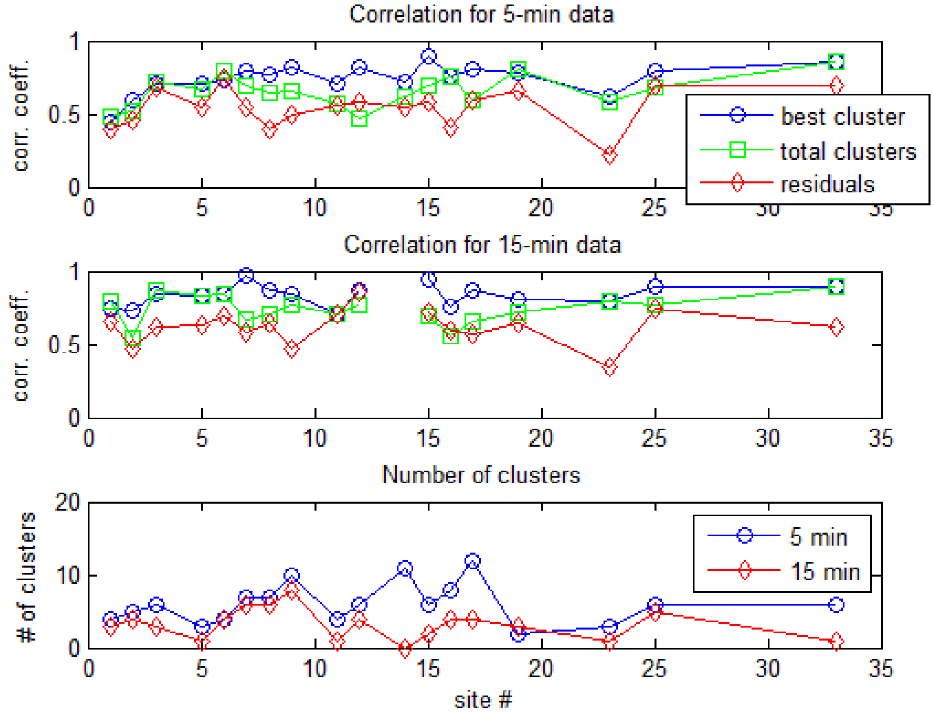
Table 13. Maximum Correlation Coefficients (15-minute data)

Cluster	Refrigerator 1	Refrigerator 2	PC	Entertainment Center	Washer	Sum of PC and Entertainment Center
Cluster 1	0.49	0.37	0.63	0.86	0.38	0.83
Residuals	0.63	0.49	0.51	0.18	0.49	0.63

Average correlations are low and do not vary much between end uses, making it difficult to determine which (if any) end use the disaggregated load clusters represent. Maximum correlation coefficients are higher and do vary between end uses. The residuals tend to be highly correlated with the sum of computer and entertainment center loads, but so do the other disaggregated clusters. In fact, the maximum correlation between disaggregated clusters and metered end uses often indicate that all disaggregated clusters have the highest correlation with the entertainment center or sum of computer and entertainment center, providing inconclusive results.

To summarize the results across sites, the team plotted the maximum correlation coefficient for the disaggregated cluster with the highest correlation, the coefficient of the disaggregated total, and the coefficient of the residual. Figure 12 shows that the residual seldom had the highest correlation coefficient and in only two of the sites (sites 3 and 6) would the residual have been identified as the best match for any of the metered end-use loads. The top two plots show the correlation coefficients for the 5-minute and 15-minute data. The bottom plot shows the number of end-use clusters identified at each site, demonstrating that the number of end-use clusters detected using this disaggregation method was always higher in the higher frequency data.

Figure 12. Correlation Results for All Sites



Conclusions

Implementation of disaggregation based on load clusters and correlations with metered data demonstrated little success in this application. It is possible that additional effort could reveal alternates or updates to the method that would provide more promising results. While research into this type of method could be explored, we believe that such research is more closely aligned with disaggregation methodology and challenges even in disaggregating large loads that it is with MEL prediction. Therefore, if the objectives of the California IOUs include establishing disaggregation methodology for low frequency data and primary as well as miscellaneous end uses, then we recommend exploring this topic further. If, however, the objectives of the IOUs are focused on studying and predicting MELs, then we recommend future research efforts outlined in Appendix B.

Appendix B. Regression Approaches for Disaggregation

In this appendix, we provide additional details on studies that used regression approaches for disaggregation of whole-home loads. We also relied on details from these studies to develop the predictive modeling approaches outlined in Research Topic 3.

In a recent study, [75] Burgett and Chinimodeled MELs as a function of home square footage and number of bedrooms. They explored an alternative where MELs are modeled as a function of both building and occupant characteristics. In this study, the authors used data collected from surveys and published energy consumption data in the Residential Energy Consumption Survey (RECS) microdata set for 12,000 respondents,[76] with MELS defined as in the Home Energy Rating System (HERS). RECS appliance surveys provided information on type and usage of appliances that contribute to two-thirds of each home's annual MEL. They created a Residual Miscellaneous Electrical Load Model (RMELM) to predict MELS and compared the results to HERS standardized occupant MELS. Occupant characteristics in the RMELM included age, income, square footage, number of household members, whether a home business was present, the size of the garage, education levels, housing type, whether residents were home during the day, number of children, home vintage, marital status, and whether occupants were retired or not.

The RMELM was specified using stepwise regression to select explanatory variables where the dependent variable was total ME load. The detailed information on television peripherals, computers, monitors, microwaves, rechargeable electronics, and rechargeable tools, was used to calculate respondent specific unit energy consumption (UEC), where UEC is an estimate of the total annual energy used by an average person for a typical appliance. For the remaining one-third of appliances not included in the RECS, the study used estimates of total annual MEL based on similar methods as used in Residential Services Energy Network (RESNET)[77] and the U.S. Department of Energy Building America Program.[78] Finally, total MEL was calculated using each method as the sum of UEC and modeled as a function of housing and occupant characteristics using the RMELM regression method and using square footage and number of bedrooms and the HERS method.

The results of each method were compared to actual observed total MEL in 24 test homes to compare the performance (accuracy) of each model. Directly metered MELS were collected using data loggers

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75 Burgett, J. and A. Chini. "Using Building and Occupant Characteristics to Predict Residual Miscellaneous Electrical Loads: A Comparison between an Asset Label and an Operational Model Specifying Residential Retrofit." Journal of Building Performance Simulation. 2015.

76 Residential Energy Consumption Survey (RECS). Accessed online June 20, 2016: https://www.eia.gov/consumption/residential/data/2009/

77 Residential Services Energy Network (RESNET). Accessed online June 20, 2016: http://www.resnet.us/standards/PropStdsRevision-01-11_Revised_FINAL.pdf

78 U.S. Department of Energy Building America Program. Accessed online June 20, 2016: http://energy.gov/eere/buildings/building-america-research

installed for two weeks and additional information was collected using household surveys and on site audits. The survey and audit information from each home was used to estimate MEL based on the RMELM model and the HERS model. The study found that the RMELM regression model provided a more accurate estimate of MEL consumption in 17 of 24 homes. The homes where the HERS model performed better had smaller total MEL consumption (less than 2,000kWh). Based on these results, the study indicates that indeed additional housing and occupant characteristics are correlated with MELS and using additional information can improve MEL estimates, especially when the MEL is larger.

In a separate study,[79] the authors developed a stochastic model for total household load profile based numerous of end-use models. The end-use portion was used to directly estimate energy consumption using information on end uses and end users including the presence or absence of appliances, appliance age, size of homes and information about customers. Appliance and household surveys were used to collect data on household characteristics, appliances (presence or absence and duration of use), and behavior. End-use metering using sensors was used to collect one second electricity data.[80] MELs were categorized into five groups and survey data provided information on the average number of end uses and the distribution of times of use in each group. These distributions were used to simulate end-use usage times and run times, overlaying them to calculate energy consumption at each time of day, and then using to model whole home energy consumption at each time point.

In a similar study,[81] the authors developed a stochastic model of whole-home energy consumption as the sum of components, including primary end uses and behaviors (sleeping, laundry, etc.). The components were modeled separately, with primary end-use models developed in a similar fashion as other reviewed studies (engineering, weather dependence, etc.). The authors used behavioral data from American Time Use Survey, an annual subsample of the Consumer Preferences Survey (CPS) administered by US Bureau of Labor Stats to stratify customers based on employment, gender, and age (5 groups). They used a Markov chain to estimate transition probabilities from one activity to another, among nine activity categories. Each chain was used to simulate a multiple day period (either working or nonworking days) based on probability distributions of the timing and length of time spent sleeping, cooking, at work, etc. Activities were translated into appliance usage and corresponding power demands based on U.S. appliance stock and average wattage (data from U.S. DOE Energy Saver program)[82] in combination with random run times. Chains for different individuals were added to estimate population total demands. For purposes of household characterization, rather than summing across all individuals

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79 Ghaemi, S. and G. Brauner. "Stochastic Model for Household Load Profile." Symposium Energieinnovation, 10.-12.2.2010. 2010. Accessed online June 20, 2016: http://publik.tuwien.ac.at/files/PubDat_185237.pdf

80 Moeller Metall-Dichtung. Accessed online June 20, 2016: http://www.moeller-metalldichtungen.de/51-2-Measuring-washers.html

81 Muratori, M., M.C. Roberts, R. Shioshansi, V. Marano, G. Rizonni. "A highly Resolved Modeling Technique to Simulate Residential Power." Applied Energy: 107 2013 465-473. 2013.

82 U.S. DOE Energy Saver Program. Accessed online June 20, 2016: http://energy.gov/energysaver/energy-saver

in the population, we could consider summing across all individuals within a home to estimate total load and also total load of each component where one component represents MELs in aggregate or particular MEL groups. Some advantages of this approach are that the components are easy to understand and inputs can be varied to study potential effects of changes on loadshapes. Models capture hourly behaviors and can be used to estimate hourly loadshapes. If insufficient data are available, the data required to build and verify several models could be cost prohibitive.

In a similar study,[83] the authors use a simulation model to forecast electricity loads where two of the three component models use Markov chains to capture changes in activities throughout the day (like the previous study) to describe appliance and domestic hot water loads. Space heating is estimated using a regression model to account for weather, household characteristics and heat loss estimated by the other two components. In one use case, the authors report that the model produces realistic demand profiles, especially in summer. This confirms that the appliance and DHW models are reliable but also suggests that the space heat model is not, in the summer.

Many studies combined statistical models with engineering models (statistically adjusted engineering (SAE) models) and survey data (home specific or national appliance saturation information).[84]

Power changes of roughly 0.1 watts and sampling rates greater than 1Hz are typically required for detecting small and miscellaneous end uses (e.g., DVD player, wireless routers, and printers). Therefore, In a California study, relationships between primary sources of demand at the household level were examined.[85] The primary interest was in estimating the relative size of different sources of demand within a single geography (California) and determining how efficiency savings potentials from major upgrades vary and are influenced (amplified or dampened) by household activity or occupant behavior. The study used CDA regression modeling to predict energy use relative to weather measures and propose combining it with engineering and building simulation models to account for physics and heating, ventilating and air conditioning (HVAC) loads. In a similar study,[86] inventories of devices in each home were combined with historical energy use characteristics of end uses to estimate operating hours and schedules (occupant-based).

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83 Sandels, C., J. Widen, and L. Nordstrom. "Forecasting Household Consumer Electricity Load Profiles with a Combined Physical and Behavioral Approach." Applied Energy: 131 2013 267-278. 2014.

84 Grandjean, A., J. Adnot, and G. Binet. "A Review and Analysis of Residential Electric Load Curve Models." Renewable and Sustainable Energy Reviews 16 2012 6539-6565. 2012.

85 Lutzenhiser, L., H. Hu, M. Moezzi, A. Levenda, and J. Wood. *Lifestyles, Buildings and Technologies: What Matters Most?* ACEEE Summer Study on Energy Efficiency in Buildings. 2012.

86 Parekh, A., P. Wang, and T. Strack. *Survey Results of User-Dependent Electricity Loads in Canadian Home*s. ACEEE Summer Study on Energy Efficiency in Buildings. 2012.