A Plug Load and Lighting Model for ZNE Residential Buildings

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ABSTRACT

California's goal is for all new residential buildings to be Zero Net Energy (ZNE) by 2020. To ensure new homes are ZNE, we must predict with an energy simulation model how much on-site renewable generation will be needed to offset each home's energy consumption. Particularly for plug loads and lighting, which represent over half of residential electricity use, this can be a considerable challenge, as many of these loads are evolving quickly. Because modeling inaccuracies may result in improperly-sized on-site generation systems, a current and easily updatable model is critically important for cost-effectively achieving ZNE goals.

This paper discusses the methodology developed by the California Statewide Utility Codes and Standards Program to model energy use of plug loads and lighting for newly constructed homes. In particular, we discuss challenges and lessons learned from developing a model that predicts energy use based on house characteristics (principally number of bedrooms and floor area). We conclude that although such a model can effectively estimate average energy use, it is unlikely to accurately predict the energy use of a given new home, because occupant behavior and consumer preferences strongly affect energy use but are poorly correlated with house characteristics.

We also present the estimated energy use breakdown for a typical home and how our results differ from the prior algorithms, highlighting the prominence of "residual MELs" and the major decrease in lighting energy use. Finally, we discuss future research possibilities, including how additional survey and submetering data can be leveraged to improve the model.

Introduction

This paper discusses the algorithms developed by the California Statewide Utility Codes and Standards Program Team (hereafter "C&S Team") to predict energy use of plug loads and lighting in newly constructed California single family and multifamily homes built in 2017 and beyond. These algorithms model Time Dependent Valuation (TDV) energy use,[1] which is used to verify compliance with the California Building Energy Efficiency Standards (Title 24, Part 6) and the California Green Building Standards (CALGreen or Title 24, Part 11).

Plug loads are defined in this paper as appliances or electronic devices that are generally plugged in to a receptacle, such as white goods and consumer electronics, while lighting includes all portable and hardwired interior, exterior, and garage lighting. Based on California Energy Commission's (CEC) estimates of annual energy consumption (AEC), plug loads and lighting

[1] TDV energy use accounts for energy used at the building site as well as energy consumed as part of power generation, transmission and distribution losses. TDV energy is assigned a valuation factor for each hour of the year to reflect the total societal cost of energy used at that time. For example, energy use that occurs during peak periods is valued more than savings that occur off-peak.

constituted the vast majority (81 percent) of California home electricity consumption in 2008 (KEMA 2010b). However, in recent years there have been significant changes in plug load and lighting energy use. Advances in efficiency, many of which have been codified into federal and state energy efficiency requirements, have reduced energy consumption from these end uses. To some extent, efficiency gains have been offset by increasing energy services from consumer electronics, such as more computers per home, larger TV screen sizes, and the proliferation of novel electronics. These technological and social trends necessitate an up-to-date model of plug load and lighting energy use. However, CEC's plug load and lighting had not been updated since 2008 (CEC and AEC 2008), and the existing algorithms tend to overestimate energy use from these end uses, with the error increasing for larger homes.

The outdated models are particularly problematic because beginning January 1, 2017, the 2016 CALGreen Standards include a voluntary requirement that newly constructed homes achieve zero net energy (ZNE), and energy use from plug loads and lighting is a key determinant of the capacity of the on-site renewable generation system that is needed for a home to qualify as ZNE. Updating the algorithms in preparation for implementing the voluntary 2016 CALGreen Standards will also put the state in a better position to achieve the statewide goal that all newly constructed California homes be ZNE by 2020. This paper focuses on the challenges and lessons learned when developing updated AEC estimates. The detailed project report explains the approach for both AEC and load profiles in more detail (Statewide Utility Codes and Standards Team 2016).

I. Generalized Methodology

An important goal for the present work was to create a model with a transparent methodology that could be easily updated with new data, as it becomes available. With this goal in mind, the C&S Team increased the number of independently modeled end uses, developed a methodology that relies on a foundation of modular components, and refrained from adding complexity to the approach unless it would substantially increase modeling accuracy.

The generalized methodology template used by the C&S Team for estimating AEC as a function of home size follows four major steps for each end use modeled:

1. **Determine product inventory and usage patterns:** Data on the number, type, and usage of products inputs was generally derived from the 2009 California Residential Appliance Saturation Study (RASS)—a detailed survey of 25,000 California households that asked respondents about the characteristics of their house, the occupants, and their devices (KEMA 2010a).
2. **Estimate likely product efficiency in 2017:** Product efficiency was based on estimates of average product age when the building is new, using applicable energy efficiency standards, ENERGY STAR® specifications, or ENERGY STAR Qualified Products Lists (QPLs).
3. **Calculate the "2017 AEC" for every household in RASS:** The C&S Team calculated the AEC for each household in RASS, assuming the products met the efficiency levels estimated for new California homes built in 2017, following Steps 1 and 2.
4. **Develop algorithms that predict AEC from number of bedrooms (NBr):** To create an equation that predicts AEC based on NBr, the C&S team performed a linear regression analysis, relating number of bedrooms (NBr) to calculated 2017 AECs for every household surveyed in RASS.

The process diagram shown in Figure 1 presents these four steps in detail.

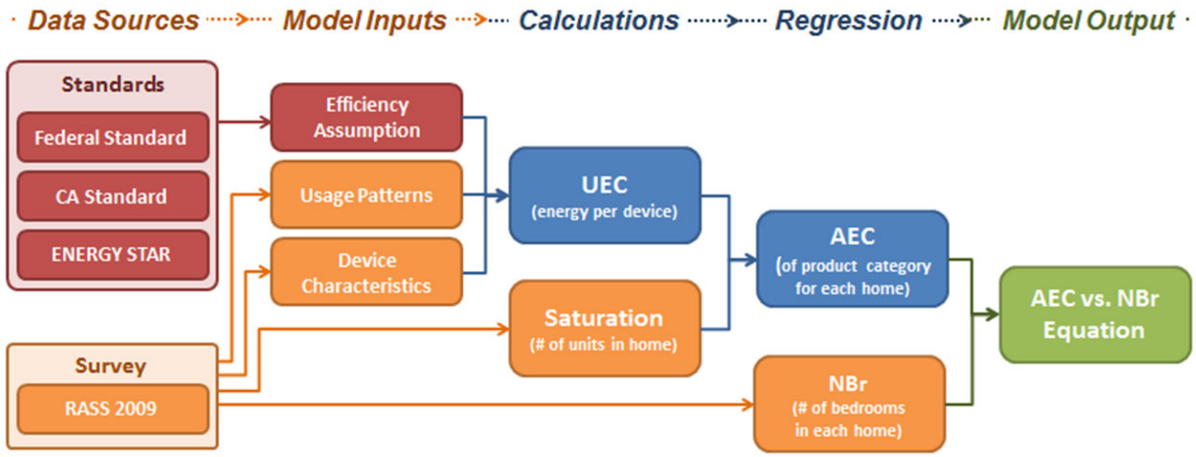

Figure 1. Process diagram of our high-level methodology for producing algorithms that predict per-household annual energy consumption (AEC) for a given product category based on number of bedrooms (NBr).

The C&S Team was able to generally follow this approach for the white goods (ovens/ranges, refrigerators/freezers, clothes washers/dryers, and dishwashers) and the three most energy consumptive "major" consumer electronics (defined here as televisions, set-top boxes, and computers and monitors). For lighting, in place of RASS, the C&S team relied on California Public Utility Commission's (CPUC) 2012 California Lighting and Appliances Saturation Survey (CLASS), which includes a detailed on-site lighting audit for every surveyed household (DNV GL 2012). Neither RASS nor CLASS were sufficient to estimate AEC of residual miscellaneous electric loads (MELs) because neither could exhaustively catalogue all of the MELs in a home. As such, residual MELs necessitated a unique approach, which is described below.

II. Challenges and Lessons Learned

Estimating AEC of Residual MELs

Residual MELs consist of a large variety of products, such as microwaves, DVD players, aquarium pumps, tablets, and all other end uses that were not modeled independently. The extreme diversity of product classes presents a challenge to developing an exhaustive model of residual MELs: some end uses may be increasing in efficiency as technologies evolve, while others may be adding new features and growing in power demand. Meanwhile, new end uses also enter the market, while others become obsolete.

The C&S Team took a bottom-up approach to modeling residual MELs, calculating AEC as the sum of the AEC of 114 constituent end-uses. The C&S team derived the largest portion of the total AEC estimate from a 2014 meta-analysis of residential energy use of residual MELs and consumer electronics (Kisch, Zakarian, and Dewart 2014). This study, led by Southern California Edison (SCE), synthesized the extant estimates of the AEC of the miscellaneous product categories with the highest statewide energy use. The C&S Team added to the SCE meta-analysis estimate the AEC of battery chargers and external power supplies for those MELs that were not included in the SCE report (DOE 2012) as well as AEC estimates from the 2014

Building America House Simulation Protocols (Wilson et al. 2014). The change in residual MELs AEC between 2013 and 2017 was modeled using a 4.3 percent growth rate, as determined by the 2013 CEC demand forecast (CEC 2014). Since no reliable method currently exists for scaling the residual MELs AEC with home size, the C&S team assumed that for a given home, residual MELs AEC scaled with consumer electronics by keeping the ratio of residual MELs AEC to consumer electronics AEC constant for all home sizes. The resulting equation for AEC vs. number of bedrooms appears reasonable in magnitude and form when benchmarked against other major models (Parker, Fairey, and Hendron 2010; Wilson et al. 2014).

Accounting for Technology Trends and Changing Product Use Patterns

Forecasting Product Inventory and Usage. Where possible, the C&S team tried to draw the inventory and usage of devices from RASS, because this is what allows the C&S Team to empirically infer the relationship between AEC and NBr.[2] Because the efficiency assumptions are fixed for individual devices/end uses, the fundamental reason that estimated AEC increases with NBr is that the average number, type, size, and/or usage of products tends to increase with NBr in the RASS data.

Unfortunately, RASS data may not always be reliable because it is self-reported and sometimes outdated. Television usage is a prime example of both of these challenges. Therefore, the C&S team instead drew the television usage assumptions from a 2012, California-specific Nielsen study, which measured daily hours of use of every television in the home (Nielsen 2012). It could be argued that because television usage patterns will have changed so much from 2012 to 2017—largely due to the rise of online streaming services (e.g. Netflix) that are shifting viewing to computers and tablets—the C&S Team should have developed an adjustment factor to account for these trends. In general, the C&S team chose not to create such adjustment factors, both because the requisite data is often unavailable and also because this would greatly complicate updates to the model.

[2] In the final methodology, the C&S Team did not rely on RASS self-reported usage data for dishwashers and clothes washers/dryers. Instead, the C&S Team scaled AEC to NBr based on how annual dishwasher/clothes washer cycles vary with NBr in the domestic water heating (WH) ruleset used in the Title 24 compliance software. Correlations from the original (RASS) approach are shown in this paper, because the final approach does not lend itself to statistical analysis. The results presented in this paper reflect the final, WH ruleset usage assumptions.

Forecasting Efficiency. For the present modeling effort, the ideal data source for estimating AEC would be a recent submetering study that analyzed a large sample of new California homes for at least a year. Lacking this perfect data, the C&S team chose a simplified engineering approach to forecasting efficiency for two main reasons. First, using older or less applicable submetering studies would have required either justifying their applicability to new California homes or adjusting the data to account for differences in time, geography, and building vintage. Second, one of the C&S Team's goals was to create a model that could be easily updated to better track with ever changing trends. To that end, the C&S team estimated efficiency using data sources that are expected to be updated regularly and employed a modeling structure that is designed to easily take advantage of new data as it becomes available.

For all products covered by federal efficiency standards, the C&S team generally assumed products are minimally compliant with the standard[3] and in some cases provided the option to override the default AEC assumptions with additional information about product efficiency, if known. One problem with estimating AEC based on efficiency standards is that the way product efficiency is measured in a laboratory (to assess compliance with the standard) can be quite different from how people use those devices in the real world.[4]

The C&S Team forecasted the efficiency of the major consumer electronics based on ENERGY STAR® voluntary specifications, relying on the specification that the C&S team expected most products would meet in 2017, given trends in the ENERGY STAR market share and average device age. One benefit of this approach is that as ENERGY STAR specifications are updated, efficiency assumptions in the model can usually be easily refreshed.

For lighting, the C&S team estimated a weighted-average lighting efficiency by forecasting the relative abundance of different lighting technology types (e.g. LED, CFL, incandescent) and then using that to weight the forecasted efficiency of each lighting technology type in 2017. A chief consideration for estimating the share of various lighting types was that Title 24, Part 6, will require high-efficiency hard-wired lighting in new homes beginning in 2017. As new data about the abundance and efficiency of different lighting types becomes available, the C&S team can update these assumptions.

Predicting AEC from Observable House Characteristics

It is incredibly challenging to develop equations that accurately predict the AEC for newly built homes based only on observable house characteristics, without knowing the number, type, or usage of the devices in the home.[5]

Figure 2 diagrams the factors that mediate the relationship between house characteristics and AEC. Arrows indicate the proposed direction of dominant causation. House characteristics

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[3] More precisely, federally covered products are assumed to be minimally compliant with the standard that was in place when the device was manufactured, based on assumptions about the typical age of devices in new homes. For example, the C&S Team assumed dishwashers are new in a new home and thus modeled them as compliant with the 2015 federal standard by default.

[4] For example, the cloth used in the DOE Test Procedure for laundry equipment tends to be smaller and thinner than real clothes. Real clothing retains more moisture, which makes the washer load heavier to spin and increases the requisite dryer energy (Calwell 2014).

[5] The C&S Team was able to use certain information about builder-supplied appliances as model inputs. For example, homes are only assigned AEC for ovens/ranges, dishwashers, and clothes washers/dryers if those devices are present. Furthermore, whether the ovens/ranges and clothes dryers use gas or electricity is dependent on what the builder reports will be installed. Builders can also receive limited credit for installing more efficient appliances.

(number of bedrooms, floor area, house type) can directly influence product characteristics (number, type, usage, and efficiency of devices), primarily because larger homes have more space for more/larger devices. Occupant characteristics (number of residents, their income, and other demographic factors), can also influence product characteristics. For example, households with more income tend to purchase more consumer electronics and households with more elderly residents tend to watch more television. There is also an indirect linkage between house characteristics and product characteristics, mediated by occupant characteristics. For example, households with more people and tend to live in larger homes and also tend to do more laundry, which contributes to and indirect correlation between home size and number of annual laundry loads. Finally, product characteristics are ultimately what determine the actual AEC of those products. If the C&S Team is to accurately estimate AEC based on NBr, there must be strong correlations between at least some of the top three layers in Figure 2.

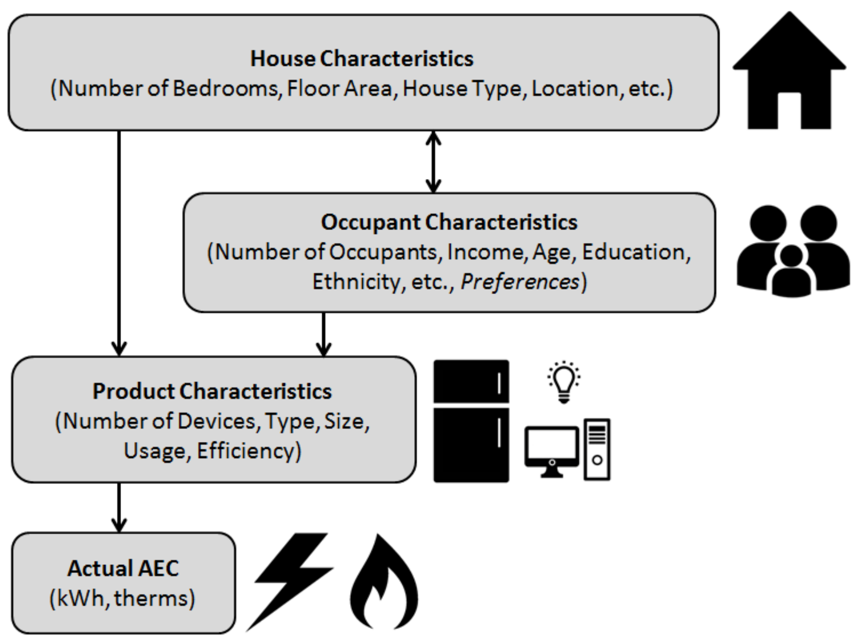

Figure 2. Layers of causation separating the possible predictor variables for a newly built home—house characteristics—from what the C&S team is ultimately trying to predict—actual AEC. Arrows represent what the C&S team theorize to be the primary direction of causation.

When analyzing the correlations between the top three layers of Figure 2, a consistent pattern emerges: there are clear, intuitive trends in the averages but no strong correlations. In statistical terms, p-values are consistently low (because there is a real trend, on average) but R^2 values are also low (because the correlations are weak).[6] Figures 3 and 4 demonstrate these patterns by quantifying the average trends and pairwise correlations between the house and occupant characteristics, based on RASS data. Figure 3 shows that as one would expect, average conditioned floor area (CFA), number of residents (NRes), and total household income (Income) all increase with NBr.[7]

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[6] R^2 is a measure of correlation strength that varies from 0 to 1, where 1 indicates a perfect correlation.
[7] This pattern reverses with 8-bedroom homes, but RASS only has data on seven of these exceptionally large houses, so the 8-bedroom average is not reliable.

Trends in Average Values by NBr (RASS 2009)				
NBr	CFA	NRes	Income	Households Surveyed
0	400	1.5	$ 34,000	362
1	600	1.8	$ 41,000	2,873
2	900	2.5	$ 49,000	7,377
3	1,600	2.9	$ 71,000	8,475
4	2,200	3.4	$ 93,000	4,286
5	2,800	4.1	$ 97,000	959
6	3,600	4.0	$ 102,000	141
7	4,000	6.4	$ 139,000	27
8	4,400	4.5	$ 80,000	7

Figure 3. Average between the house and occupant characteristics. “0-bedroom” homes are almost all studio apartments. Data bars show the relative magnitude of rows within each column *Source*: RASS 2009 raw data.

Despite the clear average trends, there are weak pairwise correlations between house and occupant characteristics—quantified by the low R^2 values in Figure 4. These low R^2 values demonstrate that NRes and Income cannot be accurately predicted for a given household based on NBr or CFA. For example, NBr explains only 11% of the variation in NRes and only 16% of the variation in Income. CFA is a comparably poor predictor of occupant characteristics, although somewhat better for predicting Income ($R^2 = 0.22$) and worse for predicting NRes ($R^2 = 0.03$). The strongest pairwise correlation is between NBr and CFA.

Strength of Pairwise Correlations - R^2 (RASS 2009)	NBr	CFA
NBr	-	0.52
CFA	0.52	-
NRes	0.11	0.03
Income	0.16	0.22

Figure 4. Correlations between the house and occupant characteristics. Data bars show the magnitude of the pairwise correlations (R^2 values) compared to the maximum possible value of 1. *Source*: RASS 2009 raw data.

Although the correlations are likely diluted because data is self-reported within the constraints of the RASS multiple choice questionnaire, these results are an important reality check: while it is reasonable to assume, for example, that larger homes will tend to have larger televisions because they have more household income on average, those average trends do not imply that NBr or CFA can be reliable predictors of television AEC for a given home.

This conclusion is supported by the results of the regression analysis the C&S team conducted to create an equation that predicts AEC based on NBr (step four of the generalized methodology). For example, Figure 5 shows the regression analysis results for computers and monitors based on the AEC values the C&S team calculated for every home in RASS, assuming products meet 2017 efficiency levels. Although the algorithm captures the trend in how computer and monitor AEC varies with NBr on average, the R^2 is only 0.14. This low R^2 is visually apparent as the large vertical spread of the per-home AEC estimates, which range from 0 to 891 kWh/yr across all home sizes in RASS. As NBr increases, the distribution of per-home AEC estimates shifts upward, but the vertical spread remains quite wide.

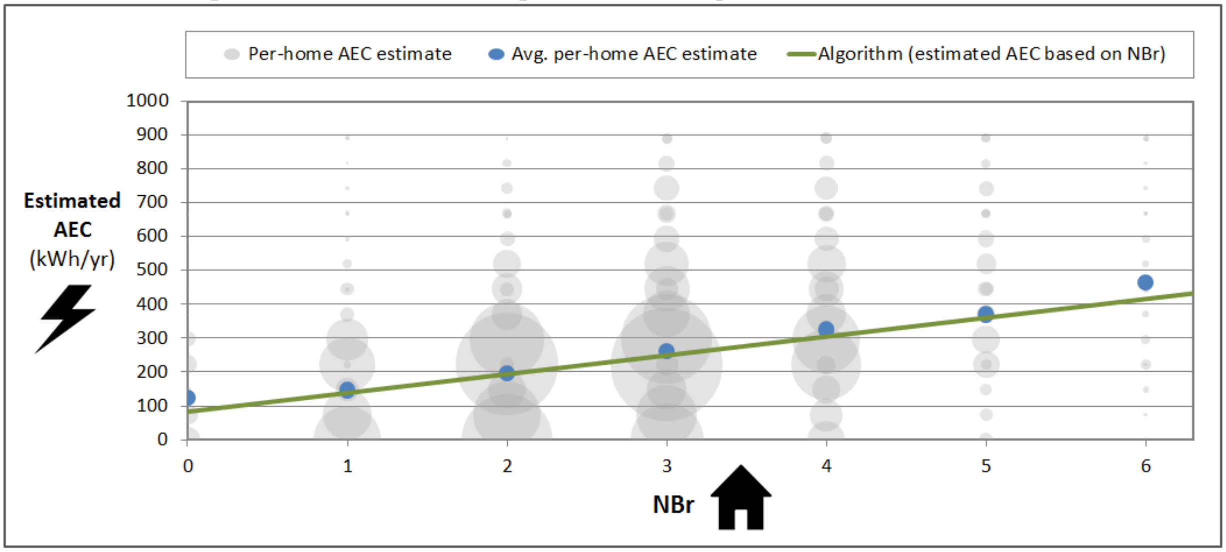

Figure 5. Regression analysis results for computers and monitors based on calculated 2017 AEC for every home in RASS. The blue dots represent the average calculated AEC for each NBr. The green line is the algorithm that predicts computer and monitor AEC based on NBr. The C&S team fit the green line by regressing the calculated AEC for each RASS household against the corresponding NBr. This underlying data is shown as gray, translucent bubbles. To show which values are most common, bubble size proportional to the number of households with a given combination of NBr and AEC. "0-bedroom" homes are studio apartments.

The computer and monitor results are exemplary of what the C&S team found when assessing the predictive capabilities of the models: the algorithms are effective at predicting the average AEC for a given NBr but do not perform well for individual homes. Figure 6 summarizes the correlations between NBr and calculated per-home AEC, as well as correlations with other house and occupant characteristics. The R^2 of the algorithms when applied to the RASS data—shown as purple bars—is always less than 0.20, ranging from 0.19 for the primary refrigerator down to 0.01 for our ovens. CFA has similar predictive power to NBr for every product category.[8] Because NBr and CFA had similarly low R^2, the C&S Team standardized to use NBr as the predictor variable for all plug load end uses and CFA for all lighting, instead of trying to optimize the choice of NBr or CFA for each one.[9]

To approximate the upper limits of how accurately one could predict AEC with knowledge of occupant characteristics and use of a more sophisticated statistical approach, the C&S team tested a "kitchen sink" multivariate regression analysis, modeling the AEC values calculated for every home in RASS based on: NBr, CFA, Income, NRes, education, and whether

[8] This is likely because: CFA and NBr are correlated with each other; they are comparably correlated with NRes and income; and they have the same mechanism of direct effect on AEC (i.e. more physical space more devices per household).

[9] The choice of NBr for plug loads and CFA for lighting was largely motivated by: a desire to harmonize with the RESNET 2013 plug load and lighting algorithms; the constraints of the RASS and CLASS data; and a preference for predictor variables that scale linearly with AEC.

the dwelling is single-family or multi-family. The C&S team found that this complex approach yielded only marginal benefits, as the R^2 was generally not that much higher in absolute terms. In other words, these results indicate that the factors that affect calculated AEC (number, type, usage of products) are not primarily a function of house characteristics or demographics. The C&S team posits that individual preferences, such as people's preference for home-cooked meals, graphics-intensive video-games, or attitudes towards energy conservation could have a significant impact on AEC as well.

Strength of Correlation (R^2)		Estimated AEC: Number and type-dependent products				
		Primary refrigerator	Computers & monitors	Other refrigeration	Televisions	Set-top boxes
	NBr	0.19	0.14	0.12	0.09	0.07
	CFA	0.18	0.11	0.14	0.10	0.07
	Income	0.11	0.13	0.03	0.02	0.06
	NRes	0.01	0.06	0.03	0.05	0.02
	"Kitchen Sink"*	0.27	0.22	0.19	0.17	0.14

Strength of Correlation (R^2)		Estimated AEC: Annual uses-dependent products				
		Clothes dryers	Dishwashers	Clothes washers	Ranges	Ovens
	NBr	0.05	0.05	0.04	0.02	0.01
	CFA	0.03	0.05	0.03	0.01	0.02
	Income	0.02	0.05	0.01	0.00	0.01
	NRes	0.19	0.07	0.18	0.05	0.02
	"Kitchen Sink"*	0.21	0.13	0.18	0.06	0.04

*Multivariate prediction using: NBr, CFA, NRes, Income, Single- or multi-family dwelling, & Education

Figure 6. Accuracy (R^2) of algorithms that predict the AEC calculated for each home in RASS based on NBr, CFA, Income, NRes, or a combination of variables. Lighting and residual MELs are not included because the C&S Team was not able to use the RASS raw data for those end uses as discussed previously. *Source:* Regression analysis using RASS raw data combined with engineering calculations to estimate 2017 AEC.

The C&S Team explored some additional methods of improving the R^2 of the algorithms, such as using ZIP code or climate zone in the multivariate analysis and nonlinear curve-fitting. None of these approaches improved the R^2 dramatically, but all introduced a series of technical challenges and added complexity. Ultimately, the C&S team concluded that a simple, standardized approach to curve-fitting best serves the goal of creating a "living model." Moreover, given the layers of poor correlations between observable home characteristics and the dominant influence of individual preferences, it follows that future improvements should focus primarily on ensuring the equations are not biased high or low, as opposed to optimizing the accuracy of the model for individual homes. Put simply, these algorithms cannot ensure that every new home is truly be ZNE, because it is not possible to account for individualized and dynamic occupant behaviors and preferences; rather, the focus should be to ensure that on average, all homes evaluated together are ZNE.

III. Results

All else equal, the largest end uses have the greatest potential to cause over- or underestimates of a home's total energy use (and the capacity of the on-site renewable generation system needed to achieve ZNE status). Figure 7 shows the modeled electric AEC for all plug loads and lighting estimated by three different energy models—including the updated and existing California algorithms—applied to an average (3-bedroom) single-family home with all electric appliances. According to the proposed model, by far the largest end use is residual MELs, followed by an electric clothes dryer (if present), primary refrigerator, and interior lighting. The most substantial change to the magnitude of the end uses is that the interior lighting AEC in the updated algorithm is roughly half the estimate of the previous California model. The dramatic decline in lighting energy is attributable to lighting efficiency requirements in 2016 Title 24, Part 6 that will effectively require the majority of hard-wired lighting to be LED. Equally noteworthy is the increased granularity of the updated modeling, which will better facilitate the use of new data to make future improvements.

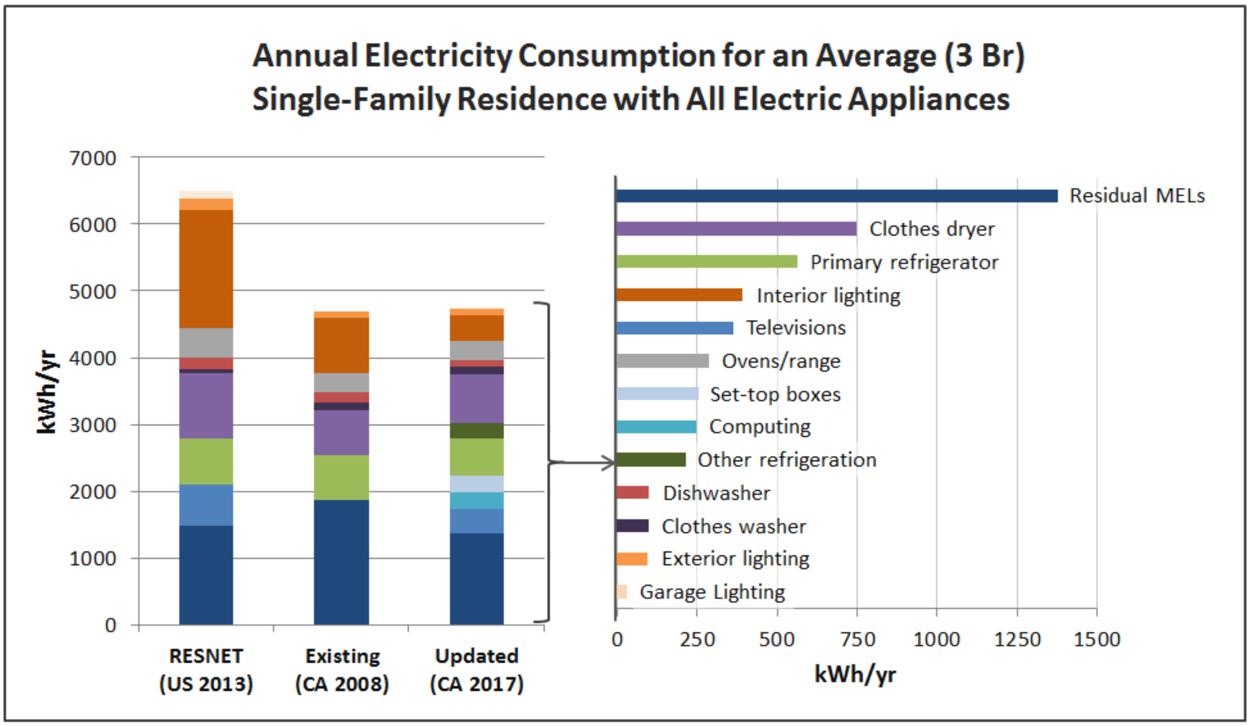

Figure 7. Comparison of estimated electric AEC for all plug loads and lighting under three energy models, including a breakdown of the updated models. Estimates are for a 3-bedroom single-family residence with all electric appliances; however the C&S Team also developed equations for gas appliances, if those are present. Multi-family dwelling units have generally very similar equations. *Sources:* Residential Energy Services Network standards (RESNET 2013); algorithms used for California's 2013 Title 24, which are based on the equations in the 2008 California HERS Technical Manual (CEC and AEC 2008); present modeling.

IV. Future Research Goals and Possibilities

Better Characterize Residual MELs. Better characterizing the composition and average AEC of residual MELs is perhaps the most consequential improvement that could be made to the updated algorithms. Residual MELs are the product category with by far the largest AEC and are also the most challenging to model. In future updates to the model, it will be important to consider how building audit and sub-metering data can be leveraged. In particular, the C&S Team should evaluate whether to keep using a purely bottom-up approach—modeling residual MELs as the sum of constituent end uses—or if this could be combined with a true “residual” approach—estimating residual MELs AEC as the leftover electric AEC after subtracting major loads.

There are many benefits to the bottom-up approach employed by the C&S Team that are important to retain. For example, modeling all of the constituent MELs makes it easier to create functional categories of MELs, each with its own assumed growth rate, scaling with home size, and time-of-use patterns. A key drawback of the bottom-up approach is that it potentially requires current data on every conceivable MEL product category.

Taking a “residual” approach instead would be extremely useful for ensuring that the whole-home electric AEC is accurate, which is ultimately the goal of the present work from a ZNE perspective. If a sufficiently large and diverse sample of new ZNE homes were submetered, measuring all loads except for the residual MELs, the residual MELs AEC could be estimated with much greater confidence than is afforded by the C&S Team’s bottom-up approach. This total could then be disaggregated into functional categories using a bottom-up engineering approach for the sake of analyses such as forecasting growth rates, targeted program design, identification of efficiency standards opportunities.

Separate Single-family and Multi-family Units. Single-family and multifamily dwelling units are very different, and could therefore have different energy usage characteristics. Within the multifamily subset, low income housing units may exhibit different energy usage characteristics as well. The existing and updated rulesets generally do not distinguish between single family and multi-family; however, using the proposed methodology and existing data sources, it is possible to analyze the differences in product characteristics between single-family and multi-family homes. It is recommended that the analysis be expanded to include separate single-family and multi-family rulesets, and possibly low-income housing rulesets, for estimating AEC.

Model Idle Loads Explicitly. To some extent, the resulting models already build AEC from standby and active mode AEC. Given the high fraction of residential electricity consumption caused by wasteful standby loads, it may be helpful to explicitly distinguish between standby and active mode AEC in future modeling results in order to support targeted efficiency measures that address this issue.

Use Data from “Smart devices” that Self-Report Energy Use. Networked devices, which record and wirelessly report their own energy use, are becoming increasingly common. Although privacy concerns are a likely barrier to using even anonymized UEC data from energy reporting, the public may have fewer concerns about releasing anonymized data on the number of devices per household. Because “smart” devices in homes generally report to a single piece of network equipment, that central node could store data on how many devices of each type there are per household. Potentially, this could be a source of real-time data on the evolving saturation patterns of major consumer electronics and certain residual MELs.

V. Conclusions

The updated algorithms are able to predict the *average* annual energy consumption (AEC) for homes of a certain size (using number of bedrooms or floor area as a scaling factor for homes size); however, the C&S Team's statistical analysis of the RASS data and the reasoning presented in this paper indicate that a home energy use model based on house characteristics cannot accurately predict AEC for *specific* homes. There is simply too much variation in product characteristics (number of devices per household, size, type, and usage) that is not well correlated with house characteristics (number of bedrooms, floor area, house type) or even occupant characteristics (number of residents, income, household demographics). The C&S Team posits that the wide variation in product characteristics (and energy use) within physically similar houses is best understood as being a product of individual preferences and behaviors. Therefore, the greatest opportunity to improve the models is not to more accurately predict specific homes, but to make sure the estimated average AEC values are not biased low or high for homes of a given size (and house type).

In particular, it will be important to refine the estimate of residual MELs AEC, as this is the highest estimated electric AEC, appears to be increasing over time, and is the most uncertain. According to the C&S Team's model, an electric clothes dryer (if present), primary refrigerator, and interior lighting are also among the top electric end uses, although interior lighting AEC will be much lower in new California homes because of building efficiency standards that require high-efficiency hard-wired lighting.

One of the greatest strengths of the methodology presented here is that it can be updated relatively easily. The modeling approach is streamlined and the underlying assumptions are transparent and well documented. Individual assumptions can be replaced with more recent data, including: more recent survey data, such as the upcoming 2018 RASS; building audit data on the number and type of devices in modern, California homes; or submetering data on power draw by mode, hours of operation in each mode, or total AEC. Moreover, the residual MELs AEC estimate total could be based on submetering data, by subtracting major loads from a whole-home (or whole-circuit) AEC measurements. A "living model" is critically important at this time when plug loads and lighting are quickly changing and detailed data on home energy use is increasingly abundant.

References

Calwell, C. 2014. *Are Test Procedures Passing the Test? Ensuring That Measured Results Are Representative of Energy Use in the Field*. Luxemburg: Publications Office of the European Union. http://iet.jrc.ec.europa.eu/energyefficiency/publication/proceedings-7th-international-conference-eedal2013-energy-efficiency-domestic-appliances.

CEC (California Energy Commission). 2014. *California Energy Demand Updated Forecast, 2014-2024*. Staff Draft Report. Accessed November 2016. http://www.energy.ca.gov/2013publications/CEC-200-2013-004/CEC-200-2013-004-V1-CMF.pdf

CEC (California Energy Commission) and AEC (Architectural Energy Corporation). 2008. *HERS—Home Energy Rating System: Topic Report (Draft)*. Prepared for: California Energy Commission. http://www.energy.ca.gov/2008publications/CEC-400-2008-013/CEC-400-2008-013-D.PDF

DOE (Department of Energy). 2012. *Energy Conservation Standards Rulemaking: Battery Chargers and External Power Supplies*. EERE-2009-BT-STD-0005. http://www.regulations.gov/#!documentDetail;D=EERE-2008-BT-STD-0005-0084

DNV GL. "Frequently Asked Questions." CLASS Web Tool. Accessed March 2016. https://webtools.dnvgl.com/projects62/Default.aspx?tabid=192

KEMA. 2010. *2009 California Residential Appliance Saturation Study*. Consultant Report. Oakland: KEMA. http://www.energy.ca.gov/2010publications/CEC-200-2010-004/CEC-200-2010-004-V1.PDF

——— . 2010b. *2009 California Residential Appliance Saturation Study: Volume 2: Results*. Oakland, CA: KEMA. http://www.energy.ca.gov/2010publications/CEC-200-2010-004/CEC-200-2010-004-V2.PDF

Kisch, T., A. Zakarian, and N. Dewart. 2014. *Literature Review of Miscellaneous Energy Loads (MELs) in Residential Buildings*. Oakland: Energy Solutions. http://www.calmac.org/publications/MEL_Literature_Review_6_10_14.pdf

Nielsen. 2012. Understanding Television Set Usage: An investigation into average TV-set usage patterns in California. Report to Pacific Gas & Electric.

Parker, D., P. Fairey, and R. Hendron. 2010. Updated Miscellaneous Electricity Loads and Appliance Energy Usage Profiles for Use in Home Energy Ratings, the Building America Benchmark Procedures and Related Calculations. Cocoa, FL: FSEC. http://www.fsec.ucf.edu/en/publications/pdf/FSEC-CR-1837-10-R01.pdf

RESNET (Residential Energy Services Network). 2013. *Mortgage Industry National Home Energy Rating Systems Standards*. Oceanside, CA: Residential Energy Services Network, Inc. http://www.resnet.us/standards/RESNET_Mortgage_Industry_National_HERS_Standards.pdf

Statewide Utility Codes and Standards Team. 2016. *Codes and Standards Enhancement Initiative (CASE): Plug Loads and Lighting Modeling*. Oakland: Energy Solutions. http://www.bwilcox.com/BEES/docs/Rubin%20-%202016%20T24CASE%20Report%20-%20Plug%20Load%20and%20Ltg%20Modeling%20-%20June%202016.pdf

Wilson, E., C. Engebrecht Metzger, S. Horowitz, and R. Hendron. 2014. *2014 Building America House Simulation Protocols*. Technical Report. Golden, CO: NREL. http://energy.gov/sites/prod/files/2014/03/f13/house_simulation_protocols_2014.pdf