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Determinants of residential electricity consumption: Using smart meter data to examine the effect of climate, building characteristics, appliance stock, and occupants' behavior

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ABSTRACT

We propose a method to examine structural and behavioral determinants of residential electricity consumption, by developing separate models for daily maximum (peak) and minimum (idle) consumption. We apply our method on a data set of 1628 households' electricity consumption. The results show that weather, location and floor area are among the most important determinants of residential electricity consumption. In addition to these variables, number of refrigerators and entertainment devices (e.g., VCRs) are among the most important determinants of daily minimum consumption, while number of occupants and high-consumption appliances such as electric water heaters are the most significant determinants of daily maximum consumption. Installing double-pane windows and energy-efficient lights helped to reduce consumption, as did the energy-conscious use of electric heater. Acknowledging climate change as a motivation to save energy showed correlation with lower electricity consumption. Households with individuals over 55 or between 19 and 35 years old recorded lower electricity consumption, while pet owners showed higher consumption. Contrary to some previous studies, we observed no significant correlation between electricity consumption and income level, home ownership, or building age. Some otherwise energy-efficient features such as energy-efficient appliances, programmable thermostats, and insulation were correlated with slight increase in electricity consumption.

1. Introduction

Residential buildings consume 39% of the total electricity in the US, more than any other sector or building type [1]. Their electricity consumption has increased by 27% from 1990 to 2008 and—provided the expected efficiency gains are realized—is projected to increase by 18% from 2009 to 2035. To meet this demand, 223 GW of new generating capacity will be needed between 2010 and 2035, 75% of which is projected to be provided by fossil fuels [2]. Detailed planning and execution of demand-side energy efficiency programs is needed to reduce or stabilize residential electricity consumption, and to prevent its harmful impact on the environment and on energy security [3,4].

To effectively plan and execute energy efficiency programs, a sound understanding of the determinants that drive household electricity consumption (such as floor area, average outside temperature, and number of occupants) is needed [5]. However, because of lack of easily-accessible, high-resolution consumption data, underlying determinants of energy use and energy-related behaviors have not been extensively examined before [6].

With growing deployment of smart meters and real-time home energy-monitoring services, data that allow studying such underlying determinants are becoming available (for examples of studies using high-resolution consumption data, see Refs. [7–9]). However, the methodologies to analyze the data and infer the results that can be used to support decision making at the household level have not yet been formalized [6].

To address that gap, this paper proposes a methodology to analyze large data sets of residential electricity consumption to derive insights for policy making and energy efficiency programming. In particular, it offers a method to disaggregate the impact of structural determinants (e.g., insulation level of the residence) from

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behavioral determinants (e.g., occupant habits). As a case study, we use a large data set of 10-min interval smart meter data for 1628 households in the U.S. The data set is collected over 238 days in 2010, and is supported by an extensive 114-question survey of household data. The household survey covers information about the climate, location, physical characteristics of the dwelling, appliances, and occupants.

After a brief review of the gaps in existing literature, this paper explains our model, experimental data set, and the results of the our analyses.

2. Summary of limitations of existing models

Several studies have analyzed residential electricity consumption and its determinants. For our purposes, we needed a bottom-up model that could make use of high-resolution electricity consumption data and a large set of information about the households. We found that most existing studies were limited in supporting our requirements, mostly because of:

(a) *Use of aggregate (low-resolution) consumption data*: Most studies in the past have used monthly billing data, mainly because the advanced metering technologies of today were not easily accessible [10–18]. However, residential electricity consumption has strong temporal variation, which is not captured with low-resolution consumption data such as monthly bills [9].

(b) *Partial set of explanatory variables*: Most previous studies have analyzed only a partial set of residential electricity consumption determinants; e.g., only appliance stock, weather conditions, or behavioral factors [19,20]. However, interactions among different factors (e.g., the relationship between weather, appliance load, lighting load, and heating load) offer considerable potential for improving energy efficiency [6]. Another limitation of some previous studies is the use of "bundle" variables (such as Zip Code) that combine (hence obscure) the effect of several underlying determinants.

(c) *No distinction between "idle" consumption of the house and peak consumption*: Most studies in the past have either used peak consumption or the total electricity load. However, analyzing the lower limit of electricity consumption (i.e., idle load) gives valuable insights on the physical characteristics of the building. For example, a leaky building may have higher idle load because the heater or AC (air conditioner) needs to run constantly. Furthermore, as we will show in the paper, the distinction between idle and maximum consumption helps to disaggregate the effect of structural and behavioral factors on residential electricity consumption.

(d) *Using energy intensity as the only indicator for analyzing electricity consumption*: Most studies have used energy intensity (kWh per square foot) to compare residential electricity consumption [21–27]. Scaling the electricity consumption by floor area implies that, for example, a refrigerator in a 2000 sq.ft house consumes twice as much as the same refrigerator in a 1000 sq.ft house. Instead, we scale only those factors whose consumption is dependent on floor area (e.g., lighting and heating loads), and use the unscaled kWh value for other factors.

3. Model setup

Our proposed model addresses the limitations of existing models by: (a) classifying explanatory variables based on their interaction with each other and with electricity consumption; (b) selecting a subset of variables that best explain electricity consumption; (c) using different load features (e.g., daily peak and idle load) to distinguish the effect of different variables on electricity consumption; and (d) using a stepwise method to rank explanatory variables based on their correlation with electricity consumption.

3.1. Explanatory variables

Through a review of residential electricity consumption models and building sciences literature [5], we identified four major categories of determinants:

1. *Weather and location*. Examples: daily outdoor temperature and climate zone; these determinants are normally outside the scope of influence of the household.
2. *Physical characteristics of the building*. Examples: level of insulation and fuel use for water heating; modifying these determinants is normally considered long-term investments [28]. In return, the effect of such modifications is likely to persist longer.
3. *Appliance and electronics stock*. Examples: the number of refrigerators or computers; modifying these determinants is normally considered medium to short-term investments.
4. *Occupancy and occupants' behavior towards energy consumption*: determinants in this category have different levels of effort and impact span. Some behavioral modification determinants are of short-term effort and impact (e.g., proper management of thermostat settings) [28]. Another group of determinants are associated with long-term effort and impact (e.g., purchasing energy-efficient appliances). Finally, some determinants in this category are outside the scope of interest to change (e.g., occupancy level during the day).

Behavioral factors show strong correlation with each other, making multicollinearity an issue for the power and stability of the regression model. We used FA (**Factor Analysis**) [29] to remove multicollinearity of the variables, and identified latent variables that are not captured by direct behavioral questions. Factor Analysis reduces the number of variables by replacing them by potentially lower number of linear combinations of original variables (called factors) while conserving as much information as possible. Because these factors are linear combinations of the original variables, they are easy to interpret and can be assigned physical significance. In short, Factor Analysis identifies the set of k *latent* factors $(f_1, f_2, \ldots, f_k)$ that drive q observable variables (responses to survey questions) indexed as $x_t = (x_1, x_2, \ldots, x_q)$, where (Equation (1) [30]):

$$x = \Lambda f + u \tag{1}$$

where Λ is the $q \times k$ matrix of factor loadings, and f and u are $q \times l$ matrices of factors and variances.

While estimating Λ by the *Maximum Likelihood* method, Factor Analysis identifies a rotation and a scale of Λ that contracts as many coefficients to zero as possible. Having a sparse matrix Λ increases the interpretability of the factor model, since any factor will be created using only a few observable variables, hence allowing us to bundle several inter-related variables and label them as a factor.

3.2. Model selection

When working with a large number of explanatory variables, even after Factor Analysis, the number of model variables may be too large to support a model that is easy to interpret and statistically stable. Furthermore, it is important to identify variables that contribute the most to the variation in consumption to inform future data collection efforts. Our preferred method for model selection is **stepwise selection** [31] because (a) it ranks the variables based on their importance; and (b) in sequentially adding variables to the model, it minimizes multicollinearity.

The *forward* stepwise algorithm starts with the mean value of the consumption (i.e., the intercept) and then sequentially adds to the model the variable that best improves the fit, as measured by the AIC (Akaike Information Criteria [32]), given by Equation (2):

$$\mathrm{AIC} = -2.\log\ L + 2\mathrm{edf} \tag{2}$$

where L is the likelihood and edf is the equivalent degrees of freedom (i.e., the number of free parameters for usual parametric models) of fit. The *backward* stepwise algorithm starts with the full model, then sequentially drops the variables that least hurt the fit, as measured by AIC. Forward and backward stepwise procedures usually result in similar models [31].

3.3. Response variables

We considered four different features of the hourly electricity consumption data: daily average, minimum, maximum, and maximum-minus-minimum (also called "range"). Daily minimum, maximum, and average values for each user were calculated for each day of the experiment (238 values for each user). Then, these 238 values for each user were averaged over the summer and winter (partial) periods, resulting in two daily minimum, two daily maximum, two daily average, and two daily maximum-minus-minimum consumption values for each user (eight values in total for each user). Then separate regression models were fitted to each load feature for each season (eight regression models). Each regression model consists of 952 response variables (one value for each user).

3.4. Regression model

We used a weighted regression model to explain the variation in household electricity consumption. Those determinants whose contribution to electricity consumption has a linear relationship with floor area (e.g., insulation level) are multiplied by the floor area of the residence, while other variables (e.g., number of refrigerators) are included without a multiplier. The regression equation of our model is given by:

$$y_j\beta_{0j} + \sum_{i=1}^{M}\beta_{ij}X_{ij} + X_j \bullet \sum_{i=M+1}^{K}\beta_{ij}X_{ij} + \varepsilon_j, \tag{3}$$

where y_j is the electricity consumption (kWh) of household j, X_{ij} is the value of the determinant i for household j, and β_{ij} is the regression coefficient for that determinant. M is the number of variables (household features) that do not depend on floor area, while K is the total number of variables, and ε is the error term.

To summarize, our method enables working with large data sets of electricity consumption data and extensive household surveys, by (a) using different load features that help to understand different aspects of consumption (e.g., long-term steady idle load versus short-term volatile peak load); (b) selecting a subset of variables that contribute the most to each load feature; (c) ranking the contribution of different variables to each load feature through a stepwise model; and, (d) properly considering the effect of floor area, by using a weighted regression model.

4. Data summary and preprocessing

We applied our model to a data set of 10-min interval smart meter data for 1628 households, collected over 238 days from February 28, 2010 to October 23, 2010. Detailed data about household characteristics were available via a 114-questions online survey, covering a wide range of characteristics including climate and location, building characteristics, appliances and electronics stock, demographics, and occupants' behavior.

Participants were provided with a device that recorded the electricity consumption of the household for every 10 min and sent the data to a central server to be stored. The device installation and server costs were covered by the experiment administrators (for more details of the experiment, refer to Ref. [33]).

Participants were employees of a technology company in Silicon Valley and voluntarily participated in the experiment. They all paid for their own electricity bill. More than 50% of the participants reported income levels higher than $150,000. However, it is worth mentioning that the mix of households in our study (i.e., well-educated, upper and middle class families who are also early adopters of new technologies such as home energy monitoring systems) is also more likely to respond to energy efficiency programs by investing in energy-efficient products [34]. Hence, the results of our analysis can be particularly helpful to energy efficiency program managers and policy makers to develop programs specifically targeted towards the households represented by our sample.

After collecting the data, 952 households for which reliable smart meter and survey data were available were selected for the analysis. Less than 3% of survey responses were inconsistent or missing, for which we imputed data using iterative model-based imputation techniques ([35,36]). After the initial screening, we did not observe any outliers in the data set. Selected households were located in 419 different Zip Codes, 140 different counties, 26 different states, and were spread across all six climate zones defined by the Department of Energy [1]. California had the largest representation (53% of households) of all states in the data set. During the data collection process, the weather conditions in most areas where participant households resided were similar to the 30-year average climatic conditions; however, some areas, especially in the north east of the U.S., experienced slightly higher-than-normal temperatures [37]. Average electricity consumption in our sample lied between California and US averages. Some structural determinants such as household size, square footage of the house, and the proportion of single family detached units in our sample were close to US population averages [33].

We analyzed the consumption data at hourly level to ensure that the fluctuations in electricity consumption are considered, but not obscured by sudden spikes in the consumption. This also makes the results of our analysis comparable with those of previous studies on smart meter data and electricity market analysis [38].

We transformed some variables to better reflect the technical characteristics of buildings. For example, we transformed the construction year to a categorical variable that indicated the residential building code that was effective at the time of the construction (i.e., different revisions of ASHRAE 90.2 [1]). We also included a categorical variable for House Size to capture the effects of the floor area that are not completely explained by square footage. For example, when a building's floor area passes a certain threshold, the type of structural and architectural material that is used in the building often changes significantly. Since we do not have a separate variable for floor area and are not dividing the electricity consumption of the dwelling by its floor area, introducing the House Size variable does not create a multicollinearity problem (Table 1).

Table 1
Summary statistics of the daily maximum, minimum, and average hourly consumption, averaged overall users in the case study. The variability in daily minimum hourly consumption is the lowest, and that of the daily maximum is the largest.

Variable	No. of days	Min	Median	Mean	Max	Standard Dev.
Daily minimum, kWh[a]	238	0.2	0.4	0.4	0.5	0.039
Daily average, kWh[a]	238	0.5	0.8	0.9	1.2	0.1
Daily maximum, kWh[a]	238	1.7	2.5	2.5	3.5	0.256

[a] Averaged overall households.

The household survey included 40 questions on the attitudes of occupants towards energy consumption. Using Factor Analysis as was explained in previous sections, and informed by behavioral sciences research, we formed 22 major factors that collectively explain more than 80% of the information included in the original 40 questions; i.e., the threshold value in the scree test for choosing the number of factors was explaining 80% of the variance. The 22 variables explain the attitudes of households in three groups: (1) Energy Efficiency Actions, (2) Information Seeking Behaviors, and (3) Home Improvements Behaviors. After Factor Analysis, adding a number of transformations of the original variables, and removing some variables, the total number of variables was reduced from 114 to 97. We fit separate models to daily maximum, minimum, maximum minus minimum, and average consumption, both for summer and winter (for the period when the data were available), and ranked the variables by their importance through a forward stepwise model selection procedure (Fig. 1).

5. Results

A comparison of the results of our models shows that the daily minimum consumption is influenced the most by weather, location, and physical characteristics of the building. On the other hand, daily maximum consumption is influenced the most by end uses that are energy-intensive and do not run constantly (e.g., electric water heater). This group of end uses mostly depends on the occupancy levels and activities of occupants. These results are summarized in Tables 2 and 3 (forward stepwise results), and Table 4 (backward stepwise results).

Overall, locality (indicated by a proxy such as Zip Code) and House Size demonstrate considerable correlation with residential electricity consumption, most likely because they are correlated with several other variables that influence energy consumption. For example, Zip Code is often correlated with climate, building type,

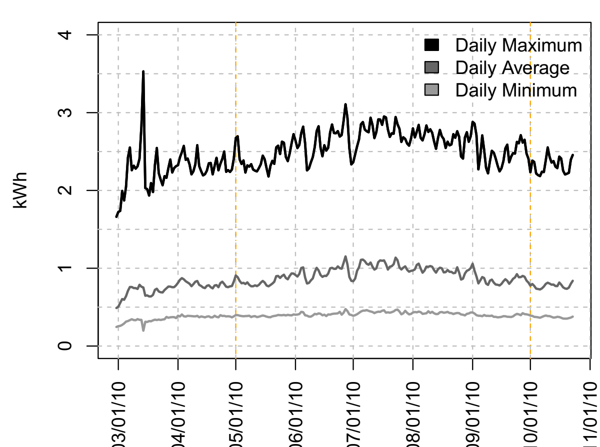

Fig. 1. Comparison of daily average, maximum, and minimum consumption, averaged over all users for each day of the experiment.

type of systems used in the building, building materials, and socioeconomic status of the household. On the other hand, House Size is often correlated with affluence, socioeconomic status, number of residents, and appliance stock.

5.1. *The effect of external determinants on residential electricity consumption*

Zip Code explains up to 46% of the variability in consumption. However, once Zip Code is removed from the models, underlying drivers of electricity consumption such as Cooling Degree Days are highlighted.

CDD (Cooling Degree Day) is the dominant factor in the summer, explaining 38% of the variability in total electricity consumption. On the other hand, HDD (Heating Degree Day) is not a significant factor, even in the winter model. We offer an explanation for this observation in Section 5.2. Other studies have also reported similar results on the effect of Zip Code and cooling load on electricity consumption [39–42].

5.2. *The effect of physical characteristics of the dwelling*

House Size is the most important factor among building characteristics in our models, while house age, type of building, and ownership status do not show significant impact on electricity consumption in our sample. Other variables such as installing double-pane windows and energy-efficient lighting fixtures show correlation with reduced electricity use. The following sections explain these results in more detail.

5.2.1. *Type of building*

Type of Building is a significant factor in the winter daily maximum model, where heating load dominates. In the winter, households who live in multifamily apartments have the lowest daily maximum consumption, followed by town houses; finally, detached (free-standing) houses have the highest daily maximum consumption in the winter. Similar results have been reported previously ([5,43]).

5.2.2. *House Size*

House Size has a dual effect on daily minimum and daily maximum consumption. Daily minimum consumption is much more correlated with House Size during the winter (House Size explains 21% of the variability in winter minimum consumption, while it explains only 2% of the variability in summer minimum). On the other hand, House Size has a much larger impact on daily maximum consumption during the summer compared with winter. Both observations can be explained by the relationship of House Size with heating and cooling loads, and the nature of these two loads. First, larger houses require more heating and cooling loads, both because they have more volume to condition, and because they have higher heat loss or gain with the outside. Also, heating load tends to have a more consistent nature, especially when systems such as radiant heating are used. Cooling load, on the other hand, tends to have a more intermittent nature, since the air conditioner compressor only needs to run intermittently to produce cool air.

5.2.3. *House age*

We did not observe any significant correlation between electricity consumption and building age. While some previous studies have observed an increase in household electricity consumption of new houses due to more penetration of air conditioning and other high-consumption appliances [44], other studies have observed the reverse, reporting a decrease in household electricity consumption

Table 2
Summary of the most important factors explaining different features of residential electricity consumption (forward stepwise regression). F: full model; P: partial model (excluding Zip Code and Floor Area). Only percentages greater than 2% are included in this table.

Variable	Min				Max				Max−Min				Average			
	Summer		Winter		Summer		Winter		Summer		Winter		Summer		Winter	
	F	P	F	P	F	P	F	P	F	P	F	P	F	P	F	P
Ave. of CDD		26%				31%				27%				38%		
Climate Zone						2%								3%		
Zip Code	12%		12%		39%		26%		37%		25%		46%		17%	
House Size	2%		21%		11%		2%		9%				12%		23%	
Type of bldg												12%		2%		
Ownership of elec. Water heater						4%	4%	11%	2%	6%	5%	12%			2%	5%
Ownership of elec. Clothes dryer						2%	2%	3%		3%	2%	4%				
Nb of Spas/Pools							2%				2%				2%	
Nb of freezers						3%								2%		
Nb of refrig's	7%	7%	7%	7%	3%	4%	4%	3%	2%	2%	3%	2%	3%	4%	6%	6%
Nb of entert't devices Except TV's		3%	2%	4%										2%		
Total nb of occup'ts							8%									
Total nb of occup'ts (sq. rt)					2%	2%	2%	4%	2%	3%	7%	4%			2%	2%
Pet ownership	2%	2%					2%	4%				3%			2%	3%
Purchasing E-Star Appl's	2%	2%	2%	3%												2%
Energy Conserv'n w.r.t. Elec. Heater Usage		2%	2%	2%										2%		
Turning lights off when not in use				19%				13%								20%
Motivated to reduce conmspt'n to address Global Warm.				2%											2%	3%
Degrees of Freedom	871	919	875	931	873	916	873	918	871	915	886	921	871	915	875	918
Adjusted R^2	0.56	0.48	0.50	0.43	0.61	0.56	0.51	0.47	0.56	0.51	0.45	0.43	0.68	0.59	0.58	0.52
F-statistic	15.9(80)	28.5(32)	13.6(76)	37.5(32)	20.3(78)	35.9(35)	13.5(78)	26.3(33)	16.0(80)	28.7(36)	13.2(65)	24.5(30)	25.8(80)	38.6(36)	18.1(76)	32.2(33)
P-value	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16	2.2e-16

Table 3
Model coefficients for statistically significant variables of forward stepwise regression models. The mean and standard deviation of each load feature are shown in parentheses at the table header. Shaded cells highlight negative values.

Mode	Min				Max				Max - Min				Average			
	Summer (0.404; 0.354)		Winter (0.358; 0.297)		Summer (2.616; 1.596)		Winter (2.307; 1.395)		Summer (2.212; 1.374)		Winter (1.948; 1.230)		Summer (0.925; 0.739)		Winter (0.769; 0.537)	
Variable	Full	Partial	Full	Partial	Full	Partial	Full	Partial	Full	Partial	Full	Partial	Full	Partial	Full	Partial
CDD		0.01	0.004	0.004	0.03	0.054	0.016	0.018	0.024	0.043		0.013	0.012	0.03	0.007	0.009
HDD			-0.006	-0.005											-0.006	
Climate Zone														*-0.15 to 0.17 (ave=-0.02)*		
Zip Code	*-.43 to 1.56 (ave=.19)*		*-.29 to 1.08 (ave=.07)*		*-1.27 to 3.64 (ave=.34)*		*-2.84 to 2.03 (ave=-1.23)*		*-1.32 to 3.12 (ave=.12)*		*-2.59 to1.45 (ave=-1.17)*		*-.66 to 2.37 (ave=.30)*		*-.74 to 1.44 (ave=-.08)*	
House Size	*-0.57 to -0.24 (ave=-0.38)*		*-0.20 to 0.46 (ave=-0.06)*		*-0.62 to 1.40 (ave=-0.15)*		*-1.65 to 0.62 (ave=-0.94)*		*-0.52 to 0.81 (ave=-0.15)*		*-1.48 to -0.02 (ave=-0.98)*		*-0.43 to 0.97 (ave=-0.03)*		*-.62 to .50 (ave=-.38)*	
Type of Bldg		*-0.06 to 0.05 (ave=0.01)*				*-0.31 to 0.25 (ave=0.07)*		*-.21 to .39 (ave=.17)*		*-0.27 to 0.27 (ave=0.09)*		*-.17 to .39 (ave=.19)*		*-0.09 to 0.14 (ave=0.05)*		*-0.06 to 0.11 (ave=0.05)*
Bldg Shell Insulation								0.074			0.069	0.072	0.04	0.033		
Energy-Efficient Lights	0.025		-0.016					-0.132			-0.082	-0.129				-0.04
Double-Pane Windows	-0.048	-0.052		0.036			-0.134						-0.093	-0.087		-0.034
Programmable Thermostat					0.142	0.14			0.124	0.123						
No. of Elec. Heaters						0.092	0.095	0.138		0.09	0.092	0.127			0.032	0.047
No. of AC	0.011	0.014														
No. of Elec. Water Heaters				0.054	0.534	0.0682	0.804	1	0.532	0.656	0.783	0.946	0.003	0.183	0.197	0.268
No. of Elec. Clothes Dryers					0.294	0.369	0.382	0.459	0.298	0.355	0.392	0.457				0.062
No. of Elec. Stoves					0.238	0.312		0.18	0.227	0.292		0.166		0.094		
No. of Spas/Pools	0.096		0.096	0.081	0.341	0.281	0.445	0.406	0.279	0.241	0.369	0.328	0.23	0.138	0.258	0.197
No. of Dishwashers					0.266	0.398			0.301	0.391						
No. of Refrigerators		0.121	0.104	0.105	0.356	0.348	0.331	0.335	0.242	0.218	0.237	0.222	0.188	0.195	0.177	0.174
No. of Freezers	0.016		0.047	0.057	0.23	0.28	0.249	0.303		0.2	0.222	0.246	0.149	0.16	0.131	0.138
No. of TV's	0.03	0.029	0.024	0.026	0.097	0.1	0.102	0.093	0.086		0.072		0.045	0.051	0.037	0.031
No. of Entertain't Devices (Except TV's)	0.011	0.022	0.016	0.02		0.059							0.031	0..042	0.019	0.023
No. of Occupants (sqrt)			0.066		0.959	0.771	0.902	0.772	0.883	0.57	0.867	0.758	0.31	0.137	0.273	0.198
Individuals under 5	0.012															
Individuals between 6 and 12		-0.013								0.049						
Individuals between 13 and 18		0.017												0.017		0.022
Individuals between 19 and 35					-0.096	-0.082	-0.047	-0.043	-0.084		-0.044	-0.036	-0.042	-0.015	-0.017	-0.011
Individuals between 36 and 54						-0.062			-0.061				-0.03			
Individuals between 55 and 65		-0.02	-0.021	-0.018	-0.15	-0.12	-0.098	-0.097	-0.128		-0.079	-0.082	-0.07	-0.045	-0.034	
Individuals Older than 65				-0.021	-0.195	-0.23	-0.156	-0.163	-0.178	-0.195	-0.14	-0.14	-0.071	-0.072	-0.058	-0.055
No. of Pets	0.037	0.039	0.023	0.027	0.126	0.128	0.157	0.166	0.085	0.073	0.135	0.139	0.06	0.059	0.055	0.057
Purchasing E-Star Appliances	0.011	0.014	0.015	0.016											0.019	0.021
Energy-Conscious Use of Elec. Heater (Thermostat Settings)	-0.023	-0.027	-0.017	-0.019	-0.082	-0.105		-0.042	-0.057	-0.08			-0.045	-0.064	-0.026	-0.027
Energy-Conscious Use of AC (Thermostat Settings)					0.036	0.035			0.032	0.032			0.01	0.013		
Turning Lights Off When Not in Use	0.064	0.022		0.022												0.046
Motivated to Reduce Consump'n to Address Global Warming	0.001		-0.012	-0.013		-0.028	-0.047	-0.049		-0.019	-0.034	-0.037	-0.015	-0.02	-0.025	-0.027

for newer houses, attributing that pattern to improved insulation and use of more efficient lighting and air conditioning stock [45,46]. Our hypothesis is that in our sample, these two forces have canceled out each other's effect, resulting in a uniform trend between household electricity consumption and the age of the house. Another possible explanation for the uniform trend in our data is that the physical conditions of buildings have been maintained through time, possibly due to the enforcement of building regulations.

When we grouped the households into different time periods based on the prevalence of different ASHRAE 90.2 residential building codes, we observed that the houses that were built before 1975 on average consumed less electricity than the houses that were built between 1993 and 2003 (p-values = 0.00266 and 0.00105, respectively). A potential explanation for this trend is the increased penetration of air conditioners and other high-consumption appliances in newer houses.

5.3. The effect of appliance stock and electronics

As Tables 3 and 4 show, number of refrigerators is a statistically significant factor in almost all models, but its effect is more highlighted in the daily minimum consumption. Former studies show that (a) refrigerators are the largest electricity consumer among household appliances (according to Ref. [44] in 2001, refrigerators consumed 14% of total electricity delivered to U.S. homes, only second to air conditioners who consumed 15%), and (b) the secondary refrigerators in the US households are on average considerably older (and less-efficient) than the primary refrigerators [44]. Therefore, the ownership of more than one refrigerator in a household implies a high probability of having an inefficient, high-consumption fixture, hence the significant contribution of the number of refrigerators to household electricity consumption.

Other than refrigerators that have a steady load, most high-consumption, intermittent appliances such as electric water heater, electric clothes dryer, and Spas/Pools primarily contribute to daily maximum consumption. These are the appliances that are not "always on" and their operating schedules are dependent on the activities and habits of the occupants. Therefore, they are indicators of (and are driven by) occupants' habits and activities rather than the location and physical characteristics of the dwelling, hence their correlation with daily maximum load. Our results are in line with former studies who have shown the large impact of high-consumption appliances on total electricity consumption. For example, according to the U.S. Energy Information Administration, air conditioners, electric water heaters, and laundry appliances consume 16.0%, 9 1%, and 6.7% of the total electricity consumption in US households, respectively [44]. Similarly in Europe, according

Table 4
Model coefficients for statistically significant variables of backward stepwise regression models. Shaded cells highlight negative values.

Model	Min				Max				Max - Min				Average			
	Summer (0.404; 0.354)		Winter (0.358; 0.297)		Summer (2.616; 1.596)		Winter (2.307; 1.395)		Summer (2.212; 1.374)		Winter (1.948; 1.230)		Summer (0.925; 0.739)		Winter (0.769; 0.537)	
Variable	Full	Partial	Full	Partial	Full	Partial	Full	Partial	Full	Partial	Full	Partial	Full	Partial	Full	Partial
CDD	0.005	0.01	0.004	0.004		0.055	0.015	0.019	0.024	0.043		0.013	0.012	0.03	0.007	0.009
HDD			-0.006	-0.004											-0.006	
Climate Zone																
Zip Code	*-0.41 to 1.57 (ave=0.19)*		*0.29 to 1.08 (ave=0.07)*		*-1.23 to 3.63 (ave=0.32)*		*-2.79 to 2.09 (ave=-1.17)*		*0.00 to 0.97 (ave=0.56)*		*-2.80 to 1.40 (ave=-1.22*		*-0.65 to 2.35 (ave=0.27)*		*-0.75 to 1.42 (ave=-0.10)*	
House Size	*-0.35 to 0.03 (ave=-0.23)*		*-0.20 to 0.46 (ave=-0.06)*		*0.64 to 1.62 (ave=-0.37)*		*-1.64 to 0.76 (ave=-0.91)*		*-0.53 to 0.79 (Ave=-0.16)*				*-0.43 to 1.01 (Ave=-0.01)*		*-0.62 to 0.52 (ave=-0.36)*	
Type of Bldg						*-0.31 to 0.28 (ave=0.08)*		*-0.22 to 0.41 (ave=0.18)*		*-0.23 to 0.27 (ave=0.09)*		*-0.17 to 0.39 (ave=0.19)*		*-0.09 to 0.13 (Ave=0.05)*		*-0.06 to 0.10 (ave=0.05)*
Bldg Shell Insulation	0.025		-0.02		0.083		0.08				0.087	0.072	0.046	0.034	0.039	
Energy-Efficient Lights								-0.121			-0.1	-0.129				-0.041
Double-Pane Windows	-0.053	-0.059		-0.036			-0.128				-0.114		-0.108	-0.089		-0.036
Programmable Thermostat	0.024				0.105	0.141		0.095	0.127	0.134						
No. of Elec. Heaters						0.083		0.133	0.065	0.09	0.99	0.127		0.024		0.049
No. of AC	0.013	0.013														
No. of Elec. Water Heaters				0.054	0.523	0.677	0.802	0.992	0.523	0.662	0.783	0.946	0.13	0.186	0.194	0.269
No. of Elec. Clothes Dryers					0.301	0.371	0.388	0.465	0.306	0.367	0.409	0.457				0.061
No. of Elec. Stoves					0.22	0.315		0.184	0.223	0.286		0.166		0.093		
No. of Spas/Pools	0.092			0.081	0.335	0.291		0.416	0.28	0.221	0.342	0.328	0.237	0.135		0.196
No. of Dishwashers					0.304	0.396		0.232	0.341	0.475		0.186				
No. of Refrigerators	0.118	0.121	0.104	0.105	0.349	0.354	0.325	0.345	0.249	0.232	0.218	0.222	0.188	0.195	0.175	0.174
No. of Freezers	0.065	0.072	0.047	0.057		0.279	0.25	0.312		0.208	0.211	0.246	0.149	0.162	0.125	0.137
No. of TV's	0.029	0.035	0.024	0.026	0.094	0.097	0.096	0.09	0.085	0.087	0.074		0.045	0.052	0.036	
No. of Entertain't Devices (Except TV's)	0.017	0.022		0.02		0.059							0.03	0.043	0.019	0.024
No. of Occupants (sqrt)	0.103	0.081	0.066	0.035	0.963	0.784	0.919	0.789	0.885	-0.858	1.062	0.758	0.311	0.151	0.27	0.198
No. of Individuals under 5											-0.036					
Individuals between 6 and 12	-0.02	-0.022														
Individuals between 13 and 18				0.014												
Individuals between 19 and 35	-0.021	-0.02			-0.098	-0.084	-0.048	-0.04	-0.084	-0.08	-0.076	-0.036	-0.045	-0.016	-0.017	-0.012
Individuals between 36 and 54	-0.015	-0.019			-0.071	-0.062			-0.061	-0.071	-0.052		-0.033			
Individuals between 55 and 65	-0.03	-0.03	-0.021	-0.018	-0.155	-0.117	-0.096	-0.094	-0.129	-0.121	-0.112	-0.082	-0.072	-0.046	-0.035	
Individuals Older than 65	-0.025	-0.026		-0.021	-0.194	-0.229	-0.155	-0.159	-0.178	-0.223	-0.154	-0.14	-0.071	-0.072	-0.057	-0.054
No. of Pets	0.038	0.042	0.023	0.027	0.119	0.125	0.155	0.166	0.085	0.084	0.124	139	0.062	0.061	0.054	0.056
Purchasing E-Star Appliances		0.104	0.015	0.016		-0.075			-0.059						0.018	0.02
Energy-Conscious Use of Elec. Heater (Thermostat Settings)	-0.023	-0.025	-0.017	-0.019	-0.085	-0.104		-0.042		-0.076				-0.065	-0.026	-0.029
Energy-Conscious Use of AC (Thermostat Settings)					0.038	0.034			0.034	0.033			0.011	0.012		
Turning Lights Off When Not in Use		0.044											-0.045			0.041
Motivated to Reduce Consump'n to Address Global Warming	-0.009	-0.011	-0.012	-0.013	-0.024	-0.028	-0.047	-0.045		-0.021	-0.032	-0.037	-0.016	-0.019	-0.025	-0.027

to EuroAce, 57% of the energy consumed in buildings is used for space heating, 25% for hot water, 11% for lighting and electrical appliances, and 7% for cooking [47].

In some models, some building shell insulation variables such as basement insulation had positive coefficients, implying that controlled for other factors, insulated houses in our sample consumed more electricity on average. However, this effect was not physically substantial. Previous studies who have examined the effect of insulation on electricity consumption have also reported mixed results. While some have verified that insulation reduces electricity consumption [48–50], some others have reported no significant correlation between insulation level and residential electricity consumption [39]. Still, another group of studies have reported that buildings with higher insulation ratings are likely to consume more electricity [51]. Several reasons may contribute to increased energy consumption in well-insulated homes. One potential reason for positive correlation of insulation and energy consumption is higher cooling load in well-insulated houses due to the heavier use of AC instead of natural ventilation [52]. This is relevant since our data set covered the entire summer but not the entire winter months, so the effect of cooling loads on our results is more significant. Another potential reason for this observation is the positive correlation of insulation with House Size, appliance stock, or income [53], all of which are correlated with higher electricity consumption. Finally, the relationship between insulation and electricity consumption may be in the opposite direction: larger houses with higher energy consumption are more motivated (and more plausible) to add extra insulation; i.e., insulation might have been a result of high consumption, not a cause for it. If it was not for the insulation, these houses would have consumed much higher energy than other houses, but insulation helps to mitigate that effect [51].

Use of energy-efficient lights was correlated with lower consumption, as did the use of double-pane windows. Finally, use of programmable thermostats was correlated with increased electricity consumption. One possible explanation for this trend is that programmable thermostats turn the air conditioner or heater on at certain times, even if the house is not occupied. Therefore they may actually increase heating or cooling load compared with manual settings, especially when the house is not occupied regularly. Finally, our data did not show a statistically significant difference in electricity consumption between rented and owned houses, contrary to several previous studies [43].

5.4. The effect of occupants

We analyzed the effect of occupants from three different perspectives: the effect of occupancy level, the effect of occupant behavior (long-term habits and preferences), and the effect of occupant socioeconomic status. The following sections summarize our results.

5.4.1. The effect of occupancy level

Number of occupants is a significant variable in daily maximum models, while it is not a significant variable in daily minimum models. This observation supports the notion that the presence of occupants primarily impacts the consumption in excess of the daily minimum. Furthermore, the models suggest a non-linear relationship between household electricity consumption and the number of occupants, selecting the square root of number of occupants over the number of occupants. In other words, our model verifies that when the number of occupants double, electricity consumption increases at a slower rate (1.4 in our data), leading to the conclusion that larger households have higher aggregate electricity consumption but lower per capita consumption. A similar concave relationship between number of occupants and electricity consumption has been reported in former studies [54–56].

Pet ownership is a statistically significant factor in the models, while the magnitude of its impact is the largest for the summer daily minimum, winter daily maximum, and winter daily maximum–minimum models. The effect is significant even after removing the effect of other significant variables. Our hypothesis for explaining the correlation between pet ownership and higher electricity consumption is two-fold: (a) it is likely that people who have pets spend more time at home, and (b) even when they leave home, they do not completely turn the AC off. Therefore, pet ownership may be a proxy for the percentage of time that the house is “active”. Further research is needed to validate this hypothesis.

Age of occupants showed a significant correlation with electricity consumption. Specifically, households with occupants older than 55 and between 19 and 35 showed lower electricity consumption. The older household members tend to be more conscious about the way they use electricity, and also tend to use less electric gadgets. On the other hand, household members between 19 and 35 are more likely to have a full-time job and therefore are less at home. These observations suggest that both the occupancy rate (how much time one spends at home) and intensity of energy use of household members influence electricity consumption [57].

5.4.2. The effect of long-term habits and preferences

Behavioral factors that have long-term impacts (such as Purchasing Energy-Star Appliances and Air Conditioners) or are considered long-term habits (such as adjusting thermostat settings moderately) are significant explanatory variables for daily minimum consumption.

As Table 3 shows, in the daily minimum model, the behavior of Purchasing Energy-Star Appliances and Air Conditioners has a positive coefficient. This suggests that, in our study sample, contrary to common belief, households that have expressed motivation to buy energy-efficient appliances and air conditioners have higher levels of daily minimum consumption, after adjusting for all other variables. Since most new higher-end appliances are energy-star, the tendency to purchase energy-star appliances may simply mean buying new, high-quality appliances, which is by itself a proxy for wealth [58–61]. Another explanation for the positive coefficient of energy-star appliances the “rebound effect”, where an increase in the efficiency of appliances results in increased use of them, hence an increase in overall energy consumption [3,6].

Another long-term habit, Turning Off Lights When Not in Use, is significant in most winter models but not at all significant in summer models. A closer look at this variable reveals a significant geographical pattern: people in the two coasts in our sample declare much higher rates of turning off lights when not in use. Also, this variable becomes insignificant when Zip Code is included in the model, which is another evidence to its geographical trend. Last, in models where this variable is indeed significant, its coefficient is positive, implying that those in our sample who declare they turn lights off when leaving the room consume more energy on average. Our conclusion is that Turning Off Lights When Not in Use is capturing a latent factor in our sample, and further data are needed to quantify the effect of energy-conscious behavior of turning off unnecessary lights.

5.4.3. Effect of income level

We did not observe any statistically significant correlation between income level and electricity consumption. The relationship between household income and energy consumption has been the subject of extensive research. While a large number of studies have concluded that energy consumption increases monotonically with income [19,28,51,62–65], a number of studies have reported observing an inverted U-path relating energy consumption and household income [59,66,67]. At the same time, the effect of income on household electricity consumption has been shown to be mediated by ownership of appliances; i.e., income of the household impacts the consumption through affecting the stock (quantity and quality) of appliances [17,27,68,69]. This is especially true for populations like our sample where households are similar to each other in socioeconomic status and therefore the income effect is minimal.

6. Conclusions

Summarizing our findings, we showed that:

(a) Factors that influence residential electricity consumption can be categorized into four major groups: external conditions (e.g., location and weather), physical characteristics of dwelling, appliance and electronics stock, and occupants.
(b) Each of the four categories above, on average, has a different time span and effort level for modification; while location, weather, and occupancy are outside the scope of influence for modification, physical characteristics of the building, appliance stock, and occupant behavior factors can be modified in long-term, medium-term, and short-term investment spans, respectively. Accordingly, the persistence of the modification effect is generally proportional to the level of effort and investment that was allocated to it.
(c) Daily minimum and daily maximum consumption are explained by different sets of explanatory factors. Daily minimum has a lower variation level compared with daily maximum, and is best explained by factors that are steady through time, such as weather (Degree Days), location (Zip Code), House Size, and number of refrigerators. On the other hand, daily maximum is best explained by large and intermittent loads such as electric water heater and air conditioners.
(d) Using our model, we were able to explain 55–65% of the variability in electricity consumption, as measured by the R^2 of the regression model. This is comparable with most studies in the past. Using variable transformations and other machine learning techniques [70], we were able to achieve R^2 values of above 70%. However, we prefer the linear model due to its interpretability. Furthermore, we deliberately did not use variables such as households’ estimate of their electricity bill (available from the survey) that improve the R^2 of the fit, but add little explanatory significance to the results of the model.
(e) Overall, weather and physical characteristics of the building illustrate more influence on residential electricity consumption compared to other categories such as occupant behavior. These

results are comparable with the work of [43] who showed that building characteristics determine 42% of the variability in residential electricity consumption, whereas occupant behavior explains 4.2%. Within the physical characteristics of the building, floor area, type of building, and use of electric water heater contributed the most to consumption, whereas within the appliance stock, number of refrigerators was the most important factor. Finally, pet ownership (which can be considered a proxy for the percent of time that the house is active) was a significant factor in explaining variation in electricity consumption.

7. Policy implications

Based on the results of our models, we highly recommend policies and regulations aimed at improving the thermal performance of buildings, including both improvements to the insulation level of the dwelling and improving the efficiency of the stock of air conditioning and electric heaters. Since certain end uses such as space heating are more prone to rebound effects [19], we strongly recommend provisions for regular home energy audits in codes and regulations [49]. Furthermore, we recommend policies and regulations aimed at improving the efficiency of the appliance stock. Certain end uses such as refrigerators illustrate great potential for consumption reduction. Policies and programs that encourage the purchase of energy-efficient refrigerators and other appliances must also devise provisions for buying back the old refrigerators or make the financial incentive contingent on households returning the old refrigerators.

Most high-consumption, intermittent appliances such as electric water heater, electric clothes dryer, and Spas/Pools demand high volume and intermittent electric loads, hence are attractive targets for load shifting programs. Since these end uses are primarily driven by occupants' habits and activities, respective energy efficiency programs should be focused on behavioral modification. For example, educational campaigns encouraging households to use larger loads of laundry, to lower the temperature of their electric water heaters, or to shift their laundry time to a more appropriate time in the day can be effective in this regard.

In terms of the impact of behavioral factors, our results agree with some previous works that residential electricity consumption is primarily determined through the way households *use* electricity, and less by the way that they *value* energy efficiency [28,40]. However, energy-saving values usually impact efficiency through "habits" such as Purchasing Energy-Star Appliances. A dual approach as suggested by Kelly [51], where less efficient homes are encouraged to perform structural changes (such as adding insulation) while more efficient homes are motivated to reduce consumption through behavioral interventions and economic incentives is supported by our analyses [40]. Energy saving values and habits are shown to respond to changes in price of electricity [63,71]; therefore, behavior modification programs can be more effective when supported by monetary and regulatory policies.

8. Future work

More data are needed to validate some of the findings of this paper. Specifically, household data from a more heterogeneous sample over a larger period of time are needed for validating the generality of these results. The use of self-reports to measure behavior may have introduced some bias in the data, called "social desirability" bias [72]. However, since the purpose of this study was to explain the *variability* in electricity consumption, and the households in our study were all from middle and upper social class, we assume that the bias in responses was uniform over the respondents and therefore the results of the model explain the variability in electricity consumption with a reasonable accuracy.

In this paper, we examined energy consumption and its features such as daily maximum and minimum consumption, and explained their variability using household data. A potential follow-up to this study is to develop a metric for quantifying energy efficiency of the households, and compare households using that metric instead of their consumption data. Such metric needs to be defined in a way that recognizes the inherent differences among different groups of households and at the same time enables comparison across those different groups.

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