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Appliance daily energy use in new residential buildings: Use profiles and variation in time-of-use

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ABSTRACT

One of the largest user of electricity in the average U.S. household is appliances, which when aggregated, account for approximately 30% of electricity used in the residential building sector. As influencing the time-of-use of energy becomes increasingly important to control the stress on today's electrical grid infrastructure, understanding when appliances use energy and what causes variation in their use are of great importance. However, there is limited appliance-specific data available to understand their use patterns. This study provides daily energy use profiles of four major household appliances: refrigerator, clothes washer, clothes dryer, and dishwasher, through analyzing disaggregated energy use data collected for 40 single family homes in Austin, TX. The results show that when compared to those assumed in current energy simulation software for residential buildings, the averaged appliance load profiles have similar daily distributions. Refrigerators showed the most constant and consistent use. However, the three user-dependent appliances, appliances which depend on users to initiate use, varied more greatly between houses and by time-of-day. During peak use times, on weekends, and in homes with household members working at home, the daily use profiles of appliances were less consistent.

1. Introduction

Currently, buildings consume approximately 40% of site energy in the U.S., over half which is consumed by residential buildings [1]. Residential buildings alone are responsible for over 37% (4.89 EJ) of electricity consumed in the U.S. [1]. In Europe, households are responsible for 25% of total energy needs, including 68% of total building energy use [2]. High peak electricity demands in the afternoon and early evening of the hot months of the year, much of which is due to fluctuation in building use, have further motivated the development of strategies to reduce electric loads during these times. These changes can only be achieved, however, if the current energy use is first understood in detail.

One of the largest portions of electricity use household is from large appliances, which, when aggregated, account for approximately 30% of all electricity used in the residential building sector in the U.S. [1]. This, together with small appliances, home electronics, and lighting, accounts for more than 2/3 of total residential electricity use. Appliances are of particular interest for study due to their high penetration rate, and increasing rate of penetration across the world [3,4]. In recent years, appliances have been targeted by manufacturers and utility companies as methods to shift or reduce peak energy use. In addition, unlike changes to heating and air conditioning use, changes to their time-of-use will not significantly affect the comfort of the indoor environment.

Four large appliances including, refrigerators, clothes washer, clothes dryers, and dishwasher, are among the most common large appliances found in U.S. homes. Refrigerators are the most common, followed by washers, dryers and dishwashers [4]. This order of penetration of appliance ownership is similar in other developed and developing countries [3], and continues to increase globally [5]. According to the 2012 American Housing Survey [4], 99%, 84%, 81% and 66%, respectively, of all single family homes in the United States have each of these appliances, each with an average annual energy consumption of 1240, 120, 1080, and 510 kW h, respectively [6]. New, more energy efficient appliances use up to 40–50% less energy than those sold in 2001 or earlier. This study specifically focuses on directly monitored electricity consumption of appliances. Other indirect impacts on energy due to hot water use, and latent and sensible heat gains that may non-linearly effect whole-home energy use are the subject of on-going research, but not included in this study. While there are many available datasets providing values

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for annual consumption (kW h) of appliances for a household (e.g. [4,6]), there is, however, limited information available regarding when, over the course of a day, these appliances are used.

Studying this, and the influencing factors associated with these use profiles is important for multiple reasons. This includes an improved understanding of the potential electricity use reductions possible from appliances during peak use times, and improved input values of appliance use to improve the accuracy of residential building energy modeling.

The most recent large-scale appliance-specific study to analyze time-of-use of appliances in residential buildings in the U.S. was conducted in 1989 [7]. This study developed daily profiles for major household appliances use using disaggregated circuit-level data, including the four discussed in the current study. It remains, to the authors' knowledge, one of the largest and most detailed studied to-date on residential appliance use in the United States. A large database of appliance energy use in European households has been complied through the REMODECE—Residential Monitoring to Decrease Energy use and Carbon Emissions in Europe project, which is discussed in [8]. For each country this typically includes several weeks of data for multiple households. Several smaller studies have also looked at time of use of appliances [9–11], and have found a wide variation in the time-of-use, with increased use [9] and variability [10] in the mid-morning and evening hours for single and multiple or groups of appliances [9–11]. Refrigerator energy use was found to be the most constant over a 24-h period with small peaks in morning [7,9] and evening hours [9,11]. Several other studies have focused on appliance use trends [12] and identification [13] in the UK, and on day ahead appliance energy use prediction in France [14] using the IRISE database included in [8].

To predict energy use, previous literature has indicated that factors such as occupant behavior and socio-economic status are important [15]. Nielsen attributed 36% of variation in energy consumption of homes to lifestyle and occupant behavior, and 64% to socio-economic influences. Other factors such as climate zone, number of occupants, income level, age of home, and size of home have also been correlated with home energy use. Compared to whole-home energy use, likely the energy use of appliances such as dishwashers, clothes washers and clothes dryers is more highly influenced by occupant behavior since they depend solely on the user for operation. With human behaviors and lifestyles constantly changing since the 1989 study, such as a more than 35% increase in the number of adults that work one or more days a week from home since 1997 [16], this may affect time-of-use of appliances. Other studies have focused on appliance energy use feedback [17]. Additionally, U.S. federal standards for new appliances set in 1987, which have been consistently reviewed and revised since, have reduced energy consumption of appliances significantly, with a predicted savings of 74 EJ of energy through 2020 [18]. Borg [19] found that in Europe, appliance efficiency did reduce energy loads, but not peak electrical demand.

Additional information is thus desired to better characterize appliance energy use in the current residential building stock. The effects on the time-of-use of these and other factors, such as the influence of residents working from home, and the day of the week have not been studied in detail. Establishing a simple and adaptable methodology to assess appliance use over time will also prove helpful as influences on appliance use patterns change. This is particularly useful to predict the potential influence that "smart" appliances, connected to the smart electric grid, and to provide updated inputs to building energy simulation loads.

This study aims to address the need for a more detailed understanding and analysis of daily energy use patterns and several of the factors that influence them. More specifically this study will explore the following questions:

(1) When do appliances use energy throughout the day, and how do their electricity use profiles look?
(2) How much do these load profiles vary each hour between homes and what are possible sources causing this variation?
(3) If appliance load monitoring is to be conducted in future studies, what is the least amount of time needed to achieve a representative load profile of home appliances?

This paper is organized into three sections. The method used to develop a normalized energy use profiles is discussed, followed by the results of using this method for each of the four studied appliances. These results are compared, and two influencing factors on these profiles are also discussed and analyzed.

2. Methodology

Energy use was monitored in this study, as discussed in Lopes et al. [20] and Crosbie [21]. One-min energy consumption data was collected for 40 homes in a concentrated area in Austin, TX. These homes are part of a 250-home smart-grid deployment project (data collected by Pecan Street Research Institute) which began monitoring home energy consumption in 2012. These homes consist of newly constructed single family homes, built in 2007 or later. Several different types of home energy management systems (HEMS) were installed in a subsets of homes to monitor energy use. This study is limited to 40 of the 250 homes monitored, since the data collected by the type of HEMS deployed in these 40 homes was, of those installed, found to provide the best agreement with the electricity utility meters. The utility meters represent the upper bound of accuracy available for HEMS.

The HEMS use "CT" (current transformer) collars which are clamped to the individual circuits of each home's breaker box, and an adapter that connects to the home's internet router for data collection. The HEMS provides root-mean-square (RMS) of current and voltage to calculate average real power and apparent power, which is saved at one-minute increments. Circuit monitoring includes consumption data for the whole house, as well as multiple different individual circuits, including individual appliances for many of the homes. Further information on the data collection methodology of these homes is discussed in detail in [22]."

One year of disaggregated energy use data (March 1, 2012–February 28, 2013) was collected for each of the 40 homes studied. The starting date of monitoring varies, however all but two homes (5%) had begun recording energy consumption data by March of 2012.

To demonstrate the characteristics of the 40 homes sampled in this study, data from home energy audits and resident surveys is compiled in Table 1. Table 1 also includes average demographic and physical characteristics of the homes for U.S. and Texas building stock. The average number of occupants per home in this study (2.86) is similar to the average U.S. residence (2.6). However, this dataset's homes are larger and newer, and have a higher household income. In addition, a relatively high percentage of households (50%) indicating they work from home twenty or more hours per week.

2.1. Appliance circuit-level data

Appliance circuit-level data was available for a subset of the 40 homes studied. Table 1 also provides information on the number of homes with each of the appliance-specific circuits used, and their

Table 1
Characteristics of all homes studied vs. homes with each appliance circuit monitored.

Category	U.S. homes (in thousands)[a]	Texas (in thousands)[a]	Homes studied[b]	Dish-washer[b]	Refrig-erator[b]	Clothes washer[b]	Clothes dryer[b]
Housing units	131,035	9869	40	9	15	12	18
Single family homes	61.70%	65.60%	100%	100%	100%	100%	100%
Year built (2005+)	5.10%	8.50%	100%	100%	100%	100%	100%
Number of bedrooms (avg.)	2.4	2.5	3.2	3.3	3.4	3.4	3.2
Area (avg.)	158	–	204	218	212	200	202
Household size (avg.)	2.6	2.79	2.86	2.88	2.69	2.2	2.63
Level of education							
Less than bachelors	71.8%	74.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Bachelor's degree	17.7%	17.4%	12.5%	11.1%	20.0%	25.0%	11.1%
Graduate degree	10.5%	8.6%	87.5%	88.8%	80.0%	75.0%	88.9%
Household income							
Up to $ 49,999	47.3%	49.2%	7.5%	0.0%	13.4%	16.6%	11.2%
$50–74,999	18.3%	18.0%	10.0%	11.1%	6.7%	8.3%	16.7%
$75–99,999	12.4%	11.8%	22.5%	22.2%	20.0%	25.0%	22.2%
$100–149,000	12.7%	12.2%	27.5%	22.2%	26.7%	25.0%	22.2%
$150+	9.2%	8.9%	32.5%	44.4%	33.3%	25.0%	27.8%
Work from home (h/week)							
None/not reported	–	–	42.5%	44.0%	33.3%	41.7%	27.8%
1–20	–	–	17.5%	11.1%	6.7%	0.0%	16.7%
21–40	–	–	27.5%	22.2%	40.0%	41.7%	44.4%
41+	–	–	12.5%	22.2%	20.0%	16.7%	11.1%

[a] American Community Survey, 2011, 1-year estimates [23].
[b] Pecan Street Inc data (see Rhodes et al. [22] for data collection methodology).

Table 2
Characteristics of all homes studied vs. homes with each appliance circuit monitored.

Appliance	Year	Types	kW (average)
Refrigerator	2008–2009	Bottom freezer (50%) Side-by-Side (44%) Top freezer (6%)	0.85
Clothes washer	2000–2009	Front load (60%) Top load (40%)	1.34
Clothes dryer	2003–2009	–	3.65
Dishwasher	2007–2009	–	1.25

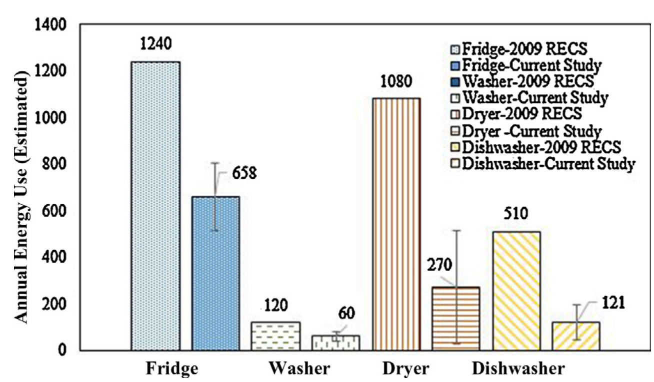

Fig. 1. Appliance Average Annual Energy Use (kW h) compared to the Residential Energy Consumption Survey (2009) [6].

corresponding average characteristics. The same subcircuits and appliances were not monitored for all homes. In each of the 40 homes, one or more of the four studied appliances was monitored. From the 40 analyzed houses, 15 homes had dedicated circuit for the refrigerator, 12 homes for the clothes washer, 18 homes for the clothes dryer and 9 for the dishwasher. The characteristics of these appliances are shown in Table 2. Comparing the 40 home average characteristics to those of each set of homes with appliance-specific load monitoring, household size (number of occupants) and home size (m^2) are less than 8% different from with the exception of those homes with monitored clothes washer. In each of the subsets over 45% of homes reported working from home twenty or more hours per week. The estimated annual energy use of each of the studied appliances is shown in Fig. 1, as compared to the Residential Energy Consumption Survey from 2009 [6].

2.2. Dataset quality control

Several quality control checks were performed on the dataset for its use in this study. The HEMS sometimes records false short peaks, so called "spikes", in electricity consumption, associated with the rebooting of the HEMS. These one-minute long spikes in the one-min data (>20 kW) were removed and assigned the value of the average of the data points before and after. Over the year studied, a total of 0–7 min (0–0.001%) data points for each home were identified as spikes for each of the 40 homes. With these spikes eliminated, the data was then aggregated into hourly time steps by summing 60 min of data (Watts). This is consistent with the methodology and units for the widely-used building energy modeling software EnergyPlus [24], BEopt [25] and eQUEST/DOE 2 [26]. The use of kW h units also allows the resulting charts to be compared with previous studies on energy consumption of homes, end-use loads and load shapes.

While whole-home energy consumption was monitored nearly the entire length of the one-year period, some appliance circuits were disconnected for a period of time, resulting in missing data. To address missing field data, [7] suggested filled missing data with previous year's data for the same day. In this study, data was only considered usable in this analysis if over a 24-h period: (1) all hours provided a non-null value, and (2) at least 1 h of data (60 min) contained a non-zero value. Table 3 shows the total number of days of available data for each appliance across all homes, including the average, maximum and minimum number of days for each house. On average, washers and dryers were monitored for 44% and 61% of

Table 3
Available days of energy consumption data across 40 homes.

	Refrigerator	Clothes washer	Clothes dryer	Dishwasher
Days monitored (across all homes)	2068	1752	3975	1330
Mean num. days monitored/house	122	159	221	121
Min. num. days monitored/house	29	29	39	29
Max. num. of days monitored/house	290	297	354	291
Standard Deviation of num. of days monitored per house	108	120	135	115

the year, and refrigerator and dishwasher were monitored for 33% of the year-long period.

2.3. Energy use data processing

To calculate the normalized load profile of a specific appliance across the entire dataset, (a) a normalized load profile was created for each house, then (b) the normalized load profiles of all homes were averaged together over each hour. This methodology is similar to the methodology used in [7], however the results provide a normalized load profile comparable to those referenced in [27], rather than a ratio of monthly load to average load. Each home's load profile was given equal weight regardless of the number of days used to create that home's load profile, so as not to weight the average in favor of homes with more available data. To complete (a) for each home, the average energy consumption for each hour $E_{avg,h}$ in each non-null day of data for a particular home was averaged for each of the 24 h using following equation:

$$\left(E_{avg,\,h}\right)_a = \left(\frac{1}{N_h}\sum_{i=1}^{N_h} E_{n,h}\right)_a \qquad (1)$$

where h is the number of the hour being averaged (e.g. $h=1$ represents 12:01–1:00 am), n is the number of the hour of monitoring being considered (e.g. $n=4$, this is the 4th day of monitoring), N_h is the total number of hours available for hour h, and $E_{n,\,h}$ is the energy use for hour h for hour number n. This creates an average load profile for house a for a particular appliance. To generate the normalized load profile for each hour, $E_{norm,\,h}$, each hour's average value was divided by the total average energy consumption for this average day, $\sum_{i=1}^{24} E_{avg,\,h}$, (Eq. (2)).

$$\left(E_{norm,\,h}\right)_a = \left(\frac{E_{avg,\,h}}{\sum_{i=1}^{24} E_{avg,\,h}}\right)_a \qquad (2)$$

To complete (b), all homes' normalized load from (a) were averaged by the hour (Eq. (3)), where A is the total number of homes averaged. Each house's load profiles was given equal weight when averaged to generate the final normalized energy use profile. $(E_{norm,\,h})_{avg}$ thus represents the percent of daily energy use used for a particular hour h for the average of the homes considered.

$$\left(E_{norm,\,h}\right)_{avg} = \frac{1}{A}\sum_{a=1}^{A}\left(E_{norm,\,h}\right)_a \qquad (3)$$

All appliance circuits for the available homes were processed using this methodology develop average normalized energy use profiles.

3. Normalized daily use profiles by appliance

The final normalized energy use profiles for each appliance are shown in Fig. 2, with the x axis showing the time of day in hours. $(E_{norm,\,h})_{avg}$, the percent of daily energy use load (PDL) of each hour, is plotted in black. The error bars represent one standard deviation in the value the normalized energy use of that hour among the homes studied. The dashed line is the normalized load profile developed from [7] and used in [25], plotted on the same graph for purposes of comparison. These results use all the energy use data available to develop the observed profiles.

For comparing the normalized daily use curves developed for each appliance to Pratt [7], the sum of squared residuals (SSR), a measure of the overall difference between the new measured data's normalized energy use profile, and the previously developed use profile (Table 4). A small SSR indicates a tight fit between the curves and thus greater similarity, and a large SSR indicating there is a greater difference between the curves. This can also be thought of as the Euclidian distance in 2-D space, where minimizing this distance for all hours indicates more similar fit of the two curves. The refrigerators have the least difference between the previous study [7] (0.001 PDL) and the dishwashers have the most (0.75 PDL).

3.1. Refrigerator

The refrigerator normalized energy use is a significantly flatter, more constant energy user than the other appliances analyzed in this study, varying between 3.5 and 5 PDL of total energy use per hour for all hours. The greatest energy use occurs in the afternoon, with the use peaking at 7:00 pm, consistent with the finding of [7,10], which also found the greatest use period during this time. The standard deviation for each hour's value is, on average 0.41 PDL. The greatest variation in use occurs between the hours of 6:00–8:00 am and 6:00–8:00 pm, consistent with times of meal preparation. Compared to the other appliances studied, this profile is the most consistent among homes, varying, on average, 5 to 9 times less between homes compared with the other appliances studied. Compared to the profile developed by [4] for refrigerators, this profile values closely match, disagreeing, on average by only 0.04 PDL.

Influences on the energy consumption of a refrigerator have been correlated with outdoor temperature [9], and can also be influenced by indoor temperature of the room in which the refrigerator is operating. A lower indoor temperature closer to the temperature maintained inside of the refrigerator increases the coefficient of performance (COP) and reduces the power required to operate the refrigerator. The nominal efficiency (nominal COP) of the refrigerator, the amount of opening and closing of the doors that occur, and the amount of food stored, or thermal mass, in the refrigerator/freezer also influence the refrigerator operations. Since 1989 refrigerators have become increasingly more efficient due to increasingly stringent regulations. However, with a small difference between the profiles from Pratt et al. [7] and the current study, this indicates that these changes do not have a strong influence on the time-of-use of energy of refrigerators. The outdoor temperatures and indoor temperatures of homes throughout the monitoring period of this study and those in [7] likely were somewhat different, due to differences in climates between the Pacific Northwest and Texas. However without indoor temperature data, this correlation cannot be confirmed. With minimal differences between the two profiles, however, this also suggests that temperature has a minimal influence on time-of-use of electricity of refrigerators.

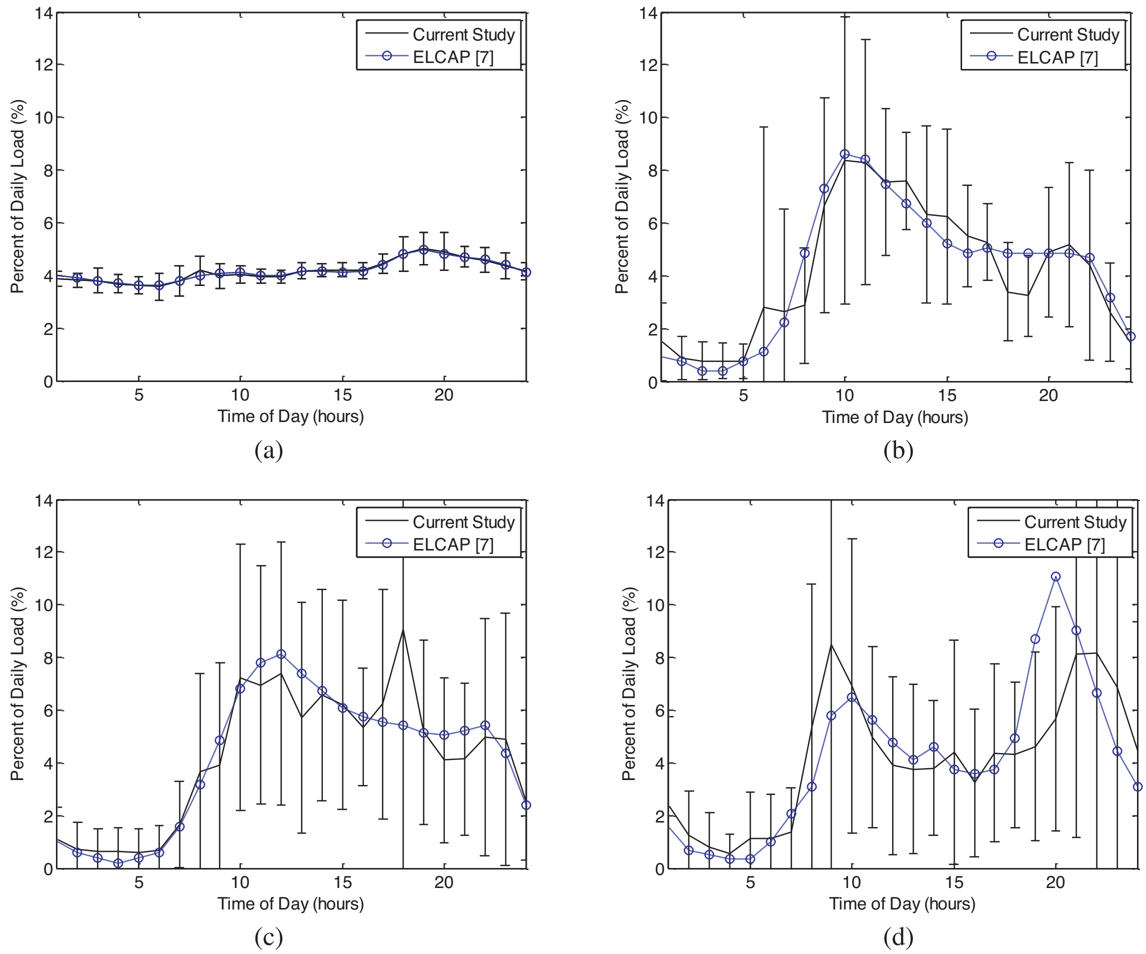

Fig. 2. Average normalized energy use profiles for (a) refrigerator, (b) clothes washer, (c) clothes dryer, and (d) dishwasher from this study (black solid) and from Pratt [7] (blue dashed). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The increased variation in the energy use of the refrigerator during the evening hours is logically best explained due to the increased influence of human use on energy consumption, through the opening and closing of doors for dinner meal preparation, and placing warm food into the refrigerated space, requiring additional energy use to cool the food to refrigerator temperatures. The opening and closing of the refrigerator causes a direct loss of cool air in the fridge to the surrounding space. Placing warm food in the refrigerator requires extra energy to cool to the refrigerator's cooler temperature.

3.2. Clothes washer and dryer

The clothes washer and clothes dryer had the greatest variation in normalized energy use by hour, with each hour varying between 0.07–8.4 PDL and 0.06–9.1 PDL as seen in Fig. 2(b) and (c). The greatest period of use occurred between 9 am and 2 pm, peaking at 10:00 am for clothes washers and 12:00 pm for clothes dryers during this high-use time. This is consistent with [7], but somewhat different than [11], which found peak use in washers and dryers in the evening hours. For the clothes dryer a higher peak occurred at 6 pm but with significantly larger variation between homes. The greatest variation among homes' profiles occurred at 6:00 am (6.8 PDL), and 10:00 am (5.4 PDL) for clothes washers, and at 6 pm for clothes dryers (12 PDL). The average standard deviation among homes was 2.5 and 3.4 PDL, respectively.

Similar to the refrigerator, the normalized load profiles of the clothes washer and clothes dryer are closely aligned with the findings of [7]. The hourly values in this study vary on average by 0.59 and 0.61 PDL, respectively. The [7] profile for clothes washers peaks at the same time, however, for the clothes dryers, this profile peaks one hour later than [7]. We also note a comparatively lower use at 6 and 7 pm for the clothes washers and a higher use of the clothes dryer at 6 pm.

The use of clothes washers and clothes dryers depend strictly on the resident's decisions. Unlike the refrigerator, the clothes washer and clothes dryer do not consistently require electricity. This explains the main difference in the load shapes of the

Table 4
Sum of the squared residuals (SSR), comparing this study's homes to previous study's results [7], and comparing segmentation of homes.

SSR	All days vs. [7] (PDL)	Weekday vs. weekend (PDL)	Work at home vs. not (PDL)	Summer vs. winter (PDL)
Refrigerator	0.001	0.02	0.01	0.01
Washer	0.27	0.62	0.85	0.71
Dryer	0.44	0.27	1.31	0.32
Dishwasher	0.75	1.06	0.72	0.20

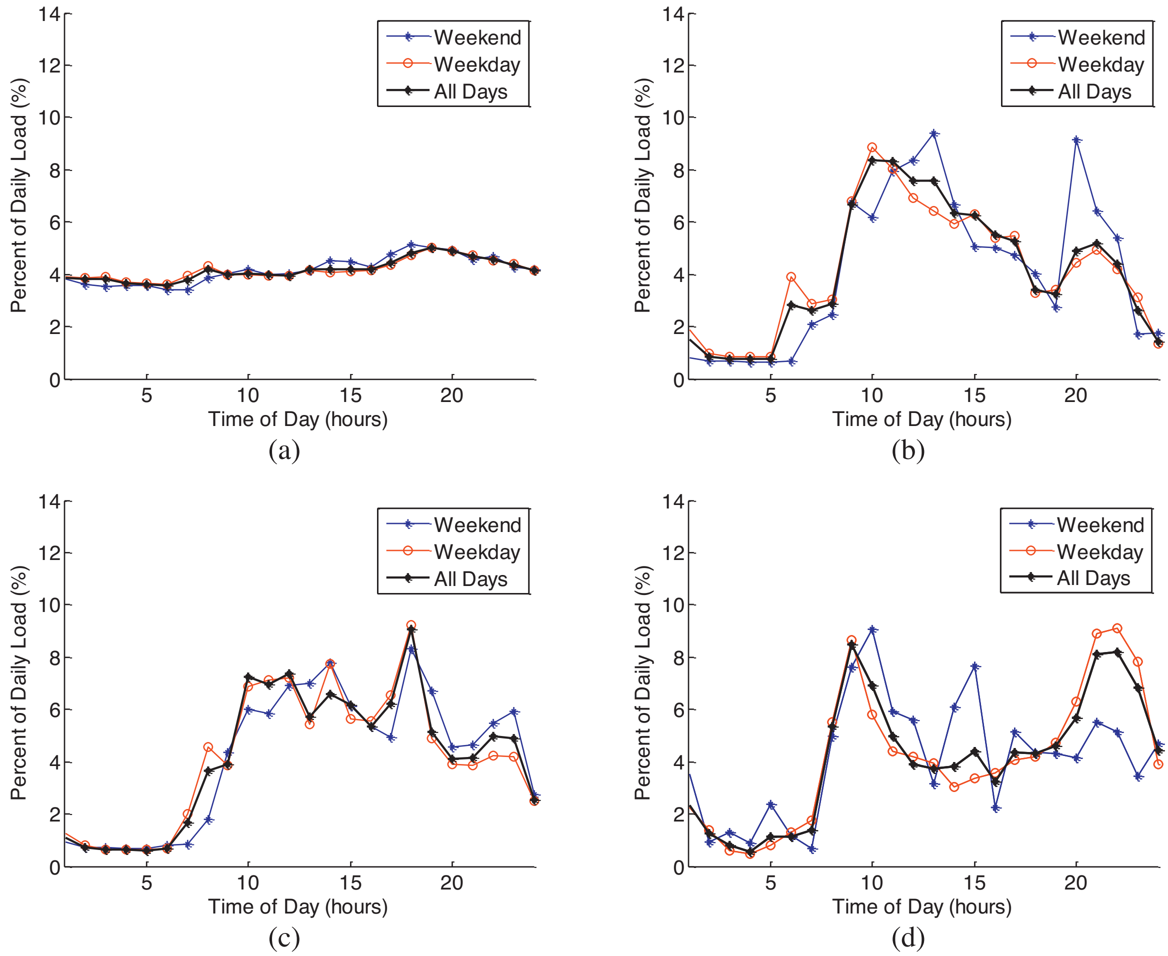

Fig. 3. Normalized energy use profiles of (a) refrigerators, (b) clothes washers, (c) clothes dryers, and (d) dishwashers on weekdays and weekends.

refrigerator and the washer/dryer. The spike in the load profile at 6 pm for dryers can be explained from the influence of several homes in the dataset that only ran their clothes dryer at this specific time throughout the period monitored. Likely, with a larger number of homes and a longer monitoring period, this spike and relative influence on the load profile would be smoothed over. Interestingly, unlike the dishwasher load profile, which peaks in the morning and evening hours when those who work away from home would likely be at home, the energy use of the washer and dryer are highest during normal business hours, with the exception of the 6 pm dryer spike. This increased use is similar to the profile found in [7]. Of the homes studied, 20 of the 40 homes (50%) indicated that one or more members of the household worked from home more than 20 h per week, which may explain some of the increased use during this time. 85% of the homes studied also had 2 or more household members, indicating that one or more of these members maybe home during the day, but not necessarily working from home, and using the clothes washer and dryer during these hours. The number of household members who were at home during the day, however, was not explicitly asked in the resident survey conducted.

3.3. Dishwasher

The dishwashers, compared to the other appliances, had a use profile that differs the most (1.2 PDL) from [7], more than twice the average difference for clothes washers as shown in Fig. 2(d). The variation in normalized energy use by hour is similar to that of washers and dryers, averaging varying between 0.05 and 8.5 PDL. The load profile shows a distinct peak at 9:00 am (8.5 PDL), and 10 pm (8.1 PDL) which is also the time with greatest variation in load across the homes (9.9 and 9.2 PDL). This variation is more than twice as much as the average variation (4.0 PDL).

Two of the dishwasher circuits monitored have energy use profiles that indicate the dishwasher is only in the morning and two houses show use only in the evening. Due to the small sample size, these homes had a significant influence on the resulting load profile. Dishwashers, similar to clothes washers and dryers, are also user-dependent, in that they use very little electricity unless specified by the user. Dishwasher use is also typically associated with meals, thus it makes sense that peaks in use would occur around meal times, in this case breakfast and dinner, similar to the observations of [15].

4. Segmentation of daily use profiles

While the appliance load profiles developed in this study somewhat closely follow that of those developed in 1989 by [7], the variability in the percent of daily energy use used each hour is significant between the homes, particularly for those hours that also have the highest average energy consumption. To assess the source of variation in these profiles, three possible influencing factors are investigated. The first two factors are energy use on weekdays vs. weekends, and energy use of households with members working at home vs. those who do not. These factors affect the relative amount of time spent in the home, and thus also the daily time-of-use of

Table 5
Energy use and variability comparison of weekdays vs. weekends.

	Average hourly variability (standard deviation)			9 am–5 pm % of daily load		
	Weekend (PDL)	Weekday (PDL)	Less variability on weekdays (%)	Weekend (%PDL)	Weekday (PDL)	Less PDL on weekdays (%)
Refrigerator	0.52	0.47	10	44	42	2
Clothes Washer	3.7	3.1	21	64	63	1
Clothes Dryer	4.2	3.9	7	63	65	−2
Dishwasher	5.9	4.2	39	44	41	3

energy due to different behavioral patterns. Energy use during the heating and cooling seasons is also discussed. To compare these factors, the SSR, as discussed in Section 3, is used. A larger value of SSR indicates a greater difference in the two compared profiles. These values are shown in Table 4.

4.1. Weekdays vs. weekends

Using the same methodology, normalized energy use profiles were created for weekdays and weekends. Fig. 3 compares the normalized energy use profiles for weekdays (Monday–Friday) and weekends (Saturday–Sunday) for each appliance. Unlike the assumptions in current energy modeling, where only the total energy use increases on weekends, Fig. 3 shows time-of-use changes as well. This segmentation of weekdays and weekends is in agreement with Arghira et al. [28], which found that the day of the week is correlated with energy use. Refrigerators, clothes washers and clothes dryers show lower energy use in the morning hours on weekends than on weekdays, but higher energy use in the afternoon and evening hours. Dishwashers, on the other hand, show higher use in the morning and early afternoon hours and lower use in the evenings. For all appliances, the standard deviation of hourly PDL is greater on weekends than weekdays (Table 5), explaining some of the variation in use among homes. Comparing the difference in the profiles (Table 4) of the three segmentations studied, the dishwasher shows the greatest difference in profiles between weekdays and weekends.

4.2. Working from home

Because the use of clothes washers, clothes dryers, and dishwashers is user-dependent, it is worthwhile to investigate the effects of an increased number of hours spent in the home due to household members working from home. The homes considered in this study indicated a significant spread in the amount of time spent working at home (Table 1).

Comparing the weekend and weekday profiles in Fig. 3 for all homes, on weekdays there is, on average, a lower percent of daily energy use during normal business hours (9 am–5 pm) as compared to weekdays (Table 6) for all but clothes dryers. This makes sense, since many of the residents work outside of the home and would not be using appliances during this time. Interestingly, refrigerators, the most user-independent appliance, show the greatest reduction in use on weekdays, as compared to the other three more user-dependent appliances. This may be explained because people have less time to cook meals at home that requires use of the fridge and storage of warm food.

Separating the energy use profiles, into those households that work twenty or more hours per week from home and those who did not, energy use of appliances during normal business hours (9 am–5 pm) in households where members do not work from home is 2–28% less than households that do work from home (Table 6). This is important to note, as the number of Americans working from home has increased in recent years [16]. Variability is also significantly less for those households with no one working from home for all but the clothes washer. Comparing the SSR values of the three studied factors (Table 4), the washer and dryer are most influenced by whether or not the household has someone working at home or not.

4.3. Heating and cooling seasonal effects

The effects of the normalized energy use profiles of the studied appliances in the heating (October to March) and cooling (April–September) were also studied. Of the homes monitored, Austin, TX is a cooling-dominated climate, with 1661 cooling degree days (CDD), and 919 heating degree days (HDD) [29]. The difference in the normalized daily use profiles for all appliances showed the least differences when comparing the profiles generated for the heating and cooling season. The values of the SSR (Table 4), over all were smallest, indicating that this factor is not as influential as the other studied factors.

5. Implications of results

5.1. Home energy use

As an estimate of the implications of the use of the appliance load shapes developed in this study, the average yearly electricity use of each of the studied appliances from the RECS 2009 [6] for refrigerators, washers, dryers and dishwashers respectively are used to provide a relative weight of each appliance's contribution to home electricity use for the profiles developed in [7] and in this research. The relative contribution (%) of each appliance to total large appliance electricity use has remained similar, despite improvements in efficiency of appliances. Of electricity consumed by all four of the studied large appliances, refrigerators, washers, dryers, and dishwashers account for 42%, 4%, 37% and 17% of total annual use in the U.S. in 1990 [30], and 49%, 4%, 34% and 13% in 2009 [6]. If all appliances are combined together to create one representative profile of large appliance electricity use (Fig. 3a), the results of [7] and the

Table 6
Energy use and variability comparison of work-at-home vs. non-work-at-home households.

	Average hourly variability (standard deviation)			9 am–5 pm % of daily load		
	Work-at-home (PDL)	Not (PDL)	Less variability on weekdays (%)	Work-at-Home (PDL)	Not (PDL)	Less PDL on weekdays (%)
Refrigerator	0.42	0.38	12	42	42	2
Clothes Washer	2.0	2.6	−22	72	61	18
Clothes Dryer	3.7	2.6	45	72	56	28
Dishwasher	4.1	3.5	18	51	43	19

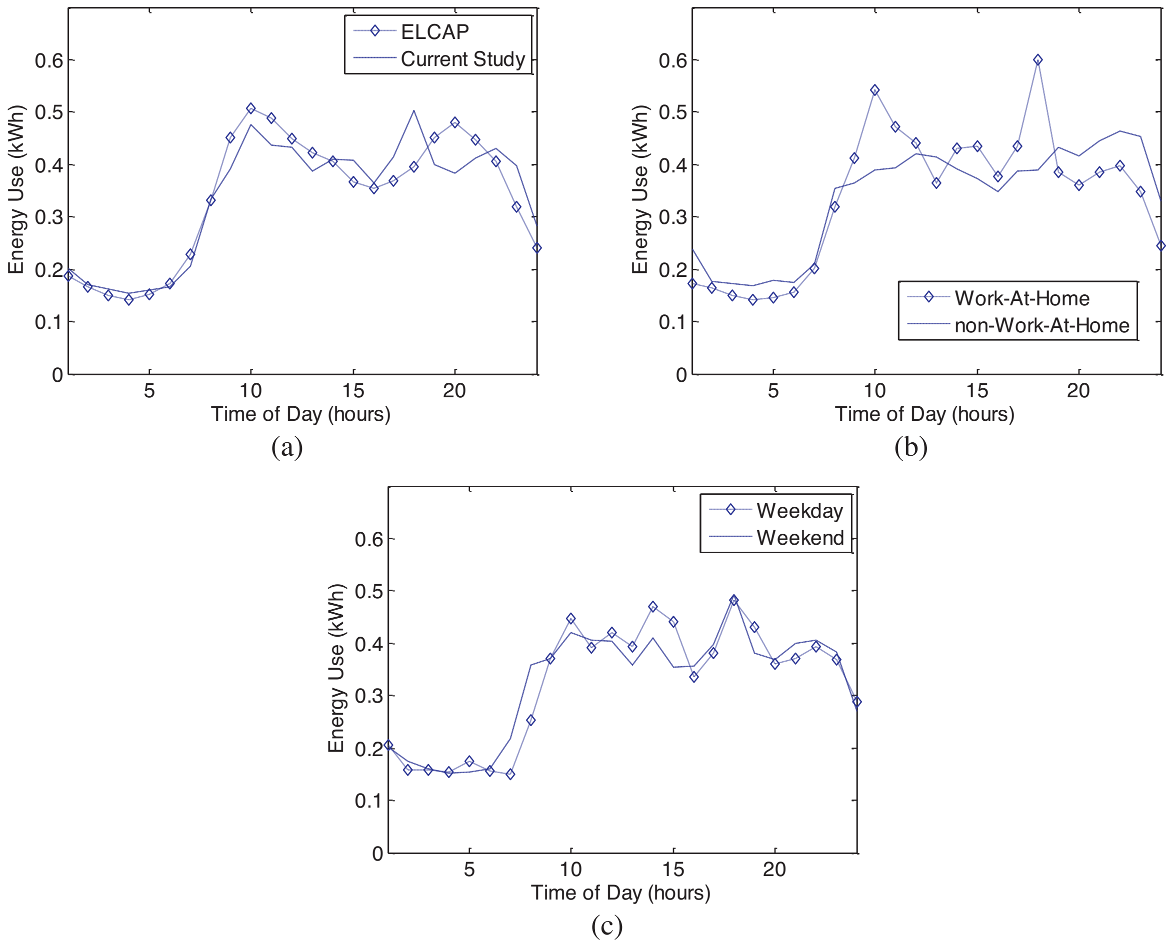

Fig. 4. Aggregated daily energy use of all studied appliances comparing (a) this study to [7], (b) homes that work from home and those who do not, and (c) weekdays and weekends.

current study are similar, with an average difference between profiles of 0.4 PDL for each hour. This profile is most influenced by the dryer and refrigerator, and less by the clothes washer and dishwasher. The dryer use profile, due to the spike at hour 18 (6:00 pm), has an influence on the load shape and causes the spike in the total use profile in Fig. 4. Further dividing the profiles by weekday and weekend (Fig. 3b) and work-at-home and non-work-at-home (Fig. 3c) we see a more significant difference in time-of-use. Assuming the same energy use values in [7] for purposes of comparison, the energy use (kW h) is consistently higher during working hours (9 am–5 pm)for work-at-home households, amounting to 48% of daily energy use, 6% (0.43 kW h) more than non-work-at-home households. Comparing weekdays to weekends, the weekday energy use begins to increase around 6 am on average, while on weekends the energy use remains low until 7 am. Since there are only two of the seven days in a week that are weekends, this trend is not visible unless two profiles are used instead of one. Additionally, energy use during normal business hours is approximately 2% lower on weekdays than weekends. These differences indicate it may be important to consider further study to quantify the effects that working at home has on the use profile, beyond the 40 homes studied in this research. Current profiles may under predict energy use during the day, particularly with increasing numbers of residents working at home.

5.2. Peak electric grid load

In warm climates, including Texas, peak electricity demand is a significant concern for utility companies. Peak demand is a concern in many other countries as well due to a variety of factors. Using the methodology outlined in this paper, a normalized profile of the Electric Reliability Council of Texas (ERCOT) during the summer months of May to September [31], shows that, on average, the hours of greatest demand occurs consecutively between 3 pm and 8 pm. This time period, 21% of a day, corresponds to 28%, 29%, 36%, and 27% of total daily load (PDL) of the refrigerator, clothes washer, clothes dryer and dishwasher, respectively. All appliances, thus, show potential to provide relief to the electric grid. Clothes dryers, with the greatest percent of daily use coinciding with peak hours on the electric grid (36%), and the second highest average daily energy use among the studied appliances [6], shows the strongest potential for reducing electric grid peak load stress in this climate. This methodology can be applied to other locations nationally and international as well by similarly identifying the peak use times of the grid, and comparing these times to the use profiles of appliances, in applications such as those developed by [32].

5.3. Building energy simulation

The results of this study are also important for building energy simulation software, which uses energy use profiles of internal energy loads as input data [25–27]. Energy simulation relies on the accuracy of the profile's underlying assumptions to produce a resulting accurate representation of building energy consumption behavior. This requires a schedule of energy use of all energy-consuming components of a building, including appliances. Residential building energy simulation uses an hourly normalized

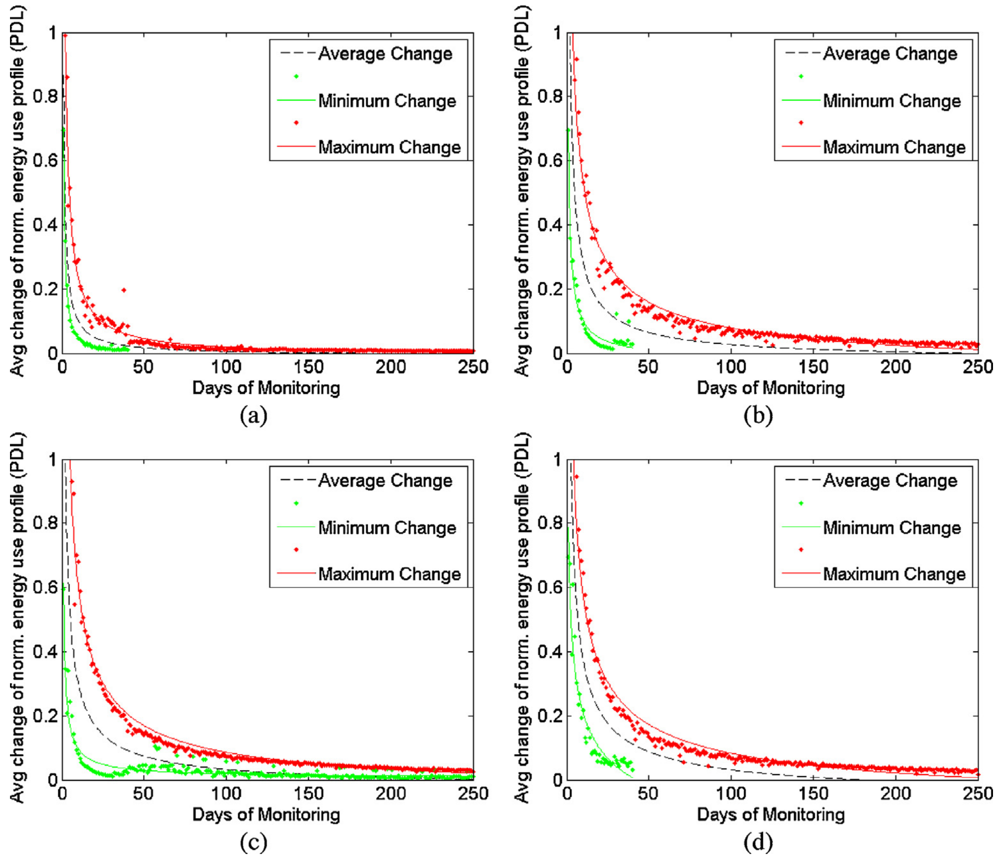

Fig. 5. Change in hourly normalized energy use with increasing number of day of monitoring for (a) refrigerators, (b) clothes washers, (c) clothes dryers, and (d) dishwashers.

daily use profile, which is multiplied by an annual energy use value (kW h), and in some cases, a seasonal or weekday/weekend multiplier [11]. These daily use are used to represent use pattern of that appliance for all days of the year-long simulation period. Currently the load shape of appliances for each day of the year is the same since it is derived from a single normalized daily energy use profile, but the relative magnitude of the load for each day is different. The use of multiple load shapes for different days of the year has not been investigated prior to this study, nor has the influence of factors, such as sociodemographic characteristics, time of year, and day of week, on these profiles. As shown in Table 4, the washer and dryer profiles are most influenced by the whether or not the residents work at home, and the refrigerator and dishwasher are most affected by whether or not it is a weekday or a weekend. This demonstrates that including multiple profiles may provide a more realistic representation of energy use of appliances over a day.

6. Limitations

The 40 homes monitored in this research consist of newly constructed, single family homes in Austin, TX. The homes are similar in size to the average newly built homes in the United States, but are limited in number and not necessarily representative of all homes in the U.S. The efficiency of the appliances has an effect on the magnitude of the total energy used by the appliances, but not the normalized use profile, which allows for comparison with previous field collected data from [7] and other sources. The number of appliances monitored within the 40 homes is limited, ranging from 9 to 18 individually monitored circuits. The data utilized, however, represents the total available number of individually monitored appliances in the field collected data.

The range of time of monitoring of energy use of subcircuit level data in buildings has ranged from several weeks [8], to several years [7]. On average, the appliances monitored in this study were monitored for between 159 and 221 days throughout the one year time period of monitoring (Table 3). To assess how long of a monitoring period is required to capture the normalized load profile of a home's energy use, the average percent change in the 24 hourly values of the normalized energy use profile was calculated for each number of days of monitoring in this study. The absolute value of the percent change was used to develop the trends shown in Fig. 5, which shows the upper and lower bounds of these values for all homes studied. These values provide a measure of the influence of an additional day of monitoring has on the normalized daily use profile. A power curve was fit to the upper and lower bounds and is also shown in Fig. 5. The equations for the maximum change, representing the worst case scenario, are shown in following equation, where $\in$ is the average change in the value of the normalized energy use profile, and n is the number of days monitored.

$$\begin{aligned} \in_{Fridge} &= 2.019n^{-0.913} - 0.0112 \\ \in_{Washer} &= 2.315n^{-0.574} - 0.0863 \\ \in_{Dryer} &= 3.027n^{-0.663} - 0.0573 \\ \in_{DW} &= 2.415n^{-0.547} - 0.1118 \end{aligned} \tag{2}$$

Table 7 provides a comparison of the number of days required to achieve average levels of change in the profile for each of the appliances based on Eq. (2). The number of days to reach a consistent profile is lowest for refrigerators. This is generally to be expected since human behavior has less of an effect on refrigerator energy use than the other appliances. If a benchmark of 0.05 is considered acceptable, for the user-dependent washer, dryer and dishwasher, a

Table 7
Days of monitoring required to achieve a desired level of average percent change in the normalized daily use profile.

% Change in avg.		5	1	05	01
No. of days	Fridge	5	24	46	147
	Washer	11	81	139	255
	Dryer	13	87	154	311
	Dishwasher	12	86	140	235

139–154 day monitoring period is required. The refrigerator, however, only requires 46 days, approximately one-third of the time of monitoring. Comparing these values to the average length of monitoring of the studied appliances (Table 3), only the dishwasher (avg. days = 122) does not meet this threshold, and is a limitation of this study.

7. Conclusions

In this study a methodology was discussed for use in the development of representative schedule of daily energy use of appliances, in particular daily normalized energy use profiles. Normalized energy use profiles were developed for four large appliances, including refrigerators, clothes washers, clothes dryers and dishwashers using energy consumption data from 40 homes in Austin, TX. The appliances studied in this research are all newer appliances and are used by households similar in size to the average U.S. household. As more energy efficient appliances come to market and are purchased, the results of this research will be relevant in predicting current and future appliance energy use. These load profiles, with the exception of dishwashers, were similar those found by [7], and those currently used in building energy modeling software. However, the significant variation in the normalized load profiles motivated further investigation as to the cause of this variation. Three factors were investigated that were found to influence the time of use of appliances, including the day of the week (weekday vs. weekend), and whether or not the household reported having one or more members working from home 20 or more hours per week. These factors were correlated with increased energy use of appliances during normal business hours. The influence of the heating and cooling season were also studied, but found to have, in total, a lesser effect on the shape of the use profile than the first two studied factors. Limitations of this study were discussed and the influence of the length of monitoring period on the resulting energy use profiles. The following conclusions can be drawn from this research:

(1) Appliance use patterns have not changed significantly since the 1989 study [7] except for in the case of dishwashers, which shows a large peak in use in the morning than in previous studies;
(2) User-dependent appliances use patterns vary more between homes and between days than automated appliances; the average standard deviation in hourly normalized energy use between homes is greatest for dishwashers (4.0 PDL), followed by dryers (3.4 PDL), washers (2.5 PDL) and refrigerators (0.41 PDL).
(3) Weekday and weekend use patterns of appliances are similar, but the average standard deviation of weekday use patterns between homes is 7–39% lower than on weekends, indicating a more predictable energy use pattern on weekdays.
(4) Weekdays and households where no one works at home have more predictable, consistent electricity use patterns than weekends and households where members work at home 20 or more hours per week.
(5) Households where members work at home use 2–28% more of their daily appliance energy use during normal business hours (9 am–5 pm) than non work-at-home households.
(6) The washer and dryer energy use profiles are most influenced by the whether or not the residents work at home. The refrigerator and dishwasher energy use profile is most affected by whether or not it is a weekday or a weekend.
(7) Of the influencing factors studied, if all appliances are considered, the heating and cooling seasonal variations have the least effect on the normalized use profiles of the appliances studied. Whether or not the residents worked at home shows the greatest difference.
(8) Electricity use varies more between houses during peak use times of day than during low-use times.
(9) All appliances use more than 25% of their daily energy use during peak use times, demonstrating the potential to reduce peak use on the electric grid if equipped with smart technologies; clothes dryers utilized the greatest percent of daily load (36%) during peak use times and thus show the strongest promise for this application according to the studied homes.
(10) 139–154 days of user-dependent appliance electricity use data is needed to represent an appliance's daily use profile at a threshold of 0.05% maximum average change in energy use. Refrigerators require approximately one third of the time, or 46 days of monitoring, to achieve the same threshold.
(11) Utilizing multiple normalized daily energy use profiles of appliance, rather than one, as inputs into building energy models may help provide a better representation of daily appliance energy use in residential buildings. This include consideration of sociodemographic characteristics such as working at home, and day of the week.

Of particular interest in the finding of this study is the increase in appliance energy use during the day of homes with work-at-home members. As it continues to become more common for adults to work from home [16], this may influence the overall load shape of the residential building sector in the long term.

Through development of normalized daily energy use profiles for each of the studied appliances and assessing influences of variation on time-of-use, a greater and more accurate understanding of appliance energy use is achieved.

The results of a this study can be used to inform utilities, manufacturers of appliances, and consumers about the role appliances currently play in residential energy consumption, and how this varies with time. It is also important to understand when residential home appliances are used in applications such as building energy modeling, a method increasingly used to identify cost-effective methods of retrofitting buildings to reduce energy consumption. Energy modeling relies on the accuracy of its underlying assumptions, which includes time-of-use of appliances. The time-of-use of appliances is also useful for utility companies, who must predict and meet the electricity needs of its customers. Understanding how different factors affect the load profile of appliances will help to predict how appliances will be used in the future, and the possibilities of peak load shifting by altering appliance use patterns.

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