The Spin Zone: Unravelling Clothes Washer and Dryer Usage Behavior from Energy Monitoring Data

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ABSTRACT

This paper presents a method for addressing the challenges when using short-interval energy monitoring data to gain insights into end user laundry behaviors. Leveraging energy monitoring data with the method described in this paper provides unique benefits relative to traditional data collection methods (like self-reports) because it reduces respondent fatigue, it expands the study time period, and it reduces self-report errors while revealing actual equipment usage behavior. A better understanding of behavioral usage patterns, as enabled by the method presented in this paper, could help in establishing appliance standard test procedures that reflect real-world usage scenarios and could also be used to inform behavior-based intervention strategies for energy efficiency programs.

The method presented in this paper determines typical clothes washer and clothes dryer usage in a sample of homes by systematically addressing the challenges inherent to monitoring data. This method attempts to identify the possible individual washer/dryer runs by allowing for varying amounts of near-zero energy use within single cycles, thereby accounting for off periods within equipment runs. This range of near-zero values produces a distribution of all possible equipment runs, which are then analyzed to determine the most likely usage patterns for each piece of equipment. This paper also presents a sample of results from when this method is applied, including typical equipment run times and specific behavioral patterns including "laundry days" (many washer/dryer runs on a single day) and redrying (short dryer runs following a longer dryer run to get clothes properly dry).

Introduction

Leveraging short-interval residential end use energy monitoring data has the potential to reveal the actual energy usage behaviors of households and how those households use a variety of appliances. While traditional methods rely on self-reported behaviors (Anderson 2016), in-situ end use energy monitors serve as independent observers of energy usage, enabling evaluators to infer actual—not self-reported—behavior. This paper presents a method for leveraging end use energy monitoring interval datasets to reveal how households use their clothes washers and dryers. This type of real-world usage data is useful for understanding the potential for behavior-based interventions—such as the potential for shifting load to off-peak times (Klaassen 2016)—and for updating appliance and electronic standards test procedures to better reflect actual in-home usage patterns in addition to typical settings (NEEA, PG&E, and Ecova 2017). This paper will provide a detailed description of the method followed by a selection of laundry behavior insights based on the application of the method.

Sources of Monitoring Data

Understanding the minute-level behavior of clothes washers and dryers requires a source of monitoring data that will support this analysis. For this paper, we had access to one-minute energy monitoring data from two large-scale energy monitoring studies: the Home Energy Metering Study

(HEMS) as part of the Northwest Energy Efficiency Alliance's (NEEA's) End Use Load Research (EULR) study, as well as Pacific Gas and Electric's (PG&E's) Home Energy Use Study (HEUS).

The main objective of NEEA's HEMS is to develop a robust characterization of continuous energy consumption of key heating and cooling measures to support clean energy goals and utility information needs. The study includes collecting one-minute interval data at both the circuit and whole-home levels from 400 homes across Oregon, Washington, Idaho, and Montana. While data collection efforts are focused on these targeted equipment types,[1] the study also collects data on other end uses including clothes washers and dryers. As HEMS will run from 2019 to 2023, much of the analysis from this study is still forthcoming, but certain data are available including those used in the analysis presented here.

Similarly, PG&E's HEUS aims to understand residential energy usage at a sample of homes in PG&E's service territory (Price, Rasmussen, and Anderson 2016). The objective of HEUS is to provide PG&E's Codes and Standards Program with detailed information regarding the usage patterns for a wide array of energy using equipment so that the program can apply the results to design and advocate for future appliance and electronics standards. This study collects one-minute interval data for the whole house, all major end uses (typically monitored at the panel), and a sample of plug loads including clothes washers and dryers. As HEUS has an indefinite completion date, much of the analysis from this study is still forthcoming. The results presented in this paper are one example of analysis completed as part of HEUS.

It is worth noting that neither of these studies were designed with the intent of capturing residential laundry usage behavior. Rather, the method presented in this paper aims to develop a new application of these data resources—the determination of real-world laundry usage behavior. Behavioral results from both of these studies are presented in the Results section of this paper.

The Data Collection Process

Evergreen Economics has developed a streamlined approach to implementing residential metering studies which both HEMS and HEUS utilize (Price, Lehndorff, and Clement 2019). We start broadly by examining the study populations to develop a sample frame. From there, we draw the study sample and then recruit sites for meter installations. This leads to data streams that are uploaded via cellular routers that securely push to the cloud-based database infrastructure. The metering study data sample is designed to be representative, allowing for inferences to be drawn across regions, states, and climate zones.

Each data point is a time-stamped reading of energy usage over the past one-minute interval for the end-use/circuit. Once data are uploaded, Evergreen runs a series of computing processes—including significant quality control and quality assurance checks—that lead to a clean, aggregated dataset, included the data used in the analysis presented here.

The Benefits of Monitoring Data

Self-report participant surveys are the most common method for understanding laundry appliance usage behavior (Anderson 2016). These surveys often ask participants to record the start time, end time, and various settings for the equipment of interest over a relatively short study period (Durand-Daubin 2013). Monitoring data has a number of unique benefits relative to the self-reports that are typically used. First, once installed, energy monitoring equipment requires no additional active engagement from participants, limiting respondent fatigue, missed self-reports, and study-related bias

[1] This includes ducted heat pumps, ductless heat pumps, heat pump water heaters, electric forced air furnaces, central air conditioners, and electric baseboard heaters.

that can occur when respondents must actively self-report. Second, the collected data set is no longer dependent on the accuracy of self-reports, as the monitoring data can identify the start, end, and usage characteristics of the equipment. Finally, while sustained data collection of surveys adds to participant fatigue, energy monitoring can continue indefinitely, augmenting collected data with no additional effort from study participants.

The Challenges of Monitoring Data

While superior to survey data in some respects, monitoring data come with their own set of limitations. Fundamentally, the expense of installing monitoring equipment may be prohibitive, making surveys or other types of sensors more realistic alternatives. Similarly, while energy monitoring can collect detailed energy usage data, certain data, like settings or laundry weight, still require additional self-reports from participants.

Beyond these fundamental issues are the challenges encountered when attempting to analyze energy monitoring data that have been collected. While self-reports provide researchers with the (potentially inaccurate) start times of a laundry run, the monitoring data provide observations for every minute that a monitor is installed—regardless of whether the equipment is actually in use or not.

Similarly, the minute-level usage patterns of washers and dryers can make the determination of start times vague. For example, in a washer run, the time when a washer fills with water (and is drawing no energy) could instead be viewed as a brief period between two separate washer runs. Figure 1 shows an ambiguous section of washer usage. In the figure, the X axis represents the timestamp of the observation while the Y axis represents the observed power. The section highlighted in red is a six-minute period of time when no energy usage was detected. This period of time can ambiguously be viewed as either the time clothes spend soaking in the washer, or the amount of time it took the participant to remove their clothes from the washer and start a new load—either could be true.

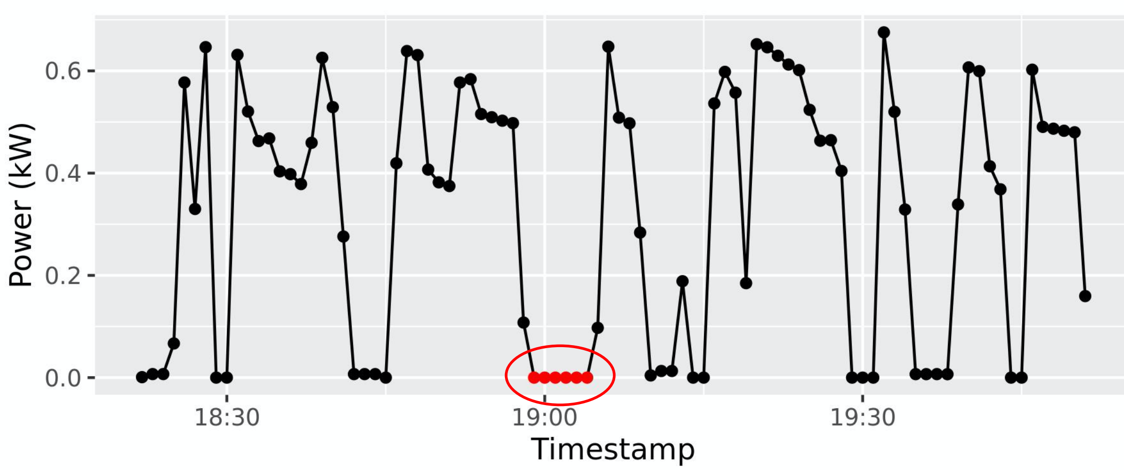

Figure 1. Example of ambiguous energy usage during washer filling. *Source:* HEMS and HEUS data.

Dryers have a similar issue with zero-usage observations. Specifically, low values between periods of usage could either represent the start of a new load of laundry in the dryer or it could represent the interval of time between when the dryer turned off and when the participant returned to restart their laundry after finding that it was not completely dry—again, the same energy usage could correspond to two different dryer usage behaviors obscuring the true length of the dryer run. Another dryer-specific issue is the advent of "wrinkle-guards" on newer dryers. This setting intermittently heats and spins laundry after the completion of a load to prevent wrinkles. Figure 2 shows the energy usage from one dryer run when wrinkle guard was active. In the figure, the X axis represents the timestamp of the observation while the Y axis represents the observed power. The section when wrinkle guard is active is circled in red. To accurately capture the length of this dryer run, these observations need to be excluded.

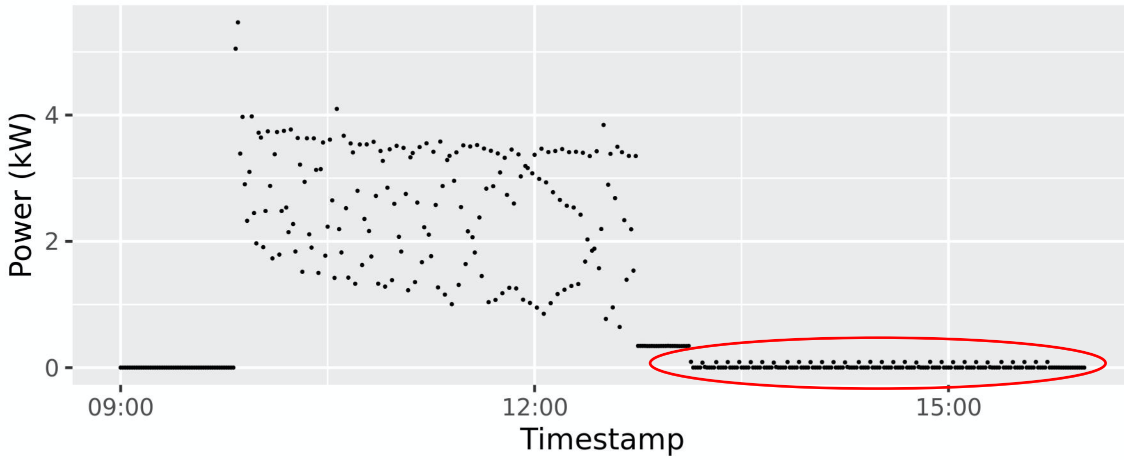

Figure 2. Example of energy usage during dryer “wrinkle guard.” *Source:* HEMS and HEUS data.

In these cases, the length of a washer or dryer run is no longer simply the number of minutes that the piece of equipment is “on.” While it might be possible to identify the start times and run lengths through manual review, a manual review process would be prohibitively time intensive to deploy at the scale of hundreds of monitored sites with thousands of individual washer and dryer runs. To address these issues and gain insights into laundry usage, we have developed a method for cleaning and interpreting laundry monitoring data.

Methodology for Determining Behavior from Monitoring Data

Our method for gaining the benefits of monitoring data has three main steps, described below.

1. Determining On/Off Thresholds

Fundamental to determining when and how long a washer or dryer is used is knowing if the washer or dryer is in use. While monitoring data make this possible, it is not as simple as identifying when usage is greater than zero. This is primarily the result of consistent, low-level energy usage caused by digital displays and other “stand-by” energy usage that occurs when clothes are not actually being washed or dried.

To determine the threshold at which energy usage values are indicative of clothes washing or drying (and not just stand-by mode), we applied change-point analysis to each of the laundry data streams. For this application, change point analysis involves ordering all observations from smallest energy usage to largest energy usage for a piece of equipment and determining the “elbow point”—the point at which the ordered usage is the farthest way from a line connecting the smallest and largest observations (as shown visually in Figure 3 and Figure 4). Figure 3 shows the minute-by-minute energy usage for an individual dryer across the time period included in this analysis. In the figure, the X axis is the timestamp of the observation and the Y axis is the observed power at that minute. The figure represents a total of 306,306 observations. Figure 4 shows the same usage data but ordered by size to determine the change-point. In the figure, the Y axis is still observed power, but the X axis is now the size-order of the observation. The red line connects the smallest and largest observation, and the vertical line identifies the point at which observations of power are farthest away from the red line—the elbow point. Observations to the left of the blue line are initially considered "off" while observations to the right are considered "on." For this particular dryer, this method identifies usage above 81W as being indicative of "on" usage. We applied this method to each of the washers and dryers in this analysis to determine on/off usage thresholds.[2]

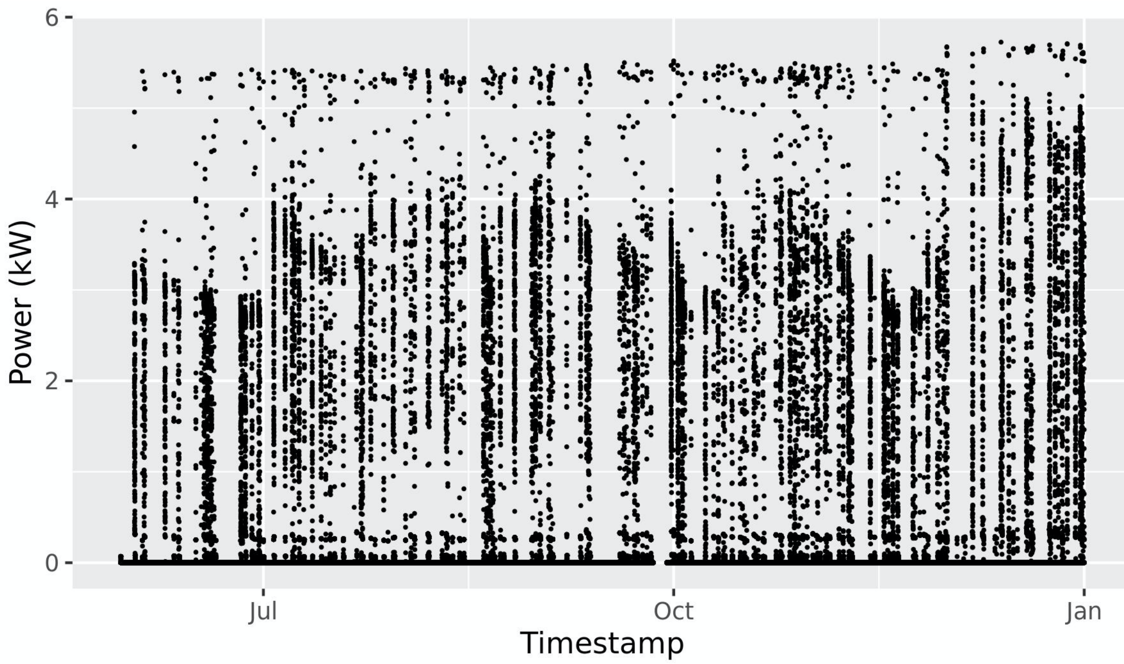

Figure 3. Power usage from example dryer. *Source:* HEMS and HEUS data.

Figure 4. Change-point threshold determination for example dryer. *Source:* HEMS and HEUS data.

[2] Given the tendency of both washers and dryers to spend most of their useful life not being actively used, the determination of these change-point thresholds is relatively easy.

As has been described, while monitoring can easily identify periods of usage, additional steps are required to clean the data and accurately assess the start times and run lengths of laundry equipment.

2. Removing Errant and Unhelpful "On" Periods

While on/off thresholds can identify all periods of usage, not all of these periods are helpful in analyzing laundry usage behavior. For example, when wrinkle guard is active, usage data show very short intervals of "on" usage surrounded on either side by "off" as the dryer intermittently turns and heats the dried clothes. If retained, these observations could give inaccurately long estimations of dryer run times. To resolve this and similar issues, our method requires that a period of "on" observations be greater than one minute for dryers and greater than 5 minutes for washers. While flexible, these thresholds reflect the minimum amount of time that either of the equipment types could reasonably be used. Figure 5 shows the same data from Figure 2 but with observations identified on the basis of "on" (blue) and "off" (black). The top chart shows on/off values based exclusively on the change-point-based on/off threshold (81W). The lower chart shows the same run after observations of on periods of less than or equal to one minute in length (wrinkle guard) have been removed.

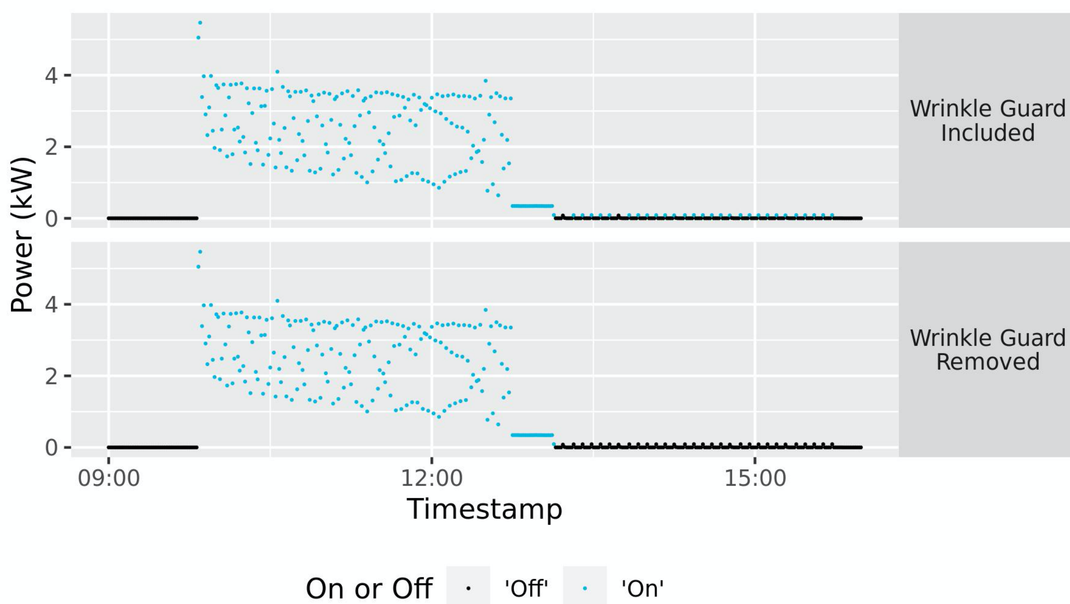

Figure 5. Example dryer with wrinkle guard identified and removed. *Source:* HEMS and HEUS data.

3. Varying Number of "Off" Minutes within Loads

With "on" periods identified, and errant/unhelpful observations removed, there still exists the challenge of interpreting "off" periods among washer and dryer runs—the periods that could either be *within* one load or *between* two loads. Our method assumes that a statistical distribution of likely run times can be determined, but that a single, perfect determination of start times and run times for every equipment use is not feasible.[3] To determine the distribution of likely run times, our method tests a range of acceptable number of "off" observations within a single, continuous run.

For example, for each washer, we begin by determining start times and run lengths assuming that 20 minutes (or less) of inactivity between "on" usage is representative of the washer filling with water or

[3] As noted, these objectives are also not feasible with self-reports.

otherwise being idle within a load. Therefore, the usage on either side of this 20-minute period can be connected to represent a single washer run. Inherently, there are cases where 20 minutes of inactivity is actually representative of a new load of laundry and not a period within a single load. Therefore, we then test fewer and fewer minutes of allowed inactivity, from 20 minutes down to one minute.[4] The goal is to have representation of the potential usage cases (e.g., one load or two loads) as reflected in the data. Our method assumes that across the years of observed data, the collective distribution of run times based on this range of potential run times will reflect the actual laundry usage behavior of study participants.

Figure 6 shows an example of how varying amounts of allowed "off" time within a washer run can affect the number of runs that are observed for a single washer over the course of about two hours. In the figure, the X axis is the timestamp of the observation and the Y axis is the power observed at that time. The color of the individual points corresponds to each separate washer run. The minutes within a run are also connected by a black line. The first chart assumes 19 minutes of inactivity can occur within a washer run, while the bottom chart allows for only one minute of inactivity with the intermediate values shown between. This figure shows that as allowed "off" time decreases, the number of runs increases and the average run length decreases. With 19 minutes of allowed inactivity, only one run is identified with a length of 142 minutes. Alternatively, with one minute of inactivity, seven runs are identified, with an average length of 14 minutes. While the truth likely lies within these charts (or as a combination of part of these charts), this figure shows how difficult it can be to determine the exact sequence of runs. The figure also shows, however, that it is possible to determine the set of *possible* runs.

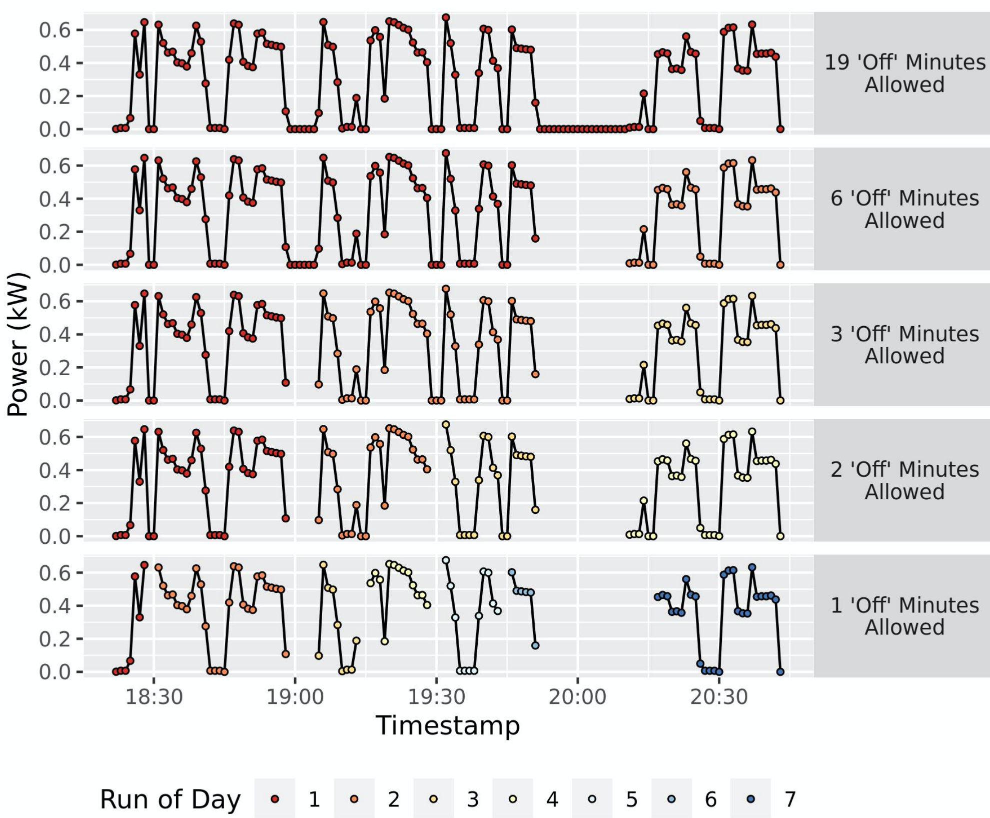

Figure 6. The various potential runs of a single washer. *Source:* HEMS and HEUS data.

[4] In cases where there are zero minutes of "off" usage within a run (i.e., it is always "on" until it turns off), this process will have no impact on the run time—the run time will be the same through each iteration.

When applied to every washer and dryer, this process creates a set of possible start times and run lengths that can then be used to conduct a variety of analyses. This includes how start times change throughout the year, the frequency of multiple loads being completed in a day, and the frequency of short dryer runs following longer dryer runs, among many other possible analysis objectives. These results can also be interpreted in light of available demographic and equipment information to assess how, for example, these metrics vary with household size, age of equipment, or household income. This paper includes a brief sample of results including variation of run length by equipment type as well as the frequency of laundry days and clothes redrying.

Results

The data used in this analysis represent 274 pieces of equipment (97 washers, 177 dryers) in a sample of single-family homes located in California, Idaho, Montana, Oregon, and Washington. The method described above was used to estimate the start time and run length for every load of laundry throughout the year 2019.[5] This method identified that a median of 131.7 loads per piece of equipment occurred during this time period, with a median of 19.7 loads per piece of equipment per month.

Run Time Results

Figure 7 presents the distribution of run times observed for washers and dryers by binned run length. Bins are inclusive of the left value and exclusive of the right value ("15 – 30" represents runs greater than or equal to 15 minutes and less than 30 minutes). The most common run length for both washers and dryers was between 30 and 45 minutes with between 45 and 60 minutes being the second most common run length. For washers, there is a steep drop between these frequencies and the next most common occurrence—the 75 minute and up bin (from around 25 percent to around 15 percent). For dryers, on the other hand, the distribution is much flatter, with the most common bins representing around 20 percent of cases and the next most common (75+ minutes) representing around 18 percent. The median run time for washers in this analysis was 48 minutes while the median run time for dryers was 47 minutes.

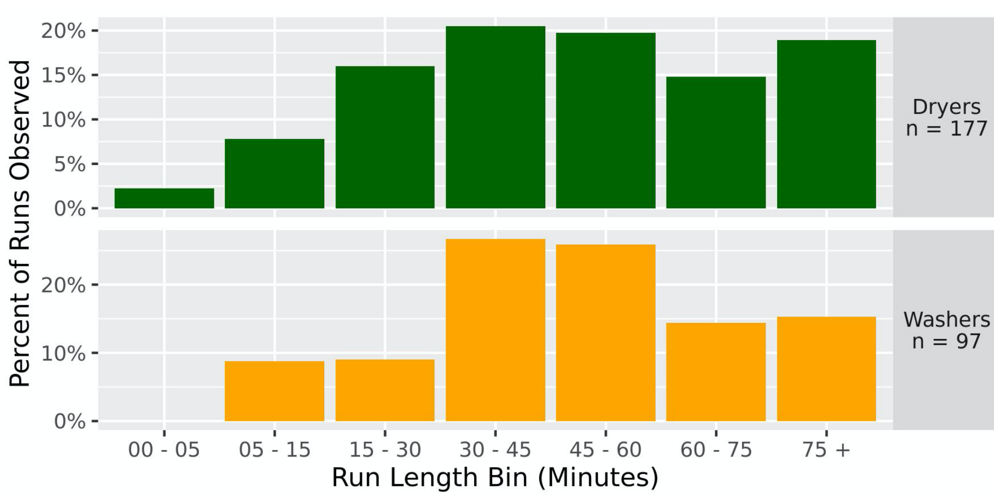

Figure 7. Distribution of run time by equipment type. *Source:* HEMS and HEUS data.

[5] This time period avoids potential impacts on laundry usage caused by the COVID-19 pandemic. If this date range were expanded, analysis could be conducted on how the pandemic affected laundry start times and run lengths.

The differences shown in Figure 7 reflect the differences in how these equipment types are used. While washers are typically started and then left until they finish their cycle, dryers are often stopped mid-load (to check or add items) or restarted shortly after completion (to finish drying or fluff items).[6]

Behavioral Results

Frequency of redrying. To better understand the frequency of redrying, we analyzed dryer run time data to identify cases where a short run (less than 15 minutes) occurred within an hour of a longer run (30 minutes or more). Given the short lengths of these runs and their proximity to a longer run, these cases were deemed to best represent redrying behavior. Among dryers that had any short runs (n = 159), approximately 10.4 percent of all runs were short runs (between 1 and 15 minutes in length). Of these, 16 percent occurred within an hour of a longer run. This suggests that in most cases, clothes are not redried/fluffed immediately after a main run.

Interestingly, the frequency of redrying seems to be independent of the frequency that short runs occur on a dryer. Table 1 summarizes how the frequency of redrying differs for dryers for which short runs were common (occurred more often that the average rate of 10.4 percent) versus dryers for which short runs were rare (occurred less often than the average of 10.4 percent). While dryers that commonly had short runs had an average of 21.3 percent of their runs be short, only 11.9 percent of these met the redrying criteria. Conversely, dryers with rare short runs had an average of only 4.7 percent of their runs be short, but 18.2 percent were re-dries. The result is that the average number of redried loads per month is similar across the two groups (6.37 and 6.07 respectively).

Table 1. Frequency of redrying by frequency of short runs

Group of dryers	Percent of all runs that were short runs	Percent of short runs that were redrying	Average number of redrying loads per month
Common short runs	21.3%	11.9%	6.37
Rare short runs	4.7%	18.2%	6.07

Laundry days. Another behavior we observed in this analysis was the tendency for people to do many loads of laundry on a single day.

Figure 8 shows how the average number of loads per day varies with the average number of days per month with at least one load. In the figure, the X axis is the average number of days per month observed to have at least one run. The Y axis represents the average number of runs for that piece of equipment on those days. Days without any runs are not included. Washers are shown in orange, while dryers are green. While the majority of laundry equipment is used less than two times per day on laundry days, the figure shows that people who use their laundry equipment more often in terms of number of days per month also tend to use their laundry equipment more often on those days. On average, observed washers were used 12.25 days per month and an average of 1.63 times per day on those days. Dryers were used an average of 13.52 days per month with an average of 1.77 times per day on those days.

[6] Again, our method does not attempt to determine whether a section of dryer usage reflects one load (redrying) or multiple loads (an entirely new load). Rather, our method aims to identify both possibilities and analyze accordingly.

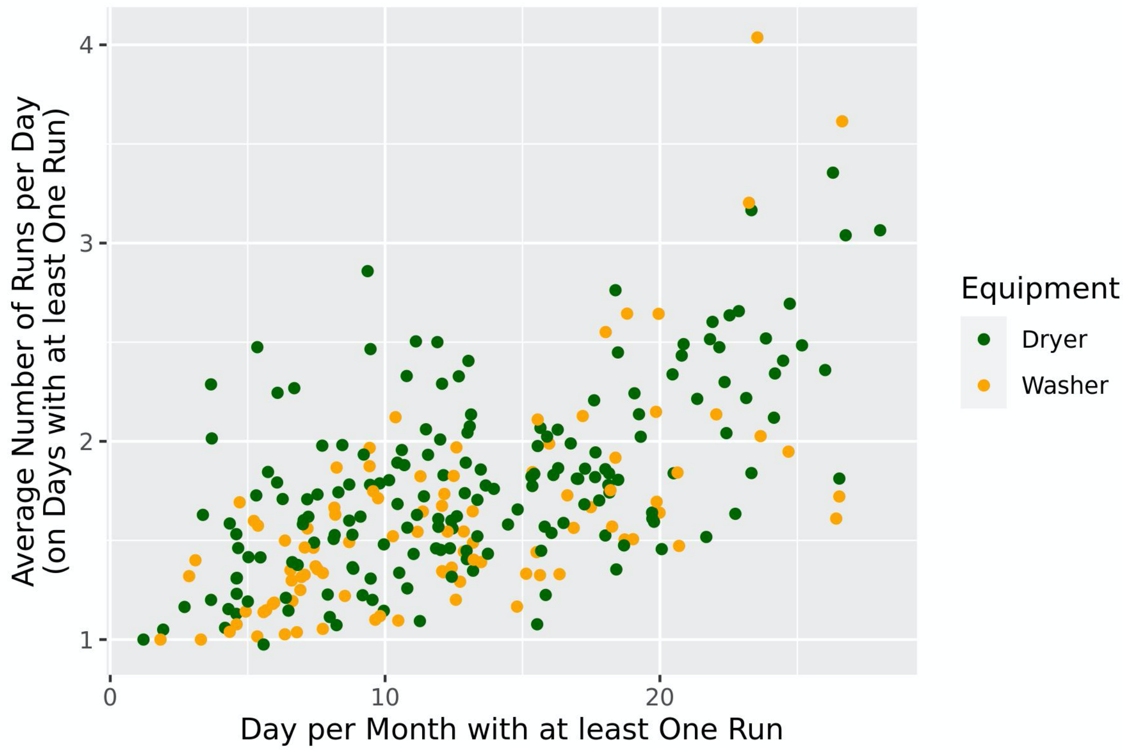

Figure 8. Daily number of runs by monthly number of runs for laundry equipment. *Source:* HEMS and HEUS data.

Table 2 summarizes these results for washers. The table splits washers into those that are used more than 15 days per month ("More frequent usage") and those that are used 15 days per month or less ("Less frequent usage"). While frequently-used washers make up only 33.0 percent of observed washers, because of their higher per-month usage and higher per-day usage, they actually account for 61.0 percent of washer runs observed in this analysis, with run lengths roughly equivalent between the two groups.

Table 2. Washer usage by frequency of use

Group of washers	Percent of all washers	Average runs per day of use	Average use per month	Average run length	Percentage of all runs
Less frequent usage	67.0%	1.41	8.66	55.22	39.0%
More frequent usage	33.0%	1.99	19.53	50.97	61.0%

Table 3 presents the same summary for dryers with the same frequency definitions. While frequently-used dryers make up only 39.0 percent of observed dryers, because of their higher per-month usage and higher per-day usage, they actually account for 63.5 percent of dryer runs observed in this analysis, with run lengths roughly equivalent between the two groups.

Table 3. Dryer usage by frequency of use

Group of dryers	Percent of all washers	Average runs per day of use	Average use per month	Average run length	Percentage of all runs
Less frequent usage	61.0%	1.64	9.07	52.69	36.5%
More frequent usage	39.0%	2.04	19.82	53.96	63.5%

The results presented here represent just a sample of the types of analysis that can be completed when this method is applied to washer and dryer monitoring data.

Conclusion

In conclusion, this paper presents a method for gaining insights into end user laundry behaviors through the analysis of short-interval energy monitoring data. This method provides useful benefits relative to self-reports because it reduces respondent fatigue, expands the study time period, and can be more accurate. This method overcomes inherent challenges in using monitoring data, such as ambiguous low-usage values, by creating a set of potential start times and run lengths for every section of usage data. This set of start times and run lengths can then be used to meet a wide range of analysis objectives.

This paper also presents example results of this method, including typical equipment run times and behavioral results including “laundry days” and redrying. Findings from this analysis include that runs between 30 and 60 minutes in length are the most common for both washers and dryers, but that dryers are more likely to have both considerably longer (75+ minutes) and considerable shorter (less than 30 minutes) loads. Our method also identified that redrying occurs at a relatively consistent rate regardless of how frequently short runs occurred. Finally, we found that people who use their laundry equipment more days per month also tend to use their laundry equipment more often on those days.

While the results presented in this paper might readily be explained by demographic or equipment characteristics (homes with many residents may use laundry equipment more frequently), the takeaway is that the method presented in this paper is capable of identifying the typical run lengths and other behavior characteristics by leveraging monitoring data. Insights from the application of this method could be used to inform appliance standard test procedures that reflect real-world usage scenarios and could also be used to inform behavior-based intervention strategies for energy efficiency programs.

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