Development of Realistic Water Draw Profiles for California Residential Water Heating Energy Estimation – Revised (March, 2019)

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Note: This paper has been revised to represent changes in the methodology since it was originally published in the Proceedings of the 15th IBPSA Conference, Building Simulation 2017. Changes are noted in the "Revisions" section near the end of the paper.

Abstract

Accurate estimation of domestic water heating energy use is critical to driving homes towards zero net energy (ZNE). Traditional approaches rely on estimating water heating energy by time of day by following an average daily profile, typically on an hourly basis. However, hot water draws tend to be short duration, high volume events that can cause water heaters to operate in recovery mode where the heaters are less efficient. New hot water event draw profiles are defined based on analysis of a large data set of measured draws from more than 700 California single-family homes. The draw data is processed to determine a set of representative days that reflect the same hourly average draws and same end-use sub-total volumes as the overall data set for six occupancy levels (1, 2, 3, 4, 5, and 6+ person homes) and three day types (weekdays, weekends, and holidays). This analysis is performed specifically for the purposes of California code compliance calculations, but the methodology may be generalized for other applications.

Objective

Most methods of defining domestic how water draw profiles rely on hourly average data (Fairey and Parker, 2004). Average daily profiles provide adequate detail for some applications with simple, high-capacity, tank water heaters where performance is relatively independent of the magnitude and duration of individual draws. However, newer water heating technologies, such as heat pump water heaters, use less efficient heat sources to recover from short duration, high volume draw events—an effect that cannot be captured by the constant, low magnitude draw represented by averaging draws throughout an entire year. This issue is illustrated in Figure 1 where the actual draws occur during 7.9% of the day and a maximum draw 10.5 times larger than the maximum of the average daily profile and only a 0.6% difference in the total daily water draw.

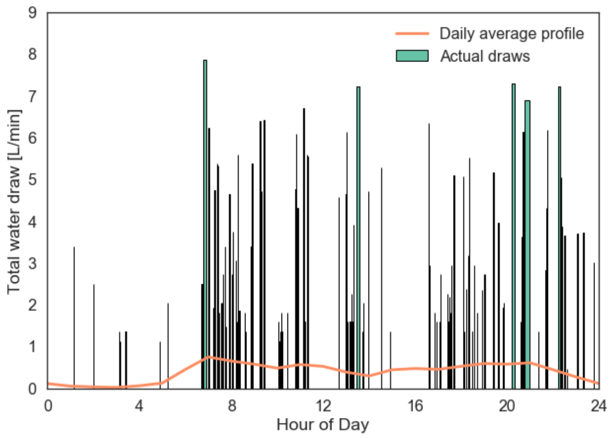

Figure 1: Example comparison between average daily profile and actual draws

Particularly of note here is the difference in the magnitude of the draws between the averaged and the real profiles. Large draws can deplete the water heater tank of hot water and have significant impacts on water heating performance, whereas the low values seen in the averaged profiles are never large enough to deplete the tank of hot water before the heater is able to recover and bring the tank back up to its setpoint. Beyond annual energy calculations, average daily profiles present a clear deficiency for calculating peak energy demand. This is particularly important to the state of California where code compliance is determined not by annual energy alone, but the time-dependent valuation (TDV) of the energy use throughout the year to reflect the actual cost of energy to the consumers, to the utility system, and to society (Horii et al., 2014).

The objective of this work is to define representative hot water event draw profiles that exercise water heating simulation models in more realistic conditions.

Current State of the Art

Recent approaches to generating realistic water draw profiles, Hendron et al. (2010) and Jordan and Vajen (2001), rely on synthesizing draw profiles from statistical data and assumptions. At a minimum, these methods require probability distributions to determine each event characteristic:

- start time-of-day (with separate distributions for week days and weekends),
- duration, and
- flow rate.

A separate set of distributions must be established for each hot water related end use (sinks, showers, baths, clothes washers, and dishwashers).
Any interactive effects, such as a difference between morning shower durations and evening durations cannot be captured. Hendron et al. (2010) attempted to capture the clustering of events related to a single activity (e.g., multiple cycles within a single clothes washer load or several sink draws while hand-washing dishes), but were unable to account for interactive clustering among different end uses.
With enough inputs, a statistical model can represent very realistic draw profiles; however, it is unlikely that all aspects of occupant behavior can be characterized adequately to ensure a realistic result. For example, neither of the current approaches prevents the frequent possibility of all end uses drawing water simultaneously.

Methodology

Rather than synthesizing draw profiles from statistical output, the approach described in this paper utilizes measured water draws directly. Aquacraft, Inc. measured water draws from a collection of 730 single family California homes characterized in the California Single-Family Water Use Efficiency Study (DeOreo et al., 2011). (This is the same data source used to develop much of the methodolgy in Hendron et al. (2010).) Meters logged mains water flow volumes every 10 seconds over a period of two weeks. Aquacraft utilized a pattern recognition algorithm to assign each draw to a specific water end use (e.g., toilet, irrigation, faucet, clothes washer, leak). Of these end uses, five are considered to be hot water related:

- showers,
- faucets,
- bathtubs,
- clothes washer, and
- dishwashers.

Draws from these end uses are used in this work to characterize the new profiles.

The occupants of many of the measured homes were surveyed to collect metadata characterizing the number of bedrooms and number of occupants. Occupancy is binned into six discrete levels for this analysis: one person through five people, and six or more people (i.e., 1, 2, 3, 4, 5, and 6+).

A representative set of daily profiles is generated for each occupancy level. Each day within the set comes directly from the Aquacraft measurements and the composite set is selected to best match the same hourly average draws and same daily end-use subtotal volumes as the overall data set. Finally the water draw events are defined in a format interpreted by the *California Simulation Engine* (CSE) for residential code compliance calculations (**?**).

The process of establishing a final set of representative draw profiles is described in 7 steps:

1. Establish the validity of measured draws from surveyed homes (investigate potential response bias).
2. Remove homes from the analysis that do not represent current design or operation (e.g., homes without dishwashers or clothes washers).
3. Normalize measured draws to represent standard distribution and fixture efficiency (any variations are modeled as simulation inputs).
4. Estimate the hot water fractions for each draw (selection of representative days is based on estimated hot water draw volumes rather than mixed draw volumes).
5. Convert discrete draw events into hourly profiles for comparison to the dataset's overall ("target") average draw profiles.
6. Search for sets of days with minimal deviation from the target average draw profiles for each combination of occupancy level and type of day (weekdays, weekends, and holidays).
7. Establish annual profiles in CSE input format–each representing the range of occupancy of levels seen in the California housing stock for a given number of bedrooms.

Survey Response Bias

There is not a 100% overlap between the homes that were measured and the homes that were surveyed in the Aquacraft study. The Table 1 shows the number of homes in each dataset. Only homes that were both measured and surveyed can be used to establish representative profiles. As any correlation of the measured event data to surveyed metadata would only include a subset of the data, we assessed the event data for potential survey response bias.

Table 1: Measured and surveyed homes in dataset

Subset	Number of Homes
All	777
Measured	730
Surveyed	509
Both	462
Only Measured	268
Only Surveyed	47

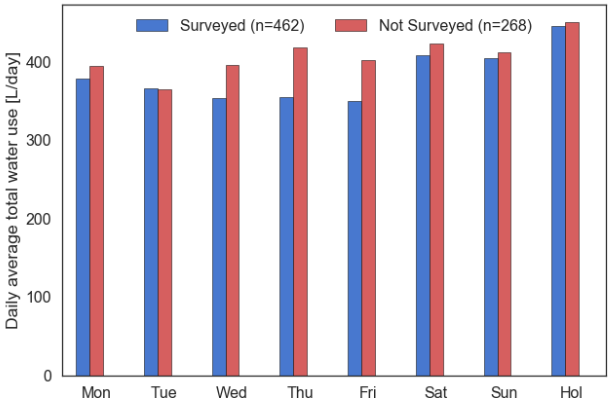

Figure 2: Average survey response bias by day

It is evident from Figure 2 that the occupants of the surveyed homes used less water on average. However, when comparing distributions of total daily water use (Figure 3), this difference is not significant enough to demonstrate that the two samples are statistically different within a 95% confidence interval.

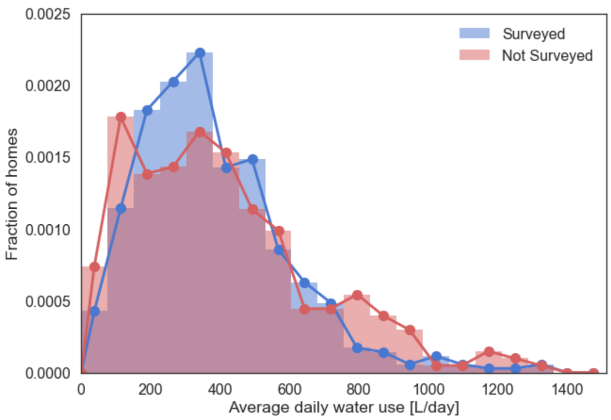

Figure 3: Comparison of daily water use

The student's t-test score is 1.49 with a p-value of 0.136. The p-value is greater than 0.05, the generally accepted cut-off below which the two sample sets would be considered to represent statistically dissimilar populations. We cannot confidently say that there is any survey response bias inherent to the data. The surveyed homes are considered to be representative of the larger population, and the data from the 462 measured and surveyed homes are utilized in this paper.

Event Sample Size

The new profiles are meant to represent water draws in newer homes. Only homes with both clothes washers and dishwashers are used to derive the target average profiles (and the respective pool of candidate days). Without this criteria, the profiles would represent unrealistic appliance draws that do not reflect the actual draws from new homes that tend to use both appliances. As a consequence, the resulting profiles are not appropriate for homes where dishes are hand-washed or clothes are laundered outside the home.

As there is no real or intended continuity between any two days in the final selected profile, some days are eliminated from the match selection process where an event spanned the midnight hour. Primarily, this criteria is enforced to prevent an incomplete set of clothes washer and dishwasher load cycles from appearing in a selected day.

The final subset of homes used in this analysis, after removing homes without clothes washers and dishwashers and homes listing zero occupants, amounted to 265 homes and a total of 3,117 possible days for the selection process. Table 2 shows the total sample size of homes and individual days used in the matching process.

Table 2: Sample Size for Matching Process

Occupancy level	Homes	Weekdays	Weekends	Holidays	Total Days
1 person	21	164	76	11	251
2 person	103	806	368	60	1234
3 person	59	467	203	26	696
4 person	48	366	169	25	560
5 person	17	126	54	9	189
6+ person	17	121	62	4	187
Total	265	2050	932	135	3117

Water Use Adjustments

The water use reported by the Aquacraft data represents mixed (hot and cold) water at each fixture. The representative draw profiles need to reflect standardized hot water draws adjusted for some of the effects that are accounted for in the analysis tool. In total, three adjustments are applied to the data:

- Fixture efficiency
- Structural Distribution Losses
- Hot Water Fractions

For each adjustment, the duration of the draws is preserved and only the volume of the draws is modified. These adjustments are described in further detail in the following sections.

Fixture Efficiency

Because fixture efficiency is a parameter input for California compliance calculations, it is important that all draws used in the representative profile reflect a standard fixture efficiency that can be scaled as appropriate for alternative fixtures.

Each end use, except bathtubs, is adjusted as follows:

- **Shower:** Any flow rates greater 7.6 L/min (2.0 gpm) are adjusted down to 7.6 L/min (2.0 gpm) (California Energy Commission, 2016a).
- **Faucet:** All faucet flow rates are reduced by 4% (California Energy Commission, 2016a).
- **Dishwasher:** All cycles within a load adjusted by the same multiplier such that the total load volume is equal to 18.9 L (5.0 gallons) (United States Department of Energy (DOE), 2012).
- **Clothes washer:** All cycles within a load adjusted by the same multiplier such that the total load volume is equal to 97.4 L (25.73 gallons) (based on data available from United States Department of Energy (DOE) (2016), California Energy Commission (2016b), and Palmgren et al. (2010)).

Structural Distribution Losses

Simulation models also account for structural distribution losses: losses related to long pipe runs that need to be cleared of un-heated water prior to receiving hot water at the fixture from the water heater. We normalize the flow durations using structural distribution loss multipliers (SDLM) to represent an idealized, "lossless" case. Structural distribution loss multipliers (SDLM) are based on the number of bedrooms in the home (Table 3) and are applied only to shower, faucet, and bathtub draws to be consistent with Ferris et al. (2015).

Table 3: Structural Distribution Loss Multipliers (SDLMs)

Number of Bedrooms	**SDLM**
0	1.076
1	1.109
2	1.171
3	1.272
4	1.341
5+	1.365

Because actual distribution losses are applied in the analysis tool, these multipliers are used to pre-adjust the draw volumes such that, when applied by the tool, the volumes are the same as those used in the original profiles:

$$V_{adj} = \frac{V}{SDLM} \tag{1}$$

The Distribution Loss Multiplier (DLM) is described in Appendix B of the 2016 Residential Alternative Compliance Manual (Ferris et al., 2015). The DLM combines two terms: the standard distribution loss multiplier (SDLM), which depends on the floor area of the dwelling unit and the distribution system multiplier (DSM) which accounts for the effects of the hot water distribution system configuration within in the dwelling unit. In the case of the Aquacraft monitored homes, lacking any information about the hot water distribution system configurations, it was assumed that they were all standard trunk and branch, so the DSM term defaults to 1.

The SDLM values are expressed as a quadratic equation in terms of conditioned floor area (CFA), where the CFA is capped at 232 m^2 (2,500 ft^2):

$$\begin{aligned} SDLM =& 1.004 + 2.17 \times 10^{-3}\mathrm{m}^{-1} \times CFA \\ & - 2.68 \times 10^{-6}\mathrm{m}^{-2} \times CFA^2 \end{aligned} \tag{2}$$

However, the calculations in Domestic Hot Water Draw Profile Selection Methodology (within Ferris et al. (2015)) are based on number of bedrooms, not conditioned floor area. The following table was used to translate number of bedrooms to equivalent CFA (Table 4). The data was derived from the 2009 Residential Appliance Saturation Study (RASS) (Palmgren et al., 2010).

Table 4: Correlation of number of bedrooms to conditioned floor area (CFA)

Bedrooms	**CFA [m^2 (ft^2)]**
0	34.6 (372)
1	51.6 (555)
2	85.7 (922)
3	152 (1,630)
4	208 (2,240)
5	263 (2,830)
6	335 (3,610)

Hot Water Fractions

Although the draw profiles developed though this work represent total (hot + cold) water draws, the representative days are selected to best match the overall hot water use in the surveyed homes. The actual fraction of hot water used in each draw depends on the inlet mains temperature and the water heater supply temperature, both of which are defined by the analysis tool. For the purposes of selecting a set of representative days, these fractions are set to constant values that closely approximate mixed water for a standard location. These fractions are listed in the table below:

Table 5: Hot Water Fractions

End Use	**Hot water fraction**
Shower	0.66
Faucet	0.50
Bathtub	0.66
Clothes washer	0.22
Dishwasher	1.00

The hot water fraction for showers and baths in the

Aquacraft data is calculated assuming a 40.6 °C (105 °F) shower temperature, a 51.7 °C (125 °F) hot water setpoint, and 18.3 ° (65 °F) mains temperature. The hot water fractions for faucet and clothes washer draws are based on the REUWS2 study (DeOreo et al., 2016) which used separate mains and water heater flow meters on a subset of homes. Dishwashers are assumed to be plumbed exclusively with hot water.

Analysis

The objective is to find a set of actual days from the event dataset that closely match both:

1. the daily average hot water draw for each end use and
2. the hourly average profile of the total hot water draw.

To begin, the draws from each home are converted from event data (start, duration, and flow rate) into hourly totals between each hour of the day (e.g., volume drawn between 6:00 and 7:00am). Draws that span multiple hours are pro-rated into each hour appropriately.

In an hourly format, the average profile for a candidate set of days can be compared directly to the "target" overall average profile of all days of the same occupancy level and day group type (i.e., weekdays, weekends, and holidays). This hourly format is the basis used for the matching process, and provides a simple means of visually comparing data (e.g., Figure 4).

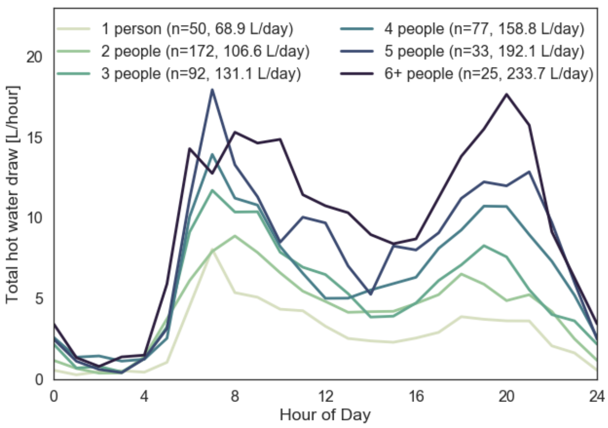

Figure 4: Average hot water profile by occupancy level across all day types

Matching Process

Where possible, 30 representative days were selected for each occupancy level (10 representative days for each day type except when there was not a large enough sample to select from for a specific combination of occupancy level and day type). The selected days may occur during any month or season of the year. We assume that water draw behavior does not vary significantly among seasons, and the more important variation among day types can be adequately captured in eight representative days.

Each day of measurements within the event dataset is characterized by occupancy level and day group (weekday, weekend, or holiday). There is relatively little difference among different types of days within a day group category (Figure 5).

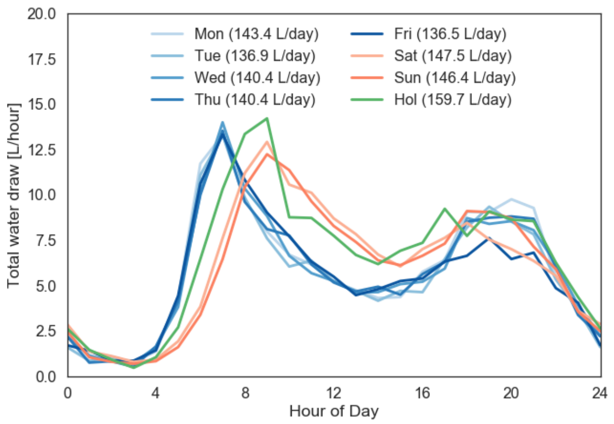

Figure 5: Averages by day type (noting similarity within day groups)

This means, for example, that the actual day selected for a Monday profile can come from a day that is actually a Thursday in the event data. This allows searching a wider range of day combinations when attempting to find the best match.

The selected weekday profiles should also represent a diverse set of days, some where the occupants use large amounts of water and some where almost no water is used. This diversity will exercise the simulation models under some of the more extreme draw patterns observed in the field. The matching process utilizes explicit criteria to avoid the situation where all days are very close to the target average for the set.

A certain level of draw diversity is ensured by selecting each day from a different bin determined by total daily hot water use. Figure 6 below shows each weekday for homes with two occupants sorted by total daily hot water use. The days are divided into 10 bins (corresponding to the number of representative weekdays). The selected days from each bin are highlighted as individual points.

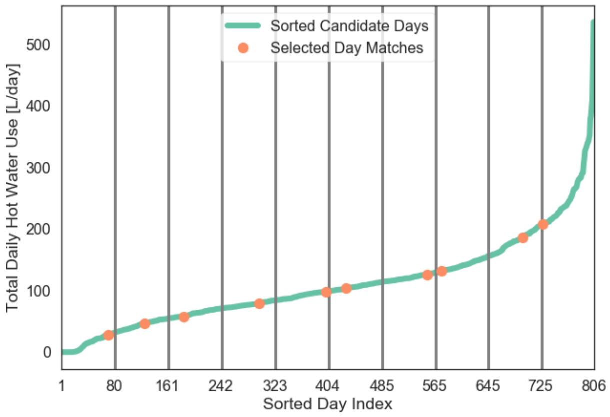

Figure 6: Weekday selections for two person homes

The matching process for weekdays, weekends, and holidays searches for the best combination of days from each of the 10 bins. The matching process searches through different combinations of days from each bin and compares them to the target average values. The "closeness" of a candidate match is determined by two metrics:

1. The root mean square deviation (RMSD) in daily end use (i.e., Shower, Faucet, Bathtub, Clothes washer, and Dishwasher [$N_{EU} = 5$]) subtotals between the candidate day set, V_{EU}, and the entire sample of days, $\bar{V}_{EU}$:

$$RMSD_{EU} = \sqrt{\frac{\sum_{EU}\left(\bar{V}_{EU} - V_{EU}\right)^2}{N_{EU}}} \qquad (3)$$

2. The RMSD in average hourly ($N_H = 24$) total hot water use between the candidate day set, $V_{H,smooth}$, and the entire sample of days, $\bar{V}_H$.

$$RMSD_H = \sqrt{\frac{\sum_{h=1}^{24}\left(\bar{V}_H - V_{H,smooth}\right)^2}{N_H}} \qquad (4)$$

For the candidate day sets, the average hourly total hot water use is calculated over the 10 combined representative days. Because 10 days doesn't ensure a smooth average the matching process artificially eliminates some of the larger, though still realistic peaks throughout the day (e.g., multiple showers within a given hour). A smoothing technique is used to ensure these events are still possible in the selected profiles. Instead of comparing the candidate average hourly profile of the day set, V_H, directly to that of the entire sample of days, a centered moving average is applied to the candidate day set average first, where the resulting hourly values, $V_{H,smooth}$, are the average of each hour including the two hours on either side:

$$V_{H,smooth[i]} = \frac{\sum_{j=-2}^{2} V_{H[i+j]}}{5} \qquad (5)$$

The two RMSD values are added in quadrature to arrive at a final deviation metric, D, used to determine the best candidate day set:

$$D = \sqrt{RMSD_{EU}^2 + RMSD_H^2} \qquad (6)$$

Minimizing this deviation results in a better balance between both RMSD values than adding them in whole (e.g., $D = RMSD_{EU} + RMSD_H$).

Search Process

For some combinations of occupancy level and day type the sample size is too large for an exhaustive search of all possible combinations of days. The resulting computation time would be prohibitive. To reduce the scope of the search, a scheme is developed to progressively eliminate less promising candidates. The search begins by evaluating all combinations from only the first and last bins (1 and 10). This is then repeated for bins 2 and 9. The top N (= number of days in each bin) combinations from each of these sets is preserved while the others are discarded. All of the combinations from the resulting two sets are then evaluated to arrive at a set of N 4-day combinations. The set of 4-day combinations is then combined with the resulting set from evaluating combinations from bins 3 and 8. This continues–progressively adding results from bins 4 and 7, and finally 5 and 6–until there is a single set of 10-day combinations (one from each bin). The 10-day combination with the lowest devation, D, is selected to represent the specific combination of occupancy level and day type.

The symmetric nature of this search is designed to balance the progressive averages of the candidate day sets and avoid skewing the days toward the extremes within a given bin.

While this search process does not ensure the selected match is the global optimum, it is much more computationally efficient than an exhaustive search of all possible combinations.

Day Selection Results

Where possible, 30 representative days were used for each occupancy level (10 weekdays, 10 weekends, and 10 holidays). This was possible for all combinations except holidays for 5 person homes (only 9 holidays), and 6+ person homes (only 4 holidays). In total, there are now 173 representative days that comprise the annual hot water draw profiles.

10 weekdays, 10 weekends, and 10 holidays for each of the six occupancy levels except 5 person houses (only 9 holidays), and 6+ person houses (only 4 holidays). The result of the selection process produces 173 representative days: 10 weekdays, 10 weekends, and 10 holidays for each of the six occupancy levels except 5 person houses (only 9 holidays), and 6+ person houses (only 4 holidays). Weekday results for two person homes are illustrated in Figures 7 and 8. Figure 7 shows a comparison between the target ($\bar{V}_{EU}$) and

matched (V_{EU}) daily end use subtotal draws. Figure 8 illustrates hourly profiles for the five representative weekdays along with comparisons of the target average profile, $\bar{V}_H$, the match average profile, V_H, and the smoothed match profile, $V_{H,smooth}$.

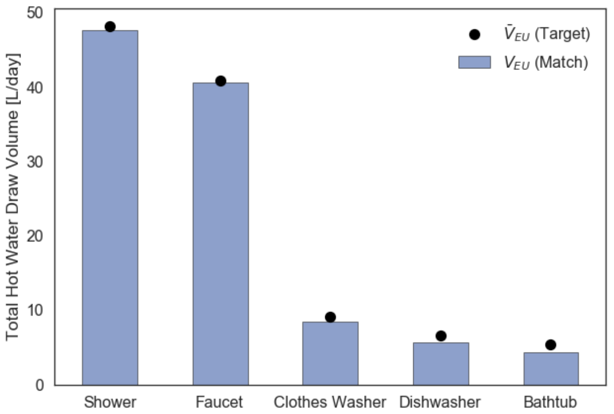

Figure 7: Daily end use subtotal draws for two person home weekday selections

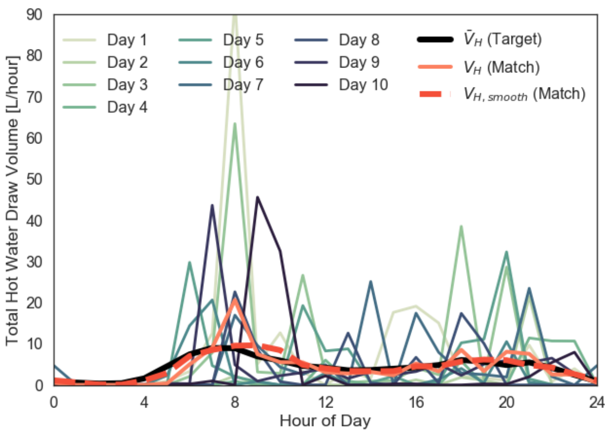

Figure 8: Hourly total draws for two person home weekday selections

The overall deviation for each set of selected day set matches is shown in Table 6. It is evident that the "closeness" of each selected day set to their respective targets is influenced strongly by the overall sample size of days to select from for each occupancy level. The worst matches are found for holidays where there is a smaller sample size to select from, and for higher occupancy levels where fewer homes were originally monitored.

Occupancy Diversity

The California code compliance rules are based on the number of bedrooms in a housing unit and not the number of occupants. From RASS data (Palmgren et al., 2010), the number of occupants in a housing unit varies widely with the number of bedrooms. Rather than assigning a single occupancy level to each number of bedrooms, the days used in an annual simulation are selected at random such that the total number of days from each occupancy level corresponds to the distribution of occupants in the RASS data (Tables 7 and 8). For example, in a three bedroom unit in a multifamily building 9.7% of all weekdays, weekend days, and holidays will correspond to the selected profiles for one person homes; 27.3% will correspond to two person homes; 28.5% will correspond to three person homes; and so on.

Table 6: Overall deviation, D, for each set of selected day matches (in L)

Occupants	Weekdays	Weekends	Holidays
1	1.91	1.56	2.14
2	1.04	2.48	3.38
3	1.52	1.49	4.06
4	2.28	1.94	5.55
5	3.65	4.31	5.42
6+	5.73	2.44	8.76

Table 7: RASS occupancy data for single family homes

	1 Bedroom	2 Bedrooms	3 Bedrooms	4 Bedrooms	5+ Bedrooms
1 Person	42.3%	26.4%	14.0%	7.4%	6.0%
2 People	32.7%	39.3%	37.4%	27.5%	16.9%
3 People	9.5%	14.3%	18.3%	17.3%	14.4%
4 People	12.3%	8.5%	16.1%	26.6%	23.4%
5 People	2.0%	6.6%	8.1%	13.0%	17.2%
6+ People	1.1%	5.0%	6.2%	8.3%	22.2%

Table 8: RASS occupancy data for multifamily homes

	Studio	1 Bedroom	2 Bedrooms	3 Bedrooms	4 Bedrooms	5+ Bedrooms
1 Person	73.5%	56.4%	25.3%	9.7%	2.0%	0.2%
2 People	19.4%	27.8%	31.6%	27.3%	16.8%	35.1%
3 People	4.1%	7.8%	18.7%	28.5%	6.0%	1.6%
4 People	2.5%	4.0%	14.7%	15.8%	35.3%	35.9%
5 People	0.2%	1.4%	4.9%	13.7%	11.1%	5.7%
6+ People	0.3%	2.6%	4.8%	4.9%	28.7%	21.6%

The profiles used for California compliance calculations must reflect this diversity in occupants in order to represent a standard baseline and proposed design regardless of the number of people occupying the home during its operation. For this reason, the annual schedules derived in this work may have limited application for the simulation of actual building operation.

For single family homes, the daily water draw profiles for each day of the year corresponds to a matched day for a certain occupancy level. The occupancy level for each day is determined randomly from the distributions described in the previous section. The specific match day selected depends on the type of day. For example, the weekday matches are each randomly assigned to the first 10 weekdays in the calendar. The next 10 weekdays are also randomly assigned, and so forth until the end of the year. The same approach is applied to weekend and holiday matches.

As an example, the final schedule for a three bedroom single family home is illustrated in Table 9 for the month of January.

Table 9: Single family, three bedroom draw profile schedule for January

Day	Day of Week	Occupancy Level	Day Type & Match Number
Jan. 1	Thu	1	Holiday 7
Jan. 2	Fri	2	Weekday 7
Jan. 3	Sat	5	Weekend 4
Jan. 4	Sun	1	Weekend 2
Jan. 5	Mon	6+	Weekday 9
Jan. 6	Tue	4	Weekday 2
Jan. 7	Wed	2	Weekday 4
Jan. 8	Thu	4	Weekday 7
Jan. 9	Fri	2	Weekday 0
Jan. 10	Sat	4	Weekend 6
Jan. 11	Sun	4	Weekend 2
Jan. 12	Mon	2	Weekday 3
Jan. 13	Tue	3	Weekday 1
Jan. 14	Wed	5	Weekday 4
Jan. 15	Thu	2	Weekday 2
Jan. 16	Fri	2	Weekday 6
Jan. 17	Sat	1	Weekend 4
Jan. 18	Sun	3	Weekend 0
Jan. 19	Mon	3	Holiday 1
Jan. 20	Tue	2	Weekday 5
Jan. 21	Wed	2	Weekday 8
Jan. 22	Thu	2	Weekday 9
Jan. 23	Fri	2	Weekday 1
Jan. 24	Sat	4	Weekend 5
Jan. 25	Sun	3	Weekend 9
Jan. 26	Mon	5	Weekday 5
Jan. 27	Tue	2	Weekday 5
Jan. 28	Wed	3	Weekday 2
Jan. 29	Thu	3	Weekday 8
Jan. 30	Fri	4	Weekday 9
Jan. 31	Sat	2	Weekend 7

For multifamily buildings with central water heating, if the same diverse draw profiles were used for all the dwelling units with the same number of bedrooms this would result in unrealistic coincident draws throughout the building. To avoid this problem, the schedule is generated 10 different times, each with different random ordering of the matches. The compliance software rulesets rotate through each of the 10 variants when assigning multiple units with the same number of bedrooms. The result is a more diverse set of draws, representative of multiple units.

Simulation Software Implementation

The days are selected based on estimated hot water (after they are adjusted for fixture efficiency and structural distribution losses). However the final profiles that are created represent the total (hot and cold) water flow at the fixture. The actual fraction of hot water is calculated by CSE and depends on the inlet mains water temperature for the building site.

The water draw events that begin within the selected days are then exported into a format readable by CSE. The flow rates are adjusted only for fixture efficiency and structural distribution losses.

Many simulation software tools do not allow for input of profile data in the form of discrete events (i.e., as a start time, duration, and magnitude), and rather tend to require input as an integrated timestep schedule. The traditional timestep schedules are unnecessarily verbose for the representation of discrete events as they often require minute-level or shorter timesteps to adequately capture event variations. Such input files are often several orders of magnitude larger than the equivalent profiles described as discrete events. CSE has been adapted to read discrete event data for hot water draws.

Conclusions

This paper presents a method of deriving realistic water draw profiles using data of actual water draw events from monitored California homes. This is the first method of generating realistic water draw profiles for simulation that does not rely on synthesizing events from a statistical model. Overall, 65 different annual draw profile variants have been established representing 1-5 bedroom single family homes and studio-5 bedroom multifamily units. These profiles are comprised of a total of 173 representative days, each based on actual measured water draws.

Revisions

In addition to other miscellaneous typos and grammar fixes, the following elements of the paper have been revised since its original publication in 2017.

Additional Representative Days

The original methodology used eight representative days for each occupancy level (5 weekdays, 2 weekends, and a holiday). While this represented the proportions of each day type there is no real reason to restrict the number of representative days. The only real limit is the number of samples available for each combination of day type and occupancy level. Increasing the number of representative days improves the diversity of loads and reduce the deviation from the target averages.

Where possible, 30 representative days were used for each occupancy level (10 weekdays, 10 weekends, and 10 holidays). This was possible for all combinations except holidays for 5 person homes (only 9 holidays), and 6+ person homes (only 4 holidays). In total, there are now 173 representative days that comprise the annual hot water draw profiles.

Number of Multifamily Profiles

There are now 10 distinct annual profiles for multifamily applications (instead of five). This ensures a greater level of diversity within a single building and reduces the probability of unrealistic, coincident large draws.

Structural Distribution Loss Adjustments

The adjustments made to the measured data related to structural distribution losses are applied to the flow duration rather than the flow rates. This change reflects that the primary effect of structural distribution losses is longer draws (waiting for hot water to reach the fixture from the water heater). This change does not impact the overall volume of heated water, but is important for calculations that rely on flow rate rather than flow volume (e.g., drain water heat recovery effectiveness).

Modeled Predicted Hot Water Use

The analysis demonstrating the application of these draw profiles was not updated following the revisions. The section has been removed from this version of the paper.

Figures

The following figures have been changed to represent the revised methodology. The original figures are shown below:

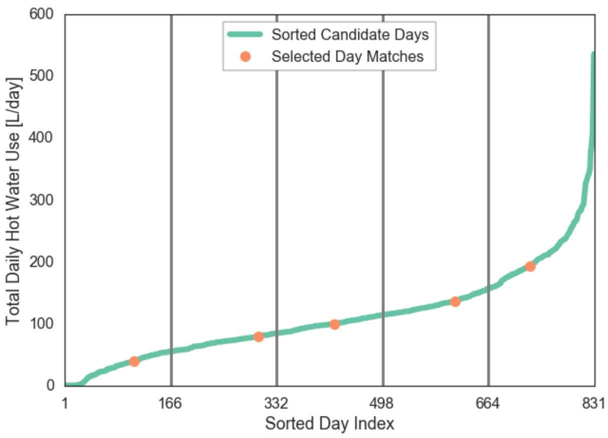

Figure 9: (Previous version of Figure 6) Weekday selections for two person homes

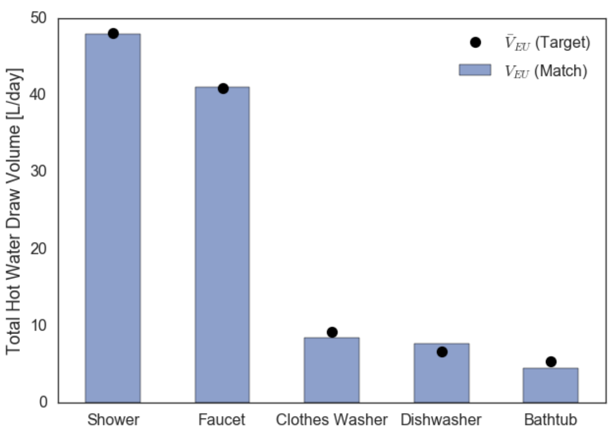

Figure 10: (Previous version of Figure 7) Daily end use subtotal draws for two person home weekday selections

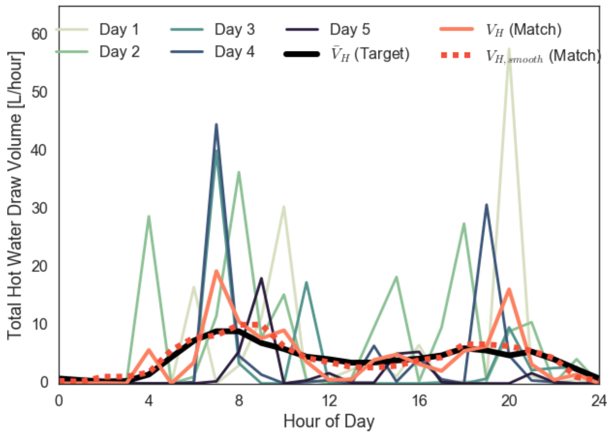

Figure 11: (Previous version of Figure 8) Hourly total draws for two person home weekday selections

Tables

The following tables have been changed to represent the revised methodology. The original tables are shown below:

Table 10: (Previous version of Table 2) Sample Size for Matching Process

Occupancy level	Homes	Weekdays	Weekends	Holidays	Total Days
1 person	21	167	79	11	257
2 person	103	831	392	63	1286
3 person	59	489	218	30	737
4 person	48	394	182	28	604
5 person	17	139	63	9	211
6+ person	17	133	65	5	203
All (1+ person)	265	2153	999	146	3298

Table 11: (Previous version of Table 6) Overall deviation, D, for each set of selected day matches (in L)

Occupants	Weekdays	Weekends	Holidays
1	1.74	3.26	8.04
2	1.12	3.42	7.00
3	1.89	3.78	9.54
4	2.38	4.65	11.41
5	3.59	7.77	15.26
6+	3.10	5.95	64.15

References

California Energy Commission (2016a). Appliance Efficiency Regulations. Technical report.

California Energy Commission (2016b). California Appliance Efficiency Database.

DeOreo, W., P. Mayer, B. Dziegielewski, and J. Kiefer (2016). Residential End Uses of Water, Version 2. Technical report, Water Research Foundation.

DeOreo, W., P. Mayer, L. Martien, M. Hayden, A. Funk, M. Kramer-Duffield, R. Davis, J. Henderson, B. Raucher, P. Gleick, and M. Heberger

Table 12: (Previous version of Table 9) Single family, three bedroom draw profile schedule for January

Day	Day of Week	Occupancy Level	Day Type & Match Number
Jan. 1	Thu	3	Holiday 1
Jan. 2	Fri	1	Weekday 3
Jan. 3	Sat	2	Weekend 2
Jan. 4	Sun	4	Weekend 1
Jan. 5	Mon	2	Weekday 5
Jan. 6	Tue	5	Weekday 2
Jan. 7	Wed	2	Weekday 4
Jan. 8	Thu	2	Weekday 1
Jan. 9	Fri	2	Weekday 5
Jan. 10	Sat	1	Weekend 2
Jan. 11	Sun	2	Weekend 1
Jan. 12	Mon	2	Weekday 2
Jan. 13	Tue	2	Weekday 1
Jan. 14	Wed	1	Weekday 3
Jan. 15	Thu	4	Weekday 4
Jan. 16	Fri	4	Weekday 1
Jan. 17	Sat	2	Weekend 1
Jan. 18	Sun	2	Weekend 2
Jan. 19	Mon	4	Holiday 1
Jan. 20	Tue	2	Weekday 3
Jan. 21	Wed	1	Weekday 5
Jan. 22	Thu	2	Weekday 4
Jan. 23	Fri	4	Weekday 2
Jan. 24	Sat	1	Weekend 1
Jan. 25	Sun	3	Weekend 2
Jan. 26	Mon	1	Weekday 2
Jan. 27	Tue	5	Weekday 5
Jan. 28	Wed	5	Weekday 4
Jan. 29	Thu	3	Weekday 1
Jan. 30	Fri	4	Weekday 3
Jan. 31	Sat	5	Weekend 1

(2011). California Single-Family Water Use Efficiency Study. Technical report, Aquacraft, Inc., Boulder, Colorado.

Fairey, P. and D. Parker (2004). A Review of Hot Water Draw Profiles Used in Performance Analysis of Residential Domestic Hot Water Systems. Technical report, Florida Solar Energy Center, Cocoa, Florida.

Ferris, T., L. Froess, and D. Ross (2015). Residential Alternative Calculation Method Reference Manual for the 2016 Building Energy Efficiency Standards. Technical report, California Energy Commision.

Hendron, B., J. Burch, and G. Barker (2010). Tool for Generating Realistic Residential Hot Water Event Schedules. In *Proceedings of IBPSA-USA SimBuild 2010*, Number August, New York, New York. IBPSA-USA.

Horii, B., E. Cutter, N. Kapur, J. Arent, and D. Contoyannis (2014). Time Dependent Valuation of Energy for Developing Building Efficiency Standards: 2016 Time Dependent Valuation (TDV) Data Sources and Inputs. Technical report, Energy and Environmental Economics, Inc., San Francisco, California.

Jordan, U. and K. Vajen (2001). Realistic Domestic Hot-Water Profiles in Different Time Scales. Technical report, Universität Marburg, Marburg, Germany.

Palmgren, C., N. Stevens, M. Goldberg, R. Bames, and K. Rothkin (2010). 2009 California Residential Appliance Saturation Survey. Technical report, KEEMA, Inc., Oakland, California.

United States Department of Energy (DOE) (2012). Federal Register: Energy Conservation Program: Energy Conservation Standards for Residential Dishwashers; Final Rule and Proposed Rule. *77*(104).

United States Department of Energy (DOE) (2016). Appliance & Equipment Standards Program Compliance Certification Database.