TOOL FOR GENERATING REALISTIC RESIDENTIAL HOT WATER EVENT SCHEDULES

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ABSTRACT

The installed energy savings for advanced residential hot water systems can depend greatly on detailed occupant use patterns. Quantifying these patterns is essential for analyzing measures such as tankless water heaters, solar hot water systems with demand-side heat exchangers, distribution system improvements, and recirculation loops. This paper describes the development of an advanced spreadsheet tool that can generate a series of year-long hot water event schedules consistent with realistic probability distributions of start time, duration and flow rate variability, clustering, fixture assignment, vacation periods, and seasonality. This paper also presents the application of the hot water event schedules in the context of an integral-collector-storage solar water heating system in a moderate climate.

INTRODUCTION

Energy savings for certain residential building technologies depends greatly on occupant behavior. Simulating realistic occupant behavior is a major challenge, because of wide variations in how households use hot water, lighting, appliances, and miscellaneous electric loads. Even an individual household has highly variable behavior from day to day, introducing a random component to the problem. Domestic hot water (DHW) use is a particularly important issue, because occupant use patterns can significantly affect the energy savings achieved by advanced hot water systems that are common in high-performance homes.

For example, gas tankless water heaters do not fire at low flow rates (usually less than 0.5 gpm), and when used with solar preheat, may not fire even at higher flow rates when the entering water is above 80°–90°F (Hendron et al. 2009). Tankless water heater efficiency is also influenced by thermal mass effects in the burner, which in turn are strongly affected by the time between hot water events.

Hot water distribution system measures such as pipe insulation, home run plumbing, and demand-controlled recirculation loops are affected by the time between draws and which fixtures produce the draw for each event (Klein 2004). High- and low-use households can have very different energy savings potentials. These effects were quantified in a study by the National Renewable Energy Laboratory (NREL) and Davis Energy Group (Hendron et al. 2009).

Other more advanced systems are also heavily influenced by hot water use patterns. The energy saved by a solar hot water system with a demand-side heat exchanger is affected by the flow rate in the heat exchanger and the overall volume of hot water use (Davidson et al. 2002). Wastewater heat recovery depends on the flow rate and duration of each event. Hot water tank and solar integrated collector storage (ICS) sizing considerations may include an analysis of the realistic peak hourly demand for hot water that randomly occurs over a year because of event clustering. The cost effectiveness of an ICS system is also strongly affected if a household uses a high or low volume of hot water each day.

Several hot water studies have developed hot water event schedules for use in energy simulations or hot water system testing, including average hourly use profiles, typical flow rates and durations, and day-to-day variability (DOE 1998, Burch et al. 1993, Christensen et al. 2000). However, many of these studies neglect realistic event clustering, seasonality, fixture use, and variable flow rates, all of which can signficantly affect the annual energy savings for advanced hot water systems. Even when those details were included, they were often addressed in a fairly simplistic manner. One recent approach used the German tool DHWCalc (Jordan and Vajen 2001) to generate annual hot water event schedules, but event durations were fixed and event clustering could only be approximated (Hendron and Burch 2007).

This paper describes the development of a spreadsheet tool that generates random event profiles based on realistic probability distributions for hot water event duration, flow rate, clustering, individual fixture use, and time between events. It also includes realistic simulation of vacation periods, weekend/weekday effects, geographic location, and seasonality. The assumptions about the profiles were derived from a variety of sources, primarily two residential water use studies conducted by Aquacraft (Aquacraft 2008, Mayer and DeOreo 1999). One of these studies included 1200 houses, but measured total water use only. The other study was a smaller 20-house study that disaggregated hot and cold water events.

TECHNICAL APPROACH

Cluster Start Times

The start time for each cluster of events in each of the five major end-use categories (sink, shower, bath, clothes washer, dishwasher) is determined by using a "dartboard" approach, where the number of darts represents a predetermined set of clusters (which will be explained in the Event Clustering section of this paper). The dartboard has 8,760 sections representing the hours of the year. Sections of the dartboard may be larger or smaller, depending on the probability that a cluster of events will begin during that hour. Each hour is assigned a probability based on the average hourly profiles defined in the Building America (BA) Research Benchmark (Hendron and Engebrecht 2010), resulting in a cumulative probability of 1.0 over the course of a year. An example probability distribution for shower use on a typical day is shown in Figure 1.

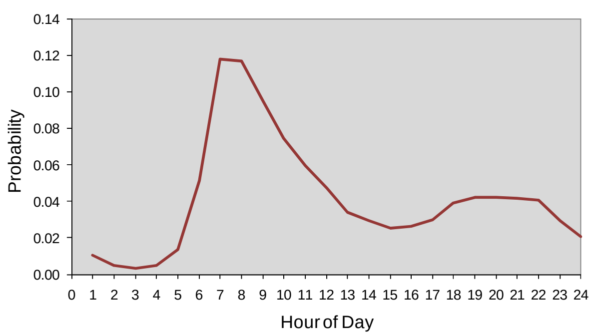

Figure 1 Probability distribution for shower use

Adjustments to the probabilities are made to reflect differences between weekdays and weekends, and seasonal differences for each month. These adjustments were derived from the 1200-house Aquacraft study (Mayer and DeOreo 1999). Three vacation periods (totaling 14 days) with no hot water use were also added, and the probabilities for the remaining days were increased accordingly. Typical vacation periods were estimated based on a published travel study (TIA 2008) combined with engineering judgment. These probability adjustments are summarized in Table 1. The monthly adjustments were eventually abandoned because the data indicated that the differences were much smaller than the statistical errors for all five end uses (see Figure 2 for an example).

Table 1 Adjustments to hourly probability distribution

Probability Multipliers:	Sink	Shwr	Bath	CW	DW
Weekend	1.15	1.05	1.05	1.26	1.04
Weekday	0.94	0.98	0.98	0.90	0.98
Vacation (May 26-28, Aug 12-18, Dec 22-25)	0	0	0	0	0
Not Vacation	1.04	1.04	1.04	1.04	1.04
January	0.97	0.99	0.75	1.01	1.05
February	0.95	1.03	1.15	0.94	0.97
March	1.03	1.02	1.27	1.01	1.03
April	1.00	1.00	1.33	0.98	1.00
May	0.98	1.01	0.95	0.94	0.95
June	1.06	1.02	1.12	1.05	0.96
July	1.03	1.00	1.12	0.94	0.97
August	1.04	0.96	1.04	1.03	0.99
September	1.03	1.02	1.02	0.99	0.90
October	0.94	0.99	0.66	1.01	1.10
November	0.99	0.98	1.02	1.03	1.09
December	0.98	0.99	0.92	1.03	1.07

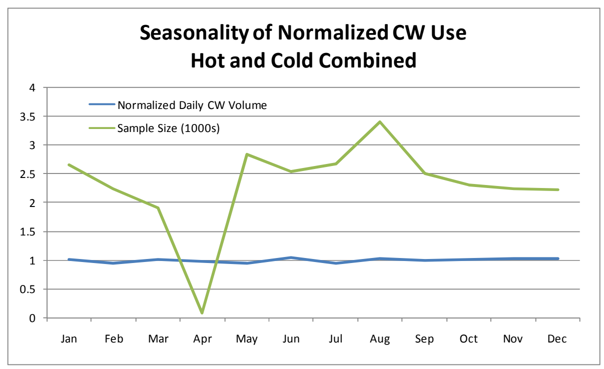

Figure 2 Seasonality of clothes washer use

The uniform random number generator in Microsoft Excel is used to assign the specific hour during which each cluster begins. Another random number is used to assign the minute and second for the start time, using a simple uniform probability distribution.

Event Clustering

Hot water events in actual households tend to occur in clusters for four end-use categories: sinks, showers, dishwashers, and clothes washers. Bath events tend to be isolated. Clothes washers have two levels of clustering. A load usually has several hot water draws associated with the various cycles (primarily wash and rinse), depending on occupant choices. In addition, several loads often occur over the course of a few hours. Dishwashers are similar in terms of multiple hot water draws per cycle, but loads are rarely clustered.

Clustering across end uses was not factored into the approach described in this study.

A simple hierarchical clustering analysis (Norusis 2006) was performed on the data from the 20-house Aquacraft study to quantify the following characteristics for each end-use category:

- Likelihood of a specific number of events in each cluster (between 1 and 10)
- Average time between events within a cluster (two levels for clothes washers)
- Upper limit for time between consecutive events classified within the same cluster

The results of the cluster analysis of hot water events are shown in Table 2.

Table 2 Results of hierarchical cluster analysis

Characteristics	Sink	Shwr	Bath	CW	DW
Average Daily Volume (gal/day, hot and cold)	25	28	7	15	5
Average Daily Events (events/day)	32.9	1.7	0.3	2.2	2.4
Annual Events (events/year)	12007	611	109	788	858
Maximum Time Between Events in Cluster (min)	15	60	60		60
Average Time Between Events in Cluster (min)	1.93	30.5			9.78
Average Events per Cluster	1.90	1.24	1.00	1.96	4.89
Number of Clusters per Year	6319	493	109	402	176
Maximum Time Between Events in Load (min)				30	
Maximum Time Between Loads in Cluster (min)				240	
Number of Loads per Cluster				1.40	
Average Number of Events per Load				1.40	
Average Time Between Events in Load (min)				4.97	
Average Time Between Loads in Cluster (min)				74.27	

Derived from AWWA 1200 house total water study
Derived from AWWA 20 house hot water study
Derived from Benchmark
Engineering Judgment

The average number of events per year for each end-use category is determined by dividing the annual hot water volume from the BA Research Benchmark (about 60 gallons/day, depending on geographic location and number of occupants) by the average event volume from the Aquacraft studies (see section on Event Characteristics). The number of clusters per year is calculated by dividing the number of events per year by the average number of events per cluster. As clusters are assigned start times, a random number is used to determine the number of events associated with that cluster. As a result, the annual number of clusters is locked in, while the annual number of events can vary slightly depending on random effects. Time between events within a cluster is held constant.

Event Characteristics

Once the hot water events are assigned a start time, the specific flow rate and duration are calculated. Again, the Aquacraft data were used to characterize the range of flow rates and durations that occur in typical houses. Flow rate and duration are treated as independent variables, because the Aquacraft data suggested a very weak negative correlation between them. For sinks and clothes washers, the smaller 20-house Aquacraft study of hot water events was used to remove the effect of cold water sink draws and cold rinse cycles. Variability was calculated as a percentage of the average duration or flow rate in each household, resulting in normalized values for standard deviation. As a result, the variability within households, rather than variability across households, determined the probability distributions used in our approach. The resulting event characteristics are summarized in Table 3.

The probability distributions for flow rate were approximately normal for all end uses, but were more diverse for duration. Sink duration was approximated by an exponential decay. Probability distributions for shower and dishwasher event duration were approximately log-normal; the draw duration for bath events was normal. Because clothes washer event durations were erratic, a discrete probability distribution was used. The probability distribution selected for showers is compared to the actual distribution from the Aquacraft study in Figure 3.

Table 3 Flow rate and duration characteristics

Characteristics	Sink	Shwr	Bath	CW	DW
Average Duration (min)	0.62	7.81	5.65	3.05	1.53
Standard Deviation for Duration (min)	0.67	3.52	2.09	1.62	0.41
Probability Distribution for Duration	Expo-nential	Log-Normal	Normal	Discrete	Log-Normal
Average Flow Rate (gpm)*	1.14	2.25	4.40	2.20	1.39
Standard Deviation for Flow Rate (gpm)*	0.61	0.68	1.17	0.62	0.20
Probability Distribution for Flow Rate	Normal	Normal	Normal	Normal	Normal
Average Event Volume (gal)*	0.76	16.73	23.45	6.95	2.13

* Hot and cold water combined for sinks, showers, baths
Derived from AWWA 1200-house total water study
Derived from AWWA 20-house hot water study

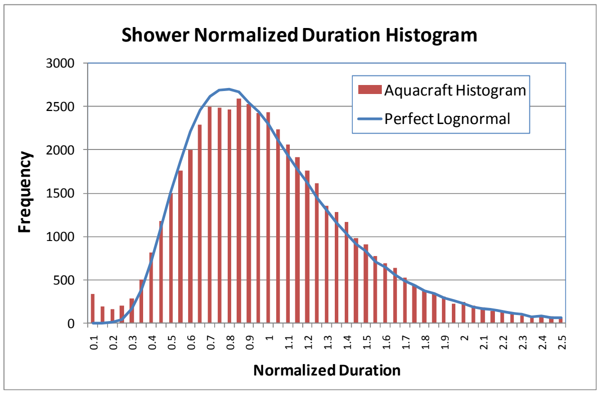

Figure 3 Curve fit of a perfect lognormal distribution to measured data for shower duration

The Excel random number generator is used to determine the specific flow rate and duration of each event. Equations 1-3 describe the calculation of event characteristics for normal, log-normal, and exponential probability distributions, based on a random number uniformly distributed between 0 and 1. The calculation for the discrete probability distribution used for clothes washer is not representable in equation form, but is straightforward to apply. For normal distributions, negative flow rates are possible, in which case the flow rate is changed to an inconsequential 0.05 gpm.

$$Y_{lognorm} = e^{\ln\left(\frac{\mu^2}{\sqrt{\sigma^2+\mu^2}}\right)+\sqrt{\ln\left[\left(\frac{\sigma}{\mu}\right)^2+1\right]}\times\sqrt{-2\ln X_1}\, x \sin(2\pi X_2)} \quad (1)$$

Where: Y = random variable with a log-normal distribution
X_1 and X_2 are two uniform random numbers between 0 and 1
μ = mean of lognormal distribution
σ = standard deviation of lognormal distribution

$$Y_{norm} = \mu + \sigma \sin(2\pi X_1)\sqrt{-2\ln(X_2)} \quad (2)$$

Where: Y = random variable with a normal distribution
μ = mean of normal distribution
σ = standard deviation of normal distribution

$$Y_{exp} = \mu \ln(X) \quad (3)$$

Where: Y = random variable with an exponential distribution
X = a uniform random number between 0 and 1
μ = mean of exponential distribution

Fixture Assignment

We assumed that a typical house has four sinks, two showers, two bathtubs, a single dishwasher, and a single clothes washer. The user of the tool can easily modify these assumptions through postprocessing. A simple probability was assigned to the fixtures in each end-use category, as shown in Table 4. Because the authors could not identify reliable references for these probabilities, we used the results from a study of seven houses by Kempton (1986), four houses monitored by NREL, and engineering judgment. Each event is randomly assigned to a specific fixture based on these probabilities. As a result, event clusters often cut across multiple fixtures.

Table 4 Probabilities that an event occurs at a specific fixture

Probability Distributions:	Sink	Shwr	Bath	CW	DW
Kitchen Sink, Master Bath Shower/Tub, Primary DW or CW	0.70	0.75	0.75	1.00	1.00
Master Bath Sink, 2nd Bathroom Shower/Tub	0.10	0.25	0.25		
3rd Bathroom Sink	0.10				
4th Bathroom Sink	0.10				

Statistical Checks

The use of random numbers in our methodology creates the potential for results that significantly deviate from expected values. To ensure the final event schedules are reasonably consistent with the probability distributions that were used to generate them, we added a series of statistical checks. The most important checks are summarized in Table 5. If any of the statistical metrics fall outside the specified limits, the event schedules are regenerated using a new set of random numbers. This process is repeated until all statistical criteria are met.

Table 5 Key statistical checks to ensure consistency between output and input parameters

Statistical Metric	Criterion*
Average Flow Rate and Duration (sinks)	<3%
Average Flow Rate and Duration (showers, DW, CW)	<5%
Average Flow Rate and Duration (baths)	<10%
Standard Deviation of Flow Rate and Duration (sinks)	<10%
Standard Deviation of Flow Rate and Duration (showers, DW, CW)	<15%
Standard Deviation of Flow Rate and Duration (baths)	<25%
Weekend/Weekday Ratio of Daily Volume (sinks, showers, DW, CW)	<30%
Weekend/Weekday Ratio of Daily Volume (baths)	<50%
Average Daily Volume (individual end uses)	<5%
Average Daily Volume (total)	<3%
Hourly Profile (4-hour increments)	<10%

* Difference between output value and input value

Postprocessing

Once the event schedules for each end use comply with the statistical checks, the five separate schedules are combined into a single annual hot water schedule with four values: start time, duration, flow rate, and fixture. Adjustments are made to the start time and duration of each event based on the desired time step. Flow rate is also adjusted to keep the event volume fixed. The user is cautioned that flow rates can become very unrealistic when the time step exceeds 1 minute, and the resulting events will not provide accurate results if the system being analyzed is sensitive to flow rate, as would be the case with a tankless water heater or wastewater heat recovery system. Additional adjustments are made to the flow rates to reflect differences in mains water temperature in different climates. The BA Benchmark mains water temperature approximation was used for this purpose (Burch and Christensen 2007).

A simple user interface was added to the spreadsheet tool to enable researchers to generate hot water events tailored to their own needs. The user interface allows the user to select the geographic location, number of bedrooms (surrogate for daily hot water use), and desired time step for the model that will be used to analyze the hot water system. Users can also choose whether the events are specified as hot water only or the total of hot and cold water for mixed events such as sinks and showers.

RESULTS

A partial hot water event schedule for a four-bedroom house in St. Louis, Missouri, is provided graphically in Figure 4, and in numerical format in Table 6. The time-step is 6 seconds, and the flow rates are expressed as the total of hot and cold water for mixed end uses. Note the cluster of three sink events beginning at 6:11 AM, and the cluster of clothes washer events within a single load beginning at 10:48 AM.

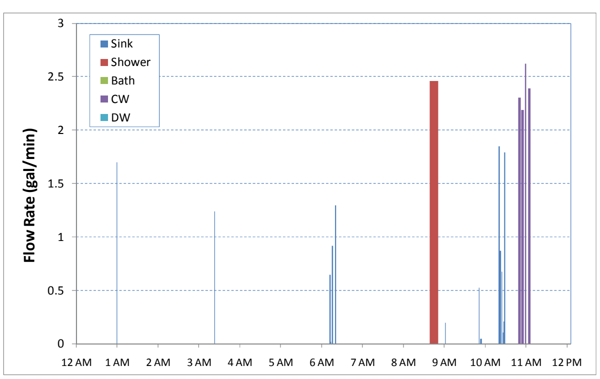

Figure 4 Example series of hot water events

Table 6 Example hot water event schedule for a four-bedroom house in St. Louis

Start Time	Duration (sec)	Flow Rate (Hot & Cold) (gpm)	Start Time
7/2 12:59:18 AM	6	1.698	Sink 2
7/2 3:22:36 AM	36	1.238	Kitchen Sink
7/2 6:11:36 AM	48	0.645	Kitchen Sink
7/2 6:13:36 AM	6	0.022	Sink 2
7/2 6:15:30 AM	24	0.92	Sink 2
7/2 6:19:42 AM	54	1.296	Sink 3
7/2 8:38:30 AM	732	2.462	Shower 2
7/2 9:01:30 AM	6	0.199	Kitchen Sink
7/2 9:50:48 AM	18	0.528	Kitchen Sink
7/2 9:52:42 AM	90	0.049	Kitchen Sink
7/2 10:20:00 AM	30	1.852	Sink 3
7/2 10:21:54 AM	12	0.871	Kitchen Sink
7/2 10:23:48 AM	12	0.673	Kitchen Sink
7/2 10:25:48 AM	96	0.105	Kitchen Sink
7/2 10:26:42 AM	6	0.107	Kitchen Sink
7/2 10:27:42 AM	42	1.794	Kitchen Sink
7/2 10:48:12 AM	210	2.304	CW
7/2 10:53:12 AM	174	2.188	CW
7/2 10:58:12 AM	48	2.619	CW
7/2 11:03:12 AM	180	2.392	CW

For sinks, the average distribution of events throughout the day is very consistent with the underlying probability distribution, as shown in Figure 5. For end uses that have fewer total events, such as baths, random effects cause the actual distribution of events to deviate from the probability distribution, as shown in Figure 6.

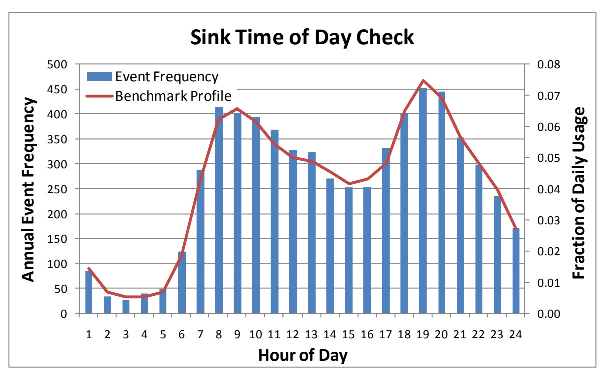

Figure 5 Comparison of outputs to inputs for sink events

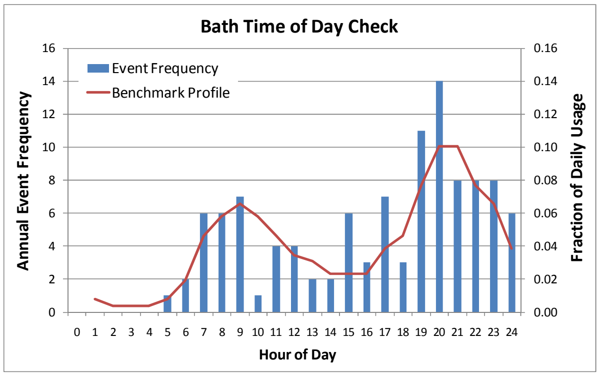

Figure 6 Comparison of outputs to inputs for bath events

EXAMPLE APPLICATION

One application of the hot water event generator was to examine the energy savings for an integral-collector-storage (ICS) solar water heating system in Sacramento, California, as a function of occupant hot water use profile. A schematic of the system is shown in Figure 7, and the key specifications are listed in Table 7. The primary goal was to determine the difference between the energy savings on average for a cross-section of representative occupant behaviors compared to a single "average" household, which could affect optimal design choices for solar hot water systems when applied on a community scale.

The hot water event generator was used to develop a representative set of 12 hot water use patterns (3 levels of hot water use and 4 hourly profiles). Each use pattern represented a "bin" of households based on the Aquacraft 1200-house study. The definition of each bin and its summary characteristics are shown in Table 8. Example hourly profiles for medium use households are shown in Figure 8. These bin characteristics defined the constraints and probability distributions imposed on the hot water event generation tool.

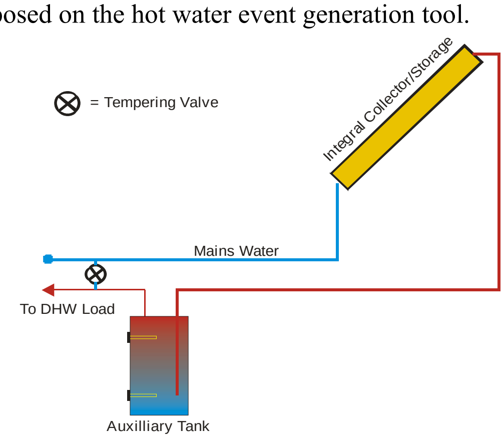

Figure 7 Schematic of solar ICS system analyzed using alternative DHW event schedules

Table 7 Specifications of solar hot water system used for analyzing alternative DHW event schedules

Collectors	
Working Fluid	Water
Total Area	32 ft^2
Volume	49 gal
Slope	18 degrees
Azimuth	-18 degrees
Optical Gain Coefficient [$F_R(\tau\alpha)$]	0.5279
Thermal Loss Coefficient (F_RU_L)	0.6818 Btu/h·ft^2·°F
Environment Temperature	68°F
Pipe Length, indoor, supply/return	10 ft
Pipe Length, outdoor, supply/return	20 ft
Auxiliary Storage Tank	
Volume	40 gal
Height	4.5 ft
R-value	10 h·ft^2·°F/Btu
Environment Temperature	68°F
Heating Element Capacity	15,353 Btu/h
Setpoint	120°F

Table 8 Hot water use pattern "bin" definitions

	Bin Categories				
Bin #	**Volume (All End-Uses)**	**Shower**	**Occupants at Home During the Day**	**Daily Use (gal)**	**% in Bin**
1	Low	Morning	At Home	27	10%
2	Low	Morning	Not at Home	28	6%
3	Low	Evening	At Home	26	7%
4	Low	Evening	Not at Home	28	3%
5	Medium	Morning	At Home	61	25%
6	Medium	Morning	Not at Home	63	10%
7	Medium	Evening	At Home	60	12%
8	Medium	Evening	Not at Home	63	3%
9	High	Morning	At Home	112	14%
10	High	Morning	Not at Home	117	4%
11	High	Evening	At Home	115	6%
12	High	Evening	Not at Home	119	2%
Avg	-	-	-	66	100%

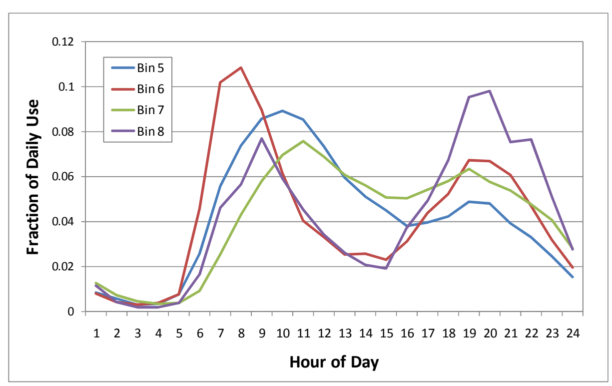

Figure 8 Hourly profiles for medium use households

The resulting event schedules were used as inputs to a TRNSYS model of the ICS system with a simulation time step of 6 minutes. In this case, relatively large time steps were acceptable because ICS systems are insensitive to flow rate and time between events. Random daily variations in hot water volume and time-of-use are more important drivers of ICS performance. The model predicted the annual energy savings associated with each of the 12 use patterns, along with the "average" use pattern. The combined "bin average" energy savings was calculated based on the average of all bins, weighted using the percentage of the population each bin represents. The model was also used to analyze whether using a simple repeated daily use pattern provides as much accuracy as the more complex annual use pattern, and whether including vacation periods in the simulation makes a significant difference. The results for all cases are shown in Figure 9. The energy savings were normalized within each series (1-4, 5-8, 9-12) based on the daily volume of the first bin in the series (1, 5, or 9), in order to illustrate the effects of different hourly profiles.

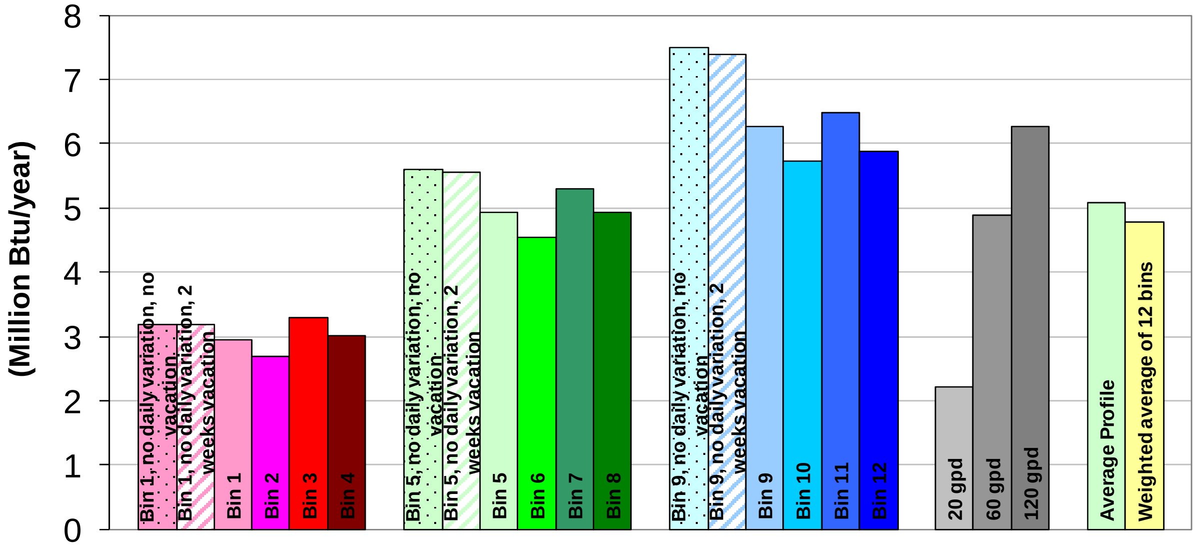

Figure 9 Energy savings for an ICS system using alternative DHW use patterns

The analysis of very high (120 gal/day) and very low (20 gal/day) households compared to a nominal 60 gal/day household demonstrates the nonlinearity of energy savings for an ICS systems. An increase in hot water use of 60 gal/day adds about 1.4 MBtu of additional energy savings; a smaller 40 gal/day decrease results in a much larger 2.7 MBtu loss in energy savings. The relationship between hot water use and energy savings is shown in Figure 10.

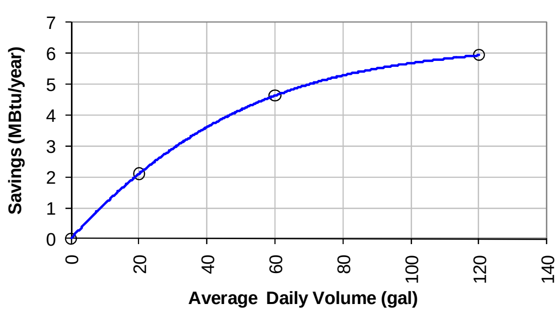

Figure 10 Non-linearity of energy savings relative to daily volume

The bin assignments, including the alternate profiles within each volume grouping, had a significant effect on annual energy savings. This suggests that for ICS systems in moderate climates, analyzing a variety of hourly profiles provides valuable information about the range of energy savings that different households might achieve, depending on their hot water use patterns. Based on the simulations, the weighted average energy savings of all 12 bins is estimated to be about 6% less than that for a single average household. This improvement in accuracy is significant, but may not be worth the additional effort when other sources of modeling error are considered.

A small decrease in energy savings can be observed when 14 vacation days with no hot water use are included in the analysis, while holding the total annual hot water use constant. This can be explained by the fact that when hot water is not being used, the collector gets very hot, and energy losses increase accordingly. Also, the assumption of no day-to-day variation results in an overstatement of energy savings because high- and low-use days do not average out over the long run. Our analysis indicates that the inclusion of day-to-day variations in hot water use, including vacation days, provides much more realistic estimates of annual energy savings. Impacts on other hot water systems and other climates will be examined in future studies.

CONCLUSION

The tool described in this paper enables analysts to more accurately predict energy savings for a variety of hot water measures that are sensitive to specific draw patterns. This improvement in accuracy was quantified for a simulation of an ICS hot water system in Sacramento, California, and shown to be significant. Using a large database of actual use patterns, combined with advanced statistical methods, the authors were able to generate more realistic draw profiles than were developed in past studies. The tool includes a user-friendly interface to enable analysts to generate a variety of use profiles tailored to specific applications. The tool is posted on the Building America website (www1.eere.energy.gov/buildings/building_america/perf_analysis.html).

ACKNOWLEDGMENTS

The authors express their appreciation to Terry Logee, Ed Pollock, and George James of the U.S. Department of Energy Building America Program for their leadership and financial support of this project. We would also like to thank Ren Anderson, Christina Haley, and Mark Eastment of NREL, Ed Hancock of Mountain Energy Partnership, and Peter DeOreo of Aquacraft for their ideas and assistance with the development of this methodology.

NOMENCLATURE

CW	Clothes washer
DW	Dishwasher
X, X_1, X_2	Uniform random numbers between 0 and 1
Y	Random variable
μ	Mean of statistical distribution
σ	Standard deviation of statistical distribution

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