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DERIVING U.S. HOUSEHOLD ENERGY CONSUMPTION PROFILES FROM AMERICAN TIME USE SURVEY DATA – A BOOTSTRAP APPROACH

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ABSTRACT

This paper presents a novel approach to derive U.S. residential building energy load profiles. This approach uses bootstrap sampling method to extract daily activity pattern of occupants of a household from American Time Use Survey (ATUS) data. The characteristics of ATUS data, the relation between time-use and load-demand, and the robustness of this approach are discussed. Virtual experiments were conducted on Energy Plus platform to study the patterns of annual load demand distribution under different household composition and thermal zoning schemes. Simulations of average 24-hr appliance and lighting load profiles were also conducted. The simulated load profiles and those from utility metering studies have good agreement. This novel approach has versatile applications in residential building energy simulation.

INTRODUCTION

A National Time Use Survey (TUS) is a large scale time use survey administrated by a national government. Each TUS record contains 24 hour period of activities of an individual with this individual's personal information. TUS records are taken from all walks of life. Scholars generally agree (Robinson and Godbey, 1997) that TUS data are the best available data that represent the time use pattern of a society.

In recent years, researchers started to explore the application of national Time Use Survey (TUS) data for simulating schedules in residential building energy consumption calculation. The roulette wheel genetic algorithm (Tanimoto et al., 2008) and Markov Chain Monte Carlo (MCMC) techniques (Richardson et al., 2008) have been applied to TUS data for occupant and load schedule simulation with some success. Two main drawbacks of these approaches come from the methodological constraints that limit the extraction of detailed information embedded in the TUS record and the lack of integration between simulated schedules and commonly used building energy simulation tools.

In general, three steps of data transformation are needed for using TUS data for residential building load demand estimation. The first step is to construct a household's daily activity schedule from TUS data, one-to-many mapping is the key characteristic of this process. i.e., to represent the range of variation of a given household's daily activity patterns, multiple schedules are simulated from TUS data. The second step is to derive the internal heat gain, lighting and appliance load schedules from a household's activity schedules. This step involves the interpretation of the spatial and temporal distribution of the occupants' activities and the corresponding appliance and energy use. The third and final step is to derive heating and cooling load demands from the combined inputs of the TUS derived occupancy, appliance and lighting load schedules, the configuration of the residence and the outdoor environmental conditions.

This paper presents a novel approach to simulate occupancy and load schedules from the TUS data in finer details. In constructing the household's daily activity schedule, the bootstrap method (DeGroot and Schervish, 2002) replaces roulette wheel and MCMC techniques for an individual's daily activity schedule simulation. Then the individuals' household demography profiles are matched for household schedule assembly. In appliance load schedule simulation, both spatial and temporal dimensions of the occupants' activities are referred. Human-physical integrative household system theory (Hitchcock, 1993) is used to explain the association between the occupants' activities and appliance load demand. In the calculation of heating and cooling load demands, Energy Plus simulation replaces the self-developed energy consumption estimation method, so the approach will be easier to propagate. Figure 1 illustrates the procedure of the approach.

Using 2006 American Time Use Survey (ATUS) data, a series of virtual experiments are conducted to observe the pattern of annual load demand resulted from this novel approach.

Results from virtual experiments indicate: 1. patterns of annual energy load demand distribution derived from different batches of randomly sampled ATUS data are highly consistent within each type of household demography, 2.increasing the number of thermal zones has far more significant impact in heating and cooling load demand reduction than increasing building envelope thermal insulation does, 3, the simulated 24-hr appliance and lighting load profiles agree with those from utility metering data.

Among the TUS-based residential building energy load schedule simulation approaches, this novel approach is the only one that simultaneously captures the dynamics of the human and physical dimensions in the operation of the residence.

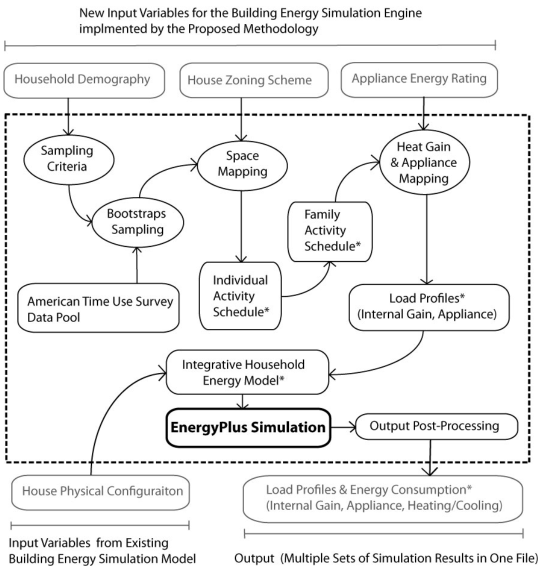

Figure 1 Load schedule Simulation procedure

SIMULATION

Characteristics of American Time Use Survey

The American Time Use Survey is administrated by the U.S. Bureau of Labor Statistics and the U.S. Census Bureau. Its data are publicly available from the government's website (BLS, 2008). An American Time Use Survey consists of approximately 13,000 individual 24-hour time diaries. It is conducted and published yearly. ATUS employs 3-tiered activity coding system that categorizes daily activity into 403 activity codes. Additional coding systems were also employed to indicate the "where" and "with whom" information of the activities (Table 1). This study uses 2006 ATUS data.

Table 1 An ATUS time diary sample

Start Time	End Time		Loc Code	Act Code	Activity Description	Location Description
4:00:00	8:00:00	1	-1	10101	Sleeping	Blank
8:00:00	9:00:00	2	1	20201	Food and drink preparation	Respondent's home or yard
9:00:00	9:45:00	3	1	110101	Eating and drinking	Respondent's home or yard
9:45:00	11:30:00	4	1	20101	Interior cleaning	Respondent's home or yard
11:30:00	13:00:00	5	-1	10201	Washing dressing and grooming oneself	Blank
13:00:00	13:45:00	6	13	180704	Travel related to shopping	Car
13:45:00	15:45:00	7	6	70104	Shopping	Grocery store
15:45:00	16:30:00	8	13	181202	Travel related to social events	Car
16:30:00	17:30:00	9	3	120201	Attending or hosting social events	Someone else's home
17:30:00	18:30:00	10	3	110101	Eating and drinking	Someone else's home
18:30:00	19:00:00	11	3	120201	Attending or hosting social events	Someone else's home
19:00:00	19:10:00	12	13	181202	Travel related to social events	Car
19:10:00	20:10:00	13	1	20201	Food and drink preparation	Respondent's home or yard
20:10:00	22:30:00	14	1	120303	Television and movies (not religious)	Respondent's home or yard
22:30:00	6:00:00	15	-1	10101	Sleeping	Blank

A limitation of the ATUS for household schedule simulation is the lack of a whole household time diary in its data. Thus, multiple ATUS records are needed to construct a household activity schedule. Literature (Robinson and Godbey, 1997) suggests that the household role has strong influence to an individual's daily activity. Thus, the household composition of an individual can be a suitable criterion for representative household schedule's assembly. To understand the quality of ATUS2006 data for this purpose, the composition of the data was analyzed. As shown in table 2, the numbers of ATUS records representing individuals in categories of interest are sufficient and in balance.

Table 2 Sample pool of ATUS 2006 data

Bootstrap Sampling Criteria*		Work Status						Total
		Self-FT Sp-FT	Self-FT Sp-PT	Self-PT Sp-FT	Self-FT Sp-N	Self-N Sp-FT	Self-PT Sp-PT	
Male with 3 Children < 18	Weekday	34	24	3	45	1	0	103
	Weekend	33	32	0	53	3	1	118
Female with 3 Children < 18	Weekday	41	3	28	2	52	0	121
	Weekend	48	1	33	5	49	1	130
Male with 2 Children < 18	Weekday	137	66	7	67	5	1	270
	Weekend	114	68	3	99	5	1	281
Female with 2 Children < 18	Weekday	148	4	73	9	68	3	289
	Weekend	169	0	69	9	66	1	304
Male with 1 Child < 18	Weekday	89	26	3	40	9	0	155
	Weekend	117	36	5	46	2	1	199
Female with 1 Child < 18	Weekday	124	3	34	17	42	1	200
	Weekend	105	9	36	10	32	3	173
Male with No Child < 18	Weekday	49	14	1	11	5	0	74
	Weekend	44	9	1	19	2	0	72
Female with No Child < 18	Weekday	65	3	13	6	12	2	90
	Weekend	67	0	5	7	12	0	84
*baseline: married male and female from 30 to 65 years old in ATUS 2006 data								
Children <18	Weekday							322
	Weekend							355

To represent the range of variation of household activity patterns, 30 household schedules are created from ATUS data for each given household composition. Take a 2 parents and 2 children household for example, one possible match of the parenting couples can come from a randomly drawn ATUS record of a full-time working married male with a full-time working spouse and two kids and a randomly drawn ATUS record of a full-time working married female with a full-time working spouse and two kids. Another possible match can be from the ATUS record of a full-time working male with part-working spouse and that of part-time working female with a full-time working spouse (Figure 2).

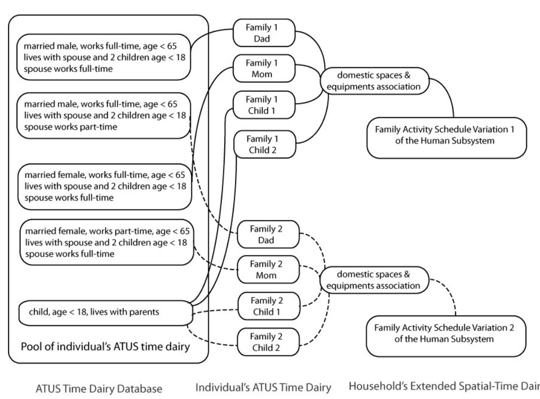

Figure 2 Multiple household activity and load schedules derived from ATUS

Three tiered energy consumption behavior

In physical-human integrative household system theory (Hitchcock, 1993), three categories of human energy consumption behavior from social perspective have been identified. They are 1.cultural and social determinants, 2.demographic and economic determinants and 3.psychological determinants. Cultural and social determinants are related to occupant's daily activity pattern; demographic and economic determinants influence the tools and equipments chosen by the occupant to assist his or her daily activities; psychological determinants affect the way these tools and equipments are used by the occupant.

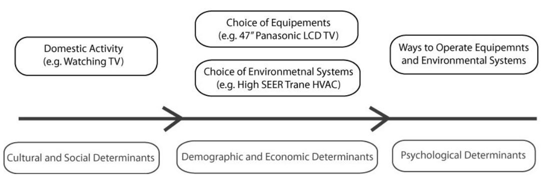

Figure 3 Links between behavior determinants and domestic energy consumption

Three categories of human energy consumption behavior form a tiered relation (Figure 3). Since the ATUS data only reflects the daily activity (time use) patterns, what the approach extracts from the ATUS is the cultural-social determined human energy consumption behavior. The demographic and economic determined and psychological determined human energy consumption behaviors are treated as control variables (appliance energy rating and building operation configuration) in building energy simulation. For this study, a fixed relationship is used for the association between activity, space, appliance and energy load demand. Key activity-space-appliance-energy relations are shown in table 3.

Table 3 Key activity-space-appliance relations

ATUS Activity Code	t0101xx	t120308, t120313	t120303, t120304	t0603xx	t1101xx
Activitiy Description	Sleeping	Computer use for leisure	TV and movies	Research and homework	Eating and drinking
Watts per person	20	150	300	150	100
Max Watts per room	20	150	300	150	1000
Equipments	night lights	task lights and computer	Audio-video system	task light and computer	kitchen appliance
Activity location	Bedroom	Office or Bedroom	Family Room	Office or Bedroom	Kitchen

Configuration of the generic house

A generic single family house is specified as the base case for the integrative household energy model simulation (Figure 4). The north-south facing 2-story 4-bedroom generic house, sitting in a Chicago suburb, is specified as 30 feet in depth and 40 feet in width with 8 feet ceiling height and 15% of exterior walls covered by windows. The generic house is composed of 9 functional quarters. Depend on the parameter setting of the virtual experiment, the thermal zoning of the house is either single or nine zones following the functional partitions; the building envelope thermal insulation of the house is either compliant to IECC 2006 standard (IECC, 2006) or comparable to a well insulated house constructed in 1990s (Table 4). The lighting load per room is specified as 100 watts when turned on. Main standby/continuous loads are from AV system and refrigerator (Table 5). The hourly air exchange rate (ACH) by infiltration is assumed to be 0.75.

Table 4 Thermal insulation specifications

Climate Zone 5	IECC 2006			Existing Good Construction		
	U [W/m2-K]	R [m2-K/W]	SHGC	U [W/m2-K]	R [m2-K/W]	SHGC
Door	1.99	0.50		2.67	0.37	
Window	1.99	0.50	NR	2.67	0.37	NR
Ceiling	0.17	5.87		0.30	3.35	
Wood Wall	0.34	2.94		0.45	2.22	
Floor	0.19	5.34		0.34	2.90	
Basememt Wall	0.34	2.98		0.51	1.95	
C.S.Wall	0.37	2.71		NR	NR	

Table 5 Lighting and standby load specifications

	Zone	Lighting (w)	Standby (w)	comment
Foraml Living -home office	z001	100	10	misc. standby load
Family Living	Z002	100	40	AV system Standby
Kitchen	Z003	100	110	Refrigerator etc
Dinning	Z004	100	10	misc. standby load
Master Bedroom Suite	Z005	100	10	misc. standby load
Bedoorm 1	Z006	100	10	misc. standby load
Bedroom 2	Z007	100	10	misc. standby load
Bedroom 3	Z008	100	10	misc. standby load
Entrance Foyer	Z009	100	10	misc. standby load

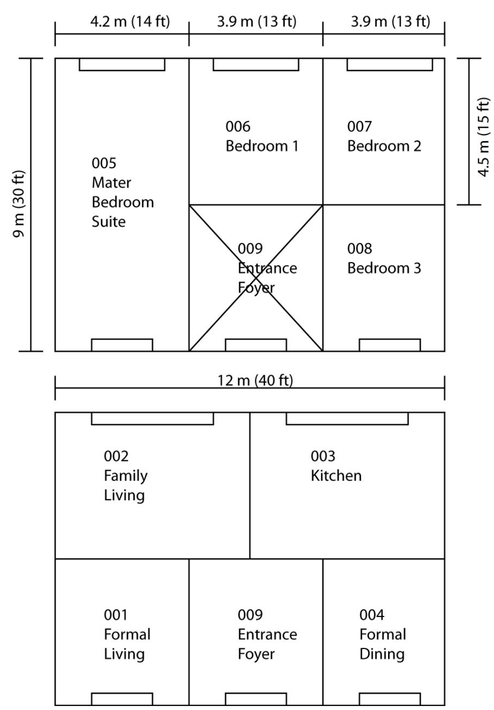

Figure 4 Layout of the generic 4-bedroom house

Virtual experiment design

Virtual experiment is a common approach used in complex system simulation. A set of simulations for a fixed parameter value set is called a cell. For a system with stochastic elements, each cell repeats itself multiple times to extract the system's stochastic behavior. Four virtual experiments were conducted in the study.

The first virtual experiment (Table 6) contains 16 cells. Each cell contains 30 simulation runs and repeats itself 10 times. When a cell is repeated, the household schedules are re-sampled from the ATUS data. This virtual experiment serves three purposes: 1. to exam the role of household composition in the annual on-site load distribution patterns, 2. to contrast the effectiveness of building envelope thermal insulation improvement and thermal zone refinement to annual on-site heating and cooling loads and, 3. to verify the robustness of this load schedule simulation approach.

Table 6 Virtual experiment I setting

Variable	Value	N
Thermal Insulation Standard	1990s Existing, IECC2006	2
Number of Thermal Zones	9, 1	2
Number of Occupants per House	5, 4, 3, 2	4

Constant		
Location	Chicago	1
Terrain	Suburb	1
Housing Type	generic 4-bdrm house	1
Air Exchange Rate Per Hour (ACH) from Infiltration	0.75	1
Temperature Band (Occupied / Unoccupied)	18C-27.5C/ 8C - 35C	1

1. This is a 2x2x4 = 16 cell design, each cell is replicated 10 times
2. Each repetition contians 30 randomly drawn family activity schedules from ATUS2006

The second virtual experiment is a 4 cell design. Each cell also repeats 10 times and has 30 simulation runs per repetition. This experiment is to exam the impact of different activity to space mapping schemes to annual heating and cooling loads of a 4 occupant household. The 4 cells are 1. A 9 zone maximum space use scheme - concurrent activities are assumed to take place at as many different spaces as possible. 2. A 9 zone minimum space use scheme - concurrent activities are assumed to take place at as few different spaces as possible. 3. A 9 zone typical space use scheme – these activities are assumed to take places in common sense fashion and 4. A single zone space use scheme - all indoor activities take place in the thermal zone that covers the entire house.

The third virtual experiment is a 2 cell design. Each cell repeats only once and has 100 simulation runs per repetition. This experiment is to exam the impact of the ATUS sample's region to the resulting 24-hr averaged load profile of a 4 occupant family. The Midwest and South are the two regions being tested.

The fourth virtual experiment is a 3 cell design. It is used to validate the assumption of the activity-to-appliance load associations that is applied to this study. The exact same ATUS samples from virtual experiment 1 are used in this experiment. The 24-hr averaged load profile of 3, 4, and 5 occupant households are simulated.

DISCUSSION AND RESULT ANALYSIS

Annual load demand grand-sum graphs

A Grand-sum graph is created by summing-up the simulation results of all sampling repetitions. Two sets of grand-sum graphs are generated from virtual experiment 1. In the grand-sum graph, each linear data cluster in the probability plot contains 300 data points (30 runs x 10 repetitions).

The first set of grand-sum graphs are the annual occupant heat gain probability plot (Figure 5) and the annual appliance load probability plot (Figure 6). Heat gain of occupants is derived by assigning heat gain to household daily activities using the ASHRAE metabolic heat gain reference table (ASHRAE, 2001). Appliance load is derived by assigning appliance energy loads associated with ATUS activities using a common sense approach (Table 3). Since both loads are derived directly from ATUS data, they are independent of the physical configuration of the house.

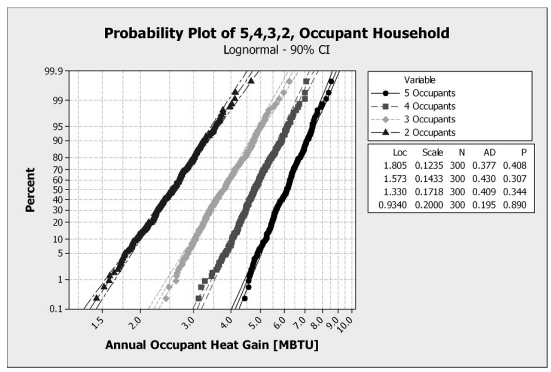

Figure 5 Annual heat gain probability plot

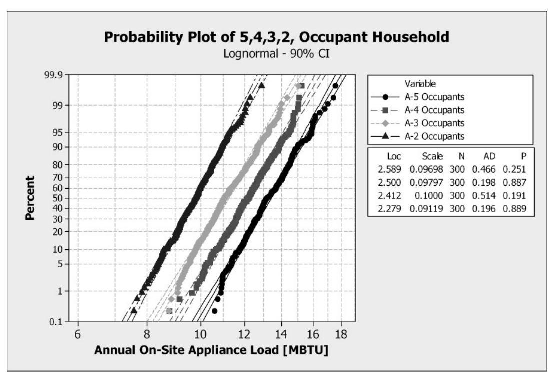

Figure 6 Annual appliance load probability plot

The second set of grand-sum graphs are the annual on-site heating load demand probability plots. Heating and cooling loads are the energy the building environmental control system needs to deliver in response to the combined effect of the natural environment, the building's physical configuration and the occupants' activities. They are derived through building energy simulation. Since Chicago is in heating load dominating climate, three heating load probability plots (Figures 7, 8, 9) are used to illustrate two distinctive heating and cooling load distribution patterns found in the virtual experiment.

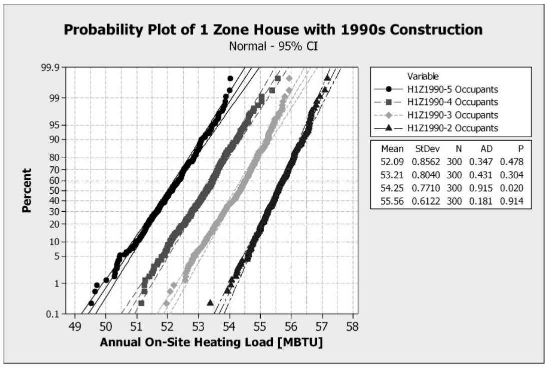

Figure 7 Annual heating load probability plot of single zone house with 1990s thermal insulation

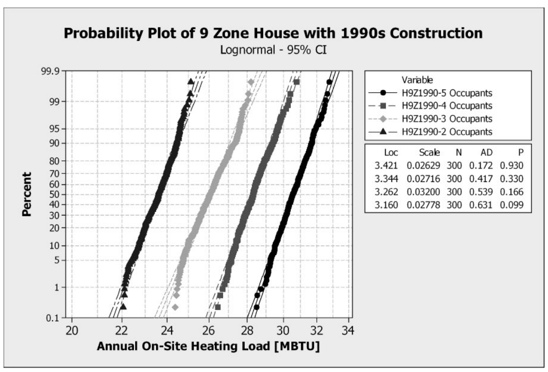

Figure 8 Annual heating load probability plot of 9 zone house with 1990s thermal insulation

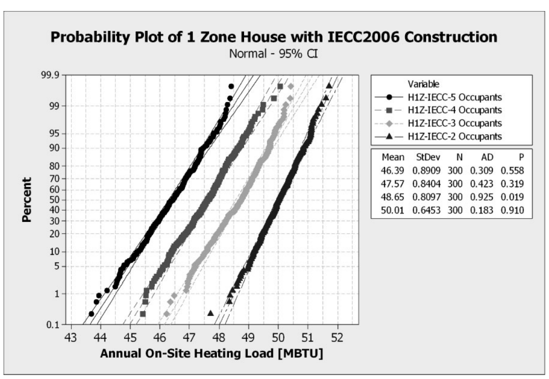

Figure 9 Annual heating load probability plot of single zone house with IECC 2006 thermal insulation

The first heating load probability plot (Figure 7) depicts the case of an infiltration dominating condition. In a single thermal zone house, the majority of the heating load is to compensate the cold air infiltrates from outside. Simulations indicate that annual heating load is of normal distribution in infiltration dominating condition. The slopes of the distribution vary slightly by household composition. The higher the number of occupants in a household, the wider the bell-shape curve is.

The second heating load probability plot (Figure 8) represents the case of an occupant activity dominating condition. In a 9 thermal zone house where an HVAC system is activated only in occupied spaces, a majority of the heating load is to provide occupants thermal comfort.

Since a larger household size means more spaces being occupied concurrently, the level of heating load demand goes up as the number of occupant increases. The heating load demands increases by the size of household. They are in the same order as occupant heat gain and appliance loads. Because of this dynamic, it is no surprise that the annual heating load of a 9 zone house shares the pattern of lognormal distribution with annual occupant heat gain and annual appliance load. Since the distributions of annual occupant heat gain and annual appliance load of different household compositions have similar slope, the slope of annual heating load is also indifferent to household size.

The third heating load probability plot (Figure 9) is another infiltration dominating condition. Simulations show that improvement of the thermal insulation of a single zone (infiltration dominating) house from 1990s condition to IECC 2006 standard can result in average 10% to 11% of heating load reduction. In essence, heating load reduction is indifferent to household composition in single zone house. Utility metering studies also presented similar findings (Emery and Kippenhan, 2006).

In comparison, increasing the number of thermal zones can achieve much higher level of heating energy reduction (Figures 7, 8). The effect of thermal zone refinement is highly sensitive to household composition. Best case comes at 2 occupant household (57.5% heating load reduction in average). Yet even in a 5 occupant household, average heating load reduction (41.2%) is still 4 times as effective as thermal insulation improvement (Figures 7,9).

Robustness of the ATUS driven energy model

The "Mean" is the most commonly used statistical inference in application of any data. It gives some sense of the "averaged behavior" of a population and with simple multiplication; the total amount of a certain property of a population can be derived from it. According to the central limit theorem (DeGroot and Schervish, 2002), the 95% confidence interval of the true mean of the population falls within the range of "Mean plus/minus 2 Standard Error of Mean" from the measured means of different batches of samples. A quick survey of table 7 reveals that, even if using only the first 10 runs of the 30 runs simulated in each virtual experiment cell repetition, their 95% confidence interval of true mean in both annual occupant heat gain and annual appliance load are still within 5.5% range of the simulation mean.

Similar phenomena have been observed across all means, 17 percentiles and 83 percentiles of annual occupant heat gain (Table 8), appliance load (Table 9), heating load and cooling load in all cells of virtual experiment. The narrow range of values of these statistical inferences offers strong support to the robustness of the ATUS-bootstrap-based residential building energy load schedule simulation approach.

Table 7 Mean and standard error of mean of the measured means of annual occupant heat gain and appliance load from 10 cell repetitions [MBTU]

runs	People [MBTU]			Appliance [MBTU]		
5 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
Mean of first 10	6.11	0.09	1.40%	13.30	0.15	1.15%
Mean of first 20	6.17	0.06	0.95%	13.44	0.09	0.67%
Mean of first 30	6.12	0.04	0.57%	13.39	0.06	0.42%
4 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
Mean of first 10	4.80	0.06	1.19%	12.13	0.08	0.68%
Mean of first 20	4.84	0.04	0.91%	12.21	0.06	0.51%
Mean of first 30	4.87	0.04	0.76%	12.24	0.07	0.53%
3 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
Mean of first 10	3.87	0.08	1.97%	11.21	0.12	1.05%
Mean of first 20	3.83	0.04	0.98%	11.20	0.07	0.63%
Mean of first 30	3.84	0.02	0.44%	11.22	0.04	0.38%
2 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
Mean of first 10	2.65	0.07	2.73%	9.82	0.12	1.23%
Mean of first 20	2.63	0.05	1.94%	9.82	0.08	0.79%
Mean of first 30	2.60	0.02	0.90%	9.81	0.04	0.36%

Table 8 Mean and standard error of mean of the 83 percentile and 17 percentile values of annual occupant heat gain from 10 cell repetitions [MBTU]

People [MBTU]	83 Percentile			17 Percentile		
5 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
first 10 runs	6.65	0.13	1.88%	5.55	0.10	1.88%
first 20 runs	6.83	0.08	1.14%	5.49	0.07	1.36%
first 30 runs	6.92	0.07	0.98%	5.46	0.04	0.82%
4 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
first 10 runs	5.35	0.07	1.27%	4.28	0.06	1.52%
first 20 runs	5.50	0.06	1.16%	4.24	0.05	1.15%
first 30 runs	5.53	0.05	0.95%	4.25	0.05	1.22%
3 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
first 10 runs	4.46	0.13	2.89%	3.34	0.06	1.70%
first 20 runs	4.52	0.07	1.48%	3.24	0.02	0.75%
first 30 runs	4.52	0.06	1.36%	3.20	0.03	0.88%
2 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
first 10 runs	3.12	0.09	2.93%	2.20	0.06	2.85%
first 20 runs	3.15	0.08	2.55%	2.16	0.04	1.94%
first 30 runs	3.09	0.05	1.75%	2.14	0.02	1.16%

Table 9 Mean and standard error of mean of the 83 percentile and 17 percentile values of annual appliance load from 10 cell repetitions [MBTU]

Appliance [MBTU]	83 Percentile			17 Percentile		
5 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
first 10 runs	14.24	0.23	1.60%	12.28	0.16	1.33%
first 20 runs	14.56	0.14	0.94%	12.23	0.15	1.20%
first 30 runs	14.60	0.10	0.67%	12.14	0.11	0.88%
4 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
first 10 runs	13.19	0.12	0.92%	11.16	0.14	1.25%
first 20 runs	13.28	0.07	0.54%	11.12	0.11	1.02%
first 30 runs	13.31	0.08	0.64%	11.23	0.12	1.10%
3 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
first 10 runs	12.23	0.19	1.57%	10.22	0.13	1.26%
first 20 runs	12.34	0.12	1.00%	10.17	0.08	0.83%
first 30 runs	12.29	0.09	0.77%	10.16	0.07	0.73%
2 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
first 10 runs	10.56	0.12	1.11%	9.11	0.13	1.40%
first 20 runs	10.63	0.13	1.19%	9.07	0.09	1.05%
first 30 runs	10.58	0.07	0.61%	9.00	0.06	0.67%

Sensitivity of activity-to-space assignment

Four cells in this experiment represent 3 different types of activity-to-space association (maximum, minimum and typical space use) in a 9 zone condition and a single thermal zone condition as reference to the existing common practice.

From the results of the 30 simulation runs, the annual average load demand can be derived from each repetition. The means and standard deviations of these "averaged" annual loads from 10 repetition of each cell were then calculated (Table 10). Two observations can be drawn from the calculations.

First, the type of activity-to-space association has little influence on the resulting annual heating and cooling load demands. There is less than 4% difference between typical activity-to-space association and the other two extreme cases in the cooling condition. In the heating condition, the difference among them is unnoticeable. In contrast, the difference of load demand between a 9 zone and a single zone setting are significant (88% for heating, 130% for cooling). This analysis shows that typical activity-to-space association is adequate for virtual experiments in this study.

Second, the standard deviations of the "averaged loads" in all cells are small compared to their means (less than 2%). Similar values of "averaged loads" across 10 repetitions in all cells again offer support to the robustness of this load simulation approach.

Table 10 Sensitivity of activity-to-space assignment

Cooling On-Site [MBTU]	Average	STDEV	Percentage
9 Zone Max Space	5.04	0.13	103%
9 Zone Min Space	4.66	0.09	96%
9 Zone Typical	4.88	0.12	100%
1 Zone	11.22	0.10	230%

Heating On-Site [MBTU]	Average	STDEV	Percentage
9 Zone Max Space	28.40	0.14	100%
9 Zone Min Space	28.33	0.16	100%
9 Zone Typical	28.35	0.16	100%
1 Zone	53.21	0.14	188%

Effect of ATUS record's region on load profile

According to literature (Robinson and Godbey, 1997) geographical location has no influence on an occupant's daily activity pattern. Since the reliability of the load schedule simulation approach depends on sufficient number of ATUS records in the sample pool, it is important to verify if ATUS records taken from different regions can be lumped together for schedule simulation purpose. In ATUS, the United States is divided into 4 regions (Northeast, Midwest, South, and West). The majority of ATUS records are from Midwest and South regions. Thus, records from the two regions are used to compare the averaged 24-hr appliance and lighting load profile of a 4 occupant household in virtual experiment 3. The experiment results show that load profiles (Figure 10) simulated from ATUS data of Midwest and South regions in fact intertwine. It indicates that ATUS records from different regions can be merged into a common sample pool as literature suggests.

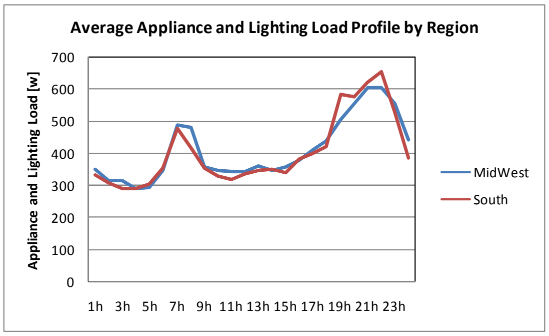

Figure 10 average 24-hr load profiles of two regions

Appliance and lighting load profile validation

Ultimately, the merit of a model depends on whether the model can accurately predict the real-life phenomena. Since most published U.S. utility metering studies are whole house based, the proposed load profile simulation approach can only be validated at whole house resolution at this stage.

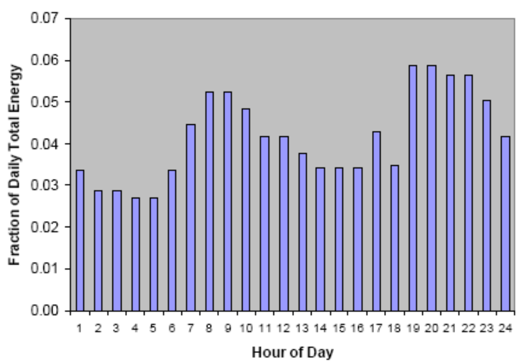

Figure 11 Example utility metering derived appliance load profile (Hendron et al., 2004, Fig. 6)

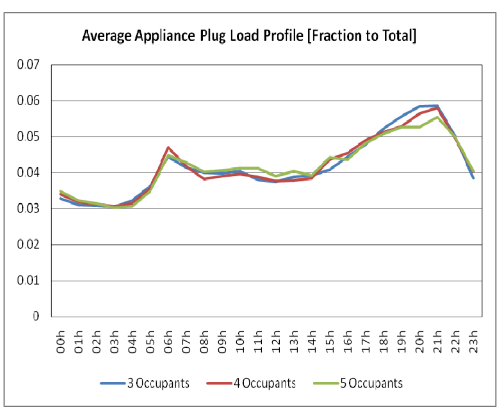

Figure 12 ATUS data simulated appliance load profiles

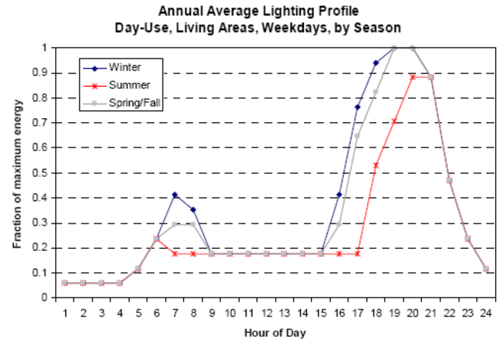

Figure 13 Example utility metering derived lighting load profile (Source: Hendron et al., 2004, Fig. 5)

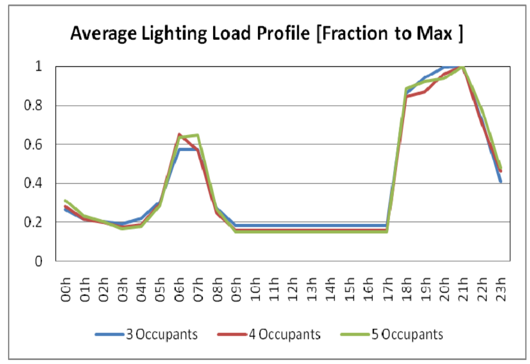

Figure 14 ATUS data simulated lighting load profiles

Using same set of ATUS samples from virtual experiment 1, the averaged 24-hr appliance load profiles and lighting load profiles of 3, 4, and 5 occupant households were simulated. They are compared to the load profile generated from utility metering studies (Hendron et al., 2004). The simulated appliance load profiles (Figure 12) and metering data derived profiles (Figure 11) are very similar both in trend and in scale. Although the simulated and field data derived profiles (Figures 13, 14) are similar, for the average 24-hr lighting load, the simulated profiles have higher peaks in the morning and also shallower valleys during sleeping hours. A possible explanation of this discrepancy comes from the modeling assumption of lighting use. The load generating approach assumes the light will be turned on in the early morning if the space is occupied. In reality, the use of artificial lighting in the morning depends on the availability of natural light. This interpretation is supported by figure 13 where the morning lighting peak load decreases in sequence from winter to spring to summer. Overall, the simulated load profiles are a good representation of the real-life load profiles.

CONCLUSION

This paper presents an occupant behavior driven approach to derive U.S. residential building energy load schedules and demands. In the proposed approach, current “static” standard whole-house schedules based on empirical utility metering data are replaced by multiple sets of sub-house schedules derived from bootstraps sampling of the American Time Use Survey (ATUS) data. In the bootstraps process, the household demography is used as the sampling criteria. The causal relationship between household demography and the residence’s energy consumption is established by linking occupants’ in-residence activities, both spatially and temporally, with the physical and operational configuration of the residence in building energy simulation. Through the proposed approach, the dynamics between household demography and the energy use of the residence can be delineated. Because of the ability to derive sub-house use pattern of the residence, the proposed approach can also be use to study the dynamics between local and global elements of the physical household system in terms of energy performance. The impact of design decisions which cannot be answered explicitly by energy simulation in the past, such as the global impact of energy use from the improvement of a local element (e.g. TV energy rating) or whether a system has responded to occupants’ actual needs, can now be addressed through the development of this approach.

In the United States, the residential sector is responsible for about 21% of the nation’s total energy consumption (EIA, 2008). Among the 105 million occupied housing units, two-thirds are single unit structures (U.S. Census Bureau, 2008). In these houses, the household demography is known, owners have full control of their properties and improvements to the building are made incrementally. Any building energy simulation tool that can inform energy efficient renovation of these buildings can have substantial societal impact. The ability to capture the dynamics of human and physical dimensions of residential building operation in sub-house resolution makes the proposed approach an ideal candidate to work with houses with such characteristics.

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REFERENCES

ASHRAE 2001. *ASHRAE Handbook of Fundamentals*, Atlanta, ASHRAE

Bureau of Labor Statistics 2008. *American Time Use Survey*, U.S. Department of Labor (http://www.bls.gov/tus/#data)

DeGroot, M. H. and M. J. Schervish 2002. *Probability and Statistics: Chapter 11 Simulation*, Addison Wesley, New York, NY.

Emery, A.F. and C. J. Kippenhan 2006. A long term study of residential home heating consumption and the effect of occupant behavior on homes in the Pacific Northwest constructed according to improved thermal standards, *Energy* 31(5): 677-693

Energy Information Administration 2008, *Residential Energy Consumption Survey*, U.S. Department of Energy (http://www.eia.doe.gov/emeu/recs/)

Internal Code Council 2006. *2006 International Energy Conservation Code*

Hendron, R., R. Anderson, C. Christensen, M. Eastment and P. Reeves 2004. Development of an Energy Savings Benchmark for All Residential End-Uses (NREL/CP-550-35917), SIMBUILD2004 Conference, Boulder, Colorado

Hitchcock, G. 1993. An integrated framework for energy use and behaviour in the domestic sector, *Energy and Buildings* 20(2):151-157

Richardson, I., M. Thomson and D. Infield 2008. A high-resolution domestic building occupancy model for energy demand simulations, *Energy and Buildings* 40: 1560–1566

Robinson, J. P., and G. Godbey 1997. *Time for Life: the Surprising Ways Americans use their Time* The Pennsylvania State University Press, University Park, Pennsylvania

Tanimoto, J., A. Hagishima and H. Sagara 2008. A methodology for peak energy requirement considering actual variation of occupants’ behavior schedules, *Building and Environment* 43: 610–619

U.S. Census Bureau 2008. *Housing Units* (http://www.census.gov/popest/housing/)