A Time Use Survey Derived Integrative Human-Physical Household System Energy Performance Model

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ABSTRACT: This study implements an operational building energy performance model based on the integrative human-physical household system theory. The behavior of human subsystem is derived from bootstrap sampling of American Time Use Survey (ATUS) data. The specification of physical subsystem takes reference from residential building industry's best practice and previous study on domestic space network structure. Through the sharing of interior spaces and appliances, the human's domestic activities and the residence's energy consumption behavior are integrated as one indecomposable human-physical household energy consumption system. Energy Plus program is chosen as the platform to run this model's building energy simulation for its flexibility and credibility. Virtual experiment is used to extrapolate the stochastic yet patterned behavior of the integrative model with different household compositions. Bell-shaped distributions are present in annual appliance, heating and cooling load demands. The simulated hourly appliance and lighting load profiles show good agreement with those generated from filed utility metering data.
Keywords: integrative household energy model, American Time Use Survey, bootstrap sampling, virtual experiment

INTRODUCTION

Although human behavior has long been identified as the key determinant of building energy consumption, until recent years, attempts to specify occupants as a parameter in building energy simulation is rare and usually do not associate with any theoretical guidance.

Till this day, a standard approach to represent the effect of occupants in building energy simulation is to refer to a set of load profiles. These load profiles are derived from large scale metering data from utility companies and referred by building energy conservation codes and standards. For their application as inputs of building energy simulation, an obvious drawback is that the fixed, empirically derived load profiles carry no causal relationship to the demography of occupants thus cannot respond to energy conservation measures that will interact with occupants' energy consumption behavior.

From the perspective of domestic energy use, the integrative household system theory [6] looks at a household as a combination of two sub-systems – the physical system and the human system. The physical system is the materials and devices of a dwelling, and the human system is the occupants that live within the dwelling. Surrounding them is the third element, the environment that influences the operation of the two household sub-systems. The purpose of the physical subsystem is to provide support and comfortable surroundings for human activities. The energy use in household is the result of the physical system providing these services. Thus, the level of energy consumption depends on the level of service required by the occupant and the efficiency of service determined by the physical characteristics of the dwelling. And the energy performance of household system will be affected by both technical and social changes.

This study implements an operational building energy performance model based on the integrative human-physical household system theory. The behavior of human subsystem is derived from bootstrap sampling of American Time Use Survey (ATUS) data. The specification of physical subsystem takes reference from residential building industry's best practice and previous study on domestic space network structure. Through the sharing of interior spaces and appliances, the human's domestic activities and the residence's energy consumption behavior are integrated as one indecomposable human-physical household energy consumption system. Energy Plus program is chosen as the platform to run this model's building energy simulation for its flexibility and credibility.

Virtual experiment is used to extrapolate the stochastic yet patterned behavior of the integrative model of a 4-bedroom house in Chicago with four different household compositions. Bell-shaped distributions are present in all annual heating, cooling and appliance load demands. The simulated hourly appliance and lighting load profiles show good agreement with those generated from filed utility metering data.

MODELLING METHODOLOGY

The proposed integrative human-physical household energy system model is implemented by repeating following steps (Figure 1): 1. Sample each family member's daily activities from ATUS data pool by bootstraps approach, 2. Determine the thermal zone of each activity individual member takes to create individual member's thermal zone-activity schedules, 3. Merge individual schedules together to form whole family thermal zone-activity schedule, 4. Assign appliance and its energy rating to whole family schedule to generate load profiles by thermal zone, 5. Merge these load profiles into the physical configuration of the house to create for building energy simulation.

The repetition of Steps 1 through 5 is designed to capture the stochastic nature of human behaviours. Thus, the energy simulation output implemented by this approach contains not only one fixed set of values but rather multiple sets of load and energy consumption values to represent the variation of energy consumption from a given household composition input. This variation can also be described by statistical inferences such as mean, standard error of means and percentiles.

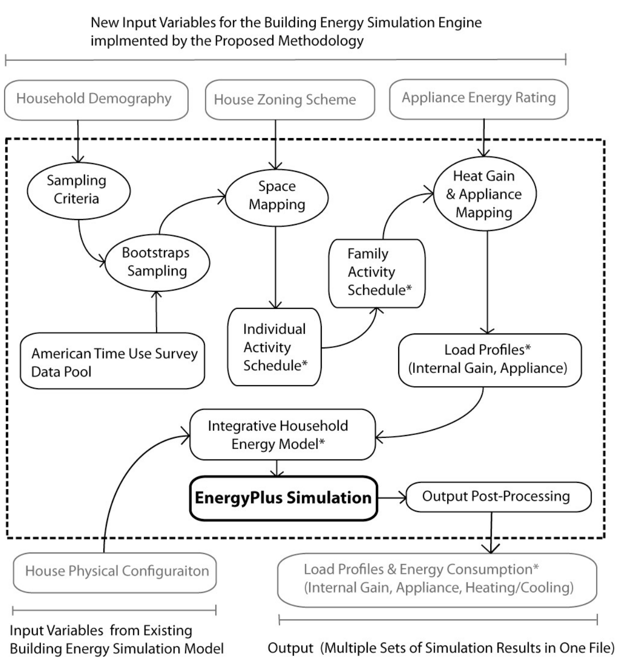

Figure 1: Model Structure

American Time Use Survey is the foundation of the proposed integrative household energy model. It is widely recognized by the time use social scientists as the most comprehensive data that documents the time use of all walks of lives in the U.S. The data is administrated by U.S. Bureau of Labor Statistics and U.S. Census Bureau. The survey [2], consisting of approximately 13,000 individual 24-hour time diaries, is conducted once every year since 2003. 2006 ATUS data is used by this study.

ATUS employs a 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. The fine resolution of ATUS time diary (Table 1), not seen in the time use survey data of other nations, contributes to the feasibility of thermal zone and appliance mapping in the proposed modeling method.

Table 1: An ATUS Time Diary Sample

Start Time	End Time		Loc Code	Act Code	Activity Description	Location Description
4:00:00	9:00:00	1	-1	10101	Sleeping	Blank
9:00:00	10:00:00	2	1	110101	Eating and drinking	Respondent's home or yard
10:00:00	11:00:00	3	1	120312	Reading for personal interest	Respondent's home or yard
11:00:00	12:00:00	4	1	20101	Interior cleaning	Respondent's home or yard
12:00:00	12:05:00	5	12	181201	Travel related to socializing and communicating	Car
12:05:00	13:05:00	6	3	120101	Socializing and communicating with others	Someone else's home
13:05:00	13:10:00	7	12	181201	Travel related to socializing and communicating	Car
13:10:00	13:40:00	8	1	20102	Laundry	Respondent's home or yard
13:40:00	14:10:00	9	1	120303	Television and movies (not religious)	Respondent's home or yard
14:10:00	14:40:00	10	1	20102	Laundry	Respondent's home or yard
14:40:00	18:30:00	11	1	120303	Television and movies (not religious)	Respondent's home or yard
18:30:00	19:00:00	12	1	110101	Eating and drinking	Respondent's home or yard
19:00:00	22:00:00	13	1	120303	Television and movies (not religious)	Respondent's home or yard
22:00:00	22:30:00	14	1	20102	Laundry	Respondent's home or yard
22:30:00	23:00:00	15	1	160102	Telephone calls to/from friends neighbors or acquaintances	Respondent's home or yard
23:00:00	23:30:00	16	1	120303	Television and movies (not religious)	Respondent's home or yard
23:30:00	0:00:00	17	1	30401	Physical care for hh adults	Respondent's home or yard
0:00:00	0:15:00	18	-1	10201	Washing dressing and grooming oneself	Blank
0:15:00	0:45:00	19	-1	10102	Sleeplessness	Blank
0:45:00	7:30:00	20	-1	10101	Sleeping	Blank

In human-physical household system theory [6], 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 is related to occupant's daily activity pattern; demographic and economic determinants influence the tools and equipments chosen by the occupant to assist her daily activities; psychological determinants affect to the way these tools and equipments are used by the occupant. Three categories of human energy consumption behavior form a tiered relation (Figure 2). Since ATUS data documents only the daily activities (time use), the proposed method extracts the cultural-social determined human energy consumption behavior from ATUS and treats the demographic and economic determined and psychological determined human energy consumption as control variables (appliance energy rating and building operation configuration) in building energy simulation.

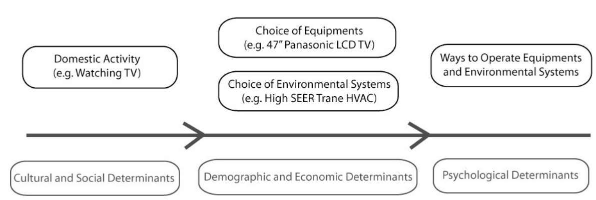

Figure 2: Links between Behaviour Determinants and Domestic Energy Consumption

Another limitation of the ATUS is the lack of whole family time diary in its database. Based on literature review [9] and ATUS samples study results, the family demography of each individual is identified as the suitable criteria to compose representative whole family schedules for energy simulation. For example, an ATUS record of a part-time working married male shows that this male has a full-time working wife and two kids. Then in composing the representative ATUS family, an ATUS record of a full-time working married female with a part-time working husband and two kids will be chosen to match this ATUS male (Figure 3).

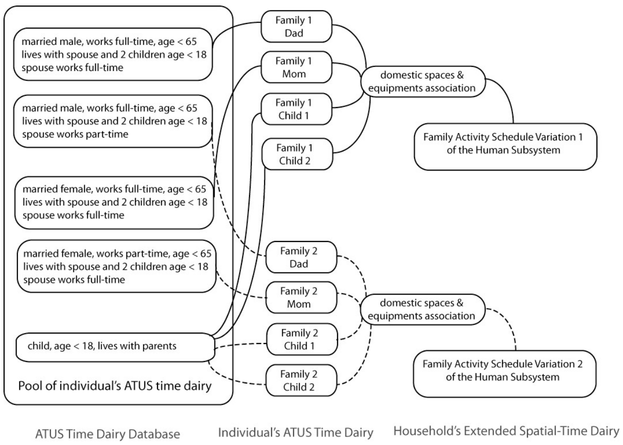

Figure 3: Family Schedule derived from ATUS Data

In statistics, there are mainly two approaches to generate large sets of data from samples of a population – Markov Chain Monte Carlo (MCMC) simulation and Bootstrap sampling [3]. MCMC approach derives the time-dependent statistical distributions of the samples then apples Monte Carlo process on the statistical distributions to generate large sets of simulated data. Bootstrap method generates large sets of data from repetitive random draws of the samples. The sets of bootstrap generated data will demonstrate properties that tell about the nature of the population. In many cases, bootstrap is a more labor intensive processes. The operation of bootstrap, however, does not rely on any preexisting interpretation of the population's property; rather, it generates data sets that can be used to examine the properties of the population.

Past efforts on integrating Time Use Survey (TUS) to residential building energy simulation have focused on Markov Chain Monte Carlo (MCMC) technique to generate various types of schedules for simulation [8, 10]. While the simulated occupant schedule in average agrees to the occupant schedule created directly from entire Time Use Survey data, it suffers from two shortcomings. First is that in order to make MCMC model manageable, the feasibility of deriving sub-house spatial distribution of occupants from TUS data cannot be explored. Second is the lack of examination of the robustness of MCMC model. For example, previous studies never state if different sub-sets of TUS data are sampled through random processes, will they generate MCMC models with similar transitional probability matrix along the time line?

Aiming to address these shortcomings, this study chooses to apply bootstraps approach to derive occupant behavior driven load profiles. And the robustness of the method can be easily examined by comparing if different batch of bootstrap samples generate in similar energy simulation results.

BEHAVIOUR OF THE INTEGRATIVE MODEL

A generic single family house is specified as the base case for integrative household energy model simulation (Figure 4). The north-south facing 2-story 4-bedroom generic house, sitting in Chicago suburb, is specified as 30 feet in depth and 40 feet in width with 8 feet ceiling height and 15% of exterior wall covered by windows. The house is composed of 9 functional quarters. Depend on the parameter setting of the virtual experiment, the thermal zones 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 [5] or comparable to good house constructed in 1990s (Table 2). The hourly air exchange rate (ACH) by infiltration is assumed to be 0.75.

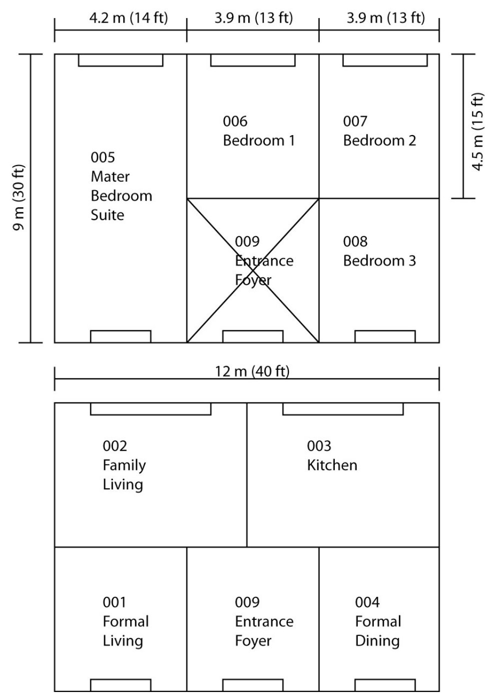

Figure 4: Layout of the Generic 4-bedroom House

Table 2: Thermal Insulation Standard of the Generic House

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	

Virtual experiment is a common approach used in complex system simulation to explore the system's stochastic behaviours. In this study, the design of the virtual experiment (Table 3) serves for three objectives. 1. To exam the role of household composition in the annual on-site load distribution patterns, 2. To contrast the effectiveness of exterior thermal insulation improvement and thermal zone refinement to annual on-site heating and cooling load. 3. To exam the robustness of the integrative model's behaviour through repetitions of sampling (bootstraps approach). Note that in term of household composition, this study contains only family made of husband, wife and dependent children.

Table 3: Virtual Experiment Settings

Variable	Value	N
Thermal Insulati on Standard	1990s Existi ng, IECC2006	2
Number of Thermal Zones	9, 1	2
Number of Occupants per House	5, 4, 3, 2	4

Constant		
Locati on	Chicago	1
Terrain	Suburb	1
Housing Type	generic 4-bdrm house	1
Air Exchange Rate Per Hour (ACH) from Infi ltrati on	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 ti mes
2. Each repeti ti on contains 30 randomly drawn family acti vity schedules from ATUS2006

Grand-sum graph is created from summing-up the simulation results of all sampling repetitions. In this study, each grand-sum graph contains 300 data points. They serve for objectives 1 and 2 of the virtual experiment.

First set of the 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 from the occupant's ATUS extracted daily activities with reference to ASHRAE metabolic heat gain reference table [1]. Appliance load is derived by common sense assumption of the appliance needed for occupant's ATUS extracted daily activities. Since both loads come directly from ATUS data, they are independent of the physical configuration of the house.

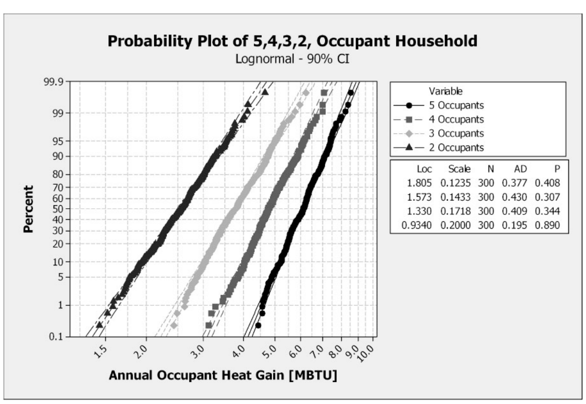

Figure 5: Annual Occupant Heat Gain Probability Plot

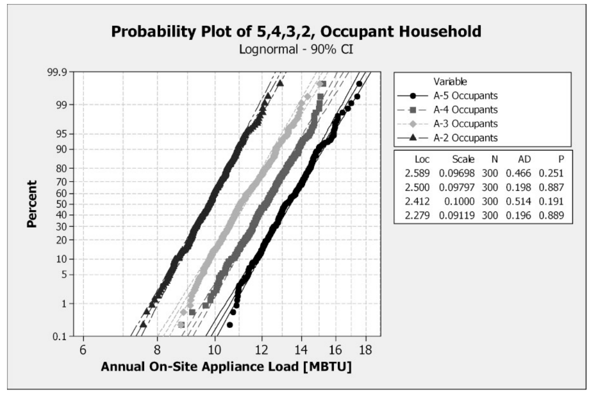

Figure 6: Annual Appliance Load Probability Plot

Second set of the grand-sum graphs are the annual on-site heating / cooling load demand probability plots. The heating and cooling loads are the energy the building environmental system needs to deliver in response to the combined effect of natural environment, building physical configuration and occupants' needs. They need to be derived through building energy simulation. Since Chicago is in heating dominate climate, two probability plots (Figures 7, 8) are used to represent two distinctive heating / cooling load distribution patterns discovered through virtual experiment.

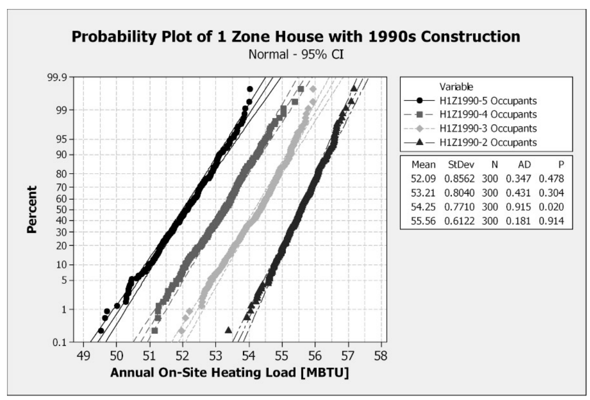

Figure 7: Annual On-Site Heating Load Probability Plot I

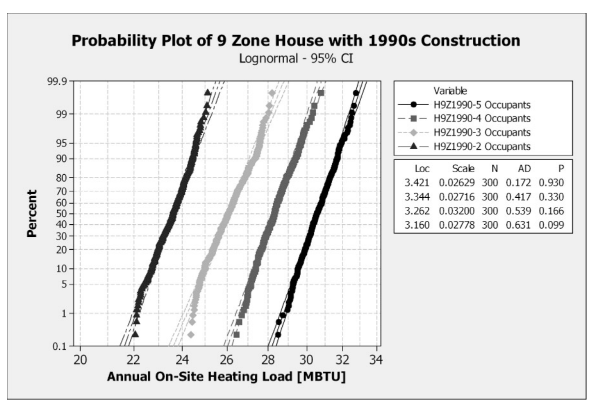

Figure 8: Annual On-Site Heating Load Probability Plot II

First heating load probability plot (Figure 7) depicts the case of infiltration dominate condition. In single thermal zone house, majority of the heating load is to compensate the cold outside air infiltrates into the house. Simulation results indicates, in infiltration dominate condition, annual heating load is of Normal distribution. The slopes of the distribution vary slightly by household composition. The higher the number of occupants in a household, the tighter the bell-shape is.

Second heating load probability plot (Figure 8) represent the case of occupant activity dominate condition. In 9 thermal zone house where HVAC system is activated only in occupied spaces, majority of the heating load is for occupant's comfort. As the system responds primary to occupants' need, its annual heating load corresponds to the loads generated by the occupants. It is by no surprise that the annual heating load of a 9 zone house shares 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 composition.

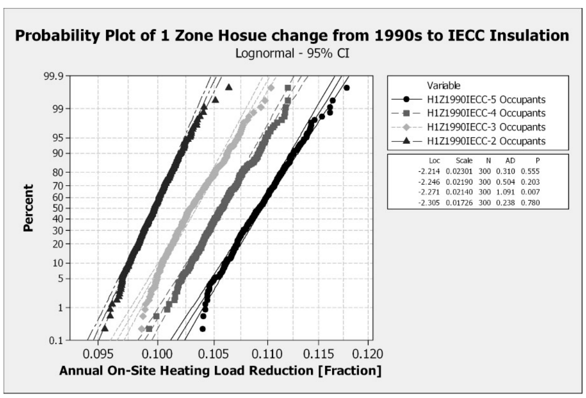

Figure 9: Load Reduction through Insulation Improvement

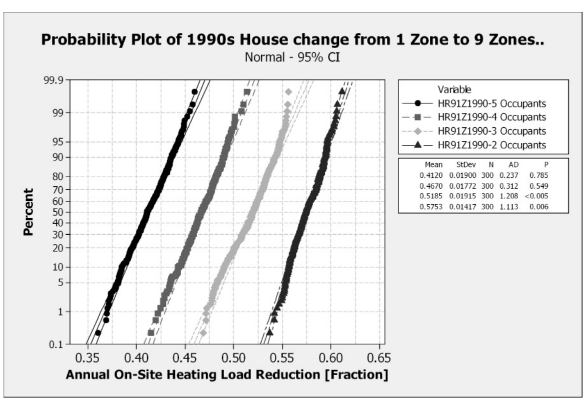

Figure 10: Load Reduction through Thermal Zone Refinement

Third and the final set of the grand-sum graphs are the heating load demand reduction probability plots.

First load reduction probability plot (Figure 9) illustrates the effect of building envelope insulation improvement of single zone house. Building envelope insulation has long been the focus of building energy conservation standards and codes for building energy efficiency improvement. This graph shows that improvement of the thermal insulation of a single zone, infiltration dominate house, which is common in reality, to IECC 2006 standard can result in averaged 10% to 11% of heating load reduction. In another word, heating load reduction is indifferent to household composition. This finding is supported by field metering studies [4].

Second load reduction probability plot (Figure 10) shows the effect of thermal zone refinement for heating load reduction. By reconfiguring the heating system from single zone to 9 zones, simulation results indicate the reduction of heating load can be multitude of that through thermal insulation improvement. 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, heating load reduction in average (41.2%) is still 4 times as effective as thermal insulation improvement. This finding strongly encourages the development of advanced residential HVAC system for future residential energy conservation.

Table 4: Mean and Standard Error of the Mean Values of Annual Occupant Heat Gain and Appliance Load of 10 Repetitions [MBTU]

	People			Appliance		
5 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
Mean top10	6.11	0.09	1.40%	13.30	0.15	1.15%
Mean top20	6.17	0.06	0.95%	13.44	0.09	0.67%
Mean top30	6.12	0.04	0.57%	13.39	0.06	0.42%
4 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
Mean top10	4.80	0.06	1.19%	12.13	0.08	0.68%
Mean top20	4.84	0.04	0.91%	12.21	0.06	0.51%
Mean top30	4.87	0.04	0.76%	12.24	0.07	0.53%
3 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
Mean top10	3.87	0.08	1.97%	11.21	0.12	1.05%
Mean top20	3.83	0.04	0.98%	11.20	0.07	0.63%
Mean top30	3.84	0.02	0.44%	11.22	0.04	0.38%
2 Occupant	Mean	SE	SE/Mean	Mean	SE	SE/Mean
Mean top10	2.65	0.07	2.73%	9.82	0.12	1.23%
Mean top20	2.63	0.05	1.94%	9.82	0.08	0.79%
Mean top30	2.60	0.02	0.90%	9.81	0.04	0.36%

"Mean" is the most commonly used statistical inference in application of any data. It give some sense of the "averaged behavior" of a population and with simple multiplication, the total amount of certain property of a population can be derived from it. According to central limit theorem, the 95% confidence interval (95.4 % to be precise) of the true mean of the population falls within the range of "Mean plus/minus 2 Stand Error of Mean" from the means of different batches of samples. A quick survey of table 4 reveals that, even only use the top 10 of the 30 data point generated in each virtual experiment repetition, the 95% confidence interval of true mean in both annual occupant heat gain and annual appliance load are within 5.5% range of the simulation mean.

Similar phenomena have been observed across all mean, 17 percentile and 83 percentile of annual occupant heat gain, appliance load, heating load and cooling load in all cells of virtual experiment. The narrow range of values of these statically inferences provide strong support for the robustness of the integrative model's behaviour.

Finally, the behaviour of the human-physical integrative household energy model is compared against the energy use behaviour of real world residences. The agreement between the load profiles (Figure 11) generated from utility metering and those (Figure 12) from simulation warrants the merit of further development of the integrative household energy model.

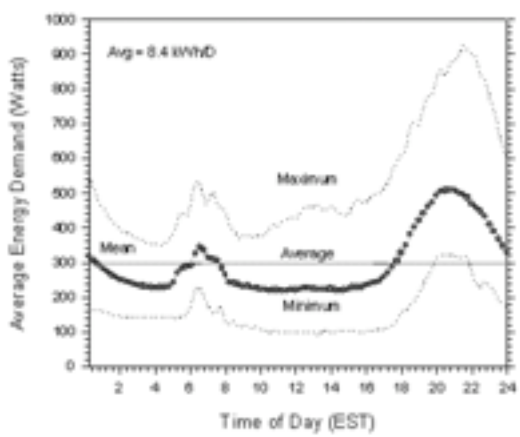

Figure 11: Daily Variation in Lighting and Appliance Plug Load Profile [Source: Figure 20 of reference 7]

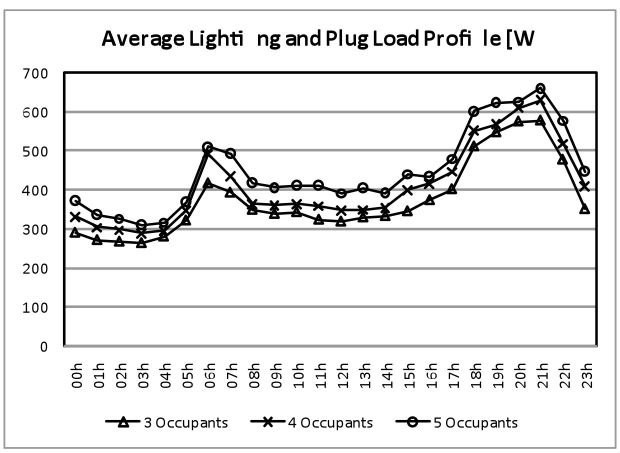

Figure 12: Averaged Lighting and Appliance Plug Load Profile by Integrative Model Simulation

CONCLUSION

The human-physical integrative household energy model provides a platform to simulate the effect of sub-house energy conservation measures. Virtual experiment showed that the use of bootstraps sampling approach on ATUS data to derive occupant's stochastic energy consumption behaviour has resulted in a robust complex system model. Virtual experiment also pointed to the development of advanced multi-zone residential HVAC system as a suitable strategy for major residential energy efficiency improvement. Furthermore, the load profiles generated from integrative model simulation agree with those from field studies. It shows that the behaviour of the integrative model is a good representation of the energy consumption behaviour of real households.

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