ResPoNSe: Modeling the Wide Variability of Residential Energy Consumption

Therese Peffer, California Institute for Energy and Environment
William Burke and David Auslander, University of California, Berkeley

ABSTRACT

People living in houses consume a substantial portion of total electricity consumption—37% of U.S. electricity end use (Energy Information Administration (EIA) 2008)—which produces greenhouse gases. U.S. households exhibit extreme variability in energy consumption from one house to another. The variation in energy consumption from differences in climate and building characteristics is well-studied; however, the effect of various appliance end use and especially the variation in the behaviors of the people that use them is less understood. Yet, this variability is critical to the effective design of technology, efficiency, and/or demand response programs in order to reduce this consumption, especially during periods of peak electricity consumption. While many techniques have been used to simulate actual residential energy consumption using models, most fail to take into account the behavioral component that contributes to the wide spectrum of residential energy consumption.

Towards this end, we have developed the Residential Power Network Simulation (ResPoNSe) to capture the spectrum—not average—of the electrical consumption of California households over the course of a hot summer day. ResPoNSe models the electricity consumption of a thousand households in order to test different demand response scenarios. Distributions of household characteristics, numbers and types of appliances per house, power consumption of the appliances, and the duration these appliances are used provide a more realistic variation of energy consumption. In turn, this simulation tool can provide a model of the spectrum of consumer response to different efficiency, marketing, or demand response programs.

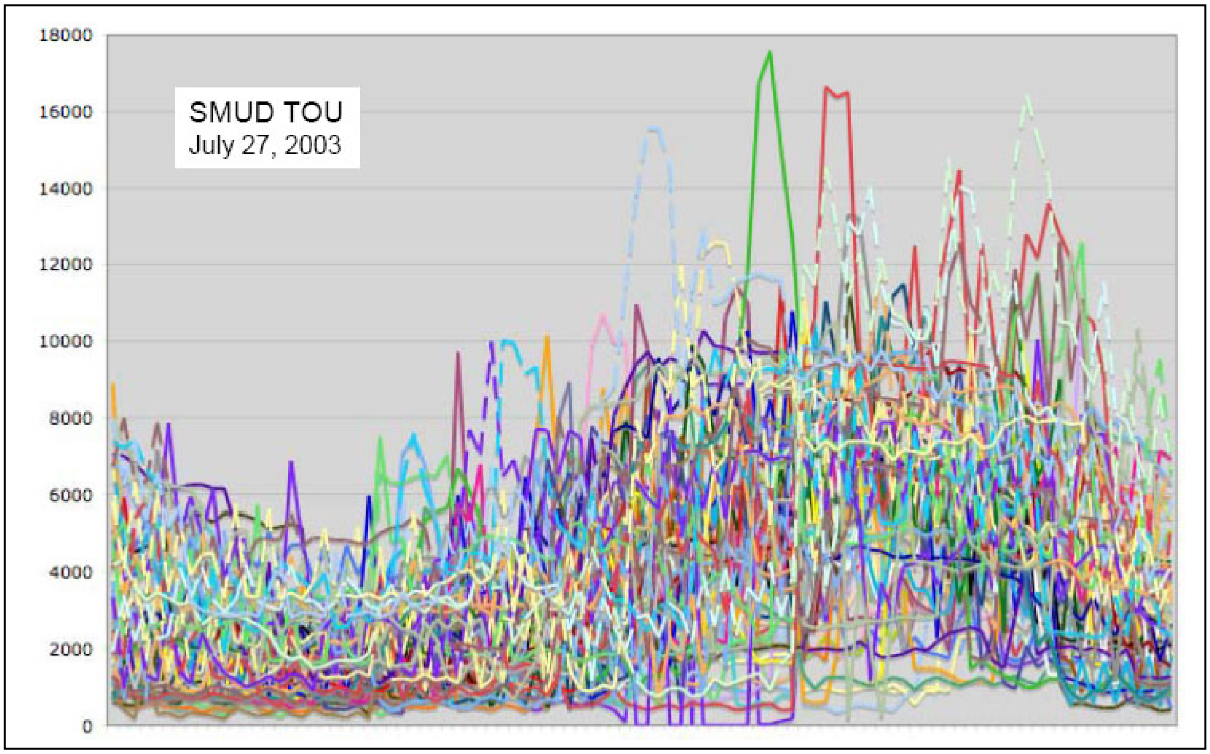
Background

The wide variation in residential energy consumption is well known, but not well understood (Lutzenhiser and Bender 2008; Lutzenhiser and Lutzenhiser 2006; Goldstein and Fairey 2010). One recent study in California showed a range of annual energy consumption from about 1000 to 22,000 kilowatt-hours per household (Lutzenhiser and Bender 2008); one quarter of the households consume nearly one half of the electrical energy (Lutzenhiser and Lutzenhiser 2006).

Many factors contribute to electricity consumption, including climate, building characteristics, and household occupant make-up and behavior. Physical factors, such as climate, the size, age, and construction of each house, the number and age of its occupants, and the amount and types of electrical appliances, are fairly straightforward. One recent study included "income, education, family size, number of people living in the home, number of hours that a home is occupied, size and type of dwelling, and stage of lifecycle (e.g., young singles, young families, families with teenagers, empty-nesters, and retired households)" as influential in energy usage (Lutzenhiser and Bender 2008).

The influence of the combinations of these factors and different behaviors due to attitudes, values, norms, income levels and so on, are somewhat more difficult, yet vital in representing the range of consumption currently seen. This same study found that of the contributors to the variation in energy consumption in California households, 39% were social variables, building characteristics explained 9%, and the environment attributed 17%; the rest (39%) was the result of the joint effect of all three (Lutzenhiser and Bender 2008). Goldstein and Fairey (2010) state that "the unexplained variance in home energy use, when using only [weather, home size, and number of occupants], is normally greater than 40% of the mean." As an example of the wide range of electricity consumption in households, Figure 1 below shows the energy consumption for one day of 70 households in the Sacramento, California area. While the early morning hours show a fairly tight range (from 200 watts to 5000 watts of power), usage during the peak period ranges from 200 to nearly 18,000 watts.

Figure 1: 24-Hour Load Shapes from 70 Households (Lutzenhiser 2008)



Many fields try to explain these differences from different perspectives, such as behavioral economics, sociology, and psychology looking at the influence of lifestyles, applying psychographics, or behavioral models (Wilson and Dowlatabadi 2007; Lutzenhiser 2009). Understanding these differences is important for forecasting energy consumption and developing both new technologies and energy conservation programs.

Several techniques have been used to simulate actual residential energy consumption using a model, such as a computer simulation tool. Swan provides an overview of various techniques to model residential energy consumption, whether top-down (econometric or technological) or bottom-up (statistical or engineering) (Swan and Ugursal 2009). Many models capture residential energy consumption, but relatively few models attempt to capture the variation imposed by occupant behavior and appliance loads. Micalek used lifestyle segmentation to develop a structural model of hourly energy use, but assumes constant energy use within each category (Michalik et al. 1997). Nishio and Asano describe using a Monte Carlo–based simulation tool to develop diverse annual household energy consumption (Nishio and Asano 2006). Tanimoto et al demonstrate a model with occupant schedule variation, but same capacity appliance loads (Tanimoto, Hagishima, and Sagara 2008). The SUNtool described by Robinson et al includes categorizing appliances and developing a stochastic model of occupant behavior to develop annual energy loads (Robinson et al. 2007). Shimoda also looks at annual regional energy by modeling various occupant household, schedules, appliance use, and weather and building (Shimoda et al. 2003). Many of these models, while they may include different occupant schedules and appliances, looked at aggregate annual energy.

For the purposes of evaluating different demand response scenarios to reduce peak electricity demand, we wanted a model that provided diverse household energy consumption on an hourly basis. In addition, we wanted to incorporate uncertainties with respect to occupant schedules and the use of appliances. Moreover, we wanted the types and capacities of the appliances to reflect reality—a wide variation of power and energy consumption. We were not after aggregate or typical behavior, but wanted to represent a sample of households with a spectrum of energy consumption throughout a given day.

Research Design

For the Residential Power Network Simulation (ResPoNSe) model, we chose a bottom-up approach using hybrid engineering methods such as distributions as well as archetypes to provide detailed end-use appliance information as well as capture broad categories of housing. Since the initial funding involved analyzing demand response scenarios in California, we focused our efforts on modeling the spectrum of California houses, especially in hot climates where air conditioning is needed.

Building Characteristics: Size, Age, and Construction Type

The initial model contained a neighborhood of houses, with each house having unique properties of construction type and air conditioner equipment. In addition, each house had a thermostat. Burke and Auslander developed a dynamic thermal model of the house which is described in detail in (Burke and Auslander 2008) and (Burke, Peffer, and Auslander 2010).

We used several sources of information to try to develop a representative sample of existing houses in California. Currently California has a little over 12 million housing units. The year a house was constructed can indicate the type of construction (i.e., insulation levels, amount of mass), and to some extent the size of the house (i.e., square footage and ceiling height) and size and efficiency of the HVAC equipment. All of these elements affect the energy consumption. California houses range from small units built at the turn of the century to large “McMansions” of the last few years over 3500 sf.

Figure 2 shows that approximately 64% of the existing housing stock was constructed before the first Title-24 energy standards took place in 1978[1]. These houses are assumed to have an insulated roof, uninsulated walls over an uninsulated crawl space (less than half had slab-on-

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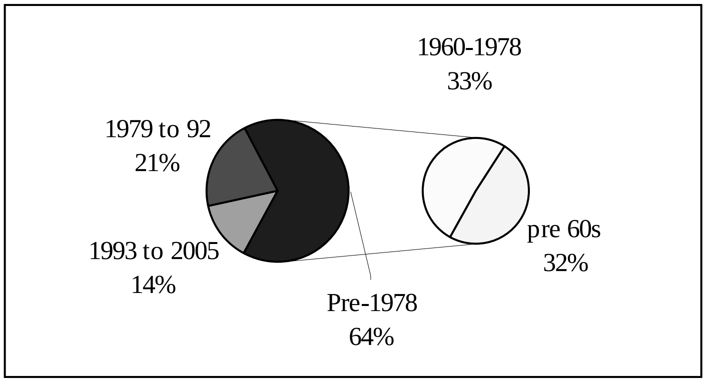
[1] We realize that for each of these categories, some houses will have been renovated with higher efficiency equipment or additional square footage. The simulation model can, but currently does not, account for this.

grade construction), single paned windows[2], and a gas furnace (0.75 AFUE) (from Table 3-7 of (California Energy Commission (CEC) 2001)). Only about 29% of all housing units constructed at this time (before 1975) have central air conditioning (with an assumed SEER of 8 or less) and another 17% have room air conditioners or evaporative units (CEC, 2004). Half of the pre-1978 houses were built before the 1960s, when the typical house size in the U.S. was 700-1200 sf (average 983 sf in 1950s). House size gradually increased, with the typical house built in 1980 at about 1600 sf.

Figure 2: Housing in California by Year Constructed (US Census 2009)



Approximately one fifth of the housing stock (21%) was constructed between 1979 and 1992. It is assumed that these houses have insulated roofs and walls, and a gas furnace (0.78 AFUE) (from Table 3-7 of (California Energy Commission (CEC) 2001)). About half of these houses have slab-on-grade construction versus uninsulated crawl space. In 1983, the energy standards changed to require double paned windows in houses, so about half of these houses most likely have single paned windows, and the other double paned windows (Nittler, LBNL, correspondence). Approximately 60% of these homes have central air conditioning (with an assumed SEER of 8-9), with about 9% with room air conditioners or evaporative units (CEC, 2004). The median size of houses from 1979 and 1983 was approximately 1600 sf, and the median size of houses constructed from 1984-1992 ranged from 1600-1900 sf (National Association of Home Builders (NAHB) 2009).

About 14% of the housing stock has been constructed since 1992 (to 2005). These houses are assumed to have insulated roofs, increased wall insulation, double paned windows, insulated ducts and a gas furnace (0.78 AFUE) (CEC ACM, Table 3-7). Half or more of these houses have slab-on-grade construction: approximately 50% in 1992, rising to 63% in 2005; the remainder would have insulated floor over crawl space construction. About 76% of these homes have air conditioning (with an assumed SEER of 10-13+), with only 1% with room air conditioners or evaporative units (CEC, 2004). The median area ranges from 1900 sf to 2300 sf. Many large houses were constructed in the last two decades. The number of homes constructed that were 2400 sf or larger was 30% in 1996, compared to 18% in 1986. In 2001, 1 in 8 (12.5%) houses were constructed that were over 3500 sf. In 2005; about 40 percent of the new homes had less

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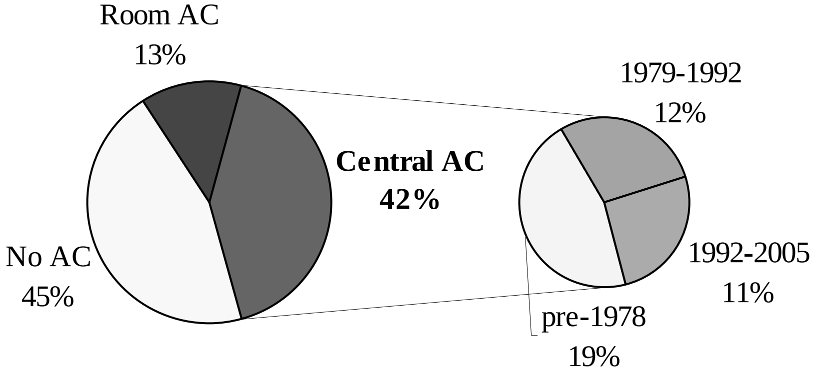
[2] A percentage of these homes have been renovated to replace the single paned windows with double paned. The RECS indicates that 53% of California houses have single paned windows (Energy Information Administration (EIA) 2005). Given that 64% were built with single paned windows, this indicates less than 20% of these houses have replaced their windows with double paned windows.

than 2,000 square feet of finished living area, while 23 percent were 3,000 square feet or larger (National Association of Home Builders (NAHB) 2009).

The ceiling height of the houses in different years of construction is difficult to evaluate. Older houses (pre-1940s) often have higher ceiling heights of 9-11 feet, depending on the scale/expense of the house at the time; old Victorian houses, for example, tend to have higher ceiling heights. Typical house construction of the 50s-70s had “standard” 8 foot ceilings. In recent years, cathedral (sloped) ceilings and 9-10 foot ceilings have been popular in residential construction. The RECS 2005 survey indicated that roughly 40% of California households responded that they had “unusually high ceilings” (Energy Information Administration (EIA) 2005).

Note that of the houses in California with central air conditioning, nearly half of these were built before the 1978 energy codes, as seen in Figure 3 below.

Figure 3: Percent of California Houses with Air Conditioning, Showing the Year of Construction of Houses with Central Air Conditioning.



The simulation tool thus “draws” a number of houses. Then it selects an area for each based on the probabilities listed in Figure 2 above for age. Next, it assigns an appropriate insulation level and chooses whether a mass floor is present. Finally an air conditioner size and efficiency are selected with some weighting on size and age of house.

Occupants: Number, Age, and Schedule

After developing the house model, its occupants are developed. Each occupant is assigned a relative age (adult or child) according to the statistics we found available. Approximately 25% of California households have a single adult; 6% have one adult plus children. About 24% of households have two adults; another 23% have two adults plus children. Finally, about 22% of households have three or more adults, with or without children (U.S. Census Bureau 2004). The number of occupants per household affects some appliance use, such as dishwashing and clothes washing and drying.

The next step is selecting a schedule for each occupant: whether he or she is asleep, awake at home, or away. Approximately 57% of houses in California have someone home all day; only about 11% of people work at home (Energy Information Administration (EIA) 2005). These occupants have a random leaving/arrival time assigned to them. Of the households where someone works, the schedule of the time one leaves to go to work varies. According to Census information, approximately half the population (53%) leaves between 6:30 am and 8:30 am; 20% leave between 12 am and 6:30 am to go to work (Reschovsky 2004). We based the probabilities of occupants leaving for work on this data. We looked at activity surveys such as in (Wiley 1991) to determine types of typical activities and how this related to energy consumption.

Appliances

After developing the house model and its occupants, appliances are also assigned. The probability that a type of appliance will be present is based on surveys of saturation rates from the Residential Appliance Saturation Survey (RASS) (California Energy Commission (CEC) 2004). The category of use framed the time and duration of usage, based on Robinson's work (Robinson et al. 2007). Robinson defined appliances as A: appliances that do not depend on occupancy, B: switched on only when occupant present for a duration of time, and C: appliances that are switched on and off by an occupant present in the house. The energy consumption was based on many sources of information on appliance energy consumption (U.S. Department of Energy 2006; Energy Efficiency and Renewable Energy 2005; California Energy Commission (CEC) 2004) and is described in more detail in (Peffer 2009). The distribution of usage was based on what information we could find, but ultimately our best guess. The distributions of appliances and data are described below:

- Category A: appliances that do not depend on occupancy
  - 100% Saturation Refrigerator/25% Saturation 2nd refrig/Freezer: steady load: 94-343 watts/hour
  - Size of house affects standby loads of miscellaneous appliances & lights: 50-100 watt/hour/1000 sf

- Category B: appliances that are switched on once when an occupant is present and continues for a period of time, then turns itself off.
  - 70% Saturation: Dishwasher: 3-7x week: 880-2600 watts/cycle: 60-90 minutes
  - 95% Saturation: Clothes washer: 1-7x/week: 250 watts for 30 minutes
  - 34% Saturation: Clothes dryer: 1-7x/week: 1800-5000 watts for 45 minutes.
  - 41% Saturation: Range/oven: 3-7x/week: 1300-2660 watts for 10-60 minutes

- Category C: appliances that are switched on and off by an individual (assumes occupant present in house)
  - 96% Saturation per household: Television: 100-300 watt/hour, 1 to 5 hours
  - 76% Saturation: Personal Computer: 160-240 watt/hour, 1 to 24 hours
  - 100% Saturation: Lights: 20-200 watt/hour, 1 to 8 hours

Thermostat

The energy consumption of the air conditioner is a dynamic relationship between the climate, building characteristics, efficiency of the HVAC system, and occupant-chosen thermostat setting. Each occupant is assigned a "motivation" and thermal comfort range. As noted by others (Ubbelohde, Loisos, and McBride 2003; Hackett and McBride 2001), the range of temperatures found to be comfortable in homes is much wider than in commercial settings.

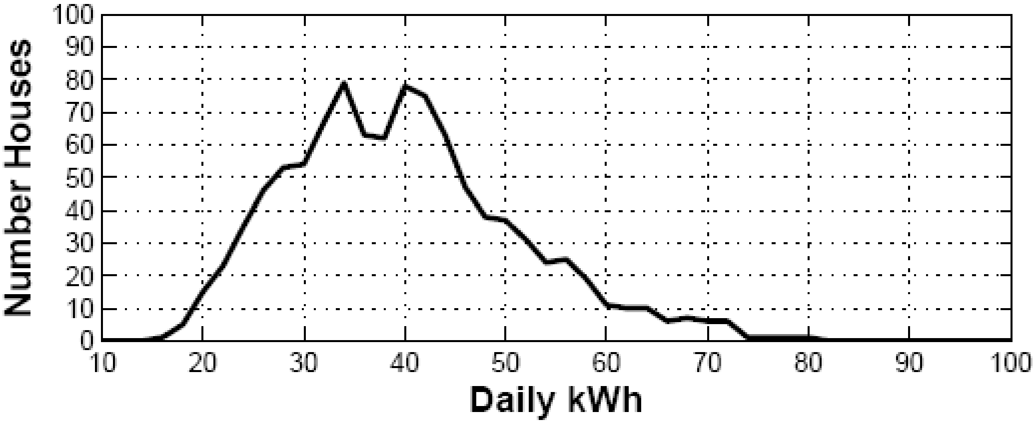
We included what we could find in the literature on residential thermal comfort. For example, some people prefer an indoor temperature of 74F in the summer; others tolerate temperatures in the mid 80s (Hackett and McBride 2001). The motivation reflects the degree to which the occupant will interact with the thermostat to change the temperature at any given point in time and provides a degree of uncertainty.

After drawing a house, its occupants with their respective motivations and schedule, and the appliances, the simulation tool then develops a neighborhood of approximately 1000 unique households. The simulation tool runs these houses over a 24 hour period on a 15 second time step through a single hot summer day, using climate data from Fresno, California.

Testing & Results

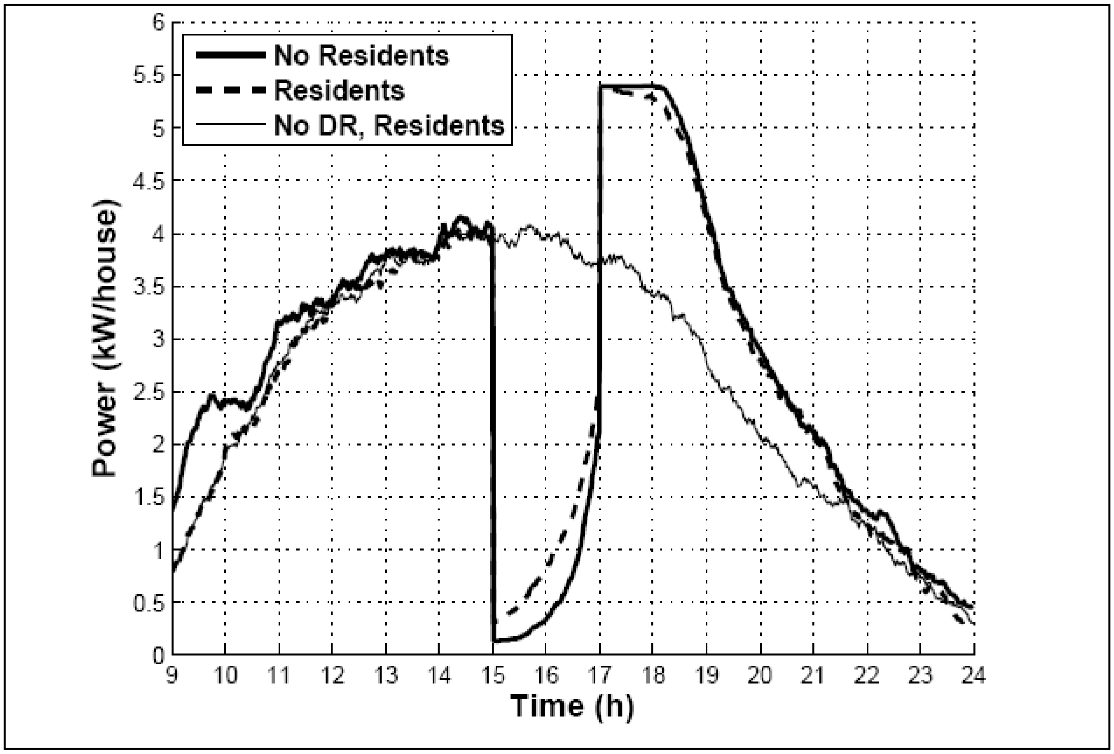
The simulation tool was tested in incremental steps. The initial tests verified the thermal house model with HVAC equipment, thermostat, and occupant presence by comparing the results with a simulation tool based on the California Non-Residential Engine (found at the heart of many of the simulation tools currently approved for establishing performance compliance with California Title 24 energy code). We selected 1000 houses to simulate, as an optimum between simulation speed and sample size. Figure 4 below shows a histogram of houses from the model, covering a spectrum of energy use just from the HVAC unit on a hot summer day.

Figure 4: Histogram of Houses Showing Energy Use from HVAC System



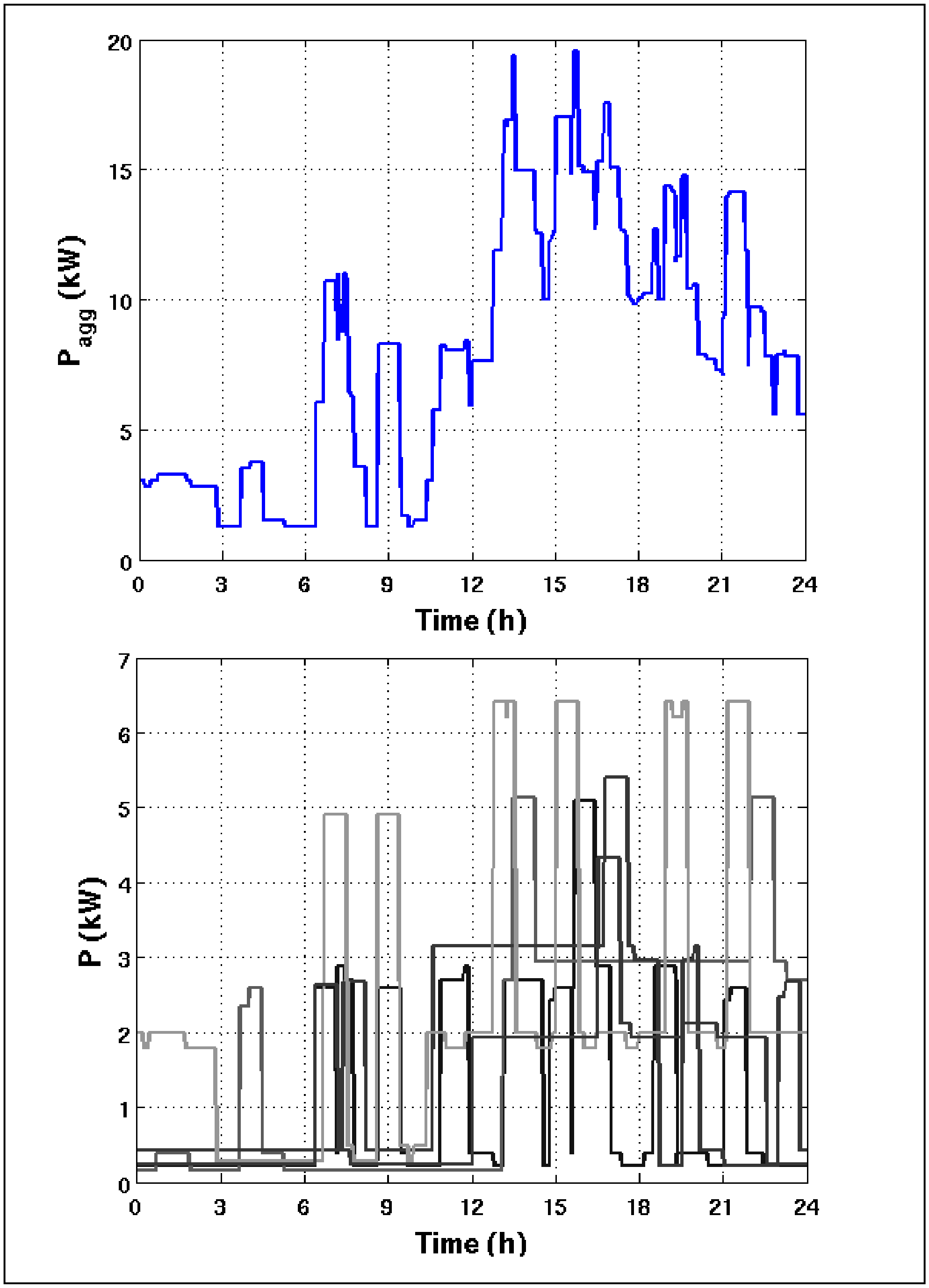
We then looked at the impact of Demand Response, with occupants having the option to reduce air conditioning use via the thermostat setpoint during peak demand events. We referred to various Demand Response (DR) pilot studies. For example, many studies show that approximately 10% of the subjects turned off the air conditioner and left home rather than pay the higher price to run the air conditioner; while many people act to decrease energy use, a percentage in each study increase energy use during peak periods. Figure 5 below shows the results of the power consumption of 1000 houses just with HVAC systems. These houses assumed the presence of a Programmable Communicating Thermostat that would automatically respond to demand response events by changing the thermostat setpoint. The presence of people in homes slightly increased the power consumption during the DR event, showing the effect of occupant thermal comfort preference sometimes overriding the DR event signal.

Figure 5: Power Consumption with or without Residents During a Demand Response Event



Finally, we added additional appliances, and looked at the overall power consumption as well as spectrum of consumption among the houses. Figure 6 below shows the aggregate and individual energy consumption for five houses in the model, from air conditioning, a refrigerator, computer, and electric clothes dryer. The plot of total energy consumption from just five houses is beginning to resemble typical peak summer time consumption; with more houses modeled, this pattern should be even more evident. The plot of the individual loads shows how this peak load is constructed.

Figure 6: The Aggregate (above) and Individual (below) Daily Energy Consumption from Five Houses with HVAC, Refrigerator, Computer and Clothes Dryer Loads



Conclusion

We developed ResPoNSe, a simulation tool that creates thermally dynamic house models, each with unique construction properties, HVAC equipment, occupants, and appliances to represent the wide variation in California residential energy use. This model is different from other current models in that it can show a spectrum of individual household energy consumption over a 24 hour period. We disaggregated whole house energy loads and invoked uncertainty in human behavior to try to represent real consumption patterns in individual houses. Simulation results with just the air conditioning show a wide spectrum of electricity consumption for a single day. The presence of people—their different thermal comfort preferences and probability of changing the thermostat setting—changes the demand response effect. The addition of other appliances shows the effect of unique and multiple occupants and appliance energy consumption.

We learned a great deal from just building the model, such as the fact that about half of the air conditioners in California houses are in houses built before the energy codes. The distribution of appliance usage was based on what information we could find, and ultimately, our best guess. We wanted to create a model that, based on our best ability to represent real end uses and behaviors, would look similar to the energy consumption of real households in Figure 1.

Currently, the results show promise in modeling the spectrum of household energy use, with more work to be done. The advent of interest and technology development in smart grid, interval metering, and plugload metering parallels the development of this tool; the tool can be refined and validated as more data becomes available. The simulation tool can be further refined by adding correlation effects among the various attributes, for example, of socio-economic class and energy consumption.

ResPoNSe can be easily modified to reflect different demographics or motivations that will affect appliance energy consumption. For example, different programs might be most effective on specific segments of the population. The tool can model various responses, instead of assuming “rational” behavior by the occupant. Our hope is that this tool can be used to demonstrate different demand response scenarios, and test the effect of different programs that target specific appliances, whether air conditioning, clothes dryers or plasma televisions.

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