A highly resolved modeling technique to simulate residential power demand

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HIGHLIGHTS

▶ Activity patterns for individuals are modeled using a heterogeneous Markov chain, calibrated with time-use data.
▶ The residential demand model allows reconstructing power consumption of a single or an aggregate group of households.
▶ A rigorous statistical validation framework has been developed to validate the proposed model.
▶ The residential demand model can serve as a tool to evaluate the effects of different technologies.
▶ The simulated residential demand loads show highly realistic patterns.

ARTICLE INFO

ABSTRACT

This paper presents a model to simulate the electricity demand of a single household consisting of multiple individuals. The total consumption is divided into four main categories, namely cold appliances, heating, ventilation, and air conditioning, lighting, and energy consumed by household members' activities. The first three components are modeled using engineering physically-based models, while the activity patterns of individuals are modeled using a heterogeneous Markov chain. Using data collected by the U.S. Bureau of Labor Statistics, a case study for an average American household is developed. The data are used to conduct an in-sample validation of the modeled activities and a rigorous statistical validation of the predicted electricity demand against metered data is provided. The results show highly realistic patterns that capture annual and diurnal variations, load fluctuations, and diversity between household configuration, location, and size.

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1. Introduction

This era of fossil fuel dependency and concern about greenhouse gas emissions has increased interest in the use of policy and technology solutions to reduce and shift energy use. The residential sector accounted for about 22% of total primary energy consumption in the US in 2009, indicating that there are major potential gains from implementing such solutions in residential settings [1]. The potential energy, cost, and emissions savings of such policies and technologies can be investigated by modeling

their impacts on residential energy demand and the resulting interactions between this demand and the power grid, renewable generation, energy storage, and plug-in electric vehicles.

Two general classes of techniques are available to model residential power demand: top-down and bottom-up models [2]. Top-down models use estimates of total residential sector energy consumption, together with other pertinent macro variables, to attribute energy consumption to characteristics of the housing sector. This class of models can be compared to econometric models, which require little detail of the actual consumption process. These models treat the residential sector as an energy sink and regress or apply factors that affect consumption to determine trends [2–5]. Depending on availability, the input data required to develop these models can include the structural characteristics of the dwellings, occupants and their behavior, appliances' characteristics, historical energy consumption, weather conditions, and macro-economic

indicators. Stochastic predictors, based on time-series approach, such as auto regressive moving average methods, are also used to forecast home energy consumption [6–8].

Bottom-up models, on the other hand, identify the contribution of each end-use towards the aggregate energy consumption of the residential sector [9–11]. Bottom-up approaches refine the modeling of energy consumption, allowing the simulation of the effects of technology improvements and policy decisions. These models calculate the energy consumption of an individual or group of households and extrapolate the results to a region or nation. This aggregate result is generally accomplished by using a weight for each modeled house or group of houses based on its representation of the sector [2]. Moreover, the bottom-up approach has the capability of determining total energy consumption of the residential sector without relying on historical data. Common input data to bottom-up models include dwelling characteristics (e.g., size and layout, building materials, and appliances' characteristics), weather conditions, household occupant behavior and related use of appliances, lighting use, and characteristics of heating, ventilation, and air conditioning (HVAC) systems. This high level of detail represents the strength of bottom-up models, providing the ability to model the impact of different technology options and allowing the implementation of energy optimization techniques. On the other hand, the use of such detailed information, in particular regarding household members' behavior, introduces great model complexity. The input data requirements are typically greater than that of top-down models.

A number of works propose using bottom-up techniques to model residential energy use. In 1994 Capasso et al. [9] propose a model for evaluating the impact of demand side management on residential customers. A Monte Carlo method is used to capture the relationship between residential demand and the psychological and behavioral factors typical of the household occupants. Richardson et al. [10] introduce a Markov-chain technique to generate synthetic active occupancy patterns, based upon survey data of people's time-use in the United Kingdom. The stochastic model maps occupant activity to appliance use, creating highly-resolved synthetic demand data. The same authors also include a lighting model, which accounts for natural daylight [12]. Widén et al. [11,13] follow a similar approach to relate residential power demand to occupancy profiles. The model is calibrated and validated against relatively small time-use and electricity consumption datasets collected in Sweden. The authors show that realistic demand patterns can be generated from these activity sequences.

In this work a highly-resolved bottom-up approach is developed to model residential energy demand in the United States. The model is calibrated to simulate an average household in the US and household members' behaviors are simulated by using a Markov process calibrated using time-use data collected in the 2003–2009 American Time Use Survey (ATUS).[1] The proposed model differs from existing bottom-up techniques in four important ways. One is that HVAC use and demand are modeled with much greater detail using an engineering physically-based approach. The second is that a large-scale time survey dataset is used to calibrate the behavioral model—existing approaches rely on much smaller datasets. Third, some of the parameters of the model, which are difficult to estimate, are calibrated using actual metered residential electricity data. Finally, rigorous statistical tests are used to validate the model by comparing estimated demand profiles generated by the model against metered residential electricity demand data. In this way the stochastic features of the modeled residential demand profiles are validated.

This model can be used as a tool to simulate the *status quo* of the residential sector and, ultimately, evaluate the impact of energy policies and different technology adoption and deployment scenarios on energy use, cost, and emissions. The proposed model can also be used as an input to detailed power system simulations, for instance determining the impacts of diurnal load patterns and renewable uncertainty and variability on day-ahead and real-time unit commitment, dispatch, and power flows. High model resolution is needed to make the model suitable to be used for such analysis. This framework allows consumers to compare costs and benefits with different load schedules and enables energy consumers to participate actively in energy markets. It can also help utilities evaluate the use of price signals as a means of shaping the electricity load in order to reduce production costs and make demand more flexible to facilitate the integration of renewable energy sources. Moreover, the proposed model can be used as an input to long-term capacity planning and expansion studies. Depending on the specific end application, the model may be used to generate a load profile for an individual household, or the load profiles of multiple buildings may be aggregated to simulate the load of a broader system.

2. Model structure

The aim of the proposed model is to generate the electricity demand profile of a residential household. Residential demand profiles are, by nature, variable and depend on multiple physical factors, such as weather, temperature, and dwelling characteristics but also on the behavior of household members. Thus the modeled demand depends on physical properties and the location of the dwelling and on the number and typology of individuals living in the household. Because the model is intended to generate a typical residential demand profile, individual behavior is modeled stochastically.

The total electricity power demand of a dwelling, $\dot{W}$, is computed as:

$$\dot{W} = \dot{W}_{cold} + \dot{W}_{HVAC} + \dot{W}_{act} + \dot{W}_{light} + \dot{W}_{fix}$$

where $\dot{W}$ is the total electric power demand, expressed in W; $\dot{W}_{cold}$ represents the power used by cold appliances, such as refrigerators and freezers; $\dot{W}_{HVAC}$ is the electric power used by the HVAC system to maintain the desired thermal comfort in the house; $\dot{W}_{act}$ is the electricity use directly related to activities of the household members, i.e., cooking or use of dishwasher, etc.; $\dot{W}_{light}$ is the electric power consumption due to lighting; and $\dot{W}_{fix}$ is a constant time-invariant term that represents ubiquitous electric consumption, i.e., lights that are always on and appliances' stand-by power.

Each of these terms includes power losses due to system inefficiencies, as well as thermal dissipation and electrical losses. The power consumption categories present different dependencies, which determine the underlying structure of the modeling approach used. $\dot{W}_{cold}$ depends only on the size and number of the cold appliances in the house—the effect of external temperature and individuals opening the cold appliances' doors are neglected. $\dot{W}_{HVAC}$ depends on the physical characteristics of the HVAC system installed, the thermal comfort required by the occupants, properties of the thermal envelope of the dwelling, and on weather conditions that the household has to withstand. $\dot{W}_{act}$ depends on the behavior of the household members and on activity to power conversion factors, namely the wattage of appliances used when energy-intensive activities are conducted. $\dot{W}_{light}$ depends on the amount of natural lighting available and building occupancy. This is captured using different lighting power conversion parameters during the day and night.

The lighting power conversion parameters and $\dot{W}_{fix}$ are difficult to assess, and are computed using a linear regression model against actual metered data provided by American Electric Power (AEP). Detailed models for the cold appliance, HVAC systems, and lighting demand components are available in the literature [14–16].

The model is flexible in design, allowing for energy consumption to be modeled at any time resolution desired by the user. The case study presented in Section 3 uses a 10-min time step to model electricity demand. Moreover, the HVAC model uses a 1-s time resolution to capture the thermal dynamic evolution of the air inside the building. The data against which the model is validated reports electricity consumption at hourly time steps. Thus, the simulated 10-min consumption profiles and the 1-s HVAC consumption are aggregated to arrive at hourly values, which can be compared to the metered data.

2.1. Cold appliance energy consumption

Recent estimates place the average nominal power rating of a refrigerator at about 725 W.[2] Moreover, the total yearly electricity consumed by cold appliances in a typical American dwelling was estimated to be 14.9% of total residential electricity consumption in 2010. The U.S. Department of Energy's Energy Information Administration reports annual per-household electricity consumption of 11,496 kWh in 2010.[3] These values imply 1,713 kWh of annual per-household cold appliance energy consumption. Assuming that a refrigerator is an on/off device that always operates at its nominal power when on, the average operating time can be estimated by dividing annual energy consumption by nominal power as:

$$t_{op} = \frac{1713 \text{ kW h}}{0.725 \text{ kW}} = 2363 \text{ h}.$$

Cold appliance consumption is simulated using a Bernoulli distribution, with the success probability fixed so the expected on time of the appliance is 2363 hours every year. Assuming that the use is evenly distributed during the year, this implies that a typical cold appliance works 27% of the time. Since the model is implemented using a 10-min time step this translates into a cold appliance running for five random 10-min intervals every 3 hours. This would yield daily energy consumption of about 4.83 kWh. Fig. 1 shows an example of the resulting power profile over a 1-day period.

2.2. HVAC energy consumption

Space conditioning end-use includes heating, ventilation, and air conditioning and represents the most significant residential energy consumption in the United States. The main purpose of an HVAC system is to maintain indoor air quality through adequate ventilation with filtration and provide thermal comfort [14]. Over 70% of residential buildings in the US use central forced-air distribution systems for heating and air-conditioning purposes [17]. The model proposed in this work uses an approach based on overall thermal resistance theory to simulate the behavior of a typical air-based HVAC system [18]. A control volume analysis, based on fundamental principles of thermodynamics and heat transfer is
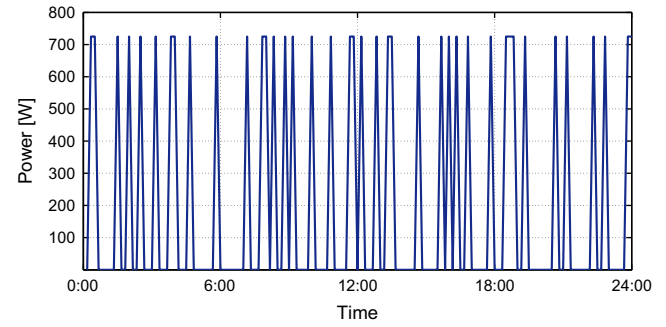
Fig. 1. Simulated power consumption of a cold appliance during a one-day period.

performed for the volume including solely the air present in the house, as illustrated in Fig. 2.

The thermal dynamic evolution of the air is given by:

$$m_a c_p \frac{dT_a}{dt} = \dot{m}_{HVAC} \cdot c_p (T_{HVAC} - T_a) - \frac{T_a - T_\infty}{R_{tot}}, \tag{1}$$

where the variables are defined: m_a as the air mass inside the control volume (kg); c_p as the air specific heat (kJ/kg K); T_a as the air temperature inside the control volume (°C); $\dot{m}_{HVAC}$ as the HVAC air flow rate (kg/s); R_{tot} as the equivalent thermal resistance of the household envelope (K/W); T_{HVAC} as the HVAC supply air temperature (°C); and T_∞ as the environment temperature (°C).

R_{tot} is computed as:

$$R_{tot} = \left[\left(\frac{1}{h_o \cdot A_{wall}} + R_{wall} + \frac{1}{h_i \cdot A_{wall}} \right)^{-1} \right.$$
$$\left. + \left(\frac{1}{h_o \cdot A_{wind}} + R_{wind} + \frac{1}{h_i \cdot A_{wind}} \right)^{-1} \right]^{-1},$$

where h_o and h_i are the outside and inside convective coefficients, respectively. A_{wall} and A_{wind} are the surface of walls and windows in contact with the environment, respectively. These surfaces are normal to the direction of heat transfer. R_{wind} and R_{wall} are the thermal resistances of the windows and walls, respectively. Values of these parameters are reported in Table 2.

The first term on the right hand side of Eq. (1) represents the energy supplied by the HVAC system, namely the energy carried by the air leaving the HVAC system and entering the household at temperature T_{HVAC}. The second term represents the heat transfer between the household, at temperature T_a, and the environment, at temperature T_∞.

Eq. (1) can be analytically solved to obtain the dynamic evolution of the temperature of the air inside the household as:

$$T_a = [T_0 - A]e^{-t/\tau} + A,$$

where

$$A = \frac{\frac{T_\infty}{R_{tot}} + \frac{\dot{m}_{HVAC} \cdot T_{HVAC}}{m_a}}{\frac{\dot{m}_{HVAC} \cdot c_p + \frac{1}{R_{tot}}}{m_a \cdot c_p}},$$

$$\frac{1}{\tau} = \frac{\dot{m}_{HVAC} \cdot c_p + \frac{1}{R_{tot}}}{m_a \cdot c_p},$$

and T_0 represents the initial condition.

The HVAC model requires several assumptions regarding the physical characteristics of the system, including the size of the ducts, fans, and thermal machines. Ductwork sizes are determined by minimizing the net present installation and operating cost [18]. The ducts and fans are sized such that the maximum air flow rate matches the worst winter and summer conditions for the location of the building being modeled (values chosen for these conditions and other HVAC design parameters described below are reported
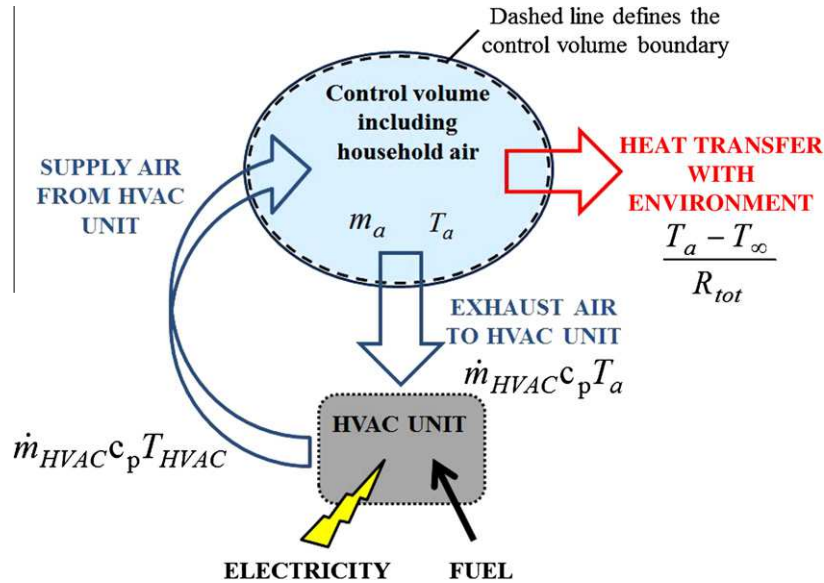
Fig. 2. Schematic of the control volume used in HVAC analysis.

Table 1
Available air flow rates and furnace sizes for residential systems and resulting temperature of the air [°C] from the furnace [1].

	Input capacity (kBTU/h)											
	45	50	60	70	75	80	90	100	115	120	125	140
Air flow (cfm)												
800	50	53	59	66								
1200	40	42	47	51	53	55	59	64				
1600				43	45	47	50	53	58	59	61	
2000							44	47	50	52	53	57

in Table 2). Once the air flow rate is chosen among the most common available options for residential systems, the furnace necessary to match the worst winter condition is selected.

The selection of both air flow rate and the nominal power of the furnace lead to a fixed value of the temperature of the air entering the household that, depending on the specific system chosen, varies from 40 to 66 °C. The possible air flow rate and furnace size combinations, as well as the returning air temperature from the HVAC system, for commercially available systems are reported in Table 1.[4] Since cooling machines are more scalable than furnaces and a greater variety of models is available on the market, it is assumed that the temperature of the air from HVAC during the summer is constant and equal to 13 °C [18].

The model determines whether each day modeled is a heating or cooling day. This is meant to replicate the decision made by the occupant to switch one of the two HVAC systems on. A simple but realistic control strategy is implemented based on a relay that allows a tolerance of 1 °C around the desired temperature, which is set to 21.1 °C (70 °F).

HVAC energy consumption is divided into two components: the power consumed by the fans to circulate the air, $\dot{W}_{fan}$, and the power absorbed by the HVAC equipment. The former can be computed as:

$$\dot{W}_{fan} = \frac{\dot{m}_{HVAC} \cdot \Delta P_{tot}}{\eta_{fan} \cdot \eta_{motor}},$$

where the total pressure drop, ΔP_{tot}, is defined to equal $P_{static} + \rho \frac{v^2}{2}$. P_{static} is the static pressure drop, ρ is the air density, and v is the air

velocity. In this work v is assumed to equal 4 m/s [18], the midpoint of the range of suggested values to avoid noise. η_{fan} and η_{motor} are the efficiencies of the fan and motor, respectively, and the product $\eta_{fan}\eta_{motor}$ is assumed to equal 0.15 [19].

The HVAC equipment energy consumption differs depending on whether the system is in cooling or heating mode. In heating operation, the energy required to maintain the desired thermal condition in the household, namely the power required to generate the necessary heat, can be obtained using two approaches: traditional furnace heating or an all-electric HVAC system. In the former case, the primary power required, $\dot{E}_{primary}$, can be computed as:

$$\dot{E}_{primary} = \frac{\dot{m}_{HVAC} \cdot c_p \cdot (T_{HVAC} - T_a)}{\eta_{furnace}},$$

where $\eta_{furnace}$ the efficiency of the furnace, which is assumed to equal 0.85.

This power is directly obtained via combustion of fuels (e.g. natural gas, fuel oil, or kerosene). In such a case $\dot{E}_{primary}$ does not contribute to the building's electricity load, which is represented solely by the power consumed to circulate the air, namely $\dot{W}_{fan}$. Alternatively the heat can be obtained using an all-electric system. In this second case the heat is converted into an electric load by means of a coefficient of performance, *COP*. Thus the primary energy required, $\dot{E}_{primary}$, equals the electricity consumption, $\dot{W}_{heating}$, which is computed as:

$$\dot{E}_{primary} = \dot{W}_{heating} = \frac{\dot{m}_{HVAC} \cdot c_p \cdot (T_{HVAC} - T_a)}{1 + COP}.$$

Note that *COP* is defined as the thermal energy added to the house per unit of electric energy absorbed by the HVAC system, or as:

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[4] The values in the table are given in imperial units, since these units are used in the design and marketing of HVAC systems in the US.

(a) Simulated temperature evolution in a typical household
on 9 May, 2010 in the Indiana/Michigan area.

(b) Hourly HVAC electricity consumption in a typical household
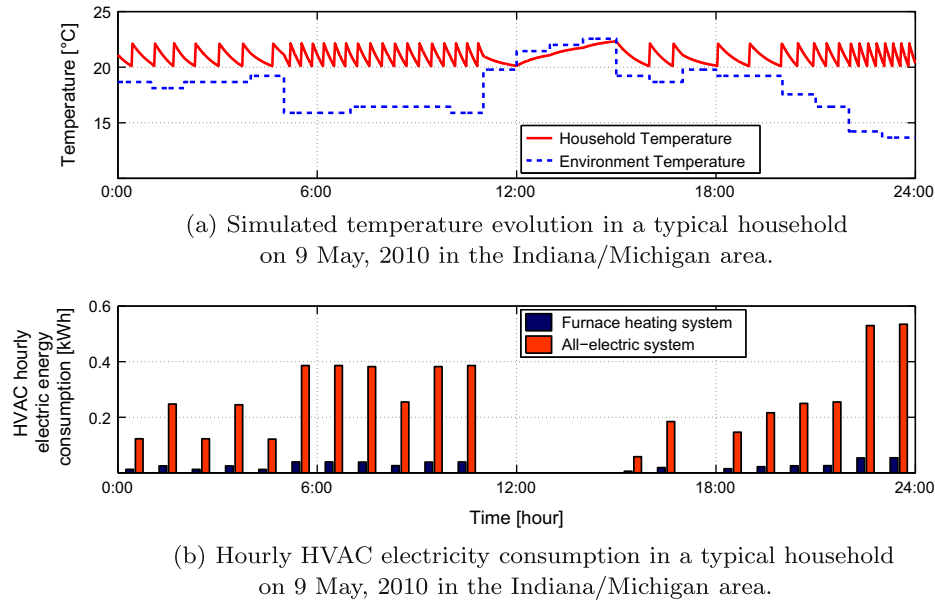on 9 May, 2010 in the Indiana/Michigan area.

Fig. 3. (a) Simulated temperature evolution and (b) resulting HVAC electricity consumption in a typical household on 9 May, 2010 in the Indiana/Michigan area.

Table 2
Parameter values used in the proposed HVAC model

Parameter	Value	Unit
Household size	223	m^2
R_{wall} (R-15)	2.64	m^2 K/W
R_{window} (single-pane)	0.183	m^2 K/W
h_i	5	W/m^2 K
h_o	30	W/m^2 K
WWR (windows-to-wall ratio)	17%	(–)
$\eta_{furnace}$	0.85	(–)
$\eta_{fan} \cdot \eta_{motor}$	0.15	(–)
P_{static}	135	Pa
v	4	m/s
SHR	0.7	(–)
COP	2.5	(–)
Desired temperature	21.1	°C
HVAC summer air temperature	13	°C
HVAC winter air temperature	50	°C
Hottest environment temperature	38	°C
Coldest environment temperature	−30	°C

$$COP = \frac{EER}{3.412},$$

where EER represents the energy efficiency ratio, the value of which is typically labeled on HVAC equipment sold in the US. EER represents the cooling output, measured in BTU, divided by the total electric energy input, measured in watt-hours, during the cooling season.

Fig. 3 shows the evolution of the air temperature in the control volume and the environment temperature on 9 May, 2010 in the Indiana/Michigan area. For the purpose of this simulation, actual historical environment temperature data are used. This figure also reports the resulting total hourly electric energy consumed by the HVAC system. This is shown for both an HVAC system coupled with a furnace and for an all-electric HVAC system. Table 2 summarizes the HVAC system parameters used. For an HVAC system coupled with a furnace, the total simulated electricity consumption for the day is 0.53 kWh, and 18.2 kWh of heat are added via the combustion of fuel in the furnace. For an all-electric system, the total simulated electricity consumption for the day is 5.2 kWh.

In summer operation the HVAC system must both cool and reduce air humidity. The total energy requirement of this process, which is proportional to the total enthalpy change, Δh_{total}, can be computed using the sensible heat ratio, SHR. This term measures the ratio between the sensible heat load (e.g. energy used to cool) and total heat load, and is defined as:

$$SHR = \frac{\Delta h_{sensible}}{\Delta h_{total}},$$

where $\Delta h_{sensible}$ is the sensible enthalpy change. Typical SHR values, which range from 0.6 to 0.9 for different locations in the US in different American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) standard years are used [20]. The cooling power in the summer is then given by:

$$\dot{W}_{cooling} = \frac{\dot{m}_{HVAC} \cdot c_p \cdot (T_a - T_{HVAC})}{SHR \cdot COP}.$$

The total electricity consumption during the cooling days can be obtained by summing $\dot{W}_{fan}$ and $\dot{W}_{cooling}$. In forecasting energy consumption for space conditioning in US residences, some level of regional disaggregation is desirable due to the wide differences in climate and the associated heating and cooling requirements. In this approach this geographic variation is captured by the variation of both the environment temperature and the SHR parameter.

In this work, the air mass of the control volume is computed for a building with an area of 223 m^2 (2400 ft^2) and a height of 2.44 m (8 ft). To maintain comfort, a system with an air flow rate capacity of 0.46 kg/s (800 cfm) coupled with a furnace with a nominal power of 13.2 kW (45 kBTU/h) is required. This implies a return air temperature of 50 °C. Table 2 summarizes the HVAC parameters used. This approach to model HVAC power consumption is presented by Muratori et al., where the details and a validation against actual data are provided [21].

2.3. Occupant behavior and related electricity use in buildings

Modeling individuals' behavior is a complex task, due to the stochastic nature of the activities performed. Factors such as the number of individuals in the household, life habits of each individual, differences in energy use associated with different activities, daily and weekly variations in behavior, and load coincidence should all be captured. This model uses a heterogeneous Markov chain to model occupant behavior and predict the associated energy consumption. Pandit and Wu [22] use a similar approach to model residential electricity demand and Widén and Wäckelgård [11]
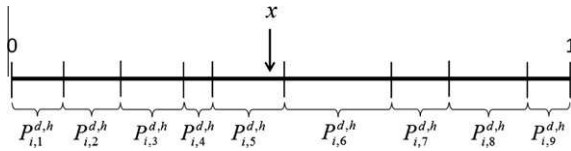
Fig. 4. Random simulation of state transition between two subsequent time periods [11].

Table 3
Summary statistics of ATUS respondents.

	Mean age	Number of respondents
Working male	43	3649
Working female	43	3978
Non-working male	57	1706
Non-working female	56	3235
Child	16	565
Total population	43	13,133

develop a similar model to predict residential demand in Sweden. As a first step a synthetic activity pattern for each household member is generated and then this pattern is converted into $\dot{W}_{act}$ by using power conversion factors associated with each activity.

All possible activities are classified into nine categories, which differ in terms of the energy required to perform the activities. These activities are:

1. Sleeping.
2. No-power activity (e.g. reading).
3. Cleaning (e.g. vacuuming).
4. Laundry.
5. Cooking.
6. Automatic dishwashing.
7. Leisure (e.g. use of the TV, stereo, computer, or videogame system).
8. Away, working.
9. Away, not working.

The Markov chain model assumes that each household member is in one of these nine states in every discrete time step. As time proceeds from t to $t + 1$ a state transition occurs. These transitions are governed by transition probabilities, $p_{i,j}^{d,h}$, which give the probability of going from state i to state j on a type-d day during hour h. Diurnal behavior patterns are reproduced by allowing transition probabilities to vary over the 24 hours, which is represented by the index h. Similarly, behavior differences between working and non-working days are captured by allowing the probabilities to vary between working ($d = 1$) and non-working days ($d = 0$). This approach requires the initial state to be chosen, which is that all individuals are sleeping at 4 a.m. of the first day simulated. Then at each time step a uniformly-distributed pseudorandom number, x, is generated and compared to the cumulative distribution of the state transition to determine which transition takes place. This is illustrated in Fig. 4. Because x is in the fifth interval in the example shown in the figure, this implies that the occupant will transition to the fifth state.

Input data of the activity-related power consumption model are the number of household members, the transition probabilities for each individual, and power conversion factors. The transition probabilities are derived from the ATUS data, and different typical agent types, such as working males and working females (with different associated transition probabilities), are modeled. Further data-related details are discussed in Section 3.

2.4. Lighting energy consumption

Lighting loads represent a large proportion of residential electricity demand, and also contributes to seasonal and diurnal load variations [23]. Proper modeling of this component requires location, solar irradiance, dwelling orientation, and lighting technology data. This work assumes that different power consumption levels during the day and the night are used to light the house when at least one member is present and doing something other than sleeping.

Sunset and sunrise times are computed based on the date and coordinates of the building being modeled using an approach developed by the US Geological Survey.[5] To estimate the diurnal and nocturnal lighting power conversion factors, a linear regression model, which is explained in Section 3.2, is used.

3. Behavioral model calibration and input data

3.1. Time-use data

In order to estimate the transition probability matrices used in the behavioral Markov chain model, detailed time use records are required. The ATUS is taken every year from a subsample of participants in the Consumer Preferences Survey (CPS) administered by the U.S. Bureau of Labor Statistics. ATUS is designed to provide researchers with detailed data on the time allocation of American adults. Though administered annually, ATUS is not a panel survey. Each annual survey is based on a different set of participants, and is therefore strictly longitudinal. ATUS respondents are interviewed on a randomly selected day about their activities on the previous day. Each activity is recorded and coded by the interviewer, along with its duration in minutes, starting at 4 a.m. and lasting until midnight. Because this survey is administered with the CPS, extensive demographic information is also available about the respondent and others sharing the same household. Moreover, because the ATUS relies on a stratified sampling technique, each respondent k has a weight, w_k, placed on his responses, which represents the weight of those data relative to the total population.

In this work, respondents are stratified into five agent types: working and non-working males and females and children. Table 3 summarizes the number and average age of respondents corresponding to each agent type. Working and non-working male and female respondents are all between the ages of 18 and 85, whereas children are between the ages of 15 and 17. ATUS data have been collected uniformly across the year during which the survey was conducted.

Because people's behavior changes on an hour-to-hour and day-to-day basis, the ATUS data are used to estimate the transition probability matrices, $P^{d,h}$, for weekdays ($d = 1$) and weekends ($d = 0$) and for each hour ($h = 1, \ldots, 24$). Given ATUS data from K respondents corresponding to a single agent type, their activities are divided into the nine categories enumerated in Section 2.3. The number of transitions at 1-min intervals between states is counted, yielding 60 observations per respondent per hour. The transition probability for that agent type is then calculated as:

$$p_{i,j}^{d,h} = \frac{w_k \cdot n_{i,j,k}^{d,h}}{\sum_k \sum_i w_k \cdot n_{i,j,k}^{d,h}},$$

where $n_{i,j,k}^{d,h}$ is the number of transitions that respondent k makes from state i to state j during hour h of day d. The resulting transition

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[5] This software tool, which is implemented in MATLAB, is publicly available for download at http://woodshole.er.usgs.gov/operations/sea-mat/air_sea-html/index.html.
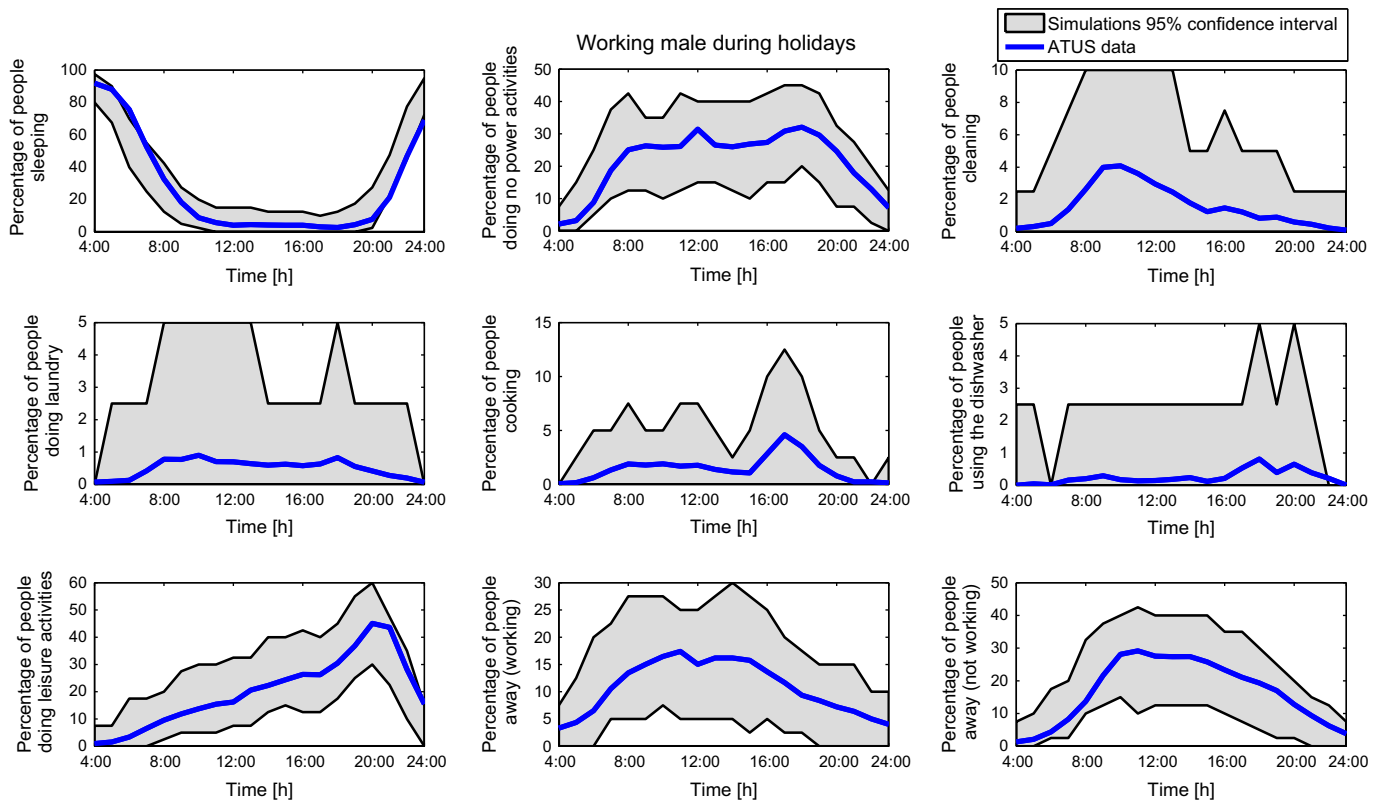
Fig. 5. 95% confidence intervals for working males during holidays for the nine different activities.

matrices represent the probability of transitioning from one state to another at 1-min time intervals. Since the case study presented in this work uses a 10-min time step, the transition probability matrices are raised to the 6th power. Each row is then scaled to sum to one, to account for the limitations of numerical precision. This gives transition probabilities from one state to another at 10-min time intervals.

An in-sample validation of the activity pattern generator is done by comparing the modeled behavior to the underlying ATUS data used to determine the transition probabilities. Muratori et al. present a graphical comparison of the underlying ATUS data to a simulation of 1000 individuals over 1000 days, showing a good fit between the two datasets [24]. A 95% confidence interval for the simulated activity patterns for each of the nine different activities can be generated by performing a sufficiently large number of simulations. Fig. 5 reports 95% confidence intervals created by simulating 40 people for 100 days for a total of 4000 person-days compared to 3854 working males present in the ATUS data. The figure shows that the behavior of the ATUS respondents is within the confidence interval for most (95.3%) of the simulated hours. The vertical scale differs between the nine activities, reflecting different relative frequencies at which the activities are performed.

Fig. 6 shows the simulated behavior pattern for a working male during a 3-working-day period. The simulated individual works an average of 10 hours and sleeps approximately 7.5 hours per day, which is a reasonable activity pattern. Moreover, the times of working and sleeping are broadly consistent with typical human behavior. Two of the high-power activities, laundry and cooking, are not performed by this agent during these three days. These activities are more commonly observed on weekends and for other agent types, such as non-working females. The total power consumed for activities in the household, $\dot{W}_{act}$, is computed by summing the power demand of each individual living in the household.
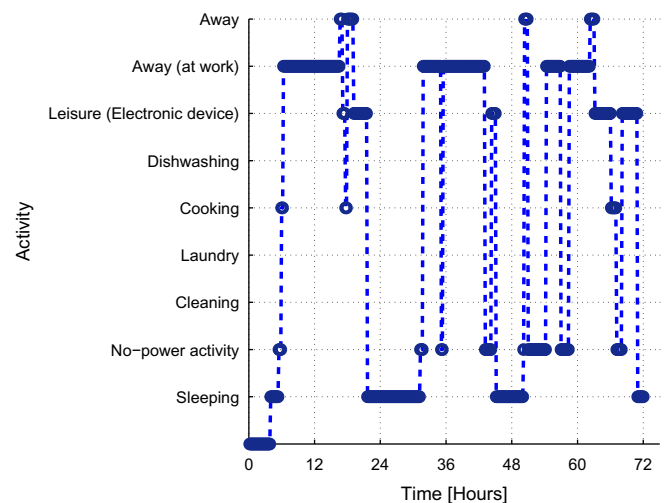

Fig. 6. Simulated behavior pattern for a working male during a 3-working-day period.

3.2. Power conversion parameters

Table 4 lists the power conversion parameters used to convert activity patterns into power demands. These are based on the average wattage of the current American appliance stock.[6] The laundry activity is divided into two parts: 30 min washing machine use,

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Table 4
Power conversion parameters used in behavioral model.

Activity	Power consumption (W)
Sleeping	0
No-power activity	0
Cleaning	1250
Laundry	425 + 3400
Cooking	1225
Automatic dishwashing	1800
Leisure	200
Away working	0
Away non-working	0

which uses 425 W, followed by 90 min of drying, which uses 3400 W. In addition, the dishwashing activity is assumed to last for one hour after it is initiated. All of the other activities are assumed to be 'instantaneous,' in that the associated power is only used when the individual is engaged in the activity.

The remaining power conversion parameters, namely lighting power during day and night and the fixed time-invariant component are adjusted according to the household location, size, and the attitudes of the building occupants toward energy use. In this work a least-squares linear regression model is used to estimate these parameters. This is done by estimating these coefficients to fit modeled consumption data to metered hourly-average per-customer electric load data provided by AEP. The AEP data report average hourly electric loads for two service territories, Indiana/Michigan and Texas. These regions differ in that Indiana/Michigan primarily has non-electric heating, whereas Texas is dominated by all-electric heating systems. The first data set is used to estimate the conversion parameters and a comparison against both data sets is reported in the next section. Temperature data, which correspond to the metered consumption data, have been provided by AEP and are used to estimate HVAC consumption.

The linear regression model has the form:

$$y = X\beta + \epsilon,$$

where y is a vector containing the difference between hourly metered consumption (reported by AEP) and the sum of modeled HVAC and cold appliance consumption, X is a binary matrix, which indicates whether each activity is performed during each hour or not, and is determined by the Markov chain model, β is the vector of power conversion parameters, and ϵ is the vector containing the random error terms. The β's corresponding to the power conversion factors in Table 4 are fixed to these values. The remaining β values are estimated using ordinary least-squares.

To run the regression model a simulation including 400 households is performed. The physical properties of the buildings are summarized in Table 2. The breakdown of household occupancy is:

- 37.5%: One working male and one working female.
- 37.5%: One working male and one non-working female.
- 12.5%: One single working male.
- 12.5%: One single working female.

The resulting electricity power factors for lighting and the fixed component are:

- Day-time lighting power: 270 W.
- Night-time lighting power: 370 W.
- Constant electric consumption, $\dot{W}_{fix}$: 230 W.

These coefficients are estimated based on the proposed cold appliance, HVAC, and Markov-based activity models and the power conversion factors given in Table 4.

4. Model validation

In this section a two-step validation methodology is presented. First, the model output is compared against the dataset used for the calibration (Indiana/Michigan) to verify that the simulated results have the same statistical features as the metered data. Second, the model is used to simulate power demand for a different region (Texas) and its output is compared with metered residential demand data from that region. Since the Texas dataset is not used for model calibration, this provides an out-of-sample model validation. Fig. 7 is a scatterplot showing hourly modeled residential electricity demand against metered demand for AEP's Indiana/Michigan service territory, which is the dataset used for model calibration. The figure shows a linear relationship between the modeled and metered data. Simulated data for the Indiana/Michigan region fit the actual data with an R^2 of 0.5107.

A non-parametric Mann–Whitney U test is performed to assess whether the distributions of two samples of independent observations are equal [25]. The test verifies if one of two samples tends to have larger values than the other, namely checking that there is a symmetry between populations with respect to probability of random drawing of a larger observation.

The test is unable to reject the null hypothesis at the 99% confidence (the p-value is 0.0965), suggesting that the modeled and metered data have the same underlying distribution. Moreover, the difference of the means of the two samples is very small (1118 W and 1122 W for the metered and modeled datasets, respectively). The difference of the standard deviations of the two datasets is larger (403 W for the metered as opposed to 425 W for the modeled data). Therefore, a Levene/Brown–Forsythe test is performed to determine if the variances are statistically significantly different [26]. Again, the test does not detect significantly different variances at 99% confidence level (the p-value is 0.024).

The model is further validated by comparing simulated and metered demand data for Texas. Fig. 8 shows modeled per-household electric power consumption for an average household in Texas and the corresponding AEP data.

The figure shows that the model, when fed with typical average data, is able to replicate the trend of the actual metered data. Simulated data for the Texas region fit the actual data with an R^2 of 0.5952. The figure shows that the model captures diurnal load patterns as well as seasonal variations in demand. Residential loads in the winter are rarely greater than 1.5 kW in the Indiana/Michigan area whereas demands above 2.5 kW are seen in Texas. This reflects the greater use of all-electric heating systems in Texas, the greater electricity consumption of which is captured by the HVAC model. Summer loads in Texas also tend to show greater peaks and span a greater number of months, showing the effect of the warmer and longer cooling period. A Mann–Whitney U test is again
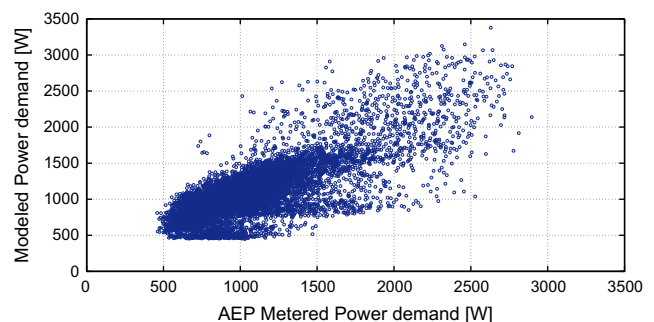
Fig. 7. Scatterplot of hourly modeled and metered residential electricity demand in AEP Indiana/Michigan service territory.
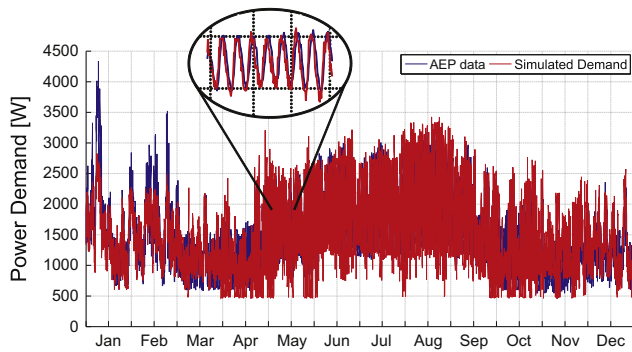
Fig. 8. Daily per-household modeled electricity consumption and AEP data for Texas.

unable to reject the null hypothesis that the distributions of the modeled and metered data for Texas are equal at the 99% confidence level (the *p*-value is 0.1376). In this second case the metered and modeled datasets present a greater difference in means, 1519 W and 1503 W, respectively. Moreover, the difference of the standard deviations of the two datasets is larger compared to the calibration case (609 W for the metered as opposed to 625 W for the modeled data). A Levene/Brown–Forsythe test does show differences in the standard deviations, but the difference is below 3% and likely due to intrinsic differences in the residential power usage of the two regions. Such a difference in the variance of simulated and metered data is in line with what is reported in the literature. Specifically, Widén and Wäckelgård [11] report descriptive statistics for the end-use-specific power demand of 14 modeled households and corresponding measurements. Their model gives means and standard deviations that differ from the metered data by 1.8% and 3.2%, respectively. Bartusch et al. [27] provide further discussion of the variance of annual electricity consumption in single-family homes as well as the impact of household features and building properties in Sweden.

5. Conclusions

This work proposes a model to simulate residential electricity consumption. The model is able to simulate the power demand of a household consisting of multiple individuals, considering cold appliances, HVAC, lighting, and activity-related power consumption. Activity patterns for individuals are modeled using a heterogeneous Markov chain, calibrated with real data collected by the U.S. Bureau of Labor Statistics. Using an in-sample validation the simulated activity patterns are shown to replicate the underlying behavioral data, demonstrating the validity of this approach. Using power conversion factors it is possible to reconstruct power consumption of a single or an aggregate group of households with desired characteristics and composition. A rigorous statistical framework is used to validate the modeled electricity demand against metered data provided by AEP. The results show reasonable demand patterns that capture annual and diurnal variations, load fluctuations, and diversity between household configuration, location, and size. The model generates electricity demand profiles with the same statistical features as residential metered data.

The effects of different technologies can be analyzed by varying the appropriate model parameters. For instance, a more efficient HVAC system can be modeled by adjusting the COP and the potential savings of high-efficiency lighting can be captured by adjusting the lighting conversion parameters. Modeling of this nature is useful as it can guide policy decisions regarding the residential stock, both old and new. By quantifying the consumption and predicting the impact or savings due to retrofits and new materials and technologies, decisions can be made to support energy supply, retrofit

and technology adoption incentives, building codes, or even demolition and re-construction. This modeling technique can also be coupled with long-term investment models to determine how energy-saving technologies would be adopted by consumers and the impact of policy and other decisions on such adoption.

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