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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.

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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.

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

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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.

[1] The ATUS data are publicly available for download at http://www.bls.gov/tus/home.htm.

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:

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

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; $\dot{W}_{\mathrm{HVAC}}$ 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.