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A multi-scale adaptive model of residential energy demand

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HIGHLIGHTS

- We extend an energy demand model to investigate changes in behavioral and usage patterns.
- The model is capable of analyzing why demand behaves the way it does.
- The model empowers decision makers to investigate DSM strategies and effectiveness.
- The model provides means to measure the effect of energy prices on daily profile.
- The model considers the coupling effects of adopting multiple new technologies.

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ABSTRACT

In this paper, we extend a previously developed bottom-up energy demand model such that the model can be used to determine changes in behavioral and energy usage patterns of a community when: (i) new load patterns from **P**lug-in **E**lectrical **V**ehicles (**PEV**) or other devices are introduced; (ii) new technologies and smart devices are used within premises; and (iii) new **D**emand **S**ide **M**anagement (**DSM**) strategies, such as price responsive demand are implemented. Unlike time series forecasting methods that solely rely on historical data, the model only uses a minimal amount of data at the atomic level for its basic constructs. These basic constructs can be integrated into a household unit or a community model using rules and connectors that are, in principle, flexible and can be altered according to the type of questions that need to be answered. Furthermore, the embedded dynamics of the model works on the basis of: (i) Markovian stochastic model for simulating human activities, (ii) Bayesian and logistic technology adoption models, and (iii) optimization, and rule-based models to respond to price signals without compromising users' comfort. The proposed model is not intended to replace traditional forecasting models. Instead it provides an analytical framework that can be used at the design stage of new products and communities to evaluate design alternatives. The framework can also be used to answer questions such as why demand behaves the way it does by examining demands at different scales and by playing What-If games. These analyses are not possible with demand forecast models built on historical samples, simply because, these forecast models and their level of accuracy are limited by their training data sets and can hardly demonstrate variations that are not present in the historical data sets.

1. Introduction

The residential sector is using almost one third of the total electrical energy in the United States [1]. According to the **F**ederal **E**nergy **R**egulatory **C**ommission (**FERC**), much of the untapped potential for reducing electricity use lies in residential behavioral changes and modifications to traditional consumption patterns [2]. This is particularly true considering that by 2030 **A**utomatic **M**etering **I**nfrastructure (**AMI**) will be widely deployed across the United States and that dynamic pricing will be widely available or at least it will be an option [2]. At the same time, the residential electricity demand is also on the verge of showing increased uncertainty as new types of home appliances/electronics are introduced and adopted. Traditionally, the major use of electricity in the U.S. residential sector can be attributed to air conditioning (both space heating and cooling), lighting, appliance/electronics, and water heating [3]. The recent rapid adoption of new home appliances/electronics, albeit many of them have become more energy efficient, has introduced new variables into the residential electricity demand. A good example is PEV with a fast sales growth rate

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Nomenclature

Index

d	index for day of week; $d \in \{0,1\}$
Φ	index for PEV state; $\Phi \in \{1,2,3\}$
i	index for household; $i = 1 \ldots I$
j	index for end use $j \in \{$**S**pace **H**eating & **C**ooling (**SH&SC**), **W**ater **H**eating (**WH**), **L**ighting (**L**), **C**old **A**ppliances (**CA**), **A**ctivities (**A**), PEV$\}$
r	index for occupant; $r = 1 \ldots R$
t	index for time of day; $t = 1 \ldots T$

Variables and parameters

A_{PCD}	PCD adoption
A_{PEV}	PEV adoption
AR	acceptable light level
$\mathrm{CAP}_{\mathrm{PEV}}$	PEV electric storage capacity
CC_t	cost associated to charging PEV
CH_t	PEV electric storage charge
CHR	PEV electric storage charge rate
$\mathrm{CP}_{\mathrm{air}}$	air specific heat capacity
DCH_t	PEV electric storage discharge
DF	daylight factor; ratio of internal light level to external light level
DHR	PEV electric storage discharge rate
EL_j	energy load associated to j-th end-use
EP	electricity price
FR	flexible lighting level range
K	Heat transfer rate with outside
$\mathrm{LUX}_{\mathrm{AL}}$	needed artificial light
$\mathrm{LUX}_{\mathrm{IN}}$	illuminance due to daylight at a point on the indoors working plane
$\mathrm{LUX}_{\mathrm{OUT}}$	outdoor illuminance on a horizontal plane from an unobstructed hemisphere of overcast sky
m_a	Air mass
$\dot{m}_{\mathrm{HVAC}}$	air mass flow rate
MCI	number of Monte Carlo iterations
MDH	miles driven per hour
MPSL	minimum percentage of storage level
NLUX	indoor comfortable light level
O%	active occupancy percentage
$p_{S_nS_m}$	probability of transition from S_n to S_m
Pspecific	buildings' specific heat loss rate
S_n	state of Markov chain; $n = 1 \ldots N$
SOC	state of charge
$\mathrm{SP}_{\mathrm{LB\&}UB}$	thermostat set-points (lower and upper bound)
T_a	Internal temperature
TEL_d^i	total energy load profile of the i-th household
T_{HVAC}	HVAC supply air temperature
$T_{S_nS_m}$	transition matrix
T_∞	ambient air temperature

which can potentially alter the residential energy demand behavior [4], and could affect directly the US electrical grid in at least two ways. First, as a new end-use it will heighten the average demand profile. Second, it could pose significant challenges to utility companies if people choose to recharge their PEVs during peak hours. Without proper management strategies to reshape or curtail such heightened demands, the utility companies may be forced to build new power plants to meet these demands, which, in turn, lead to less efficient use of energy resources.

Fortunately, devices that provide feasibility for utility companies to influence consumer consumption behavior and for householders to save energy and to take benefits of DSM strategies are emerging and have seen rising applications in the residential sector. These devices are commonly referred to as **P**rogrammable **C**ommunication **D**evices (**PCD**). PCDs are designed to receive real-time energy price and adjust consumption not only by household specific conditions but also by the exogenous market driven changes (e.g., electricity price). A common set of these devices include, but are not limited to, Intelligent Thermostats ($\mathrm{PCD}_{\mathbf{IT}}$), Price Responsive Thermostats ($\mathrm{PCD}_{\mathbf{PRT}}$), Smart Electric Plugs ($\mathrm{PCD}_{\mathbf{SEP}}$), and **A**utomated **D**immer **S**witches ($\mathrm{PCD}_{\mathbf{ADS}}$). These devices have the potential to shift or curtail energy consumption and contribute to the development of energy efficient behaviors. But when the adoption of these devices is coupled with the introduction of new loads such as those from the PEVs, there is still very limited understanding of how they interact and influence each other, and of their collective impacts on the residential energy demand. Furthermore, to design appropriate DSM strategies, energy demand consumption models need to be developed to simulate different scenarios for energy users.

This research aims at developing a high-resolution residential energy demand model to gain better understanding of how different residential electricity demand patterns emerge with the emergence of new loads, such as PEVs, the adoption of new technologies, and the implementation of DSM strategies in terms of price responsive demand.

2. Review of energy demand models

In a deregulated market, demand forecasting is vital for the energy industry. Forecasting models are used to set electricity generation and purchasing, establish electricity prices, switch loads and plan for infrastructure development [5]. Demand forecasting can serve short-term and long-term goals. Short-term forecasting plays a very important role in operating functions such as energy transactions, unit commitment, security analysis, and economic dispatch [6]. On the other hand, long-term forecasting focuses on the role of policy formulation and supply capacity expansion. Long-term forecasting tries to predict consumption behavior changes under the influence of adoption of new technology or changes in policies for energy use. Short-term and long-term forecasting often requires different modeling approaches. More specifically, short-term forecasting usually employs a top-down approach, while for long-term forecasting, a disaggregated bottom-up approach is often used. The top-down approach treats individual sectors as energy sinks and is not concerned with individual end-uses. The bottom-up approach, on the other hand, identifies the contribution of each end-use towards aggregate energy consumption.

In the context of residential energy consumption, both top-down and bottom-up models have been developed to model and predict residential energy demand. For example, a few studies utilized historic aggregate energy values and regressed the energy consumption of the housing stock as a function of top-level variables such as macroeconomic indicators (e.g. gross domestic product, and inflation), energy price, and general climate [7,8]. The bottom-up approaches extrapolate the estimated energy consumption of a representative set of individual houses to the regional and national levels [8]. There are two types of models used in the bottom-up approach: statistical and engineering models. Statistical models apply a variety of statistical techniques to regress the relationship between end-uses and energy consumption. Techniques such as regression [9,10], conditional analysis