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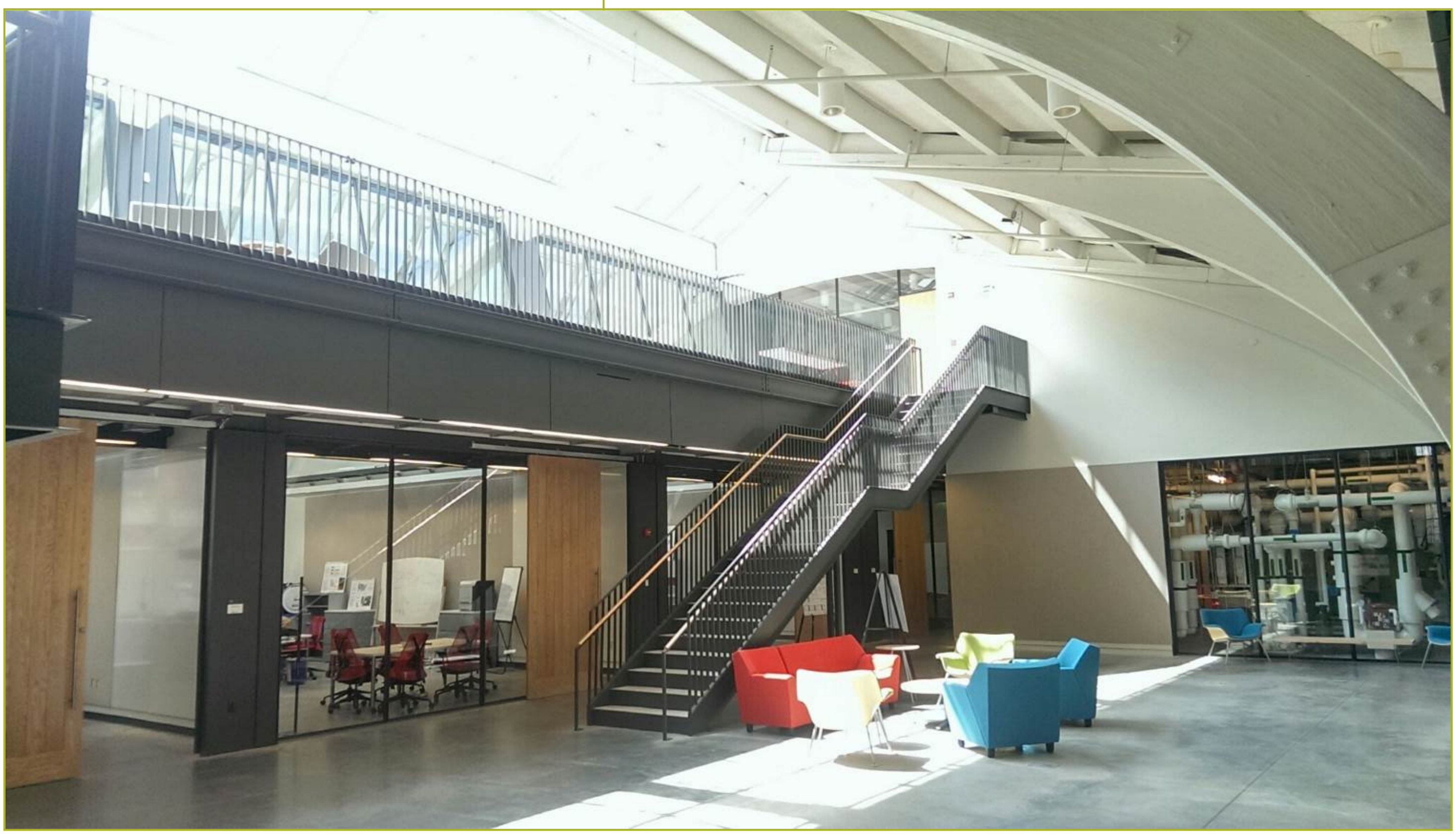

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Report Abstract

The paper provides a survey of recent literature that highlights the influence of factors, such as social, cultural, environmental and regulatory, on electricity consumption behavior.

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A Review of Electricity Consumption behavior

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Abstract

Energy use in the buildings accounts for 40% of the total energy demand of which the residential buildings account for 22% and the commercial buildings account for 18% of all energy usage. To manage the growing demand for energy there is a need for energy system modernization and optimization. This kind of system must incorporate the energy profiles of individuals and their interactions with the buildings through their activities such as watching TV, heating, cooling, cooking etc. In this paper we provide a survey of recent literature that highlights the influence of factors, such as social, cultural, environmental and regulatory, on electricity consumption behavior. It gives us an understanding of the key determinants of electricity consumption and their effects on individuals' consumption behavior in the residential and commercial sectors. Finally, this paper reviews ways to model consumers' behavioral characterisitcs, their activity driven demand for electricity and its spatio-temporal variation.

1 Introduction

Electricity consumption behavior can be seen at an institutional level, in households, in schools or enterprises - while using appliances, heating apartments or driving cars. Ongoing transformation of electric grids into smart grids provides the technological basis to implement demand-sensitive pricing schemes aimed at using the electric power infrastructure more efficiently. Consumer behavior is primarily based on individual decisions, which is often driven by external factors such as economic incentives, existing demographics, environmental variables, social norms and infrastructure. Thus, it is important to understand behavior by taking into consideration specific contexts.

Figure 1 is an overview of the various factors that contribute to electricity consumption from the perspective of a consumer. It specifies the different categories and further subcategorizes them based on the significance of each factor in its particular domain. Identification of these factors and their contribution in determining the energy demand is critical for finding ways to influence consumer behavior and making them more energy efficient.

The broadened view accounts for the physical factors (e.g. buildings, or infrastructure), social practices (e.g. everyday routines, social interactions, policy interventions) and economic aspects (e.g. market, prices). In this survey we aim to understand how consumer behavior is influenced by these factors. This is important because the appropriate behavioral adjustments can help (1) shed load at the peak time and make the load curve smoother, (2) improve storage of electricity through the use of electric vehicles, (3) sell electricity back to the grid at peak times as the smart grid allows two way flow, (4) control prices through elastic demand and active participation in the sale/purchase of electricity.

2 Electricity Consumption behavior: Residential Sector

Households constitute an important target group for energy conservation. The present study aims to systematically examine whether different types of energy use and savings are related to different

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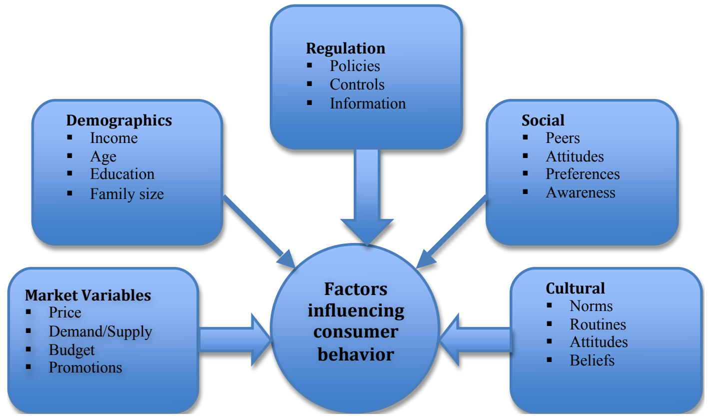

Figure 1: Factors affecting consumer behavior

behavioral antecedents, with a specific focus on the relative importance of socio-demographic variables. The key contributing factors are summarized in Figure 2. The following subsections provide an in-depth explanation of these factors and their relative importance.

2.1 Demographic Factors

A recent SMR research study summarized in [SMRProspectus2009] looked into demographics of U.S. consumer energy consumption and energy waste. In both [SMRProspectus2009] & [Brounen et al.2011], it was observed that electricity consumption depended heavily on ownership of energy intensive appliances, which, in turn depended on income and the size and composition of the household. Families with teenagers consume more electricity, possibly due to the fact that they own a lot of energy-intensive appliances. Also, elderly households, probably by virtue of owning less energy-intensive appliances, consume less electricity than middle-aged couples [Brounen et al.2011]. Both papers find that the dependence of consumption on the age of the house (sometimes also referred to as its vintage) was insignificant and much less than previously thought. Research by [SMRProspectus2009] discards the notion that higher education, which may lead to greater awareness of the necessity of conserving energy, leads to actual savings in energy. Conversely, it finds that the higher education is positively correlated with greater consumption, presumably via its positive correlation with higher income. Similar findings are shown by [Leahy2009]. However research by [Gatersleben et al.2002] observes that there is no definite relation between education and electrical consumption.

Regarding the influences of the home's vintage, it is noted that newer households have more energy efficient features however the consumption is not reduced due to larger number of appliances. In relation to floor area, houses use approximately 70% more electricity than residential units [Holloway2006] due to increase in the need for cooling and heating ([Abrahamse2007]; [Abrahamse2009]).

Work by [Reiss and White2005] studies short run demand elasticity. Since this is highly influenced by existing stock of appliances in a household, the demand is specified as a function of individual appliances. The demand was modeled as a linear function of price, income, observable & unobservable characteristics on a per-appliance basis (e.g., electric cookers/ranges are noted to be the appliances which cause the most peak load). The results are reinforced in [Reiss and White2005]'s work, which state that income effects on short-run (i.e. appliance utilization) demand elasticity are minimal when compared to income effect on long-run (i.e. appliance ownership) elasticity.

The baseline utilization (i.e. of the most essential appliances) tended to be highly inelastic, as expected. Higher price-elasticity was observed for energy-intensive appliances like electric space heating and air-conditioning. Also, as expected, lower income households were more price-elastic than the higher-income households. This is because the ownership of appliances determined consumption in the

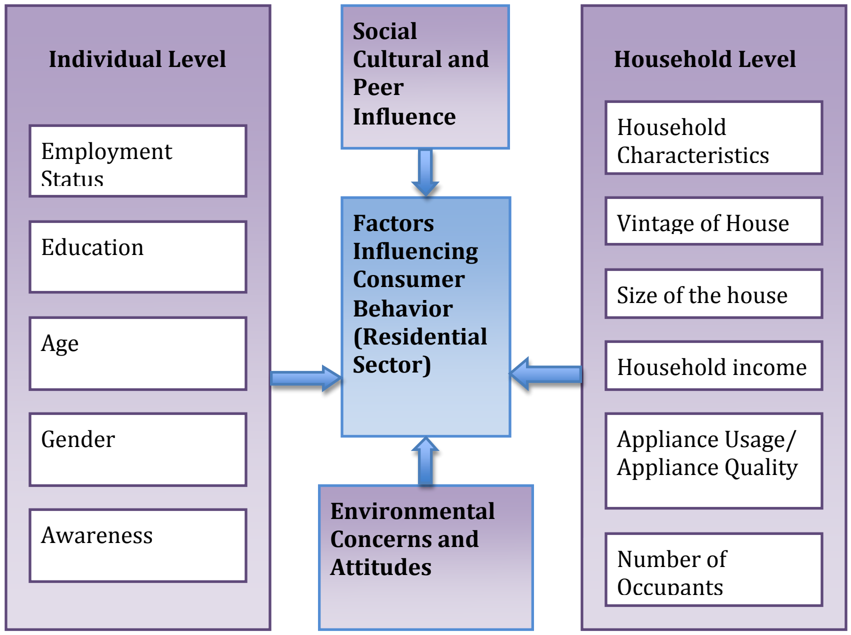

Figure 2: Factors affecting consumer behavior (residential)

short run but the ownership of appliances is determined by the income in the long run. Households with high consumption are usually higher income households, which show relatively lower elasticity. Further, they suggest that (a) there is a weak correlation, if at all, between income and ownership of energy intensive appliances, and (b) that households with rising incomes may be correlated with ownership of inelastic appliances.

Similar observations are collected in the literature survey conducted by [Grantham], in which she studies a set of papers different from the ones studied in the current review. Regarding income effects, she notes that wealthier people were seen to have ownership of large number of electric appliances which may be less energy intensive [Lenzen et al.2006], [Abrahamse2009]. On the hand, the trend amongst poor people was exactly the opposite, with more use of older technology with lower energy efficiency rating [Clancy and Roehr2003]. Further, the influence of age of the constituents of the household is recorded: families with teenagers consume more electricity. Household with very elderly or very young occupants need space heating and cooling for longer periods during the day [Abrahamse2009] which is mainly driven by health concerns. It was also noticed that younger women consumer more electricity than the older ones. In order to reduce consumption, older women agreed to change their behavior but younger women preferred technological methods.

In Ireland, [O'Doherty et al.2008] suggest that "an increase of 100,000 pounds in the market value of a home is likely to increase the number of energy-saving features by 3.4%, but is also likely to increase the number of energy-using appliances such that its potential energy use goes up by 5%"

2.2 Social Factors and Peer Influence

Work by [Ayres et al.2009] reports findings from two experiments that study the impact of adding feedback on peer usage to the utility bills of the consumers (usually, neighbors). They conclude that in general the peer feedback helps in reducing consumption. They note that there is not much statistically significant difference in providing feedback monthly as opposed to quarterly – seemingly suggesting that frequency of feedback was not important. Although, in [Brohmann et al.2008], it was found that bills based on electricity meter readings at 60-day intervals reported saving averaging 10% for customers as opposed to the four standard bills, three of which were estimates [Gaskell et al.1982], [Wilhite and Ling1995].

This measure further increased to 12% when frequent bills were distributed so that the consumers could validate their actions and optimize consumption. The "boomerang effect" (see [Cialdini et al.1991]) was noted – households that were more efficient users than their peers tended to increase their consumption. It is suggested that in order to avoid this phenomenon, feedback should only be send to the high energy consuming households. Another interesting observation is that households with higher-value homes tended to save less than those with lower-value homes. This again could be tied to the income effect.

Work by [SELIGMAN et al.1977] was an early study to measure the impact of various kinds of feedback on residential electricity consumption. Three different approaches were studied and positive results, to varying degrees were obtained. In the first study daily feedback of peer consumption details were provided; this led to reduced consumption by 10.5%. In the second study the consumption reduced by 13% when a difficult conservation goal was asked to be adopted. In the last study, a device used to signal to homeowners when to cool the house – a reduction in consumption by 15.7% was seen. These studies were done to (i) understand consumer attitudes and (ii) observe how they relate to energy consumption. It was also seen that the attitudes of people vary based on the type of energy being consumed. For example the use of heating depends on the alternative fuel options, concern about green environment etc. while the use of air conditioning depends on the willingness to deal with discomfort. The effect on health often plays an important role in making most of these decisions.

Authors in [Wood and Newborough2002] surveyed domestic cooking for 44 households in a UK field study and measured the energy-savings impact of providing electronic feedback via Energy Consumption Indicators (ECI), as opposed to only providing paper-based feedback. In [Darby2006], the study focuses on domestic electric cooking. 14 out of 31 households achieved savings of greater than 10% and 6 achieved savings greater than 20%. Average savings with ECI was 15% and without, 3%. Individuals often prefer to buy less efficient cheaper equipment than expensive and higher efficiency equipment. Replacing existing housing stock with energy-efficient buildings on a national scale is a slow process (e.g. 1% per annum in the UK)[Darby2006]. Therefore, the only remaining alternative to reducing domestic energy consumption is the achievement of "energy-conscious" behavior among end users.

Antecedent (general) information has a positive impact on savings [Dennis et al.1990] although, the "fallback effect" [Winnett et al.1984] of regressing to old behavioral patterns after the initial positive reaction, is also manifest [Hayes and Cone1977]. Another caveat that is warned against is the "Hawthorne effect" [Miller1984] – behavioral changes shown by the subjects because of the sheer knowledge that they are being studied, which was shown in [Stern1992] to have influence on research that studied responsiveness of consumers to energy savings information. In the context of these caveats, feedback is proposed as an alternative method of feedback, although the Hawthorne effect is still not completely avoidable. The authors cite research [Wilhite and Ling1995] indicating the positive impact of providing actual energy consumption feedback on the bill. However, they also mention other research [Darby1999] that suggests that disseminating written information on a bill may not be the ideal solution due to relatively low reading and math literacy rates on a national scale and the practice of automatic/pre-payment for utilities.

Social commendation and recognition [Seaver and Patterson1976], along with feedback, can have significantly positive impact on controlling consumption. Also, according to [Hayes and Cone1977], monetary rewards which are proportional to savings have a great positive impact. Feedback is also seen to avoid the "Fallback" effect that comes from just providing antecedent behavior.

Here, again, it is acknowledged that the frequency of feedback is not as important as the immediacy of feedback after an action that attempts to save energy ([Stern1992]; [Raaij and Verhallen1983], [Ammons1956]). Also, feedback is more effective if it relates to individual appliances rather than in a generalized form [Senders and Cruzen1952].

In one of the earliest studies of providing electronic feedback [McClelland and Cook1980], done in the US, it was shown that there was a 12% reduction in electricity consumption. (Incidentally, the "Hawthorne effect" was minimized in this study). In another study in Canada [Dobson and Griffin1992], software feedback was provided for household cost of usage for appliances using data that was monitored and updated quasi-real-time – here, a 12.9% reduction was observed. In a similar study done in the UK, where data had to be entered manually, a reduction of 15% was observed. Also, PC based feedback was seen to be more effective – 80% of households with this kind of feedback reduced consumption compared to only 55% of households receiving other kinds of feedback.

The authors then describe their field investigation of the impact of electronic feedback for electric cooking, especially with respect to comparing the relative impacts of paper-based antecedent information with electronic feedback and their simultaneous use. The results show that ECI feedback resulted in more significant savings and more household savings than providing antecedent information only – 66% of antecedent information households showed a drop ranging from 1 - 13% and the rest showed an increase ranging from 1 - 7%, whereas 70% of ECI households showed a drop ranging from 11 - 39% and the rest showed increases ranging from 6 - 9%.

Simultaneous use of both methods does not seem to make a significant difference – although post-study feedback from the subjects suggests that learning was mostly from the ECI feedback when simultaneous method was used.

2.3 Qualitative Aspects

[Brohmann et al.2008] is a report on an EU Commission project (IDEAL EPBD) on energy efficiency. This paper analyzes consumer barriers to improving energy efficiency in buildings, in particular residential buildings. At the outset, they note that, in buildings [Ecofys2005], insulation is known to have considerable effects in reducing electricity consumption. When it comes to energy consumption behavior, individual behavior can be seen through the lens of conservation / cautious use of resources or as an attempt to achieve efficient buying decisions [Martiskainen2007]; although, it is hard to quantify which of these are more effective in domestic energy savings.

Other qualitative results in the same paper include the observation that some individuals were seen to buy appliances based on brand name [Mari and Heiskanen1997] alone. This supports their contention that a lot of consumption decisions are limited to routines due to restricted capacity to process information ([Kahneman and Tversky2002] and [Belz and Bilharz2005]). The authors also summarize behavioral demand responses to energy prices (inclusive of taxes). Two important conclusions are that (a) energy demand is inelastic, and (b) short run and long run elasticity are almost the same. Various prior work are cited, that emphasize the importance of consumers being informed and aware of the necessity of energy conservation. It is noted that knowledge about choices and costs as strongest internal determinants of behavior and the possibility of choice as the strongest external determinant [Uitdenbogerd2007].

Sociological factors are also noted to be important in consumer behavior. It is contented that energy needs and expectations of comfort and convenience are not created by users alone, instead, they are also co-constructed by producers of energy-using equipment and systems of provision ([Shove2003]; [Van Vliet et al.2005]). Furthermore, the idea that consumption is a form of expressing and underlining social status is found in the groundwork of [Bourdieu2003] and further work by [Bartiaux2003].

2.4 Activity Based Household Demand Modeling

In [Chiou2009], the authors use a bootstrap sampling method to extract daily activity patterns of a household in order to derive residential energy load profiles. They use the American Time Use Survey (TUS) data, which contains activities of a representative individual for a period of 24 hour period as well as his demographic information. The ATUS has been used for occupant and load simulation studies by other researchers who used genetic algorithms [Tanimoto et al.2008] and MCMC [Richardson et al.2008] techniques for their estimation.

In [Chiou2009], the authors instead use a bootstrap sampling method. They outline three steps required for residential building demand estimation from the ATUS data – (1) construct entire household's daily activity schedule using the bootstrap method, (2) deriving internal heat gain, lighting and appliance load schedules from a household's activity schedules, and (3) deriving heating and cooling load estimates from steps (1) and (2) above, and external factors like the configuration of the residence and outdoor environmental conditions. The simulations results are calibrated to agree with the utility metering data.

Furthermore, they show that improvement of thermal insulation (from 1990s levels to IECC 2006 standards) led to modest heating load reductions ($\tilde{1}0\%$), especially in a single zone house. They find that, in comparison, increasing the number of thermal zones can achieve much higher level (up to 4 times) of average heating energy load reduction (best case of 57.5% for 2 occupant households and 41.2% for 5 occupant households).

The key contribution of the paper was the construction of in-building energy load profiles using occupant's activity pattern. But the paper takes into account only the activity schedule of the individuals who responded to the ATUS survey. For detailed disaggregated demand analysis, one needs to build individualistic activity schedules for every household member. Next, the activities need to be mapped to appliance usage, the time for which it was used. For some activities, that occur simultaneously for multiple members of the household, correlations need to be accounted for carefully so as to avoid double counting. For example, if everyone in the household is watching TV, the energy usage by the TV should be counted only once. To further estimate the load from activities, an association of appliance usage to energy demand should be modeled. For example if cooking is the activity a household member performs, one needs to know the appliances used (electric stove and microwave) in this activity and the amount of energy required by the appliances.

3 Electricity Consumption Behavior: Commercial Sector

The commercial and industrial sector contributes daily to a large amount of electricity consumption. Specifically the industries use 32% of all US energy use and commerical sector uses 18%. In order to optimize electricity consumption, different approaches of pricing techniques could possibly change energy use patterns. In the commercial sector, there are many infrastructure details that vary the electricity coonsumption for offices and other building. As discussed in the previous section with reference to the residential sector, building characteristics, vintage, type of the building and floor area contribute significantly in electricity consumption for the particular building. In addition to those characteristics, the number of occupants at any period of time determines the surge and fall in consumption patters. It also depends on the functioning hours of the building and the equipments housed in the building. Regardless of all the above mentioned factors, every building has a base electricity consumption accounted for the maintenance and sustenance of the building independent of whether or not the building is in use. All these factors have been grouped and illustrated in Figure 3.

In the following sections, we study various pricing techniques and consumers' response. In contrast to the residential sector, pricing mechanisms play an important role in determining the efficient usage of electricity in large contexts.

3.1 Demand Response Under Mandatory Time-Of-Use (TOU) Pricing

In [Jessoe and Rapson2011], The authors studied the impact of time-of-use (TOU) pricing on commercial/industrial (C/I) electricity usage and found that it did not lead to reduction in the peak load. Along with the lack of any perceptible change in usage, it detected a slight increase in bill volatility.

Marginal costs vary by the minute, but retail prices are time invariant. This leads to substantial economic inefficiency. Price disparity that exists between wholesale and retail leads to chronic over- or under-consumption and also allows producers to exploit market power. Therefore, they hypothesized that real-time pricing (where retail price varies according to wholesale price) eliminates inefficiencies by transmitting changes in marginal cost to retail consumers [Jessoe and Rapson2011].

[Borenstein and Holland2005] is referenced as an important related work which shows through simulations that moving some retail customers to real-time pricing (RTP) would increase allocative

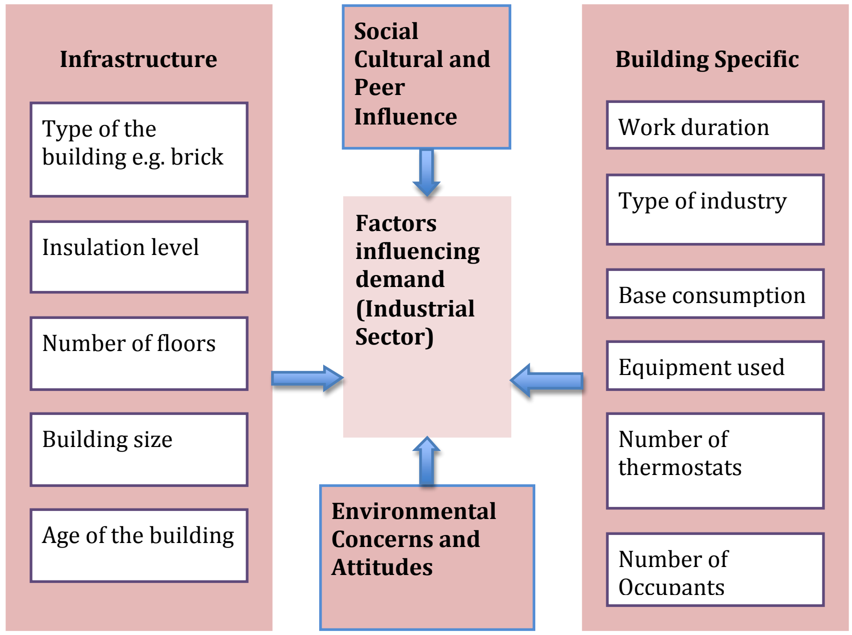

Figure 3: Factors affecting consumer behavior (Commerical/Industrial)

efficiency and reduce peak capacity requirements, while static time-invariant pricing presents a barrier to both.

The authors note that RTP is costly to implement and that a coarser version – time-of-use (TOU) – is used in practice. Though this approach transfers some of the variation in wholesale prices to the demand response, it has not yet been significant. They also cite prior work that show voluntary and temporary TOU is at best moderately effective in a C/I setting. In contrast, in the authors work, they study the impact of mandatory permanent rate changes on usage, peak load and expenditure for firms whose peak load exceeds a threshold.

The analysis yields the following results: 1. Little evidence of change in usage or load from TOU pricing. 2. After adjusting for the implicit rate class discount, which caused a decrease in the average firm electricity bills, there was no impact on monthly expenditure. 3. Increases in bill levels and bill volatility are minimal, with only a small number of firms being adversely affected. In summary, the impact of TOU was found to be economically and statistically insignificant for C/I customers. They hypothesize the reasons for these negative results as follows: (1) the peak to off-peak differential is not high enough to induce a response; (2) TOU prices are too coarse to be effective; in other words, they are not effective in transmitting meaningful economic incentives to customers (3) in the short-run, firms cannot adjust their electricity load profile – in other words, firms may be inelastic in the short-run (4) rational inattention (if electricity was a small line-item expenditure) or principal agent contracting imperfections (when the bill-payer does not make electricity usage decisions).

3.2 Commercial Demand Modeling

In [Zhang. et al.], the authors develop a simulation model that integrates organizational energy management policies, technology, appliances (their type number) and human behaviors, in order to compare different electricity consumption management strategies.

The authors note that, in the UK, existing analyses of office energy consumption carried out by the government does not take into account behavioral or office management policy factors. Prior research that does take these factors into account, uses either empirical models for actual measurements ([Rijal et al.2007], [Mahdavi et al.2007], [Nicol2001], [Reinhart2004]) or static simulation models

([Hoes et al.2009]). In contrast, the authors objective is to computationally simulate all of dynamically interacting processes.

In [Firth et al.2008], the authors classify office appliances as base (e.g. servers, refrigerators) that are always on; and flexible (heating, games consoles, coffee machines, dishwashers, etc.) The authors based their model on an academic office building at the University of Nottingham, for which they were provided with data about electricity management technologies and consumption. Two specific questions that the authors sought to answer through their study included (a) Is automated lighting more energy-efficient than manual? (b) What are the proportions of electricity controlled by lights and computers respectively?

The authors distribute the subject population (of staff, students and faculty) into three different stereotypes (early birds, timetable compliers and flexible workers). They then model the subjects activities using a state-transition diagram that encapsulates a variety of electricity usage behaviors. We refer the reader to section 3.2.1 of their paper for details. Furthermore, they model light and computers as passive agents, that can either be on or off, or, in the case of computers, in standby.

The first simulation study conducted by the authors involves setting the model to an automated lighting scenario in order to see if the simulation results resemble the actual usage data of the school. The results turn out to be indeed similar, thereby, providing validation for the authors model. The second simulation experiment aims to compare results that would be obtained in the manual scenario vs. the automated one. The results indicate that the automated management scenario is more energy efficient than the manual one.

4 An overview of modeling techniques

As is clear from the preceding sections, energy consumption can be explained using a combination of physical, demographic and behavioral characteristics of a dwelling and its occupants. Work by [Swan and Ugursa2009] provides a fairly exhaustive review of the pros, cons and applicability of various modeling techniques for residential energy consumption. Two distinct approaches reviewed are: top-down and bottom-up, which we outline in the next subsection. We further study agent based modeling and its significance to the field of energy consumption. Table 1 describes some of the models and their strengths and limitations.

4.1 Top-down vs. Bottom-up approach

Top-down approaches model energy consumption as a function of macroeconomic factors, price and climate, using techniques such as regression over historical averages, etc. These approaches model the effect of long-term changes and macro (system-level) socio-economic and ecological variables on energy consumption. Since this methodology utilizes only aggregate macro-level data, it is relatively simpler to develop. The authors note that appropriate weighting and using actual historical data provides "inertia" to the predictions made by the model, especially since paradigm shifting events are rare in the housing sector. For example, if housing construction increased the number of units by 2%, an increase in total residential energy consumption of 1.5% might be estimated by the top-down model, as new houses are likely to be more energy efficient. However this strength can also be a drawback, since reliance on historical data does not lend itself to modeling discontinuous advances in technology or severe supply shocks. Comparing energy use at a large scale [Kavgic et al.2010] makes it difficult to identify specific areas to mitigate and improve energy consumption.

On the other hand, bottom-up approaches model the energy consumption of a representative set of individuals and then extrapolates them to a larger (regional or national) scale. The authors further classify bottom-up approaches into two distinct sub-methodologies: statistical and engineering. Statistical methods (SM) rely on historical information and types of regression analysis which are used to attribute dwelling energy consumption to particular end-uses, which are then used to estimate the energy consumption of dwellings representative of the residential stock. Engineering methods (EM)

Description of the data	Related links and papers	Features and relevance to demand modeling	Strengths	Limitations
Data from the American Time Use Survey (ATUS)	ATUS website - http://www.bls.gov/tus/ Paper: [Chiou2009]	Building residential energy load profiles based on activities of individuals using demographics as the sampling criteria	Models electricity consumption at a household level	Does not model individual elecricity consumption thereby limiting observations on how individuals can affect overall consumption by changing their consumption patterns
Data from the School of Computer Science, in Jubilee Campus at the University of Notingham provided by the Estate Office responsible for the maintaining records for the electricity consumption	[Zhang. et al.]	Modeling office building energy consumption based on user behavior, electrical appliances, energy management technology and policies	Gives insight on the effects of energy management policies to optimize office electricity consumption	The agents have fixed electricity consumption profiles which cannot be changed. Moreover, there is no complex human-electric appliance interaction modeled
Data from a workday activity profile (24h) of a family in France	[Kashif et al.2011]	Modeling of behavior in a domestic setting for energy management taking into account perceptual, psycological and social behavioral elements	It demonstrates how agents learn from previous simulations and try changing behavior to improve energy efficiency and incur savings	The data was from a single household which limited broader perspective from a set of reference households
Data collected from a 1000sq ft graduate student room accomadating 10 students for a period of 60 months located at the ground floor of a multistory university building in Madison-Wisconsin	[Azar and Menassa2010]	Agent based occupant simulation model; It shows how the presence of occupants changes the electricity consumption by 20%	It shows how peer influence (word of mouth) changes the energy consumption and justifies that it plays an important role in energy estimation	It only models the "word of mouth" effect. This model can be optimized to incorporate other deciding factors thereby widening its scope in dynamic energy estimation
Data on synthetic population of 1.6 million individuals created by the TRANSIMS tool for Portland, Oregon	[Atkins et al.2007]	Spatio temporal activity driven model which takes into consideration the power demand at a location and varies based on individual demographics and time duration of activity	The demand profile at a location is further computed as a function of demand by all the consumers at that location varying based on the kind of location	Location's micro-level activities are not considered while calculating the demand function

Table 1: Summary of Models

explicitly model end-use energy consumption using power ratings, frequency and duration of use, heat transfer behavior, etc. Input requirements for bottom-up models are very intensive – they include structural characteristics, number/type/use of appliances, climate factors and occupant demographics. While this level of detail is the model's main strength, the main disadvantage is that the input data requirements are very high. Another advantage that is noted is the ability to model free-energy gains, such as solar energy gains.

4.2 Modeling behavioral characteristics

Most of the existing models for energy consumption in households and the commercial sector are econometric models and have been criticized for lacking response to behavioral factors in the abstraction of total demand. Some of the recent applications of such models can be seen in [Reiss and White2005] and [Davis2008]. To simulate energy consumption in home context, modeling dynamic group behavior is of key importance. Context elements– to represent behavior are categorized as individuality (state), activity (human needs expressed as 'what' and 'how'), location (spatial arrangements) and time (current or any virtual time) and relations [Andreas et al.2007].

Modeling social behavior integrates interaction between people from a single household and objects. Interesting results were noted after the implementation of Brahms [Kashif et al.2011]. The agents were provided with potential consequences of possible actions learned from previous simulations in anticipation to find energy efficient behavior and savings. Adjusting the list of beliefs and facts dynamically after each simulation within parametric space could be interesting to identify generalized energy related behavior.

In order to incorporate behavioral aspects to energy models, we study activity based models which include the different activities performed and the duration of time it takes. While trying to model the same, we can already see potential drawbacks dealing with shared appliance usage and performing multiple tasks in the same time frame. Some authors contend that results from complex activity specific simulations are not so different from the simpler models ([Armstrong2001];[Craig et al.2002]).

While not explicitly mentioned, the extrapolation step for bottom-up approaches typically involves agent-based simulation modeling (ABM). This can be seen in a recent application of ABM for energy estimation in buildings [Azar and Menassa2010].

Agent based simulations help include individual behavioral changes and its impacts on other individuals while modeling the energy demand. Agent based models treat individuals as objects and assign states to them with specific rules of behavior. This allows us to study variations in consumption based on different influential factors. It can also be used to estimate the impact of occupants' energy usage characteristics [Clevenger and Haymaker2006].

4.3 Spatio-Temporal Activity Driven Modeling

In a recent paper by [Atkins et al.2007], the authors used an agent based computational framework to model activity based demand profiles in order to study their effect on various economic variables, such as clearing price, quantity, profits and social welfare. They formulated a demand function based on the location and the time duration of different activities performed by individuals. The demand varies by time and demographics of the individuals. Specifically, the demand profiles are derived as a function of individual's income, activity and location. The profiles for every hour, total of 24 hours, were constructed for each of the individuals [Atkins et al.2007].

The contribution of an activity that begins at time σ_i and ends at time τ_i to the power demand during the time interval $[t_i, t_j]$ is proportional to the length of the interval $[\sigma_i, \tau_i] \cap [t_i, t_j]$, which is the duration of overlap of the activity with the time interval $[t_i, t_j]$. The multiplier to represent the contribution of this activity is given by the factor $\frac{[\sigma_i, \tau_i] \cap [t_i, t_j]}{[t_i, t_j]}$ This factor is equal to 1 if $\sigma_i \leq t_i$ and $\tau_i \geq t_j$. The power demand is computed during each hour of the day by iterating $t_i = 0, 1, 2, \ldots, 23$ and $t_j = t_i + 1$. The demand is aggregated over a period of one hour and assumed to be constant over this entire period.

The power demand at location l_i at a given time t, denoted by (l_i), is a function of the price per unit power p, and is given by

$$(l_i) = \alpha_i + \frac{\beta_i}{p}$$

where the coefficients α_i and β_i are computed as follows. Let $A = \{a_1, a_2, \ldots, a_k, \ldots\}$ be the set of all types of activities. For instance, a type of activity could be being at school, at home, or at work. For each k, let $c(k)$ be the quantity of power required for activity type a_k.

For a location l_i, ${}_i(k)$ denotes the fraction of the location that is used for activity type a_k. Hence, $0 \leq_i (k) \leq 1$ and $\sum_k {}_i(k) = 1$. Independent of the number of individuals present at location l_i at time t, a base quantity of power is demanded at l_i which is given by $\sum_k {}_i(k) \cdot c(k)$.

If P_i denotes the subset of individuals present at l_i at time t, then for each $x \in P_i$, let $(x) \in A$ denote the unique type of activity performed by individual x at location l_i at time t. Then, the demand of individual x is given by the function $c((x)) + \frac{\gamma \cdot (x)}{p}$, where (x) denotes the annual income of the individual and γ is a small constant (typically, $\gamma \approx 0.001$). The first term models the inelastic demand of the individual, while the second term represents the elastic demand.

The power demand at location l_i is the sum of the power demand that is independent of occupancy and the sum of the demand functions for all individuals at l_i. Therefore,

$$\begin{aligned}\alpha_i &= \sum_k {}_i(k) \cdot c(k) + \sum_{x \in P_i} c((x)) \\ \beta_i &= \gamma \sum_{x \in P_i} (x)\end{aligned}$$

This paper uses a detailed activity information on each individual to calculate his time varying demand estimate. It also captures variation in the energy consumption behavior using fine grained spatio-temporal detail [Atkins et al.2007]. We will use the activity based demand modeling techniques from this paper and from [Chiou2009] to motivate and build a richer individual based model of electricity demand.

5 Conclusions & Future Work

The interrelationship between different influential factor shows how consumers react and respond to various determinants of electricity consumption. Their behavior varies according to the specific context of the individual consumer. Further studies can be done to understand how these factors can be channeled to optimize energy consumption and build energy efficient buildings. Reviewing the literature helps to determine why certain policies do not realize their targets of improving energy efficiency and provides insights on how different factors might be manipulated to improve energy efficiency in the future.

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