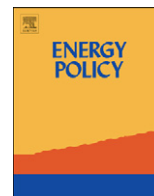




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Improving energy efficiency and smart grid program analysis with agent-based end-use forecasting models

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ARTICLE INFO

Article history:

Received 16 December 2009

Accepted 25 February 2010

Available online 23 March 2010

Keywords:

Energy efficiency
Agent-based model
End-use model

ABSTRACT

Electric utilities and regulators face difficult challenges evaluating new energy efficiency and smart grid programs prompted, in large part, by recent state and federal mandates and financial incentives. It is increasingly difficult to separate electricity use impacts of individual utility programs from the impacts of increasingly stringent appliance and building efficiency standards, increasing electricity prices, appliance manufacturer efficiency improvements, energy program interactions and other factors. This study reviews traditional approaches used to evaluate electric utility energy efficiency and smart-grid programs and presents an agent-based end-use modeling approach that resolves many of the shortcomings of traditional approaches. Data for a representative sample of utility customers in a Midwestern US utility are used to evaluate energy efficiency and smart grid program targets over a fifteen-year horizon. Model analysis indicates that a combination of the two least stringent efficiency and smart grid program scenarios provides peak hour reductions one-third greater than the most stringent smart grid program suggesting that reductions in peak demand requirements are more feasible when both efficiency and smart grid programs are considered together. Suggestions on transitioning from traditional end-use models to agent-based end-use models are provided.

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1. Introduction

Electric utilities and regulators face difficult challenges evaluating new energy efficiency and smart grid programs prompted, in large part, by recent state and federal mandates and financial incentives. Utility programs are typically required to be cost-effective; that is, to provide a future stream of financial benefits for utility customers that are greater than total program costs. However, it is increasingly difficult to separate electricity use impacts of individual utility programs from the impacts of increasingly stringent appliance and building efficiency standards, increasing electricity prices, appliance manufacturer efficiency improvements, energy program interactions and other factors.

Without careful scrutiny, utility programs are prone to the same kinds of inefficiencies often found in other programs designed to elicit certain consumer and firm responses. The recent US “cash for clunkers” automobile program is a recent example of a “free rider” problem where the program apparently benefited primarily those who would have purchased a new automobile without the program.¹ This free-rider problem has

long been recognized as an issue that should be considered in utility energy-efficiency program evaluation (California Measurement Advisory Council, 2009; Environmental Protection Agency, 2007) and an issue that is unevenly addressed in existing energy efficiency studies (Energy Center of Wisconsin, 2009).

The interaction of related programs is of greater concern with the growing focus on smart grid programs. Consider, for instance, the difficulty of separating utility smart grid program impacts from reductions in air conditioning loads that would have occurred anyway because of federal appliance efficiency standards, state building standards and utility customer voluntary purchases of more efficient equipment.

No existing utility program analysis model provides a comprehensive quantitative analytical framework consistent with utility and regulator needs to evaluate and assess individual utility efficiency and smart grid program impacts while simultaneously taking into account the many other factors that will determine future electricity use and hourly loads. Development of such a framework is critical in effectively achieving legislative, utility and regulatory goals as resources applied to inefficient programs reflect a lost opportunity to invest in more efficient programs.

This paper presents an agent-based end-use modeling methodology as an analytical framework that can achieve these objectives. The next section provides a summary overview of existing methods for analyzing energy efficiency and smart grid

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¹ Edmunds.com analysis estimates that only 125,000 of the nearly 690,000 vehicles were sold during the program are attributable to the program (Edmunds.com, 2009).

program impacts. Section 3 describes the agent-based end use model applied in this study while Section 4 presents example analysis results for an example utility. The final section summarizes the study.

2. Traditional program evaluation

Energy efficiency and smart grid program evaluations require adjusting “gross” program impacts for free rider, spillover and rebound effects to derive net program impacts (Environmental Protection Agency, 2007; Vine and Jayant, 2000; Fels and Keating, 1993). Spillover effects reflect additional savings beyond the program parameters such as behavioral changes prompted by program participation that would not have occurred in the absence of the program while rebound effects reflect additional incremental energy use as a result of the reduction in the cost of providing the energy-related services (e.g., reduction in thermostat settings with more efficient air conditioners). Difficulties arise in estimating both gross and net impacts. This discussion is divided into two categories: (1) short-term energy impacts over a period of several years and (2) future energy and hourly load impacts over a longer time horizon.

2.1. Short term impacts: energy efficiency

Short-term energy-efficiency impacts are usually determined with engineering-based analysis that multiplies either the number of program participants by savings per participant or the number of technologies by savings per technology (see Environmental Protection Agency, 2007 for a nontechnical description of program evaluation approaches). For example, a rebate program for compact fluorescent lamps will provide information on the number of lamps purchased with the rebate. Typically, the difference in watts of incandescent and compact fluorescent lamps of comparable lumen output is multiplied by an assumed number of operating hours. Better estimates of operating hours may be obtained with information on rebate applications or with survey results from a sample of the participating customers. Free-rider impacts are typically determined by surveying program participants and/or appliance retailers.

Multivariate statistical analysis of longitudinal monthly billing electricity use data including months before and after program participation and/or analysis applied to both program participant and nonparticipants can be used to estimate impacts for programs that have measurable impacts on monthly electricity use (e.g., Tiedemann, 2007; Pacific Northwest Laboratory, 1995). While this conditional demand analysis can potentially estimate spillover and rebound impacts, its application requires a great deal of customer information to explain variations across participating and nonparticipating households caused by factors other than the program. In addition, correlation of program participation with other variables that reflect participant behavior more inclined to be energy-consciousness can bias program impacts upward. Conditional demand analysis does not typically address free rider impacts.

Challenges in statistical estimation along with limited resources typically result in utility program analysis conducted with the simpler and less resource-intensive engineering-based evaluations with judgmental estimates used to reflect free rider, spillover and rebound effects. EPA (2007) reports one utility program estimate of 10% free riders and 14% spillover effects for a net gain of 4% in the impact of the program. The extent to which these and similar utility estimates reflect overly optimistic program impacts is difficult to determine. However, a good deal of anecdotal evidence suggests that net savings are considerably

smaller than gross savings. For example, a recent study of Southern California Edison’s 2006–2008 Home Energy Efficiency Rebate Program (Kema, 2009) found 66–73% of refrigerator, whole house fan, and evaporative cooler participants said they were “very likely” to have purchased the more efficient equipment in the absence of rebates. Reported free rider levels were 47–53% for the room air conditioner, pool pump, and cool roof rebates. These responses suggest that free rider range from about half to three-fourths of participants in this program though these estimates may overstate free rider impacts because of self-reporting bias.

Accuracy of utility-provided efficiency program costs and benefits has been questioned for some time (Joskow and Marron, 1992); however, the first comprehensive study to provide evidence that program costs may be considerably greater than typically assumed was conducted by Rand Corporation economists only recently (Loughran and Kulick, 2004). The Loughran and Kulick study found the often-quoted 3–4 cents/kWh energy efficiency cost estimate (Gillingham et al., 2004, Fickett et al. (1990); Nadel and Geller, 1996), computed by dividing utility-reported program costs by estimated electricity savings, increases to 14.6–22.9 cents/kWh after accounting for free-rider impacts. This study analyzed temporal and cross-section variations in residential electricity use and energy efficiency program expenditures for 324 utilities over the 1989 through 1999 period in a study for the US Department of Energy. While Auffhammer et al. (2008) have criticized these conclusions, their argument rests on the fact that confidence intervals around the point estimates are so large that the utility-reported savings of 2–3 cents/kWh cannot be rejected. However, these results also reinforce the view that utility-reported data are of questionable accuracy.

2.2. Short term impacts: smart grid

Smart grid impacts in this paper refer to the impacts of smart meters, smart grid enabling technologies such as programmable communicating thermostats, utility pricing programs such as critical peak pricing, conventional load control programs and other communication and control technologies and programs instituted by utilities to reduce electric demand during peak periods. Short term smart grid impacts are typically evaluated as percentage changes or elasticities based on pilot programs. A small number of pilot studies have been completed to date reflecting a wide range of responses for smart grid technologies and peak period pricing (Faruqui and Sergici, 2009). Free riders are a relatively small problem with smart grid programs as most customers do not reduce peak period electricity use in the absence of smart grid technologies and pricing programs; however, estimating population impacts based on a customer sample is subject to sampling error, especially if sample customers have been treated differently (e.g., personal contacts and motivation) than the population of customers.

2.3. Future impacts: energy efficiency

Future energy and hourly load program impacts are much more difficult to predict and coincidentally much more important in determining program cost-effectiveness. Most energy efficiency programs and all smart grid programs require savings benefits over a fairly long period to achieve cost effectiveness. For example, the program life of a compact fluorescent lamp (CFL) give-away program is determined by the lamp lifetime. With a 10,000-h life and an average 4-h use per day, the lamp will continue to provide benefits for nearly seven years.

Energy efficiency program cost/benefit analysis is formally conducted by summing savings over each year of the program and comparing future benefits to program costs. Future benefits are discounted, that is reduced, by the factor $1/(1+r)^t$ where r is the discount rate and t the number of years in the future. Discounting reflects the fact that future savings are worth less than current savings. The CFL program described above would have a benefit cost ratio of 2.1 if the cost of the lamp program were \$6.00 per lamp, the value of avoided kWh is \$0.05/kWh and future benefits are discounted at a 5% rate. However, if half of the CFLs purchased by program participants would have been purchased in the absence of the program, then the program becomes marginal, providing about the same benefits as costs. If free riders are more than 50%, the program is not cost effective.

In addition to accounting for free rider impacts, future utility program benefits must be adjusted to reflect the impacts of appliance and building standards and other factors that impact electricity use in the future including energy price increases, changes in income, new technologies, spillover effects and other factors.

Traditional end-use models provide the only systematic method for estimating future year free-rider and the other complicating factors described above. End-use models were first developed in the mid-1970s (Hirst and Carney, 1977; Jackson et al., 1978) specifically to model and evaluate federal energy-efficiency programs and have formed the methodological basis for most policy-oriented energy forecasting models in use today including, most notably, the US Department of Energy's NEMS model (US Department of Energy 2009a). End use models, sometimes referred to as "bottom-up" models determine electricity and other energy use for detailed customer/end-use segments and sum energy use across segments to determine total utility, state and regional energy use. The following equation is a typical "demand equation" used to estimate electricity use (kWh) for the single family/central air conditioning segment (SFCAC). Electricity use is represented as the product of the number of single family air conditioning customers (CUST), average base year single family/central air conditioner kWh use (UEC) and factors that, over time, reflect changes in equipment utilization (U), efficiency (E) and dwelling unit thermal efficiency (TE).

$$\text{kWh(SFCAC)} = \text{CUST(SFCAC)} * \text{UEC(SFCAC)} * U(\text{SFCAC}) * E(\text{SFCAC}) * \text{TE} \quad (1)$$

The U , E and TE variables begin the forecast period with values of 1.0 and change to reflect new values in future years as appropriate. Efficiencies change as equipment fails and is replaced with more efficiency equipment and as new dwelling units are added to the stock. Utilization, the intensity of use of equipment, changes in response to weather, electricity prices, income and other factors. The thermal index of the building is determined during construction and can be modified by adding insulation and other building shell measures.

Values of the individual components of the basic demand equation are forecast separately and multiplied to estimate dwelling unit/end-use segment electricity use. Utilization indices are forecast based on historical customer responses to increase in energy costs, usually with a short-run elasticity representation. Efficiency index values are typically forecast with a representation of available technology efficiencies and a technology choice model component. Most end-use modeling applications recognize sub-optimal residential efficiency investment choices by applying high discount rates or low payback requirements. Other factors that deviate from the "rational actor" model can also be incorporated in the efficiency choice model component.

Values of forecast end-use model components can often be applied to estimate adjustments to engineering and statistical

program impact estimates to account for free riders, other "naturally occurring" efficiency improvements and other extra-program factors. For example, efficiency choice estimates of compact fluorescent lamp purchases can be used to estimate the fraction of compact fluorescent lamps that would have been purchased in the absence of a utility incentive program.

Alternatively, individual program impacts on utilization (U), efficiency (E), and thermal efficiency (TE) can be incorporated explicitly in the end-use models and compared to baseline forecasts to estimate program impacts.

The problem with this approach is that the endogenously determined efficiency increase represents an average for all single-family/central air conditioning households while efficiency programs typically impact significantly different subsets of customers within each model segment. For example, participants in an air conditioner rebate for old systems and participants in a free programmable thermostat program are likely to reflect different dwelling unit sizes, demographics and other characteristics. Deducing the average efficiency and utilization improvements for the single-family/central air conditioning segment from each of these programs applies adjustments that are incompatible with program participant customer characteristics. Incorporating program impacts in the end-use models is equally problematic; U , E and TE values must be adjusted to reflect segment subset impacts on the basic dwelling unit/end-use segment value.

2.4. Future impacts: smart grid

Most utility-specific smart grid analyses have focused on short-term pilot program results; consequently, little analysis has been conducted of long term impacts. Longer term forecasts of potential smart grid impacts have been conducted with aggregate analysis at the national and state level (Walter et al., 2004; Federal Energy Regulatory Commission, 2009); however, these analyses apply elasticity-based models which are notoriously unreliable when the structure of the economic system is undergoing significant change. None of these smart grid modeling approaches allows joint consideration of energy efficiency, appliance standards or other programs.

Based on these observations, one can conclude that many of the limitations of traditional program evaluation approaches are a result of a limited analytical focus and/or limitations of the analysis tools.² The end-use modeling approach provides a comprehensive framework that conceptually can resolve these shortcomings; however, the traditional aggregate customer segmentation limits its applicability. Modeling individual utility customer end-use electricity use for each household in a statistically representative sample of customers can solve this mismatch between model segments and utility program representations. The advantage of the agent-based approach is discussed in the next section.

3. Agent-based vs. traditional end-use modeling

The designation "agent-based end-use model" is used here to reflect the fact that energy use is modeled at the individual agent or household level and at the end-use level within each household. The same relationships involving end-use efficiency, utilization and structure thermal characteristics applied in traditional end-use models are applied here to each individual utility customer in the utility customer sample.

² The link between program evaluation and implementation is critical in achieving program goals (Vine, 2008).

This approach is also characterized as a microsimulation process because it simulates the behavior of individual economic agents over time.³ Goett and Mcfadden (1982) developed an early energy forecasting microsimulation model for the residential sector in a project for the Electric Power Research Institute; however, it was never applied for policy analysis. Jackson (1986, 1994) extended the traditional practice of modeling segment average efficiency and fuel choice by incorporating microsimulation modeling for a sample of households and firms in these two components; however, individual samples were drawn for each year and the results were averaged and passed back to the basic demand equation which only partially resolves the dwelling unit/end-use customer segment-efficiency program mismatch.

The agent-based end-use model applied in the current study also belongs to a larger class of agent-based or multi-agent models where individual agents can be influenced by other agents. This feature is important in modeling new technologies and utility programs that rely on dissemination of information from one household to another. For example, the diffusion of new technologies, such as solar photovoltaic systems, is driven in large part by personal knowledge of other household experience with the systems. This representation is easy to implement in the agent-based methodology applied here, though its application is outside the scope of the present study.⁴

Agent-based models are widely used in applications outside the utility industry and reflect many of the extensions and insights provided by experimental economics and other disciplines that are increasingly applying analytical frameworks that more closely reflect underlying economic and behavioral relationships important in public investment decisions. Application areas include electric wholesale markets, health care, transportation, and many others. See Tesfatsion and Judd (2006) for a comprehensive overview of agent based models and their applications.

Agent-based electricity end-use modeling methodology is intuitive. The utility service area is represented by a sample of utility customers. End-use equipment holdings, end-use electricity use and hourly loads along with income, demographic and other variables characterize each customer. Each customer record is updated in each year of the forecast to reflect changes in end-use equipment efficiency and the impacts of changes in income, demographics, electricity prices and other factors. Customers are added to the sample to reflect growth in the service area over time.

Conceptually the agent-based end-use modeling approach is illustrated in Table 1 for a sample of five residential central air conditioning utility customers. The utilization and thermal efficiency terms are omitted from the basic equations to simplify the example. In the base year, t , the efficiency index, E , has a value of 1 for each agent or utility customer providing an average value of 1.0. In year $t+1$, household number 3 and 5 participate in a utility low-income air conditioner replacement program with a reduction of 40% and 30% in the efficiency index for those two households where the differences reflect the age of the replaced air conditioning system. In year $t+2$ household number 1 replaces a worn-out air conditioner with a new more efficient air conditioner. In each year energy use changes only for

Table 1
Agent-based end-use model representation.

	Household	kWh	=	UEC (kWh)	*	E	Income (\$)
Year t	1	3100	=	3100	*	1.00	95,000
	2	2400	=	2400	*	1.00	21,000
	3	1800	=	1800	*	1.00	16,000
	4	4200	=	4200	*	1.00	170,000
	5	1600	=	1600	*	1.00	18,000
	Average kWh	2620		Average E		1.00	
Total kWh		13,100					
Year $t+1$	household	kWh	=	UEC (kWh)	*	E	% Change E
	1	3100	=	3100	*	1.00	0.0%
	2	2400	=	2400	*	1.00	0.0%
	3	1080	=	1800	*	0.60	-40.0%
	4	4200	=	4200	*	1.00	0.0%
	5	1120	=	1600	*	0.70	-30.0%
Average kWh	2380		Average E		0.86		
% Change	-9.2%		% Change		-14.0%		
Total kWh		11,900					
Year $t+2$	Household	kWh	=	UEC (kWh)	*	E	% Change E
	1	2790	=	3100	*	0.90	-10.0%
	2	2400	=	2400	*	1.00	0.0%
	3	1080	=	1800	*	0.60	-40.0%
	4	4200	=	4200	*	1.00	0.0%
	5	1120	=	1600	*	0.70	-30.0%
Average kWh	2318		Average E		0.84		
% Change	-11.5%		% Change		-16.0%		
Total kWh		11,590					

Table 2
Traditional end-use model representation.

	Household	kWh	=	Customers	*	UEC (kWh)	*	Average E	Income (\$)
Year t	1	13,100	=	5	*	2620	*	1.00	95,000
Year $t+1$	2	11,900	=	5	*	2620	*	0.91	21,000
Year $t+2$	3	11,590	=	5	*	2620	*	0.88	16,000

those customers whose CAC efficiency changed and each change is maintained for the customer until the equipment is replaced again.

A comparison with the traditional end-use model representation of the example above illustrates the advantages of the agent-based approach. Table 2 shows changes that occur with the traditional single family/central air conditioner segment in the three years.

The difficulty with this traditional representation is that the average E can only be computed with the knowledge of the actual kWh. In year $t+1$, Table 2 indicates that the average E value must be 0.91 to yield the correct total kWh forecast, not the 0.86 that represents the numeric average across all customers as shown in Table 1. That is, because the efficiency index operates on the UEC and because UECs vary by customer, the correct E value must be weighted by UECs of the individual customers to provide a weighted average E value that produces the correct forecast. The same situation occurs in year $t+2$ and following years. This example shows that the end-use energy use diversity of individual utility customers significantly impacts utility program savings and that ignoring this diversity provides erroneous program savings estimates.

This algebraic weighting-aggregation issue is secondary, however, to the basic problem of determining the correct E , U and TI values in the absence of detailed customer data. Actual kWh from Table 1 is divided by 13,100 determined (5 times 2620) to determine the correct average E in Table 2. In actual

³ Microsimulation models, originally suggested and most notably promoted by Guy Orcutt (see Orcutt, 1957; Orcutt et al., 1976; and Orcutt et al., 1986). Microsimulation models have been widely applied in government tax and social program policy analysis (Halpin, 1999), transportation (Raney et al., 2003) and other areas Gupta (2000).

⁴ See Jackson (2007) for a study that used commercial sector agent-based modeling and a cellular automata information diffusion process to test the hypothesis that high standby rates are inhibiting the implementation of combined heat and power technologies.

Table 3
MAISY agent-based end use model methodologies.

Relationship/Program	Methodology	Variables
Equipment efficiency and fuel choice	Discrete agent (residential households) equipment/fuel choice models applied during equipment new purchase and replacement	Equipment operating cost (efficiency and energy prices), initial cost, agent payback requirements distribution, utility and other incentives and program variables
Equipment utilization	Behavioral-based econometrically estimated short-run elasticities	Operating cost (efficiency and energy price), income, demographics, weather
Equipment replacement	Replacement with new equipment when equipment fails	Lifetime distributions, accelerated by utility incentive payments and other cost-related factors
New construction, demolitions	Age-determined demolitions, new construction to meet forecast residential customers	Total residential utility customers, age-related demolition distributions, historical dwelling unit type distributions
Household income, demographics changes	Adjustments to agent weights to reflect changes in demographic and income	Forecast income, demographics
Energy price changes	Changes equipment fuel choice, efficiency choices for new equipment, utilization of existing equipment	Electric, natural gas, fuel oil prices, equipment operating costs
Equipment and building efficiency standards	Limits menu of choices in discrete choice models to include only standards-compliant equipment	Minimum appliance and dwelling unit requirements
Efficiency programs	Impacts fuel and efficiency choices, and utilization	Purchase incentives, monthly operating cost incentives, other financial incentives, program participation
Demand response/smart grid programs	End-use load smoothing and reduction, additional behavioral utilization impacts for peak period pricing programs	Agent end-use hourly loads, direct load control characteristics, enabling technology characteristics, peak period prices, program participation

applications, knowledge that 2 of the 5 customers participated in the program with 40% and 30% reductions is insufficient to calculate the true E value without information on the individual UECs. Knowledge of individual UECs is required to determine 0.91 as the correct value. However, if one has all of this information, why not simply model energy use at the agent level rather than aggregating to averages to be applied to the segments?

The problems associated with determining segment averages in traditional end-use models become even greater when utilization and thermal efficiency terms are considered in the demand equation. The unavoidable conclusion is that information required to accurately reflect detailed utility efficiency and smart grid programs is consistent with the information required to support an agent-based end-use modeling methodology.

The end-use model applied in this study includes end-use hourly loads for each customer record. Changes in efficiency, utilization and thermal efficiency are applied directly to end-use loads providing a direct representation of efficiency and smart grid programs.

The next section describes modeling relationships applied in agent-based utility modeling application at a mid-west US electric utility.

4. Agent-based end-use modeling relationships

In addition to resolving difficulties in determining traditional end-use model segment averages, this agent, or utility customer, approach provides direct access to all customer detail required to represent and assess utility efficiency, smart grid and other utility program impacts.

As indicated above the agent-based end-use modeling approach applied in this study, this modeling approach develops information on a sample of utility customers and updates that information over time as the number of utility customers increases, as customers replace worn-out equipment and purchase equipment for new dwelling units, as customers respond to changes in electricity and other energy prices, income and demographics and other factors, when dwelling unit thermal characteristics are updated and so on. In other words the model

simulates actual energy use of a representative sample of customers within a utility service area over time.

These relationships are summarized in Table 3. This study reflects a departure from past efforts by integrating each of these modeling relationships in a single comprehensive agent-based energy-modeling framework.

As indicated in the table the model's framework explicitly represents energy efficiency programs, smart grid programs, appliance and building standards and other extra-market efforts to reduce energy use and peak demands.

Efficiency standards act to remove equipment and building options from the menu of choices changing efficiency and fuel choices and end-use energy use. Modifying the purchase cost or other characteristics of equipment and building options through utility or other efficiency incentive programs changes the efficiency and energy use outcomes of household choices as well as utilization of the new equipment to reflect the rebound impact.

Smart grid programs are modeled at the customer level by smoothing individual central air conditioner and water heating hourly loads over peak hours to reflect utility and customer-sited control technologies and by additional reductions in electricity use based on price responsiveness revealed in pilot pricing programs. The peak hour impacts of other appliance-specific programs such as electric clothes dryers, refrigerator defrosting and so on can also be represented. This smart grid analysis provides a more reliable estimate than aggregate elasticity-based estimates typically used to evaluate smart grid potentials because estimated hourly load reductions are based on actual end-use equipment information, including end-use hourly loads, in individual households in the service area.

5. Example utility application

The Duke Energy Indiana service area was selected as a case study application to illustrate the agent-based analysis. The example analysis shown here focuses on residential customers. Duke Energy was not involved in this study and all information on Duke customers used in this study is available in public sources.

Duke Energy Indiana provides electricity to approximately 675,000 residential customers in 69 counties in the central, north

central, and southern parts of the state. Duke Indiana customers will experience a 20% rate increase over the next five years to pay for a new coal gasification plant now under construction. Duke Indiana provides a number of energy efficiency programs (<http://www.duke-energy.com/indiana/savings.asp>); however, these programs have a limited impact. Duke's estimate of all energy efficiency program impacts is a reduction of 1.6% in residential electricity use in 2007 (US Department of Energy, 2009b).

A sample of 1350 Duke Indiana residential customers including their electricity use, hourly loads, income, demographics and so on was applied in this study. Weights are applied to each sample customer to reflect the number of customers represented in the service area population. These weights are calculated with US Census data for the utility service area (US Census Bureau, 2009). Individual customer data were drawn from the 2001 and 2005 Residential Energy Consumption Databases (US Department of Energy, 2009c). These customer data provide dwelling unit, appliance, demographic, annual electricity use detailed by end use, and other information for individual sample customers. This study developed hourly electric use profiles for each end use that were calibrated to reported end-use electricity use.

Seventy-four percent of Duke residential customers live in single-family dwelling units with 18% in multifamily units and 8% in mobile homes. Electricity use by end use is shown in Fig. 1. In 2008, the average Duke Energy Indiana residential customer used 13,785 kilowatt hours (kWh) of electricity, 23% more than the US average. This greater use reflects greater average air conditioning and electric space heating saturations as well as historically low electricity prices. The average US residential electric price was 11.36 cents/kWh in 2008 compared to 8.79 cents/kWh for Duke Indiana customers. In 2000, the average US price was 8.24 cents/kWh compared to the Duke Indiana price of 6.34 cents/kWh in 2000.

The remainder of this section provides forecast scenarios for several energy efficiency and smart grid program target analyses to illustrate agent-based model applications. A residential customer growth rate of 1.2% was used in the forecast period, consistent with the 1998–2008 growth rate. A discussion on the use of agent detail for program marketing is also included in this section.

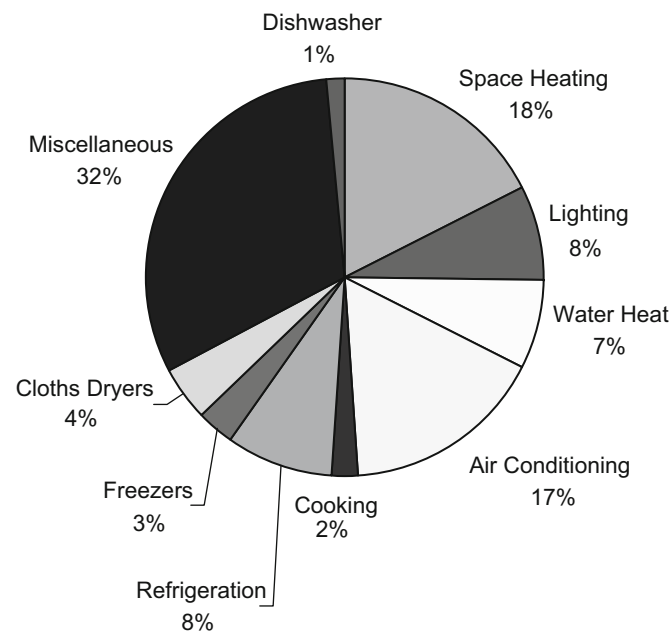


Fig. 1. Duke Indian residential electricity use by end use.

5.1. Efficiency program potentials

Most energy efficiency program potentials are determined with engineering analysis applications where average current efficiencies and technology characteristics are assumed and technical, economic or achievable potentials are determined by efficiency improvements that are technically possible, economic or can potentially be achieved with utility programs.

Technical potential analysis is not terribly useful for program analysis since it assumes that the most efficiency end-use equipment will be used, regardless of costs. Economic potential analysis results are also of limited use since households have a well-recognized reluctance to invest in energy efficiency equipment. Achievable potential is relevant to utility program development since it presumably identifies how much efficiency and smart grid programs can actually save in kWh or peak demand. Achievable potential estimates typically reflect the extent to which utility programs can modify efficiency and behavioral choices based on either past program experience or assumptions about how programs change household choices and behavior.

The agent-based model also supports another approach to evaluate an achievable potential determined by the existing distribution of end-use energy-use characteristics. After adjusting for household size, or in the case of air conditioning and space heating, dwelling unit size, the distributions of existing end-use energy use provide useful targets for what can be achieved with utility efficiency programs.

This distribution approach is similar to targets provided by the US EPA and DOE Energy Star program. A 75 percentile efficiency target assumes that the entire population of residential customers will achieve energy efficiency at least as good as the best 25% of existing customers and a 50% target assumes that all customers will meet or surpass the 50th percentile. These benchmark targets are based on actual energy use characteristics of existing customers and, consequently reflect targets that are, within reasonable bounds, achievable for the entire population since some customers have already achieved them.

Figs. 2 and 3 show five Duke Energy Indiana energy (MWh) and peak demand (MW) forecasts provided by the agent-based end-use model. The frozen efficiency forecast provides an estimate of annual electricity use in GigaWatt hours (GWH) and peak loads in MegaWatts (MW) over the next fifteen years assuming equipment efficiencies and utilization remain constant.

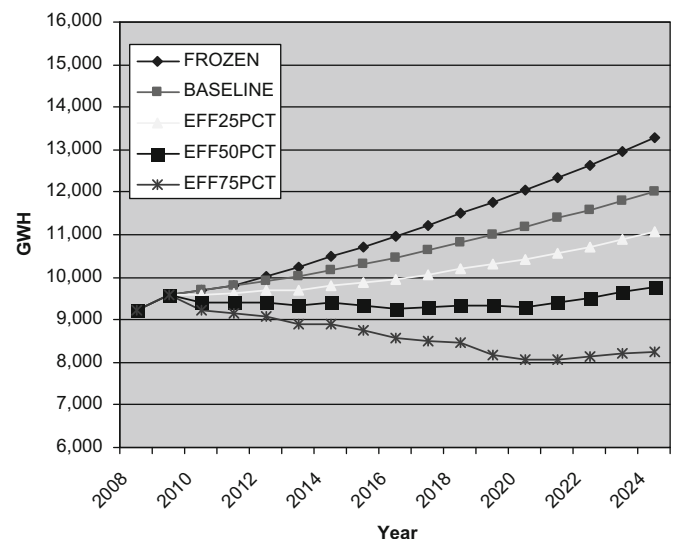


Fig. 2. Efficiency program energy use impacts.

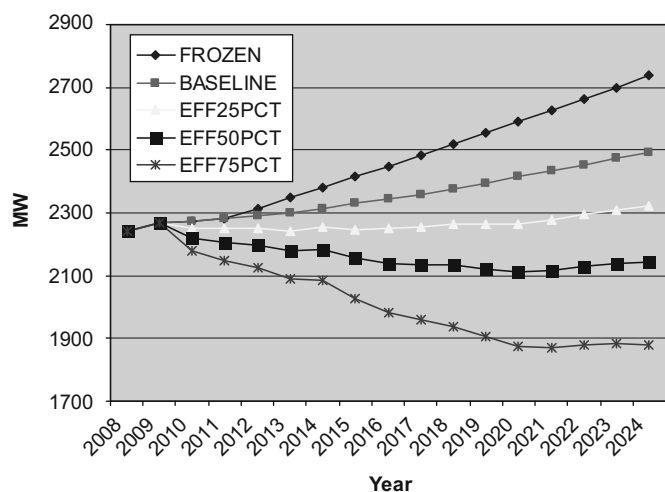


Fig. 3. Peak load program energy use impacts.

That is, in the absence of the impacts of appliance standards, building standards, electricity price increases and so on. Under this scenario annual electricity use increases at an annual rate of 2.3% and peak residential load increases at an annual rate of 1.3%. This forecast scenario is included to show forecast of energy and peak trajectories that could be expected if one were to ignore structural changes currently underway.

The baseline forecast shows annual energy increases of 1.6% and annual peak load increases of 0.6%. The reduction compared to the frozen efficiency case is a result in large part of the 20% electricity price increase that occurs through 2011 and the impact of appliance and building efficiency standards as well as voluntary efficiency improvements.

The 25th, 50th and 75th percentile efficiency targets reveal substantial additional potential for energy efficiency programs with 1.1 and 0.3 and –1.7 annual percent GWH growth rates and 0, 2, –0.4 and –1.2 annual percent MW growth rates. The 25th percentile efficiency target requires reducing electricity use only of those 25% of customers with the most electricity use per end use, adjusted for household size and dwelling unit size which is a presumably modest target. The 50th percentile target might be considered comparable to an achievable potential since it involves reductions in electricity use of customers in the 50th percentile to the current average kWh/customer. The 75th percentile target is roughly equivalent to achieving energy star energy targets for the 75% of least energy-efficient customers.

5.2. Smart grid program potentials

Two program participation rates were assumed in the smart grid forecasts. A 20% participation was included as a reasonable lower bound with a 50% participation reflecting something close to a maximum achievable voluntary pricing program participation. Smart grid programs have little impact on energy use (MWH) so only the peak demand (MW) impacts are shown here.

Fig. 4 shows five Duke Energy Indiana smart grid forecasts provided by the agent-based end-use model. The frozen efficiency, baseline, 20% and 50% participation scenarios and a combination of the least stringent 25th percentile efficiency and 20% participation scenario. The smart grid 20% participation scenario shows the impacts of a smart grid program that impacts central air conditioning and water heating and includes peak hour pricing incentives. It is assumed that participation grows to 20% in the first ten years of the forecast and is maintained at 20% through the remaining five years. The smart grid program reduces peak

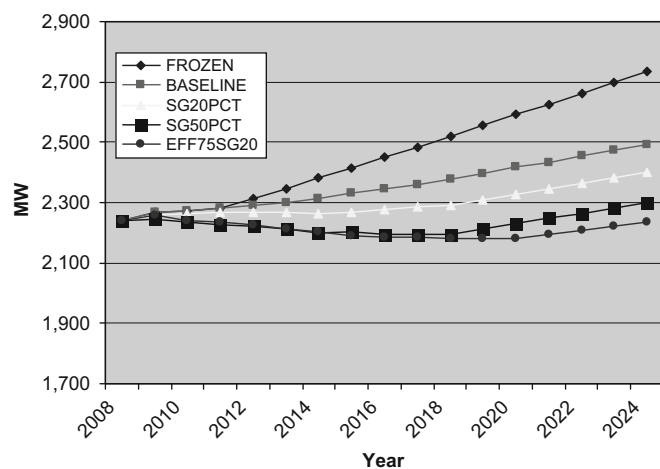


Fig. 4. Smart grid peak hour forecasts.

annual growth to 0.4% and provides a total residential peak demand reduction of 91 MW at the end of fifteen years.

The smart grid 50% participation scenario indicates that a comprehensive smart grid program achieving 50% participation by the tenth forecast year could reduce peak annual growth to 0.2% and reduce peak demand by 192 MW. The final scenario is the 25th percentile efficiency target and the 20% smart grid program participation rate. Peak demand reductions achieved with the three scenarios are 91, 192 and 256 MW with growth rates of 0.4, 0.2, and –0.1. These smart grid and smart grid/efficiency peak demand savings reflect reductions of 3.7%, 7.7% and 10.3% relative to the baseline forecast.

It is interesting to note that the combination of the two least stringent scenarios, the 25th percentile efficiency target requiring reduction of the most energy inefficient 25% of households to the 25th percentile and the 20% smart grid program participation rate provide peak hour reductions 64 MW greater than the much more stringent requirements of the 50% smart grid participation program by itself.

5.3. Program interactions

One of the complicating factors mentioned earlier in this paper is that of program interactions. Ignoring energy efficiency program interactions in traditional program analysis can lead to double counting. For example programs that provide free programmable thermostats interact with high-efficiency air conditioner rebate programs because savings from automated thermostat settings will be less with higher efficiency air conditioners.

- Since agent-based end-use models reflect individual households, this interaction is automatically reflected. That is, program-driven thermostat temperature reductions are applied to air conditioner energy use and hourly loads which will have been reduced if the household also participated in the high-efficiency air conditioner rebate program.
- The interaction of related programs is a serious complication in calculating benefits associated with smart grid program where benefits are often required for a decade or more to pay the large up-front costs of meters, an advanced metering infrastructure, information technology costs, pricing program development and marketing, and other program costs. Most smart grid hourly load savings are provided by technology-enabled and behavioral reductions in peak hour

air conditioning electricity use. A reduction in smart grid program participant air conditioning electricity use of 10% over a decade as a result of equipment replacement and increased electricity prices will reduce smart grid savings by the same amount.

The frozen efficiency forecast above excluded appliance and building standards, voluntary efficiency upgrades and electricity price increases, all of which are incorporated in the baseline forecast. Comparing efficiency and smart grid programs impacts to the baseline forecast excludes those complicating factors; however, evaluating these two programs individually and summing their impacts overstates savings if both programs are implemented. For example, the combined peak load impact of the least stringent 25th percentile efficiency program and the 20% participation smart grid program is 8% less than the sum of the two program impacts evaluated separately. This interaction effect increases with increased efficiency targets and smart grid program participation and when participation in the two programs is correlated.

5.4. Program marketing

Fig. 4 illustrates the importance of smart grid program participation. Most utilities report relatively small efficiency program-related energy and peak demand reductions achieved to date (US Department of Energy, 2009b) suggesting, at least in part, relatively ineffective program marketing efforts. For example Duke Energy Indiana reported a 2007 total electricity use reduction of only 1.6% attributable to all current and past energy efficiency programs.

However, the potential exists to significantly expand both efficiency and smart grid program participation by applying traditional marketing principles of segmenting markets based on customer wants and needs, offering well-designed programs that provide value to customers within the individual market segments and actively marketing programs to individual customers.

The utility customer-detailed nature of the model supports this targeted marketing effort. Agent detail provides direct evaluation and insight on energy efficiency and smart grid program design. For example, Fig. 5 shows a majority of air conditioning smart grid potential in income segments with annual incomes greater than \$50,000 while a majority of water heating potential exists in households with annual incomes less than \$50,000.

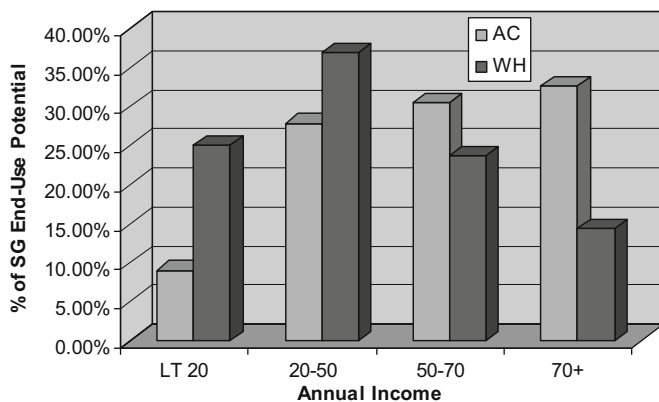


Fig. 5. Air conditioning and water heating smart grid potentials by income category.

6. From traditional end-use models to agent-based end-use models: the data issue

End-use modeling is now a well-accepted approach for forecasting future electricity use and peak demands at the national and utility level and for evaluating the impacts of end-use specific energy-efficiency and other programs (Ameren, 2009; US Department of Energy, 2009a, Emmrich, 2008; Kandel and Kavalec, 2008; Swan and Ugursala 2009; Swisher et al., 1997).

Additional data development and modeling resource requirements are likely to be seen as a significant obstacle to the transition from end-use models to agent-based models. A traditional end-use model may require 30 prototype dwelling unit/end use segments (e.g., 3 dwelling unit types, 10 end uses) to model electricity use. Moving from 30 dwelling unit/end use segments to 1000 or more individual households suggest an exponential increase in data and model development and resource costs. However, an agent-based modeling approach reflects a straightforward extension of traditional end-use modeling. The following steps describe a process that utilities and regulatory agencies can apply to extend traditional end-use models to an agent-based end-use modeling process.

6.1. Step 1. From 30 segments to 1000 agents

A traditional end-use model represents independent dwelling unit/end-use customer segments. Moving to an agent-based model requires information on each customer's joint appliance holdings. That is, in a traditional model, appliance holdings information reflects the number of appliances in each segment; however, in an agent-based model, the presence of each appliance is required for each household. This information is typically available in appliance saturation surveys conducted by most utilities. If appliance saturation data are not already available, a mail survey of customers can be undertaken for at a modest cost.

Each appliance saturation survey record can be used as an individual sample household in the agent-based model with a weight that identifies the number of customers each household represents in the population. This information is ordinarily available from the sample design used in the appliance saturation survey.

6.2. Step 2. Apply parameters and relationships and extend the model software

If the same parameters and relationships used for the traditional end-use models are applied to end-uses within each household and the model calculation loops are extended to incorporate 1000 (or more) households, results of the agent-based model will, at this stage, be identical to results of the traditional dwelling unit/end-use segmented model because the same algebraic operations are being performed. In the agent-based application, the calculations are performed for each household and summed instead of being performed for the average and multiplied by the number of customers. At this point, the traditional and agent-based model analysis and forecasts provide identical results. This equivalence is illustrated by considering Eq. 2 in an agent-based representation below where HH(SFCAC) has a value of 1 if the single family household has central air conditioning and 0 otherwise and the summation occurs across all households.

$$\sum \text{HH(SFCAC)} * \text{UEC(SFCAC)} * \text{U(SFCAC)} * \text{E(SFCAC)} * \text{TE} = \text{kWh(SFCAC)} \quad (2)$$

where UEC is single family/central air conditioner kWh use, U the equipment utilization, E an efficiency index and TE the dwelling

unit thermal efficiency. Since the UEC, U , E and TE parameters are the same across households, the equation can be written as

$$\text{UEC}(\text{SFCAC}) * U(\text{SFCAC}) * E(\text{SFCAC}) * \text{TE} * \sum [\text{HH}(\text{SFCAC})] = \text{kWh}(\text{SFCAC}) \quad (3)$$

However, since $\sum [\text{HH}(\text{SFCAC})]$, the sum of the binary HH variable equals the number of customers, $\text{CUST}(\text{SFCAC})$, we can rewrite the previous equation as

$$\text{CUST}(\text{SFCAC}) * \text{UEC}(\text{SFCAC}) * U(\text{SFCAC}) * E(\text{SFCAC}) * \text{TE} = \text{kWh}(\text{SFCAC}) \quad (4)$$

which is the same as Eq. 1 presented earlier for traditional end-use models.

6.3. Step 3. Differentiate customer characteristics

Section 3 of this paper illustrates the value of recognizing variations in household electricity use characteristics and the difficulties that such variations create in traditional end-use model representations. Since monthly billing data are available for customers included in the utility saturation surveys, estimating space heating and air conditioning electricity use for each household with weather data is a straightforward statistical application. Replacing segment average electric space heating and air conditioning with estimated UECs now provides a significant advantage relative to the traditional end-use model. At this point, UECs for other end uses can be calibrated for individual households with additional information from the saturation survey such as number of household members, size of water heater and so on.

6.4. Step 4. Other extensions

The agent-based end-use model developed at the end of Step 3 provides program analysis advantages associated with agent-based modeling relative to traditional dwelling unit/end-use modeling described in earlier sections of this paper.

At this stage, the framework exists to expand the agent-based model representations. For example, household information on the age of the air conditioner, the age and size of the refrigerator and other data typically available in customer appliance saturation surveys can be used to infer current efficiency ratings. Utility customer data from a variety of sources can be used; for example, detailed information collected with in-home energy audits can provide valuable information on end use equipment and building shell characteristics.

6.5. Step 5. Matching model and data resources with analysis needs

The steps outlined in this section show that many of the benefits associated with moving from a traditional end-use model to an agent-based end-use model can be achieved with modest extensions of existing end-use models and existing utility data resources or modest data development activities. A variety of issues have arisen in recent years that recommend these modeling and data development activities. Increased emphasis on promoting energy efficiency investments, concerns over public policy cost-effectiveness, mandates to achieve energy efficiency and peak load reductions, constrained electric utility transmission and distribution systems and concerns over carbon reduction are some of the most visible of these issues. Developing cost effective strategies to address these new issues requires utilities and regulatory agencies to improve modeling and analysis capabilities to reflect the detailed nature of programs targeted to these areas. Results of the Duke Energy example analysis presented above

demonstrate the ability of agent-based models to provide this detailed analysis.

The incremental approach described in this section provides a framework by which individual utilities and regulatory agencies can match analysis objectives with model and data resource needs to better address some of these increasingly pressing issues.

7. Summary

This study describes shortcomings in traditional analysis of electric utility energy-efficiency and smart-grid programs. The inability of these approaches to simultaneously address free riders, appliance and building efficiency standards, electricity price increases and other factors within a comprehensive analytical framework limits their application in utility and regulatory cost-effectiveness studies and in providing reliable electricity use and peak demand forecasts.

An agent-based end-use modeling methodology which models end-use energy use detail of a representative sample of utility customers that is shown to resolve issues associated with these traditional methods. Data for a representative sample of utility customers in a Midwestern US utility are used to illustrate the end-use modeling process. The agent-based model is applied to forecast electricity use and hourly loads over a fifteen year horizon. Energy efficiency targets are developed based on achieving efficiency improvements for the most energy intensive 25%, 50% and 75% of households. Results show that reducing energy use of the most energy intensive half of the population holds electricity use roughly constant at its 2000 level while the less stringent 25th percentile efficiency target maintains something close to current peak demand and generating capacity requirements.

A central air conditioning and water heating smart grid programs are specified and evaluated for programs with 20% and 50% customer participations. 50% participation was determined to be necessary to keep future peak demand at current levels.

A combination of efficiency and smart grid initiative for the two least stringent scenarios, the efficiency program reducing the most energy-inefficient 25% of households to the 75th percentile target level and the 20% smart grid program participation rate provides peak hour reductions 33% greater than the much more stringent requirements of the 50% smart grid participation program by itself. These results suggest that reductions in peak demand requirements are more feasible when both efficiency and smart grid programs are considered together.

Utility customer information provided by the agent-based framework can provide useful insights to help market energy efficiency and smart grid programs. Suggestions on transitioning from traditional end-use models to agent-based end-use models are provided.

Acknowledgements

The author gratefully acknowledges comments and suggestions from an anonymous referee.

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