Agent Based Technology Adoption Model for Program Planning and Design

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ABSTRACT

One of the challenges in developing an energy efficiency (EE) or demand reduction program is estimating the actual adoption of EE technologies by building owners and operators. The decision to adopt any particular technology is a complex interrelation of capital costs, financing and incentive availability, energy and cost savings, non-energy and cost benefits of the technology, and the risk profiles of the building owners. Argonne National Laboratory has developed CoBAM, a commercial building agent based tool, for studying the adoption of energy efficient technologies in the marketplace. In the tool, energy and costs savings estimates of different technologies are generated using building energy models and fuel price predictions. This information is combined with information about installation costs, non-energy characteristics of the technology, and owner weightings of the different characteristics to predict what technology, if any, the owner will select for retrofit. The tool was designed for a variety of uses including technology research and development prioritization, local and regional policy planning, and EE program planning. In this paper some model validation results are presented.

Introduction

Agent-based modeling (ABM) is an approach to modeling systems with autonomous, interacting entities called agents. These agents have behaviors, usually described by simple rules for decision-making processes, and interact with other agents, which in turn can influence their own behaviors. Agents are heterogeneous, and the variations in decision processes and interaction rules give rise to a complex behavior of the system as a whole. This “ground-up” approach to modeling often leads to the emergence of self-organization, patterns, and structures that are not explicitly programmed or assumed by the models.

A typical ABM has three main elements:

1. A set of agents who have unique attributes and behaviors.
2. A set of agent relationships and methods of interactions. These relationships and interactions describe how and with whom agents will interact.
3. The agents’ environment with which the agents interact.

Agents are able to act autonomously, i.e. without external direction, in response to the stimuli they receive. Some agents are active and initiate actions to achieve internal goals, while others are passive and merely respond to other agents and the environment. Because of their abilities to model social systems, ABMs have become fairly popular for modeling various marketplace interactions. An example of a very detailed market analysis model is the “virtual market learning lab” developed by Argonne National Laboratory and Proctor & Gamble (North et al. 2010). Agent models are also successfully being used to look at the adoption and diffusion of technology (Kiesling et al. 2011, Nan, Zmud, and Yetgin 2013, Jiang and Jiang 2015). Compared to the traditional aggregate analysis that frequently uses the Bass diffusion model (Bass 1969), agent-based models offer a microscopic description of the process which allows users to better understand the influence of different parameters and interventions on adoption and to study the adoption of products early in the product life cycle (Lanciana and Oteiza-Aguirre 2014, Przybyła, Sznajd-Weron and Weron 2014). Agent-based modeling has been particularly effective at modeling the regional adoption of solar panels (Zhang et al. 2014, Macal, Graziano, and Ozik 2014). A more complete introduction of agent-based models is beyond the scope of this introduction, but readers can find more information in the review and tutorial papers by Tefatsion (2002) and Macal and North (2009).

Methodology

Researchers at Argonne National Laboratory have developed the Commercial Building Agent Model (CoBAM) as a tool for energy efficiency program and policy analysis (Martinez-Moyano et al. 2011; Zhao, Martinez-Moyano, Augenbroe 2011). The basic diagram of most major components and interactions is shown in Figure 1.

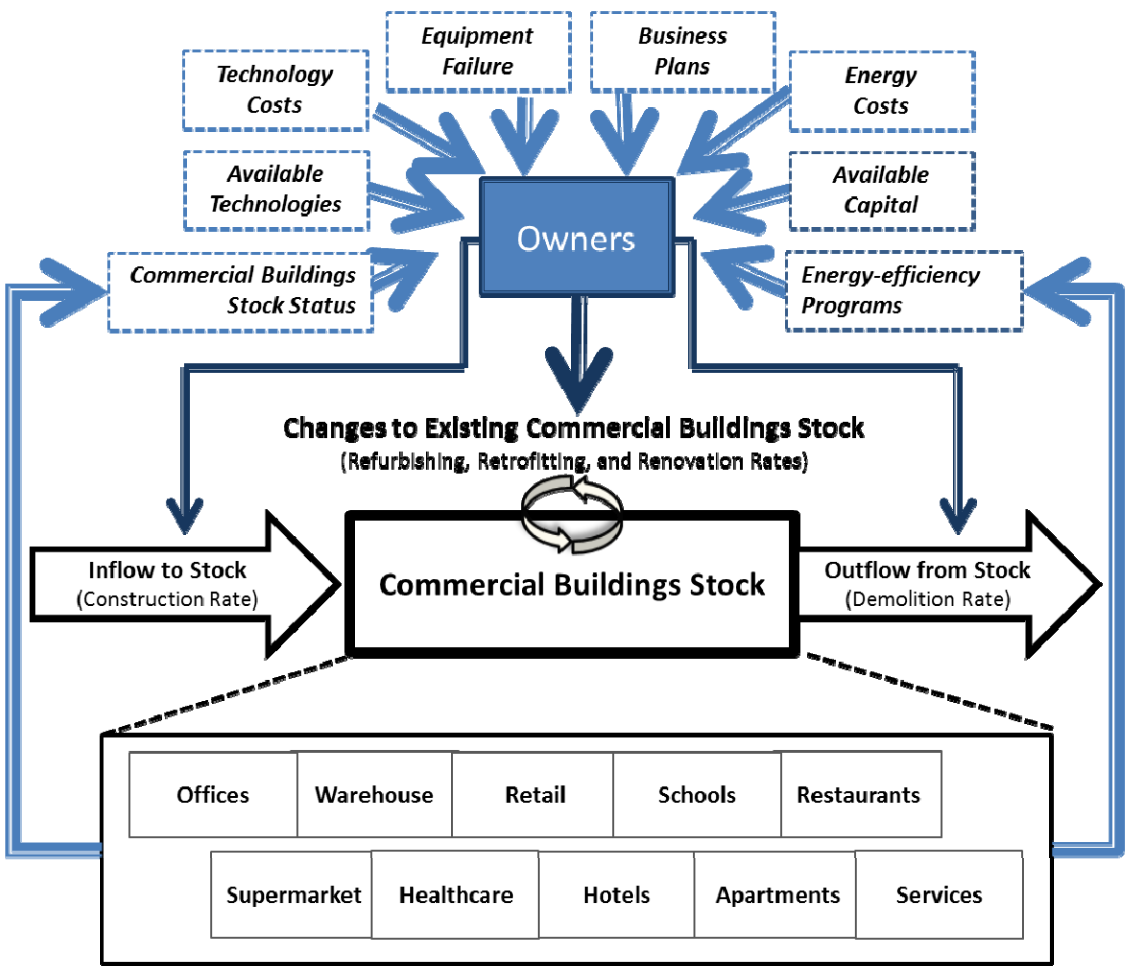

Figure 1: Diagram of major CoBAM components and basic interactions.

The CoBAM agent model is implemented in Repast Simphony, a widely used free and open source agent based modeling software platform developed by Argonne and the University of Chicago (North et al. 2013). The long term plan for CoBAM is to develop a highly detailed model of the commercial building marketplace with all the major market participants being represented by agents, including building owners, occupants, developers, financiers, designers, suppliers, and regulators, among others. At this point in time, CoBAM has implemented building owners as active decision making agents and buildings themselves as passive agents. Buildings are modeled as agents because their characteristics changed in time in response to the actions of the owners (e.g. a retrofit was chosen) or through the simple natural evolution of systems (e.g. equipment failure or degradation of system performance with aging).

For large scale analysis, CoBAM utilizes several levels of aggregation as shown in Figure 2. Individual buildings and owners are aggregated at an agent level where one building agent and one owner agent represent an aggregated number of like buildings whose owners have similar decision characteristics and exist in the same geographic region. Most analyses in CoBAM are made over a large geographic region and the agents are thus aggregated into a single regional output for any selected index of performance.

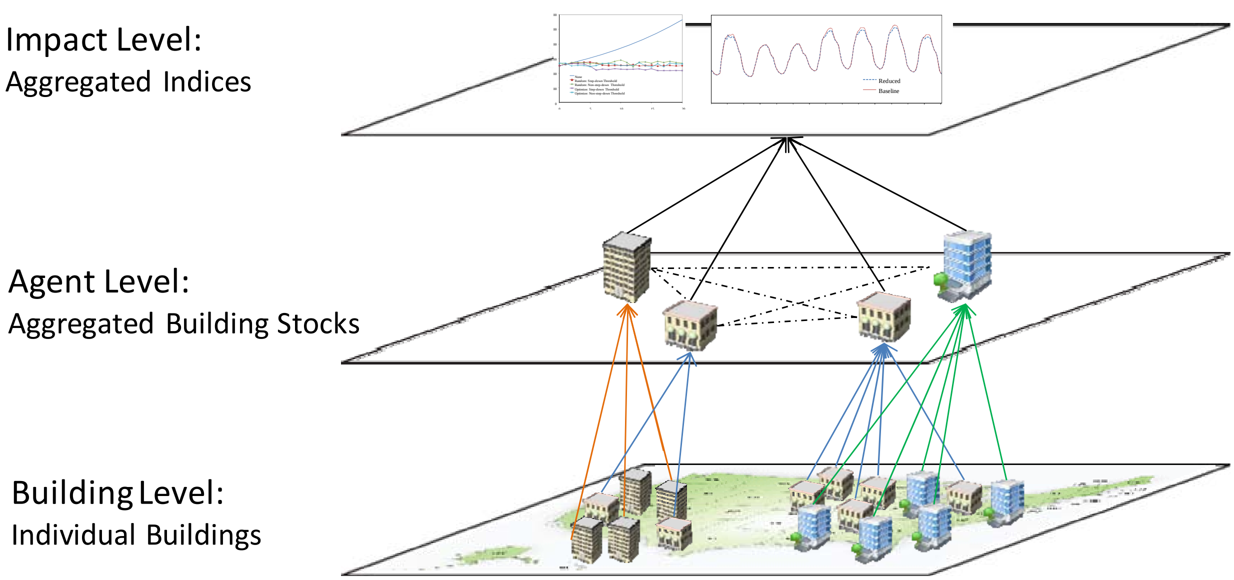

Figure 2: Multiple aggregation levels available in CoBAM.

An agent-based model could theoretically be developed that includes every individual building and owner in the region of interest. This capability would allow for fully characterizing the diversity of existing building stock and building owner decisions, more accurate modeling of the demolition of old stock and the introduction of new stock, and greater fidelity in consideration of the social interaction and networking of individual building owners. However, the detailed information and resources needed to create individual building models for individual building analysis is typically outside the scope of typical projects and the computing requirements necessary for larger scale analysis (state or national level) using individual buildings would necessitate the use of high performance computing.

Building Energy Model

CoBAM implements a reduced order monthly energy model based upon ISO 13790 and associated standards that have become the modeling core of the European Union (EU) Energy Building Performance Directive (EBPD) (van Dijk 2009). The model is appropriate for study of a wide variety of retrofits but some retrofits that require detailed systems modeling, such as advanced control systems, cannot be modeled. However, the model runs extremely fast which is essential when a CoBAM simulation requires hundreds of thousands to millions of energy simulations. This ISO model has been described by Muehleisen et al. (2014) and has been validated by comparison to EnergyPlus using the DOE reference buildings by Guzowski et al. (2014) as shown in Table 1.

Table 1: Comparison of CoBAM ISO energy model EUI predictions to EnergyPlus in kBtu/ft^2

	Phoenix			**Chicago**			**San Francisco**		
Building Type	**E+**	**ISO**	**% Δ**	**E+**	**ISO**	**% Δ**	**E+**	**ISO**	**% Δ**
Large Office	62.0	64.0	−3.3	63.1	55.6	11.8	51.3	49.3	3.8
Medium Office	64.6	65.0	−0.6	66.0	59.6	9.7	51.0	52.9	−3.7
Small Office	68.8	79.4	−15.4	72.2	76.4	−5.8	55.5	66.0	−18.9
Stand-Alone Retail	90.6	84.5	6.8	130.2	103.9	20.2	84.7	74.6	11.9
Strip Mall Retail	99.9	96.4	3.4	143.1	130.2	9.0	92.5	101.3	−9.5
Quick Service Restaurant	554.9	647.0	−16.6	682.7	714.2	-4.6	546.3	573.3	−4.9
Warehouse	22.6	28.0	−23.9	58.9	54.3	7.7	24.8	31.2	−25.9
Mid-rise Apartment	52.1	58.9	−13.0	79.3	87.6	−10.5	49.9	44.6	10.6

Source: Guzowski et al. 2014

Building Stock Description

CoBAM allows the user to completely define the building characteristics and the region or city where the building resides (through selection of the weather file). For the validation study discussed below, a set of typical buildings based upon the sixteen DOE Commercial Reference Buildings (Deru et al. 2011) was developed: large, medium and small offices, large and small hotel, primary and secondary schools, outpatient health care and hospitals, stand-alone and strip mall retail, full- and quick-service restaurants, supermarkets, midrise apartments, and warehouses. Deru et al. (2011) defines the sixteen buildings for three vintages, pre 1980, post 1980 and new construction which is based on ASHRAE 90.1 2004. In CoBAM, these models are used as the basis for large scale regional analysis.

Technology Description

Technology that can be installed into the building (e.g. a new chiller) or a retrofit operation that can be performed on a building (e.g. retro-commissioning) has five basic descriptors: building efficiency/operation change, cost, time span of availability, equipment lifetime, and a non-energy technology descriptor. A retrofit technology could be a single piece of equipment or a number of items installed together that affect many building parameters at the same time. The first descriptor is the performance of the equipment if the retrofit is a replacement/installation of an actual technology. When the new technology is installed, the values of the new technology will replace the values of the existing technology within the building energy model. The cost descriptor should include initial capital costs (equipment and installation costs), as well as ongoing operation/maintenance costs. Fuel costs associated with operation are not part of the technology descriptor as fuel consumption is determined by the building energy model and fuel costs are utilized. The time span of availability descriptor is used to tell CoBAM when the technology is available first for consideration of installation in the building and when it will no longer be considered to be in the marketplace. The technology lifetime descriptor is the mean time between failures for the equipment and is used to estimate when equipment will have to be replaced because of failure. The final descriptor is the non-energy benefits of the technology. Fleiter, Hirzel, and Worrell (2012) developed a classification scheme which was adapted for use in CoBAM as shown in Table 2. The selection of characteristics and initial weightings for different owner types were obtained through elicitation of subject matter experts.

Table 2: Non-energy technology characteristics used in CoBAM

Characteristics	**Attributes**			
Design/Install Skill	**Tech expert**	**Engineering**	**Maintenance**	**Owner**
Installation Downtime	Months	Weeks	Days	Hours
Procurement Time	Months	Weeks	Days	Hours
Durability	0-1 yr	1-5 yrs	5-10 yrs	>10 yrs
Serviceability	Weekly	Monthly	Yearly	Never
Non-Energy Performance	Negative	None	Small	Large
Visibility of Benefits	Owner	+Employees	+Tenants	+Public
Embedded Energy	High	Med	Low	None

For each technology, each characteristic is assigned a value of 1 to 4 based on matching the technology attribute to one of the four column descriptions. It is anticipated that forcing users to match a technology characteristic to one of four columns rather than assign a continuous value from 1 to 4 will lead to consistent characterization between different users making the assignment. These values are then divided by the values assigned to a reference "conventional" technology in the same general category as the technology under review (i.e. the reference for a gas water heater might be a low cost, non-condensing, normally insulated unit) to generate a relative value of 0.25 to 4.0 for each characteristic of each technology. Conventional technologies will have a 1.0 for each technology and values greater than 1.0 indicate that the characteristic for the technology in question is "better" than conventional technology while values less than 1.0 indicates the characteristic is worse. These characteristic values are compared to those of conventional technology and combined with owner weightings for each characteristic to create a non-energy technology adoption factor that is used as part of the adoption decision process.

Owner Decision Process

CoBAM considers four owner types, which are modeled after the adoption categories defined by Rogers (2003) for distinguishing the innovativeness of building owners. In this context, innovativeness refers to both a building owner's knowledge of and willingness to purchase emerging, cutting edge technology. The four owner types modeled within CoBAM are Laggard, Follower, Leader, and Federal Government.

The Laggard owner type represents building owners who are suspicious of innovations. Laggards are modeled as having no preference to invest capital into energy efficiency measures and having extremely limited information or misinformation of available technologies. This owner type is equivalent to the "laggard" adopter category of Rogers.

The Follower owner type is representative of the majority of building owners who are willing to invest in EEM technologies if they make financial sense. This owner type encompasses the "early majority" and "late majority" adopter categories defined by Rogers.

The Leader owner type is representative of building owners who are highly motivated to reduce energy consumption and operations and maintenance (O & M) costs within their building. The Leader owner type is also representative of building owners who are highly informed of emerging, cutting edge technology and are willing to purchase such equipment before it has been widely utilized and established a track record (i.e. the performance and reliability of the technology may be uncertain). Leaders exemplify Roger's adoption categories of "innovators" and "early adopters."

Lastly, a separate Government owner type is modeled in CoBAM. While most building owners are required to bring their building up to code when they are making major retrofits to their building, government owners may be mandated by law or executive order to bring their buildings up to code within a specified time period after new building code is published. Likewise, government owners may be required by law to evaluate investments in energy efficiency with no expectation for return on investment as a way of accelerating adoption of EEM technologies within facilities.

Each of these four owner types has a different associated risk preference that reflects how much risk the owner is willing to take with respect to the retrofit as an economic investment. The risk preference is related to an internal discount rate used in the economic calculations.

Each owner type also has set of weightings that are used to reflect the relative importance of the different technology characteristics along with weightings of the relative importance of economic considerations and energy savings considerations.

The economic calculations combine the technology initial costs with annual operation and maintenance costs and annual fuel costs using an owner specific internal discount rate and owner specific weighting of the relative importance of the three types of costs. The economic calculations for each technology are compared and used to create a technology financial score (FS). Energy savings for each retrofit are also computed and compared against each other to create an energy score (ES) for each technology. These two scores are then combined using owner specific relative weightings to create an overall Technology Score (TS). The technology with the highest TS is selected for retrofit if its TS exceeds the threshold set by the owner. If no retrofit exceeds the threshold, then CoBAM checks to see if the retrofit opportunity was because of equipment failure. If so, then the lowest initial cost technology is selected and used to replace the failed equipment in the building.

Basic program flow

The main CoBAM program flow consists of a main outer loop that runs through each year of the simulation period. Following initialization where much data describing the technologies, building stock, and owner characteristics are assigned, each building owner agent is individually processed through the technology evaluation process where the economics and energy savings of the technology are computed for each retrofit under consideration. The highest scoring technology is adopted as a retrofit. This process is repeated for every owner agent in the simulation and for every year of the simulation.

Model Validation

In order to validate the underlying energy model and basic decision models, CoBAM was calibrated and validated using predicted overall US energy use for water heating and comparing to the output of the National Energy Model System (NEMS) used by the DOE Energy Information Agency for use in the Annual Energy Outlook (EIA 2014). Ideally, one would like to compare CoBAM to studies of actual technology adoption and not another model, but unfortunately, there is a lack of published studies that include actual technology adoption numbers that include the required efficiency, cost and equipment lifetime data required to generate a CoBAM run for comparison. The EIA, however, makes the cost and efficiency data used for their predictions available to the public. In addition, EIA publishes the detailed information about the building stock breakdown as a function of age, vintage, and region and about the risk profiles for building owners used within the NEMS model. Those data thus were used as the basis of the building stock and owner profiles used by CoBAM. The research team will continue to pursue opportunities to obtain data for real-world validation.

NEMS breaks down the building stock into characteristic building types of several vintages. The building types are Assembly, Education, Food Sales, Food Service, Health Care, Lodging, Office – Large, Office - Small, Mercantile, Warehouse, and Other (everything that does not fit into one of the other 10) and vintages are pre 1900, 1900-1919, 1920-1945, 1946-1959, 1960-1969, 1970-1979, 1980-1989, 1990-1999, 2000-2003, and every year after 2004. The NEMS building types were mapped to the DOE reference buildings as shown in Table 3. No mapping was made for the "Other" building category – the buildings and associated energy were excluded from the comparison due to the high level of uncertainty regarding buildings in this category. Buildings built in pre 1900 through 1979 were mapped to the pre 1980 vintage of the DOE reference buildings, buildings built in 1980-2003 were mapped to the post 1980 vintage and buildings built in years after 2003 were mapped to the New Construction vintage.

Table 3: Mapping of NEMS Building Category to DOE Reference Buildings

NEMS Category	**DOE Reference Building**
Assembly	Medium Office
Education	Primary School
Food Sales	Supermarket
Food Service	Full Service Restaurant
Health Care	Hospital
Lodging	Large Hotel
Mercantile	Stand Alone Retail
Office – Large	Large Office
Office – Small	Small Office
Warehouse	Warehouse
Other	No Mapping

NEMS separates its building stock into nine regions that correspond to census divisions across the US. One city in each region was selected to represent the region and to choose a TMY weather file for use in energy analysis as shown in Table 4 below.

Table 4: Mapping of NEMS census division to TMY3 city file

NEMS Census Division	**Assigned TMY3 City**
New England	Portland, ME
Middle Atlantic	State College, PA
East North Central	Chicago, IL
West North Central	Minneapolis, MN
South Atlantic	Atlanta, GA
East South Central	Nashville, TN
West South Central	Houston, TX
Mountain	Denver, CO
Pacific	San Francisco, CA

NEMS also defines 7 risk categories that relate to internal discount rates used by the owners in evaluating the economics of various technologies. CoBAM maps these to owner types as shown in Table 5 below. The relative share of building owners in each risk category is also shown.

Table 5: NEMS risk categories and mapping to CoBAM owner types

Risk Category	**CoBAM Owner Type**	**Share of Owners**
1	Laggard	0.263
2	Follower	0.235
3	Follower	0.202
4	Follower	0.183
5	Follower	0.099
6	Leader	0.010
7	Government	0.007

As a first validation study, the predicted total US energy usage for water heating from CoBAM was compared to NEMS predictions. Water heating energy was chosen in part because there is little interaction between water heating and other building components and also because water heaters fail and will need to be replaced several times over the 30 years of the validation period.

For comparison of CoBAM predictions of energy use with NEMS, the output of NEMS from years 2003 to 2013 is used for calibration and from years 2014 to 2040 are used for comparison. During the calibration process, the owner financial and energy weightings were adjusted to minimize the difference between the CoBAM and NEMS predictions for natural gas and electricity use. The results from the calibrated model are shown in

Figure 3 below.

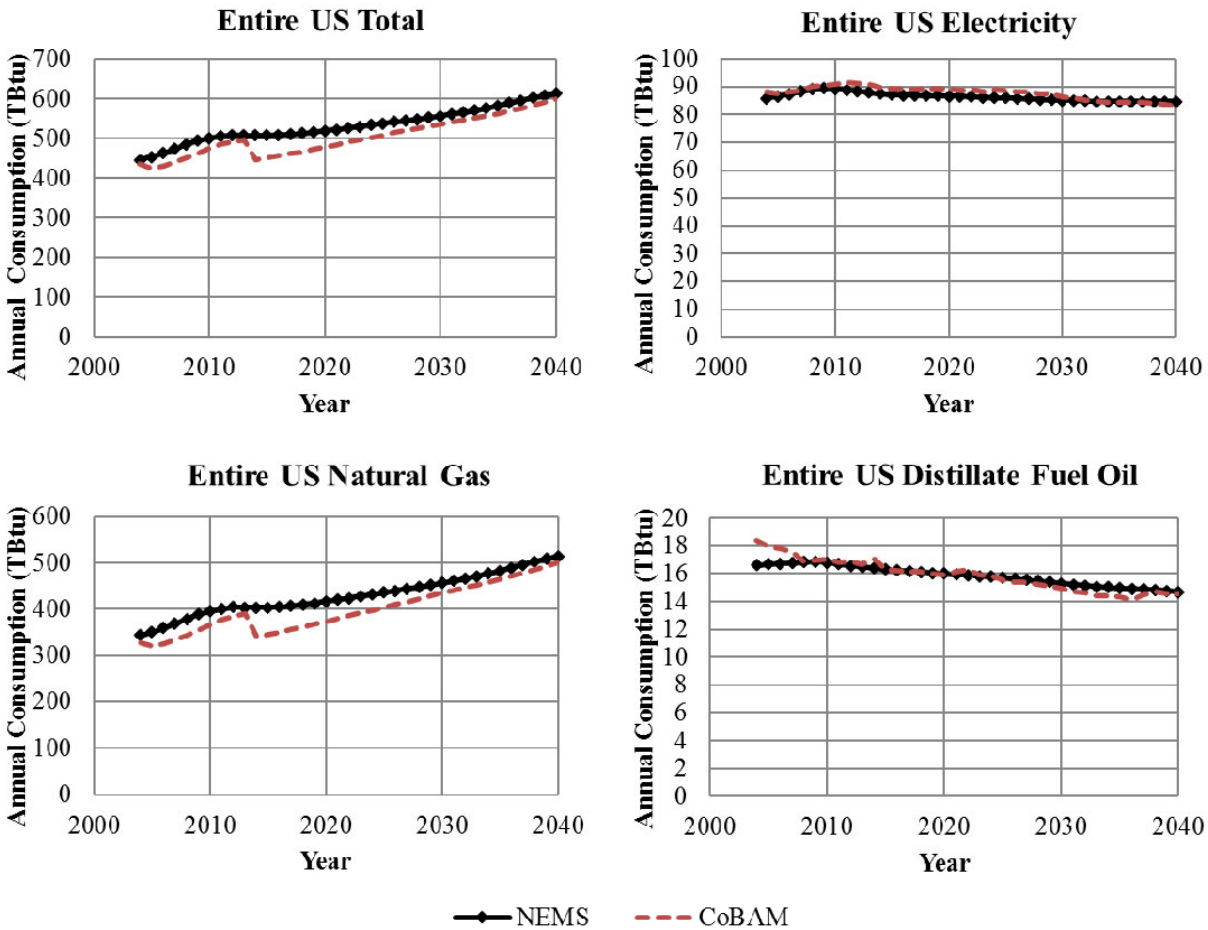

Figure 3: Comparison of NEMS and CoBAM US water heating energy consumption projections for the overall total, total electricity, total natural gas, and total distillate fuel oil.

Discussion

The results in Fig 3 clearly show that CoBAM does an acceptable job at modeling the overall energy use of a technology which means the model also does an acceptable job at modeling adoption of new technologies. The predictions were good for natural gas, electric, and distillate fuel types in addition to overall. While water heater technology will improve over time, the overall energy use dedicated to water heating is expected to rise because of the growth rate of the building stock is expected to outpace the increase in water heating efficiency.

The largest discrepancy between the NEMS and CoBAM occurs at the year 2014. The reason for this is because the NEMS input data describes a new hot water technology arriving in year 2014 that is both cheaper and higher efficiency than the conventional technology and thus nearly everyone who is considering a water heater retrofit will chose that new technology. The method that NEMS uses for estimating technology adoption does not lend itself to generating such high adoption rates after the introduction of such a breakthrough technology.

Unfortunately, a more realistic scenario that includes the evaluation of multiple technologies at once (e.g. window replacement, chiller replacement, retro-commissioning) has not yet been defined for CoBAM, and thus CoBAM has not yet been more fully validated.

Conclusions

This paper described the development of a new agent model for studying and predicting the adoption of energy efficient technology. The model evaluates the economic, energy, and non-energy benefits of possible technologies for retrofit or replacement and uses a decision model to predict what is adopted by different owners given a wide variety of owner characteristics such as internal discount rate and the relative importance of economic, energy, and non-energy characteristics. The predicted total energy use from adopted water heating technologies in CoBAM was compared to the estimates prepared by EIA using the NEMS model. The comparison was good for all three fuel types: natural gas, electricity, and fuel oil. The next step for CoBAM is to develop a scenario that includes multiple technology categories for consideration for a more complete validation study.

Acknowledgements

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