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A microsimulation model of urban energy use: Modelling residential space heating demand in ILUTE

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ABSTRACT

Rapid urbanization, climate change and energy security warrant a more detailed understanding of how cities today consume energy. Agent-based, integrated microsimulation models of urban systems provide an excellent platform to accomplish this task, as they can capture both the short- and long-term decisions of firms and households which directly affect urban energy consumption. This paper presents the current effort towards developing an urban energy model for the Integrated Land Use, Transportation, Environment (ILUTE) modelling system.

As a first step, a model for the residential space heating system evolution of the Greater Toronto–Hamilton Area was developed. A bottom-up approach, where individual uses are aggregated, was then employed to estimate the region's space heating demand. Conventional bottom-up methodologies often suffer from insensitivity to either technological or behavioral factors. It is argued that coupling a discrete choice model with building energy simulation software solves this problem. A joint logit model of heating fuel and equipment choice was developed and estimated using Toronto household microdata. The HOT2000 software was then used to compute individual dwelling unit space heating use. The entire residential energy analysis was performed in tandem with the housing market and demographic evolution processes. This allows the endogenous formation of the required inputs as well as adherence to the core ILUTE framework of integrated modelling.

This residential space heating model is a first step towards a comprehensive urban energy end-use model. Further steps include developing similar models for other residential end-uses, such electricity and hot water consumption, as well as extensions to the commercial and transportation sectors. The entire effort aims to introduce an alternate methodology to modelling urban energy consumption that takes advantage of agent-based microsimulation to enhance and address issues with current approaches.

1. Introduction

Cities today contribute about two-thirds of the world's primary energy demand. By 2030, this fraction is projected to increase to three-quarters, matching the urban sector's expected share of global energy-related CO_2 emissions (International Energy Agency Office of the Chief Economist, 2008). These figures can be attributed to both the increasing global population and urbanization, evident from the 3 billion people who reside in cities today (United Nations Department of Economic and Social Affairs, 2007). The current urban energy outlook, along with climate change and energy security warrants a detailed understanding of urban energy use.

Disaggregate methods of analysis have historically been popular for this task. Previous energy studies though, were static and only examined individual components of the urban system, such as the demand from the residential (Nesbakken, 1999) or transportation (Berkowitz, Gallini, Miller, & Wolfe, 1990) sectors. However, cities consume energy as a result of human activities and decisions. It is people turning their lights on in the morning, driving their cars to work, using their computers at the office, and running their dishes after dinner that generate the demand for energy. As such, the energy demands of the main urban sectors (residential, commercial and transportation) are linked through this human activity system.

Recognizing these interactions is critical in estimating the net effect of a new policy. For example, congestion pricing can incur short- (switch to public transit) and/or long-term (relocate closer to work) responses from households. However, some metropolitan regions, such as Toronto, have a higher residential energy demand per capita in their CBDs than their suburbs due to older

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infrastructure and laxer building codes (VandeWeghe & Kennedy, 2007). Hence, in the long-term response, a portion of the energy savings from a shorter commute may be offset by higher heating energy use. This is not to say that congestion pricing is ineffective, but it makes a compelling case for a holistic approach to urban energy analysis and management.

Recently, there has been a growing interest in developing urban energy models to begin addressing similar concerns. There has been work on models that evaluate urban energy use scenarios while simultaneously linking the demands from both the transportation and residential sectors (Boydell et al., 2010). Microsimulation models are being developed to evolve entire urban regions to predict future energy use (Almeida et al., 2009; Tirumalachetty, Kockelman, & Kumar, 2009). There has also been progress on building software to support city planning from an optimal resource flow perspective (Keirstead, Samsatli, & Shah, 2010; Robinson et al., 2009). While these new models have different designs, scopes and objectives, one overarching goal appears to be clear: devise a better tool for assessing urban energy-related policies.

A number of these urban energy models can be embedded within integrated land use transportation models, since these integrated models provide many of the elements required for developing comprehensive urban energy models. For instance, integrated models often have a disaggregate representation of energy consuming agents (e.g. households and firms) which can easily facilitate a bottom-up estimation of a region's energy demand.

One example of a model that can be extended to include urban energy analysis is the Integrated Land Use, Transportation, Environment (ILUTE) model system. ILUTE is an agent-based microsimulation model of the Greater Toronto–Hamilton Area (GTHA). ILUTE has reached a level of maturity where 20-year historical validation runs are being undertaken (Miller, Farooq, Chingcuanco, & Wang, in press). While the validation to date has focused on ILUTE's simulation of the region's housing market and demographic evolution, the exercise demonstrates that ILUTE is at a sufficiently advanced stage where it can serve as a modelling and computational foundation for different kinds of urban process models.

At present, ILUTE is only capable of modelling the energy consumption and related emissions of a region's transportation sector through integration with TASHA (Travel/Activity Scheduler for Household Agents) (Hao, Hatzopoulou, & Miller, 2010). However, to have a more complete understanding of an urban system's energy use, the other sectors also have to be included in the analysis. Due to ILUTE's structure and operational status, it has the potential to accomplish this task.

This paper presents the current effort towards developing an urban energy model (UEM) for the ILUTE model system. The paper is organized as follows. First, a short introduction to the ILUTE model system is provided. Second, a conceptual framework for an ILUTE urban energy model is laid out. To help envision this framework, relevant work is briefly reviewed. A residential space heating demand model, which is the first step towards a UEM for ILUTE, is then presented. This includes a review of residential energy modelling techniques, as well as an overview of the space heating demand model's design and implementation. This is followed by a brief discussion of the data used, along with initial results. Finally, the future directions of the research are outlined.

2. An urban energy model for ILUTE

The objective of this section is to provide a conceptual framework for an ILUTE urban energy model. Before this high-level structure is laid out, a brief overview of ILUTE is first provided. This is then followed by a selective review of recent work in order to help guide the design of an ILUTE UEM.

2.1. An overview description of ILUTE

ILUTE is a comprehensive, integrated modelling system designed to project the evolution of demographics, land use and travel within an urban region over time. It is an object- and agent-based, microsimulation modelling system, where the system state is evolved from an initial base case to some future end state one time-step at a time. In ILUTE, the system state is defined in terms of the individual persons, households, dwelling units, firms, etc. (the agents) that collectively define the urban region being modeled. ILUTE evolves the attributes of these agents by simulating their behavior (changes in residential location, labor force participation, activity/travel, etc.) over time. Fig. 1 summarizes key elements of the current implementation of the model system. Elements in red are external inputs provided to the ILUTE model system, while those in green are processes that are currently

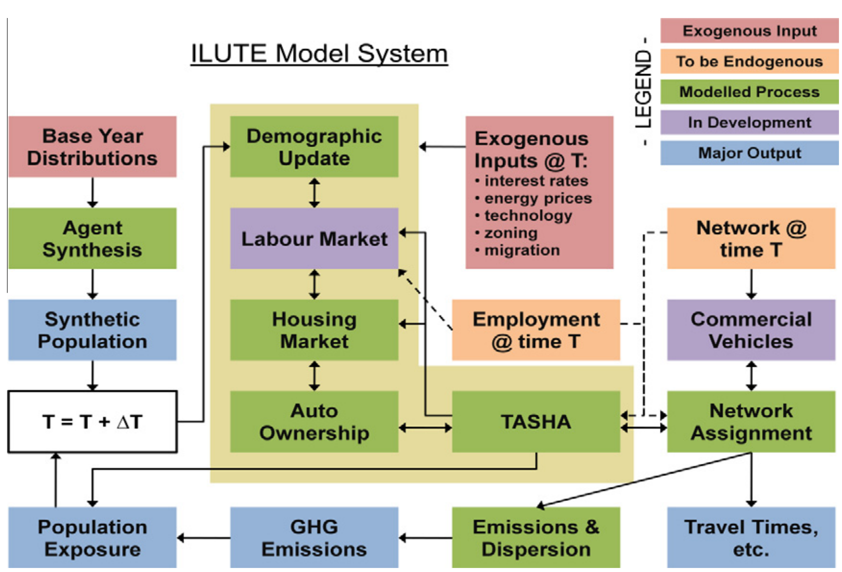

Fig. 1. High-level flowchart of ILUTE processes.

modelled. Items in blue are the major outputs of these models, while those in purple and beige are still under development.

As shown in this figure, key processes modelled within ILUTE include:

- The model system is initialized with a set of agents/objects which are synthesized from base year Census (and possibly other) data. A 100% population of persons, families, households and dwelling units for each census tract in the study area has been constructed for 1986 using a modified iterative proportional fitting (IPF) procedure (Pritchard & Miller, 2009) that:
  - Simultaneously generates these four objects in a consistent manner.
  - Permits a large number of attributes to be included in the synthesis.
  - Is computationally efficient.
  - Makes full use of multiple multivariate tables of observed data.
  - Is extendable to include additional elements (e.g. household auto ownership).
- For model testing purposes, either the full 100% population can be used, or a smaller subset, which is randomly drawn from the full population, can be used to speed up run times.
- The current implementation models all processes using a standard 1-year time step, but also permits individual processes to occur at finer time steps (down to a 1 month resolution level).
- Resident population demographics are updated each time step. These include processes for birth, death, education, marriage, divorce and driver's license ownership. In- and out-migration processes are also dealt with, given that the GTA has been growing (and is projected to continue to grow) by approximately 100,000 people per year.
- The labor market component evolves the labor force over time in terms of:
  - Entry and exit of persons to/from the labor market over time.
  - Mobility of workers within the labor market from one job to another.
  - Allocation of workers actively seeking employment to currently available jobs in the market.
  - The determination of worker wages/salaries by occupation, industry and location over time.
- The housing market component similarly evolves the residential location of households over time. It includes the endogenous supply of housing by type and location, as well as the endogenous determination of sales prices and rents.
- Household auto ownership is dynamically evolved using the models of household vehicle transactions and vehicle type/vintage choice developed by Mohammadian and Miller (2003).
- Once household demographics, labor market characteristics, residential location and auto ownership levels have been determined, the activity/travel patterns for each person within each household for a typical weekday are estimated using the agent-based microsimulation model TASHA developed by the ILUTE team (Miller & Roorda, 2003).

Other significant developments include interfacing TASHA with a variety of network assignment models such as EMME and MATSIM (Gao, Balmer, & Miller, 2010), as well as developing an environmental modelling component within ILUTE (Hao et al., 2010; Hatzopoulou, Miller, & Santos, 2007). There is also intent to develop a firmographic model, as well as a microsimulation model of commercial vehicle movement (Roorda, Cavalcante, McCabe, & Kwan, 2010). For a more detailed description of ILUTE's current operational status, see Miller et al. (in press).

From the brief comments above, it is clear that ILUTE contains some key components (e.g. demographic evolution, housing market models, travel patterns estimation, etc.) that would support the inclusion of an urban energy analysis component. For instance, a household's total income and dwelling attributes (e.g. size) can be used as inputs to a space heating demand model. A conceptual framework is needed to facilitate extending the existing ILUTE platform to include urban energy analysis. To help outline this structure, a brief review of relevant work is first carried out.

2.2. Literature review of urban energy models

This subsection provides a selective review of some newly developed UEMs and related models to guide the development of an urban energy model for ILUTE. The following certainly does not encompass the growing body of literature regarding urban energy modelling, but it is hoped that the selected work would cover some of the key ideas and approaches researchers have been recently adopting.

A number of recent UEMs employ agent-based microsimulation to evolve an urban region and compute its future energy use. Examples include the iTEAM (Integrated Transportation and Energy Activity-Based Model), which is a tool to evaluate green policies (Almeida et al., 2009). Likewise, a greenhouse gas emissions model for Austin, Texas uses a similar approach (Tirumalachetty et al., 2009). These models represent households and firms (the agents), model their decisions, and convert these decisions to their respective energy demands. Both models focus on the population's behavior to draw projections of the urban region's energy consumption.

On the other hand, some models concentrate on finding an optimal design for an urban energy system rather than predict its future state. One example is CitySim, which is an engineering model of energy flows in buildings, and is the first step towards developing a comprehensive model for optimizing urban resource flows (e.g. waste, water, transport) (Robinson et al., 2009). Similarly, the SynCity ("Synthetic City") toolkit is an integrated modelling platform of urban energy systems (Keirstead et al., 2010). SynCity first optimizes for an ideal city layout, and then uses microsimulation to estimate the energy demand from human activity modulated by this arrangement. Afterwards, a macro-level energy supply network is designed to meet the spatially and temporally distributed demand. Engineering models are then used to interface with the macro-level network to provide more technical end-use detail. Unlike the two previous examples, CitySim and SynCity (among other purposes) aim to optimize urban energy systems as well as utilize technical engineering models rather than purely econometric approaches.

Whether the chosen methodology is predictive or normative, two key characteristics of UEMs clearly emerge. First, UEMs link the models for the different urban sectors together in one integrated framework. Arguably, this aspect brings the cohesion lacking in simply developing a series of separate energy models for each of the urban sectors. Second, as energy use is a function of both the choice of technology (e.g. the efficiency of the vehicle or furnace) and utilization, UEMs need to be sensitive to both technological and behavioral factors. That way, a wide range of urban energy-related policies such as home retrofit rebates or time-of-use pricing can be accurately tested out. These two characteristics can form the criteria that guide the high-level design for an urban energy model for ILUTE.

2.3. Urban energy model conceptual framework

Based on the two criteria above, the first guideline is met by virtue of ILUTE's modelling framework. Its agent-based

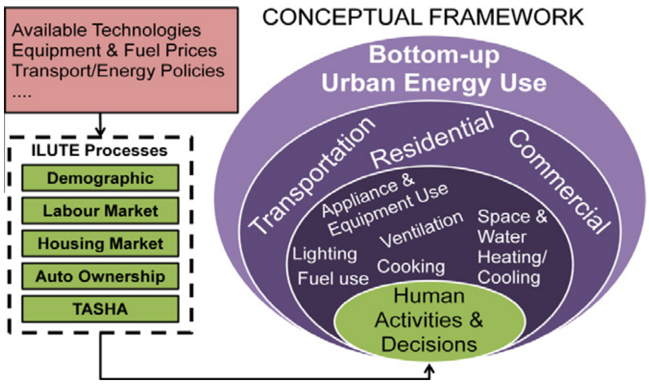

Fig. 2. Conceptual framework for an ILUTE urban energy model.

microsimulation approach provides the connections that form an integrated urban energy model, as it is the actions of and interactions among these agents that link the energy consumption of the residential, commercial and transportation sectors together. To meet the second guideline, engineering and econometric models will be used to capture the technological and behavioral sensitivities respectively. Both approaches are suggested, as tradeoffs often exist between the two, such as the case in current models for residential heating energy demand (Aydinalp-Koksal & Ugursal, 2008; Larsen & Nesbakken, 2004). This is discussed in further detail in the next section.

Fig. 2 illustrates this conceptual framework. The ILUTE urban energy model will build upon the existing ILUTE platform and maintain the model system's philosophy. It will employ a bottom-up approach in which the energy consumption of the region emerges from the individual end-uses for each of the urban sectors. These end-uses are derived from the activities and decisions of the region's energy consuming agents (i.e. households and firms). Hence, as the population and building stock of the region evolves, so will the vehicle, equipment and appliance distributions that directly affect energy consumption. These distributions, along with the agents' consumption patterns, can then be used as inputs to other engineering or econometric models to compute the total energy demand for the urban region.

Individual models for each of these end-uses have to be developed and integrated with ILUTE to build a comprehensive urban energy model. The remainder of this document will be devoted to a residential space heating demand model, which is the first step towards developing a complete UEM for the ILUTE model system.

3. Residential space heating demand model

Swan and Ugursal (2009) provide a thorough review of residential energy end-use modelling, which is summarized in this section. Afterwards, a case is made to address the inadequacies of existing methods through the ILUTE modelling approach. Following this, a residential space heating demand model for ILUTE is presented.

3.1. Residential end-use energy consumption models

This residential sector consumes secondary energy in the form of space heating and cooling, domestic hot water, lighting and appliance usage. These end-uses are influenced by many factors, including climate, dwelling size, and appliance efficiencies. Complex interactions may exist across these factors, such as the extra heat gained by a house when appliances are used. Models that examine end-uses and work at a micro-level are considered "bottom-up" (as opposed to "top-down"). Here, the energy use of a representative set of households is extrapolated over the entire region. There are two approaches to bottom-up modelling, which are the statistical and engineering methods.

Table 1
Comparison of the statistical and engineering "bottom-up" methods.

Statistical methods	Engineering methods
Advantages	
Captures occupant behavior	Models new technologies
Includes socio-economic and macroeconomic factors	Includes gains additional heat gains (e.g. solar, appliance, etc.)
Uses billing and simple survey data	"Ground up" estimation
Disadvantages	
Multicollinearity	Assumptions on behavior
Reliance on historical data	No economic factors
Large survey samples required	Intense data and computational requirements

Statistical methods use household energy use data, such as billing information, to regress the relationship between energy consumption and end-use. In most cases, they can also use macro-level data (e.g. energy prices), which are relatively easy to obtain. Other key strengths of these methods are their ability to include occupant behavior, as well as macroeconomic and socioeconomic factors. However, statistical methods heavily rely on historical data and require large survey samples to be effective. Further, as in most regression type models, multicollinearity can be a problem.

On the other hand, engineering methods account for energy consumption based on the ratings and characteristics of different end-uses. As these methods do not depend on historical data, they have the highest flexibility in modelling new technologies. These methods are also able to capture occupant, appliance, and solar heat gains. However, engineering methods suffer from detailed data and intense computational requirements. More importantly, these models do not account for occupant behavior, thus requiring some assumptions to be made. Table 1, which is based from Swan and Ugursal (2009), summarizes the strengths and weaknesses of the two approaches.

3.2. A residential energy end-use model

As shown in Table 1, one main disadvantage of statistical methods is their inability to model technology explicitly. While engineering methods are excellent for this purpose, they conversely lack the sensitivity to behavioral factors. Researchers have been

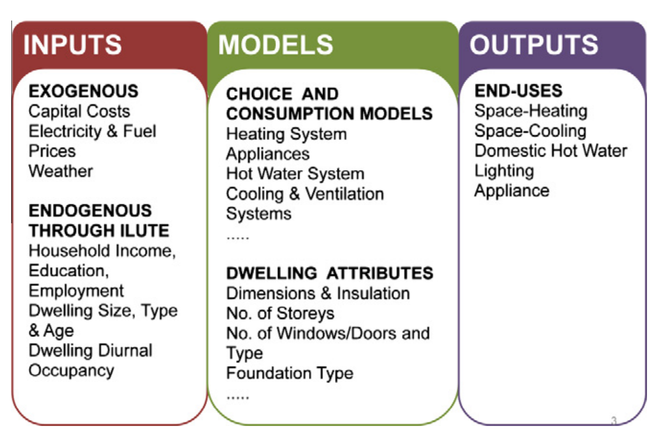

Fig. 3. High-level design of ILUTE residential energy end-use model.

developing hybrid models that combine the strengths of these two methods and overcome their shortcomings (Aydinalp-Koksal & Ugursal, 2008; Swan, Ugursal, & Beausoleil-Morrison, 2008). Such a hybrid energy model is being built for ILUTE and is presented below. The proposed approach has been developed under the ILUTE urban energy model conceptual framework outlined in Section 2.

The high-level design of the ILUTE residential energy end-use model is shown in Fig. 3. Exogenous factors such as equipment costs and energy prices are the first inputs to the model and can be used to test policies and scenarios (e.g. effect of higher electricity prices). On the other hand, household income, dwelling attributes and other socioeconomic inputs are endogenously generated through ILUTE using the existing modules for demographic updating, housing market, etc. These exogenous and endogenous set of inputs enter the sub-models that make up the core of the residential energy end-use model. Note that households choose dwelling units through ILUTE's housing market simulation, and these dwelling units have specific attributes (e.g. size, type, age) assigned to them. Hence, consistency is maintained across all the endogenous inputs to the proposed model. Using these inputs, choice models are employed to determine household appliance and equipment ownership as well as dwelling unit attributes that are relevant to residential energy use (e.g. dimensions, insulation, etc.). Then, consumption models are used to estimate how much these durables are utilized.

Afterwards, the appliance/equipment distributions and consumption patterns are used in conjunction with standard residential building energy simulation software to calculate the end-use demands for all the dwellings in the urban region. In effect, this methodology takes advantage of the technical strengths present in engineering models but also maintains sensitivity to behavioral factors through the choice and consumption models employed in ILUTE. This approach can be extended to include models for conservation decisions, as well as estimates for GHG emissions and other environmental impacts.

The interaction of choice and consumption models underscores an important feature of residential energy demand, which is its intrinsic dependence on household durables. This relationship can cause households to have different short and long run responses to shocks. For example, if heating fuel prices are raised, a household might be limited to behavioral changes (e.g. lowering the thermostat) in the short-term. In the long-term however, a household might adjust by switching heating fuels. The proposed framework can capture both short- and long-term responses by using consumption and choice models in accordance with ILUTE's ability to simulate with different time-steps. In this case, the choice of heating equipment for every household in ILUTE could be evaluated at each time-step (i.e. once a year), which would correspond to a long-term response. However, the households' expected energy consumption for that year could be conditioned on previous years' energy prices and bills, which would capture any short run responses. The next section presents a model that focuses on the long-term response while laying the foundation to include short-term behavioral changes.

4. Methodology

The section presents a model for space heating demand which is the first realization of the framework described above (Fig. 3). The work combines a discrete choice model with building energy simulation software. Implementation details are also provided.

4.1. A space heating demand model for ILUTE

The ILUTE space heating demand model is depicted in Fig. 4, which shows a joint logit model of heating equipment and fuel coupled with the HOT2000 building energy simulation software (CanmetENERGY, 2011). HOT2000 was chosen specifically as it was designed for Canadian houses and is available for free. The

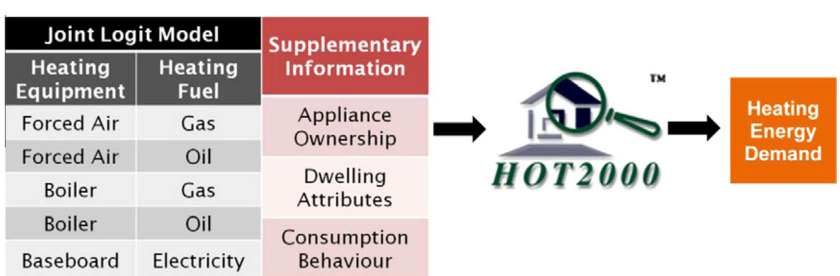

Fig. 4. ILUTE space heating demand model.

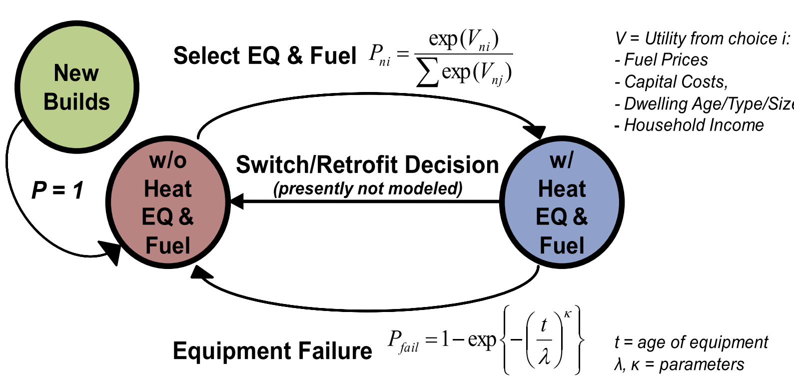

Fig. 5. State diagrams for heating equipment (EQ) and fuel choice (yearly time-step).

logit model is used to determine the heating equipment and fuel choices by a household, which serve as inputs to the HOT2000 program that computes the household's space heating demand. Auxiliary models for household appliance ownership, dwelling attributes and consumption behavior are used to generate the other necessary inputs for HOT2000.

The proposed hybrid model deviates from using a fully econometric discrete–continuous approach which has been popular in the literature (Dubin & McFadden, 1984; Nesbakken, 1999; Vaage, 2000). While both methods can consistently model the energy consumed by a household and its dependence on the chosen equipment, the hybrid space heating model is preferred as it introduces engineering arguments in the modelling exercise. In particular, its technical nature provides the flexibility to evaluate the impacts of new technologies which is useful for policy testing.

4.2. Model implementation in ILUTE

Fig. 5 shows the state diagrams for the household heating equipment and fuel model in ILUTE. All new households (including those in the initialization phase) are assigned their heating equipment and fuel using a joint logit model. The choice attributes that enter into the utility expression include fuel prices, capital costs, dwelling characteristics (age, type and number of rooms), as well as household income. In addition, the event of an equipment failure is also simulated every year. The failure probabilities are described using a Weibull distribution with the parameters obtained using the expected equipment service lives (for the scale) and via calibration (for the shape). A Monte Carlo approach is used throughout the entire procedure. Randomly generated numbers are evaluated against the logit choice and failure probabilities to determine the chosen alternative and the occurrence of a failure event. The design also houses a potential switch/retrofit decision model which is not included in this paper.

At the end of each simulation year, ILUTE generates the inputs required by the HOT2000 program (e.g. dwelling unit type, income, etc.) for each individual household. A batch version of HOT2000, which was provided by Natural Resources Canada, is called to go through every household's output file and compute its annual space heating demand. In addition to the inputs generated by ILUTE, the HOT2000 program requires other detailed information such as the dimensions and construction material for windows, doors and walls. The next section discusses these supplementary input data provided to HOT2000 as well as the data used to estimate the joint logit model.

5. Data

Due to the large amount of detailed data required, it was necessary to pool datasets from multiple sources together. Unfortunately, mixing data implicitly assumes that these records are compatible and consistent, which is particularly critical for parameter estimation. On the other hand, combining data together can reduce the random bias from a single dataset and also provide a more comprehensive picture of the system being modeled (Sivakumar, 2009). Other researchers developing urban energy models have also taken this approach (Almeida et al., 2009). Furthermore, this allowed many applicable and readily available datasets to be used together at no cost. Hence, the merits of pooling existing data were deemed to outweigh any potential issues and justify their use for building a first version of the ILUTE space heating demand model.

Table 2 summarizes the sources of data used, while Tables 3 and 4 outline the variables that enter the discrete choice model and HOT2000 respectively. The letters beside each variable in Tables 3 and 4 match up with the letters in Table 2 to allow the sources to be identified.

Table 2
Summary of data sources used.

Key	Title	Author and source (see references)
A	Canadian census (1986–2006)	Statistics Canada (2011)
B	Survey of household spending (1988–2006)	Statistics Canada (2010)
C	Survey of household energy use (1993)	Statistics Canada (1993)
D	Residential energy prices (1986–2006)	Natural Resources Canada (2010)
E	Study of life expectancy of home components	Seiders et al. (2007)
F	Repair and remodel cost guide 2000	Marshall and Swift (1999)
G	Prototype building descriptions	Akbari and Konopacki (2004)
H	Canadian housing stock building descriptions	Swan et al. (2009)

Table 3
Overview of data used for the logit model (number of observations = 6714).

Variable	Ave.	Std. dev.	(**A**) Dwelling type	%	(**A**) Year built	%
(**B**) Household income ($)	77,250	51,358	Single detached	81.2	Before 1921	9.4
(**B**) Operating costs ($)	1062	444	Double	9	1921–1945	11.3
(**F**) Capital costs ($)	1853	620	Row or Terrace	7.5	1946–1960	16.2
(**A**) Number of bedrooms	3	1	Duplex	1.4	1961–1970	16.8
(**E**) Mean age of heating equipment (years)			Apartment	0.8	1971–1980	19.5
Boiler [30], forced air [18], baseboard [20]			Other	0.1	1981–1990	20.6
					After 1990	6.2

Table 4
Overview of supplementary inputs to the HOT2000 program.

Variable	Mode (%)	Variable	Ave.
(**C**) Floors	2 (49.4)	(**A**) Bedrooms	5.8
(**C**) Heated area (m^2)	94–140 (43.9)	(**A**) Bathrooms	1.5
(**C**) Wall materials	Brick (78.0)	(**C**) Single pane windows	7.8
(**H**) Foundation	Basement (95.0)	(**C**) Double pane windows	6.9
(**C**) Basement heating	Yes (76.3)	(**C**) Triple pane windows	4.1
(**C**) Temperature (°C)	20–21 (53.7)	(**C**) Wooden non-storm doors	0.6
		(**C**) Wooden storm doors	1.5
Other data used		(**C**) Steel non-storm doors	0.8
(**G**) Wall, roof and basement *R*-values		(**C**) Steel storm doors	1
(**H**) Housing dimensions (roof area, dwelling unit perimeter, etc.)			

An overview of the data used for the logit model is shown in Table 3. The main dataset used in the estimation procedure was (**B**) supplemented by the capital cost data from (**F**). Dataset (**B**) has 6714 observations pertaining to households. These include the households' heating equipment and fuel, heating expenditures, income, and dwelling attributes (type, age and number of bedrooms). This dataset is housed under the Computing in the Humanities and Social Sciences (CHASS) data centre at the University of Toronto. Access to CHASS is available to all registered subscribers of CANSIM, which is a Canadian socioeconomic database maintained by Statistics Canada.

These records only include the predominant heating system choices for the GTHA: forced air (natural gas and oil), boiler (natural gas and oil), and baseboard (electricity). However, not enough data was available to include an efficiency component to the heating equipment choice. Residential energy prices, expected heating equipment service lives and dwelling related data from (**D**), (**E**) and (**A**) were not used in the estimation process but were employed as ILUTE inputs to simulate the evolution of heating equipment and fuel in the GTHA.

Similarly, Table 4 lists out some of the key variables that enter the HOT2000 program. For these variables, the average or most frequent value are listed. Many of these items describe housing characteristics including wall material, number of floors, number of bathrooms etc. Distributions from (**C**) were employed to assign these characteristics to ILUTE dwelling units. *R*-values from (**G**), which are measures of how efficient houses are insulated, as well as other housing dimensions (e.g. roof area) from (**H**) were also required by HOT2000. Other key parameters (e.g. solar gains, airtightness, etc.) also determine the heating demand in HOT2000. In most cases, either the values from the data sources above or the default values from the Batch HOT2000 manual (Natural Resources Canada, 2009) were used. In the few cases where defaults were not available, such as dwelling orientation, values were randomly assigned (e.g. random draw assigning north, northeast, east, etc.). Interested readers could refer to the Batch HOT2000 manual, which elaborates on all the required inputs.

Table 5
Description of logit model variables.

Variable	Definition
Constant	Alternative-specific constant
Operating cost	Operating cost ($)
Capital cost/income	Ratio of capital cost to income
pre1946	1 if dwelling is built before 1946, 0 otherwise
pre1971	1 if dwelling is between 1946 and 1970, 0 otherwise
not Detached	1 if dwelling is not a single detached unit, 0 otherwise
# Bedrooms	Number of bedrooms

6. Results and discussion

Table 5 displays the variables for the logit model. All variables, except operating cost and capital cost/income are alternative-specific. Similar to Fig. 4, there are five choices modelled: boiler and natural gas (B_NG), boiler and oil (B_O), forced air and natural gas (FA_NG), forced air and oil (FA_O) and baseboard electricity. For this model, baseboard electricity serves as the reference choice. Table 6 then presents the estimation results. Note that for the alternative-specific variables, the code corresponding to the chosen alternative identifies which utility expression these variables enter. For example, B_NG:constant is the alternative-specific constant for the boiler and natural gas choice, while the variable B_NG:pre1946 increases the utility for choosing B_NG by 4.11 whenever the dwelling unit is older than 1946.

Many of the parameters are statistically significant at a 95% level and most exhibit their expected signs. For instance, parameter estimates for the operating cost and capital cost/income variables are negative, which agree with utility theory. However, it was expected that older houses would show an affinity to baseboard electricity as demonstrated by the building age dummy variables' signs due to baseboards being relatively older technology. These contradicting results can be rationalized by considering that older dwellings are more likely to have retrofitted and replaced their previous heating systems with more efficient and newer technology. Similarly, contrary to what was expected, the choice of heating equipment and fuel does not seem to be influenced by the dwelling unit type (it was hypothesized that detached homes would have a preference for gas furnaces as it is the existing standard among developers). On the other hand, the number of bedrooms decreases the likelihood that baseboard electricity is chosen, presumably due to the higher costs associated with this inefficient option. Sensitivities were carried out by slightly varying a parameter's value while holding all other parameters constant to see the effect on market shares. After these tests, it was noted that the operating cost was the single critical factor in determining a household's heating equipment and fuel choice.

The estimated parameters were coded into ILUTE and used to simulate the evolution of heating equipment and fuel in the GTHA for 1986–2006. This is shown in Fig. 6, which displays how the shares of heating systems change with time for an initial sample population of 10,000 households. The core ILUTE models for demographic evolution and housing market were executed in conjunction with the space heating demand model, using the former models' outputs as inputs to the latter. The ILUTE results (left) were compared against representative historical Greater Toronto–Hamilton Area data (right). Overall, the model displayed a fairly strong performance but showed some divergence near

Table 6
Logit model results (B – boiler, FA – Forced Air, NG – natural gas, O – oil).

Variables	Estimate	*t*-stat	Variables	Estimate	*t*-stat
B_NG:constant	−1.08E+01	−9.63	B_NG:pre1971	1.63E+00	3.17
B_O:constant	−6.60E+00	−5.21	B_O:pre1971	1.77E+00	2.55
FA_NG:constant	−4.90E+00	−4.62	FA_NG:pre1971	−1.59E−01	−0.36
FA_O:constant	−3.30E+00	−3.24	FA_O:pre1971	1.15E+00	2.55
Operating cost	−1.02E−02	−24.27	B_NG:not Detached	4.66E−01	0.84
Capital cost/income	−6.01E+00	−2.30	B_O:not Detached	−3.22E−01	−0.49
B_NG:pre1946	4.11E+00	6.48	FA_NG:not Detached	2.25E−01	0.42
B_O:pre1946	3.80E+00	4.85	FA_O:not Detached	−1.41E+00	−2.57
FA_NG:pre1946	7.33E−01	1.25	B_NG:# Bedrooms	−8.10E−01	−2.79
FA_O:pre1946	2.65E+00	4.51	B_O:# Bedrooms	−7.19E−01	−2.23
			FA_NG:# Bedrooms	−1.03E+00	−3.69
			FA_O:# Bedrooms	−8.23E−01	−2.97
Log-likelihood:	−2256.3		McFadden R^2:	0.345	

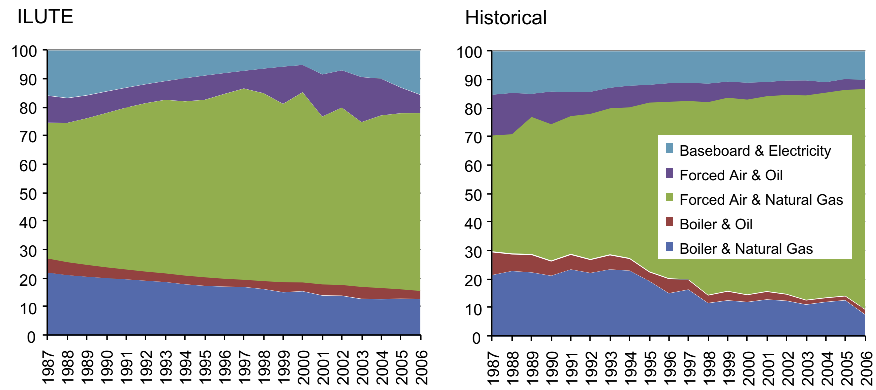

Fig. 6. Market share evolution of heating systems in the GTHA. The left plot shows the results from ILUTE while the right plot displays historical values.

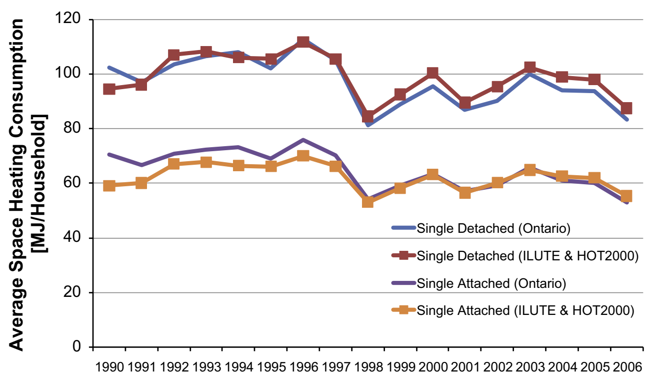

Fig. 7. Average space heating energy consumption for single detached and single attached units in ILUTE (GTHA) and Ontario.

the end of the 20 year simulation. In particular, the model's sensitivity to operating costs was evident from the pronounced variations in the early 2000s, which are years when the input energy prices displayed significant fluctuations.

Fig. 7 shows the average space heating demand for single detached and single attached dwelling units in ILUTE, with historical Ontario values plotted for comparison. The modelling effort focused on these two dwelling types since they comprise about 70% of GTHA houses, and majority of the available data pertain to them as well. Since a static weather file was used throughout simulation, the output heating demands from HOT2000 were adjusted using a historical heating degree day index for Ontario. The ILUTE results track the Ontario values fairly well. It is noted that when both ILUTE and Ontario values are weather normalized (using heating degree days), the average consumption for dwelling units appear relatively constant.

While the model showed a strong performance in reproducing historical results, it was felt that the intense data and computational requirements can possibly offset the accuracy gains that come from this hybrid bottom-up procedure. In particular, using building simulation software such as HOT2000 requires very detailed inputs (e.g. wall material, foundation type, number and types of windows and doors, etc.) regarding individual dwelling units. While data was available for the chosen study area, these inputs may not be readily obtainable for other cities. Though, depending on factors such as building code standards and the general age distribution of houses in a region, it may be possible to transfer data from one city to another. Further research may still be required to evaluate the benefits of the proposed model and compare it against conventional methodologies.

However, the work presented has some clear advantages over traditional approaches. For instance, this hybrid method would be able to easily model new technologies (e.g. solar water heating) which historically popular methods (e.g. discrete–continuous modelling) would not be able to due to the lack of data. Hence, this research offers a more flexible avenue for testing out policies related to new technology, such as the effectiveness of rebates to encourage the adoption of new higher efficiency heating equipment.

More importantly, what this hybrid bottom-up procedure brings is the ability to explore the interrelationships between different types of policies related to land use, transportation and energy use. Being able to simultaneously and comprehensively evaluate these policies is the main value of adopting the proposed methodology. Now that this urban energy framework is in place, it would be easier to build additional models to complement the existing work. As such, future research should continue expanding the scope of the ILUTE urban energy model so that these interrelationships could be further explored.

7. Summary and future directions

This paper put forward a model for residential space heating demand, which is the first step towards building a comprehensive ILUTE urban energy model. The research involved coupling a logit model of heating equipment and fuel with the HOT2000 building energy simulation software. The work shows promise in estimating urban residential energy demand while addressing concerns with existing methods.

The evolution of heating equipment and fuel along with the associated demands were simulated from 1986 to 2006 for the GTHA. The model displayed strong results when compared with historical patterns, though further analysis may be needed to assess the effectiveness of the proposed model as compared to conventional approaches. Nonetheless, being able to track 20 years worth of market share and heating demand data can only increase one's confidence in the proposed approach. Finally, this paper also demonstrated ILUTE's capability to serve as a computational and modelling platform for different kinds of urban processes.

Further steps include developing similar models for other residential end-uses, such as electricity and hot water consumption, which can be used as dynamic inputs to the HOT2000 program. In addition, the existing sub-models can be refined by using discrete choice models to generate HOT2000 inputs (e.g. housing characteristics) instead of frequency generated probabilities. An equally significant improvement to the model is to add an efficiency component to the equipment and appliance choices. Models of retrofit decisions can also be included, which will be useful in testing policies related to residential energy. It is also important to note that HOT2000 was not designed to evaluate larger residential buildings (e.g. high-rise condominiums). As such, future work could either move towards more flexible heating demand tools or complement the existing model with other software that cater to larger residential buildings.

Multiple detailed datasets were required to develop the hybrid space heating demand model. While pooling free data has its advantages, it is still desirable to obtain and utilize a comprehensive dataset for the ILUTE residential energy end-use model. This is evident from the fact that majority of the survey data used (Table 2) were not designed for developing residential end-use models. Hence, compromises on how the data were employed were often required. Besides pursuing original data collection efforts similar to SynCity and iTEAM, another approach could be to use a database collected specifically for residential building energy simulation such as (Swan, Ugursal, & Beausoleil-Morrison, 2009).

In the long term, the ILUTE urban energy model can be extended to encompass the commercial and transportation sectors as well. Similarly, through integration with activity-schedulers, models for day-to-day energy consumption can be developed and integrated with the existing ILUTE annual residential energy use model. SynCity, for example, has been attempting to integrate TASHA with their urban energy model (Sivakumar, 2009). Under the proposed urban energy framework, these models for the different urban sectors could be used to simultaneously and comprehensively evaluate a variety of policies related to transportation, land use and energy.

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