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An Overview of the Buildings Module of the Canadian Integrated Modelling System (CIMS)

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Executive Summary

Analysts interested in energy policy assessment and estimation of the cost of reducing energy-related GHG emissions generally consider the use of some type of energy-economy model. Traditionally, there are two strands of such models; the top-down (economic) and the bottom-up (engineering) energy-economy models. The two approaches are known to have contrasting predictions about the effectiveness of energy-efficiency policies and the costs of GHG emissions reductions. Efforts to integrate technological detail in the economic models and economic feedbacks in the bottom-up models have resulted in the hybrid modelling framework. Hybrid models are viewed as being more realistic than the traditional top-down models and as incorporating more realistic economic considerations than bottom-up models.

In this report we consider the use of a hybrid energy-economy model called the Canadian Integrated Modelling System, or CIMS. This model was developed at Simon Fraser University by the Energy and Materials Research Group in collaboration with M. K. Jaccard and Associates (EMRG/MJK). This report provides a review of the buildings module of CIMS, as well as an overview of energy-economy models in general, and considers the potential for future development and use of this module.

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1. Introduction

In the context of residential energy demand in Canada, homeowners who participated in the EnerGuide for Houses (EGH) Program were provided with an energy audit of their home and a list of suggested home upgrades that would help improve its energy efficiency. While homeowners were free to adopt as many or as few of these recommendations as they desired, for any participating homeowner government subsidies were available to offset some of the cost of the recommended improvements if enough of them were implemented. Since the motivation for the program – at least in part – was to reduce residential energy consumption (and hence greenhouse gas (GHG) emissions) attributable to the residential sector, it is of considerable interest to know the extent to which the program achieved its goals, and whether there are particular modifications that may have made the program more successful. While "success" is difficult to define in this context, questions that might be asked could include what would be the likely path of GHG emissions had all the recommended upgrades been implemented, whether a larger subsidy would have induced homeowners to adopt more of the recommended upgrades, and whether the method of financing the subsidy – such as from general revenues or from a broad-based carbon tax across all sectors – is likely to have had any effect on the outcomes.

These kinds of energy policy assessments require the use of an integrated energy-economy model, so that developments in the energy sector can be viewed within the context of what is happening in the entire economic system. Since actions in one sector can have impacts on energy flows in other sectors, an integrated modeling approach is necessary to enable the various feed-backs to be accounted for and to be traced to the particular policy being analyzed. In addition, with energy policy analysis we are often interested in tracking the time paths of various changes, such as the extent of any GHG emission reduction emanating from a policy action, in order to evaluate whether the policy action can help us achieve a particular target within a specified a time limit, such as the Kyoto targets for GHG emissions. By evaluating the deviation of the actual level from the target level of GHG emission reduction, energy models can be used to carry out analysis of alternative policy scenarios. They can also be used to estimate the likely cost to the economy of GHG emission reductions or of some particular climate policy.

In this report we consider the use of a hybrid energy-economy model called the Canadian Integrated Modelling System, or CIMS. We begin in the following section with a brief review of energy-economy models in general, followed in Section 3 with an overview of CIMS. The residential sector of CIMS is examined in further detail in Section 4, while Section 5 contains an outline of how CIMS might be used in an application with residential data pertaining to the EGH program.

2. An Overview of Energy-Economy Modelling

Analysts interested in energy policy assessment and estimation of the cost of reducing energy-related GHG emissions generally consider the use of some type of energy-economy model. Traditionally, there are two strands of such models; the top-down (economic) and the bottom-up (engineering) energy-economy models. The two approaches are known to have contrasting predictions about the effectiveness of energy-efficiency policies and the costs of GHG emissions reductions (Jaccard, et al 2002; Jaccard and Bailie, 1996). In most of the studies undertaken to estimate the likely cost of reducing GHG emissions using the top-down macroeconomic models, the findings are in stark contrast to the findings of the bottom-up analyses (Krause, et al, 1993).

Cost estimates of the two approaches usually differ, with bottom-up analysts tending to estimate substantially lower costs of GHG abatement (Jaccard, et al, 2004). As a result, policy makers are invariably frustrated by competing answers and competing policy recommendation emanating from the two approaches (Krause et al, 1993; Jaccard et al, 2003).

In most cases, the top-down models predict that emission reduction goals would require high taxes and would unavoidably slow down economic growth, while the engineering (bottom-up) models predict that programs aimed at cost-effective but unrealized efficiency improvement could cut emissions while saving energy bills and without slowing down economic growth (Krause, et al, 1993; Brown et al, 1998; Jaccard, et al, 2002; Jaccard and Bailie, 1996). Bottom-up models maintain that there is significant potential for energy efficient technologies (energy efficiency gap) that are not optimized and that can be tapped with less cost to the economy (Browne et al, 1998, Sutherland, 2000) through appropriate policies and programs. By reviewing four recent studies using bottom-up models, Browne et al (1998) conclude that all the studies document the existence of numerous cost-effective, energy-efficient technologies that remain underutilized in each end-use sector of the economy. Energy efficiency policies, although costly, would generate energy cost savings by inducing adoption of such technologies. Hence, the net cost of climate policy is the cost of the program less the energy costs saved, which in some cases can even be positive.

As pure economic models, top-down models do not have explicit representation of technologies. Instead, technologies are represented by the elasticity of substitution and an autonomous energy efficiency index that evolve exogenously. Since they are based on actual data, the assumption of rational agents' behavior suggests that the existing allocation is efficient and hence any deviation from this path must be costly (Jaccard and Bailie, 1996; and Baker and Ekins, 2004). There are generally two branches of the top-down models; the macroeconometric and computational general equilibrium (CGE) models. Even within the group of top-down models, the macroeconometric models tend to predict higher costs than the CGE models (Baker and Ekins, 2004; Sutherland, 2000).

The sharp contrast between the two predictions has become more critical with analysts using the top-down economic framework predicting huge costs while those employing the engineering approach predicting small costs, or even a benefit, to the US economy of meeting the Kyoto target (Jaccard et al 2002; Baker and Ekins, 2004). Sutherland (2000) notes that most top-down studies have indicated that reducing emission according to the terms of the Kyoto is highly costly to the US economy. His review of the literature indicates that while the study based on the economic (top-down) model estimates the financial cost of meeting the Kyoto target to be as high as $432.6 billion in carbon taxes, studies based on bottom-up models generally predict an absence of net cost and mostly estimated a benefit. Baker and Ekins (2004) criticize the method of measuring the cost using carbon taxes because taxes are partial measures as compared to the change in GDP which is more general. While carbon taxes measures always imply that mitigation polices are costly, GDP based measures can predict either an increase or decrease in GDP depending on the modeling approaches. For example, if the model allows for tax revenue recycling, the predicted cost is smaller and can even be negative.

By looking at three main macroeconometric studies of the cost of Kyoto to the US economy, of which two were meta analysis of several other studies, Baker and Ekins (2004) show that the estimated costs are higher when tight targets – both in terms of the percentage of the reduction and the time horizons – are imposed. This phenomenon was also discussed in Jaccard et al (2002). Similarly, they show that while the macroeconometric models consider carbon emission permits as the instrument to the mitigation, they did not consider recycling of the revenue, a factor considered a reason for the high cost estimates.

Similarly, Krause et al (1993) provide review of twelve bottom-up and top-down studies of the likely cost of reducing carbon emission in various OECD countries. Once again, the review shows that all else being equal, the cost estimates from the bottom-up analyses always remain well below those found in top-down studies. The review concludes that the top-down studies arrive at the conclusion that GHG emission reduction goals would require high carbon taxes and would unavoidably slow economic growth by ignoring important lower-cost policy options. The lower cost programs are programs aimed at cost-effective but unrealized efficiency improvement and cogeneration options that could cut emissions while reducing national energy bills; hence enhancing growth and employment. Such programs can most effectively be implemented by relying on instruments other than carbon taxes; a least cost approach emphasizes non-price policies, with carbon taxes playing an important supplementary role. Krause et al (1993) conclude that conventional macroeconomic modeling assessments are ill-suited as the principal basis for assessing the cost of carbon reduction policies and hence much greater emphasis should be placed on bottom-up analyses that identify market barriers and unrealized efficiency potential by technology and end-use. The studies based on macroeconomic modeling can make unique contributions in the investigation of energy tax recycling options, distributional effects, and trade effects under carbon reduction policy regime. This conclusion suggests that both have features that make them important, and neither of the two is complete by itself.

The view that both approaches have their own merits was more profoundly described long ago by Hoffman and Jorgenson (1977). These authors argue that evaluation of new and existing energy policies must incorporate information from detailed engineering studies of specific technologies emerging from research and development programs (the bottom-up approach) and must include the assessment of policy impacts on the structure of the energy sector and on the overall level and composition of economic activity (the top-down approach). Hence, a satisfactory framework for the assessment of the full range of alternative energy policies requires an approach that encompasses both approaches. To this effect, they provide a first attempt to integrate both approaches. Following this, there have recently been efforts to develop models that encompass both features.

The main deficiency of top-down models is lack of technological detail. This is an important deficiency since policies seeking to mitigate GHG emissions through improvement in energy efficiency aim at achieving these goals by inducing adoption of energy efficient technologies. Furthermore, since climate policies are long-run objectives during which technologies and consumer preferences change, policy makers need to know if and how their policies can influence both the long-run evolution of technologies as well as consumer preferences (Rivers and Jaccard, 2005). Hence, there have been efforts to render technological detail to top-down models. Most of such modifications are considered in the context of CGE models, perhaps due to their more detailed representation of economy-wide interactions (see for example McFarland et al 2004, and Sue Wing, 2006).

There have also been efforts to address the main deficiencies of the bottom-up modeling approaches. Most importantly, bottom-up models rely on a comparison of the financial cost of different technologies using social discount rates. This type of analysis ignores several important factors such as the risks, uncertainties and option values that are not captured by the social discount rate; in contrast the top-down approach takes these factors in to account (Rivers and Jaccard, 2005). This has led to attempts to integrate these bottom-up models with the top-down approaches so that a model with sufficient technological detail and with behaviorally realistic cost estimates and equilibrium feedbacks can be derived (e.g. Nyboer, 1997, Bataille, 2005 and Jaccard et al 2002). Worrel et al (2004) discuss the approaches to improve the "realism" and policy relevance of engineering models. This has mostly been reflected by integration of macroeconomic feedback in the models. For example, the widely used bottom-up model called *MARKAL* was integrated with a macroeconomic model called *MARKAL Macro* so that the macroeconomic feedbacks are ensured (Jaccard et al, 2002).[1]

The efforts to integrate technological detail in the economic models and economic feedbacks in the bottom-up models resulted in the ***hybrid*** modelling framework. Hybrid models are more realistic than the traditional top-down models and have better economics than bottom-up models (Jaccard et al 2002). Hybrid modeling should, however, be built upon the strong sides of the two modeling frameworks (Hoffman and Jorgenson, 1977). Accordingly, a good hybrid model is one

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[1] See Bataille (2005) for a list of most of the energy-economy models with a discussion of their characteristics.

that has sufficient equilibrium feedbacks and technology details with a behaviorally realistic cost estimates.

Since the hybrid models are constructed by drawing upon the strong sides of two types of models, any weakness common to the two remains unresolved. One common weakness to the traditional bottom-up and top-down models is lack of the framework that accounts for endogenous technological change. In both bottom-up and top-down models, technical change is exogenous. Energy conservation policies are assumed to induce adoption of the existing technologies, and hence increase energy efficiency – a variable measured by the autonomous energy efficiency index (AEEI) in top-down models, and by the rate of adoption (change in market share) of the efficient technologies in the bottom-up framework. However, the policies themselves could also induce technological change (Grubb, et al, 2002; Buonanno et al 2003, and Jaccard et al, 2004, 2006). Hence, GHG emissions abatement policies realize their objectives not only through the speeding up of adoption of the exiting superior technologies, but also by speeding up the innovation in such technologies. If the model is set in such a way that economic growth is tracked, endogenous growth theories suggest that the increased research and development (R&D) in the economy induces economic growth, and hence it would be the model’s prediction that the GHG abatement policies result in economic growth. Similarly, the endogenous technological change suggests a sigmoid diffusion curve which can be captured by introducing learning curves/declining cost curves in micro-scale models (Grubler et al, 1999). The current direction in energy modeling is to incorporate this feature in the hybrid models.

3. An Overview of CIMS

CIMS is a hybrid model developed and operated jointly by the Energy and Materials Research Group (EMRG) at Simon Fraser University and the MK Jaccard and Associates. It is specifically developed for Canada, although it is flexible enough to be reconstructed to suit conditions in other countries. Its technological detail is reflected in its being built upon a version of the bottom-up model called the "Intra-Sectoral Technology Use Model (ISTUM)" which forms the individual sub-component modules of CIMS. ITSUM is built upon a cost-minimizing algorithm that combines financial costs with "intangible costs", thus incorporating "behavioral realism" (Nyboer, 1997; Jaccard and Bailie, 1996; Bataille, 2005). Hence, the three pillars upon which CIMS is built are technological detail, behavioral realism, and equilibrium feedbacks (Bataille, 2005; Jaccard et al 2002).

The behavioral realism is attained by using cost estimates that are not merely financial, but take into account intangibles and utilize private as opposed to social discount rates, thus incorporating risks and options values. The equilibrium feedbacks incorporate both the convergence in energy demand and supply and macroeconomic feedbacks. Note that traditional bottom up models track changes in energy service demand regardless of the supply. CIMS allows and takes into account the feedback in energy supply through price adjustments to changes in energy service demands. The macroeconomic integration is captured through goods and services demand feedbacks via an adjustment factor that makes use of the price elasticities and financial costs of the product.[2] Hence, CIMS constitutes three modules: energy service demand, energy supply, and macroeconomic. The energy demand module consists of the industrial, residential, commercial and transportation sectors. The energy supply module consists of refining, natural gas

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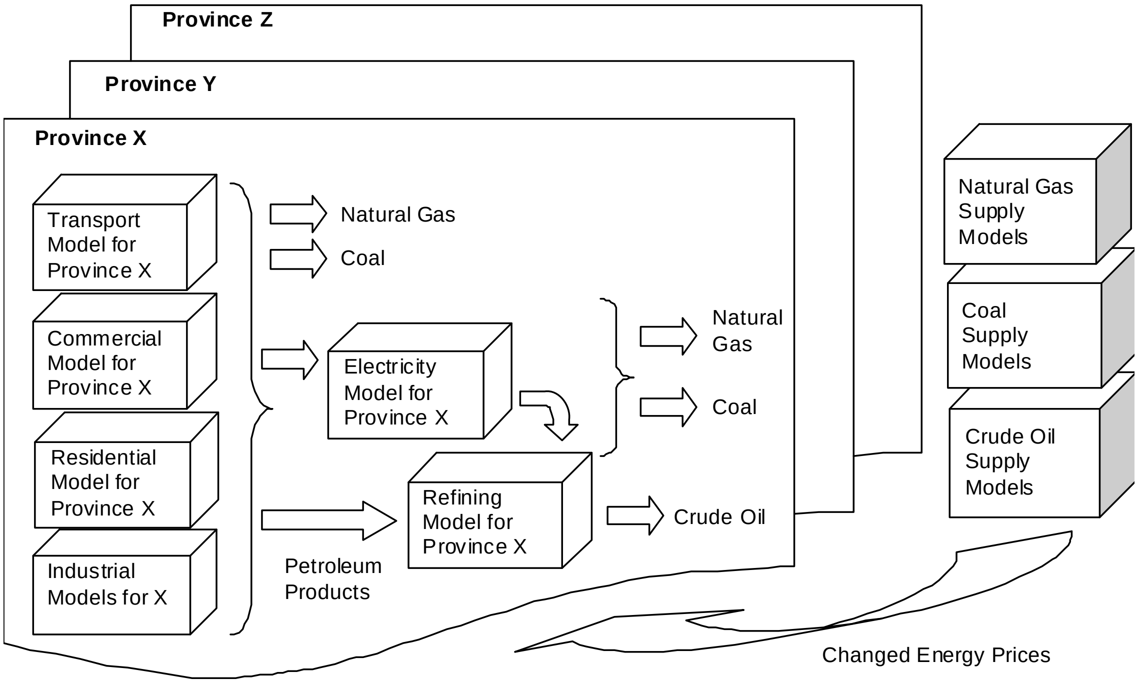
[2] See Bataille (2005) for a detailed description of how the multipliers are derived.

processing and electric generation. Generally, CIMS simulations iterate between the energy demand, energy supply, and the macroeconomic feedback modules.

CIMS tracks end-use energy demand by simulating for acquisition and use of energy using technologies, both under the business-as-usual (BAU) and specified policy scenarios. As a technology based model, CIMS tracks the evolution of technology stocks over time through retirements, retrofits, and new purchases (Rivers and Jaccard, 2003). Since CIMS' technology database includes levels of existing stock in terms of physical characteristics such as energy, emissions, and costs, any policy that affects the life cycle cost of the technologies will generate a range of results emanating from the changes in the composition of the technology stock caused by the change in the relative life cycle costs. The technology stocks at any point in time determine energy service demand by sector. The supply module then responds to the demand. The interaction between demand and supply determines the equilibrium energy price (CIMS uses a specified convergence criterion in determining the equilibrium). The macro-economic module tracks the change in the cost of energy and calculates the effect on macroeconomic variables such as investment, and the employment rate (Bataille, 2005, EMRG/CIEEDAC, 2006). Hence, any change in energy demand, apart from directly affecting the level of GHG emissions, will feed into the economy through the supply side reactions and hence changes in equilibrium energy prices.

Figure 1 CIMS' Energy Supply and Demand Flow Model



Source: CIMS manual, EMRG/CIEEDAC, April 2006

The iteration begins by forecasting the BAU energy service demand for the first five years, given the stock of equipment and technologies. Then, at five year intervals, the algorithm retires equipment whose age warrants scrapping, while allowing for premature retirement through retrofits. This process generates the associated trend in energy service demand. The energy supply module then responds to changes in demand, which sends a price signal back to the demand module. Based on the new price signal, which is part of the cost of capital, demand adjusts. This process continues until demand and supply converge (CIMS use a 5% confidence interval for the convergence in demand and supply). The price determined by the interaction of demand and supply forces is linked to the economic module through the energy price elasticity of the demand for energy in the production sector. Jaccard et al (2002) indicate that the extent to which the price changes feed into the macroeconomy is mediated by a community energy management module which links efforts to influence the evolution of urban forms and infrastructure to the level of energy service demand and the opportunities for different types of energy supply.[3]

The basic construct of CIMS is the technology (equipment) market share equation which is an inverse power function of the life cycle costs of the alternatives competing in the market. This is because CIMS is basically a technology vintage model, a model based on the explicit simulation of the evolution of detailed energy-using technology stocks by tracking the equipment choices in an economy. Its only difference from the pure bottom-up models is that it takes into account the non-financial operating cost and benefits associated with the technologies. CIMS limits the extent of the market penetration of a certain technology in such a way that the prediction is realistic by using the market heterogeneity variable, *v*:

$$MS_{jt} = \frac{\left[CC_j * \frac{r}{1-(r+r)^{-n}} + MC_{jt} + EC_{jt} + i_{jt} \right]^{-V}}{\sum_{k=1}^{N} \left\{ \left[CC_k * \frac{r}{1-(1+r)^{-n}} + MC_{kt} + EC_{kt} + i_{kt} \right]^{-V} \right\}} \qquad (1)$$

where: MS_{jt} is the market share of technology j at time t;

CC_j is the upfront cost (purchase price of the technology);

r is the discount rate; n is the life span of the technology,

MC_{jt} is the maintenance and non-fuel operating cost;

EC_{jt} is energy cost;

i_{jt} is the intangible cost or benefit, and

v is the measure of market heterogeneity (variance) specified at each technology competition node.

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[3] Additional detail about, and references pertaining to, CIMS can be obtained from the website www.emrg.sfu.ca.

The term $[CC_j * \frac{r}{1-(r+r)^{-n}} + MC_{jt} + EC_{jt} + i_{jt}]$ is referred to as the levelized (annualized) life cycle cost (LCC) of each of the particular technology competing in the market. For some sectors, the market share equation is specified by first dividing the LCC by the service outputs of the technologies, a factor simply normalized to unity for the residential sector.

While a literature survey and expert opinion were originally used to assign values to the behavioral parameters (Nyboer, 1997; Bailie, et al, 1998 and Jaccard and Bailie, 1996), the use of discrete choice studies to estimate them has been pursued more recently (see Sadler, 2003; Horne, et al, 2004, Rivers and Jaccard, 2004; Rivers et al, 2003). These authors estimate the parameters on the basis of stated preference studies that they or others have conducted. The discrete choice analysis makes use of random utility theory whereby the utility associated with an alternative *j* (U_{j}) is the sum the explained (V_j) and the unexplained parts (ε_j); that is, $\mathrm{U}_j = V_j + \varepsilon_j$. Generally, a utility is estimated for each alternative being studied, with the utilities specified linearly as $U_j = \beta_j + \beta_{oc}OC + \beta_{CC}CC + \beta_i I + \varepsilon_j$, where U_j is a measure of desirability of alternative j (the utility associated to alternative j); *OC* is operating costs and *CC* is capital costs. The OC is sometimes disaggregated into fuel cost and non-fuel operating cost. The last term "*I*" is a variable aimed at capturing the intangibles such as comfort (in shell retrofit options) and represents some characteristics such as heat responsiveness of furnaces in the heating system upgrade choice set.

In residential sector studies, a distinction is generally made between the heating technology and shell retrofit choices. That is, all heating technologies (heating system upgrade options) are considered to compete with each other and hence represent one choice set. Similarly, all shell retrofit options compete with each other and hence represent another choice set. Hence, the estimations are carried out separately for these two categories. Once the choice probabilities are estimated, the CIMS parameter values are computed from the estimated parameters as $r = \frac{\beta_{cc}}{\beta_{oc}}$ and $i = \frac{\beta_j}{\beta_{OC}} + \frac{\beta_i I}{\beta_{OC}}$.

Once the parameter values are estimated, it will be possible to compute the probability that a particular alternative is chosen using the basic logit equation $P(j) = \frac{\exp(V_j)}{\sum_j \exp(V_j)}$, where V_j is the deterministic component of the utility equation. The third parameter, the measure of market heterogeneity is computed such that the probability predicted above (an approximate measure of the market shares of the alternatives) resembles the market share predicted by the CIMS equation. That is, *v* is solved so that $P(j) = \frac{LCC_j^{-V}}{\sum_k LCC^{-V}} = MS_j$.

The rationale for calculating the discount rate (*r*) using the given formula is that the ratio represents the trade-off between capital and operating costs; and this ratio is used to calculate the discount rate. This is because the ratio of the coefficient of capital cost to that of the operating cost – assuming that energy price do not change in real terms – is equal to $r / (1-(1+r)^{-n})$, which can be solved for *r* given the useful life span (*n*) of the technology and the estimates of the two coefficients (Hausman, 1979; Train, 1985). If we assume that *n* is significantly large, the ratio simply reduces to *r*, and this is the approach adopted in CIMS.

The idea behind calculating the intangible benefit or cost using the formula specified earlier is mainly based on the perception that U_j is the measure of utility derived from alternative j. Hence, the constant term is the alternative specific constant which captures some unquantifiable attributes specific to the alternative, which can be good or bad in the sense that it is either an addition or deduction from the utility value. Similarly, attempts were made to identify some attributes that are assumed to capture some of the intangibles. For example, Sadler (2003) attaches certain comfort levels to the shell retrofit (energy efficiency retrofits) in her revealed preference studies so as to be able to estimate the intangible benefits. In particular, she used the level of heat responsiveness of the various furnaces as a measure of the intangible benefits. The reason for dividing through by β_{oc} is simply to express the intangible benefits in dollar values. For example, β_j is the utility level when everything else is zero and hence is measured in terms of *utils*. Since the coefficient of the operating cost, β_{oc} is, in this set up, *utils* per dollar, the ratio of β_j to β_{oc} gives us a value in dollar terms which a monetary measure of intangible benefit or cost.

In revealed preference studies, it is possible to design the experiment in such a way that it would be possible to capture the effects of some attributes perceived to account for the intangibles, as conducted in Sadler (2003), and Horne, et al (2004). However, if the dataset contains revealed preference data, the only factor accounting for the intangibles will be the alternative specific constant. Another difficulty is that it has been documented that the intangible cost parameter i is computed by comparing all the non-cost parameters to the operating cost parameter (Sadler, 2003; Rivers et al, 2003). This raises a question as to which non-cost parameters should be included in the choice equation. In particular, this definition requires that all the variables included in the choice equations must be the attributes of the choice alternatives. Apparently, the utility is dependent upon several factors which are not peculiar to the choice alternatives. It is quite common to include individual specific attributes such as income and such factors as regional dummies to capture the effects of variation in weather, policies and neighborhood effects.[4]

Another characteristic of the intangible benefit or cost is that it is only expressed in relative terms when it is estimated using the alternative specific constant. This is because in assigning a dummy variable accounting for the alternative specific constant, estimation is possible only if we choose to leave out the dummy belonging to one of the alternatives. It is easy to show that the estimated constant terms perceived as the alternative specific constants (ASCs) are actually the difference between ASCs of the alternative being evaluated and the alternative considered to be the baseline alternative (i.e., it is characterized relative to the dummy variable taking a value of zero)[5].

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[4] See the summary of various studies in Train (1985), and the broader discussion in Train, (2003).

[5] To demonstrate this, consider a choice set that has two alternatives, i=1 and i=2. Defining the random utilities of the alternatives as $\mathrm{U}_{\mathrm{i}} = V_i + \varepsilon_i$, the probability that alternative 2 is chosen is given by $P(2) = P(V_2 + \varepsilon_2 \geq V_1 + \varepsilon_1)$. When we include the alternative specific dummies, the utility equations are given by $\mathrm{U}_{\mathrm{i}} = K + V_i + \varepsilon_i$ where K is the alternative specific constant. This does not affect the choice experiment since we are generally interested in the ordinal rankings of the utilities gained from the alternatives in the random utility choice analysis. Furthermore, let us re-write the random component as $\varepsilon_i = \bar{\varepsilon}_i + \mu_i$ where $\bar{\varepsilon}_i$ is the average of the unexplained parts, and the remaining μ_i is purely random. Then the choice probability becomes $P(2) = P(K + V_2 + \bar{\varepsilon}_2 + \mu_2 \geq K + V_1 + \bar{\varepsilon}_1 + \mu_1)$.

In line with the general direction of the research in the energy modeling, CIMS, in its more recent version, incorporated declining technology cost functions reflecting the learning effect (Jaccard, et al 2004; Rivers and Jaccard, 2006) so as to account for endogenous technological change. Thus, capital costs are calculated each period using the following equation:

$$CC_t = GCC_t \times \left[\left(\frac{N_t}{\sum_{p=1}^{P} \left(N_o + BaseStock \right)_p} \right)^{\log_2 (PR)} \right] \qquad (2)$$

where CCt is the capital costs of technology k in time t;

GCCt is the capital costs of technology k after it has been adjusted for accumulative production in other countries;

Nt is the accumulated production of technology k in CIMS;

BaseStock is the base stock of technology k, which is pre-set in CIMS;

N_o is the value that reflects total global production of the technology up to the year 2000, and the N_o in all provinces should add to the total global production;

PR is the progress ratio, which is exogenously given; and

P is the number of provinces in the simulation.

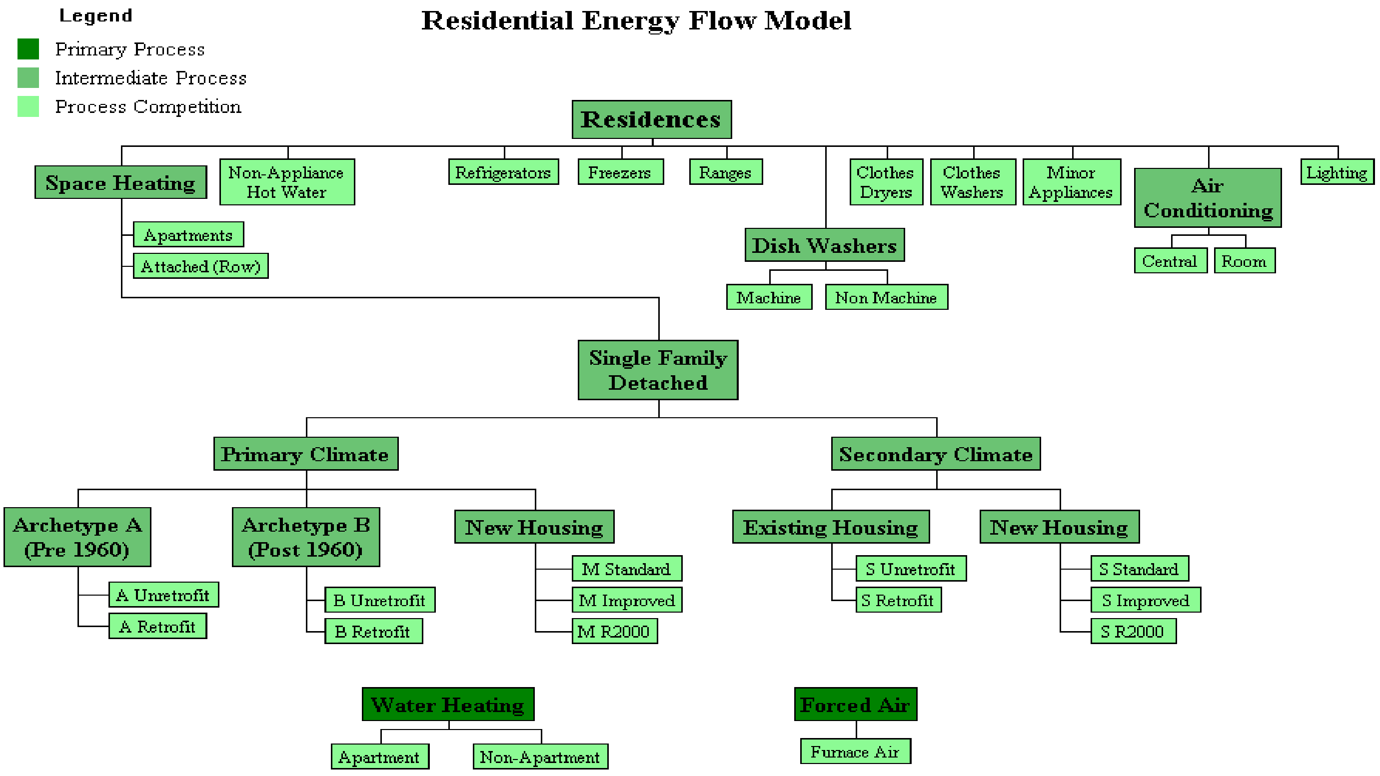
Estimation requires that we can have the alternative specific constant K for only one of the two alternatives. Suppose we select the first alternative to be the baseline reference, so that its alternative specific constant is zero. This is the same as equating K to the negative of the average of the unexplained part of the utility of the first alternative $(K = -\bar{\varepsilon}_1)$ so that $P(2) = P(V_2 + \bar{\varepsilon}_2 - \bar{\varepsilon}_1 + \mu_2 \geq V_1 + \mu_1)$. This shows that the alternative specific constant actually estimated for the second alternative is the difference between the averages of unexplained parts of the utilities of the two alternatives, which is interpreted as the difference between the alternative specific constants.

4. The Residential Energy Flow Model of CIMS

We will now focus on the residential sector. CIMS modelers use a flow model, a graphical representation of energy flows within a sector to demonstrate the model in a simplified way. The CIMS flow model reflects primary or major points of energy consumption in an industry or a sector (e.g. residential, commercial, transportation). It represents hierarchically the energy services utilizing nodes at three levels, the top node being the primary nodes, followed by the intermediate and the competition nodes (EMRG/CEEIDAC, 2006).

In the residential sector, the primary node is the number of households. The split into heating, non-appliance hot water, etc., is simply based on their historical share in residential energy consumption. The split into the various house types is also based on the actual Canadian housing stock data. Whether the household location is in a primary or secondary climate area is also important and the split is again made based on actual data. For the primary climate area, a further subdivision according to the year of construction of the houses is also made based on actual data. All these sub-divisions are required because the exact nature of energy consumption depends on all of these factors.

Figure 2: Residential energy flow model in CIMS



It is important to note the difference between the water heating and non-appliance hot water nodes. Non-appliance hot water use refers to the hot water required for baths, showers, hand washing and cleaning. Water heating mainly depends on the technologies used to supply services of non-appliance hot water, dish washing, and clothes washing. For water heating, the two types of technologies modeled are storage tank and non-storage tank water heaters. The technologies relevant to hot-water node are shower heads, faucets, etc.

We consider only the two archetypes since the new houses node is meant to deal with the competition between M-Standard, M-improved and M-R2000 house types in the stocks of the houses to be constructed after the current period, and hence does not deal with the existing housing stock. There are two technology competition nodes within each archetype. The first node is called “unretrofit” and represents housing stock without shell retrofits, while the second node is the “retrofit” node, and thus represents the stock of houses getting shell retrofits. Within each of these nodes, the heating system technologies compete against each other. In the CIMS formulation, an archetype is a set of physical measurements for components such as floor space, window area, insulation levels, and rate of air exchange. Hence, each archetype is characterized by its own heat load, cost of retrofitting, and energy savings. The technologies that compete within each shell archetype are oil furnaces, natural gas furnaces with various efficiency levels, and electric baseboard heating, etc.

Given this set up, it is important to understand how the shell retrofit and heating system upgrades interact at the competition nodes. The shell retrofit competition takes place first, so that the stock of houses at the “retrofit” and “unretrofit” nodes are determined before the node tracking the actual technology competition among the heating systems. The confusion is that, in the technology file of CIMS, we see that the technologies competing at the bottom nodes are stated in terms of a particular heating system combined with information as to whether the house was retrofitted or not, such as “single detached retrofit high efficiency gas furnace.” The reason for stating the technology competition in this format is due to the fact that a shell retrofit affects the heat load of the heating system. However, it should be underlined that the simulation process takes care of the shell retrofits separately in such a way that in each period the number of the houses that are retrofitted is determined and hence defines the movement between the “retrofit” and “unretrofit” nodes. This will determine the type of technology competition we have at the bottom nodes in the sense that same heating system (same fuel type and efficiency level) will act as different technologies depending upon whether the house is retrofitted or not, since the heat load varies across the nodes.

5. Future Work: Estimation of CIMS parameters using the EGH dataset

In this section we provide a very preliminary outline of how data from the EnerGuide for Houses (EGH) program might be used in the CIMS modeling framework to address issues outlined in the introduction pertaining to the efficacy of certain residential retrofit policies. Since space and water heating account for more than 80 percent of total residential energy consumption in Canada – a percentage that appears to be even higher in the EGH dataset – and because recommended upgrades resulting from the energy audits as well as reported upgrade actions fall in categories related to one of these two energy uses, it would appear to be most beneficial to focus the analysis on these two types of heating.

As reported in the previous sections, determination of the CIMS parameters for the residential sector has been based principally on stated preference studies where survey participants are asked to make choices between various alternatives, but where they are not required to actually invest their own resources in one of these alternatives, often because the alternatives do not actually exist as yet. This is advantageous in the sense that it enables consideration of technology that is not yet available or viable, but it means that it is not necessarily representative of actual consumer choices or behaviour. In contrast, using actual survey (revealed preference) data means that the parameters that are derived will reflect actual consumer choices. The drawback is that choices are limited to those that are currently available under current (or past) economic conditions. In any event, to date CIMS parameters for the residential sector have not been estimated using revealed preference studies (actual data). Thus, estimation of the parameters using the EGH dataset will fill this gap. In addition, a comparison of the parameters obtained from the two types of studies – to the extent possible – may help indicate the extent of the uncertainty revealed from the two types of information because stated preference data has some shortcomings as it does not represent what has actually taken place.

To date, estimation of the parameters for the residential sector has been carried out in such a way that the two choice sets – heating system and shell retrofit – are distinctly modeled, and the estimations were carried out without regard to the possible interdependences of the decisions regardless of which choice set they belong to (Sadler, 2003). However, homeowners' choices of energy saving opportunities can be difficult to group in distinct sets that are independent from one another. Grouping is, however, important to generate discount rate estimates applicable to each choice set. Therefore, it is desirable to utilize an estimation method that will enable us to estimate discount rates for each choice set while taking into account the interdependence across the groups. An estimation technique that would be appropriate in this case is the nested-logit approach.

The EGH dataset is created in such way that energy auditors evaluated the exiting situation and hence provided upgrade options relevant to the specific conditions. That is, the choice set facing the homeowner is the list of the upgrade cases recommended, whether they are shell retrofits or heating system upgrades. If the homeowners decide not to implement the recommended upgrades, it implies that they are choosing to continue with the status quo. This implies that the decision to adopt the recommended upgrade depends on whether the upgrades make the homeowners well off as compared to the initial condition, given the costs and several other factors. Furthermore, homeowners may have to prioritize the implementation of the recommended upgrades depending on their own conditions and the characteristics of the upgrade cases. Hence, there is a competition among the list in the choice set they are facing.

When it comes to modeling the choice problem however, homeowners consider the competing upgrade cases. More conveniently, we can classify the options into three choice sets: the shell retrofit; and upgrades of space heating equipments and of domestic hot water heating systems.

Under the shell retrofit set, homeowners have the choice of upgrading windows and doors, ceiling insulation, main wall, and basement wall and exposed floor insulation. Hence, these are the competing options in the shell retrofit subset from which homeowners have chosen at least one option. Several households undertook more than one retrofit activity. Hence, we have multiple choices, which calls for a multinomial choice analysis. The empirical model therefore has to take this reality into account.

In order to indicate the types of estimation issues that arise, let us specify utility from alternative j as a linear function of its arguments:

$$U_j = \beta_j + \beta_1 y_i + \beta_2 EC_i + \beta_3 CC_j + \sum_k \alpha_k H_{Ki} + \eta_j$$

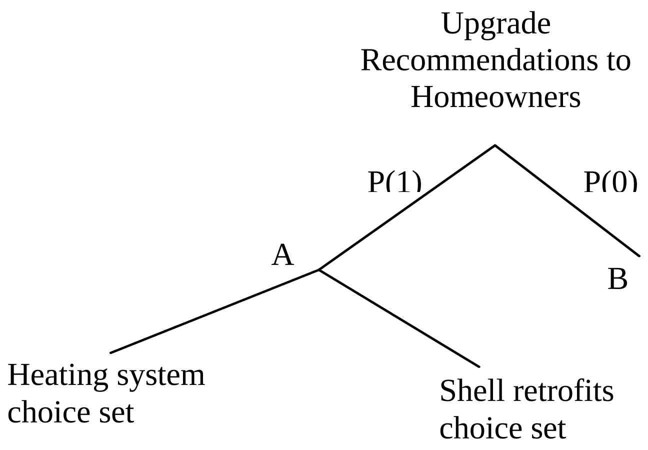
where *y* is real income; *EC* is real fuel cost after the upgrade; *CC* is the real capital cost, and the last term captures the effects of unobservable measure of comfort level indicated in the utility function. The constant term is the alternative specific constant and $\sum_{k} \alpha_k H_{Ki}$ is the sum of all other factors explaining the comfort level.

In the stated preference studies carried out by Sadler (2003), the coefficients of this equation are estimated by considering the alternatives that fit in to one choice set; mainly shell retrofit and heating system choices, and then specifying the probability equation based on the multinomial logit model (MNL). As noted earlier, in discrete choice models of this sort, only parameters belonging to those factors variable across the alternatives can be identified (Greene, 2003; Train, 2003). One possible way to consider the effect of individual specific attributes, such as income, is to include them in the estimation equation by cross multiplying them with the alternative specific constants so that they are allowed to be variable across the alternatives (Greene, 2003).

In the EGH program, the list of recommended upgrades provided to homeowners can be considered as factors that belong to the same choice category in the sense that homeowners consider implementing upgrades from among all the possible recommendations they are given. Hence, all the alternatives in the EGH upgrade recommendations are competing alternatives and in effect belong to the same choice set. However, estimation of the discount rate requires that we need to group the choices in to two sets – heating system and shell retrofit – so that we will be able to estimate two different discount rates for the two choice sets. Otherwise, we will estimate only one discount rate, a result incompatible with the CIMS framework. It would be possible to estimate the discount rates applicable to each alternative if we treat each alternative as the only choice faced and hence use a binary choice model. This, however, contradicts the multiple discrete choices faced by the homeowners.

The other implication of the nature of the dataset that we have to emphasize is that the decision problem is relative. We have postulated that the homeowners consider those upgrade options that would make them well off as compared to the status quo. That is, the decision to upgrade or not is based on the level of utility from upgrading relative to that from doing nothing. Given this decision criterion, and its implication for which explanatory variables to include in our estimation, we consider the approach that enables us to estimate two discount rates, for the heating system and shell retrofit choice sets separately. However, we recognize the correlation across the two nests. The following diagram shows the structure of the empirical model.

Figure 3: Potential Structure of the Empirical Model



Homeowners facing the upgrade recommendations may decide to undertake any number of them which leads them to the utility level received at point A. Similarly, homeowners may decide not to undertake any upgrades in which case they would be characterized by point B.

In the estimation process, therefore, we condition our analysis on the fact that homeowners are at point A (say P(1)). Then, the probability of choosing the heating system nest is given by $P(h|1)$ whereas the probability of choosing the shell retrofits nest is given by $P(s|1)$. Furthermore, the probability of choosing any one upgrade alternative j from the heating system nest is given by $P(j|h|1)$ and similarly, the probability of choosing any one upgrade choice k from the shell retrofit nest is given by $P(k|s|1)$. However, if we focus just on homeowners that did some upgrades then we begin at point A and simply deal with the two choice sets.

Our objective is to derive the parameter estimates for CIMS. The first CIMS parameter is the subjective discount rate which is computed as a ratio of coefficient of the capital to that of the operating cost (the negative of energy saved). The second parameter is the intangible benefit or cost which is computed, generally, as the ratio of the alternative specific constant to the coefficient of the operating cost. In our framework, the intangible benefit or cost is the unexplained part of the change in consumer surplus associated with an upgrade. In other words, the intangible benefit or cost can be defined, in our framework, as the amount by which utility increases/decreases if the operating costs that are saved are fully offset by the capital cost of the upgrade.

Since we have based our analysis on the utility difference between the upgrade and no upgrade cases, the value we actually estimate is the change in consumer surplus resulting from the upgrades. Hence, the alternative specific constant in the estimated equation is simply the unexplained part of the welfare change if we divide it by the coefficient of the operating cost (negative of energy cost saved). This will be what we consider as the intangible benefit or costs.

Note that while we will be able to estimate only one discount rate per a choice set, we can identify intangible benefits or costs for all but one of the specific upgrades in a choice set. Hence, we will use the average of the upgrade specific intangible benefits or costs as an input for CIMS. Finally, the heterogeneity parameter v will be estimated as a calibration parameter during the simulation process as has been done in previous analysis using CIMS, as discussed previously.

While much work is required to use the EGH dataset in conjunction with the CIMS modeling and simulation framework, based on the preliminary outline provided here it appears to be feasible and to have the potential of offering useful insights into both the effectiveness of existing programs as well as the implications of alternative policies that might be considered.

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