From Practices to Behaviors: Estimating the Impact of Household Behavior on Space Heating Energy Consumption

Jean-Michel Cayla, Centre de Mathématiques Appliquées (Mines Paristech) - EDF R&D
Benoit Allibe, CIRED (CNRS, EHESS, ENPC, Agro Paristech) - EDF R&D - ECLEER
Marie-Hélène Laurent, EDF R&D

ABSTRACT

Energy consumption in residential buildings is a complex phenomenon that stems from the combination of technical features and practices of occupants. Despite the central role occupants play, long-term modeling exercises at large scale often lack behavioral realism and explicitness. This study shall focus on the integration of conservation behaviors in the long-term modeling of space heating energy consumption in the residential sector. Based on a recent survey on 2,012 French households, we shall compare three energy demand models: an engineering model with normative behavior, an engineering model that includes several space heating practices, and a statistical model that captures the impact of all variables (technical, practices and socio-demographic). Our results confirm the importance of behavior in the explanation of energy consumption and quantify the role played by explicit practices on one hand and socio-demographic variables on the other. Nevertheless significant differences can be observed between calculated and actual energy consumptions, suggesting several potential uncertainties in the calculations. Consequently, we investigate how these uncertainties might impact the results of a prospective study focused on behavioral changes.

Introduction

Residential space heating is responsible for about 20% of energy consumption and 15% of greenhouse gases emissions in France [CEREN, 2007; CEREN, 2009; DGEMP, 2008]. Many technical solutions to reduce energy consumption are well known, well developed and may lead to long-term financial benefits [Laurent et al., 2009]. This makes this sector very attractive for national long-term energy policies [Levine, 2009].

Many models aim at quantifying the energy savings that can be achieved through technological, economical or behavioral changes. However, large-scale long-term studies tend to focus either on technical potential or on the purchase decision of energy-efficient equipment. Indeed, very few large-scale studies have explicitly considered the impact of conservation behaviors per se (i.e. without technical change) until recently [BC Hydro, 2007; Dietz et al., 2009; Gardner and Stern, 2009]. Given the importance of possible behavioral changes on mid- and long-term scales, our paper focuses on the implementation of conservation behaviors in a prospective model on a national scale.

Conservation behaviors regarding residential space heating mainly consist of the following practices:

- Temperature management: lowering the internal temperature and heating only when and where occupants are at home,
- Ventilation rate management: reducing the amount of time when windows are open.

It has been shown that behavior may affect residential energy use to the same extent as do more efficient equipment and appliances [Linden et al., 2006]. In terms of space heating more specifically, thermal simulations have shown that the energy consumption of a dwelling may differ by a factor of 3 depending only on temperature and ventilation rate management (with the same technical context) [Allibe, 2009].

Based on these observations, we tried to integrate these behaviors into different models in order to have a more comprehensive view of conservation behaviors. Thus, we made a complete survey of 2,012 French households to quantify to what extent space heating energy consumption is due to behavioral or technical attributes (see Section 2). The questionnaires gave information on the technical performance of the dwelling (shell and equipment) as well as on the household's heating practices and their socio-demographic attributes. The statistical analysis of energy consumption confirms the importance of behavior and allows us to distinguish practices from socio-demographic impact. Statistics also suggest several sources of uncertainty. Therefore we shall investigate the way these uncertainties might impact the results of our prospective model.

The first section of the paper shall review some demand models and their ability to simulate long-term behavioral changes. The survey shall be presented in the second section, followed by model results in Section 3. Finally, uncertainties and their consequences on long-term prospective model results shall be investigated in Section 4.

A Review of Space Heating Energy Consumption Models and Their Ability to Model Long-Term Behavioral Changes

Many models aim at calculating the space heating energy consumption of dwellings. They are applied on different scales, from a single house to the world housing stock. They also reveal different views with regard to the factors that determine energy consumption, with emphasis either on direct factors (for instance technical features or explicit practices) or on more indirect ones (for instance income or energy price). Technically speaking there are two main groups of energy consumption models: top-down and bottom-up [Hourcade et al., 2005; Swan et al., 2009]. Top-down models offer an aggregate view of energy consumption and are mainly used in economic prospective studies. They generally have a good macroeconomic and microeconomic realism but lack technological and non-purchase behavioral explicitness. These features make them unable to represent the disaggregate effect of single practices, which is why we had chosen not to use them. Conversely bottom-up models aggregate individual energy consumption to provide a global one. Furthermore, some of them can be used without any historical data, thereby allowing them to represent future trends independently of past ones, a significant advantage for a prospective study. Their ability to depict energy demand in a comprehensive and explicit way makes them an adequate tool for the objectives of our study.

Bottom-up models can be categorized into two main groups: statistical and engineering models [Swan et al., 2009, Kavgic et al., 2010]. Statistical models are based on an analysis of the actual energy consumption of households depicted by a group of variables whose level of detail can vary. Statistical analysis then estimates the impact of each variable on energy consumption. These models fit quite well with actual consumption data but contain some inexplicit energy consumption that may not remain constant in the long-term (for instance, the constant in a linear regression). The engineering models are not based on actual energy consumption but on an engineering description of the technical infrastructure: shell and systems performances, and their use by households: mean internal temperature and ventilation rate (that are often normative through the use of heating degree hours and standard ventilation rate for each ventilation technology). This description of the energy consumption determinants provides a physical realism that is crucial for long-term models (whose resulting physical coherence must be checked due to the magnitude of changes that can be modeled in the long-term). This kind of model allows for great technical and behavioral flexibility in the long-term. However, such models are not able to represent the impact of non-technical and non-practice variables (like income or energy prices) if they are not directly correlated with practices or technical variables.

The representation of human behavior in long-term energy consumption models is often limited to purchase behavior [Moezzi, 2009], which models households as more or less rational economic actors. Conservation behaviors can be present in models in the form of short-term elasticity [Haas and Schipper, 1998] or the utilization intensity factor [Schuler et al., 2000], but are seldom tackled explicitly, with the exception of some rare studies like the BC Hydro Conservation Potential Review [BC Hydro, 2007].

Space heating practices in the residential sector are numerous and variable, which makes them difficult to measure on a large scale. In the survey we designed and used, we asked about practices that are measurable by the household, like the mean internal temperature during the space heating period, the frequency and duration of windows being left open, or the presence of a little- or non-heated room in the house. As presented above, such a high level of detail requires a bottom-up model. Consequently, we used the two types of bottom-up models (engineering and statistical) and compared their results. The statistical model provides a quantifiable and realistic impact of separate practices whereas the engineering model provides physical explicitness and theoretical impact.

Presentation of the Survey

In order to be able to integrate behavioral aspects into the thermal simulation engineering model we launched a self-administered paper survey among 2,012 French households in June 2009 and asked them to fill out both technical items and consumption practices.

Table 1. Type of Items Asked in the Paper Survey

Type of information	Housing characteristics	Space heating system	Environment	Socio-demographic	Practices	Energy consumption
Number of survey items	39	9	4	16	12	5

In order to get representative results on a national scale, respondent households were then weighted according to income quintile, urban density of the geographical location, type of family, ownership status, type of housing, age of the head of family and age of the housing. The annual energy bills declared by households in the survey for 2008 were then collected, but the space heating part (SH) had to be separated from the overall fuel bill. We then used a regression methodology developed by CEREN[1] [CEREN, 2007] for domestic hot water (DHW) and cooking end-uses. For other specific electricity end-uses[2] we ran a multi-linear regression (R^2=0.53) among the households (N=348) that employ electricity only for these uses. We then deduced the space heating energy consumption SH for each fuel type i.

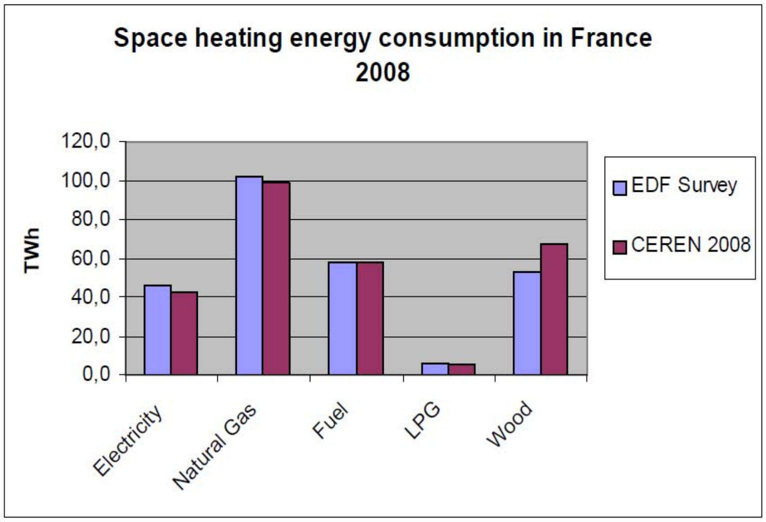
$$SH_i = Total_i - DHW_i^a - Cooking^a{}_i - Other_i^b$$

a: estimated with CEREN methodology
b: Estimated with a multi-linear regression ran on survey panel

[1]CEREN is a French research centre on energy economics and provides reference national data on energy consumption by domestic end-use.
[2] This includes lighting, cooling, cleaning and multimedia end-uses for instance.

We then compared the space heating energy consumption obtained from the survey results with the national residential space heating energy consumption data provided by CEREN in 2008.

Figure 1. Space Heating Energy Consumption in Residential French Sector



These results suggest that our sample is representative of space heating energy consumption: we observe very slight differences in overall space heating energy consumption and in the comparison by fuel type.

Statistical Model and Engineering Model Results

Statistical Results

The size of the sample was first reduced to N=923 respondents. This is due to the fact that some respondents do not have energy bills, either because their rent includes space heating (especially in apartments) or because they have not declared any. We also excluded about 100 households for whom the final space heating energy consumption does not fall between 20 and 400 kWh/m^2 [3]. Then we ran various multi-linear regressions on the sample of respondents in order to explain the variation in total household space heating consumption. Our goal here is not to build a model that may be reused to predict energy consumption, but rather to show the weight of the different types of determinants.

We first built a quite complex model with a multi-linear regression approach that takes into account the whole bundle of variables mentioned in the survey (about 150 degrees of freedom). This model (model 1) allows us to explain about 57% of the variance in space heating consumption. This first model is interesting because it gives an upper bound to the variance that may be explained with the help of these variables. That is, this 57% of variance explained will be useful when comparing the accuracy of the statistical model and the engineering model.

Then we built a second model (model 2) which is easier to manipulate and understand with only 17 variables (28 degrees of freedom). We considered the variables that are quite

[3]These values correspond to lower and upper bounds for very old and poorly insulated housing and for recent housing that follows the latest thermal regulation [DGUHC,2006].

significant with a (Pr>F) < 0.2. This means that there is a more than 4/5 chance that the variable is useful in explaining the variance in consumption.

The following results show that thanks to the different variables we can explain nearly 50% of the total variance in space heating energy consumption. We can further observe that the regression model is reliable as the global Pr>F value is < 0.0001.

Table 2. Results for Multi-Linear Regression : Model 2

Analysis of Variance

Source	DF	Sum of squares	Mean square	Value F	Pr > F
Model	28	13601	485.734388	32.43	<.0001
Error	858.99	12866	14.978248		
Corrected Total	886.99	26467			

Model Fit Statistics

R-Square	0.5139	Adj R-Sq	0.4980
AIC	2431.9433	BIC	2435.8992
SBC	2570.8231	C(p)	29.0000

Table 3 details the types of variables used in the regression. The degrees of freedom and Pr>F values given for each variable explain the level of disaggregation and the level of contingency of the variables.

Table 3. Definition of Variables Used in the Regression

Variable definition[4]	Degrees of freedom	Pr > F
Technical and weather variables		
Useful living area	1	<0.0001
Construction year	5	<0.0001
Type of housing +	1	<0.0001
Number of rooms	1	<0.0001
Existence of thermostat	1	0.0087
Heating degree hours *	1	<0.0001
Surface heat loss**	1	0.0002
Efficiency of heating system	1	0.0070
Practices variables		
T°C in the main room	1	<0.0001
Global T°C management***	1	0.0001
Length of ventilation per week	1	0.1785
Part of house not heated	1	0.1091
Days spent outside home	1	0.0344
Socio-demographic variables		
Income	1	0.0195
Type of housing +	1	<0.0001
Age of head of household	3	0.1550
Size of family	6	0.0602
Space heating energy price	1	<0.0001

+: Type of housing is also considered as a socio-demographic variable[5] *: HDH is a calculated variable
: Surface heat loss is a calculated variable *: Global T°C management is a global mark that reflect the fact that the household is reducing the temperature during nights and vacancies (half-days, week-ends and weeks).

Table 4 provides details about the magnitude and the sign of the effect the different variables have on space heating useful energy consumption.

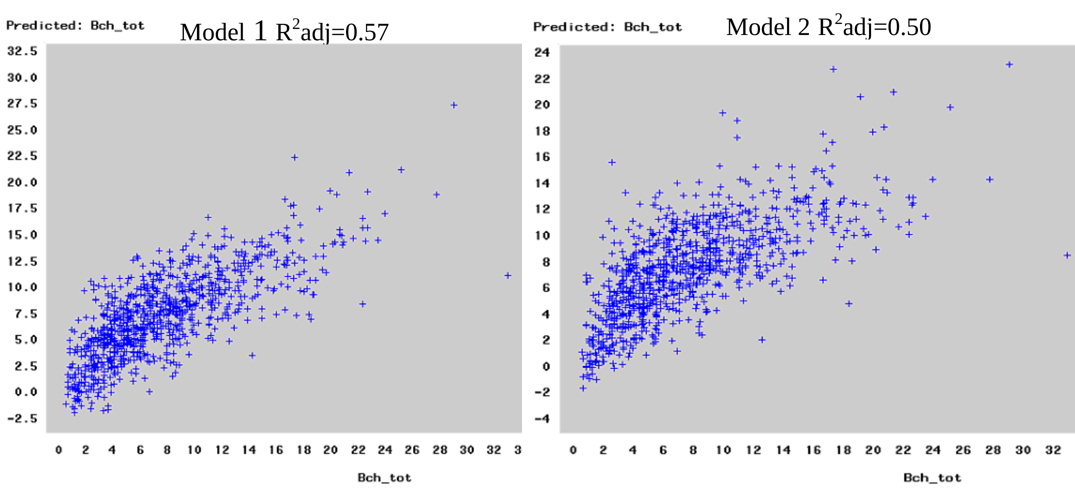
[4]Some variables are relevant only for individual houses, others only for apartments; we have thus added respectively the term IH or CH in the variable definition.

[5]Type of housing implies thermal characteristics but it also implies a certain way of life and it is linked to the type of urban area.

Table 4. Effect of the Variables in the Model 2

Variable definition	Estimate	Pr > |t|
Intercept	-15.80	<0.0001
Useful living area (m2)	0.048	<0.0001
Construction year < 1914	1.27	<0.0001
Construction year 1915-1948	0.64	0.0673
Construction year 1949-1974	0.83	0.0039
Construction year 1975-1988	-0.33	0.2576
Construction year 1989-2000	-0.71	0.0603
Type of housing - Individual house	0.79	<0.0001
Number of rooms	0.62	<0.0001
Existence of thermostat	-0.34	0.0087
Heating degree hours * (K.h)	0.000061	<0.0001
Surface heat loss** (W/Km2)	1.08	0.0002
Efficiency of heating system	-0.58	0.0070
T°C in the main room (°C)	0.40	<0.0001
Global T°C management***	0.14	0.0001
Length of ventilation per week (min)	0.0028	0.1785
Part of house not heated	-1.39	0.1091
Days spent outside home	-0.19	0.0344
Income (keuros)	0.024	0.0195
Age of head of household - <30 y.o	0.10	0.6967
Age of head of household - 30-45 y.o	-0.34	0.1708
Age of head of household - 46-60 y.o	-0.26	0.2376
Size of family - 1 person	1.95	0.0128
Size of family - 2 persons	1.49	0.0373
Size of family - 3 persons	0.81	0.2706
Size of family - 4 persons	0.89	0.2218
Size of family - 5 persons	0.90	0.3193
Size of family - >5 persons	3.01	0.1061
Space heating energy price (euros/kWh)	0.20	<0.0001

Figure 2. Space Heating Energy Consumption Predicted by the Two Models



We also crossed regressions that include only technical variables or only socio-demographic and practices variables to show the relative relevance of these variables groups in explaining the variance in space heating consumption.

Table 5. Importance of the Different Types of Variables in Space Heating Consumption

Type of variables	R^2 adjusted	Part
Total	**0.50**	100%
Technical + Environment	0.33	**66%**
Socio-demographic[6] + Practices	0.17	**33%**
of which socio-demographic	0.13	**75%**
of which practices	0.04	**25%**
Technical + Environment + Practices	0.37	74%

We found that technical variables seem to explain 33% of total consumption variance in the second model and 37% in the first one. This is quite in line with what Santin, Itard and Visscher (2009) found[7] in a similar exercise conducted with data on German households. But unlike them we also found that socio-demographic attributes and behavior play a strong role in space heating energy consumption: an additional 17% of the variance is explained (21% in the first model). Afterwards we analyzed separately the role of explicit practices and socio-demographic variables. It may be surprising to note that the role played by explicit energy practices seems quite modest (4% of the total 17%). In fact socio-demographic attributes such as age, income or size of family are relevant variables to draw social classes that are consistent with a certain way of life. These ways of life imply different arbitrations between budget items, different kinds of practices and different levels of intensity in these practices [Bartiaux 2006, Moussaoui 2005]. This demonstrates why these general socio-demographic attributes play such a great role in space heating energy consumption: they are excellent proxy variables for the intensity of space heating practices that are very difficult to capture with a paper survey. Indeed it is difficult to ask households about more than their habits. It would have required us to have them fill in a logbook with such data as how long they reduce temperature, by how much, in which room, and for how many days.

Thermal Simulation Engineering Model Including Behavioral Components

As we have previously seen a lot of classical engineering models can be found, but they often predict biased energy consumption, as only a few of them include behavioral components. Moreover with the regressions we have seen that variables such as temperature of the main room, space (between rooms) and time (during vacancies and nights) management of the temperature in the home, or else duration of manual ventilation during the week are far from negligible. But even if such a behavior module were to be designed, modelers would often face a dramatic lack of data to cross building shell characteristics and household practices.

In our study we are able to provide data about main space heating consumption practices and to include them in the SimFast model, a dynamic thermal simulation model developed by EDF R&D [Deque et al., 2000]. We shall present here the results obtained with SimFast, which we will then compare to actual household space heating energy consumption. In order to assess the importance of the behavioral part in one case we ran simulations considering the practices declared by the respondents in the survey, and in the other case we took into account a normative and uniform behavior.

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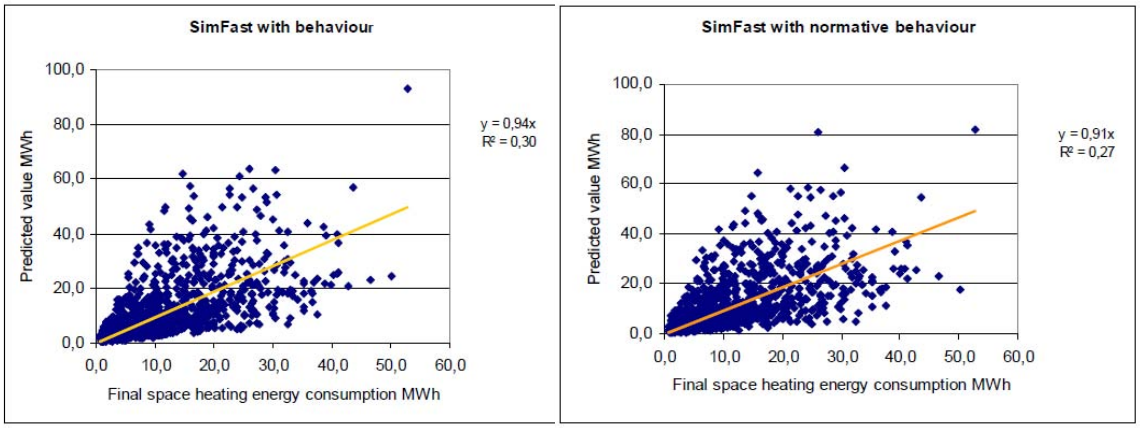
[6] Socio-demographic variables also includes economic variables as income and energy price.

[7] In their paper Santin & alii [2009] found R^2=0.42 for technical attributes and an additional R^2=0.04 for sociodemographic and practices variables.

Figure 3. Results with SimFast Model



The values predicted by SimFast improve slightly when we include some behavioral components, as the R^2 is better. The technical, meteorological and practices variables together seem to explain 37% (and 42% in the first model) of the variance in space heating consumption according to Table 5. As our model reaches R^2=0.3 we consider ourselves to have succeeded in capturing most of the actual weight of these variables in the engineering model. The quality of the thermal model and its behavior module are confirmed by the experimental values. In the context of prospective studies multi-linear regression models would not be very helpful as we do not know how the different coefficients would change over time. In fact these statistical models are generally used to predict energy consumption in the short-term. This is why this engineering model would be very useful in quantifying the impact of different behavior scenarios: with an engineering model we know how consumption would vary with different inputs.

Impact of Uncertainties on the Results of Prospective Models

What Are the Uncertainty Sources in Our Models?

As presented in Section 3 only 57% of space heating energy consumption variance in the sample is explained with the statistical model using all the variables, which is built to fit best with the data. The unexplained variance is due to various sources of uncertainty, including the inputs and the statistical method. Since the data were collected via a self-administrated paper survey we may of course face a declarative bias as people might not have actually acted as they declare and this is especially true of qualitative items and practices. Thus people may not be able to answer particular items; for instance, a respondent may not be able to know the thickness and the type of insulation material of his walls or he may not remember the amount of time and the exact number of rooms that are heated less than the rest of the house during the cold season. Note that it is normal for even a statistical model to not provide a perfect explanation of individual energy consumption. This is due to the human dimension of the observed phenomenon: even if a household is characterized by numerous attributes (income, professional activity, age, etc) its behavior is not totally determined by them. The engineering model fits less with actual space heating energy consumption (R^2=0.3), which is due to the same input uncertainties, but also to the physical database quality that is a bias specific to engineering models. In fact, engineering models use physical variables that are not directly mentioned in the questionnaire. The values of these attributes come from the model database that indicates the values corresponding to attributes that can be indicated by households (for example, the shell performance can depend on the localization and the age of a building). Thus, the quality of an engineering model strongly depends on the quality of its database.

We present here four types of uncertainty that affect our statistical and engineering models.

Table 6: Uncertainties and Their Impact on the Models

Type of uncertainty	Statistical model	Engineering model
Questionnaire bias	Declared values can be false or approximate averages (e.g. length and frequency of windows opening, internal temperature). Errors on actual energy consumption affect only the statistical model.	
Database quality	Not concerned (No database is used)	Physical database values based on regulation or expert judgment may be unrealistic (e.g. actual ventilation rates [APUR, 2007])
Heterogeneity of real values for the same answer (intra-segment heterogeneity)	If there is heterogeneity in values for a same attribute or combination of attributes (e.g. for the same dwelling age and region, many different thermal resistances are observed [Cantin et al., 2010]; or for the same income and activity, many different behaviors are observed), then the regression will be mathematically weaker.	
End-use extraction	Heating is one of the many end-uses in a household. Its amount is deduced from the energy bill thanks to an algorithm that induces errors at an individual scale (and then a weaker R^2 than with end-use metering)	Not concerned (end-use “heating” is the direct output of the model)

Impact of Behavioral Uncertainties on Long-Term Energy Prospective Studies Using an Engineering Model

In a long-term prospective study based on an engineering model dedicated to space heating, the following parameters are crucial and require an adequate modeling of behaviors:

- **Maximum and minimum levels of heating intensity**. These boundaries are chosen by the modeler and considered as stable in time. The upper value should correspond to the maximum internal temperature without conservation behavior and the lower value should correspond to the lower internal temperature with all conservation behaviors considered in the model. They provide part of the physical realism of the engineering model as they introduce limits of energy consumption results that are due to behavioral considerations. This kind of realism is absent in a linear regression model. For instance, a very strong income growth will lead to very high energy consumption in a linear regression model. When converting this consumption into physical values, it can lead to internal temperatures higher than the maximum temperature observed today in homes where the service level is considered as saturated by the modeler. A realistic choice of extreme levels of heating intensity is then necessary to avoid such incoherent results. Thus, model results are very sensitive to the modeler’s choice of these values, especially in the context of extreme scenario simulations.
- **Technical infrastructure performance for the reference year**. Performance estimates have a direct impact on the technical potential but also on the conservation potential of energy consumption reduction. In fact the impact of a practice can vary greatly depending on the building’s technical performance. Moreover, the magnitude

of the rebound effect (an increase in service heating intensity after an improvement of building performance) seems to be correlated to initial building performance [Haas et Biermayr, 2000]. Thus, a good estimate of the initial dwelling stock technical performance is needed to correctly estimate the impact of behavioral changes. As explained previously, the technical performance of a dwelling is given in the engineering model database that is based on expert judgment, norms or measurements. However, thermal performance of the shell of buildings, and especially for old ones, is very heterogeneous and very few field assessments are available [Cantin et al, 2010]. Thus, an easy way to estimate their performance is to calculate their thermal performance empirically from their heating energy consumption, environment variables and declared behavior if data are available (Schüler, Weber and Fahl (2000) had a similar approach but they did not take comprehensive behaviors into account). If old building performance is estimated in this way, the quality of the estimate depends directly on the quality of the behavioral impact estimate.

- **Energy Efficiency Market Heterogeneity.** The heterogeneity of the heating equipment and shell insulation markets is a fundamental parameter of prospective models in the residential sector [Jaccard and Dennis, 2006] because of its crucial influence on the evolution of dwelling stock performance. This heterogeneity is formed by demand and supply heterogeneities. The demand for energy efficient improvements is basically determined by the current dwelling stock performance, space heating intensity and energy price. As heating intensity depends directly on households heating behavior then market heterogeneity depends on a correct estimate of this behavior.
- **Number and type of behaviors considered.** Almost every potential study dedicated to behavioral changes considers a different portfolio of conservation behaviors. This choice is not trivial as it reveals the opinion of the modeler on the kind of behavior that can change over time. Note that curtailment behaviors (which substantially reduce energy service, e.g., reducing internal temperature during the occupants' presence) can be voluntarily ignored (e.g., in BC Hydro Conservation Potential Review). As a consequence of the modeler's choice regarding the number and type of behaviors considered in the study, the difference between behaviorally contrasted scenarios in terms of energy consumption can vary greatly. As the impact of these behaviors depends on the building performance, the accuracy of the calculation is partly determined by the quality of the engineering model database. Moreover, the savings potential of a practice depends on the initial number of household that already do it. A bias in the questionnaire regarding the declaration of a certain practice has a direct impact on the energy saving potential estimate regarding this practice.
- **Behavior status.** Behaviors can be modeled as independent or influenced by other variables. Various significant relationships between certain behaviors and other variables can be found in literature but there is no case where a behavior is fully determined by another variable or a group of variables. Thus, the modeler has to decide what type of status he wants to give to the modeled behavior, based on his understanding of this behavior and the available data. Depending on this status the most appropriate type of prospective model will differ. If behaviors are considered as independent of other variables then the prospective study can be exploratory (the proportion of households that will adopt a certain behavior and the magnitude of this behavior are left to the modeler's choice). On the contrary, if they are considered as

linked to other variables then future behavioral changes can be seen as a result of the other variables' evolution in the prospective study. In this case, the range of behavioral changes will be smaller than in an exploratory study.

Conclusion

First we have been able to statistically explain almost 60% of the residential space heating energy consumption, the remaining unexplained consumption may be due to many factors. As the data were collected via a self-administrated paper survey we may of course face a declarative bias as people do not act in reality as they declare, and this is especially true for qualitative items and practices. This has therefore led us to ask rather technically basic and general questions that may encompass only a part of the useful information needed about space heating. This statistical study shows that technical attributes are responsible for almost 2/3 of the explained variance in space heating energy consumption while attributes linked to the household explain the remaining 1/3 of the explained variance.

Furthermore, thanks to our engineering model and its behavior module we have been able to explicitly explain the impact of the technical, weather and practices variables on space heating energy consumption. In other words, we are able to estimate more accurately the energy efficiency potential and to quantify the impact of technical and behavioral scenarios. Both are very useful for prospective studies. But we can see that the explicit energy practices in our survey do very little to explain the observed variance. For instance the impact of socio-demographic attributes is four times higher as shown by Table 4. This means that further work is needed in order to better capture the diversity and complexity of the energy practices in the different household segments and to be able to better link socio-demographic attributes with explicit energy practices. It also means that the behavioral potential of energy consumption reduction in the residential sector could be far greater than that calculated only with explicit practices.

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References

Allibe, B. 2009. "**Impact of Comfort Level on Dwelling Space Heating Energy Demand: A Retrospective and Prospective Study**", Behavior Energy and Climate Change Conference, Washington DC, poster session.

[APUR] Atelier Parisien d'Urbanisme. 2007. *Consommations d'énergie et émissions de gaz à effet de serre liées au chauffage des résidences principales parisiennes.*

Bartiaux, F., G. Vekemans and K. Gram-Hanssen. 2006. "**Sociotechnical Factors Influencing Residential Energy Consumption**", SPSDII, SEREC.

[BC Hydro] British Columbia Hydro and Power Authority. 2007. **Conservation Potential Review**, by Marbek Resource Consultants Ltd.

Cantin, R., J. Burgholzer, G. Guarracino, B. Moujalled, S. Tamelikecht and B.G. Royet. 2010. "**Field Assessment of Thermal Behaviour of Historical Dwellings in France**" *Building and Environment*, 45, 2010, p. 473-484.

[CEREN] Centre d'études et de recherches économiques sur l'énergie. 2007. *Estimation des consommations de gaz à usage eau chaude sanitaire et cuisson*.

———. 2009. *Suivi du parc et des consommations d'énergie*.

Deque, F., F. Ollivier and A. Poblador. 2000. "**Grey Boxes Used to Represent Buildings with a Minimum Number of Geometric and Thermal Parameters**" Energy and Buildings, 31, issue 1, 2000, p. 29-35.

[DGEMP] Direction Générale de l'Energie et des Matières Premières. 2008. *Bilan énergétique de la France pour 2007*.

[DGUHC] Direction Générale de l'Urbanisme, de l'Habitat et de la Construction. 2006. *Décret relatif aux caractéristiques thermiques et à la performance énergétique des constructions*. Décret n° 2006-592.

Dietz, T., G.T. Gardner, J. Gilligan, P.C. Stern and M. P. Vandenbergh. 2009. "**Household Actions can Provide a Behavioral Wedge to Rapidly Reduce US Carbon Emissions**" *PNAS*, no. 44, vol. 106, November 3, 2009, p. 18452-18456.

Gardner G.T. and P.C. Stern. 2008. "**The Short List: The Most Effective Actions U.S. Households Can Take to Curb Climate Change**" *Environment*, 50, 2008, p. 12–23.

Haas, R. and P. Biermayr. 2000. "**The Rebound Effect for Space Heating. Empirical Evidence from Austria**" *Energy Policy*, 28, 2000, p. 403-410.

Haas, R. and L. Schipper. 1998. "**Residential Energy Demand in OECD-Countries and the Role of Irreversible Efficiency Improvements**" *Energy Economics*, 20, 1998, p. 421-442.

Hourcade, J.-C., M. Jaccard, C. Bataille and F. Ghersi. 2005. "**Hybrid Modeling : New Answers to Old Challenges, Introduction to the Special Issue of The Energy Journal**", Special Issue "Hybrid modelling of energy-environment policies: reconciling bottom-up and top-down", International Association for Energy Economics.

Jaccard, M. and M. Dennis. 2006. "**Estimating Home Energy Decision Parameters for a Hybrid Energy-Economy Policy Model**", *Environmental Modeling and Assessment*, 11, 2006, p. 91-100.

Kavgic, M., A. Mavrogianni, D. Mumovic, A. Summerfield, Z. Stevanovic and M. Djurovic-Petrovic. 2010. "**A Review of Bottom-Up Building Stock Models for Energy Consumption in the Residential Sector**", *Building and Environment*, 45, 2010, p. 1683-1697.

Laurent, M.-H., D. Osso and E. Cayre. 2009. "**Energy Savings and Costs of Energy Efficiency Measures: A Gap from Policy to Reality?**", ECEEE 2009 summer study, La Colle sur Loup, France, p. 571-582.

Levine, M., D. Ürge-Vorsatz, K. Blok, L. Geng, D. Harvey, S. Lang, G. Levermore, A.Mongameli Mehlwana, S. Mirasgedis, A. Novikova, J. Rilling and H. Yoshino. 2007. *Residential and commercial buildings*, in Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [B. Metz, O.R. Davidson, P.R. Bosch, R. Dave, L.A. Meyer (eds)], Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Linden, A.-L., A. Carlsson-Kanyama and B. Eriksson. 2006. "**Efficient and Inefficient Aspects of Residential Energy Behaviour: What are the Policy Instruments for Change?**" Energy Policy, 34, 2006, p. 1918-1927.

Moezzi, M., M. Iyer, L. Lutzenhiser, and J. Woods. 2009. **Behavioral Assumptions in Energy Efficiency Potential Studies**. Oakland, Calif.: California Institute for Energy and the Environment. 2009.

Moussaoui, I. 2005. "Maîtriser son confort, rendre confortable sa maîtrise: gestion des flux domestiques, maîtrise de l'énergie et valeurs de modération, chez les familles propriétaires " *EDF R&D*, 2005.

Santin, O., L. Itard and H. Visscher. 2009. "**The Effect of Occupancy and Building Characteristics on Energy Use for Space and Water Heating in Dutch Residential Stock**", *Energy and Buildings*, 41, 2009, p. 1223-1232.

Schuler, A., C. Weber and U. Fahl. 2000. "**Energy Consumption for Space Heating of West-German Households: Empirical Evidence, Scenario Projections and Policy Implications**" *Energy Policy*, 28, 2000, p. 877-894.

Swan, L. G. and V. I. Ugursal. 2009. "**Modeling of End-Use Energy Consumption in the Residential Sector: A Review of Modeling Techniques**" *Renewable and Sustainable Energy Reviews*, 13, 2009, p. 1819-1835.