Statistical and Stochastic Modelling of French Households and Their Energy Consuming Activities

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Abstract

There often is a significant difference between predicted energy performance of buildings and measured energy performance once buildings are operational. Actual occupant behavior is often different from the assumptions made in the design stage, and this is regarded as one of the main reasons for the performance gap. The diversity in occupants' sociological and behavioral characteristics must then be taken into account when predictions are undertaken, in order to determine confidence intervals of the expectable performances. Software tools must then be made available to design firms, letting them generate statistically representative sets of occupants and plausible activity and appliance use scenarios. Here we introduce two tools developed at CSTB, named Qiriel and Croniq, focused respectively on statistical generation or inference of dwellings, appliances and households, and on stochastic simulation of occupants' activities and the implied appliances activation and power consumption. They are built upon French national databases on households and time use surveys. These tools enable their users to generate in a short amount of time hundreds of occupancy, activity and power consumption profiles for specific sociological profiles or for representative sets of households. The obtained sets of series can then be used to determine median and extreme configurations of building usage, and the implied range of building performances. Such tools can also be useful at the building design stage, in order to evaluate how robust a building, its HVAC systems and their regulation can be when confronted to a large variety of usage patterns.

Keywords - energy performance gap; occupant behavior; prediction; building design

1. Introduction

Several causes can affect the energy consumption of a building: its physical properties, HVAC equipments, weather and also user behavior. The environmental context engages the industry in developing efficient building components, faster and faster. This need, associated with the need of guaranteed energy consumptions, has made inevitable the use of energy simulation programs, from building design to building operation.

Even if many developments have been pursued to ensure more detailed and faster building energy simulations taking into account the building envelope, HVAC systems and weather conditions, most simulations still rely on static, constant, *a priori* determined occupancy profiles for modeling occupancy and its impacts on building energy performance. As a result, in more and more energy-efficient building where specific energy consumptions weigh more and more, the random aspect of user behavior can play a great part in the gap between predicted and actual performances.

The question that we can formulate is then: are we able to compute, not a single deterministic prediction of building energy consumption using many assumptions, but a range of probable building energy consumption values taking into account the uncertainties linked to building construction defaults or user behavior? Answering to the last part of this question leads us to observe, describe and model occupants and the diversity of their activities.

The modeling paradigm which suits this need of reproducing transient phenomena with switches between different states correlated to many possible variables, particularly with the time of the day and the day of the week, is stochastic modeling. In this class, inhomogeneous Markov chains are well suited for modeling time series of the presence and activity of occupants in a building.

Following early publications focused on the correct evaluation of the benefits of managing lights, first references of stochastic models appear concerning office presence modeling [1], then first approaches [2] and their consolidation [3] for modeling window opening behaviors.

Stochastic modeling of the presence and activity of occupants is then further studied in papers and PhDs under the supervision of Darren Robinson. Based on stochastic presence models ([4], [5]), Robinson then focuses on thermal comfort adaptation behaviors [6], and details this approach further in window opening models [7] and interaction with blinds. Haldi's PhD thesis gathers these results on thermal comfort adaptation behavior in [8].

Simultaneously, stochastic models of the activity of occupants in dwellings are developed by Richardson [9] in order to estimate the instantaneous power loads of specific appliances.

Following these works, review papers were issued in 2012 about window opening behavior [10] and interactions with blinds [11].

Lastly, two recent PhD works have summed up many previous references on occupancy modeling: Wilke's PhD thesis [12] is focused on the simulation of specific energy consumption, and Vorger's [13] implements a set of models from the literature along with new models.

2. Statistical Generation of Dwellings and Households : QIRIEL

QIRIEL is a Python module for sampling populations of occupants, dwellings and household appliances, the characteristics of which are based on national studies, or for inferring missing characteristics.

Fig. 1 shows, on an example of a sample of 1000 dwellings, a subset of the dwelling characteristics that can be generated: number of occupants, socio-economic classification of each occupant, age and marital status of the dwelling's reference occupant, dwelling area and number of rooms, dwelling type and occupation status, construction year, heating type and fuel, and the mutual information between these dwelling sociotechnical characteristics.
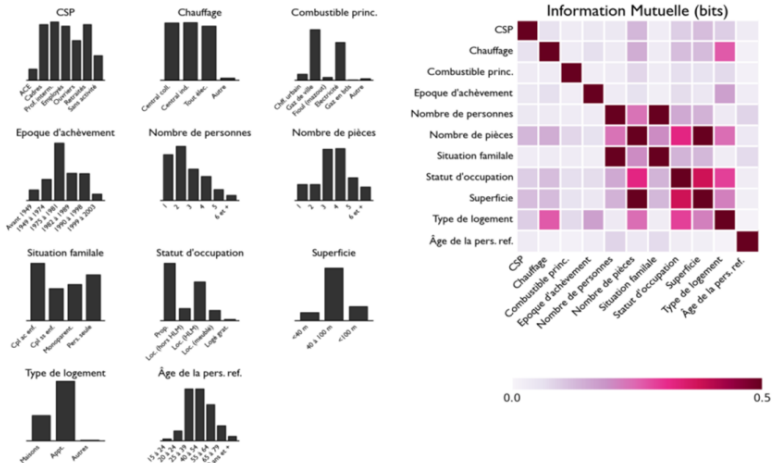
Champs-sur-Marne, 1000 tirages

Fig. 1: Dwellings and households sociotechnical characteristics generated by QIRIEL

Sample generation in QIRIEL is based on a Bayesian network modeling the joint distribution of variables in the national census [14] and studies [15] on housing. Samples can be generated representing the population of the whole country, or smaller territories of France, even on a scale smaller than the city scale.

A Bayesian network is a way of describing a multivariate probability distribution taking into account the statistical dependences between variables, via a directed acyclic graph. Said differently, a probabilistic graph

describes a joint probability using a set of conditional probabilities. Taking as an example random variables x, y and z, we can draw:
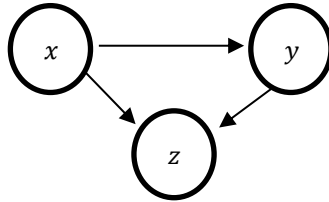

Fig. 2: Example discrete Bayesian network

Fig. 2 illustrates that y depends on x and z depends on x and y. In this case, we can factorize the expression of the joint probability $P(x, y, z)$:

$$P(x, y, z) = P(z|x, y)P(y|x)P(x)$$

where $P(y|x)$ is the probability of x given y. If these variables are discrete, the Bayesian network is also called discrete. For more details on Bayesian networks, the reader should turn to [16].

In QIRIEL, a Bayesian network has been built using data from the French national studies. The structure of this network is illustrated by Fig. 3.

The generation step (network sampling) is based on successive random selection of variables from the network conditionally to their parent(s) in the network. It is implemented through a Markov Chain Monte-Carlo method called Gibbs sampling. Once draws have been made, we get a sample of dwellings described by discrete variables. Continuous variables are generated from discrete ones using uniform draws in each discretization interval.
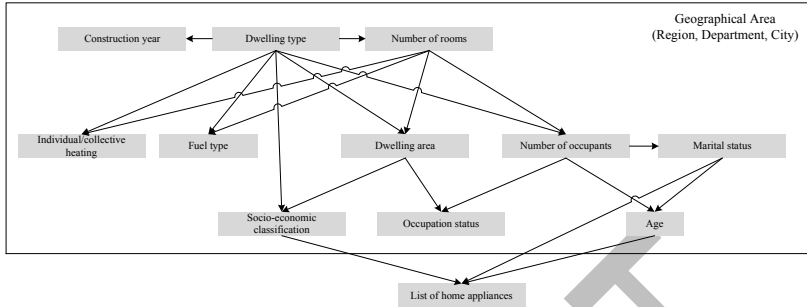
Fig. 3: Bayesian network for Qiriel

3. Stochastic Simulation of Occupants' Activities : CRONIQ

CRONIQ is a Python module for the stochastic modeling of occupant presence and activity, and for the simulation of specific electricity power load of home appliances. It is based on the results of the French national Time Use Survey [17] and measurement campaigns conducted by Enertech [18].

The Time Use Survey concerned 12000 French households over one year, using in particular daily notebooks where surveyed individuals must write, every 10 minutes, what their activities are, possible activities being categorized.

In its current version, CRONIQ implements a kernel of activity modeling on which is built a set of appliance activation models. Once an appliance is activated, a power consumption model is called. CRONIQ's kernel of activity modeling is composed of a set of transition matrices corresponding to inhomogeneous Markov chains.

A discrete time Markov process is a sequence $X_0, X_1, X_2, X_3, ...$ of random variables with values in state space E. X_n is the state of the process at time n. When E is finite or countable, the process is called a *Markov chain* or *discrete state space Markov chain*.

For CRONIQ, E is the set of possible activities:

$$E = \begin{Bmatrix} \text{Sleeping, Washing, Cleaning,} \\ \text{Cooking, Multimedia, Other, Out of dwelling} \end{Bmatrix}$$

The main property of a Markov chain is that all the information needed for the prediction of a future state is contained in the present state:

$$\forall n \geq 0, \forall (i_0, \dots, i_{n-1}, i, j) \in E^{n+2}$$

$$\mathbb{P}(X_{n+1} = j \mid X_0 = i_0, X_1 = i_1, \dots, X_{n-1} = i_{n-1}, X_n = i) = \mathbb{P}(X_{n+1} = j \mid X_n = i)$$

Probability $\mathbb{P}(X_{n+1} = j \mid X_n = i)$ is called *transition probability from state i to state j*. Denoting this transition probability as $p_{i,j}^n$, we call $P = \left(p_{i,j}^n\right)_{(i,j) \in E^2}$ the *transition matrix* of the Markov chain at time n.

Activity modeling in CRONIQ is based on such transition matrices: by applying Hierarchical Ascendant Classification and self-organizing maps algorithms on the whole set of daily activities from the TUS, we determined a set of typical days, and the corresponding transition matrices for each time of day. These transition matrices are used successively, with probabilities of being used depending on occupants' sociological characteristics.

Each of these typical days is composed of activities which can be linked to presence, internal gains and the activation of home appliances, the power consumption of which is then simulated.

4. Application Results

In order to demonstrate the possibilities of QIRIEL and CRONIQ, in this section we show example results of running these tools for the sampling of dwellings and households in two French cities: Paris and Brioude, a little city located in the department of Haute-Loire.

Statistical Generation of Dwellings and Households

Using QIRIEL, we can generate 500 dwellings in each city, and illustrate the sociotechnical differences between households in these two cities, as they are described by INSEE studies. Figs. 4 to 7 illustrate some dwelling or household characteristics that can be computed.
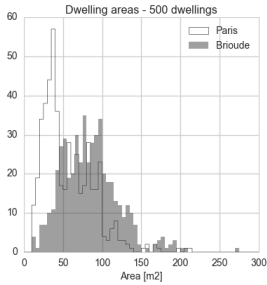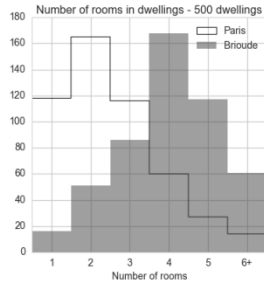
Fig. 4: Areas of generated dwellings

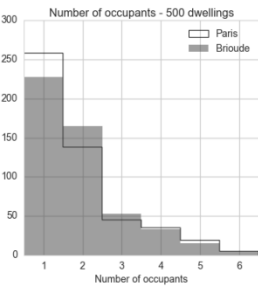Fig. 5: Number of rooms in generated dwellings

Fig. 6: Number of occupants in generated dwellings
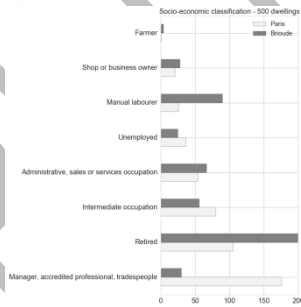

Fig. 7: Socio-economic classification of occupants in generated dwellings

Stochastic Simulation of Activities

Using CRONIQ and the sets of dwellings and households generated by QIRIEL, we can simulate the activity and specific energy consumption in all dwellings. Figs. 8 and 9 illustrate the activity profiles and implied energy consumptions that can be computed.
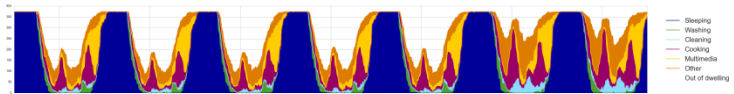

Fig. 8: Activity profiles of all occupants in generated dwellings over one week, in Paris
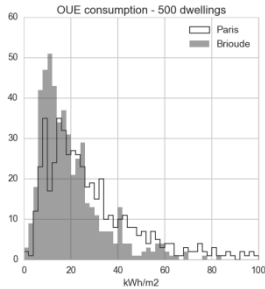
Fig. 9: Histogram of the specific electricity consumptions (per square meter) for 500 dwellings in each city
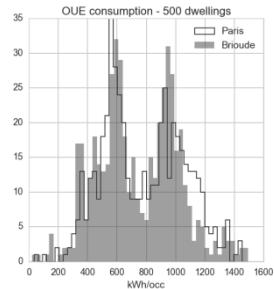

Fig. 10: Histogram of the specific electricity consumptions (per occupant) for 500 dwellings in each city

5. Conclusion and Perspectives

Using QIRIEL and CRONIQ enables the generation of varied profiles of presence, activity, internal gains and specific electricity consumption for population samples with statistically representative socio-technical characteristics.

The mathematical framework behind QIRIEL and CRONIQ has nothing specific to the residential sector, or to the French territory: perspectives then include the extension of these tools to other sectors, provided sufficiently representative datasets are available, or the application of the statistical and stochastic methods to other countries where census data and Time Use Surveys are available.

Acknowledgment

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