TAKING HUMAN BEHAVIOR INTO ACCOUNT IN ENERGY CONSUMPTION SIMULATION

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ABSTRACT

In recent years, continuously growing energy requirements have become an issue. This is particularly true concerning electrical energy as resources to produce it are limited. Numerous studies have shown that human behaviour plays a key role in the global consumption. Thus modelling human activity is part of the sustainable developpement challenge. To achieve good simulating and predicting performances in the field of electric consumption, various statistical and behavioural methods that take human factors into account have been implemented. Both families of methods have their respective strengths and weaknesses. We propose a review of these methods.

Signal processing techniques have been widely used to solve this problem. New methods based on behavioural models are promising. A recent work proposed by the authors is based on a psychological model that highlights the nature of decision-taking processes related to electrical consumption.

Keywords: sustainable development, energy consumption, inverse system.

1. INTRODUCTION

World energy use is quickly growing and has already raised concerns over supply difficulties, lack of energy resources and heavy environmental impacts such as green-house effect. Current predictions show that this trend will probably continue several decades. In recent years energy efficiency measures have made the energy end-user increasingly important and influential on the whole sustainable developpement challenge. One example is distributed electricity generation in low-voltage grids, where the impact of widespread on-site generation on network voltages is influenced by the matching with domestic electricity demand Thomson, M., & Infield, D. G. (2007). Modeling of domestic electricity demand for a large number of individual households is a complex task. In a realistic simulation, the shape of the demand curve must be reproduced taking account of variations between households and spread of demand levels for different end-uses over time. Markov-chains models can simulate adequately power consumption(Widén, J., & Wäckelgård, E.2010).

However, the inhabitant's behavior, which is an important factor, is poorly considered in such stochastic modeling. Figures of predicted consumption may be strongly impacted by human factors. The multi-agent framework allows to takes account of inhabitants behavior. By explicitly defining a behavior model, a link between perception and action may be defined and used to predict energy consumption on the basis of the perceived surrounding. However, personal preferences –and important underlying factors of behavior- are still hard to take into account. In section 2 we propose an overview of the behavioral impact on energy consumption. Numerous simulators exist to predict energy consumptions. The main issues are discussed in section 3. There are two main approaches: the statistical approach is presented in section 4 and the behavioral one, which has been followed by the authors, is developed in section 5.

2. IMPACT OF HUMAN BEHAVIOR ON ENERGY CONSUMPTION

To illustrate how human factors have a strong influence on energy consumption, in figure 1, we show the mean daily consumption of two habitations. In spite of their same number of inhabitants, similar electrical equipment, same location and same type of habitation, the consumption profile is very different (Remodece database 2008).

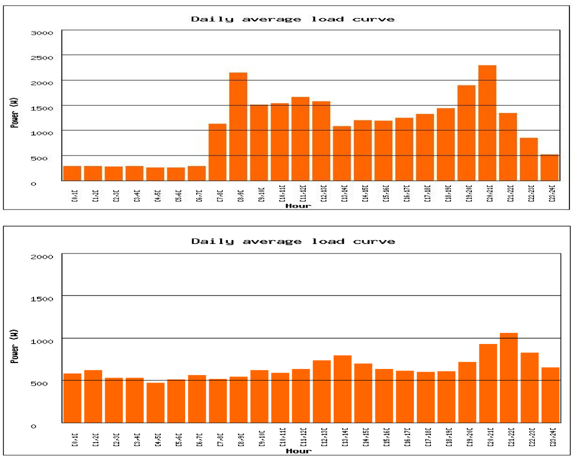

Figure 1: two different energy consumption profiles.

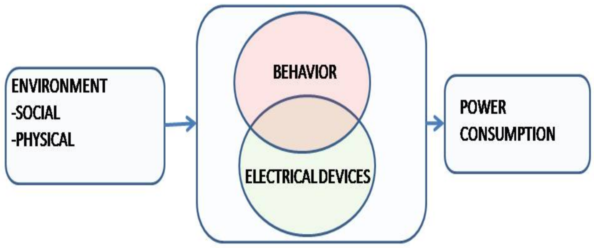

Figure 2: general model that links environment, behavior and power consumption.

Energy consumption in buildings depends on many parameters that can be split into three categories (see Figure 2):
- Environment: this category includes the local climate, the local context (close to a forest, a high building, a river, etc.) and the orientation of the house. It also includes the social context. At the conception level, the social context includes architectural constraints that are usually imposed by municipal administration and national rules. At the user level, the social context includes the profile of the inhabitants (family with children, old persons, students, socio-professional category, etc.).
- Physical devices: this category includes all electrical devices of the house and eventually other heat production devices.
- Behavior: this category includes all human behaviors. A behavior is usually defined by three parts: A perception process (perception of cold for instance), a decision process, and an action process (Merleau-Ponty 1976), (Fiske, Susan T & Neuberg, Steven L. 1990). Behaviors have an important impact on consumption. Humans have an impact on the conception of the house, taking into account ecological issues, costs issues, but also comfort, well-being and uses. At the realization level, there are human factors linked to the professionalism of the building teams, time constraints and costs, which may lead to errors and structural defects. At the user level, behaviors also have an important impact. Here are some examples:

- There are gender differences in the comfort temperature, which has a direct impact on thermostat regulation. (Karjalainen, S. 2007)
- A cultural behavior exists for window opening, even in modern houses with automatic ventilation.
- Some people leave their television switched on day long, even when there are not watching it (Remodece database 2008).

3. ENERGY CONSUMPTION SIMULATION

Power consumption can be seen as the output of a system that takes environment e (physical as well as social), electrical equipment a, and inhabitants' behavior b as inputs, whereas electrical consumption C is the output. The forward model can be expressed as $f(e,a,b) = C$. Figure 2 represents this general model.

In order to simulate energy consumptions, we need a model for the environment, models of physical devices including the house and behavioral models.
Modeling human behaviors is a very difficult task. Software solutions such as Pleiades-Comfie or Sketchup reduce human factors to basic stereotyped behaviors.

Fundamentally modeling behaviors can be seen as solving an inverse problem. In order to do so, electrical consumption data have to be collected. C becomes a known parameter and the inhabitants' behavior b becomes the output. Hence partial inversion of the model $f(e,a,b) = C$ is necessary, and can be expressed as $g(e,a,C) = b$ this partial inversion is illustrated in figure 3.

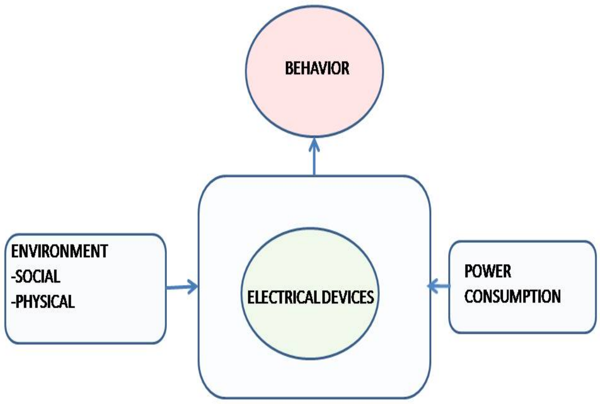

Figure 3: General model partially inverted to simulate behavior.

4. STATISTICAL APPROACH

In this case, the function $f(e,a,b) = C$ is a stochastic function that can be a linear combination of known probability distributions that describe the database in a parsimonious way. Markov-chain models are part of this framework (Widén, J., & Wäckelgård, E. 2010). Non linear probabilistic models are also used (Page, J., Robinson, D., Morel, N., Scartezzini, J.-L.2008) and succeed to reproduce non-repetitive behavioral patterns.

In both cases, methods to recover the g function earlier defined are well-known, and allow obtaining results that are close to actual measures if the database is well-suited. However, in this framework, behavior is entirely deduced from the database, and the parameters of the g function are a purely statistical description of the human factor. In this case, the results strongly rely on the relevance and exhaustivity of the database. Minor changes on the electrical equipment or on the habits of the studied population cannot be taken into account to adjust parameters of the g function.

5. BEHAVIORAL APPROACH

Methods presented earlier aimed to partially inverse the consumption function f. Since this function is not analytical and depends on complex hidden factors such as human behavior, this can be seen as an ill-posed problem. In the statistical approach, authors face the problem by looking for a mathematical solution that is optimal in the least-squared error sense.

Behavioral methods are not based on a mathematical solution, but rather on a distributed solution that does not need to be expressed in a closed-form. There exist a plenty of methods to model the decision process that defines the behavior -BDI methods, competitive, collaborative, reactive, expert systems… - (Ferreri, Salotti, Favier 2014, Russell et al. 1995)
In order to do so, the multiagent framework has proven to be useful (Le, et al 2010).

In such a framework, each human is represented as a simplified system that aims to satisfy needs by optimally using resources at disposal. Specific scenarios can be programmed and simulated to empirically adjust the way the agents reach optimality from their point of view. This distributed non-analytical version of the least-square error allows a better understanding of the influence of human behavior.

6. CONCLUSION

Methods presented in this review try to take account of human behaviors in energy consumption simulations. Statistical methods allow obtaining quick results which are compatible with time-user databases. However, technologies are evolving, habits are changing, new norms are appearing, and motivations and beliefs concerning ecology and sustainable development are more and more taken into account. Hence the statistical approach based on past data is biased and the behavioral one might be more appropriated.

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