A Cooperative Multi-Agent System to Accurately Estimate Residential Energy Demand

(Extended Abstract)

Márcia Baptista,
Helmut Prendinger
National Institute of Informatics
2-1-2 Hitotsubashi, Chiyoda-ku
Tokyo 101-8430, Japan
marcia.baptista@ist.utl.pt, helmut@nii.ac.jp

Rui Prada
INESC-ID and Instituto Superior Técnico, Universidade de Lisboa
Av. Prof. Cavaco Silva, Taguspark Porto Salvo
Lisbon, Portugal
rui.prada@ist.utl.pt

Yohei Yamaguchi
Sustainable Energy and Environmental Engineering
Graduate School of Engineering, Osaka University
2-1 Yamada-oka, Suita, Osaka
565-0871, Japan
yohei@see.eng.osaka-u.ac.jp

ABSTRACT

In recent years much attention has been devoted to understanding and predicting when and how occupants perform their daily routines and use electric appliances within buildings. The purpose here is to better estimate energy consumption. Despite efforts to capture individual behavior with precision, models often neglect how occupants interact with one another. Concretely, they do not accurately reproduce how occupants perform joint activities, such as having a meal or watching TV together, or sole activities, such as self-caring. Such inaccuracies, in turn, influence energy demand estimation, as joint and sole activities involve sharing and non-sharing of electrical appliances. Therefore, in this extended abstract, we propose a cooperative multi-agent system, where interaction of occupants is explicitly modeled by Interactive Markov chains. A preliminary study using data from five households in Osaka, Japan suggests this technique is better suited to capture interaction between occupants than the traditional Markov chain approach.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Multi-agent systems; I.6.3 [**Simulation and Modelling**]: Applications

General Terms

Algorithms, Experimentation, Theory

Keywords

Multi-agent systems, Interactive Markov chains, Energy demand

1. INTRODUCTION

The transition to the so-called 'smart (energy) grid' has long been focus of research in the field of autonomous agents and multi-agent systems (MAS). Among the most challenging questions of the field is the increase of accuracy of energy demand models.

Appears in: *Alessio Lomuscio, Paul Scerri, Ana Bazzan, and Michael Huhns (eds.), Proceedings of the 13th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2014), May 5-9, 2014, Paris, France.*

Energy demand models can serve as useful tools for electric utilities and regulators to evaluate energy efficiency and smart grid programs. For instance, they can be used to predict energy consumption and CO_2 emissions of large residential areas or to quantify the impact of energy-saving policies in buildings. Hence, these models strive for a high level of accuracy in their estimations. This has led to increasingly sophisticated models in recent years. As energy consumption patterns in buildings are largely dependent on the behavior of its occupants, several studies have focused on how to model the presence of people in buildings and the actions they take to change their indoor environments [3].

Energy demand models often take a MAS approach to occupant behavior modeling [4, 5]. Here, the household or building is conceived as a multi-agent system where occupants are autonomous agents that interact with their surroundings, i.e., with other occupants and electrical appliances. So far, these systems have been designed as *independent* multi-agent systems, i.e., the flow of activities of an (occupant) agent is derived with no regard to the activities of other occupants.[1] This follows from the traditional use of discrete time non-homogeneous Markov chains (MC) to simulate the daily routines of occupants from survey data.

The independence between the daily activities of agents introduced by Markov chains does not well reflect actual behavior of people in buildings. In real life, people regularly interact either (1) to perform joint activities,[2] such as having common meals, or (2) to avoid performing certain activities simultaneously, such as self-caring in the bathroom, which is a sole activity. Accuracy in modeling such forms of interaction can significantly impact load curves as energy consumption changes according to whether occupants share electrical appliances in joint activities, or use different appliances in unrelated activities.

Therefore, to increase the performance of energy demand models, the accurate estimation of agents' sole or joint activities is important. In this work, we claim that Interactive Markov chains (IMC) [1] are better suited to model behavior of occupants in buildings than (standard) Markov chains. We argue that this technique promotes multi-agent systems to demand estimation as *cooperative* MAS rather than *independent* MAS [2].

[1]We follow Franklin's taxonomy [2] of multi-agent systems as independent or cooperative systems.
[2]We interpret 'joint activity' as joint-in-purpose (having meal, having bath, etc.), rather than joint-in-time or joint-in-location.

2. INTERACTIVE MC AS COOPERATIVE MULTI-AGENT SYSTEM

In classical Markov chain approaches, the process by which an agent decides its activities is modeled independently from the activities of other agents in the same building or household. Each agent chooses its next activity based solely on current activity and random uniform number. As a result, some of the original interaction patterns present in the survey data may be lost. Fig. 1 provides an example on how MCs can fail to preserve a pattern of joint activities. In the original data, activities **a** and **b** are never performed together. Nevertheless, the probability of each activity to occur is 50%. Accordingly, it is possible for a Markov chain to generate occupants performing **a** and **b** simultaneously.

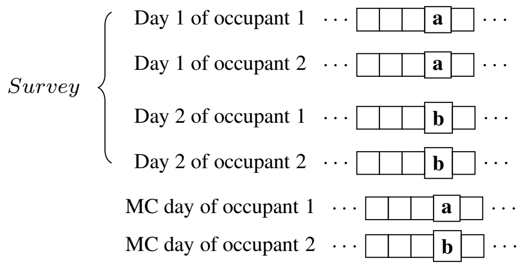

Figure 1: Example of Markov chain not preserving original interaction patterns of joint activities.

To preserve patterns of interaction such as joint and sole activities, we propose the use of Interactive Markov chains. This technique was formally proposed by Conlisk in 1976 [1], as a generalization of (standard) Markov chains. Interactive Markov chains extend Markov chains with intentional social interaction between individuals by having the transitions of each individual depend on the population's distribution over several states.

To preserve the individuality of the interacting agents we propose an adaptation of Interactive Markov chains where transition probability matrices are parameterized with the activity of a single 'leader' agent instead of a vector of population frequencies per activity. We call our model Interactive Markov chain with a Leader process (IMC-LP) and define it as follows.

Definition 2.1 (IMC-LP)**.** *An Interactive Markov chain with a leader process is a set of discrete time stochastic processes $\{X_n^1, \dots, X_n^M\}$ where each process can be represented as a tuple $< S, \tau >$ where:*

- $S = \{1, 2, \dots, N\}$ *is a finite and countable set of activities*
- $\tau : \mathbb{N} \times S \times S \times S \to [0, 1]$*: is a stochastic transition relation that assigns each combination of time $n \in \mathbb{N}$ and activities $i, j, k \in S$ a probability $\tau_{ij}(n, k)$ that the system will evolve from activity i to j from time n to $n+1$ with the 'leader' agent in activity k at time $n+1$:*

$$\tau_{ij}(n, k) = P(X_{n+1} = j | X_n = i, Y_{n+1} = k)$$
$$\textit{for processes } X_n, Y_n \in \{X_n^1, \dots, X_n^M\}, n \in \mathbb{N}$$

The probability $\tau_{ij}(n, k)$ is calculated from survey data as follows where $\eta_{ij}(n)$ stands for the number of transitions between activities i and j from n to $n+1$, with 'leader' in activity k:

$$\tau_{ij}(n, k) = \frac{\eta_{ij}(n, k)}{\sum_{j=1}^{|S|} \eta_{ij}(n, k)}$$

To decide its next activity, an IMC-LP agent indexes a probability matrix. The selection of this matrix depends on the current time frame and activity of the 'leader' agent. The 'leader' agent is selected randomly among all occupants. The matrix is indexed according to the current activity of the agent and a random number:

$$\tau(n, k) := \begin{bmatrix} \tau_{11}(n, k) & \dots & \tau_{1N}(n, k) \\ \vdots & \ddots & \vdots \\ \tau_{N1}(n, k) & \dots & \tau_{NN}(n, k) \end{bmatrix}$$

Using an IMC approach, agents are able to coordinate their activities explicitly. As they observe and react to the behavior of 'leaders', agents can cooperate with each other, either to achieve common goals or to avoid conflict, as in joint and sole activities. This is not possible with Markov chains, where agents pursue their own agendas independently of others. Hence, with the Interactive Markov chain approach energy demand models can be conceived as cooperative multi-agent systems, rather than independent multi-agent systems.

3. COMPARISON OF MC AND IMC

We have been conducting some preliminary studies with survey data from five households in Osaka, Japan. The members from two 4-person households and three 3-person households agreed to document their daily routines in diaries during 14 days.

We compared the accuracy of standard Markov chains with our proposed IMC-LP model. The results indicate that IMC-LP model is significantly more accurate than the MC model in estimating the time a household member performs an activity as a joint or sole activity. An important observation is that since the IMC-LP model coordinates the activity of an occupant with only one 'leading' agent, the IMC-LP model has better results for the 3-person household than for the 4-person household.

The results further indicate that the increased accuracy of occupant behavior modeling translates to an increased accuracy in energy demand estimation.

ACKNOWLEDGMENTS

This work was partially supported partly by the 'Global Lab' Grand Challenge grant from the National Institute of Informatics (NII), the NII Int'l Internship Program, and Fundação para a Ciência e a Tecnologia, under project PEst-OE/EEI/LA0021/2013.

4. REFERENCES

[1] J. Conlisk. Interactive Markov chains. *Journal of Mathematical Sociology*, 4(2):157–185, 1976.

[2] J. E. Doran, S. Franklin, N. R. Jennings, and T. J. Norman. On cooperation in multi-agent systems. *Knowledge Engineering Review*, 12(3):309–314, 1997.

[3] A. Grandjean, J. Adnot, and G. Binet. A review and an analysis of the residential electric load curve models. *Renewable and Sustainable Energy Reviews*, 16(9):6539–6565, 2012.

[4] Y. Shimoda, Y. Yamaguchi, T. Okamura, A. Taniguchi, and Y. Yamaguchi. Prediction of greenhouse gas reduction potential in Japanese residential sector by residential energy end-use model. *Applied Energy*, 87(6):1944–1952, 2010.

[5] J. Widén, A. Molin, and K. Ellegård. Models of domestic occupancy, activities and energy use based on time-use data: Deterministic and stochastic approaches with application to various building-related simulations. *Journal of Building Performance Simulation*, 5(1):27–44, 2012.