Study of Human Activity Related to Residential Energy Consumption Using Multi-Level Simulations

Thomas Huraux[1,2,3], Nicolas Sabouret[2] and Yvon Haradji[1]
[1]*EDF Research & Development, Clamart, France*
[2]*LIMSI-CNRS, UPR 3251, University of Paris-Sud, Orsay, France*
[3]*LIP6, CNRS UMR 7606, - Pierre and Marie Curie University, Paris, France*
[thomas.huraux, yvon.haradji]@edf.fr, nicolas.sabouret@limsi.fr

Keywords: multi-agent systems, multi-level modeling, simulation, electrical consumption

Abstract: In this paper, we illustrate how multi-agent multi-level modeling can help energy experts to better understand and anticipate residential energy consumption. The problem we study is the anticipation of electricity consumption peaks. We explain in this context the benefit of the coexistence of microscopic (human activity) and macroscopic (social characteristics, overall consumption) levels of representation. We present briefly the SIMLAB model (Huraux et al., 2014) that extends the SMACH simulator (Amouroux et al., 2013) with coexisting levels on different modeling axes. We then present a model of the households activity and its electrical consumption consistent with energy experts' observations in the residential sector. We show the impact of different social factors, such as individual sensitivity to price or to personal comfort, on the apparition of peaks on the consumption. We illustrate the contribution of multi-level modeling in the understanding of macroscopic phenomena.

1 INTRODUCTION

As energy consumption increases, one major issue for electricity suppliers is to adapt in real time to customer demand to maintain a stable frequency. In this context, understanding and analyzing inhabitant behavior is a major issue for the reduction of energy consumption. Two solutions are possible to study and anticipate human behavior. First, experiment in real situations allows psychologists and experts in ergonomics to study human activity around the principles of action and situated cognition (Relieu et al., 2004). Second, simulation can, at the cost of some computer simplifications, reproduce related consumption phenomena (Kashif et al., 2012; Muratori et al., 2013; Amouroux et al., 2013). We seek to assemble these two approaches by directly integrating *in situ* knowledge into simulations to provide new tools for experts to connect behaviors and electrical consumption. To this purpose, we propose a multi-level simulation model for the study of human activity both at the microscopic level (individuals) and at a macroscopic level (household) and we show how it can be used to study household energy consumption.

In the our model, three dimensions are considered: the temporality of human activity (from actions to habits), the diversity of populations (from individuals to social groups) and the complexity of the environment (from electrical appliances to residential area). We extend the SMACH simulator[1], a modeling and simulation platform (Haradji et al., 2012; Amouroux et al., 2013) for the study of human behavior which allows energy experts to study the everyday life of households in relation to their electrical consumption, and in particular, how organization of household activities impact on energy consumption. We add micro-macro dynamics in these three dimensions and we will show in this paper how studying back and forth between levels of representation can enable energy experts to better understand the phenomena related to consumption and human activity.

In section 2, we present works that are interested in the simulation of human activity and multi-level simulations. Section 3 briefly present SIMLAB, our multi-level agent-based model based, among others, on an inter-level influence mechanism and the concept of modeling axis. Section 4 presents the representation of households with our model. After presenting our various action strategies, we present different experiments and the corresponding results in section 5.

[1]http://www.youtube.com/watch?v=DViBg3-crxM

2 RELATED WORK

2.1 Human Activity

In the residential sector, a Markov process calibrated using time-use data can be used to simulate an average household (Muratori et al., 2013). The limitation of this approach applied in the residential sector, is to be based on the use of human behavior models as average households. But as pointed out by (Morley and Hazas, 2011), there is no average household in our society in the context of energy consumption. To overcome this limitation, (Grandjean, 2013) uses inhabitant and activity profiles based on stochastic models, which introduces some diversity in the behavior. This approach allows to reconstruct a load curve in the residential context and to observe overall phenomena, but it does not allow a micro vision for studying practices of everyday life.

The work of (Lee et al., 2011) relies on a micro modeling of activities in the professional context and use simulation to optimize the building performance. They use simulation to make prediction on real systems, combining individual activities (*e.g.* opening windows) with more macro information (*e.g.* holiday periods, meeting habits, ...). In the SMACH model, we want to go further in the modeling of activities and interactions between individuals, which naturally leads us to turn to multi-agent simulations.

2.2 Multi-Agent Systems

A large part of human activity results from cooperation, knowledge sharing, negotiation and adjustments within interactions (Haradji et al., 2012). This is the kind of dynamic between intrinsic properties, actions and interactions that can be found with multi-agent systems (MAS). For instance, this paradigm is used by (Yang and Wang, 2013) to controls the building environment through installed actuators with data from sensors and occupants as inputs. The MAS predicts occupant preferences through learning their behaviors Nevertheless in simulation models, although some agent based models have studied the electricity market, such as (Zhou et al., 2007), little work has been done on the simulation of human activity. Or the models are focused on one aspect of the activity such as comfort (Alfakara and Croxford, 2014).

Kashif (Kashif et al., 2012) works in the residential context to design a detailed model of human behavior for energy management. The authors also depart from the premise that human behavior is an important element of energy consumption of buildings. Based on the analysis of activity logs, they propose an inhabitant behavior model based on BDI agents (Rao et al., 1995). The model requires precise frameworks, which is difficult to implement with domain experts (not computer scientists) and that does not always seem necessary (Haradji et al., 2012). That is why we propose in this paper an approach that combines a microscopic description of human activity with the use of domain expert macroscopic knowledge, as the phenomenon of overall consumption peaks. We propose in our work to use a multi-level approach.

2.3 Multi-Level Simulations

Representation of macro phenomena in MAS can be done using multi-level models (Morvan, 2012). However, most models do not consider the coexistence of different levels within the same model during simulation. Some models combine different levels, as in hierarchical models like SWARM (Minar et al., 1996) where macro levels take control of micro levels. Similarly, in the crowd simulations (Navarro et al., 2011) macro entities are seen as aggregations to speed up simulations. The system automatically selects, for each agent, the appropriate level of representation to allow a significant computation gain and one level is enabled at a time. In all these approaches, the micro and macro levels do not co-exist within a single simulation.

Among more generic approaches, AA4MM (Camus et al., 2013) proposes to combine levels with a multi-modeling approach: coordination is done using information sharing. The interaction between the different levels is limited as the levels correspond to heterogeneous models. PADAWAN (Picault et al., 2011) allows the co-existence of agents and environments corresponding to different spacial and temporal scales in the IODA model (Kubera et al., 2011). All concepts are represented by agents that can change level (*i.e.* environment) based on their activity. The IRM4MLS approach (Morvan et al., 2011) offers a meta-model based on the principle of influence-reaction (IR) where the influence represents the "desire" of the agent to modify its environment and the reaction represents the consequence according to the state of the world. The links between levels are represented by directed graphs and allow to have a particular temporality for each level.

In our work, we share the view that a more systemic approach (*i.e.* coexisting levels) can enhance our model by extending it with macro entities which is not allowed by approaches based on aggregation with average behaviors. We retain the Picault's idea that all concept must be represented by an agent and Morvan's idea of representing the influences between levels. However, we are not interested by different time scales or level changes (*i.e.* conceptualization by energy experts), but we want to take into account the different levels in the system modeling itself and to combine models from different domains. We seek to show that the direct introduction into the model of levels that coexist during the simulation, not as different visualizations of a same phenomenon but to connect expert knowledge within a model to improve it. It will help us to study large-scale phenomena. So we proposed the SIMLAB model that we will briefly present in the next section.

3 THE MULTI-LEVEL MODEL

The SIMLAB model[2] (Huraux et al., 2014) is based on two major proposals for modeling and studying multi-level phenomena. First, agents that share common features for the study are grouped within *modeling axes* that capture the representation of cross domains properties at different levels. Second, we distinguish between *interactions* of agents (*i.e.* the exchange of information or queries) and intra-axis *influences* on properties, which represent the inter-level dynamics of these cross domains components.

3.1 Modeling Axis

Our model is positioned in the context of multi-expert modeling and simulation. In each domain of expertise, shared properties can be identified. But also, in each domain of expertise, these notions appear with different levels of abstraction. For example, the energy consumption is a shared property of the axis grouping appliances, rooms, housings. This is why we define modeling axes. These particular properties make the modeling process easier by encouraging reflection on what is common to all levels.

Let Ω be the set of agents. An axis $\chi_c \subseteq \Omega$ is associated with the concept c of the studied system and a set of shared properties $\mathcal{P}^{\chi_c}$ specific to the axis, which represents the domain. And in each axis, we then define the agents representing the different levels. For example the heater, the room, the housing, all calculate their energy consumption in the consuming environment axis. We denote $\sqsubset$ an inter-level relationship between two agents. An axis χ_c form a connected subset of Ω for the relationship $\sqsubset$. We assume that the inter-level relationship is non-transitive and acyclic, but an agent can have several super-agents.

[2] SIMLAB Is Multi-Level Agent Based

3.2 Agent description

Each agent $\omega \in \Omega$ has certain level of abstraction in a modeling axis. It is defined by the tuple $\langle \Omega_{sup}\Omega_{sub}, \mathcal{P}, \mathcal{A}, I, \mathcal{F} \rangle$ where ω_{sup} and ω_{sub} represent the access of the agent to his direct super and sub-agents. $\mathcal{P}$ is the set of internal variables manipulated by the agents, called properties. These concepts capture the characteristics of the modeled entity. A property can be atomic (real, boolean, ...) or more complex (list, set, function, or even a reference to another agent). $\mathcal{A}$ is the set of internal actions to enable the agent to modify its properties. A precondition is associated to each action, and at each step of execution, an agent performs all actions whose preconditions are satisfied. Finally, I and $\mathcal{F}$ are the sets of interactions and influences of the agent (see 3.3).

3.3 Inter-agent relationships

Interactions are at the heart of agent based modeling. However, these are not sufficient when entities of several levels are added into the model. Therefore, we also introduce inter-level influences to describe the relations between levels within a modeling axis.

3.3.1 Interactions

Our mechanism of interaction between agents is a simplified version of the intentional communication model proposed by FIPA (FIPA consortium, 2003). Performatives used by agents are modeled specific concepts and may involve several axes (for example, agents-individuals use performative action to inform each other of their desire and their availability for the realization of common tasks, as we will see in the next section). Each agent is provided with a set of reactions $\mathcal{R}(\omega)$, *i.e.* actions triggered only by interactions. Like actions, reactions act on the internal properties and are associated with pre-conditions. Every agent ω has a set of interactions $I(\omega)$, where each $i \in I(\omega)$ is a tuple $\langle target, reactions \rangle$ with $target \in \Omega$ the recipient and $reactions \subseteq \mathcal{R}(target)$ a set of reactions by the recipient.

Example: Let n and h be two agents $\in \Omega$ corresponding to an individual and a heater, $h.temp \in \mathcal{P}(h)$ the temperature property of h and $increase \in I(n)$ the possible interaction of n on h define as :

$$increase = \langle h, \{h.temp := h.temp * 1.1\} \rangle$$

The operator ":=" describe the effect of the action, given a value $\omega.p := v$ means that v *is allocated* to the property p of the agent ω. Here, if the individual performs the *increase* interaction on the heater, it will increase the temperature by 10%.

3.3.2 Influences

Levels are linked by an influence function that change the value of a super or sub-agent property, based on some properties of the influencing agent. These influences are defined in the agents properties and not on instances of these properties. For example, if a property of an individual influences a group, all the individuals in this group benefit from this influence.

An influence $f \in \mathcal{F}$ is characterized by a tuple $\langle \omega_e, \omega_r, P_{src}, p, infl \rangle$. It allows an agent ω_e to influence the value of a property of one of its super or sub-agents called ω_r, based on some of its properties. $P_{src} \subseteq \mathcal{P}(\omega_e)$ is the set of properties of ω_e used to compute the influence on ω_r, $p \in \mathcal{P}(\omega_r)$ the changed property and $infl$ the influence function which change the property. We denote $f(P_{src})$ the value that ω_r must integrate in p (with the relation $:=$).

Example: Let n be a sub-agent of f. They correspond to an individual and its family. $t \in [0,1]$ is an individual's property which represents its tendency to increase the heater. $prio \in \{co, sp\}$ describes if the family gives priority to its comfort or its spending. We define $f \in \mathcal{F}$ the following influence:

$$\langle f, n, prio, t, \begin{cases} t * 0.5 & prio = sp \\ t & prio = co \end{cases} \rangle$$

Here, the individual's tendency to increase the heater is halved when its family give priority to spending.

The introduction of influences allow us to define specific properties called recursive. They are properties defined for all the agents of an axis and the influence function is directed from sub-agents to super-agents (*n.b.* recursive properties are also shared properties). A change of value on a recursive property spreads as a recursive function whose computation is from the agent to the sub-agents. This mechanism allows the modeler to establish automatic consistency in behavior between different levels (*e.g.* establishing a link between the preferences of an individual and those of a group he belongs).

In the next section, we present a practical example of modeling that combines a micro representation of individuals and human activity with a macro representation of household and housing. We show how the dynamics between levels can help business experts to better understand the complex system studied.

4 HUMAN ACTIVITY SIMULATION

We now illustrate the potential of multi-level modeling to facilitate energy studies, we simulate everyday life of households in relation with the electrical consumption and their thermal comfort. In the following, we present our multi-level modeling realized with SIMLAB. It is based on three axes with several levels. We will show in section 5 some simulation results and why they are interesting for the experts.

4.1 Three axes representation

The problem is based on three concepts : population, human activity and consuming environment. To apply the previously presented model, we define respectively the following three modeling axes (as shown on figure 1):

The **populations axis** assemble individuals or groups of individuals. Each agent in this axis can perform activities and have preferences for these. To select the current activity, agents use a priority function.

The **human activity axis**, in this example, is reduce to a set of tasks characterized by preconditions (*e.g.* do the laundry is precondition of ironing) and links with possible objects in the consuming environment (*e.g.* ironing necessitate an iron). When an activity is triggered, associated elements of the environment are activated. The task model in SMACH has been presented in details in (Amouroux et al., 2013).

The **consuming environment axis** represents entities related to energy consumption (from the appliance to the housing). An agent in this axis is characterized by an electrical power, a consumption function (as a *recursive properties*, see section 3.3) and an activation state (off, standby or on).

4.2 Micro level

The micro level can be summarized as follows, each individual will perform tasks which may activate appliances within rooms that will produce electricity consumption. For each of these agents, we will present the various characteristics.

4.2.1 Individual

Individuals represent household's members and are characterized by an age, a gender, a thermal comfort, a cold-sensitivity level and a clothing level. Individuals interact with the tasks to achieve them based on their internal states. An individual associates priorities for each tasks and performs the task with the highest priority. Household's members must communicate to exchange information or request the participation of others in tasks. In addition to the individuals internal state, the priority may be influenced by external factors such as energy price level or other individuals invitations. Our model also includes inhabitants

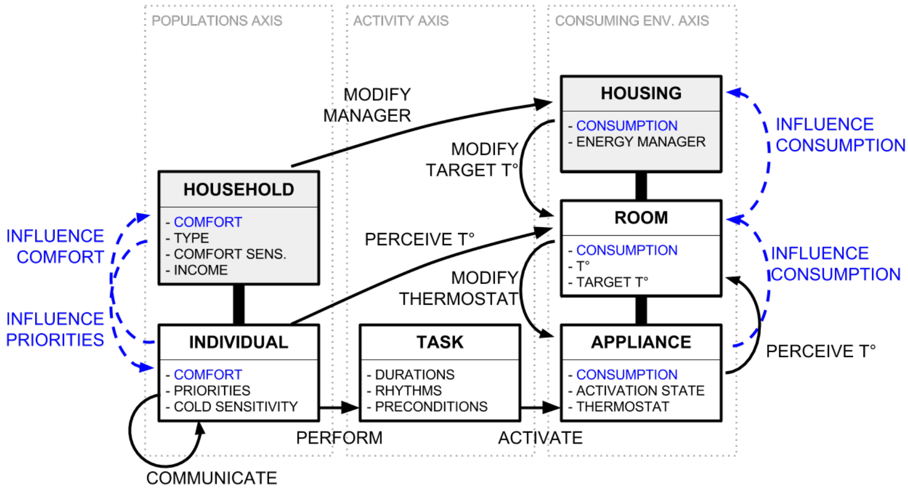

Figure 1: A simplified view of our three axes representation.

adaptation capabilities to the energy price level. The cold-sensitivity changes the thermal comfort level felt by individuals which is computed using the Fanger's equation (van Hoof, 2008) depending on their properties, mainly the temperature and the clothing level. To communicate, the individuals have a set of speech acts (*e.g.* to ask another inhabitant what it does, to encourage someone to perform an activity, ...).

4.2.2 Task

A task represents a generic activity in the house. It can be done individually or collectively and can have a rhythm corresponding to a certain regularity in its realization which modifies the probability that an individual achieves it (*e.g.* dinner occurs every day between 7 and 9 pm and lasts approximately 1 hour). A task can have pre-conditional tasks (*e.g.* the dinner must be prepared). An individual can perform a given task if and only it has the information that all pre-conditional tasks. Finally, a task can interact with an appliance to change its activation state (*e.g.* doing the laundry activates the washing machine).

4.2.3 Appliance

An appliance updates its electrical consumption and can perceive the room temperature. Electrical consumption profiles of appliances come from the database REMODECE[3] measured in real situations. The appliances can have a standby power (such as television, computer, ...) and a thermostat (heater). Heaters can interact with their room to modify the temperature. All appliances influence the room's temperature according to their radiation property, characteristic of running electrical appliances.

4.2.4 Room

We define a room as a super-agent of appliances characterized by a number of present individuals, a current and a target temperature for heaters. A room update its temperature using a thermodynamic model and perceive the number of present individuals.

4.3 Macro level

We extend our model by adding two macroscopic entities: the *household* and the *housing*. These new agents are represented with a gray background in the figure 1.

4.3.1 Household

A household is defined by its type (couple, single-parent, ...), its comfort sensitivity (eco-oriented, medium, comfort-oriented) and its income. It has a thermal comfort and acts on the energy manager in the housing to regulate the target temperatures in the rooms depending on its properties. As it is defined as a recursive property (see 3.3.2), the houshold updates its comfort depending on the influences of the sub-agents (individuals). Household properties influence individuals properties and also modify their activity. We associate an influence on tasks priorities of individuals. Depending on the household sensitivity, this influence reduces the priority when an energy-consuming appliance (*e.g.* an oven or a washing machine) is needed to perform the corresponding task.

[3]REMODECE : European database on residential consumption - http://remodece.isr.uc.pt

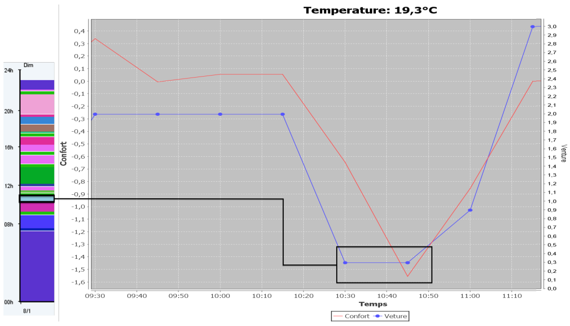

Figure 2: An example of cold discomfort feels by an inhabitant.

4.3.2 Housing

A housing is composed of rooms. It is characterized by a presence indicator which perceives if at least one individual is present in the housing. The housing can, depending on its energy manager, interact with the rooms to change the target temperatures. The energy manager also controls the presences of individuals to not uselessly heat the housing. The electrical consumption, defined as a recursive property, depends on the influences of the sub-agents (rooms).

5 EXPERIMENTS

This section describes two experiments we have conducted. The first one illustrates the micro level as an important aspect for energy experts studies. The second one studies the influence of household types on individuals and its effect on the consumption.

5.1 Experimental setup

For our experiments, we generate 50 households using a populations generator with socio-statistical data based on a modified version of the Gargiulo's algorithm (Gargiulo et al., 2010). Also, generated households properties such as the income, the surface of the housing or the number of children are statistically relevant. As it is sufficient for our experimental needs, we consider that all individuals have the same set of tasks they can perform (working, eating, sleeping, ...). The housings have a set a appliances (*e.g.* TV, heater, computer, ...) spread in the rooms. The tasks preferences are randomly set following a linear distribution.

5.2 Observation of micro behavior

During the simulation experts will want to observe situations that can impact the comfort or the energy consumption and to connect it to the activity that was performed at that time, so as to detect typical everyday life situations. For example, we can focus on the periods when inhabitants are cold and to compare this with the clothing level. The figure 2 presents on the right the thermal comfort (red line) and the clothing level (blue line) of an inhabitant and, on the left, an extract of its activity diagram corresponding to this period. This graphical representation of activity, where each color corresponds to a task, allow the experts to visualize inhabitant's behavior during the day. So, this diagram allows to precisely retrieve the activity of an inhabitant on a given simulation step.

The example in figure 2 shows a decrease in the clothing level (the agent removes his clothes) causing an important degradation oh his thermal comfort level around 10h45. By observing the extract of the corresponding activity diagram, we observe that the comfort gap is caused by the realization of the task "taking a shower" (in sky blue, boxed in the diagram).

This simple example illustrate how a micro representation of activity between several axes identify phenomena very localized in time that cannot be taking into account by more macro models. Indeed, a study of just an average comfort is not pertinent for a household because, as showed by (Zélem, 2013), two individuals in a same household can have different perceptions (or even opposite perceptions) of there comfort, and also different reactions: one can increase the heater temperature, the other put on a pullover or change his activity. The interest of a fine grain description is to reproduce the diversity and the complexity of human behaviors.

This simple example also illustrates how our model can be used to simplify the modeling process. Once the modeling axes (population, activity and environment) have been identified and the corresponding entities are reified in the model, the expert only needs to determine the key observable parameters and to relate them. Using agents for every entities gives a more direct access to experts knowledge specific to each axis: experts are familiar with the individual-centered modeling. For example, ergonomists can define the notions that intervene in the definition of the activity, while energeticians will define the consumption based on the thermal characteristics, *etc.* We show in the next section how the intra-axes common structure of agents, based on influences between properties, allows us to easily define macro-level agents that interact with each other. This addition of such agents is limited to the definition of the new properties, specific to these new agents, and the inter-level influences on these properties.

5.3 Adding macro agents

We now study the consuming activity profile of a set of households. We aim to investigate the addition within our model of macro agents at the household-housing level. As describe in 4.3.1, the household agent is defined as a super-agent of individuals (the household members), it will influence the priority of the individuals' tasks and modify the energy manager of housing based on its comfort (calculated from individuals' influence) and its sensitivity. Thus an eco-oriented household will have a lower target temperature in the housing that individuals should be compensate, to the extent possible by their clothing levels (to each type of sensitivity is also associated a level of minimum and maximum clothing, for example in some households more focused on comfort, members wear rarely more than a T-shirt). Moreover, the members of such a household (eco-oriented) are incitated by an influence to avoid performing consuming tasks.

We perform one-day simulations of our 50 households (see 5.1) whose number of consuming tasks per hour is shown in the figure 3. Contrary to the first experiment (see 5.2), we now take the similar households but we add the two macro agents (the household and the housing) with their associated interactions and influences. The households we choose to study in this particular experiment are eco-oriented as describe in the previous paragraph. The consuming tasks profile is shown graphically in figure 3 with the green curve. The red curve represents the reference profile without the macro agents and their influences.

We first notice that adding macro agents reduce significantly the consuming activity due to the influence of the eco-oriented households. As illustrated by the red curve, we note that meals are structuring tasks in our modeling as they produce two gaps at 12am and 8pm. They correspond to a certain synchronization of the meal tasks which are specified as non-consuming. Also, meal preparations produce consumption peaks as shown with the green curve. As the need of electricity remain important for these tasks, the number of consuming tasks tend to decrease only slightly with the influence of the household.

This choice of measure (number of consuming tasks) allows us to focus on human activity without being concerned about avoiding eventual bias in the consumption model of electrical appliances. It must be emphasized that some other models are able to reproduce a residential load curve, however the interest of multi-level modeling is the ability to relate macro knowledge, *e.g.* here households typologies and energetics housing management with more micro elements (as the example presented in the previous section). Experts can easily test different working hypotheses such as the impact of different pricing policies on consumption practices, to test the effectiveness of energy strategies (*i.e.* heating management) or indeed the relationship between human activity and consumption peaks. The previous experiment fall within an approach to study how different types of household with the same housing can produce different consumption profiles.

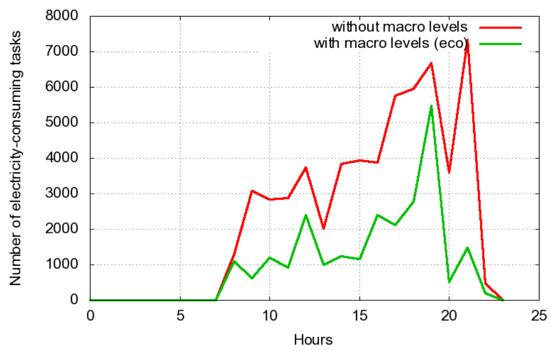

Figure 3: Number of consuming tasks per hour.

As mentioned previously, macro knowledge is available in many areas. Their explicit representation helps the experts to study the connection with micro concepts to make them co-evolve. More precisely, if a household gives more importance to its comfort or expenses, there is a theoretical link (*i.e.* an influence) on how people will manage their heating energy consumption. However, this relation does not prevent the diversity of behavior in so far as household members (individuals) preserve their autonomy.

6 CONCLUSIONS

In this paper, we briefly introduced SIMLAB, a multi-agent model based on the use of agents of different levels and influences to capture the inter-level dynamics. The main interest of our approach is the definition of axes for the analysis of complex systems, highlighting shared properties. We have shown how multi-level modeling can enable energy experts to better understand and anticipate the residential energy consumption. We believe that our model is able to reproduce micro and macro phenomena, both interesting for energy experts, allowing energeticians to consider possible incentives to reduce consumption peaks.

We consider several perspectives in the context of our work. We are currently working on extending our model with more macro concepts such as lifestyle and social groups to perform large-scale simulations with several households and housings. We believe that the addition of these new levels from different fields such as sociology, allow us to validate the model as generic, in terms of modeling axes and influences. An large-scale study will be soon performed by EDF using the SMACH platform. Interviews of households will be used to create more realistic simulation. Results will be compared to real data from a several year *in situ* experiment with sensors in the clients' housings. We are also exploring the possibility of our agents to dynamically change the MAS organization proposing to add observations and transformations to detect and reify potentially useful macro-entities to help the modeler. To go further in this direction, it would be interesting to study in more detail the characterization of emergent phenomena.

REFERENCES

Alfakara, A. and Croxford, B. (2014). Using agent-based modelling to simulate occupants' behaviours in response to summer overheating. In *Proceedings of the Symposium on Simulation for Architecture & Urban Design*, page 13. Society for Computer Simulation International.

Amouroux, E., Huraux, T., Sempe, F., Sabouret, N., and Haradji, Y. (2013). Simulating human activities to investigate household energy consumption. In *Proc. of the 5th International Conference on Agents and Artificial Intelligence (ICAART).*

Camus, B., Bourjot, C., and Chevrier, V. (2013). Multi-level modeling as a society of interacting models. In *Proceedings of the Agent-Directed Simulation Symposium*, page 3. Society for Computer Simulation International.

FIPA consortium (2003). FIPA Communicative Act Library Specification and FIPA ACL Message Structure Specification. Technical report, Foundation for intelligent physical agents.

Gargiulo, F., Ternes, S., Huet, S., and Deffuant, G. (2010). An iterative approach for generating statistically realistic populations of households. *PloS one*, 5(1):e8828.

Grandjean, A. (2013). *Introduction de non linéarités et non stationnarités dans les modèles de représentation de la demande électrique résidentielle*. PhD thesis, Thèse de doctorat, Mines Paristech.

Haradji, Y., Poizat, G., and Sempé, F. (2012). *Human Activity and Social Simulation*, pages 416–425. CRC Press.

Huraux, T., Sabouret, N., and Haradji, Y. (2014). A Multi-Level Model for Multi-Agent Based Simulation. In *Proc. of the 6th International Conference on Agents and Artificial Intelligence (ICAART)*, Angers, France.

Kashif, A., Ploix, S., Dugdale, J., and Le, X. H. B. (2012). Simulating the dynamics of occupant behaviour for power management in residential buildings. *Energy and Buildings (online pre-print).*

Kubera, Y., Mathieu, P., and Picault, S. (2011). Ioda: an interaction-oriented approach for multi-agent based simulations. *Autonomous Agents and Multi-Agent Systems*, 23(3):303–343.

Lee, Y. S., Yi, Y. K., and Malkawi, A. (2011). Simulating Human Behaviour and its Impact on Energy Uses. In *Proc. of the 12th Conference of International Building Performance Simulation Association (IBPSA)*, pages 1049–1056.

Minar, N., Burkhart, R., Langton, C., and Askenazi, M. (1996). The swarm simulation system : a toolkit for building multi-agent simulations. *GEMAS Studies in Social Analysis*, Working Paper 96-06-042.

Morley, J. and Hazas, M. (2011). The significance of difference: Understanding variation in household energy consumption. *ECEEE Proceedings of the 2011 Summer Study*.

Morvan, G. (2012). Multi-level agent-based modeling-bibliography. Technical report, LGI2A, Univ. Artois, France.

Morvan, G., Veremme, A., and Dupont, D. (2011). Irm4mls: the influence reaction model for multi-level simulation. In *Multi-Agent-Based Simulation XI*, pages 16–27. Springer Berlin Heidelberg.

Muratori, M., Roberts, M. C., Sioshansi, R., Marano, V., and Rizzoni, G. (2013). A highly resolved modeling technique to simulate residential power demand. *Applied Energy*, 107:465–473.

Navarro, L., Flacher, F., and Corruble, V. (2011). Dynamic level of detail for large scale agent-based urban simulations. *Proc. of 10th Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS 2011)*, pages 701–708.

Picault, S., Mathieu, P., et al. (2011). An interaction-oriented model for multi-scale simulation. In *IJCAI Proceedings-International Joint Conference on Artificial Intelligence*, volume 22, page 332.

Rao, A. S., Georgeff, M. P., et al. (1995). Bdi agents: From theory to practice. In *ICMAS*, volume 95, pages 312–319.

Relieu, M., Salembier, P., and Theureau, J. (2004). Introduction au numéro spécial activité et action/cognition située. *Activités*, 1(2):3–10.

van Hoof, J. (2008). Forty years of Fanger's model of thermal comfort: comfort for all? *Indoor Air*, 18(3):182–201.

Yang, R. and Wang, L. (2013). Development of multi-agent system for building energy and comfort management based on occupant behaviors. *Energy and Buildings*, 56:1–7.

Zélem, M.-C. (2013). Le confort thermique, norme technique ou norme sociale ? *Débat National sur la Transition Energétique, Note 12*.

Zhou, Z., Chan, W. K. V., and Chow, J. H. (2007). Agent-based simulation of electricity markets: a survey of tools. *Artificial Intelligence Review*, 28(4):305–342.