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Multi-Agent based simulation of human activity for building and urban scale assessment of residential load curves and energy use

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Abstract

Simulating the actions and decisions of occupants in buildings is necessary to evaluate energy performance and understand its causes in a more reliable manner. While various models exist, all recent state-of-the-art reviews on occupant behavior models identified unresolved scientific issues. Here, these issues are classified, and we present the SMACH multi-agent model of human activity in buildings (based on cognitive ergonomics) and its application to assessing residential load curves and energy consumption. We show how the model can be used to address each of the unresolved scientific questions and present the validation process that we carried out.

Key Innovations

This work presents: (i) a condensed summary of currently unresolved scientific issues regarding occupant behavior modeling, (ii) a multi-agent architecture to provide a holistic modeling approach of human activity in buildings, and (iii) a demonstration of how the model can be used to address the scientific issues identified in (i).

Practical Implications

Occupant activities affect building energy consumptions. It is possible to use multi-agent systems in an effective way to generate more realistic annual consumption data. Simulating realistic activity can help sizing systems by understanding the coincidence of local energy generation and demand.

Introduction

According to the International Energy Agency (IEA), in 2018 the residential sector amounted to 21% of worldwide energy consumption. A better understanding and control of residential electricity consumption is a major challenge. Local and global load and demand forecasting are pivotal for both utility companies and grid operators, especially with the development of new trends such as energy self-consumption and local energy communities. Researchers studying these issues require models capable of reproducing observed data, and estimating load curves of future scenarios, both at the individual and aggregated scales (district, city, state, etc.).

Electricity consumption is greatly impacted by daily life activities of humans (Janda 2011). However, occupant behavior (OB) is often inadequately accounted for in buildings energy simulations (BES) (Happle et al. 2018). Occupant behavior models (OBMs) are often overly simplistic using static, schedule-based, or predetermined inputs which introduces significant discrepancies between the simulated and observed energy consumptions (Li et al. 2019). Many BES require knowledge of various aspects of OB (e.g., presence/absence, clothing and thermostat adjustment, appliance use, etc.) (Carlucci et al. 2020) and appliance use (heating, domestic hot water (DHW), specific consumption, etc.) (Berger et al. 2020). Furthermore, an increasing amount of occupant-centric data is becoming available through the spread of urban sensing, Internet of Things (IoT), big data and population censuses and surveys (Salim et al. 2020). They offer new insights into OB which improves the associated models and their estimates of how OB impacts energy consumption.

In the next section, we present a summary of the state-of-the-art of OBM and what have been identified in the literature as unresolved issues. We then present our agent-based model of OB and demonstrate how it can be used to address these unresolved issues. The model is validated and applied to load curves and energy use assessment, before presenting our overall conclusions and future perspectives.

State of the art

OBMs and unresolved scientific issues

Over the past years, the field of OBM research has gained a strong interest resulting in numerous publications from the building energy simulation community, particularly in the IEA Energy in Buildings and Communities Annex 79 “Occupant-Centric Building Design and Operation” (O’Brien et al. 2020a, 2020b). Several studies have identified specific issues that still need to be addressed to achieve further progress in the field.

For example Li et al. (2019) called for an OBM that incorporates aspects from both social and psychological sciences to reveal the underlying motivations behind OB. Henceforth, we will refer to this as the “*social and psychological science issue*”. The same authors also called for the use of data from large-scale surveys and long-term data measurement (henceforth referred to as the “*data issue*”).

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Salim et al. (2020) pointed out how many OBMs typically neglect any impact from physical, biological, psychological and social factors. They advocate for an OBM that integrates experts and modeling methods from the field of building science, social science and psychology to better identify the causes of OB (*social and psychological science issue*). They also identified the problem of upscaling from individual buildings to the urban scale and suggest that it could be addressed using so-called level-of-detail techniques to explore the relation between OBM complexity and accuracy (the "*scaling-up issue*").

Despite their thorough OBM review, Carlucci et al. (2020) were unable to find OBMs capable of both explaining and accurately predicting occupant behaviors and their interactions with their environment based on combined actions (i.e., simultaneously considering several factors such as presence, movement, window operation, shading operation, lighting operation, thermostat and clothing adjustment, and appliance use). As all these behavioral aspects are interlinked and they need to be taken into account in their entirety to obtain a wider, more comprehensive and more precise view of human behavior. Consequently, the impact of OB on energy consumption and the understanding of human comfort would be more accurate. We will refer to this as the "*coupling of non-independent behaviors issue*".

The literature offers a broad spectrum of different modeling techniques; a selection will be briefly summarized in the following section.

Choice of modeling technique

With regards to the "*emergence and variability issue*", deterministic and rule-based models were considered outdated for a long time as they could not adequately account for variability in OB (Happle et al. 2018). Li et al. (2019) consider statistical models as inefficient to dynamically simulate OB variability ("*adaptive and dynamic issue*"). Furthermore, according to Happle et al. (2018), stochastic/probabilistic models (typically Markov chain models) usually treat each aspect of OB separately (e.g. presence at home, window opening, thermostat adjustment, etc.) through independent ad-hoc parametrizations (which refers again to *the coupling of non-independent behaviors issue*). In addition, such models consider individuals of a same household to act independently of each other. We believe that such hypotheses have several flaws which limits the realism and variability of such an OBM, e.g. it cannot model collective self-organization within a household (Happle et al. 2018) (collectively preparing and sharing meals, shared use of the bathroom, taking care of children, etc.) and thus fail to address this "*collective behavior issue*".

Happle et al. (2018) believed that Agent-based models (ABM) were relevant for OBM modeling and they called for an urban-scale OBM (*scaling-up issue*) capable of incorporating demographic changes, changes in behavior over time, and occupants' adaptation to economic or environmental changes (*adaptive and dynamic issue*).

Berger et al. (2020), in a recent review on agent-based modeling of OB, underlined the ability of ABMs to capture the flexibility, complexity, dynamics, and emergent characteristics of individual and group behavior (*emergence and variability issue*, as well as *adaptive and dynamic issue*) as a result of learning and adaptation processes. The flexibility of these models allows them to be applied to system-, building-, and city levels (*scaling-up issue*). Moreover, these models facilitate the integration of social and psychological factors, and are therefore well-suited for examining the social and psychological impacts on OB (Li et al. 2019) (*social and psychological science issue*).

ABMs are thus good candidates to perform OB modeling although weaknesses present in classical ABM approaches need to be overcome.

Limits of ABM

Carlucci et al. (2020) reminded us that the OBMs need to be data-driven (*data issue*) which was confirmed by Berger et al. (2020) who reproached ABMs for them frequently lacking detailed information about agent behaviors and their interactions. Berger et al. (2020) also found it difficult to judge the fidelity of insufficiently documented agent profiles given the emergent complexity of ABM application results. Furthermore, the scope and complexity of ABM applications can grow rapidly, resulting not only in extensive computational costs ("*computational load issue*") but also in a certain degree of opacity in the computational results ("*black-box issue*"). Finally, they found results difficult to replicate ("*reproducibility issue*").

Li et al. (2019) state that the real-time communication between ABMs and building energy simulation programs made them more difficult to use since these programs typically use custom coding languages and protocols ("*real-time communication issue*"). Finally, they state that the addition of granularity of occupant diversity in ABMs would significantly increase the computational cost, which in turn makes the models more difficult to scale (i.e., the *computational load issue* impacts the *scaling-up issue*).

In this paper, we present the ABM-based SMACH platform ("Simulation of Activity and Consumption in the Home") and show how this model can be used to address the previously identified scientific issues.

SMACH: an Agent-Based Model for a Holistic Approach to Occupant Behavior

General presentation

SMACH is an AI-based multi-agent simulation platform of human activity that has been developed since 2010 as a collaboration between EDF's R&D and several academic research laboratories. Over time, developments of this ongoing research project have been described in artificial intelligence scientific conferences (Reynaud et al. 2017). In this paper, we focus on its application to model OB addressing the unresolved scientific issues mentioned above in order to obtain better estimates of residential electricity consumption. Our model attempts to

capture the complexity of human activity, the dynamics of daily life, household self-organization, and cooperation between individuals. To address the *social and psychological science issue*, the approach is based on cognitive ergonomics research on human activity which has shown that multi-agent systems are suitable to model human activity realistically (Haradji et al 2012). SMACH applies a holistic approach that aims to consider human actions and decisions as the main causative factors of energy consumption (Amouroux et al. 2013). We use the terminology "human activity" (rather than "behavior") to account for actions that take place in a specific situation, consisting of interactions based on determinants that are cognitive, social and physiological. These actions are linked to an individual or collective story and to the environment in which it unfolds. The challenge of such a simulation is to devise a model that employs an adequate reduction of human activity that does not focus on a specific dimension (e.g., solely on the motivational dimension). We use an approach known as "situated cognition".

Applied to the assessment of energy consumption, SMACH produces forecasts of electrical loads and energy demand in the residential sector based on the modeling of intelligent and autonomous agents: the humans that consume electricity. A household's electrical load curve is estimated by accounting for the use of electrical appliances and interactions between household members, and of each member with their environment. This model is co-simulated with a building energy model presented in the following sections. The SMACH architecture generates virtual populations that are representative of targeted populations (cities, states, countries, etc.). Individual households are simulated using a multi-agent engine. Each virtual household member can make individual decisions that affect their actions, taking into account their individual preferences, goals, and the state of the environment. We simulate the daily activities of household member using a 1 min time step, which was chosen in accordance with previous cognitive ergonomics studies (Amouroux et al. 2013).

To address the *data issue*, SMACH uses large-scale data sets like time-use surveys (TUS), population censuses and specific surveys to provide a calibrated framework for the simulated actions of individuals (Reynaud et al. 2017; 2018). This data is used for generating virtual populations with individual characteristics, housings and households, and for calibrating actions taken by the virtual individuals.

Population Generation

To address the *scaling-up issue*, it is necessary to precisely simulate both individual households and entire populations. This is achieved by generating a virtual population that is statistically representative of the studied population based on a population synthesis approach (Müller et al. 2011). The specific population generation process used in SMACH is based on Auld et al. (2010). The generated populations are statistically representative of the target population in terms of households types and sizes (couples, families, etc.), age, gender, socio-professional categories, professional situation of individuals, housing situation (e.g., type, surface and thermal performance), weather data (e.g., outside temperatures and solar radiation), type of heating and DHW, type of electricity tariff and geographical location (region/county/district, type of urban area, etc.). Whenever the information is available, we also include probabilities for the presence and number of certain electrical appliances present in each dwelling, as well as their main technical characteristics (e.g., power and energy class of refrigerators; power, temperature, capacity and efficiency of DHW tanks, type of washing machine cycles used, etc.).

For now, we have only applied our architecture to mainland France (cities like Paris or Lyon, French departments, and the country as a whole). Most of the data used for the population generation comes from the French national institute of statistics and economic studies (INSEE): the population census data, housing surveys, and household equipment censuses. Nevertheless, the model can be applied to any other country as long as the necessary data is available.

A hybrid data-based agent model

Real activity data from the latest French TUS (2009-2010, produced by INSEE) was used to model the activities of individual agents in SMACH. TUS are daily surveys in which respondents describe their day as a series of episodes. Many statistical methods in the field of energy simulation use TUS to simulate human activity and calibrate their models at a macroscopic level. Conversely, we use this data at a microscopic level to generate a weekly provisional activity schedule for each individual (i.e. a list of activities to perform). Based on the TUS data, each action has an estimated duration and a preferential time of the day to be carried out.

SMACH uses a hybrid reactive and cognitive agent model where each individual is modeled as an intelligent agent with goals (based on their individual provisional schedule described above), knowledge (other agents' activities, price of energy, etc.) and preferences (e.g., whether one's preferred indoor temperature is based more on economic or personal comfort considerations – using both quantitative and qualitative surveys). Each agent has an individual decision module that will determine the actions that are actually performed. The action selection process uses priority levels that vary dynamically for each action, depending on the agent's knowledge, preferences and context. The agent model is described in more detail in (Reynaud et al. 2018). Furthermore, each activity is performed in a specific location inside or outside the building which determines building occupancy.

Each action also has a "collectivity level" indicating how the individuals organize themselves to carry it out (alone or rather in a group, etc.) taking into account their personal schedule and situation. Some activities (e.g. "taking the children to school") can obviously only take place involving several people and a strong degree of coordination. Hence, our agents are able to modify their actions according to the actions taken by others (e.g. "My

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regular schedule is to take my shower first and then to have lunch, but the shower is currently occupied so I take my breakfast first."). This capability of the model can be used to address the *collective behaviors issue*.

According to the energy policy of the household (e.g., "comfort-oriented household" or "money-saving household"), each agent can modify its actions based on current energy prices (e.g., "I was supposed to use the washing machine in the morning, but since the price will be lower tonight I postpone it."). Agents can also modify their actions depending on specific events (e.g. "A friend rings the doorbell while I was watching TV, so I interrupt my activity, open the door, and start a discussion") or weather conditions (e.g. "It is freezing outside, I increase the temperature on the thermostat"). This model allows agents to exhibit emerging, reactive and adaptive human activities that addresses both the *emergence and variability and adaptive and dynamic issues***.**

All agent decisions are recorded by the model, allowing the model operator to review them, adding a high level of transparency and explanatory capacity that prevents any *black-box issues*. Each individual is driven by a unique decision-making process that essentially puts all the modeled aspects of human activity in competition, addressing *the coupling of non-independent behaviors issue*. These types of decisions processes are configurable and allow the creation of a single model that is capable to integrate heterogeneous data (as a way to address the *data issue*) from various sources (censuses, surveys, field or simulation studies, etc.), contexts (countries, building types, etc.), and research foci (human activity, energy consumption, thermal performance, etc.), which also contributes to overcome the *social and psychological science issue*. For the results shown in this study, we always preferentially used real survey data rather than ad-hoc models. Furthermore, the model outputs all individual characteristics as well as the random number generation seed allowing any simulation to be reproduced, either with identical or modified parameter settings (addressing the *reproducibility issue*). Also, the types of human activities and actions to be included in the model can be chosen, based on the available activities in the TUS, allowing to adapt the model complexity in accordance to the available data.

Application to the assessment of residential load curves and energy use

The assessment of household load curves is currently one of the main applications of SMACH. A household's global energy consumption is calculated based on the interaction of the household's individuals with their environment where the energy consumption is driven by their actions and decisions related to comfort and consideration of energy prices.

SMACH simulates electricity consumption by four categories of appliances: controlled (including heating, cooling and DHW), programmed (e.g. a dishwasher programmed to start at a specific time), directly associated with an activity (e.g. a TV for the activity 'watching TV'), and constant use (e.g. an internet router). The power demand of each appliance can be constant, cyclic, or the consequence of a dynamic thermal model. Several appliances can be associated with the same activity, depending on the activity model and the available appliances in the studied household. For instance the 'cooking' activity can involve the use of an electric stove, an extractor hood and/or a microwave oven. The 'watching TV' activity can involve the use of a TV, a DVD-player, a game console, etc.

Thermal comfort and feedback on activity

The simulated individuals have a preferred temperature setting (both for heating and cooling appliances) and individual sensitivities to heat and cold. Their dynamic comfort attribute is derived from the predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD) indices (Ekici 2013). The comfort temperature is the temperature at which an individual at rest and lightly dressed (shirt/trousers) is in a state of thermal comfort (neither too hot nor too cold). The comfort level is also impacted by the physical effort associated with an individual's activity. For instance, 'cleaning the room' involves a greater physical effort than 'watching TV'.

Thermal discomfort can lead to several reactions. Individuals can decide to change their clothing level, thermostat setting, or close/open windows and blinds. The priority attached to each of these actions depends on the individual's comfort policy and attention to energy prices. For instance, an individual whose policy is exclusively based on personal comfort would tend to adjust the thermostat setting, while an individual who finds themselves in a status of "energy insecurity" will prefer a less costly alternative like changing their clothing.

The set thermostat temperature is calculated as the mean of the comfort temperatures of all household members. As part of the collective decision mechanisms in SMACH, other approaches can also be implemented such as negotiations between household members that result in an accepted temperature setting that is kept for a given duration.

Heating, cooling and ventilation consumptions

In order to calculate the energy consumption associated with heating, cooling and ventilation (HVAC), SMACH implements a co-simulation between the activity model and a building energy model (Figure 1).

The co-simulation is performed according to version 2 of the functional mock-up interface (FMIv2) interoperability standard for co-simulation (Blockwitz et al. 2012). SMACH uses the JavaFMI wrapper (Galtier et al. 2017) to act as the Master in the co-simulation and control the building energy model (Plessis et al 2014a). In this co-simulation loop, the building model calculates the room temperatures which are sent to the occupants to update their comfort attribute which in turn may provoke a reaction in case of thermal discomfort (e.g., changing the thermostat set point temperature or adjusting the windows/blinds).

Internal heat gains due to occupants are derived from their occupancy in each room, while the ambient interior air

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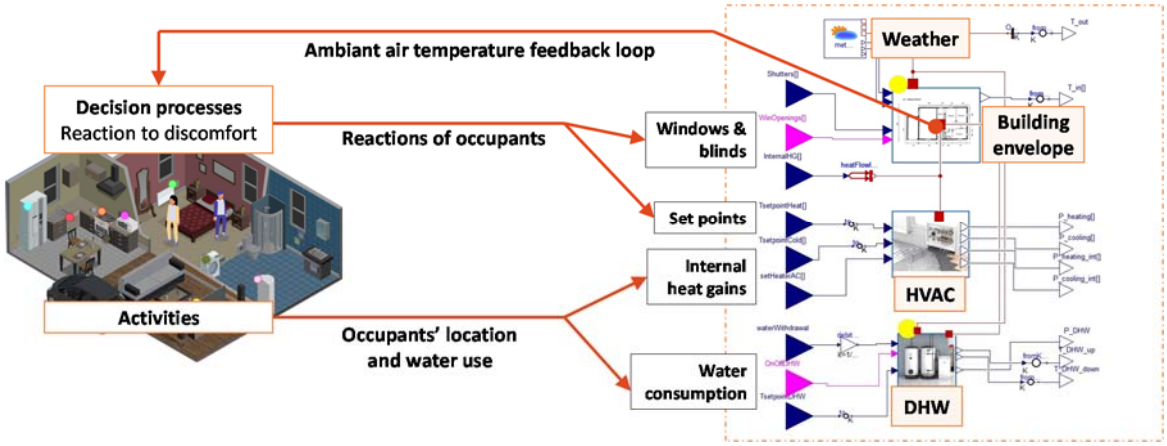

Figure 1: Co-simulation diagram between the activity model and building energy model

temperature impacts the heat losses of DHW tanks and refrigerators.

SMACH uses a Modelica-type building model which consists of a detailed multi-zone building envelope model that accounts for heating, cooling systems and their PI control based on three set point temperatures for each room (comfort, economy, and absence) (Figure 1). The thermal DHW model described below is also included in this building model. It has been developed according to the modeling principles of the Modelica BuildSysPro library (Plessis et al. 2014b).

As we applied SMACH to the model of French residential energy consumption, we incorporated typical building typologies for individual houses and apartments based on the French "Mozart" and "Matisse" typologies, respectively, as defined by the French Scientific and Technical Center for Building (CSTB). The building's thermal characteristics are defined according to French national regulations in force on the building's construction date. Other parameters such as floor space or water tank volume are taken from the same data sets used for the population generation.

The coupling between the SMACH activity model and the building energy model is achieved by using a set of common inputs and outputs (Figure 1). These can be modified in order to incorporate new phenomena or appliances (e.g., local energy storage). We set the synchronization time step parameter to 10 min. As this co-simulation is generic, it can be used in combination with any building energy model as long as it is compliant with the FMI interoperability standard and uses the same inputs and outputs. This ability alleviates the *real-time communication issue*.

Specific electricity and hot water consumption

SMACH simulates individual appliances from the following categories: home appliances (washing machine, dryer, dishwasher, and fridge), small/kitchen appliances (vacuum cleaner, stove, microwave, oven, and extractor hood), lighting (individual light bulbs in each room), consumer electronics (TV, DVD-player, game console and computer), electric vehicle charging and domestic hot water. There is also a "miscellaneous" category that includes all appliances that are not explicitly modeled. Each appliance has a specific power demand model, associated with an "off", "standby" or "in use" mode. Washing machines, dryers and dishwashers are programmable and use energy consumption cycles based on laboratory measurements.

The model for DHW is a dynamic thermal model derived from the energy balance of water and takes into account the quantity of hot water consumed by individuals based on their actions (Plessis et al. 2014b). Water consumption is calibrated using the French 2016 national survey on hot water needs in households. The DHW control is associated with the household's electricity tariff (e.g., in peak/off-peak type tariffs, DHW can only be produced during off-peak hours).

Household- and urban scale load curve assessment

SMACH continuously meters the use, status, and energy consumption of each appliance in order to calculate the power load curves of the household. Other SMACH outputs include activity diagrams of each occupant or the appliances' on/off status.

For large scale simulations, each household is simulated individually and independently, as we consider that there are no interactions between households. The individual results are then aggregated to calculate the global load curve of the population. The simulations can therefore be massively parallelized and each household can be simulated on a separate processor or cluster core (which also contributes to address the *scaling-up issue*).

With an i5 2.3 GHz based laptop computer, the population generation process for 1000 households requires 30s. The activity model without co-simulation takes about 25s to perform a one year simulation of a two person household. The full co-simulation with the current multi-zone energy model takes around 5 minutes. Despite SMACH's bottom-up approach, the computational cost remains tractable, addressing the *computational load issue*, due to the relatively simple decision choices performed at each simulation time step. Due to this high level of parallelization, SMACH proposes to address the *scaling-up issue* without simplifying the activity or building model (Reynaud et al. 2018) and can simulate human activities and energy consumption at both local (one

household) and population scale (one district, one state, etc.) using personal computers or clusters.

Validation of a human activity-centered simulator

To account for the specificities of an agent-based model based on situated cognition, we performed two types of validations: (i) at the microscale (household level) and (ii) at the macroscale (population level), always considering both human activity and energy consumption (Table 1).

Table 1: Validation strategies and evaluation criteria

	Microscale	Macroscale
Human activity	Realism of activity. Adaptive traits of agents	Representativeness compared to statistical data
Energy	Comparison of metered and simulated household load curves	Global energy consumption, load curve dynamics

While each point required a different approach, for the sake of brevity, we will only present the microscale validation in some detail and will just provide a brief outline of the macroscale approaches.

Model validation at the household level

Before delving into the quantitative validation, we start with the qualitative part that assesses the capacity of SMACH to reliably simulate human activity at the household level. This is achieved by implementing a specific ergonomics approach known as "participatory simulation" (Haradji et al 2012) and conducting an experiment with the participation 10 real-life families from the "OpCo" demonstrator in Brittany, France, an experiment with real households aimed at studying distributed load shedding. We conducted interviews with each family to identify the main characteristics of each family's activities and habits. Then, we set up a specific simulation scenario to represent each household and asked the participants to judge how well the simulation results reflected their real daily lives. We developed a dedicated human-computer interface, where the user controls an avatar of themselves and is able to observe and modify the course of the simulation (Figure 2).

Figure 2: Interface for SMACH participatory simulation

The feedback of the participants showed that our model was able to reproduce human activity at an individual/household level with a high degree of plausibility, and that such a simulation relating to the organization of daily life and its dynamics was well understood. The participants considered that the formation of collectives and the dynamics of their evolution was realistic. In the example illustrated in Figure 2, the mother and daughter agents are playing together, but will have separate activities or associate with other agents later in the simulation. The results of the experiment were conclusive as none of the simulation mechanisms (autonomous agents, individual and collective dynamics, interaction with the environment) were called into question. While this study validated the fundamental mechanisms of the simulation, we also identified methodological limits to this approach. For example, we confronted each participant with a week of their daily life, but in doing so the participants tended to focus on the regularities of daily life rather than its variability (Haradji et al. 2018).

For the quantitative validation of the simulations, we used the metered load curves of 8 of the OpCo households over 8 to 15 weeks at a 30 min time resolution. It should be noted that the simulated load curves were intended to represent a realistic and "usual" week in each household. Therefore, the chosen approach was as follows: for each day and 30 min interval, we calculated the 95% confidence interval (CI) using

$$\left]\bar{x} - 1.96\frac{\sigma(X)}{\sqrt{n}}; \bar{x} + 1.96\frac{\sigma(X)}{\sqrt{n}}\right[\quad (1)$$

where X is the distribution of measured points and $n = 48$ the number of points per day. We simulated 3 consecutive weeks with SMACH and compared the average weekly load curve day-by-day to the confidence intervals from the metered load curves. The characteristics of electric appliances such as DHW tanks or washing machines and the global standby power were mostly unknown and were calibrated iteratively by performing several simulations with different parameters and selecting the result that was closest to the measured energy consumption.

We chose two validation metrics: the percentage of simulated points within the 95% CI for each day, and the relative deviation between the measured and simulated weekly energy consumption (Figure 3).

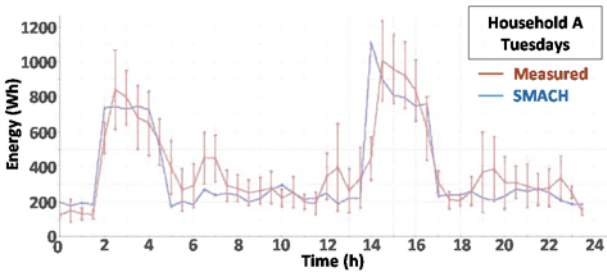

Figure 3: Comparing CI of measured load curves and simulated SMACH results for Household A for Tuesdays

The results showed that the simulations were able to capture the dynamics of energy consumption throughout the day for each household (HH). The relative deviation between the simulated and measured weekly energy consumptions ranged between -26% and 14%, with an average of -3.5% (Table 2). Two outliers (C and G) were

identified and the deviation explained by differences related to the timing of laundry and meal preparation, which differed between the initial interview and the SMACH simulations. When aggregated over all 8 households, 60 to 77% of all data points were within the CI. Thus, SMACH was capable to adequately simulate the load curves dynamics associated with the daily lives of real families.

Table 2: Percentage of data points within the 95% CI and deviation on energy consumption for each household

HH	Min	Max	Avg.	SD	Relative deviation on weekly energy
A	44	73	60	9.3	2 %
B	40	88	63	17.6	- 2 %
C	44	73	54	9.0	14 %
D	58	75	70	5.6	- 1 %
E	48	67	57	6.8	- 11 %
F	46	71	56	9.0	- 2 %
G	52	73	63	7.2	- 26 %
H	54	77	67	9.4	- 2 %

Model validation at the aggregated scale

In this section, we briefly show the validation at the aggregated scale for both activity and energy consumption. First, we verified that the emergence properties of the simulated actions, while allowing for a strong variability, were still consistent with the data at the aggregated scale. For each type of activity (e.g., 'sleep', 'cooking', etc.), type of individual, and type of day, we compared the results of 100 simulated days to the statistical data available in the TUS data. The evaluation criteria included the average duration, rhythm, number of repetitions, preferred periods and sequence of activities for each type of action. Figure 4 illustrates this approach for the 'cooking' activity. The maximum gap between the simulated and observed percentage of people performing the cooking activity was evaluated at 3 percentage points, and the maximum time gap at 20 minutes. Similarly, the simulation results were considered sufficiently close to the statistical data for all tested activities.

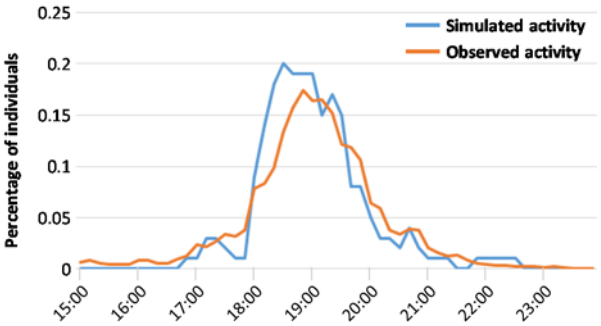

Figure 4: Comparing results of SMACH (simulated) and TUS (observed) 'cooking for dinner' activity

To validate the load curve and energy consumption results, we generated a population of 1,000 representative French households and compared the aggregated load curve with the open data profiles used by the French distribution system operator (DSO) for the assessment of injection and withdrawal flows on the electricity distribution network. The aim was to ensure that the SMACH results agreed on the main characteristics of residential consumption. In France, there are two main categories of electricity tariffs: "Base" (single-rate) and "Heure Creuse" (off-peak rate). An excerpt of the comparison of the load curve profiles and simulated results for these two categories are presented in Figure 5.

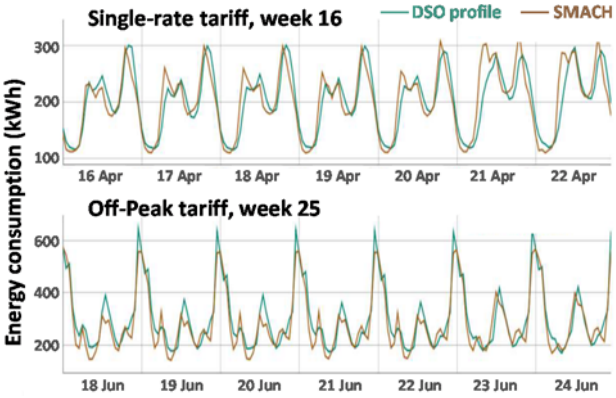

Figure 5: One week load curve profiles (DSO) and simulated (SMACH) for Single-Rate and Off-Peak tariffs

Each household from the population of 1,000 is associated with a specific location and therefore a weather file. Weekly energy levels over one year were compared for two distinct weather conditions: 20 year average (Meteonorm type construction) and the actual weather for the year 2012 (including a period of extreme cold) (Figure 6). By comparing the aggregated data for all tariffs and periods of the year, we showed that SMACH was capable to reproduce the main values and dynamics of the reference load curves. During this validation, we noticed that the specific and dynamic efficiency of heating systems such as heat pumps need to be taken into account.

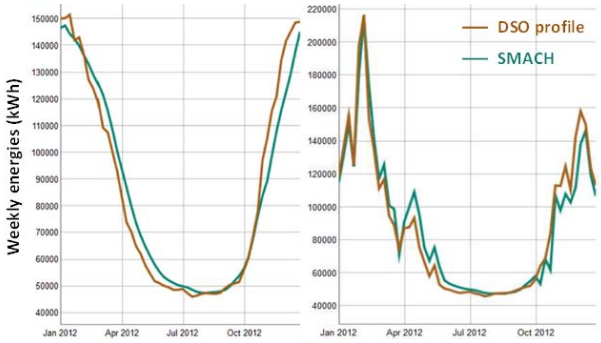

Figure 6: Comparison of weekly energy consumption for one year under the Peak / Off Peak tariffs for averaged meteorological data (left) and the year 2012 (right)

Conclusion and perspectives

Based on a review of the literature, we identified eleven main scientific issues related to the simulation of occupant behavior in buildings. We presented how the agent-based SMACH approach, which combines ergonomic activity models, building energy simulation, statistical data and AI architectures, can be used to address each of these issues. Our model is currently used for research and industrial applications, e.g. to devise

strategies for electric vehicles charging, electric network sizing, or to study the impact of new electricity tariffs. SMACH has been built as a flexible platform that evolves constantly by integrating new knowledge and data, illustrating its ability to aggregate heterogeneous domains. For instance, we recently extended the platform for simulating collective self-consumption (Albouys-Perrois et al. 2019).

Future works may address issues such as representing the temporal evolution of household (new activities or equipment, changes in family composition, etc.), the seasonality of certain activities, the modeling of demand response based on individuals' reactions to signals or incentives, the integration of pollution exposure assessed with dedicated indoor air quality models, and sociological models for crisis situations. Such models would allow to improve this human-centered approach and study the impact of these domains on energy consumption.

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