Li-BIM, an agent-based approach to simulate occupant-building interaction from the Building-Information Modelling

Alice Micolier, Franck Taillandier, Patrick Taillandier, Frédéric Bos

Li-BIM, an agent-based approach to simulate occupant-building interaction from the Building-Information Modelling

Alice Micolier, Franck Taillandier, Patrick Taillandier, Frederic Bos

Li-BIM, an agent-based approach to simulate occupant-building interaction from the Building-Information Modelling

Alice Micolier[1], Franck Taillandier[2], Patrick Taillandier[3], Frédéric Bos[1]

[1] *Univ. Bordeaux, I2M, CNRS, UMR 5295, France (alice.micolier@u-bordeaux.fr)*
[2] *Irstea, Aix Marseille Univ, RECOVER, Aix-en-Provence – France*
[3] *MIAT, INRA, UR875, France*

ABSTRACT.
Building design involves many challenges and requires to take into account the interaction between the building and the users. Different occupant behaviour models implemented with building simulation tools (thermal, air quality, lighting) have been proposed. Among these, models based on the agent approach seem to be the most promising. However, existing models poorly describe human cognition and the social dimension. Moreover, they are often oriented towards a specific use (thermal simulation, waste management) without being transposable to another field, and they require a significant instantiation effort for each new case, making their use difficult. This article proposes an agent-based model called Li-BIM that simulates the behaviour of the occupants in a building and their indoor comfort. Li-BIM model is structured around the numerical modelling of the building –BIM- (with standard exchange format IFC), a high-resolution cognitive model, and the coupling with various physical models. Li-BIM simulates the reactive, deliberative and social behaviour of occupants in residential dwellings based on the Belief-Desire-Intention architecture. This model, thanks its ease of use and flexibility, is an operational and relevant tool to support building design process with a human-centred approach. An application of the model is presented, focusing on energy consumption and the inhabitants' comfort. In-situ data obtained from the instrumented house that served as case study have been compared with simulation results from Li-BIM and a standard energy simulation software, demonstrating the reliability of the proposed model.

KEYWORDS. Occupant's behaviour; Building design; Agent-based model (ABM); Belief-Desire-Intention (BDI); Building Information Modelling (BIM);

Introduction

1.1. The gap between performance evaluation and reality

The construction industry, representing 44% of the French total final energy consumption and 21% of total CO2 emissions (CGDD 2012), is recognised as a major hotspot of environmental impacts. Causing half of primary resources extraction, third of the water consumption and a third of the waste generated in the European Union (*European Parliament*, 2014), this sector has a central place in the use of worldwide resource. Traditionally, this issue has mainly been considered through the prism of energy performances, and extensive research has been investigating improvements both in products efficiency (equipment, materials, etc.) and geometrical settings (volume, orientation, etc.). However, promoting low energy building should be completed based upon environmental concerns (climate change, etc.), economic (investment cost, etc.) and social considerations (comfort, etc.) to address sustainability. One of the biggest challenges of the construction industry sector is to be able to propose low environmental impact buildings while limiting cost and keeping (or even increasing) building usability.

Nevertheless, optimal performances cannot be considered only with regards to technical aspects. More important than technological efficiency is the effective interaction between occupants and building systems to achieve their comfort needs and ensure their health. Indeed, occupants' behaviour and their operating use of the building strongly affect different aspects of the building design: air quality (Andersen, Fabi and Corgnati, 2016), lighting (Heydarian *et al.*, 2016) and particularly thermal studies (Gaetani, Hoes and Hensen, 2016). Several studies showed that a huge gap exists between the simulated energetic consumption and the measured one which is mainly due to the user attitude (Branco *et al.*, 2004; Cayla, Allibe and Laurent, 2010; Calì *et al.*, 2016). This difference is even more striking in the context of low energy building in which building systems are highly efficient. In dynamic simulations commonly used both in the industry and by researchers such as EnergyPlus, Trnsys, or eQuest for example, the occupant is only considered as a homogeneous and linear object. No distinction is done between diverging schedules, energy-use habits, the standard of living, green awareness, etc. This lack of consideration of the impact of the users' behaviour on the indoor environment prevents from achieving accurate energy performance and from identifying behaviour-determined energy savings potential.

Furthermore, most building models currently address a single aspect of building performance, primarily energy performance. However, designing sustainable buildings is challenging since the indoor environment is a complex system in which different physical realities should be evaluated: the relative improvement of one criterion should not alter the others. (Yan *et al.*, 2015) take the example of the window: maximising the window area in energy simulation leads to solar gain maximisation, thus minimizes energy consumption. In reality, though, huge windows raise glare issues that are likely to incite occupants to close blinds and rely on electric lighting instead of daylight, increasing electricity needs. The optimal window size from an energy-efficiency point of view may be found by taking into account the interaction between the users and the building's design. Consideration of human behaviour could also be useful in comparing design alternatives on both the building level (e.g., the percentage of glazing) and the system control level (e.g., the type of blinds' system control).

1.2. Towards human-centred building design

This naturally leads to the question of the impact of the users and their behaviour on operating use and building design choices that can help enhance their operating use. Given this situation, a rising issue in building design is to take into account the users' behaviour and their comfort in a holistic way, whether they are tenant or owner in residential dwellings or employee in an office building. Many international standards (ASHRAE Standard 55 - Thermal Environmental Conditions for Human Occupancy (2010), RT 2020 French thermal regulation) have now shifted from energy efficient centric regulations to human-centric guidelines, acknowledging that building design now needs to integrate occupant comfort and health.

Expectations of comfort vary widely from households to households, even in situations where households have the same environmental background or access to similar infrastructures, as emphasised by Chappells and Shove (2004). According to (O'Brien *et al.*, 2017), understanding and modelling diversity of occupants is more critical on a small scale (household) rather than a larger scale (district energy systems) since the impact of individuals is much more important than the aggregated behaviour of all inhabitants. People do not act nor have the same comfort standard according to their gender, age, social class, etc. As a result, a considerable heterogeneity in household lifestyle exists. (Perrels and Weber, 2000) analysed the impact of lifestyles determined by socio-demographic variables (age, income, education level) on energy demand and demonstrated that final energy consumption for a stagnation-type household is 1.5 times higher than for a sustainable through reflective consumption household. Furthermore, social interactions are an essential consideration (Chapman, 2017) since they lead to decisions on a household level (e.g., opening windows) that differs from what an agent alone would choose (e.g., occupant bothered by the cold).

1.3. Current occupants' behaviour modelling

To better guide building design, a high-resolution bottom-up model with easy-to-handle data input is required to consider human behaviour during the design phases of a building. Modelling more precisely the user behaviour and coupling it with dynamic simulation tools have already been done through different approaches: probabilistic methods (Jang and Kang, 2015) (Jang and Kang, 2015), agent-based modelling (Klein *et al.*, 2012), statistical analysis (Peng *et al.*, 2012) or even data mining (D'Oca and Hong, 2015). Gaetani et al. (2016) classified in five categories the different behaviour models that can exist: schedules, deterministic, non-probabilistic, probabilistic and agent-based stochastic. For example, (Buso, D'Oca and Corgna, 2014) developed realistic schedules from the statistical processing of field monitoring data in dwellings. Their model allows a better prediction of electricity and thermal loads than the standard schedule used in traditional energy simulation tools. However, the resolution of such models is relatively low since they ignore the diversity by averaging occupants' profile and buildings' parameters. Obversely, Artificial Intelligence techniques are best capable of supporting high resolution, and complex problems and ABMs are particularly promising in modelling human cognition according to Gaetani et al. (2016).

ABMs adopt a bottom-up approach and model individuals at the micro-scale in order to catch emerging phenomena at the macro-scale. The agent-based approach seems to be the most appropriate one for describing dynamics mainly driven by human behaviours; it particularly suits the modelling of human beings considering their faculty to adapt, react and interact, following rational and un-rational behaviour (Langevin et al. 2015). Furthermore, contrary to black-box models such as those obtained by data-mining, agent-based models provide an explicit and natural representation of the human behaviour ensuring to (a) imply non-computer scientists in the modelling process (domain expert, final users), (b) facilitate the monitoring, management and understanding of the simulation and (c) incite the different stakeholders to reflect on their practices and role in the design process. However, the use of ABMs is time-consuming as it requires antecedently describing all the buildings and users' characteristics. This last concern turned out to be a stumbling block during the building design process during which time is precious and multiple actors are involved, each with their speciality, tools, stakes and vision of the building. Thus, a consistent agent-based behavioural model that allows easy data handling is currently missing.

1.4. Building Information Modelling, a major digital innovation for the building sector

Building Information Modelling (BIM) has high potential to address this issue by easing the description step (Succar, 2009). Many of a building's sub-systems are designed, constructed, operated, and administered by separate entities (e.g., electrical and plumbing subcontractors) that may or may not interact and share information. BIM is designed as an exchange platform for all the stakeholders of the construction project (client, architect, contractor...) (Zuppa, Issa and Suermann, 2009) (Dino Zuppa & Raja Issa 2008). The key element of BIM software tools is their interoperability via a standardised exchanged file called Industry Foundation Classes (IFC) (ISO 16739: 2013). By allowing the different stakeholders of the project to work on the same support, BIM presents a high potential to ease the coordination between different actors and monitoring work (Ghaffarianhoseini *et al.*, 2017) (Ghaffarianhoseini et al. 2017). The numerical modelling of a building is growing in popularity: more and more building projects are integrating a BIM component. The regulatory context (BIM is recommended in France since 2017 for all new public projects) and the potential of BIM regarding cost and time saving should lead to the generalisation of BIM for every construction projects in the upcoming years. Thus, BIM is a promising entry point for any decision-making support tool aiming at integrating key dimensions of building performances to the design process. BIM provides valuable geometric information with an object-based approach. Andrews et al. (2011) were the first to evoke the potential of a BIM-based ABM and to date, several studies on emergency evacuation integrate BIM data to set up the simulation environment in ABM (Liu, Du and Issa, 2014; Zhang and Issa, 2015; Cheng *et al.*, 2018; Sun and Turkan, 2019). However, the integration of BIM into ABM has never been done in studies on human-building interaction in order to simulate the occupant's behaviour in her/his daily life.

1.5. Goal of the present work

Given this situation, an operating model is needed that accounts for (a) an advanced cognitive model and (b) interoperability and ease of use. In response to these needs, we have developed a tool, Li-BIM (Life in BIM), to guide early building design choices with a user-centred approach that meets these two criteria. Li-BIM is an innovative agent-based framework that simulates the user behaviour and its interpersonal relations in a residential building from its digital representation BIM. The main goal is to enhance physical models by considering the interaction of the occupants with their dwelling as well as their mutual interactions. We first review the existing literature on occupants' behaviour ABMs for residential buildings to identify the scientific challenges that should be addressed. Based on this review, we propose an agent-based architecture to model the building occupants' interaction. Then, we present how the model has been currently implemented to quantify the energy demands in a dwelling and the resulting thermal comfort, and we illustrate its implementation with a case study. Finally, we discuss the model and future possible developments.

Literature review on existing ABMs for occupants' behaviour modelling in dwellings

To date, ABMs have been mostly used to simulate occupants' behaviour in office (Zhang, Siebers and Aickelin, 2011; Langevin, Wen and Gurian, 2015; Carmenate *et al.*, 2016; Chen, Hong and Luo, 2018; Hajj-Hassan and Khoury, 2018) or for occupancy patterns in commercial buildings or university campus (e.g., Azar and Al Ansari, 2017; Azar and Menassa, 2010; Erickson et al., 2009; Liao, Lin and Barooah, 2012; Lee and Malkawi, 2014). This review intends to collect papers using ABM to simulate user behaviour in dwellings. The exhaustive search was performed with international bibliographic databases, Scopus, ISI Web Science, Science Direct and Google Scholar, with a combination of keywords relating to "Agent-based model*" (or "ABM" or "Multi-agent system" or "MAS") AND "Residential building" (or "Household" or "Dwelling"). Articles without a case study or a proof of concept were discarded.

Among the 22 articles that were found, two articles use ABMs to investigate the evacuation safety performance of the residential building (Ying, Zi-Min and Jian, 2017; Mirahadi, McCabe and Shahi, 2019). ABMs have also been widely used to simulate the diffusion of practices among households: Cao *et al.* (2017) and Hicks *et al.* (2015) simulated lighting adoption patterns; Jensen, Holtz and Chappin (2015); Zhang, Siebers and Aickelin (2016) and Anderson *et al.* (2014) studied the spreading of energy-use feedback; Rasoulkhani *et al.* (2018) explore the adoption of water conservation technology and (Mohandes, Sanfilippo and Al Fakhri, 2019) investigate the residential adoption of solar energy. A literature review has been conducted by (Hesselink and Chappin, 2019) specifically on ABM studies of energy efficient technologies adoption by households. Since the authors focus on diffusion mechanisms, occupants are likely to be modelled as households rather than individual entities and their daily life is mostly shaped by two states: being at home or out. In the same way, Liang *et al.* (2019) explore the effectiveness of incentive policies on energy consumption thanks to an ABM and the authors model the likelihood that building owner launches an energy efficient retrofit project.

However, they do not address the behaviour of occupants in their dwelling. Therefore, these articles were excluded from the analysis. Finally, 12 papers were identified as simulating user behaviour in dwellings with an agent-based framework. These articles are compared in Table 1 according to a set of eight criteria.

In two articles, electric appliances are represented as agents. These agents only react to actions from occupants to change their on/off state in Abdallah, Basurra and Gaber (2018)'s work. In Walzberg *et al.* (2018)'s article, electric appliances are described as intelligent agents able to share energy consumption feedback to the occupants and optimise their load time. In (Evora *et al.*, 2011; Hauser, 2013), occupants are modelled at the household level. To represent a household as a whole entity does not allow to distinguish between household tasks and personal activities, nor to express different levels of energy awareness among a family for example.

Four of the twelve papers used existing platforms to implement their ABM (Alfakara, 2010; Andrews *et al.*, 2011; Hauser, 2013; Abdallah, Basurra and Gaber, 2018). Existing platforms have the advantage to ease the implementation process by proposing existing cognitive architecture and graphical outputs. However, these platforms may hinder coupling with other existing physical models. The decision-making process is based on probabilities in forty per cent of the studies (Alfakara, 2010; Azar and Menassa, 2010; Tröndle and Choudhary, 2017; Abdallah, Basurra and Gaber, 2018; Chapman, Siebers and Robinson, 2018).

In (Alfakara, 2010 and Amouroux and Sempé, 2013), the main variable considered for representing households is the age of the occupants. The rules governing social interactions are based on this age. (Chapman, Siebers and Robinson, 2018) defined three household profiles (adult with children, an adult without children or retired adult) upon which activity choices depend. In the same way, Hinker, Pohl and Myrzik (2016) proposed four different types of household composition, introducing variability in the occupancy pattern. However, such models cannot assess behaviour variability between different population segments at the occupant's level. A finer representation of household heterogeneity is proposed by Azar and Menassa (2010) which defined three categories of occupants according to their energy usage degree: "high", "medium" or "low" consumers. In Andrews *et al.* (2011) 's work, four profiles (green activist, a good citizen, healthy consumer, traditional consumer) based on occupant responses to a survey introduce variation in occupant's illumination preferences (darker or brighter) and the potential actions in response. Walzberg, Samson and Merveille (2018) implemented a probability of engagement in pro-environmental behaviours that depends on four sub-types of consumers as proposed by Valocchi *et al.* (2007): passive ratepayers, frugal goal seekers, energy epicures and energy stalwarts. These profiles are a first attempt to differentiate actions according to different behaviour pattern. Household attributes such as income or education level are essential to differentiate socio-demographic profiles. Evora *et al.* (2011) and Hauser (2013) deepened this aspect by proposing a real sociological approach in which nine household archetypes are defined based on the equipment level and the modernity of the lifestyle. These typologies of lifestyle have been first developed by the sociologist Otte (2005).

Interpersonal relations could lead to different sets of actions since human people do not behave the same way when they are alone or among a community (Yan et al. 2015). Simple rules have been set to resolve conflicting desires: (Andrews *et al.*, 2011) proposed a framework in which the last agent to behave will win while in Alfakara (2010)'s work the older person takes the decisions. Amouroux *et al.* (2013) developed a procedure to exchange information or request the participation of others in task-sharing. This way, appliances and activities can be shared between occupants (e.g., watching TV).

Hauser and Evora did not use any thermal model since the energy consumption from heating devices are based on the data collection realised by the European Institute for Energy Research (EIFER). In the same way, Amouroux *et al.* (2013) and Walzberg, Samson and Merveille (2018) developed a model focusing on residential load-curve with the goal to understand and further predict energy peak. Energy consumption of electrical appliances is based on the notion of activities: energy demand profiles are generated according to the household activities achieved at each time step. The dependence between space heating and outdoor conditions is based on the heating and cooling degree days. As a consequence, they do not consider the physical parameters from the building envelope. This lack of a multidisciplinary approach could be detrimental during the building design phase. Indeed, finding the set of design solutions involves to satisfy the best trade-off between the goals of the different trades and requires a systemic approach. For example, (Alfakara, 2010) aims at determining the response of occupants to summer overheating but does not take into account blinds position and light control strategies according to the position of the sun and the building's exposition, which are key parameters in summer influencing indoor temperature.

Table 1. Analysis grid for the papers simulating human behaviour in residential buildings with ABM

References	Goal	Design aspect	Type of agents	Decision-making architecture	Socio-demographic attributes	Social interactions	Share of activities	Implementation platform
(Abdallah, et al., 2018)	Energy waste	Energy consumption	Occupants; Electrical appliances	Probabilistic models	Employment type, age	Yes (no rules explained)	No	REPAST
(Alfakara, 2010)	Response to summer overheating	Thermal (TAS software)	Occupants; Rooms	Probability profile based on temperature thresholds	Age (for seniority)	The older takes decision)	No	REPAST
(Andrews et al., 2011)	Lighting design performances	Lighting (design simulation tool RADIANCE)	Occupants	Belief-Desire-Intention and Theory of planned behaviour	Four profiles of occupants	The last one to act wins	No	NetLogo
(Amouroux and Sempé, 2013)	Households activities	Energy consumption peak	Occupants	Brahms	Age (for responsibility level)	Cooperation mechanism among individuals	Share of domestic tasks	SMACH
(Azar and Menassa, 2010)	Energy prediction	Energetic (eQuest software)	Occupants	Probabilities	Three profiles of occupants	Word of mouth effect	No	Not mentioned
(Chapman et al.; 2018)	User behaviour	Energetic (EnergyPlus software)	Occupants	Time-dependent probabilities	Three household types	No	No	C++
(Evora et al., 2011)	Lifestyle impact on residential load-curve	Appliance model	Households	Mission-Decision-Action maker	Nine lifestyle typologies	No	No	Tafat
(Hauser, 2013)	Lifestyle impact on residential load-curve	Appliance model (from Evora et al., 2011)	Households	Mission-Decision-Action maker	Nine lifestyle typologies	No	No	Anylogic
(Hinker et al., 2016)	Energy efficient refurbishment strategies	Thermal comfort (calculation kernel of VDI 6007-1)	Occupants; Building	Thermal comfort	Four household types	Negotiation among occupants	No	Not mentioned
(Kashif et al., 2013)	Energy management in smart homes	Energetic (EnergyPlus software)	Occupants	Brahms	No	Social behaviour influence on activity choice	Group activity	Not mentioned
(Tröndle et al., 2017)	Energy prediction	Energetic (EN ISO 13790)	Occupants; HVAC system; Building	Time-heterogeneous Markov chain	Economic activity and age	No	No	Not mentioned
(Walzberg et al., 2018)	Energy rebound effect in smart homes	Electricity load profiles (from (Paatero and Lund, 2006)	Occupants; Electrical appliances	(Kaiser, Byrka and Hartig, 2010)'s social-psychological model	Four profiles of agents	No	No	Not mentioned

From this literature review, it can be concluded that all the existing agent-based behavioural models for residential buildings have been built toward one specific use, but none of them proposes a systematic approach to handle the huge amount of inputs data. The use of these models in the building sector still faces a lack of interdisciplinary and data acquisition automation. Therefore, the key concepts of the developed framework are (a) to propose a flexible structure that allows its use in different (or multiple) civil engineering domains and (b) to use for the first time the potential of the BIM as a data centraliser. Furthermore, the analysis of these articles highlights the current methodological challenge of integrating social interactions. Therefore, the proposed occupational, cognitive model should be based on a complex reasoning procedure integrating both the deliberative and social behaviour of occupants. This way, the heterogeneity of the human factor could be treated both at the individual as well as at the household level.

Model Design

Li-BIM architecture

3.1.1.Model structure

The developed framework aims at modelling the building occupants' interaction to assess the impact of the occupants' behaviour on the building performances as well as the occupants' response to physical conditions in the building. As illustrated in Figure 1, its structure is based on an agent-based model simulating the behaviour of the occupants (Block 2) that interacts with physical models simulating the behaviour of the building (Block 3). The agent-based model does not depend on a specific physical model and can interact with one or several models. Therefore, the physical models can be external and the exchange of data made through CSV files. The multi-agent system (MAS) architecture of Li-BIM allows intelligence distribution between agents and collective decisions making. It has been implemented under the open source multi-agent platform GAMA (Grignard et al. 2014). Pre-defined inputs data can be used for the inhabitants' and environment's components (Block 1.1 and 1.3 respectively). Building data (Block 1.2) are made of the BIM representation of the building in IFC-format. Once the building has been designed with a traditional BIM software, the obtained IFC files can be directly imported in Li-BIM at the beginning of the simulation.

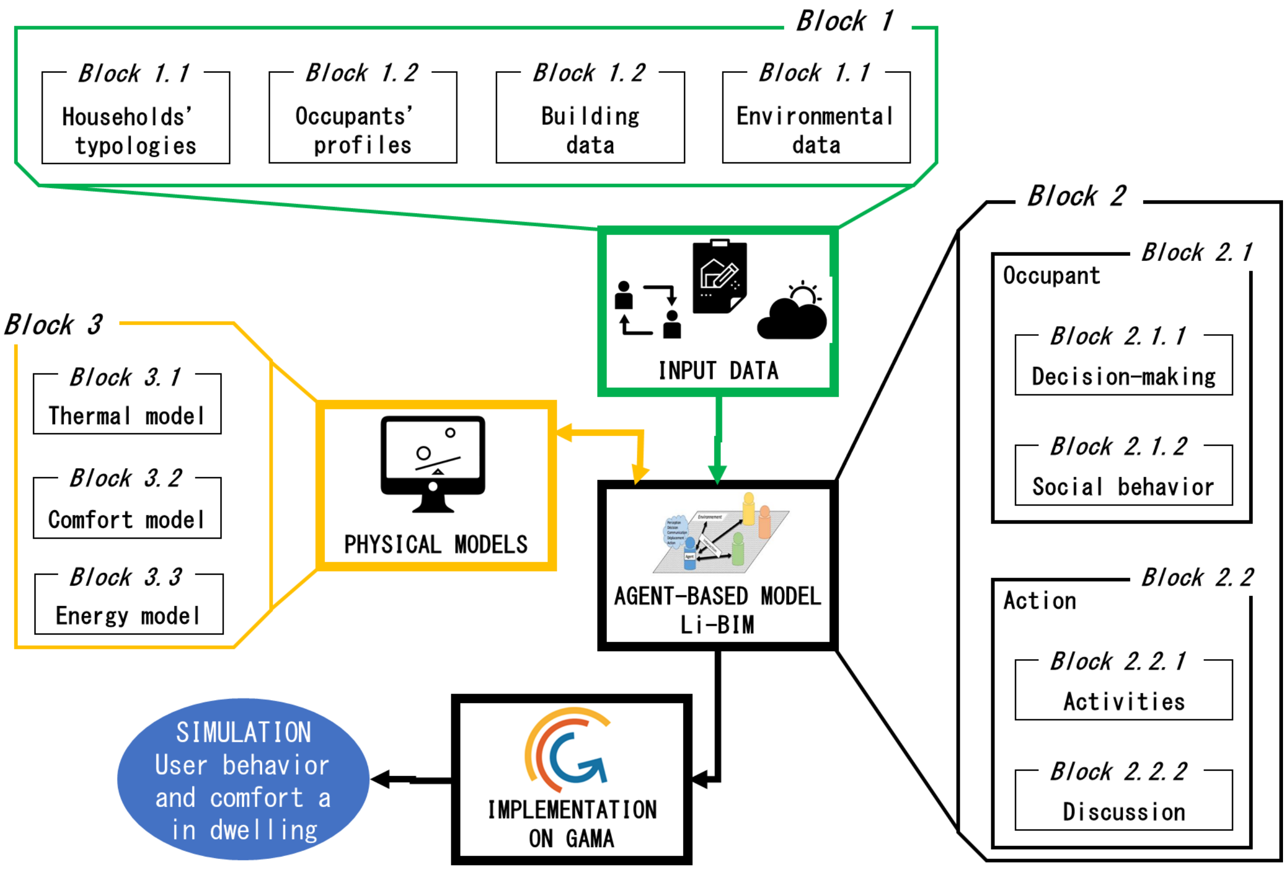

Figure 1. Li-BIM Framework

3.1.2. Agents

Li-BIM model is composed of agents "*Occupant"* representing the occupants of the dwelling and agentified objects "*IFC Components*" representing the functional elements of the building. In their article, Barata and Camarinha-matos (2003) proposed an agent-based architecture in which the manufacturing resources of a shop floor are agentified as "manufacturing agents". In the same way, we agentified the functional elements constituting the building: every object in the IFC files is transformed into an agentified object (*IFC Components*) that are linked to one another by spatial relationships. According to the terminology used by Barata and Camarinha-matos (2003), the aggregation of agentified components that can cooperate through their spatial relationships forms a coalition. A coordinating agent (CA) is specialized in coordinating the activities of the coalition. Following this approach, the whole set of agentified objects *IFC Components* composes a coalition in which the coordinating agent *Building* manages the global indicators (total energy consumption, global warming potential, etc.). Similarly, a coalition is formed by the aggregation of the agents *Occupants* living in a common housing unit; whose activities are coordinated by the CA *Household*. This second coalition is part of the previous coalition, and the CA *Building* simultaneously coordinates the agentified objects *IFC Components* as illustrated Figure 2. In the current version of Li-BIM model (i.e. a single house), *Occupant* agents are directly considered as part of the same housing unit.

Agents *Occupant* exhibit the three capabilities required to be "intelligent agents" as defined by (Wooldrige, 2009): (1) reactivity: they can perceive their environment and to adapt their behaviour in order to satisfy their objectives; (2) pro-activeness: they can exhibit goal-oriented behaviour and take initiatives to satisfy their objectives; (3) social ability: they can interact with other agents to satisfy their objectives. Agents and agentified objects can have two types of attributes: (a) characterisation attributes that are constant during the simulation, and (b) dynamic attributes evolving at each time step of the simulation according to the environment and the agents' action. Agents Occupant are dynamic and can interact with all other agents, as well as the agentified objects of the system (for example, one member of the family (agent Occupant) put the heater on (agentified object IFC Component)). Agentified objects can be dynamic (e.g., a Window can be open or close) or static (e.g., a Wall).

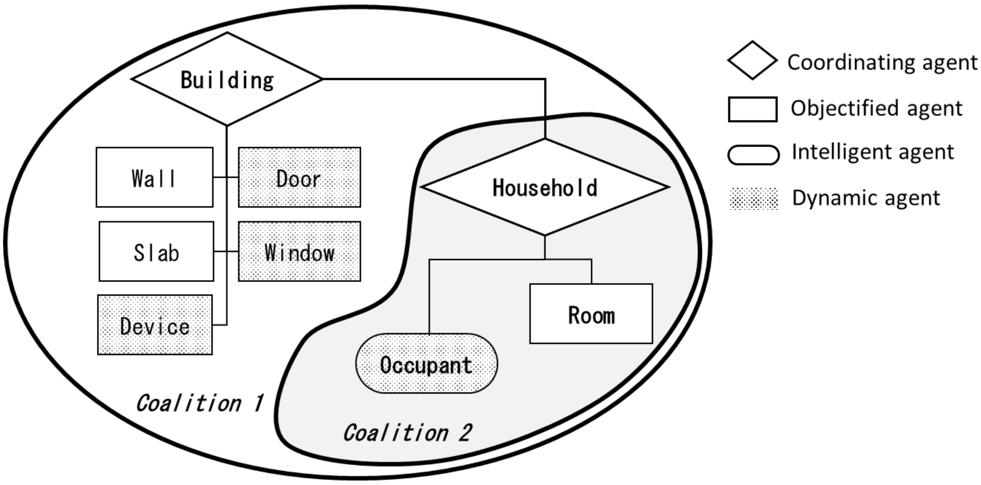

Figure 2. Li-BIM Agents and agentified objects

3.1.3. Model components (Block 1)

Households' archetypes (Block 1-1). Four household archetypes (one-person households, lone-parent households, a couple without children, couple with children) are determined based on the statistics of the French National Institute of Statistics and Economic Studies (INSEE, 2018). The number of resulting adults and children as implemented in Li-BIM is defined in Table 2. At the beginning of the simulation, the user of Li-BIM model has to define a household archetype as well as the social class to which the future occupants are likely to belong. Table S2 of the Supporting Information (SI) details the categorisation of the household into five social classes according to the monthly income of the household and its archetype as defined by INSEE (2017).

Table 2. The different household archetypes and their representativeness in the French context. N_{bed} stands for the number of bedrooms, Rnd(1,2) is a random integer between 1 and 2

	One-person households	**Lone-parent households**	**Couple without children**	**Couple with children**	**Other types of households**
Percentage of households in the French context %	35,1	7,9	27,0	27,2	2,8
Number of Adults in Li-BIM	1	1	2	2	Rdn(1,2)*N_{bed}
Number of Children in Li-BIM	0	Rdn(1,2)*N_{bed}	0	Rdn(1,2)*N_{bed}	0

Occupants' profiles (Block 1-2). Occupant's variability can be represented by characterising the occupants with a set of attributes likely to influence their behaviour. Four attributes for each *Occupant* were set up:

- "Wealth" depends on the level of income and the household type (Poor, Middle class or Upper class/Rich)
- "Green Conscious" establishes how aware of the environment is the occupant (Unaware, Aware or Concerned)
- "Building Knowledge" determines how the occupant is aware of her/his building's functioning (Comfort first or Values first)
- "Individualism" represents if the occupant will put the priority on her/his comfort first (No knowledge, Basic knowledge or Advanced knowledge)

These four attributes are occupants' specific and determined randomly, except the attribute "Wealth" (as explained in the previous section, "Wealth" is representative of the household and must be entered by the user of Li-BIM). This characterisation is established for adults but not for children since the authors consider that children's profile would be mostly dependent on the profile of their parents. Thirty different profiles come up from the association of these attributes. Different behaviours in the same given situation results from the diversity of these profiles. These profiles differentiate four different actions that an occupant is willing to do -or not: switch off appliances when stopping using it, put on heaters as soon as feeling discomfort, buy or replace appliances of Class A and energy saving bulbs, adjust blinds to maximise solar gain. Profiles that are likely to execute such actions are detailed in Table S4 of the SI.

Occupants also have a set of parameters describing their habits or schedule more precisely. Parameters can be provided thanks to a spreadsheet interface (in CSV-format) that has been developed for this application. When no specific data about the future occupants are known, default values have been set based on literature or experts and are provided Table S5 (SI).

Building data (Block 1-3). To overcome the challenge of the time-consuming building description phase, the methodological approach adopted is to acquire the input data regarding the building from the BIM systematically. To do so, we have mapped how the information is structured in the IFC file. Figure 3 shows the mapping of the information for the object *Wall* (the mapping of the other building elements are available in Section S3 of the SI). A specific operator in GAMA (operator *ifc_file*) has been developed to directly create agentified objects from the objects composing the IFC file. The implementation in Li-BIM is realised by importing the IFC File with the operator *ifc_file* as a file of type *geometry*. The content of an ifc_file is a list of geometries corresponding to the objects contained in the IFC file. The attribute *shape* is used in the global context to create the size and shape of the environment. The agentified objects corresponding to each type of IFC objects are created. The properties of the objects contained in the IFC file are stored in their corresponding GAMA *geometry* and used as an attribute for the agentified objects. The data that are extracted from the IFC files and their corresponding parameters can be found in Section S3 of the SI.

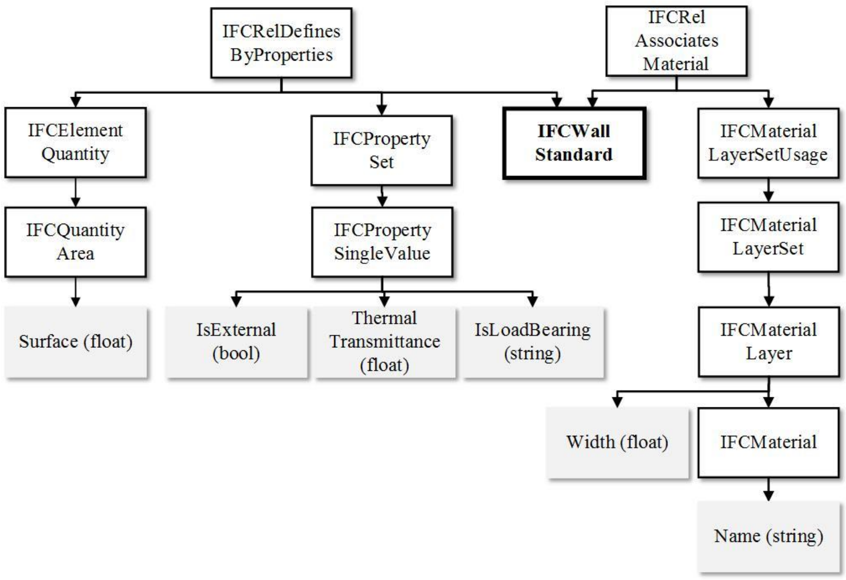

Figure 3. Mapping of the IFC information for the building element Wall

Environmental data (Block 1-4). In the same effort of facilitating the operational use of the model, weather data have been collected for twenty cities in France from Météo France database (Portail Climatik 2017). The climatic area corresponding to each city is generated automatically according to the geographic breakdown stated by the French thermal regulation RT2012 while the sunrise and sunset time are directly calculated thanks to the latitude and longitude of the future building implantation in the geographic coordinate system.

Modelling the behaviour and actions of the occupants

3.2.1. Model dynamic

Each simulation step follows the same process (Figure 4). Firstly, the model updates the environmental data (e.g., outside temperature, humidity) imported as CSV files and, based on this latter, building data (i.e. dynamic parameters of the agentified objects*)* are updated. Different physical models can be used to calculate the new values of these parameters. For example, the inside temperatures can be computed by a thermal model thanks to the environmental data (e.g., outside temperature) and the *IFC Component*'s characteristics (e.g., the thermal resistance of wall). The actions previously performed by occupants can impact these characteristics (e.g., opening of windows). Finally, the *Occupant*'s attributes regarding their physical/psychological state (e.g., comfort, tiredness, hunger, cleanliness) are updated.

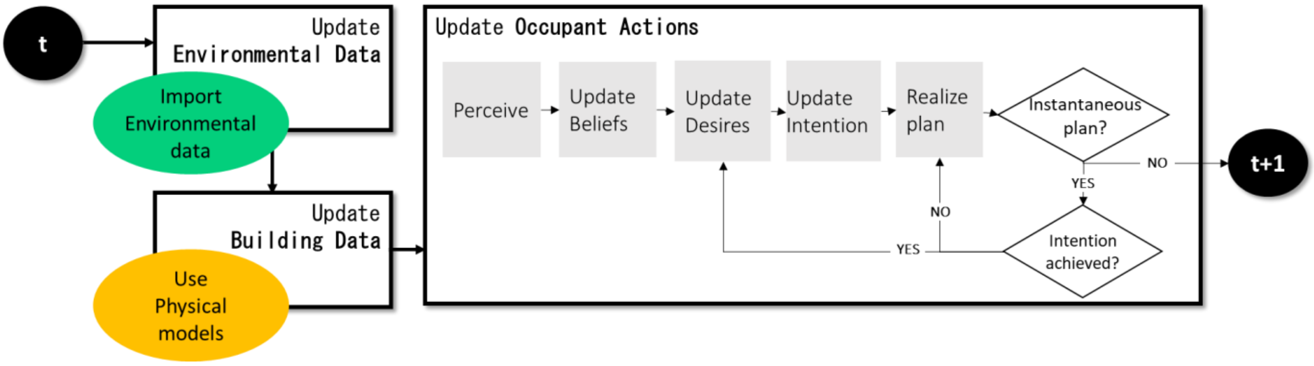

Figure 4. Li-BIM Dynamic

Some plans carried out by the *Occupant* agents can last more than one simulation step, and thus, in order to finish its plan, the agent will keep the same intention for the required numbers of simulation steps. A plan can be composed of several actions. However, some actions can be instantaneous (e.g., switch on the heater) or can be performed simultaneously with other actions (e.g., discuss with another occupant). In this case, and if the intention is not yet achieved, the agent will keep its unfinished intention and continue to execute the current plan (i.e. the other actions of the plan). If the intention is achieved, then the desire base is updated, and the agent selects a new intention corresponding to the desire with the highest priority and executes the most appropriate plan to fulfil this intention. The user can set the duration of a simulation step according to the accuracy needed since every time variables and counts are expressed according to this parameter.

Li-BIM proposes two types of experiments to run simulations: (a) a GUI experiment with 3D-graphical visualisation and (b) a batch mode with CSV files available at the end of the simulation. Mode (a) proposes to follow in real-time the processing of the simulation. In this graphical mode, several variables evolving at each simulation step are available in different panels (Figure 5):

- 3D Model (3D representation of the house, occupants, current day and time)
- Radar (physical state for each occupant)
- Activity Graph (the activity of each occupant)
- Indicator curves (inside and outside temperature, thermal comfort range of each user)

These windows help to perceive and understand the simulation easily. It is possible to hide the objects composing the building (carpentry, roof) in order to enhance the clarity.

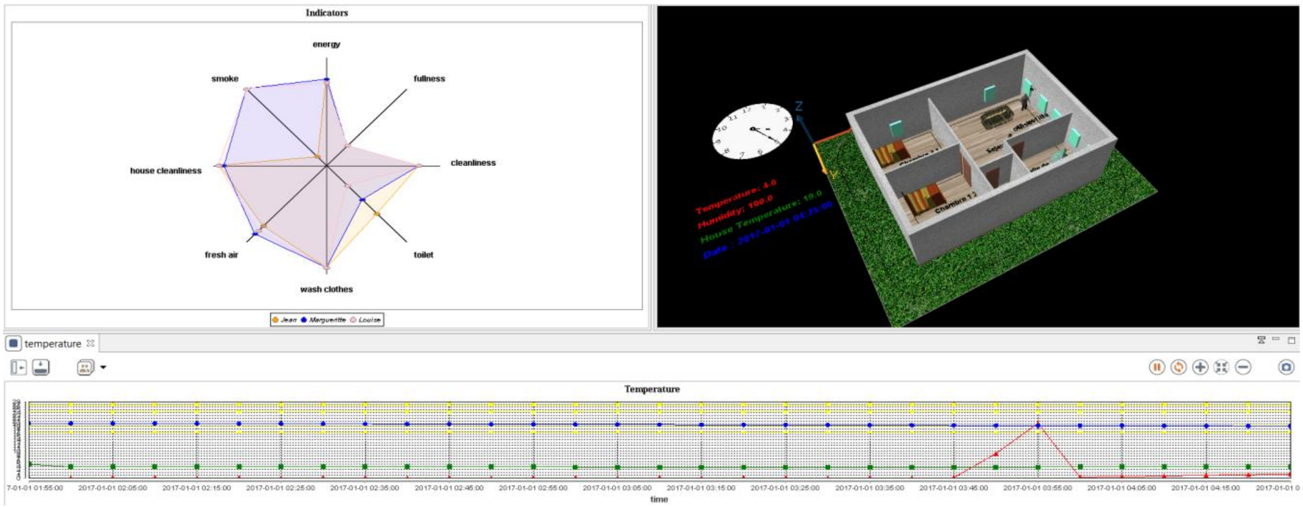

Figure 5. Simulation Interface

Mode (b) proposes to run simulations without any graphical interface in order to increase the simulation speed. This mode enables to obtain the results on one year, which is considered as a representative period to analyse the behaviour of occupants, in a reasonable time (i.e. less than one hour). A CSV file is generated at the end of the simulation reporting all data fitting the focus/requirements of the Li-BIM user.

3.2.2.Modelling individual behaviours and social interactions

Humans react instinctively to stimulus but also react according to their desires and knowledge of their environment. Similarly, discussions with others will influence more or less strongly their behaviour. To efficiently model the occupant's individual behaviour and social interactions resulting in collective actions, *Occupant* agents are based on the combination of two cognitive models: a BDI architecture for the decision-making process with a social behaviour model.

Decision-making process (Block 2-1-1). These last years, several architectures have been proposed to model the agent behaviour and decision making as classified by Balke & Gilbert (2014) in their critical review. Among all these architectures, the most popular for social simulation is the one based on the BDI paradigm (Bratman 1991). This paradigm proposes a straightforward formalisation of human reasoning through intuitive concepts. Several works have already shown the interest of using BDI architectures for social simulation (Adam & Gaudou 2016; Adam et al. 2017; Truong et al. 2015). Several architectures based on this paradigm have been proposed such as PRS (Myers 2001), JACK

(Howden et al. 2001) and JADEX (Pokahr et al. 2005) for the most famous. In this work, we chose to use the BDI architecture proposed by Caillou et al. (2017). In addition to its integration to the GAMA platform, the architecture has several advantages: it is simple to use as shown by Taillandier et al. (2016), allows distributed computation (Taillandier et al. 2017), and proposes a direct link to a social relation engine (Bourgais et al. 2017).

BDI architecture provides agents with three cognitive databases:

- The belief base represents what the agent knows. This knowledge can be true or false or even contradictory and can concern the agent itself or the surrounding environment.
- The desire base corresponds to the goals of the agent. These desires will be prioritized according to their importance at the current time.
- The intention base corresponds to the desires the agent is currently trying to fulfil.

These bases have a dynamic evolution according to the actions of the *Occupant* agent and its environment. At each time step, the *Occupant* agent will "perceive" its well-being and needs thanks to different physical/psychological state values that vary in the range [0; 1]. Its perception of itself, the knowledge of the current time (hour and date) as well as the knowledge about the weather (outside temperature and rain) will modify its belief base. These beliefs will help the agent to express desires. Based on the priority the *Occupant* agent gives to these desires, the *Occupant* agent chooses one intention and finally tries to realise through the application of a plan. A plan can be composed of several actions performed by the *Occupant* agent (Figure 6).

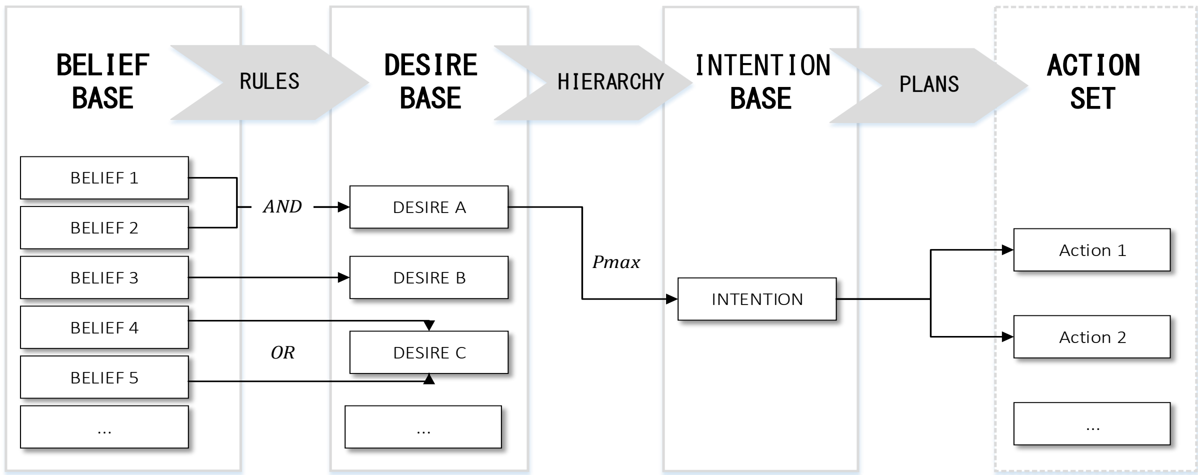

Figure 6. BDI reasoning system

For example, if the *energy* state reaches 0%, then the *occupant* agent gets the belief "*I am tired*". If, moreover, the agent has the belief "*It is time to go to bed*", it will get the desire "*Go to bed*". It will then compare this desire with other potential desires (desire "*Eat*" for example). If the agent judges this desire as more important, "*Go to bed*" is added to the intention base, and the agent will execute the plan "*Sleep*". Some actions can only be achieved if some tasks have been done before. For example, one agent will be able to eat if it -or another person of the family-, has cooked before.

This internal reasoning, called rules, allows the agent to create its thoughts without extracting them directly from the environment. The combination of the three databases and the rules enables the agent to build its complex reasoning to reach its goal and get credible behaviour.

Social behaviour modelling (Block 2-1-2). The model used to describe the social link between the *Occupant* agents is based on the work of Bourgais et al. (2016). This work proposes to describe social relation using the four dimensions defined in the dimensional model of interpersonal relationships of Svennevig (2000): the *liking*, the *dominance*, the *solidarity*, the *familiarity*. *Dominance*, *solidarity* and *familiarity* are set between 0 and 1 and *liking* between -1 and 1. L*iking* represents the affinity that a person feels toward another. *Dominance* is the control capacity that someone has over another. *Solidarity* describes the degree of consensus between two agents that results in our model in sharing empathy.

Familiarity represents the intimacy level which alters the amount and the nature of the exchanged information between two persons.

A relationship is oriented, that is to say that the relationship between agent A and agent B is not necessarily the same as the relation between agent B and agent A. This is particularly true for the adult-child relation, for which dominance and solidarity will take higher values from the adult to child than in the other way. The *Occupants* who live together are part of a *Household,* and the value of their familiarity is automatically set to 1.

This social model is used in order to model different actions:

- convince another person to take one decision ("*I am cold, it would be better if I put on the heater*"): Higher the *dominance* of agent A over B and the *solidarity* and *liking* from agent B to agent A is, higher are the chances to convince agent B
- propose another person to do something ("*I want to go out for a walk, do you want to go with me?*"): *liking* and *familiarity* must be strong enough in both ways
- carry out collective tasks ("*Should we prepare the dinner?*"): *solidarity* and *dominance* must be high
- communicate and exchange information ("*Outdoor air pollution today, it would be better to close the windows*"): *familiarity* and *liking* must be high values

In order to formalise occupant feelings and perceptions, nine state attributes are updated at each simulation step (Table 3). When the value of these state attributes reaches zero, it triggers the appropriate need to the belief base as defined by the BDI architecture (block 1.1).

Table 3. Occupant's state and their respective meaning

State	Value 0%	Value 100%
Energy	Exhausted	Well-rested
Hunger	Starving	Full
Cleanliness	Dirty	Clean
Toilet	Urgent	Perfect
Comfort	Discomfort	Comfort
Wash clothes	Nothing clean to wear	All clothes are clean
Smoke	Urgent	Ok
Fresh air	Need to go out	Do not need to go out
House cleanliness	Dirty	Clean

3.2.3. Modelling human activities and interactions (Block 2-2)

Activities (Block 2-2-1). The belief, desire and intention bases of the *Occupant* agents are updated at each time step according to the BDI architecture explained section 2.2. Depending on the intention selected, the *Occupant* agents finally execute an activity among the 19 implemented ones referenced in Table 4. One activity can lead to several types of outputs: (i) mutual knowledge (MK) that will enrich the belief base of the inhabitants, (ii) the update of parameters used for the thermal model (TM) or (iii) an instantaneous action (*). We took the hypothesis that collective tasks (#) already carried out belong to mutual knowledge, i.e. is known by the other interacting agents. For example, when someone has prepared the meal, all the other occupants will know it. What is more, *Occupant* agents are considered as gullible, i.e. they will believe everything they will be told about. The personal heat gains P_{occ} that are taken into account in the thermal model are not the same depending on the activity that is performed. The values come from in-situ measurement for a medium person of 70kg and 1.70m (LeGuay 2016).

Table 4. Implemented occupant activities (*U* stands for thermal transmittance, *Q* for internal heat gain, and *Switch-on* for the power mode of the appliances, *MK* for mutual knowledge, *TM* for the thermal model, * Instantaneous action, #Collective action)

Activity Name	**Trigger**	**Outputs**	**Room**
Blinds pulling down/up*	Sleeping state Solar gain	U_{blinds} (TM)	Bed room
Changing clothes*	Thermal discomfort		Anyroom
Cooking#	Current time Hunger	Q_{occ} & Q_{app} (TM) Cooking & Hot water devices *Switch-On* (TM) Meal ready (MK)	Kitchen
Discuss*			Any room
Eating	Meal ready (activity *cooking* achieved by one of the occupant)	Q_{occ} (TM) Dishes to wash (MK)	Livingroom
Going outside	Weather & Current day Discussions with others		Outside
Ironing#	Wash machine ready (activity *washing clothes* achieved)	Q_{occ} & Q_{app} (TM) Cleaning devices *Switch-On* (TM) Ironed clothes (MK)	Livingroom
Toilets	Peeing state	Q_{occ} (TM)	Toilets
Heating regulation*	Thermal discomfort	Heating device regulation *R* (TM)	Any room
House cleaning#	Cleaning frequency	Q_{occ} & Q_{app} (TM) Cleaning devices *Switch-On* (TM) Clean house (MK)	Every room
Relaxing	Default action	Q_{occ} & Q_{app} (TM) Relaxing devices *Switch-On* (TM)	Living room
Showering	Cleanliness	Q_{occ} (TM) Hot water device *Switch-On* (TM)	Bath room
Sleeping	Current time Tiredness	Action *Pull down blinds** Q_{occ} (TM)	Bed room
Smoking	Smoking frequency	Action *Open window* *	Any room
Turn on lights*	Lightness Sleeping state	Q_{light} (TM) Light device *Switch-On* (TM)	Any room
Washing clothes#	Washing frequency	Q_{app} (TM) Wash machine *Switch-On* (TM) Clean clothes + Clothes to iron (MK)	Bath room
Washing dishes#	Meal finished (activity *eating* achieved by all the occupants)	Q_{occ} (TM) Dishwasher *Switch-On* (TM) Clean dishes (MK)	Kitchen
Windows opening*	Thermal discomfort Smoking activity	$U_{windows}$ (TM)	Any room
Working	Current time		Outside

Interactions (Block 2-2-2). Discussion can be used by an occupant to propose to share activity and convince another member of the family before proceeding with any further action that could impact the well-being of the whole family. The agreement of the other family members depends on the informal rules of conduct that are likely to be followed within a family. In Li-BIM model, these social conventions are considered as only dictated by the links that unite family members. At each time step, a list of the available person to speak with is updated according to two conditions: *being at home*, and *not sleeping*. The Discussion process has been implemented to deal with the situation of thermal discomfort. Every occupant *i* feeling in uncomfortable because of the indoor temperature will speak with all the other members *j* of the family before deciding since all of them must first agree. If they are all feeling the same discomfort, the adequate action to provide comfort will be executed. If they are in a situation of thermal comfort, the occupant must reach the agreement of all the members of the family as shown in Figure 7.

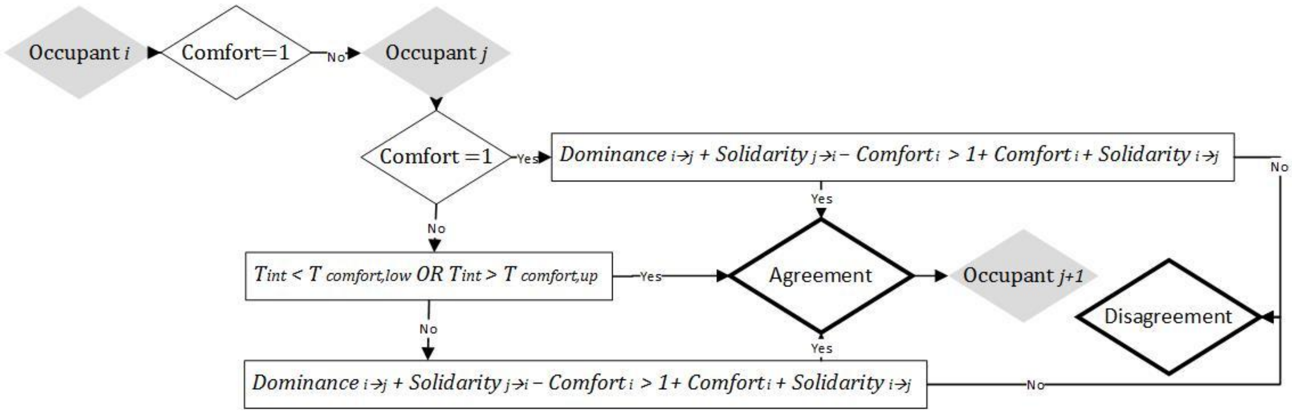

Figure 7. Implemented discussion process for comfort

Thermal comfort and energy consumption

Modelling building thermal behaviour (block 3.1)

The thermal behaviour of the building has been modelled to assess at each time step the inside temperature $T_{in}(t)$ on which is based the comfort model and the energy model. The thermal model has been adapted from the work of Belazi *et al.* (2018) and Mckone *et al.* (2010) and is based on classical flow equations (Eq. 1.1 & 1.2). As illustrated in Figure 8, these equations enable to compute the heat exchange between (a) *Boiler* to *Heating devices*, (b) *Boiler* to *Heat water tank*, (c) *Heating devices* to *Dwelling* (indoor), (d) *Dwelling* (indoor) to *Wall surfaces* and (e) *Wall* surfaces to *Outdoor*.

$(dT_A / dt) = Q_{B\rightarrow A} / C_A$ (Eq. 1.1)
with T_A the temperature of A, $Q_{B\rightarrow A}$ the power given by B to A, and C_A the thermal capacity of A.

$Q_{A\rightarrow B} = (T_A - T_B)/ R_{A\rightarrow B}$ (Eq. 1.2)
with T_i the temperature of *i*, $Q_{A\rightarrow B}$ the power given by A to B, and $R_{A\rightarrow B}$ the thermal resistance from A to B.

The occupant adjusts the thermostat *R* to fit her/his comfort temperature range. Hence, the power of the boiler is dependent of the choices made by the occupant (Eq. 2).
$Q_{boiler} = R \cdot Q_{boiler,max}$ with $R \in (0,1)$ (Eq. 2)
with $Q_{boiler,max}$ the maximum power of the *Boiler* and *R* the regulation coefficient; *R*=*0* for off-boiler and *R*=1 for full power.

At each time step, the outside temperature T_{out} is updated based on environmental data (see section 3.1.3); the solar heat gains through the windows Q_{solar} are calculated according to the global solar radiation (calculation can be found in Table S12 in the SI); the internal heat gains $Q_{internal}$ due the electrical appliances Q_{app} in operation, lights on Q_{light} and the occupants Q_{occ} (as a function of their activity) are evaluated. All the default value of the variables used in the thermal model are detailed in Section S5 in the SI.

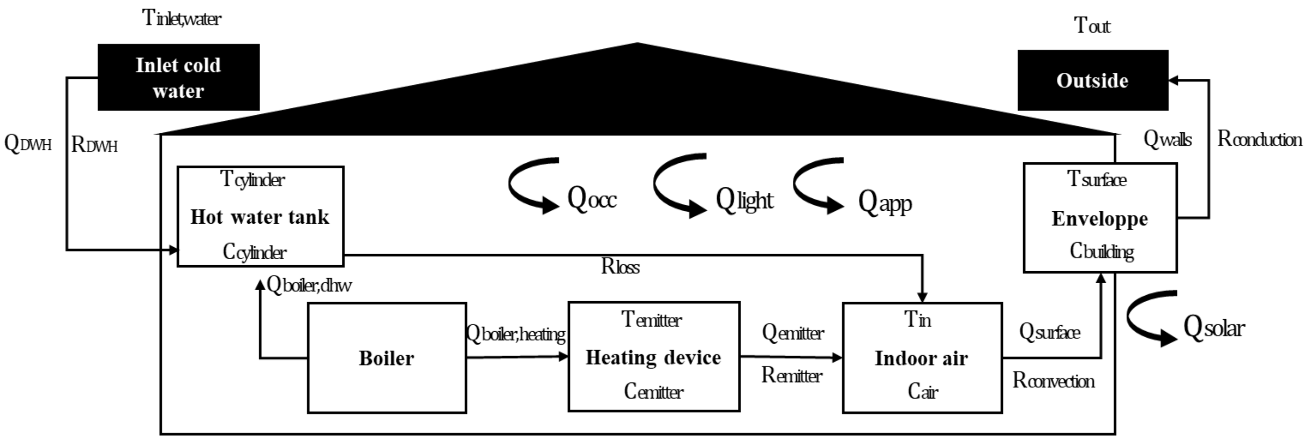

Figure 8. Thermal model

Simulating the occupants' thermal comfort (block 3.2)

The thermal comfort is conditioned by the occupant’s characteristics (sensitive to cold, clothing, etc.) and by the external environment (relative humidity, indoor temperature, etc.). The developed comfort model determines a comfort temperature range for each user at each time step which depends on both a temperature of comfort and how sensitive to cold they are. Computation of the comfort range temperature $T_{comfort,low}$ and $T_{comfort,up}$ is based on the work by Peeters et al. (2009) and only depends on the outdoor weather conditions. A differentiation is made according to the type of room where the occupant stands (for example, usually, people need to feel warmer in a bathroom than in a bedroom). In order to take into account the sensitivity of some person to cold and warm, a coefficient α specific to each occupant (previously set in the input file *Occupant*) is then applied to define a lower and upper temperature of discomfort (Eq. 3.1 and Eq. 3.2).

$$T_{discomfort,low} = T_{comfort,low} - \alpha_{cold} \qquad \text{Eq. 3.1}$$

$$T_{discomfort,up} = T_{comfort,up} + \alpha_{warm} \qquad \text{Eq. 3.2}$$

The level of comfort LC is defined as a number from 0 to 1 that depends on the indoor temperature at the current time step *t*. The level of comfort is optimal (i.e. equal to 1) when the indoor temperature lies in the comfort temperature range (Eq 4.1) whereas it is minimal (i.e. equal to 0) when the indoor temperature is not in the discomfort temperature range (4.2). LC evolves linearly when the indoor temperature lies between the comfort and the discomfort temperature range (4.3 and 4.4).

$$LC\big(T_{in}(t)\big) = 1 \; if \; T_{in}(t) \; \in \left[\, T_{comfort,low}, T_{comfort,up}\right] \qquad \text{Eq. 4.1}$$

$$LC\big(T_{in}(t)\big) = 0 \; if \; T_{discomfort,up} < T_{in} \; or \; T_{in} < T_{discomfort,low} \qquad \text{Eq. 4.2}$$

$$LC(T_{in}(t)) = \max\left\{0,1 - \frac{T_{comfort,low} - T_{in}}{\alpha_{cold}}\right\} if \; T_{in}(t) \in \left[T_{discomfort,low} \;, T_{comfort,low}\right] \qquad \text{Eq. 4.3}$$

$$LC(T_{in}(t)) = \max\left\{0,1 + \frac{T_{comfort,up} - T_{in}}{\alpha_{warm}}\right\} if \; T_{in}(t) \in \left[\, T_{comfort,up}, T_{discomfort,up}\right] \qquad \text{Eq. 4.4}$$

According to the level of comfort in which the indoor temperature $T_{in,i}(t)$ of the room *i* at the current time step *t* lies, the user has several choices possible in order to adapt or restore its comfort. Occupants can operate on manually adaptive systems: clothes, windows and thermostat (Figure 9). The first rational reflex when being in thermal discomfort will be to alter clothing and/or open/close windows. After ten more minutes of discomfort, the time the body needs to adjust to the new thermal conditions, the next set of actions are determined by the profile of the occupant: if she/he puts the priority on her/his comfort, she/he will control heating devices in order to obtain the temperature wanted. In return, the occupant can choose to wait if she/he puts the environment forth.

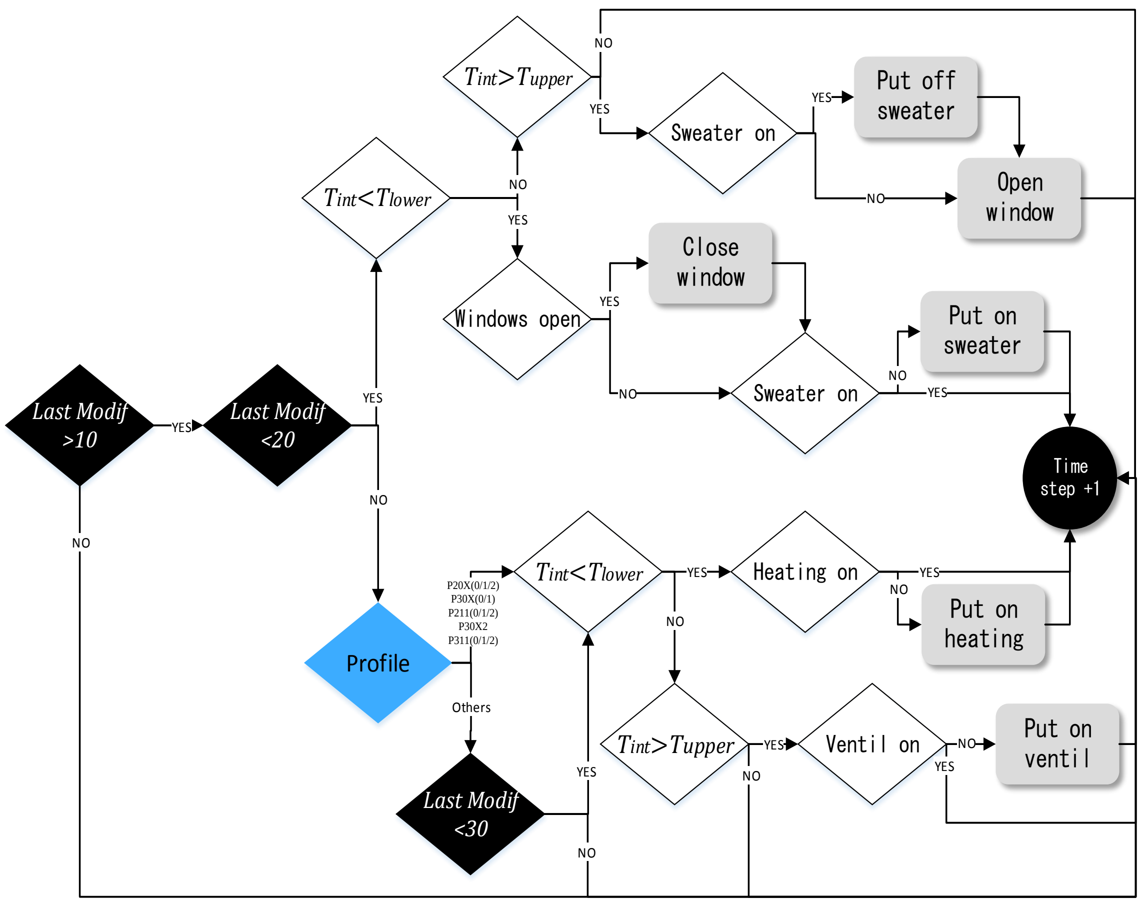

Figure 9. Comfort model process

Assessing energy consumption (block 3.3)

In order to assess the energy consumption, each device computes its energy consumption at each time step depending on its status (*Switch-On*, *Stand-by*, *Switch-Off*). The device status depends on the occupant activity (e.g., when cooking, the occupant turns on the cooking device). After its use, the device will be turned off or put in standby mode according to the occupants' profile and to the device category:

- Category A: independent of occupant presence (e.g., fridge)
- Category B: switch-on is user-dependent, switch-off is not (e.g., washing machine)
- Category C: switch-on and switch-off are user-dependent (e.g., television)

The process described Figure 10 had been implemented in order to (1) evaluate the running devices and then (2) determine the energy consumption. By the same reasoning, we made the hypothesis that the occupant switches on the light in the room where she/he is only at night, except during sleeping time. Table 18 from Section S5 of the SI details the default input data for devices such as the instantaneous electrical consumption of the household appliances according to its states. Several datasets have been used in an effort of collecting data comprehensively (ADEME, CCE and CRES, 2002; Almeida and Fonseca, 2006; INSEE, 2013; Grinden and Feilberg, 2015; Kreitz, 2016; McKenna and Thomson, 2016).

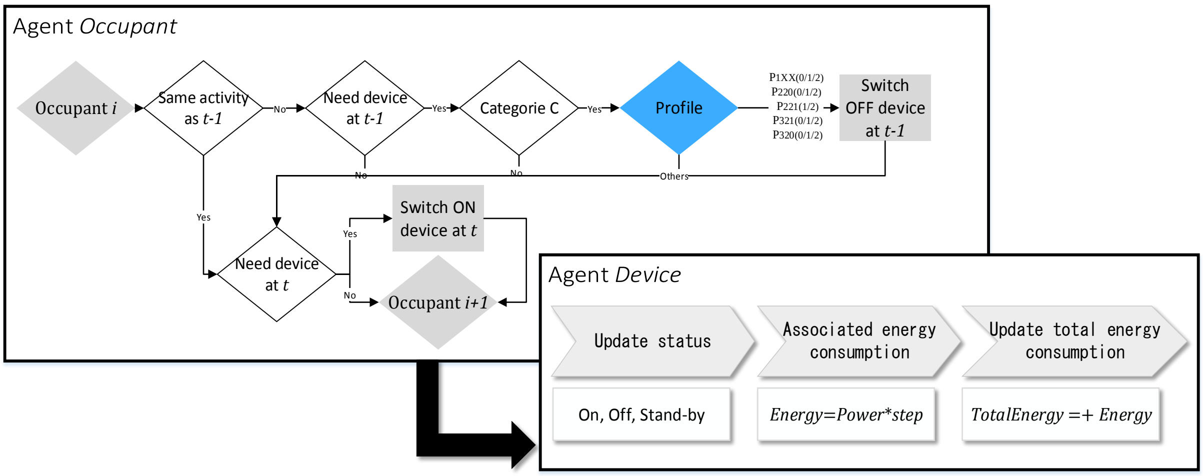

Figure 10. Energy consumption protocol followed at each time step

Results and discussion

Application

Case study presentation. The use of Li-BIM model is illustrated through an application of a dwelling situated in La Riche, a small town of North-Est of France. We have benefited from in-situ data in thirty instrumented house measured by the engineering office Cabinet Hacsé as part of a broader project on energetic consumption in a new district composed of energy efficient residential buildings. Every electrical appliance has been instrumented for one full year from May 2015 to May 2016 with an hourly step time. Surveys have been conducted in the form of individual interviews to analyse awareness of inhabitants about energy saving issues in a particular sociological context.

The dwelling under study is inhabited by two adults (Mr X., 64 years old, who is retired and Mrs X., 60 years old, who has a thirty-five hours a week job) and their 20 years old child Miss X. The BIM model represented Figure 11 has been realised with Revit (Autodesk) based on the final implementation plan of the house. Occupants' parameters have been initialised thanks to the interviews that give an excellent overview of their living standards, and the family profile has been set to low middle class, no green consciousness, comfort first and basic building knowledge. The 75m² house was designed as a low energy consumption building (< 50 kWh/m^2/year). To meet this objective, construction materials have been chosen to provide a high thermal mass to the structure. The building envelope is made of heavy concrete, external glass wood insulation and wooden cladding. The carpentry is composed of aluminium doors, and argon filled double glazing windows. Details of the house envelope composition and thermal properties are reported in Section S7.1 in the SI.

Figure 11. 3D modelling of the house with a BIM software (Revit ©)

Activities. The time spent daily by the three occupants on the different activities is compared with a survey on the time usage of 12000 households conducted by the French National Institute of Statistics and Economic Studies INSEE (Degenne et al. 2002). For five out of the seven proposed activities (*Sleep*, *Work*, *Go out*, *Shower* and *Eat*), results obtained for Mrs X. are very close to INSEE values (<5% difference). *Relax* and *Household chores* activities present differences of 48% and 39% respectively with INSEE value that could be explained by (i) interpersonal variation, (ii) age difference since INSEE proposes the agenda of a worker-age woman between 25 and 54 years old and (iii) data splitting in categories and their underlying definition. The daily percentage of time spent at each activity averaged over one year for both Mrs X. and Mr X. is presented in section S7.3 in the SI.

Energy consumption. The devices load curves for the X. family were generated over one day with a five-minute time step to compare the relevance of the power consumption pattern with the measured in-situ data (hourly monitoring). In Figure 12, the highest peak is likely to come from the use of energy-intensive consuming devices such as the oven or washing machine for example whereas the cooking activity is likely to cause the three peaks correlated to meal time (7 o'clock, 12 o'clock and 20 o'clock). The electrical consumption during the night can be explained by the devices still operating (e.g., refrigerators) or the devices in standby mode (e.g., TV). The peak of energy consumption simulated by Li-BIM model between 6 am, and 8 am corresponds to morning activities (cook breakfast and have a shower). It has been measured in-situ at 3 am, which could correspond to a delayed washing machine during the night electricity tariff or a late return home. These differences can be explained by the difficulty to find a "typical day", and the stochasticity of the model depicts this variability from one day to the next. However, the global representation of the phenomena that are likely to occur during one day (cooking, taking a shower, start a washing machine) is good since data are well correlated in time.

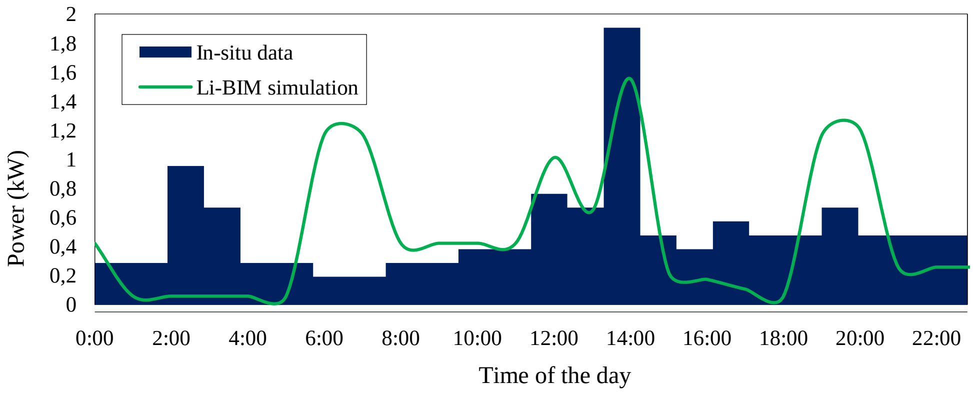

Figure 12. Total electrical consumption of the X. family over one day (Monday 07.09.2018)

Energy consumption results from May 2015 to May 2016 obtained thanks to Li-BIM are compared with the data collected in-situ as well as results simulated with the dynamic thermal simulation software Graitec©. The total energy consumption during one year simulated by Li-BIM is 3% higher than the one measured in-situ whereas the value obtained with Graitec© is 24% higher. Variability in household lifestyle cannot be perceived by traditional dynamic thermal simulation modelling which uses standard occupancy profiles and a temperature setpoint of 19°C. This variability is particularly striking in this case study since the interview reports particularly economical inhabitants. The comparison between the simulated annual indoor temperature profiles and the measured one are presented in section S7.2 in the SI.

Scenario comparison. Energy strategies adopted by the occupants are a trade-off between energy consumption and thermal comfort and are closely linked to the occupants' profile. To explore the lifestyle-induced variability on energy performance, the energy consumption and the level of comfort averaged over one year have been generated for the 30 profiles. For clarity, only five profiles are represented on Figure 13 (a), and the complete map is available in section S7 in the SI. To apprehend how much the building knowledge parameter influences both outputs (energy consumption and thermal comfort), profiles P3110 (low knowledge) and P3112 (high knowledge) are compared: the total energy consumption is decreased by 2% while the thermal comfort increases of 2%, mainly due to a higher comfort in summer when blinds can be closed in order to prevent heat from coming in. Green profiles (Px2xx) are among the profiles that consume the least amount of energy per square meter per person per year. The reduction can be mainly explained by lower electrical consumption of the appliances of class A, as well as a lower temperature setpoint of the heating devices. It results in a lower average winter indoor temperature, and the level of thermal comfort is decreased. This tendency tends to be inhibited by the individualism of some profiles (Pxx1x). For example, P3211 consumes 11% more energy than P3201 but achieve a level of comfort 3% higher. The impact of individualism on energy consumption is even more accentuated for non-green profiles: P3112 consumes 19% more energy than P3102.

Simulations have been repeated ten times for each profile to investigate the intra-profile variability. Vertical and horizontal error bars represent the standard deviation of the level of comfort and the energy consumption data set respectively. Profiles P3112 and P3110 are less stochastics than profiles P3201, P3102 and P3211. This can be explained by the fact that green conscious (Px2xx) and non-individualist (Pxx0x) profiles: (i) have a higher number of actions that are differentiated (e.g., add a sweat) and triggered partly by random variables and (ii) are more dependent on the interaction with the other occupants. The relative standard deviation of the level of comfort data set is one and a half times bigger than the one of the energy consumption data set. This discrepancy can be explained by the highly variable *sensitivity to cold*, part of which varies according to age and gender (Kaikaew *et al.*, 2018), and the other part is randomly assigned.

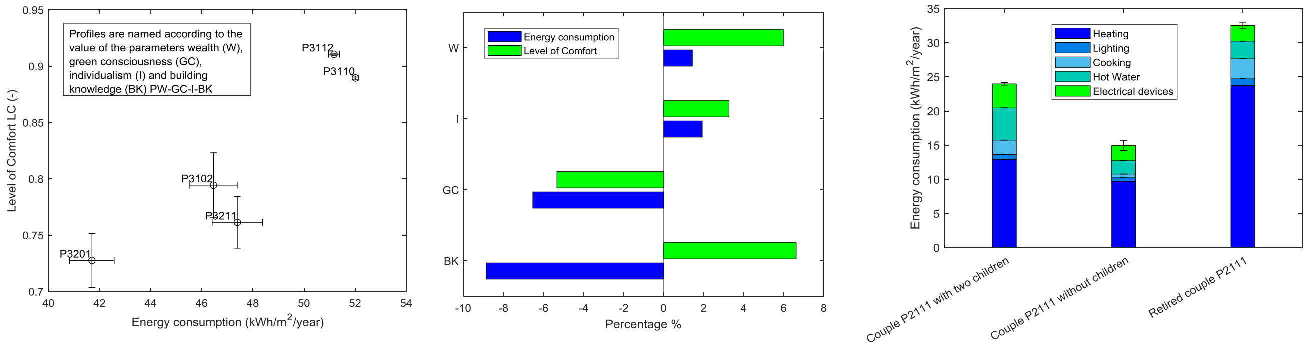

Figure 13. (a) Energy consumption and averaged level of thermal comfort over one year according to different occupants' profiles and **(b)** Influence of the wealth (W), green consciousness (GC), individualism (I) and building knowledge (BK) factors on the energy consumption and the level of comfort and **(c)** Energy consumption in different expenditure categories according to different household's composition

In order to quantify to which extent the occupant's attributes impact the energy consumption and the level of comfort, a design of the experiment is used (Montgomery C., 2007). Each one-year simulation is run ten times with a different combination of the four attributes used to generate the occupants' profile (wealth, green consciousness, individualism and building knowledge). The various sets of attributes considered in the design of the experiment are presented in section S7 (SI). Figure 13 (b) illustrates the sensitivity of the model to these four factors regarding energy consumption and the level of thermal comfort. The *Green consciousness* factor influences energy consumption and the level of comfort negatively. Both *Individualism* and *Wealth* factors influence energy consumption and the level of comfort positively. As seen in the previous paragraph, the interaction between green consciousness and individualism strongly affect both outputs. The *Building knowledge* factor influences the level of comfort positively and negatively energy consumption, which could help to achieve the best trade-off. This sensitivity analysis allows quantifying the interest in promoting a green consciousness or a better knowledge of the physical behaviour of a building to reduce the energy consumption while considering the comfort of the occupants. However, it remains theoretical and raises at least two questions: (1) what is concretely the meaning of a high green conscious and (2) how to ensure such building knowledge.

Besides, the dwelling energy performance for different household's archetype are presented in Figure 13 (c). This figure shows the amount of energy consumed for each energy expenditure categories on a per-capita basis for three household's compositions with the same profile (P2111). The retired couple consumes the most significant amount of energy per square meter per year because they use electrical appliances, cooking devices during the day. Besides, cold-sensitivity is more important for older people (Watts, 1972), which explains that more than 70% of energy consumption is due to heating devices. The energy consumption of the couple with two children is 27% higher than for the couple without children but smaller on a per-capita basis.

Discussion

Limitations. The application that has been presented cannot be used to validate our model as it would have required to compare the results for a hundred different buildings. However, the application demonstrates that Li-BIM is operational and offers significant improvements compared to traditional modelling approaches. As a consequence of the wide variety of real occupants' behaviour, it is difficult to ensure the capacity of the Li-BIM model to catch reality and thus produce precise forecasting.

Special attention should be paid to the input data regarding the occupants. They can come from data provided by the client if the future occupants are known or standardised profiles using typology of occupants as defined in the article. This latter can be chosen according to the type of the targeted population, household projections (for example the planning tool OMPHALE by INSEE 2008) or synthetic population generation tool (for example SPEW developed by Gallagher et al. 2017). However, it should be noted that Li-BIM has been developed for a French context that could be transposable in western Europe countries but is less likely to be relevant in another context. Considerable differences in occupant beliefs and adaptive capacity may arise from socio-cultural settings. For example, (Chappells and Shove, 2004) demonstrate that strategies of heating are related to cultural standards about comfort and even social interaction.

Perspectives. An interesting development would be the simulation of a multiple-unit residential building since it represents an important part of the built residential buildings (57% in 2015 in France according to (Logisneuf, 2017)). The adaptation of the model for such buildings would require two main improvements: (a) physical models able to consider different areas for the different apartments and (b) relation between the occupants from different households to integrate complex social interactions such as the dissemination of environmental friendly behaviour between neighbor's families or the establishment of collective strategies to improve waste management. In the same way, the behaviour model that has been presently developed is appropriate for residential dwelling, but the adaptation of some decision-making rules to the work context would make it usable for offices.

Finally, Li-BIM is currently implemented to evaluate thermal comfort, but the implemented actions of the agents already cover a good variety of domains (e.g., smoking or opening windows for air quality, shower or wash dishes for water waste management). Therefore, the impact of the occupant behaviours (and its comfort) on a wide variety of building behaviour could be investigated. At this stage of the project, Li-BIM is a promising approach to conduct scenario analysis based on design choices comparison. This approach paves the way for identifying design choices that can enhance the building operating use according to a specific occupant's archetype.

Besides, in the proposed model, BIM's object-oriented approach is used to agentify the functional elements of the building. This approach could be further exploited to simulate smart homes and investigate to what extent the occupants adopt this technological home environment, modifies occupants' behaviour and encourages the occupants towards greener energy behaviours.

Conclusion

In this article, we propose an agent-based model, Li-BIM, evaluating the comfort of the occupants of a residential building based on the modelling of their behaviour and social interactions. The model uses Artificial Intelligence techniques with a multi-agent system paradigm in which the human preferences and collaborative decision-making process are based on a Belief-Desire-Intention architecture. Intelligence is distributed between agents representing active entities (the occupants of the building) who interact with agentified objects (building components and devices). This architecture offers a credible representation of the reactive and deliberative behaviours of the occupants. To better represent the population variability both at the household and the occupant's level while achieving reliable results, users' profile and households' typologies have been settled.

Li-BIM model offers the opportunity to evaluate the performances of a set of design solutions with an approach sensitive to users' behaviour and their dynamic interaction with the building. By linking the numerical model of the building BIM with a behaviour model, it becomes possible for the architect to apprehend the effect of any design parameter modification on the occupants' comfort and in return to quantify the impact of the occupant's behaviour on the building performances.

The case study carried out shows that this model allows to quantify the thermal comfort of the occupants and the comparison with energy consumptions measured in-situ proves that results obtained with Li-BIM are consistent. The simulation of different household profiles demonstrates their impact on both the comfort of the occupants and the energy consumptions, allowing to quantify behavioural changes and paving the way to address guidance to occupants.

Li-BIM, as currently implemented, focuses on residential dwellings, a sector addressing strong economic issues and for which the occupants have a significant role. However, promising improvements can still be made as discussed: extension of the model for multi-dwelling building, adaption for office buildings and the addition of physical models. Li-BIM model has been structured to allow the adaptation of the model to specific uses or new developments.

Acknowledgement

The author would like to acknowledge Cabinet Hacsé for sharing their data from their measurement campaign.

References

Abdallah, F., Basurra, S. and Gaber, M. M. (2018) ‘A hybrid agent-based and probabilistic model for fine-grained behavioural energy waste simulation’, *Proceedings - International Conference on Tools with Artificial Intelligence, ICTAI*, 2017–Novem, pp. 991–995. doi: 10.1109/ICTAI.2017.00152.

Adam, C. and Gaudou, B. (2016) ‘Open Archive TOULOUSE Archive Ouverte (OATAO) BDI agents in social simulations : a survey’, 31.

Adam, C., Taillandier, P. and Dugdale, J. (2017) ‘Comparing Agent Architectures in Social Simulation : BDI Agents versus Finite-State Machines’, pp. 267–273.

ADEME, CCE and CRES (2002) *End-use metering campaign in 400 households of the European Community - Assessment of the Potential Electricity Saving, Project EURECO*. Available at: http://www.eerg.it/resource/pages/it/Progetti_-_MICENE/finalreporteureco2002.pdf.

Alfakara, A. (2010) ‘UNDERSTANDING OCCUPANTS ’ BEHAVIOURS USING DETAILED AGENT- BASED MODELLING PhD student , The Bartlett School of Graduate Studies , UCL , London , UK Senior lecturer , The Bartlett School of Graduate Studies , UCL , London , UK’, (June 2014).

Almeida, A. De and Fonseca, P. (2006) ‘Residential monitoring to decrease energy use and carbon emissions in Europe’, *International Energy …*, pp. 1–14. Available at: http://www.isr.uc.pt/~remodece/news/Paper_DeAlmeida.pdf.

Amouroux, É. *et al.* (2013) ‘Simulating human activities to investigate household energy consumption’, *Proceedings of the 5th International Conference on Agents and Artificial Intelligence*, 2, pp. 71–80. Available at: http://perso.limsi.fr/sabouret/ps/icaart2013.pdf%5Cnhttp://www.scopus.com/inward/record.url?eid=2-s2.0-84877934700&partnerID=40&md5=c6bd44ccfaf680bd92cdab3ca0243456%255Cnhttp://www.scopus.com/inward/record.url?eid=2-s2.0-84877934700%257B&%257DpartnerID=40.

Amouroux, E. and Sempé, F. (2013) ‘Dynamic organisation of the household activities for energy consumption simulation’, *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 7879 LNAI, pp. 13–24. doi: 10.1007/978-3-642-38073-0-2.

Andersen, R. K., Fabi, V. and Corgnati, S. P. (2016) ‘Predicted and actual indoor environmental quality: Verification of occupants’ behaviour models in residential buildings’, *Energy and Buildings*. Elsevier B.V., 127, pp. 105–115. doi: 10.1016/j.enbuild.2016.05.074.

Anderson, K. *et al.* (2014) ‘Impact of Social Network Type and Structure on Modeling Normative Energy Use Behavior Interventions’, *Journal of Computing in Civil Engineering*, 28(February), pp. 30–39. doi: 10.1061/(ASCE)CP.1943-5487.0000314.

Andrews, C. J. *et al.* (2011) ‘Designing buildings for real occupants: An agent-based approach’, *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans*, 41(6), pp. 1077–1091. doi: 10.1109/TSMCA.2011.2116116.

Azar, E. and Al Ansari, H. (2017) ‘Framework to investigate energy conservation motivation and actions of building occupants: The case of a green campus in Abu Dhabi, UAE’, *Applied Energy*. Elsevier Ltd, 190, pp. 563–573. doi: 10.1016/j.apenergy.2016.12.128.

Azar, E. and Menassa, C. C. (2010) ‘A conceptual framework to energy estimation in buildings using Agent based modeling’, in *Winter Simulation Conference*, pp. 3145–3156.

Balke, T. and Gilbert, N. (2014) ‘How Do Agents Make Decisions ? A Survey Introduction : Purpose & Goals Dimensions of Comparison Production Rule Systems’, 17(2014), pp. 1–30. doi: 10.18564/jasss.2687.

Barata, J. and Camarinha-matos, L. M. (2003) 'Coalitions of manufacturing components for shop floor agility – the CoBASA architecture', 2(1), pp. 50–77.

Belazi, W. *et al.* (2018) 'Uncertainty analysis of occupant behavior and building envelope materials in office building performance simulation', *Journal of Building Engineering*. Elsevier Ltd, 19(June), pp. 434–448. doi: 10.1016/j.jobe.2018.06.005.

Bourgais, M., Taillandier, P. and Vercouter, L. (2016) 'An agent architecture coupling cognition and emotions for simulation of complex systems', in *Social Simulation Conference 2016, Rome, September 19-23, 2016*.

Bourgais, M., Taillandier, P. and Vercouter, L. (2017) 'Enhancing the Behavior of Agents in Social Simulations with Emotions and Social Relations'.

Branco, G. *et al.* (2004) 'Predicted versus observed heat consumption of a low energy multifamily complex in Switzerland based on long-term experimental data', *Energy and Buildings*, 36(6), pp. 543–555. doi: 10.1016/j.enbuild.2004.01.028.

Bratman, M. (1991) 'Intentions, plans, and practical reason', *The Philosophical Review*, Vol. 100, pp. 277–284. doi: 10.2307/2185304.

Buso, T., D'Oca, S. and Corgna (2014) 'The influence of realistic schedules for the use of appliances on the total energy performances in dwellings', in *9th International Conference on System Simulation in Buildings*.

Caillou, P. *et al.* (2017) 'A Simple-to-use BDI architecture for Agent-based Modeling and Simulation', *In Advances in Social Simulation 2015*.

Calì, D. *et al.* (2016) 'Energy performance gap in refurbished German dwellings: Lesson learned from a field test', *Energy and Buildings*. Elsevier B.V., 127, pp. 1146–1158. doi: 10.1016/j.enbuild.2016.05.020.

Cao, J., Choi, C. H. and Zhao, F. (2017) 'Agent-based modeling of the adoption of high-efficiency lighting in the residential sector', *Sustainable Energy Technologies and Assessments*. Elsevier Ltd, 19, pp. 70–78. doi: 10.1016/j.seta.2016.12.003.

Carmenate, T. *et al.* (2016) 'Modeling Occupant-Building-Appliance Interaction for Energy Waste Analysis', *Procedia Engineering*. Elsevier B.V., 145, pp. 42–49. doi: 10.1016/j.proeng.2016.04.012.

Cayla, J., Allibe, B. and Laurent, M.-H. (2010) 'From Practices to Behaviors : Estimating the Impact of Household Behavior on Space Heating Energy Consumption', *ACEEE Summer Study on Energy Efficiency in Buildings*, (April 2015), pp. 26–38.

Chapman, J. (2017) *Multi-Agent Stochastic Simulation of Occupants in Buildings*.

Chapman, J., Siebers, P. O. and Robinson, D. (2018) 'On the multi-agent stochastic simulation of occupants in buildings', *Journal of Building Performance Simulation*. Taylor & Francis, 11(5), pp. 604–621. doi: 10.1080/19401493.2017.1417483.

Chappells, H. and Shove, E. (2004) 'COMFORT : A review of philosophies and Elizabeth Shove', *Indoor Air*, (March), pp. 1–37.

Chen, Y., Hong, T. and Luo, X. (2018) 'An agent-based stochastic Occupancy Simulator', *Building Simulation*, 11(1), pp. 37–49. doi: 10.1007/s12273-017-0379-7.

Cheng, J. C. P. *et al.* (2018) 'Automation in Construction Developing an evacuation evaluation model for o ff shore oil and gas platforms using BIM and agent-based model', *Automation in Construction*. Elsevier, 89(October 2017), pp. 214–224. doi: 10.1016/j.autcon.2018.02.011.

D'Oca, S. and Hong, T. (2015) 'Occupancy schedules learning process through a data mining framework', *Energy and Buildings*, 88(May), pp. 395–408. doi: 10.1016/j.enbuild.2014.11.065.

Degenne, A., Lebeaux, M.-O. and Marry, C. (2002) 'Les usages du temps : cumuls d'activités et rythmes de vie', *Economie et statistique*, 352(1), pp. 81–99. doi: 10.3406/estat.2002.7394.

Erickson, V. L. *et al.* (2009) 'Energy efficient building environment control strategies using real-time occupancy measurements', *Proceedings of the First ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings - BuildSys '09*, p. 19. doi: 10.1145/1810279.1810284.

Evora, J. *et al.* (2011) 'Agent-Based Modelling of Electrical Load at Household Level', *ECAL 2011: CoSMoS - Proceedings of the 2011 Workshop on Complex Systems Modelling and Simulation*, (May 2014), p. 12.

Gaetani, I., Hoes, P. J. and Hensen, J. L. M. (2016) 'Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy', *Energy and Buildings*, 121(March), pp. 188–204. doi: 10.1016/j.enbuild.2016.03.038.

Gallagher, S. *et al.* (2017) 'SPEW: Synthetic Populations and Ecosystems of the World', pp. 1–34. Available at: http://arxiv.org/abs/1701.02383.

Ghaffarianhoseini, A. *et al.* (2017) 'Building Information Modelling (BIM) uptake: Clear benefits, understanding its implementation, risks and challenges', *Renewable and Sustainable Energy Reviews*, 75(November), pp. 1046–1053. doi: 10.1016/j.rser.2016.11.083.

Grignard, A. *et al.* (2014) 'GAMA 1 . 6 : Advancing the art of complex agent-based modeling and simulation', *PRIMA 2013: Principles and Practice of Multi-Agent Systems*, pp. 117–131. doi: 10.1007/978-3-642-44927-7_ 9.

Grinden, B. and Feilberg, N. (2015) 'Analysis of Monitoring Campaign in Europe', (November), pp. 0–45.

Hajj-Hassan, M. and Khoury, H. (2018) 'Behavioral and parametric effects on energy consumption through BIM, BEM and ABM', in. doi: 10.3311/CCC2018-106.

Hauser, W. (2013) *Analysis and Agent-Based Modelling of Lifestyle Aspects Influencing the Residential Energy Demand in France and Germany*. doi: 10.1007/s13398-014-0173-7.2.

Hesselink, L. X. W. and Chappin, E. J. L. (2019) 'Adoption of energy efficient technologies by households – Barriers, policies and agent-based modelling studies', *Renewable and Sustainable Energy Reviews*, 99, pp. 29–41. doi: 10.1016/j.rser.2018.09.031.

Heydarian, A. *et al.* (2016) 'Lights, building, action: Impact of default lighting settings on occupant behaviour', *Journal of Environmental Psychology*. Elsevier Ltd, 48, pp. 212–223. doi: 10.1016/j.jenvp.2016.11.001.

Hicks, A. L., Theis, T. L. and Zellner, M. L. (2015) 'Emergent Effects of Residential Lighting Choices: Prospects for Energy Savings', *Journal of Industrial Ecology*, 19(2), pp. 285–295. doi: 10.1111/jiec.12281.

Hinker, J., Pohl, O. and Myrzik, J. (2016) 'Impact assessment of inhabitants on the economic potential of energy efficient refurbishment by means of a novel socio-technical multi-agent simulation Impact assessment of inhabit ... Impact assessment of inhabitants on the economic potential of energy e', (November). doi: 10.4225/50/5810785526981.

Howden, N. *et al.* (2001) 'JACK intelligent agents-summary of an agent infrastructure', *Management*, p. 6. doi: 10.1.1.133.8934.

INSEE (2008) *Omphale : un outil de projections de population*. Available at: https://www.insee.fr/fr/statistiques/1289993.

INSEE (2013) *Statistiques sur les ressources et les conditions de vie (SRVC) - Equipements de biens électroniques des foyers français*.

INSEE (2017) *Niveau de vie moyen des individus selon le type de ménage en 2015*.

INSEE (2018) *Insee Références - Ménages, Familles*.

Jang, H. and Kang, J. (2015) 'A stochastic model of integrating occupant behaviour into energy simulation with respect to actual energy consumption in high-rise apartment buildings', *Energy and Buildings*. doi: 10.1016/j.enbuild.2016.03.037.

Jensen, T., Holtz, G. and Chappin, É. J. L. (2015) 'Agent-based assessment framework for behavior-changing feedback devices: Spreading of devices and heating behavior', *Technological Forecasting and Social Change*. Elsevier B.V., 98, pp. 105–119. doi: 10.1016/j.techfore.2015.06.006.

Kaikaew, K. *et al.* (2018) 'Sex di ff erence in cold perception and shivering onset upon gradual cold exposure', *Journal of Thermal Biology*. Elsevier Ltd, 77(May), pp. 137–144. doi: 10.1016/j.jtherbio.2018.08.016.

Kaiser, F. G., Byrka, K. and Hartig, T. (2010) 'Reviving Campbell ' s Paradigm for Attitude Research'. doi: 10.1177/1088868310366452.

Kashif, A. *et al.* (2013) 'Simulating the dynamics of occupant behaviour for power management in residential buildings', *Energy and Buildings*. Elsevier B.V., 56, pp. 85–93. doi: 10.1016/j.enbuild.2012.09.042.

Klein, L. *et al.* (2012) 'Coordinating Cccupant Behavior for Building Energy and Comfort Management Using Multi-Agent Systems', *Automation in Construction*, 22, pp. 525–536. doi: 10.1016/j.autcon.2011.11.012.

Kreitz, T. (2016) *ADEME - Rapport final - Campagne de mesures des appareils de production de froid, des appareils de lavage et de la climatisation*.

Langevin, J., Wen, J. and Gurian, P. L. (2015) 'Simulating the human-building interaction: Development and validation of an agent-based model of office occupant behaviors', *Building and Environment*. Elsevier Ltd, 88, pp. 27–45. doi: 10.1016/j.buildenv.2014.11.037.

Lee, Y. S. and Malkawi, A. M. (2014) 'Simulating multiple occupant behaviors in buildings: An agent-based modeling approach', *Energy and Buildings*. Elsevier B.V., 69, pp. 407–416. doi: 10.1016/j.enbuild.2013.11.020.

LeGuay, M. (2016) *Confort thermique dans les lieux de vie*. Available at: http://eduscol.education.fr/sti/sites/eduscol.education.fr.sti/files/ressources/pedagogiques/3486/3486-confort-et-ambiance.pdf.

Liang, X. *et al.* (2019) 'Making incentive policies more effective: An agent-based model for energy-efficiency retrofit in China', *Energy Policy*, 126(November 2018), pp. 177–189. doi: 10.1016/j.enpol.2018.11.029.

Liao, C., Lin, Y. and Barooah, P. (2012) 'Agent-based and graphical modelling of building occupancy', *Journal of Building Performance Simulation*, 5(1), pp. 5–25. doi: 10.1080/19401493.2010.531143.

Liu, R., Du, J. and Issa, R. R. A. (2014) 'Human Library for Emergency Evacuation in BIM-based Serious Game Environment', in *Computing in Civil and Building Engineering*, pp. 544–551.

Logisneuf (2017) *Statistique Immobiliere*. Available at: http://www.logisneuf.com/statistique-immobiliere.html.

McKenna, E. and Thomson, M. (2016) 'High-resolution stochastic integrated thermal-electrical domestic demand model', *Applied Energy*. Elsevier Ltd, 165, pp. 445–461. doi: 10.1016/j.apenergy.2015.12.089.

Mckone, T., Rosenbaum, R. K. and Meent, D. Van De (2010) '- User manual -'.

Mirahadi, F., McCabe, B. and Shahi, A. (2019) 'IFC-centric performance-based evaluation of building evacuations using fire dynamics simulation and agent-based modeling', *Automation in Construction*. Elsevier, 101(January), pp. 1–16. doi: 10.1016/j.autcon.2019.01.007.

Mohandes, N., Sanfilippo, A. and Al Fakhri, M. (2019) 'Modeling residential adoption of solar energy in the Arabian Gulf Region', *Renewable Energy*, 131(2019), pp. 381–389. doi: 10.1016/j.renene.2018.07.048.

Montgomery C., D. (2007) 'Design and Analysis of Experiments', pp. 60–126. doi: 10.1002/qre.458.

Myers, K. (2001) 'Procedural reasoning system user's guide', *Artificial Intelligence Center, SRI International, Menlo …*. Available at: http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Procedural+Reasoning+System+User+'+s+Guide#3.

O'Brien, W. *et al.* (2017) 'A preliminary study of representing the inter-occupant diversity in occupant modelling', *Journal of Building Performance Simulation*. Taylor & Francis, 10(5–6), pp. 509–526. doi: 10.1080/19401493.2016.1261943.

Otte, G. (2005) 'Entwicklung und Test einer integrativen Typologie der Lebensführung für die Bundesrepublik Deutschland', *Zeitschrift für Soziologie*, 34(6), pp. 442–467. doi: Article.

Paatero, J. V. and Lund, P. D. (2006) 'A model for generating household electricity load profiles', *International Journal of Energy Research*, 30(5), pp. 273–290. doi: 10.1002/er.1136.

Peeters, L. *et al.* (2009) 'Thermal comfort in residential buildings: Comfort values and scales for building energy simulation', *Applied Energy*, 86(5), pp. 772–780. doi: 10.1016/j.apenergy.2008.07.011.

Peng, C. *et al.* (2012) 'Quantitative description and simulation of human behavior in residential buildings', *Building Simulation*, 5(2), pp. 85–94. doi: 10.1007/s12273-011-0049-0.

Perrels, A. and Weber, C. (2000) 'Modelling Impacts of Lifestyle on Energy Demand and Related Emissions', *Energy Policy*, 28, pp. 1–39.

Pokahr, A., Braubach, L. and Lamersdorf, W. (2005) 'Jadex: A BDI reasoning engine', *Multi-agent programming*, pp. 149–174. doi: 10.1007/0-387-26350-0_6.

Rasoulkhani, K. *et al.* (2018) 'Understanding fundamental phenomena affecting the water conservation technology adoption of residential consumers using agent-based modeling', *Water (Switzerland)*, 10(8). doi: 10.3390/w10080993.

Resource efficiency opportunities in the building sector, Communication from the commission to the European Parliament (2014).

Succar, B. (2009) 'Building information modelling framework: A research and delivery foundation for industry stakeholders', *Automation in Construction*. Elsevier B.V., 18(3), pp. 357–375. doi: 10.1016/j.autcon.2008.10.003.

Sun, Q. and Turkan, Y. (2019) 'A BIM Based Simulation Framework for Fire Evacuation Planning'. Springer International Publishing, pp. 431–438. doi: 10.1007/978-3-030-00220-6.

Svennevig, J. (2000) *Getting acquainted in conversation: a study of initial interactions (Vol. 64)*. John Benjamins Publishing. doi: 10.1075/pbns.64.

Taillandier, P. *et al.* (2016) 'A BDI agent architecture for the GAMA modeling and simulation platform'.

Taillandier, P. *et al.* (2017) 'Using parallel computing to improve the scalability of models with BDI agents'.

Tröndle, T. and Choudhary, R. (2017) 'Occupancy based thermal energy modelling in the urban residential sector', *WIT Transactions on Ecology and the Environment*, 224(1), pp. 31–44. doi: 10.2495/ESUS170041.

Truong, Q. T. *et al.* (2015) 'Multi-Agent Based Simulation XVIExploring agent architectures for farmer behavior in land-use change. A case study in coastal area of the Vietnamese Mekong Delta', (May 2015), pp. 1–12. doi: 10.1007/978-3-319-31447-1.

Valocchi, M. *et al.* (2007) 'Plugging in the consumer', p. 28. Available at: http://www-05.ibm.com/de/energy/pdf/plugging-in-the-consumer.pdf.

Walzberg, J. *et al.* (2018) 'An Agent-Based Model to Evaluate Smart Homes Sustainability Potential', *IEEE*.

Watts, A. J. (1972) 'Hypothermia in the Aged : A Study of the Role of Cold-Sensitivity', 126, pp. 119–126.

Wooldrige, M. (2009) *An Introduction to MultiAgent Systems*.

Yan, D. *et al.* (2015) 'Occupant behavior modeling for building performance simulation: Current state and future challenges', *Energy & Buildings*. Elsevier B.V., 107, pp. 264–278. doi: 10.1016/j.enbuild.2015.08.032.

Ying, Z., Zi-Min, Z. and Jian, C. (2017) 'EvacAgent: A Building Emergency Evacuation Simulation Model Based on Agent', pp. 1–7. doi: 10.1145/3080845.3080872.

Zhang, J. and Issa, R. R. A. (2015) 'Collecting Fire Evacuation Performance Data Using BIM-Based Immersive Serious Games for Performance-Based Fire Safety Design', in *International Workshop on Computing in Civil Engineering*. Austin, Texas. doi: 10.1061/9780784479247.076.

Zhang, T., Siebers, P.-O. and Aickelin, U. (2011) 'Modelling electricity consumption in office buildings: An agent based approach', *Energy & Buildings*, 43, pp. 2882–2892. doi: 10.1016/j.enbuild.2011.07.007.

Zhang, T., Siebers, P. O. and Aickelin, U. (2016) 'Simulating user learning in authoritative technology adoption: An agent based model for council-led smart meter deployment planning in the UK', *Technological Forecasting and Social Change*. The Authors, 106, pp. 74–84. doi: 10.1016/j.techfore.2016.02.009.

Zuppa, D., Issa, R. and Suermann, P. (2009) 'BIM's Impact on the Success Measures of Construction Projects', *Computing in Civil Engineering*, (352), pp. 56–58.