Towards Better Buildings Performance Estimations?A Framework for Integrating Dynamic Occupant Behaviour in Dynamic Buildings Simulation Tools.

Alaa Alfakara[1], Ben Corxford[1]
[1]UCL Institute of Environmental Design and Engineering (IEDE), London, UK

Abstract

This paper presents the development of a co-simulation system that links an Agent-Based Model (ABM), which simulated dynamic occupant behaviour, to a dynamic building simulation model (DBSM). The ABM was linked to EnergyPlus using the Functional Mock-up Interface standard (FMI), allowing for a real-time exchange of inputs/outputs at short time intervals between the two dynamic models. The ABM does not yet contain many of the requisite features for a fully-fledged ABM model, but does provide a robust framework for building up to a complete feature-set. The results of the co-simulation system showed a considerable variation when compared to a conventional DBSM simulation. The study has delivered insights into the importance of accounting of dynamic occupant behaviour, and has provided a framework for a new approach to enhance occupant behaviour modelling in current DBSM models.

Introduction

The latest Synthesis Report produced by the Intergovernmental Panel on Climate Change (IPCC), confirmed that human activities are progressively influencing the climate system. The built environment has been identified as one of the most effective areas with the largest potential for significantly reducing GHG emissions (IPCC, 2014). This led to the introduction of building regulations to set the standards for energy efficiency in buildings, and building simulation models are now widely used as a cost-effective method to assess buildings' impact during the design process to support energy efficient design and operation of buildings, and to provide compliance with performance-based energy regulations (Foucquier et al., 2013). However, there is a growing concern regarding the disparity between predicted and actual energy performance of buildings, the so-called "performance gap", which hinders the application of DBSMs in the industry (De Wilde, 2014). Many factors contributing to the performance gap are pointed out in literature, which include the lack of knowledge about building details and the underlying physical processes, the uncertainty regarding the systems assembly and the quality of building components, the lack of information on actual energy performance of existing building and, the unpredictable behaviour of future occupants (Menezes et al., 2012; Hoes et al., 2009). However, there is a growing consensus that the over-simplification and the static representation of occupants and their behaviour in DBSM, amongst other factors, contributes to the disparity of energy consumption estimations. Current DBSMs implement the lowest level of complexity in modelling occupant behaviour through the deployment of diversity factors or profiles, that are fixed and provided as a priori schedules (Mahdavi and Tahmasebi, 2016). Schedules are defined independently of the predicted conditions during the simulation, and occupant behaviours are modelled as fully foreseeable and repeatable parameter. Moreover, they consider occupants as static entities in the modelling process with similar energy consumption patterns and profiles and do not account for occupancy-related behaviour (Yan et al., 2015). Energy consumption in buildings is widely affected by the behaviour of their occupants, with many studies suggesting significant variations of energy consumption between similar buildings as the result of varying occupant behaviour (Hoes et al., 2009; Guerra Santin, 2011; Fabi et al., 2013). Occupant behaviour greatly influences energy use directly and indirectly by interacting with building systems such as heating systems and windows (Peng et al., 2011). Therefore, understanding occupant behaviour is crucial to achieving an in-depth understanding of buildings energy use, and research efforts have been focusing on understanding the relationship between occupants and buildings (Hensen and Lamberts, 2012; Motuziene and Vilutiene, 2013). Many occupant behavioural models have been developed to simulate realistic occupant behaviours in buildings based on stochastic or probabilistic approach. Although this approach provides a better representation of occupant in comparison to the deterministic approach (a priori schedule), however, these models require a high number of runs to achieve reliable results, and the model cannot reflect the change of behaviour over time due to a sudden event as the model has to re-run for many iterations (Wagner et al., 2013). A more complex simulation framework is emerging that uses Agent-based models (ABM). ABM is an approach for modelling complex systems with interacting, autonomous agents, which is gaining popularity in many fields such as engineering, economics, biology and social sciences (Macal and North, 2010). ABM is capable of modelling individuals, their mutual interactions and the interaction with the building systems, and their response to change through adaptation and learning (Gilbert, 2004; Held et al., 2014). Thus, it offers the potential to advance the understanding of the impact of occupant behaviour on energy consumption. Despite the growing research in using ABM to model energy-related occupant behaviour, it has not been interoperated in current DBSMs. The majority of research on occupant behavioural models did not consider implementing these models into DBSMs in a dynamic real-time manner and was developed in isolation of addressing the contribution of occupant behaviour to the performance gap. The preceding discussion highlights the importance of integrating dynamic occupant behaviour models with DBSMs, as it will enable researchers and practitioners to simulate and study occupant behaviour in buildings, include the change of behaviour over time, and helping to match simulated results with the actual energy use. Consequently, this paper presents the development of a co-simulation system that dynamically links ABM of occupant behaviour to EnergyPlus. The objective of developing this co-simulation system is twofold: a) develop a framework to model dynamic occupant behaviour in buildings and; b) to dynamically link occupant behaviour to a DBSM.

The development of the co-simulation system

Occupant behaviour is always a dynamic entity, changing over time and reacting to its environment. Therefore, the model must also be dynamic, and allow representing the complex and nonlinear processes within the system. ABM was selected as a modelling approach as it provides a new dimension to the range of issues that can be addressed with formal means. Opposite to the reductionist notions, with ABM it is possible to formalise how occupants actions and decision making occur, allows addressing change in behaviour, adaptation and learning. Most importantly, ABM offers flexibility due to the iterative model construction process, which is particularly useful when attempting to model complex behaviour like occupant behaviour (North and Macal, 2007). The ABM was linked to the widely used EnergyPlus (EnergyPlus, 2014) building simulation model using the Functional Mock-up Interface standard (FMI)(FMI, 2015).

The Agent-based Model

The ABM was built and developed in Repast Simphony (Java) platform (Argonne National Laboratory, 2015). The ABM modelled a case-study of an existing energy-efficient dwelling located in Gosport, UK, and it included three types of agents: Person-agent representing the occupant, a Room-agent representing a room in the dwelling and a Flat-agent that represented the dwelling. In exploring the framework to develop ABM, different methods were developed to test how to model behaviours and to conceptualise what would influence occupant behaviour when confronted with a thermal discomfort. The following methods were proposed:

1. **Family types:** Four family types were included within the ABM, and each family type was identified by a unique location probability (for every person for each room in the flat), and a unique occupancy profile (describing occupancy pattern) based on dummy data. Family types considered within the ABM included the following:

   - Family type (1): a family of a young working couple.
   - Family type (2): a single working person.
   - Family type (3): a family of four members. A working parent, a child at school, a stay at home parent and an infant.
   - Family type (4): a family of an elderly couple.

   The occupancy patterns in this study have been derived from the information gained from literature (Marshall et al., 2016; Guerra Santin, 2011), to identify common household scenarios to reflect a diversity of typical UK households, although not claiming to represent all households.

2. **Personal thermal thresholds:** Every occupant (Person-agent) had a temperature thresholds profile that was based on the principles of adaptive comfort theory, where acceptable comfort ranges were defined and Person-agents attempted to maintain the indoor temperature within their thermal comfort range. For the sake of simplicity, the ABM model focused on indoor mean air temperature as a measure to define comfort ranges in the model. The calculation of the "most likely comfort temperature T_c", was achieved by deploying the adaptive comfort theory developed by Nicol and Humphreys (2002). CIBSE Guide-A (CIBSE, 2015) uses the exponentially weighted running mean $T_{out,rm}$ of the daily mean temperature as a predictor where:

$$T_c = \begin{cases} 22.6 + 0.09 \times T_{out,rm} & (T_{out,rm} \leq 10°\text{C}) \\ 18.8 + 0.33 \times T_{out,rm} & (T_{out,rm} > 10°\text{C}) \end{cases} \tag{1}$$

   Moreover, the British Standard European Norm (BS EN) 15251:2007 introduced the concept of "acceptable indoor comfort temperatures" for four categories of buildings. The classification is related to the ability of the occupants to modify and tolerate their environments (British Standards, 2007). The identification of "most likely

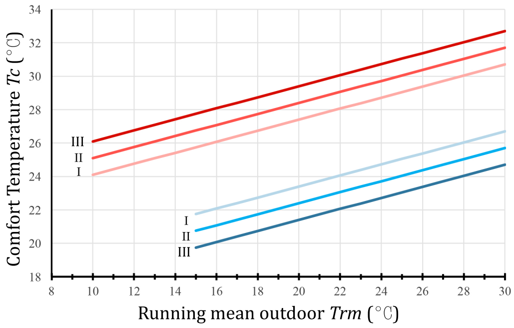

Figure 1: Indoor comfort temperatures for free running buildings as a function of the running mean outdoor temperature, for the three building categories ((British Standards, 2007))

comfort temperature T_c", and the British Standard categories was adopted in the design of family types used in the ABM. Families of Type 3 and Type 4 are of *Category I*, where Person-agents were sensitive and vulnerable to wide change of indoor temperature, and maintaining thermal comfort was the main priority. Whereas Family type 1 and type 2 are of *Category II*, where Person-agents were less vulnerable and would tolerate more thermal discomfort.

3. **Environmental attitude:** Environmental attitude as a method of modelling occupant behaviour was facilitated. Under "stronger" environmental attitude, Person-agents would compromise slight thermal discomfort to save energy. Two scenarios were considered to represent the impact of different environmental attitude: 1) Comfort-scenario with Person-agent behaviours were directed to maintain their thermal comfort range; 2) Conserving-scenario where Person-agents were trying to save cost of energy consumption by tolerating slight thermal discomfort.
4. **Seniority:** The concept of seniority was introduced in this model where the Person-agents with a higher seniority would be the one responsible for decision making when presented with another Person-agent in the same room. It was aimed to introduce conflict between different Person-agents with different personal thermal profiles.

The Person-agent class included all the information regarding the occupant, where every Person-agent had unique attributes such as ID, seniority, the location within the dwelling, the time where occupant was at home or not, window opening probability, and the adaptive comfort range. The Room-agent class held attributes such as ID, room temperature, the status of window, the heating system, mechanical ventilation with heat recovery (MVHR), and the number of occupants in the room.
The range of agents' (occupant) interactions with the dwelling included the following:

1. Turning the heating on or off.
2. Deciding on the thermostat set-point.
3. Opening windows.
4. Using the fan boost of the MVHR of the flat.

1-Heating System: Person-agents interactions with heating system control (turning on and off, and setting the thermostat temperature) were simulated. For turning heating on/off during winter, the following contingencies were considered: (1) turning on the heating system when Person-agent wakes up and turn it off before going to sleep, (2) turning on the heating system when Person-agent comes back home, and turning it off before leaving the dwelling. As for setting the thermostat, it was simulated following the Person-agent decision to turn on the heating system, and it was determined by the Person-agent based on the personal thermal comfort range, which was defined by using Equation 1, and the category of the family.
2-Window opening: For the window open model, two contingencies were considered: (1) opening the window when the occupant feels hot (2) allowing for habitual opening of the window for morning ventilation. For the window closing model, the two contingencies were considered: (1) closing the window when leaving the dwelling (2) closing the window when feeling cold. The function to calculate the probability of opening the window implemented the algorithm that was developed by Schweiker et al. (2012), which validated Rijal et al. (2008) algorithm for the application in residential buildings. At every timestep, the probability of observing a window to be open is independently determined by a logistic model including indoor temperature T_i and outdoor air temperature $T_{outdoor}$ as predictors. Schweiker et al. (2012) thus refined Rijal et al. (2008) logistic regression model equation as follows:

$$log\frac{p}{1-p} = 0.711 + (-0.3077) \times T_i + 0.3813 \times T_{out} \quad (2)$$

From regression Equation 2 the probability P_{op} of opening the window can then be computed as:

$$P_{op} = \frac{\exp(0.711 + (-0.3077) \times T_i + 0.3813 \times T_{out})}{1 + \exp(0.711 + (-0.3077) \times T_i + 0.3813 \times T_{out})} \quad (3)$$

3-MVHR: As for MVHR model, the Person-agent interacted with the system by increasing the exhaust fan speed in the kitchen and the bathroom. For increasing the exhaust fan speed, two contingencies were considered:(1) increasing the fan exhaust when occupying the kitchen (2) increasing the fan air exhaust when using the bathroom. Then the air flow was resumed to default flow rate once Person-agent left the space.
The Room-agent class was responsible for checking if there was any Person-agent in the room at every timestep, and if so, provided the Person-agent with the current internal condition so the Person-agent would

decide whether to perform any action with any system based on their comfort status. Then the Room-agent would update the systems status and mapped the variable to the Flat-agent. The Flat-agent is the collection of Room-agents and Person-agents representing the dwelling. The Flat-agent itself acted as the controller, as it was responsible for governing the co-simulation between EnergyPlus and the ABM. It controlled the flow of input/ output between the two models and determined the simulation period in EnergyPlus model. The Flat-agent class provided Person and Room-agents with instantaneous external temperature and the updated internal temperature from EnergyPlus at every timestep, and provided EnergyPlus with the resulting interactions with the dwelling's systems. The real-time exchange of these input/output was facilitated through the deployment of FMI standard.

Functional Mock-up Interface (FMI)

The coupling of DBSM with external programs was realised either by creating specific interfaces for the external programs in the DBSM source code (Hensen, 1999; Zhai et al., 2002) or using The Building Controls Virtual Test Bed (BCVTB) middleware (Nouidui and Wetter, 2014). The major limitations of the former are the computational complexity and the lack of re-usability since the interface is only for a specific program. For the latter, having an additional transaction layer into the communication increases the complexity of the co-simulation. This led to the development of Functional Mock-up Interface (FMI) (FMI, 2015), which is a standard that acts like a communication port allowing different programmes to "talk" to each other and exchange information. FMI is an open, independent and non-proprietary standard to support both model exchange and co-simulation of dynamic models during run time, using a combination of Extensible Markup Language XML-file, C-header files, and C-code in source or binary form (MODELISAR, 2015). A simulator exported with FMI is called a Functional Mock-up Unit (FMU), which is a zipped file (with file extension .fmu) containing all of the model files to allow for the co-simulation process.

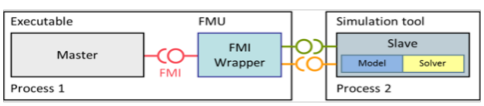

Figure 2: Co-simulation with tool coupling. Source: Modelsar Association (2015).

EnergyPlus was exported as an FMU for co-simulation using the Functional Mock-up Interface (FMI) standard version 1.0, to allow importing EnergyPlus within the ABM model. *EnergyPlusToFMU*, a python package developed by Berkeley Lab Simulation Research Group (Nouidui et al., 2015), was used to export EnergyPlus as an FMU for co-simulation. The general workflow for generating FMU, presented in Figure 3, starts by creating a *temporary* EnergyPlus input file (.idf) of the building to be modelled, which would include information related to the FMU such as the name of the FMU and properties of the FMU variable including their names and input/output types, besides the regular EnergyPlus input and information about the modelled building (geometry, materials, systems etc.).

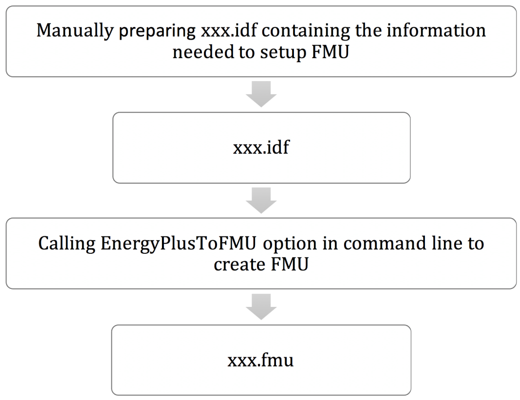

Figure 3: Workflow for the creating FMU

Once the temporary .idf file has been configured correctly with all the FMU inputs/outputs have been identified and mapped within EnergyPlus .idf file, EnergyPlusToFMU tool will be called using the command-line, requesting EnergyPlusToFMU to run and create an FMU named after the .idf file name. Once the EnergyPlus is exported as an FMU, it can be imported to the ABM model to conduct the co-simulation. As EnergyPlus will be imported with the ABM, therefore, ABM acts as a co-simulation master which is responsible for initiating, running and terminating the co-simulation.

The realisation of the co-simulation system

The ABM was developed to allow implementing the FMI wrapper to import the created EnergyPlus-FMU. To establish co-simulation between the ABM and EnergyPlus-FMU, the following methods have to be performed in the ABM:

- Unpacking the FMU,
- Creating an instance of the FMU,
- Initializing the FMU,
- Setting the input variables of the FMU,
- Getting the output variables of the FMU,
- Conducting the time integration,
- Terminating and freeing the memory of the FMU.

A wrapper for importing EnergyPlus-FMU was developed within the ABM model. The ABM wrapper was built upon a Java library called JFMI (Ptomely, 2013), that translated some of the main functionality of FMI standard to Java syntax. The JFMI had to

be modified to be compatible with EnergyPlus-FMU, and to suit the particularities of Repast platform. The wrapper developed within the ABM allowed for parsing the EnergyPlus-FMU created in accordance to the methods explained earlier, and then integrating it in the ABM simulation.
An overview is given in the following flowchart (Figure 4), which illustrates the overall process of the ABM co-simulation process. All the logical decision points, which are represented as a yellow diamond shape, were applied to every Person-agent in each room in the flat. At the very first time step, the ABM started with an initial room temperature of 18^{o}C in winter and 21^{o}C in summer simulation periods, windows were assumed to be closed, and the MVHR was assigned to default flow rates, which were all defined in the ABM model. The following procedures, apart from the initialisation and termination of the simulation, were repeated until the simulation terminated. The entire length of simulation was calculated in seconds to allow the synchronisation with EnergyPlus, and the step size was set to 15 minutes (also calculated in seconds) in both ABM and EnergyPlus. Upon the start of the co-simulation, the the following function were performed, at every time step until the co-simulation terminated, which are summarised as follows:

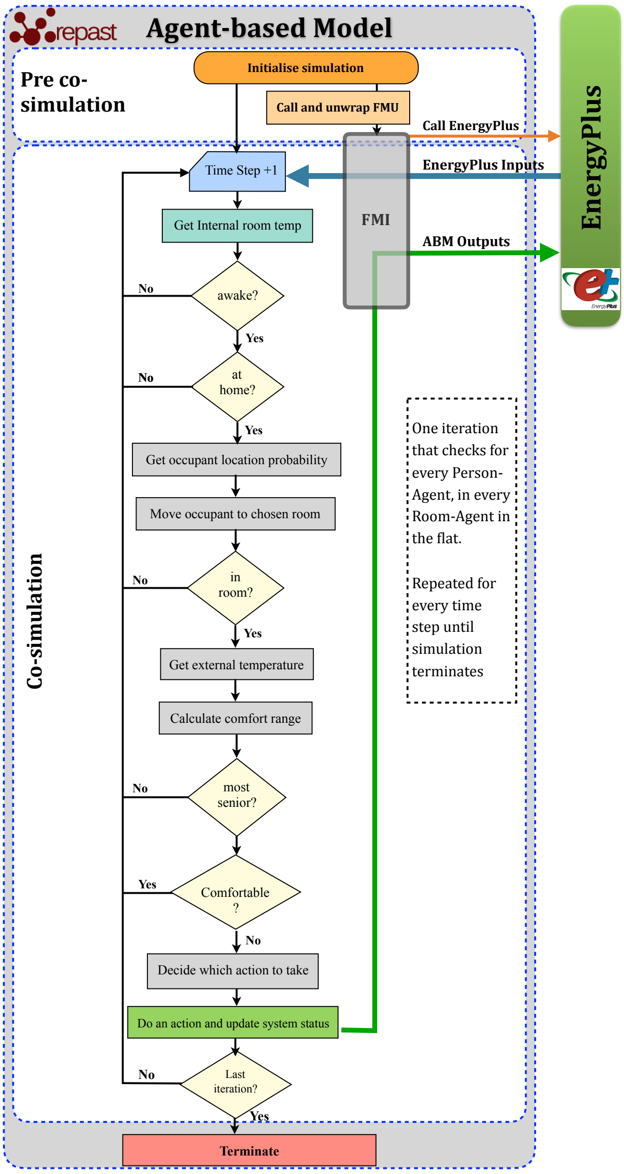

Figure 4: The co-simulation flowchart

- For every time step, and for every occupant, check if the Person-agent (occupant) was present at home, then if the Person-agent was at home checked whether Person-agent was awake. This function returned a true/false value for *Home?* and *Asleep?* boolean variables of the Person-agent. If the Person-agent was not at home or asleep, its location was updated (if asleep), and all systems were assumed off apart from the MVHR, and the simulation moved to the next time step. Otherwise, the simulation proceeded to the next check.
- If the Person-agent was at home and awake, the probability of being in a particular room was calculated. Based on probability, the model determined the location of the Person-agent, as the Person-agent would move to the Room-agent with the highest probability. Consequently, each Room-agent declared the number of Person-agent(s) present at that time step.
- After moving to the Room-agent, based on the internal temperature and on the individual Person-agent comfort range, the Person-agent would decide whether to turn on/off the heating, setting the thermostat set point, and whether to open/close the windows. The air flow of the MVHR remains constant unless the Person-agent was present in the kitchen or bathroom where the Person-agent would boost the fan extraction. When more than one Person-agent were present in the same room, the Person-agent with the highest seniority was the decision maker.
- Every action taken by the Person-agent to modify any of the systems within the dwelling was mapped as an input to EnergyPlus through the FMI interface, and EnergyPlus would perform *one step* of simulation. EnergyPlus outputs (the updated internal indoor temperature for every room and the external temperature) were mapped to the ABM through the FMI interface, and used in the following timestep of the simulation.
- The model checked whether to terminate the co-simulation. If the check was negative, the simulation timestep was increased by one, and the model reiterated through the aforementioned procedures. Otherwise, the model terminated.

It is important to point that the flow of exchanging input/output between ABM and EnergyPlus started with the ABM providing the input to EnergyPlus first, based on Person-agent behaviour, then EnergyPlus was requested to perform one simulation timestep based on the ABM input, which in return, produced outputs that were used by ABM for the next co-simulation timestep. The order of these methods is crucial which is illustrated in the following Figure 5.

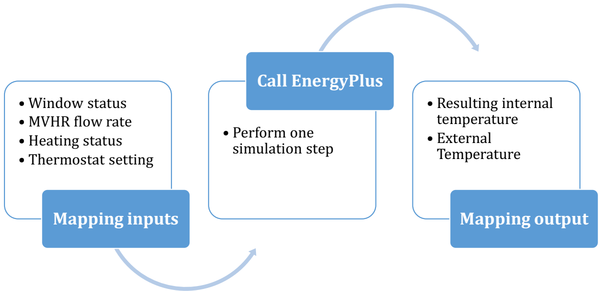

Figure 5: Co-simulation process of mapping input/output and conducting one co-simulation step.

The Case Study

In an aim to verify the co-simulation system, a case study of an existing energy-efficient residential block, located in Gosport Hampshire, was selected. The building (Block-B) is three stories high, and encompasses twelve flats, four flats on each floor. Block-B was monitored by Zero Carbon Hub (ZCH) as a part of the Building Performance Evaluation Programme (BPE) funded by Innovate UK (ZCH, 2015). Data included internal conditions such as temperature and humidity besides gas, electricity and water consumption. An EnergyPlus model (EnergyPlus V8.3) was created for the entire Block B buildings. Flat B5 , which is occupied by a pensioner, on the first floor (highlighted in red in the following figure 6) was used for co-simulation as it had most extensive data, and to allow assessing of the impact of different occupancy in the same dwelling. A weather data file for Gosport,

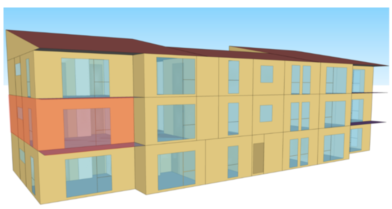

Figure 6: EnergyPlus model of the case-study building

UK was used for the simulation, and the EnergyPlus model was developed based on the design specifications of the materials and the systems as provided by ZCH. Systems modelled included the heating system, domestic hot water and MVHR, in addition to lighting and electrical equipment. Given that there is limited guideline on residential occupancy, the guideline provided by the National Calculation Methods (NCM) (Energy Performance of Buildings Directive, 2015) were used while constructing the model. NCM specifies occupancy schedules during the weekdays and weekends, equipment use schedules, lighting levels and schedules, heating, and domestic hot water requirements to represent a "typical" occupancy. The EnergyPlus model of the case study building was exported as an FMU that could accept the following inputs:

1. Heating temperature set-point.
2. Heating status (On/Off).
3. Window opening status.
4. MVHR flow rate for every room in the dwelling.

While the FMU output was set to:

1. Room mean air temperature (for every room in the dwelling)
2. External temperature

The co-simulation period spanned over an entire year, with a 15 minutes timestep interval, and modelled the dynamic interactions of occupants with the aforementioned systems that were exchanged at every timestep with EnergyPlus through the FMI interface. The co-simulation was tested extensively for all family types, under both comfort and conserving scenarios, to ensure correct functioning of the co-simulation system.

Results

To allow comparison with the co-simulation system results, a conventional EnergyPlus simulation was performed to cover a period of one year starting from the beginning of August 2012 till the end of July 2013 to match the monitoring period. Figure 7 shows the annual electricity and gas consumption (for space heating) estimated by EnergyPlus, compared to the monitored consumption provided by ZCH for the same period. The results show a significant disparity between estimated and actual energy consumption, as EnergyPlus overestimated the annual energy consumption by nearly 40%.

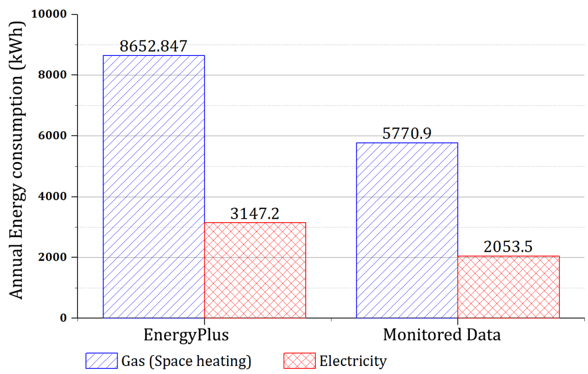

Figure 7: A comparison of actual and simulated annual energy consumption in flat B5

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The following Table 1 presents a comparison of the annual energy consumption obtained by the conventional EnergyPlus simulation and the co-simulation under comfort and conserving scenarios for all family types. Based on occupancy types, Family type 1 (working couple) can be compared to the conventional EnergyPlus simulation, while Family type 4 (Pensioners) can be compared to the actual occupancy of the dwelling. Under the conserving-scenario gas consumption estimation was reduced by up to 64% in comparison to conventional EnergyPlus estimations, while for electricity it was reduced by up to 11%.

Table 1: Comparison of co-simulation results under comfort and conserving scenarios and conventional EnergyPlus estimations.

(kWh)	Monitored data	EnergyPlus conventional Simulation	Co-simulation Type1	Co-simulation Type2	Co-simulation Type3	Co-simulation Type4
Gas: Comfort	5771	8653	3654	3657	5374	4986
Gas: Conserve	5771	8653	3153	3211	4290	4301
Electricity: Comfort	2054	3147	2989	2988	3121	3033
Electricity: Conserve	2054	3147	2994	2800	3115	3029
Percentage of Change (%)						
Gas: Comfort/ Conventional		--	-58	-58	-38	-42
Gas: Conserve/ Conventional			-64	-63	-50	-50
Gas: Conserve/Comfort			-14	-12	-20	-14
Electricity: Comfort/ Conventional		--	-5	-5	-1	-4
Electricity: Conserve/ Conventional			-5	-11	-1	-4
Electricity: Conserve/ Comfort			0	-6	-0	-0

The variation in gas consumption, amongst the different family types, was more dominant as the interactions of Person-agent included setting the thermostat and turning the system on/off. However, the variation in electricity was less significant due to limiting the interactions of Person-agents to the fans of MVHR, while the interactions with the rest of electrical systems/ equipment were not considered at this stage. Results illustrate that Person-agents behaviour, amongst different family types, exhibited a variety of energy consumption patterns and different load peaks. For instance Figure 8 illustrates that dur-

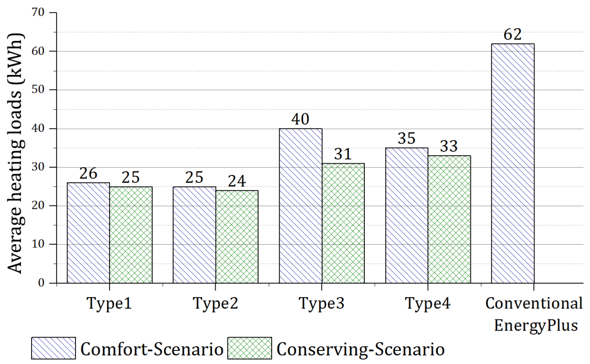

Figure 8: Comparison of heating loads during the coldest week for all family types under comfort and conserving scenarios.

ing the coldest week (15-19Jan), the average heating loads between the four family types varied by up to 39% more heating loads for family type3 in comparison to family type2. When compared to conventional EnergyPlus simulation, the average heating load was reduced by more than 50% for family type 1.

When it comes to estimating internal temperatures, Figure 9 shows the frequency distribution of simulated and recorded internal temperature of the living room throughout the entire simulation period. It shows that EnergyPlus estimations results in a different distribution: a bimodal distribution with two dominant frequencies of 18^oC and 22^oC is observed. The bimodal shape is a result of the magnitude and duration of upper and lower bounds of internal temperatures estimated by EnergyPlus. The distribution

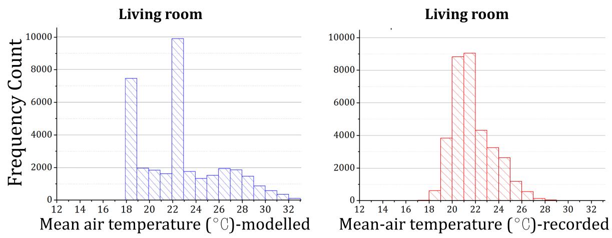

Figure 9: Recorded and simulated internal temperature frequency distribution in the living room throughout the entire simulation period.

of recorded temperatures is shown as a right-skewed distribution, with a well-defined peak at 21^oC and 22^oC. Although, similar to the assumptions in EnergyPlus model, during the heating season the internal temperature remained in the range of $19-21^oC$, the bimodal shape is not observed in the monitored internal temperature. This can be attributed to the way EnergyPlus estimates the maintenance of heat and heat loss. Figure 10 presents the frequency distribution of internal temperature in the living room, throughout the entire year obtained from the co-simulation.

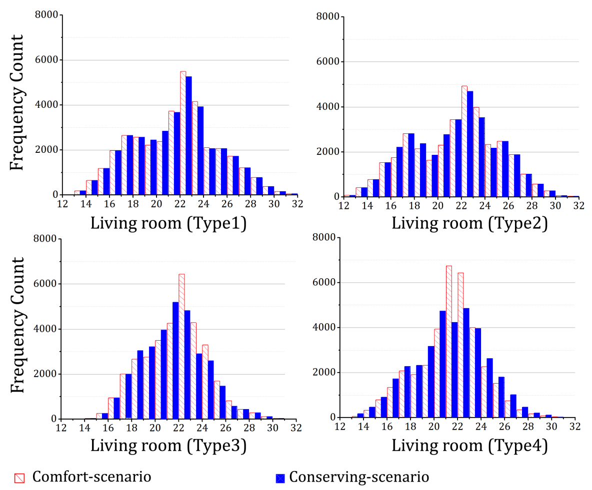

Figure 10: Modelled living room temperature frequency distribution for the four family types, under comfort and conserving scenarios.

The frequency distribution of internal temperature, for all family types, shows a different trend than the one observed in conventional EnergyPlus estimations, as the phenomena of the binomial distribution of modelled internal temperature is not present any more. Under conserving scenario, although for family type 1 and family type 2 the change in frequency distribution was minimal as they occupied the dwelling for less time, results show that for family types 3 and 4 the highest frequency of internal temperature ranged between $20-23^oC$, whereas the frequency distribution under comfort-scenarios had a dominant, well-defined peak at the range of $22 - 24^oC$, thus, a higher reduction in gas consumption was observed for these family types.
To demonstrate the deployment of dynamic occupant behaviour within EnergyPlus, a comparison between the co-simulation results for family types 1 and 3 under both comfort-scenario is presented, covering two days in winter (16-17 January). The purpose is to show the different behaviours of Person-agents (occupants) at the finest level of detail (15 minutes intervals) when interacting with the dwelling's systems. Figure 11 shows the different timing of using the heat-

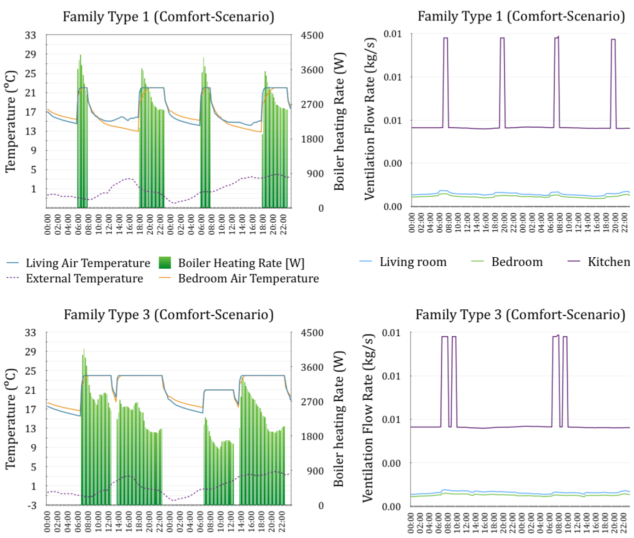

Figure 11: Comparison of family type 1 and 3 interaction under comfort scenario (16-17 Jan).

ing system and heating loads, the thermostat setting point and when using MVHR, which captures the dynamic interactions of Person-agents with the building systems under different occupancy types.

Discussion

The co-simulation system provides an approach that may enhance current DBSMs by capturing the diversity and the dynamic nature of occupant activities in buildings rather than using homogeneous user schedules. The co-simulation system enables researchers and practitioners to include less pre-defined and more dynamic occupancy schedules into DBSMs. The co-simulation enables and implements interoperability between occupants behavioural models and existing DBSMs. The ABM model was developed as an exploratory approach and was facilitated to emphasise the supplement of dynamic occupant behaviour to DBSMs. The main limitations of the ABM concerned the design of behavioural rules, and the validation of the ABM model. Thermal stimulus may not be the dominant variable influencing occupant behaviour. Also, thermal acceptability, in the current ABM, is linked only to operative air temperature, whereas thermal comfort is linked to a range of other parameters such as metabolic rate, clothing insulation, radiant temperature, air velocity and relative humidity which is recommended as future improvement to the model. Moreover, the Person-agents negotiated decisions only based on seniority concept, whereby the most senior agents, when present with other Person-agents, made a decision. Key aspects that relate to making decisions such learning, influence of others, habitual and contextual factors are not modelled in the current version. The ABM, however, had the capability to allow for future inclusion of decision making through learning and social negotiation with other Person-agents, in addition to including a wider range of behaviours and interactions.
Given that this co-simulation tool is a combination of two simulation programmes, one of which is the well-established and validated model (EnergyPlus), validation is sought to be regarding the ABM model. As ABM has become more prevalent in the social sciences and public policy, there has been an increasing emphasis on developing methods for validation. However, validation of the ABM relies on field data. Due to the very large number of variables and parameters involved in the ABM, careful collection and preparation of sufficient and representative empirical data is a must, yet, challenging. One of the biggest challenges associated with data collection is the lack of standardised data and the amount of equipment and time required, resulting in the data collection often being a costly process. Arguments over the appropriate sample size for measurement duration frequency and the number of occupants exist. Furthermore, knowledge of the most suitable explanatory variables requires better data streamlining processes (Yan et al., 2015). Due to the complexity and the great discrepancy of occupant behaviour, capturing the diverse aspects of behaviour in co-simulation with DBSM proves challenging. Therefore, future work must include interdisciplinary collaboration with experts from social and behavioural sciences to define and simulate occupant behaviour in a consistent and standard way. To establish a scientifically sound evaluation process, a high level of transparency and consistency is required for the entire process of model development and implementation.
Despite the limitations and the exploratory nature of

the current ABM, the model captured the dynamic nature of some occupant behaviour. The results of this study indicate that there is a deviation between the conventional and co-simulation modelling approaches, with the co-simulation results demonstrating the variety of peak loads and internal temperature peaks and distributions under different occupancy scenarios. Average annual gas consumption for space heating showed a wide variability amongst the different family types, and for all scenarios modelled, it was observed that compared to a conventional EnergyPlus simulation, space heating consumption was reduced. Similar trends were observed for annual electricity consumption, however, the reduction in the estimations was far less, as in the current model the interactions with electrical systems were limited to Person-agent boosting the extraction fans of the MVHR systems, and the electricity consumed when turning the heating on/off. Schedules of using artificial lighting, electrical equipment were assumed, for the sake of simplicity, constant (depending on family type) throughout the co-simulation. Once the interactions of Person-agents expand to cover the interactions with more electrical equipment, the impact of occupant behaviour will be more observed. The co-simulation system yields a comprehensive set of potential implementations, once an improved behavioural model is deployed, which may prove useful. The possibilities may include the potential change and impact of occupants behaviour due to climactic conditions, policy change, environmental attitude, social interactions, ageing, installing new systems, technology advancement, refurbishment of buildings etc.

Conclusion

This paper presented the development of a co-simulation system that links dynamic occupant behaviour simulated using the agent-based modelling approach to a dynamic building simulation model (DBSM). The study addressed the inflexible conventional modelling approach of occupants in DBSMs which disregards the various dynamic occupant behaviour and interactions with building systems that affect energy consumption buildings. The ABM was developed as a framework where different methods were tested to investigate how to model occupant behaviour. The ABM was developed in REPAST (Java) which was coupled to EnergyPlus using Functional Mock-up Interface standard (FMI) allowing for a real-time exchange of input/output. Although, many limitations encompassed the validation of the ABM, the analysis of the results show indeed a potential impact on the estimation of energy consumption and operative internal temperature by EnergyPlus. The study has delivered insights into the importance of accounting of dynamic and changing occupant behaviour, necessitates more advanced occupant behavioural models that simulate how occupant use buildings, to be implemented in existing DBSMs. Moreover, it has provided a framework for a new approach to enhance occupant behaviour modelling in current DBSMs programs. Future versions of the co-simulation system might be useful in investigating the discrepancies that arise between simulated and actual building energy use in buildings, as the integration of occupant behaviour models with existing DBSMs enables researchers and practitioners to simulate occupant behaviour in buildings, which may help to match simulated results with the actual energy use.

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