Simulating Occupants' Behaviour for Energy Waste Reduction in Dwellings: A Multi Agent Methodology

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3 authors:

Ayesha Kashif
Grenoble Institute of Technology

Julie Dugdale
University of Grenoble

Stéphane Ploix
Grenoble Institute of Technology

SIMULATING OCCUPANTS' BEHAVIOUR FOR ENERGY WASTE REDUCTION IN DWELLINGS: A MULTI AGENT METHODOLOGY

AYESHA KASHIF [a]

[a] Laboratory of Grenoble for Science of Design, Optimization and Production (G-SCOP)
46 Avenue Felix Viallet, 38031 Grenoble – France
ayesha.kashif@g-scop.inpg.fr

JULIE DUGDALE [b]

[b] Grenoble University, Grenoble Informatics Laboratory (LIG), University of Agder, Norway
110, Av de la Chimie, 38400 Saint Martin d'Hères, France
Julie.Dugdale@imag.fr

STEPHANE PLOIX [a]

[a] Laboratory of Grenoble for Science of Design, Optimization and Production (G-SCOP)
46 Avenue Felix Viallet, 38031 Grenoble – France
Stephane.ploix@inpg.fr

Energy waste due to inhabitants' behaviour in residential buildings has emerged as a potential research area due to the increasing worldwide population and growing energy needs. However, existing approaches for simulating energy consumption are mainly limited to office buildings and are based on static profiles. In this paper we propose a 4-step co-simulation methodology to assess how inhabitants' interactions with household appliances affect energy consumption. The approach is validated using a case study showing how human activities influence the energy consumption patterns of a refrigerator. The fridge was specifically chosen because it is a high energy-consuming appliance that is strongly affected by inhabitants' behaviours. In addition, modelling the fridge is non trivial, and in choosing this appliance we show that it is possible to apply the approach to less complex appliances. A co-simulation approach is adopted with the fridge being physically modeled in Matlab and with human behaviour being modeled in the Brahms language and simulation environment. The consumption distribution from the simulated scenario is compared with the actual distribution (using data from a consumption database), to find optimum values of tuning parameters with less than 10% variation. This methodology enables us to simulate how human behaviours affect energy appliance consumption.

Keywords: energy waste reduction; agent based dynamic behaviour simulations; behaviour influenced appliance consumption modelling

1. Introduction

An increasing shift in the population towards urban areas and growing energy needs have resulted in escalating housing and energy demands [24]. The worldwide contribution towards energy consumption in buildings is 30 – 35% [1]. In Europe, however, buildings account for 40-45% of the energy consumption. Various factors affect the total energy consumption in buildings [2], such as, climate, building related characteristics (e.g. orientation and type), user related characteristics (e.g. presence), services (e.g. space heating/cooling), indoor environmental quality, occupant behaviour, and social and economic factors [3]. There are also a multitude of human behaviour factors that influence energy consumption. For example public information on the energy problem, energy related personal interests, economical differences, home characteristics (internal arrangement, decision to insulate), lifestyle consciousness about energy saving, values, personality, acceptance of responsibility, social norms, knowledge about energy use and appliances' purchase, usage and maintenance related behaviours [3].

The framework proposed in this article is part of the SUPERBAT project. The objective of the project is to improve energy prediction by co-simulating the energy impacting behaviours of inhabitants together with more accurate physical models of buildings and appliances. The interaction between inhabitants and physical aspects can be seen in Figure 1. The bottom-right corner shows the communication from the power supplier or smart grid to the inhabitants through electrical signals e.g., the information about peak usage periods, energy tariffs for different hours. Similarly, inhabitants can communicate back their choices. These interactions help in reducing the delivered electricity costs and are beneficial to both the grid and the environment.

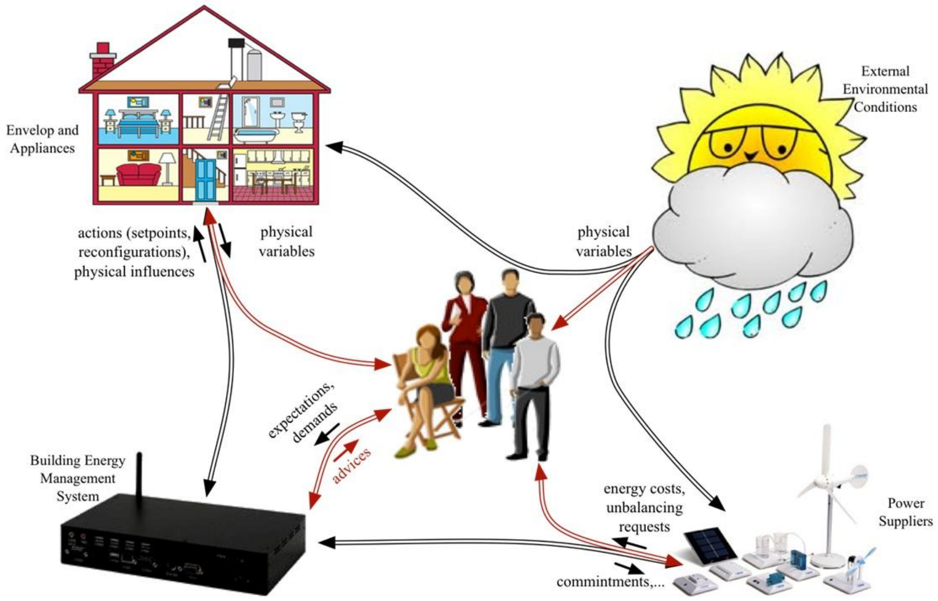


Figure 1 – Co-simulating occupants' behaviour with the physical aspects of buildings

Today information coming from the smart grids is increasingly complex, making it difficult for inhabitants to react accordingly. An energy management system (EMS) could help to optimize energy consumption and allow inhabitants to make better decisions regarding energy use. The EMS receives the signals from the grid and informs the inhabitants, in a clearly understandable way, about the availability of energy, the price details, and energy consumption by different household appliances etc. The inhabitants can communicate with the EMS, expressing their energy needs and asking for advice.

Similarly, the values for different physical variables coming from the building envelop or the appliances are captured by the EMS and the inhabitants. The inhabitants can interact with appliances either directly, by adjusting the set points, or indirectly, through the EMS. Since the inhabitants play a key role in the energy consumption of home appliances in this article we focus specifically on capturing their reactive behaviours. Also in energy simulations, it is more realistic to represent home situations dependent on human actions. For example, if inhabitants are not at home, the shutters couldn't open and close by themselves.

In order to evaluate our model of the human behaviour, we have defined some requirements that the model must satisfy. The model must be:

a) able to simulate interdependent individuals that dynamically interact with a physical simulator and an EMS,
b) consistent with reasons behind inhabitants' actions, these are obtained by questioning or observing the occupants,
c) consistent with long term (month, seasons, etc.) observation data for the selected household

In the first step however, it is necessary to model some reactive and dynamic behaviour of inhabitants. Modelling inhabitants' behaviour in this way will help to create situations in simulations which are closer to what could possibly happen in daily life of inhabitants in home situations. Since, at home the behaviour is quite complex and difficult to predict as compared to at work, the modelling and co-simulation of random behaviours with home appliances can provide an opportunity where the impact is interesting to analyse and can lead to more interesting and unseen situations.

In order to study these interactions, it is necessary to include inhabitants' dynamic and reactive behaviour in energy simulations. Before introducing energy management system into simulation, it is important to first study the behaviour of occupants in relation with home appliances that is what has been done in this paper. An example is taken in this paper in order to establish the fact that how inhabitants' reactive behaviour affects the energy consumption of home appliances. However, in order to show it more clearly, it is necessary to model the complex and dynamic aspects of human behaviour and how it can be introduced in energy simulations. The physical models for home appliances are needed that give the typical behaviour of these appliances with and without interactions by inhabitants. The inhabitants and appliance behaviour is modeled and simulated in Brhams multi agent system and matlab/simulink respectively.

Simulating human behaviour in energy management is useful for different people concerned with energy management. Building managers may adjust the EMS taking into account the complexity of occupants' behaviours, or assess the robustness of different energy strategies with the possibility to try alternative ones. Building designers can study the impact of their designs and different EMS. Energy providers can use knowledge of behaviours to understand the impact of providing different information e.g. tariffs, status of grids etc. Finally, inhabitants can consider and adapt their own energy consuming behaviours, or help them to decide whether to renew or not an application.

Some previous works have already established that inhabitants' behaviour has a significant impact on energy consumption and energy waste reduction [2]. The energy prediction models for electrical appliances are mostly based on presence/absence profiles. Such profiles could be helpful for the appliances that are comparatively simple to model e.g. the lights, television. These appliances consume energy, and a constant amount, only when they are turned on.

On the contrary, for some appliances, such as a fridge/freezer, simple presence/absence profiles are unsuitable. Furthermore, it is difficult to associate the turn on or turn off patterns with consumption. Taking the fridge as an example, the compressor uses continuous energy consumption cycles, which vary considerably depending on what type of human action is performed on the fridge (e.g. opening the door, adding warm food). A scheme to predict the energy demand of cold appliances has been proposed by Widén and his colleagues [11]. However, they assume that the functioning of cold appliances is unrelated to human actions. We argue that in modelling appliances, specifically cold appliances, it is important to consider dynamic human behaviours in order to accurately predict energy consumption.

This article has two objectives: (i) to model cold appliances and their impact on energy consumption due to inhabitants' behaviour (ii) to instigate a shift from using static profiles to using dynamic profiles in energy simulators for a more accurate assessment of energy consumption. The difference between static and dynamic profiles is that in static profiles the inhabitants' presence/absence or actions are hard coded in the simulation, whereas the dynamic profiles, that we apply, are used to simulate the daily life behaviour of the inhabitants randomly. We also model and simulate more complex behaviours, such as social and group behaviour, as well as reactive and deliberative behaviours of inhabitants. The randomness and dynamism is introduced by adjusting various input parameters.

In order to explain our work, we use the case study of a fridge. This appliance has been selected because, as can be seen in figure 2, it is a high energy consuming appliance, and it is strongly affected by inhabitants' behaviours.

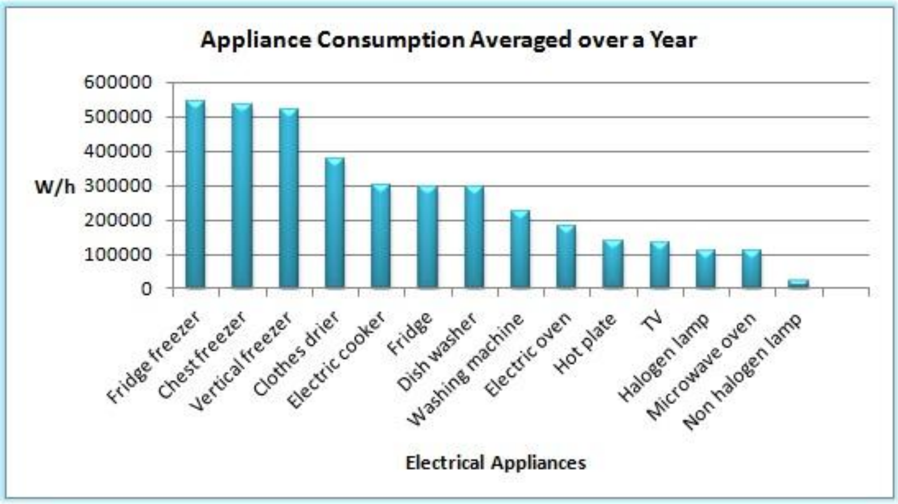


Figure 2 – Annual consumption of household appliances

The results of an experimental analysis of the IRISE dataset are presented in Figure 3. The x-axis shows the number of people in each house and the y-axis shows the energy consumption. Each point in the graph corresponds to the energy consumption of a fridge-freezer averaged over the period of a year along with the size of the fridge-freezer e.g. 172l/94l. In some cases the energy consumption depends upon the size of the fridge-freezer and the number of people in the house, but in others it does not. An example of where the energy consumption does not depend upon the number of people in the house nor on the size of the fridge freezer is shown with an oval. This shows that the energy consumption of the fridge-freezer does not necessarily depend upon the number of people in the house, nor on the size of the appliance (sizes against each consumption are shown on the graph). Instead it depends on how the inhabitants' use the appliance, i.e. their behaviours. These experimental results also provide a good justification that simple presence/absence profiles are insufficient in order to model the household behaviour for cold appliances.

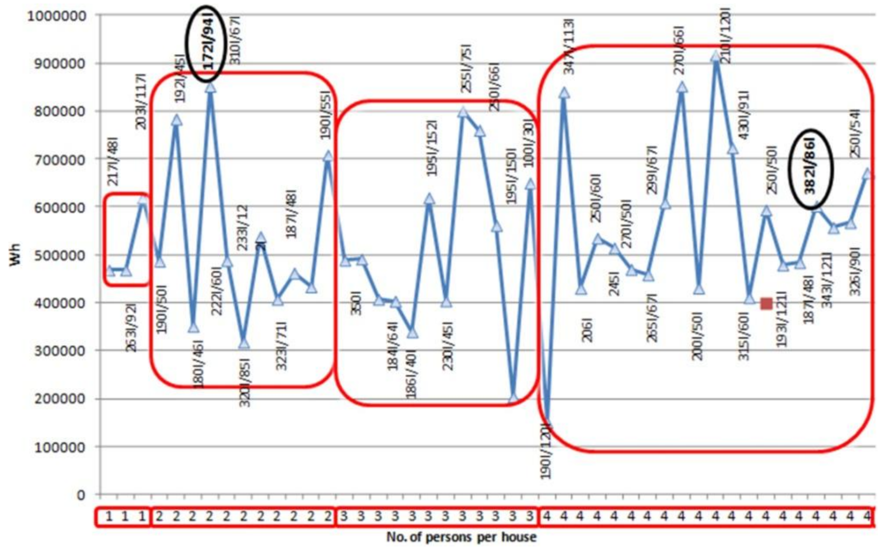


Figure 3 – Fridge Consumption patterns from IRISE dataset

We propose a 4-step methodology: (i) construct physical models of the appliances that will help to identify high energy consuming activities, (ii) generate energy consumption distributions for the appliance from an energy consumption database (IRISE), that we will use as a reference[1], (iii) question or observe occupants in a selected household regarding their high energy impacting behaviours. This is used to design a parameterized model and simulation. (iv) use long term (month, seasons, etc.) observation data for the selected household in order to adjust parameters. This step includes calibration of the simulator by finding values for the tuning parameters where simulated consumption becomes closer to the reference consumption distributions generated in (ii).

This methodology will allow us to accurately model how human behaviour affects energy consumptions of electrical appliances.

This article is divided into 5 sections. Section 2 presents the literature review on existing approaches to energy management, focusing on presence/absence profiles, agent-based models and issues in representing human behaviours. The proposed 4-step methodology, the case study and the results are presented in section 3. Conclusions and future perspectives are presented in sections 4 and 5 respectively.

2. Literature Review

2.1 *Existing approaches using presence/absence profiles*

[1] IRISE dataset is part of the European Residential Monitoring to Decrease Energy Use and Carbon Emissions (REMODECE) project [26].

Human behaviour has previously been considered in simulations as occupancy profiles. Richardson et. al [5] used the time use data to generate active synthetic occupancy data used in future energy demand simulations. Capasso et. al [6] proposed a residential load model where “availability at home” profiles are used for each occupant. Other authors have stressed the importance of occupancy patterns in order to represent diversity [7], and for accurate prediction of energy demand load profiles for home appliances [8]. The factors considered important for occupancy patterns include: the number of occupants, time of the first person getting up and the last person going to sleep, and the unoccupied period during the day. Page et. al. build a time series of presence/absence from the data collected from single person offices and use a Markov chain to reproduce the presence profiles through simulations [9]. The purpose of generating such profiles was to use them further in occupant behaviour models within building simulation tools. Dong and Andrews developed an event based pattern detection algorithm for sensor based modelling and prediction of user behaviour [10]. They connected behavioural patterns (Markov model) to building energy and comfort management through EnergyPlus simulation tool for energy calculations.

Most of the above works focus on office buildings where the behaviour of occupants is not as complex as in home situations. So whilst simple presence/absence profiles could be suitable for offices, for example in managing lighting, they do not capture the complexity of behaviours seen in home situations.

If we consider appliances, other than lighting, then we should also change the way behaviour needs to be captured. Behavioural parameters that are sufficient to study the impact on one appliance, such as lighting, might not be sufficient for another. Thus complexity increases as we shift from office buildings to home situations and with the choice of appliance. Cold appliances, such as fridges, are highly sensitive to inhabitants’ behaviours (e.g. opening/closing the door and introducing food items) and cannot be modeled using simple presence/absence profiles. In order to take into account such behaviours we must move towards more complex and dynamic behaviour profiles that are generated randomly.

Thus our work on human behaviour modelling differs from previous approaches since we are concerned with home situations containing complex appliances. In addition we also attempt to analyse and model: how other environmental variables, such as external temperature affects behaviours; what is the relationship between different appliance usage (e.g. fridge and cooker); and what are the underlying reasons behind the inhabitants’ actions.

2.2 *Agent based approaches for energy management*

More recently, multi agent systems (MAS) have been used in the domain of energy management within buildings. One of the main characteristics of MAS is that they are composed of autonomous interacting components, each with their own characteristics and actions. This strong focus on distributed behaviours has made them an ideal candidate for managing the individual elements in energy systems. The approach is also well suited to modelling and simulating inhabitants, since we can represent each inhabitant (or a group of inhabitants), as having its own characteristics (e.g. age, beliefs, etc) and actions (e.g. turn on appliance). Thus MAS provide a good way to model the behaviour of both occupants and household appliances. A MAS approach has been used in monitoring and controlling the HVAC system (Heating, Ventilation and Air Conditioning) and lighting in office buildings [17]. In smart homes, the approach has also been used for the anticipatory and reactive control of HVAC and lighting [21]. Likewise, an agent based control system was used for the optimization of a simulated residential water heating system [18]. The prediction of the mobility patterns and device usage of inhabitants has been done in the MAVHome project in order to satisfy the tradeoff between cost and comfort [19]. Abras and his colleagues [20] gave the control of appliances and sources to the software agents that are used in a home automation system. Liao and Barooah developed a multi agent systems approach to predict and simulate the occupancy at room and zone level in commercial buildings [22].

Although the agent based approaches described above have been used both to manage and simulate energy systems, they do not model how complex human behaviour affects the energy consumption patterns of appliances. In the above works either the energy system is controlled using agents, or, when agents have been used to represent inhabitants', the level of detail is minimal (e.g. tracking just the displacement of inhabitants in a location).

Our work extends those above by increasing the level of detail on what is modeled about inhabitants. Rather than dealing with simple movements, we model the beliefs that an agent has about the world, the facts in the environment, the way these beliefs and facts influence agents' thought process, and also how they perform various actions. The reason for modelling these levels of details in an energy simulation is to make it closer to a home situation where inhabitants are considered as active, intelligent 'agents' for energy waste reduction in buildings. This complexity of behaviours and increased number of parameters in energy simulations will provide with more reliable results for its subsequent use in energy load/demand estimation and prediction.

2.3 *Representing human behaviour*

Since human behaviour is an important factor in energy simulations [2, 4], this section looks at the elements that form such behaviours. Perception, cognition, memory, social and emotional factors, and psychomotor aspects are some of the basic elements that are considered important in representing and modelling human behaviour. In order to perform complex tasks, procedures are proposed by Kieras and Meyer that focus on perceptual, cognitive and motor processes [12]. The SOAR (State, operator and result) architecture sees behavioural problem-solving as a movement through the problem space. This is implemented by searching for states that bring the system closer to its goal [13].

These approaches focus on very low-level cognitive states. An alternative approach was suggested by Sierhuis, which looks at higher abstraction behaviours and enables modelling people's daily activities. Practically, this was realized through a modelling environment called BRAHMS (business redesign agent-based holistic modelling environment). This environment is able to represent, people, places, objects, behaviour of people over time and their social behaviour [14]. This is the modelling environment that we have used for representing and simulating the daily activities of inhabitants [15].

3. Proposed Methodology

The proposed 4-step methodology to simulate how behaviour influences appliance consumptions using multi-agent approach is shown in Figure 4 below:

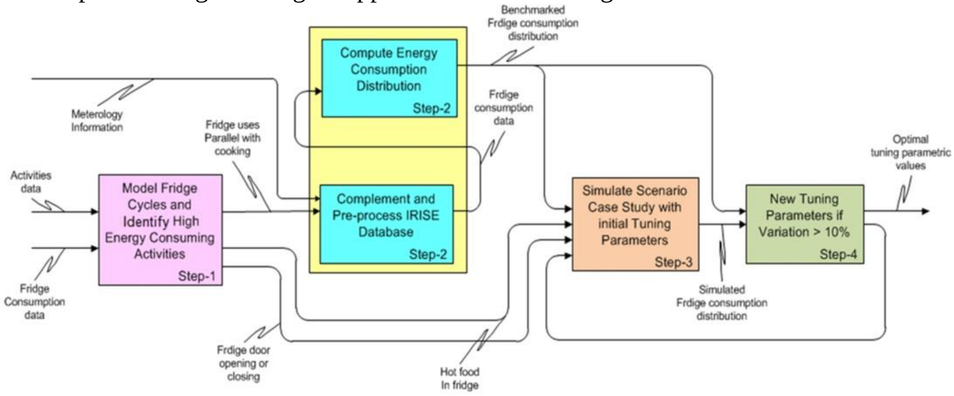


Figure 4 – 4-Step Methodology to how behaviour influences appliance consumptions

In step-1, a physical model of the fridge is constructed, that is used to identify the high energy consuming activities, e.g. keeping the fridge door open for long time periods or introducing hot food inside. The important inputs for this step include the data about the household activities and the data about the consumption of the fridge. Full details of the data collected and the physical model are given in section 3.1. In step-2 an analysis of the IRISE energy consumption database is performed to find the energy consumption behaviour of the households. The data in IRISE is further complemented with some additional information in order to understand the affect of certain other parameters on the energy consumption behaviour of households. This information includes the day of the week (i.e. weekend or weekdays), holidays, and the state of the weather. The historical data about the weather profile is taken from the web [23]. In order to capture the energy consumption behaviour of the households, we have computed the probability distributions for the consumption of the appliances used in a particular house. Since we are focusing on fridge, a complete detail of how this step is performed is given in section 3.2. In step-3 a scenario of a family has been implemented taking into account the different parameters that could possibly effect the consumption distributions of the household appliances. In step-4 we tune the values of these parameters, such as the probability of cooking on weekdays, on weekends, the outside weather, etc. The simulation results for the consumption cycles of the fridge are then used to compute the probability distributions. These distributions are then compared to the actual distribution obtained from the IRISE database. The purpose of this comparison is to see that how close the proposed behaviour model and scenario implemented in Brahms, is to reality. The process of tuning the parameters continues until the error is less than 10%.

We have chosen to use the fridge as the appliance to be modeled and simulated. The fridge is used as a target device based on three factors *(i)* it has a strong impact on energy consumptions, *(ii)* fridge cycles are highly influenced by the inhabitants' behaviours and *(iii)* it is complex to model the fridge consumption cycles. Let us follow the proposed methodology and discuss each step in detail. In this methodology we have used the IRISE database, that contains energy consumption data, for each appliance from 98 French houses, recorded at every 10 minutes, over a one-year period. The relationship between consumption data, from IRISE, and data on inhabitants' activities is shown in Figure 5 below.

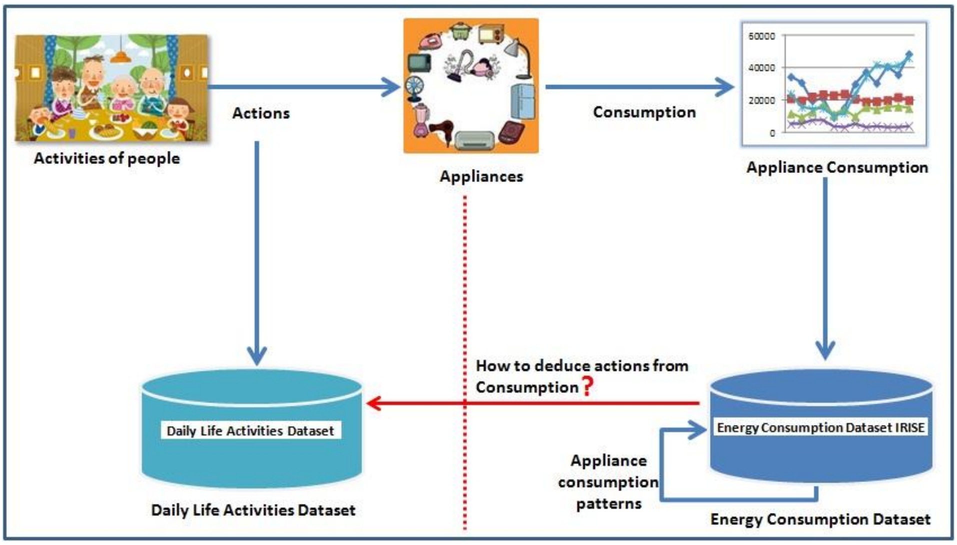


Figure 5 - The scope of the IRISE dataset

Figure 5 shows that the two datasets, IRISE and Daily Life Activities, are disconnected; the red dotted line is used to show this separation. The inhabitants perform certain actions at home that can be registered in the daily life activities dataset. However, this dataset only contains the information about the activities of people. It does not provide any information about how the activities affect the consumption of appliances. Conversely, energy consumption of home appliances is stored in the IRISE dataset. The IRISE energy consumption dataset is the key in extracting activity specific energy consumption patterns (step-2) and simulation of inhabitants' behaviour (step-3), however it lacks the information about inhabitants' actions behind certain appliance consumption patterns. The link between these two types of datasets is critical to capture the influence of inhabitants' behaviour on energy consumption as well as the usage patterns of home appliances.

For some appliances it is easy to deduce the actions behind consumption patterns. Figure 6 shows the power consumption of a TV over 3 consecutive days. It can be seen that it is easy to deduce actions behind these consumptions. When the appliance is turned on it consumes a constant amount of power until it is turned off.

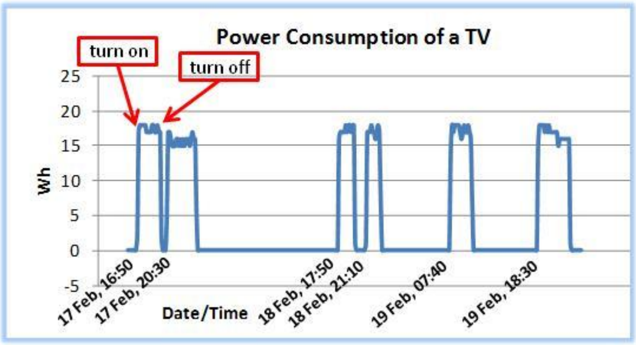


Figure 6 – Power consumption pattern of a television

However there are other appliances, such as a fridge-freezer, for which it is not easy to deduce the actions behind the consumption patterns. Such a situation is shown in Figure 10(a and b), where the compressor cycles of the fridge-freezer have different lengths even during the same day. In this case it is not easy to deduce actions behind the consumption patterns, thus building a model for these types of appliances is more challenging as compared to lamps or televisions.

Also, unlike a television or lamp, the impact of some actions on these appliances is not immediate. The impact could not only affect the current cycle, but also subsequent ones depending on the nature of the action being done e.g, for how long the door was opened, the temperature or weight of the food put in the fridge, etc.

There are also other parameters that affect the inhabitants' behaviour regarding the consumption of the fridge. In Figure 7, the monthly consumption of the fridge freezer is computed over the whole year for 2 different houses in the IRISE database. It shows that the consumption of the fridge-freezer varies with the seasons and also the time of the day. In the early hours of the morning, i.e. 0h – 6h (blue curve), the inhabitants' have very little or almost no interactions with the fridge-freezer, so the consumption is smaller compared to the other periods of the day when it is more likely that the appliance consumption is affected by human behaviour. Conversely, in the evenings, i.e. 18h – 24h, (purple curve), the inhabitants are more likely to be at home, cooking, and interacting with the fridge-freezer; hence the increased consumption of the fridge-freezer.

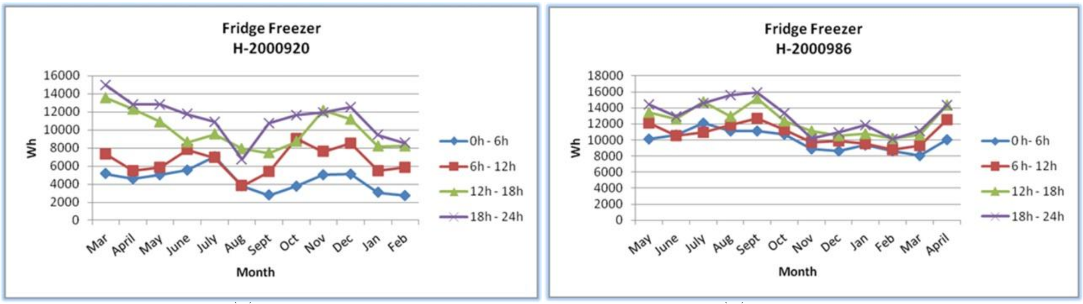


Figure 7 – Comparison of fridge/freezer consumption for different houses from the IRISE dataset

Concerning fridge efficiency, it is likely that the fridge in figure 7(a) is very efficient since it is more sensitive to human actions compared to the one in figure 7(b) [25].

Figure 8 shows that some other parameters, such as the weekdays/weekends, or the inhabitants' cooking activity, also affect the energy consumption of the appliances. We can see that the duration of the average compressor cycles for the fridge-freezer are larger at weekends than at weekdays. Also, the use of the cooker affects the average duration cycles of the fridge-freezer since the two appliances are often used together in a cooking activity, with the inhabitants' opening the fridge door more often, etc.

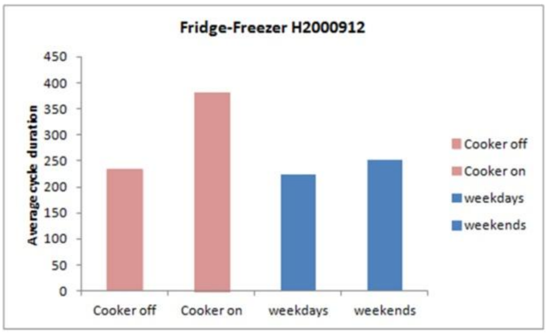


Figure 8 – Fridge consumption patterns from the IRISE dataset

3.1 *Fridge Cycle Modelling and High Energy Consuming Activities Identification (Step-1)*

The first step is to build a physical model of the fridge that can be subsequently used during simulations to generate virtual fridge cycles for the energy consumptions patterns. This step is further divided into three sub-steps *(i)* experimental data collection, *(ii)* physical fridge model and *(iii)* co-simulation for the fridge model validation.

3.1.1 Experimental Data Collection and Analysis

In this step we collect and analyze the experimental data collected from a fridge/freezer along with details of inhabitants' activities (Figure 9). The objective is to identify the reasons behind certain activities and to link these to consumption data in the IRISE database. For example we may see how the fridge consumption is affected by different aspects, such as it being the weekend, or the arrival of guests, etc. The data is collected through personal experiments on a fridge-freezer over the period of two different weeks and is used to deduce the energy impacting behaviours. These behaviours are then mapped to data in the IRISE database in order to provide heuristic rules that will be used in the co-simulator. In order to see if the simulated behaviour is realistic or not, the energy consumption trends of the fridge-freezer that resulted from the behavioural simulator are compared to the studied house from the IRISE database.

The experiments are performed in the controlled environment where outside temperature and humidity were within specific defined ranges. The activities are initially noted in the activity journals and were later transferred into Excel software for easy processing. The energy consumption data is collected with power meters and zigbee wireless sensors, whereas environmental and physical variables like food weight, food temperature, and the temperature inside the fridge and in the room containing the fridge (inside and outside temperature) are captured through wireless sensors, a food-weighing machine and thermometers respectively. The sensor data is collected through a program written in Python and results are provided in the form of flat files which are further processed in Excel using macros written in VBA.

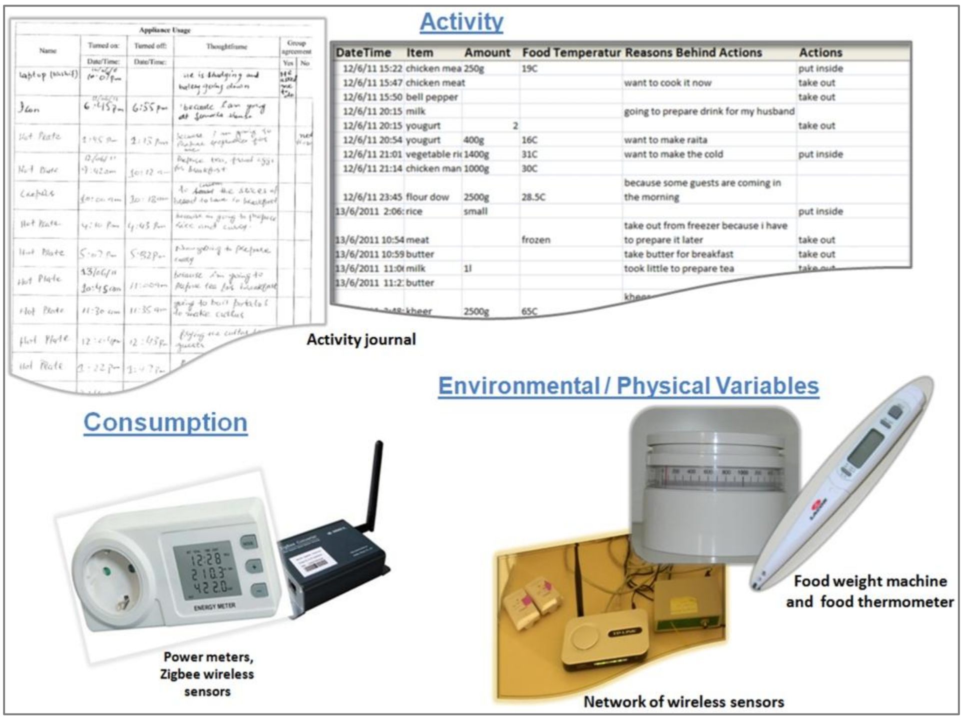
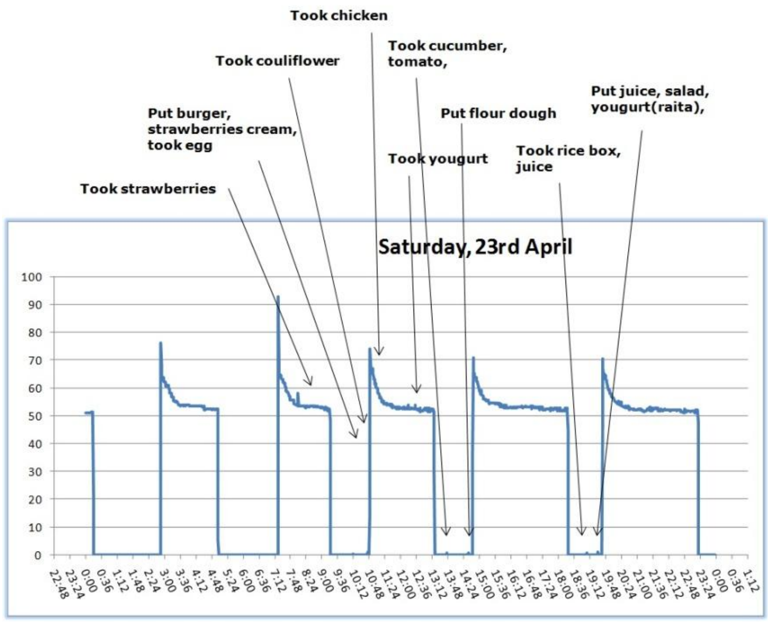
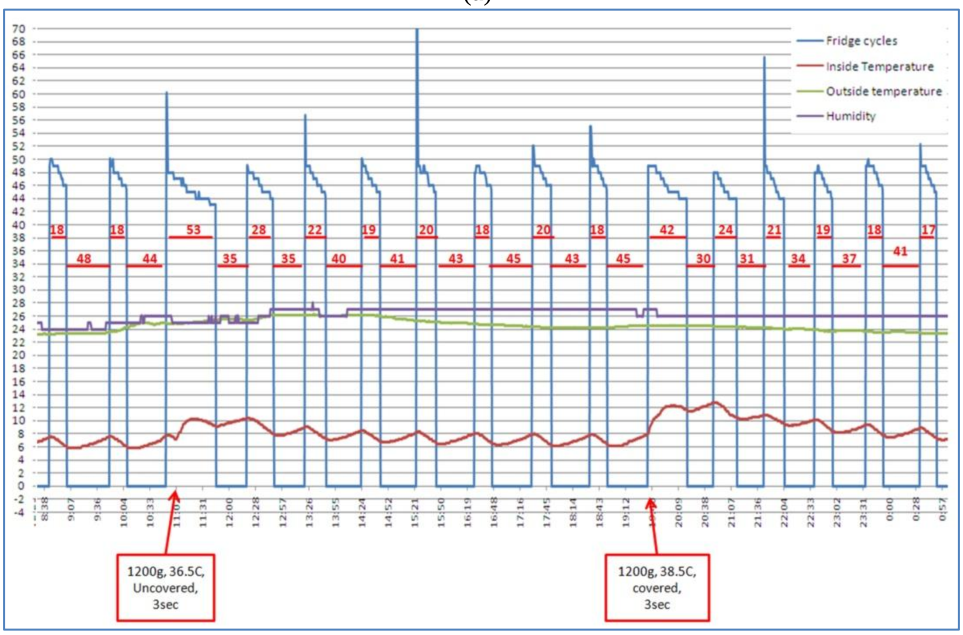


Figure 9 – Experiments on the fridge/freezer and data collection

The initial analysis results from the experimental data are presented in figure 10 below. Figure 10(a) shows that the fridge/freezer cycles vary based on the actions performed by inhabitants. Figure 10(b) shows the values for the environmental and physical variables captured during experiments in relation to the fridge/freezer cycles. These results affirm our hypothesis that it is difficult to model fridge cycles as the impact on the cycle duration follows the inhabitants' actions. The experiments are very carefully designed to model the impact of an action on the fridge/freezer cycles to predict (i) when the current fridge cycle shall end, (ii) what will be the length of the next fridge cycles, (iii) how many cycles it shall take to reach to a stable cycle period and (iv) its duration. We started by first modelling the empty fridge cycles against controlled experimental conditions and then food with different characteristics as (i) different quantity, (ii) different temperature and (iii) covered/uncovered was added to the fridge at different fridge cycle positions, e.g. start, middle and end of cycle periods. An online tool was developed to monitor the live fridge cycles based on data captured through the zigbee wireless sensor in the xml or flat files.



(a)



(b)

Figure 10 – Experimental data analysis results

The normal compressor cycles are regular in figure 10(a) during the middle of the day, and during the first two cycles in figure 10(b). As there are more interactions with the fridge the cycle durations change according to the type of activity performed, i.e. the amount and temperature of food, the duration of opening the door of the fridge, etc. That is why in figure 10(b), when food is put into the fridge at two different times, the cycle durations are different. The cycle where the first time food is introduced is longer than when food is introduced for the second time; this is because the food was uncovered the second time. So even though the temperature was lower in the fridge just before the first food was added, compared to the second time, the compressor cycle duration was longer.

One of the most interesting rules derived from the experimental data analysis is that fridge/freezer cycles were larger when the cooker was used (figure 11), hence cooking activity is strongly related with the actions on the fridge. This link is exploited in step-2 to complement IRISE database: similar patterns are classified as the cooking activities, whereas the rest of the fridge usage patterns are classified as non cooking activities.

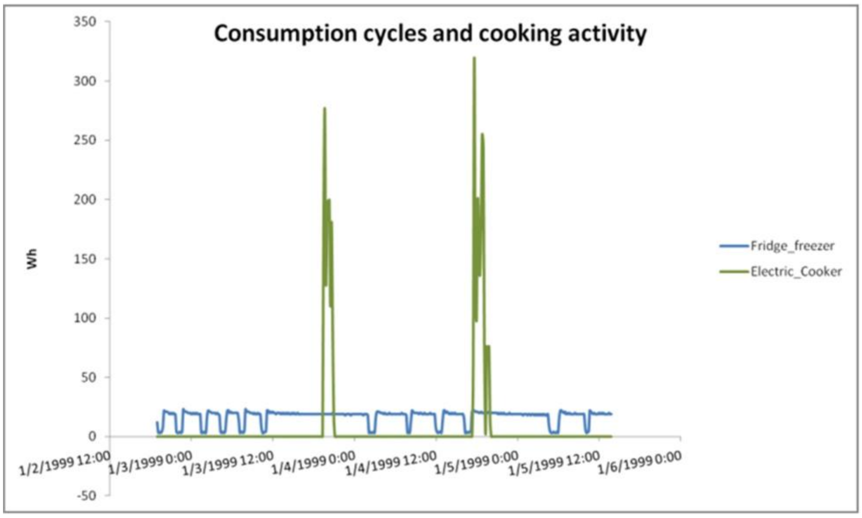


Figure 11 – Effect of cooking activities on fridge consumption cycles

In these experiments we confirmed that inhabitants' actions have strong impact on fridge cycles, which leads to high energy consumption. The high energy consuming activities listed below, however we found one low energy consuming activity i.e. putting frozen food into fridge:

- ***a)*** Putting a large quantity of food inside
- ***b)*** Food with high temperature
- ***c)*** Keeping the door open for long time
- ***d)*** Opening the door more often
- ***e)*** Putting in uncovered Food

3.1.2 Physical Fridge Cycle Model

Based on the experimental results (section 3.1.1), a theoretical physical model for the fridge consumption cycles has been derived, shown in figure 12:

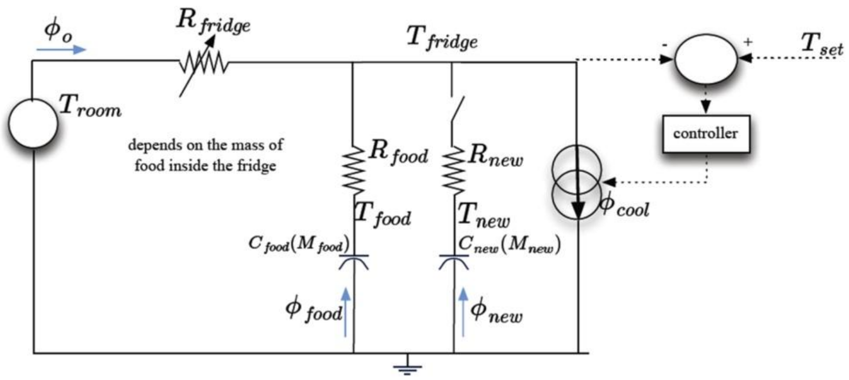


Figure 12 - Physical Model for the Fridge Cycle

The description of variables is given in Table 1.

Table 1 – Variables Description for Physical Model of Fridge

Variable	Description	Variable	Description
$T_{fridge}(k)$	inside fridge temp during reactive time k, => $T_{fridge}(k)$ ε $[T_{min}; T_{max}]$	$T_{set}(k)$	set-point temperature
$T_{room}(k)$	ambiant room temperature	M_{food}	food quantity
C_{food}	$M_{food}C_p$, capacity of what is inside fridge	M_{new}	quantity of a new food
T_{new}	New food temperature	R_{food}	resistivity to heat exchange between food and fridge
C_{new}	$M_{new}C_p$, capacity of a new food added to fridge	R_{new}	resistivity to heat exchange between new food and fridge
R_{fridge}	Ropen + ζ (Rclose - Ropen) resistivity for heat exchange between inside fridge and room		
σ	Dead zone: represents the temperature zone where compressor stops the refrigeration cycles		

In this model we have made the following assumptions: (i) variation in the quantity of food inside the fridge is negligible, (ii) $R_{food} = 0$ and food temperature inside the fridge is assumed to be the same as the inside temperature of the fridge. Following figure 12, the cooling power φ_{cool} is provided by the controller to maintain the setpoint temperature of the fridge. Similarly φ_0 is the heating power coming from the room that affects the inside temperature of the fridge depending on the resistance Rfridge. Φ_{food} and Φ_{new} are the heating power coming from the food already present in the fridge and the newly introduced food respectively. Their affect on the fridge temperature depends upon their capacity and mass as well as the corresponding resistance. In this model however Φ_{food} is considered to be the same as the fridge.

The heat pump is an important element in modelling fridge cycles; let ρ be the performance factor of the heat pump that yields $C_{elec} = \rho\ \varphi_{cool}$ .The fridge controller is made to follow the following criteria:

$$T_{fridge}(t) - T_{set}(t) < -\sigma \quad \rightarrow \quad \zeta(t + dt) = 0 \tag{1}$$

$$-\sigma \geq T_{fridge}(t) - T_{set}(t) \leq -\sigma \rightarrow \quad \zeta(t + dt) = \zeta(t) \tag{2}$$

$$T_{fridge}(t) - T_{set}(t) > -\sigma \quad \rightarrow \quad \zeta(t + dt) = 1 \tag{3}$$

$$\Phi_{Cool}(t) = \zeta(t)\ \Phi_{Cool} \tag{4}$$

We have modeled three major events for the fridge: *(a)* permanent mode, where the fridge operates following the normal refrigeration cycles, *(b)* temporary mode when the fridge door is opened and closed; as a result, heat is exchanged and the inside temperature rises to impact the instantaneous refrigeration cycles and *(c)* temporary mode when food is introduced in the fridge.

a) The model for the permanent state or normal cycles is proposed as under:

$$\frac{d}{dt}\left[T_{fridge}\right] = \left[-\frac{1}{R_{fridge}C_{food}}\right]\left[T_{fridge}\right] + \begin{bmatrix} \dfrac{-\rho\phi_{cool}}{C_{food}} & \dfrac{1}{R_{fridge}C_{food}} \end{bmatrix}\begin{bmatrix} \xi \\ T_{New} \end{bmatrix} \tag{5}$$

$$T_{fridge}(0) = T^{init}_{fridge} \tag{6}$$

The model of the permanent state (1st order) is obtained when $T_{new} = T_{fridge}$.

b) The model for the temporary mode follows that of the permanent state, but with a change in the resistance of the fridge as under:

$$R_{fridge} = R_{open} + \xi\left(R_{close} - R_{open}\right) \tag{7}$$

c) The model for the mode when new food is introduced is proposed as under:

$$\frac{d}{dt}\begin{bmatrix} T_{fridge} \\ T_{new} \end{bmatrix} \doteq \begin{bmatrix} -\dfrac{R_{new}+R_{fridge}}{R_{new}R_{fridge}C_{food}} & \dfrac{1}{R_{new}C_{food}} \\ \dfrac{1}{R_{new}C_{new}} & -\dfrac{1}{R_{new}C_{new}} \end{bmatrix}\begin{bmatrix} T_{fridge} \\ T_{new} \end{bmatrix} + \begin{bmatrix} \dfrac{-\rho\phi_{cool}}{C_{food}} & \dfrac{1}{R_{fridge}C_{food}} \\ 0 & 0 \end{bmatrix}\begin{bmatrix} \xi \\ T_{room} \end{bmatrix} \tag{8}$$

With $T_{fridge}(t) - T_{set}(t) < -\sigma \rightarrow \quad \zeta(t + dt) = 1 \tag{9}$

$$-\sigma \geq T_{fridge}(t) - T_{set}(t) \leq -\sigma \rightarrow \quad \zeta(t + dt) = \zeta(t) \tag{10}$$

$$T_{fridge}(t) - T_{set}(t) > -\sigma \rightarrow \quad \zeta(t + dt) = 0 \tag{11}$$

$$\zeta(0) = 0 \tag{12}$$

$$\Phi_{Cool}(t) = \zeta(t)\ \Phi_{Cool} \qquad (13)$$

We make the following assumptions in modelling the fridge:

(i) Opening the door modifies R_{fridge}
(ii) Removing food from the fridge is assumed to have a very small impact (except for the door opening)
(iii) Adding food sets a new value to T_{new} (the temperature of the food) and parameters like C_{new} and R_{new} may be adjusted depending on the food

3.1.3 Inhabitants' Behaviour Modelling

We have seen that simple presence/absence profiles are insufficient for modelling human behaviours. We have chosen to use an agent based approach because of its ability to represent an interacting, heterogenous community of entities, each having its own autonomous decision making ability and characteristics. Thus we can model each inhabitant's characteristics, their ability to interact and communicate, and their ability to perceive changes in their environment and react to them.

We use a belief-desire-intention (BDI) agent architecture to model human behaviours [27]. The representation, shown in figure 13(a) is derived from the observations from our field studies. The figure 13(a) shows the high level representation of the proposed behaviour model where each agent has three different states as (i) perception, (ii) cognition and (iii) action. The perceptive state can be influenced by an outside cause (e.g. weather), inside cause, (e.g. feeling of hunger), and/or social behaviour (e.g. interaction with other agents). Based on these initial beliefs the agent advances to the cognitive state. In this state the agent goes through decision-making process where it may be influenced by social norms, family rules, or culture. Following cognitive decision-making, the agent performs certain actions, which may be planned or unplanned. For example, the planned action to fulfill hunger is to open the fridge, take the food out, cook it and then eat; but the unplanned actions upon the perception of a sudden pleasant change in the weather is to go to the restaurant and eat there. Actions finally constitute the behaviour of the agent.

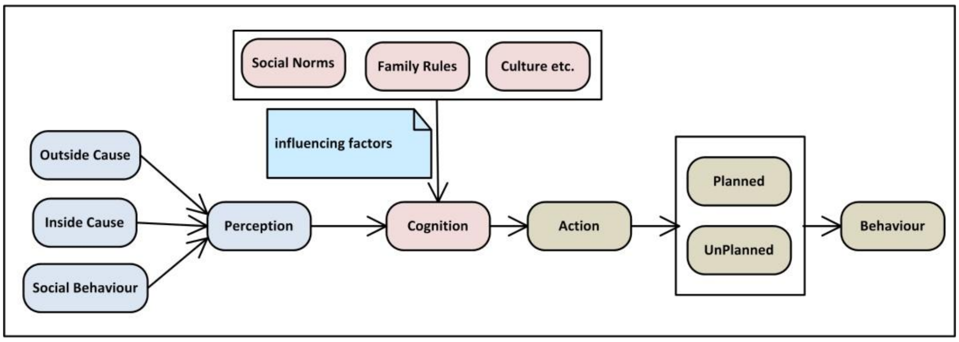


Figure 13 (a) – Behaviour representation

Figure 13(b) and 13(c) shows more specific examples of the behaviour model, where the agent's perception is changed by different parameters. These parameters include the behaviour of the agent upon the perception of: the weather outside, communication/interaction with the other agent, whether it is a weekday or weekend, and the arrival of some guests. In figure13(a) when the agent-1 perceives that it is time to cook, he starts thinking about how to follow the cooking process, e.g. what to cook, use the food items already present in the fridge, etc. this cognitive process finally leads the agent towards the sequence of actions that it performs on household appliances or objects. If, however, the agent perceives some other information from the environment (e.g. the agent-2 suggests to agent-1 to go out to eat based upon its perception of beautiful sunny weather outside), agent-1 will again go through the cognitive process, taking into account other influencing factors, e.g. how the decision of going out instead of cooking at home will affect the other agents in the environment or other actions that it has planned for the day etc. Taking into account all of the important factors, agent-1 will finally agree or disagree with agent-2. This agreement/disagreement that is communicated by agent-1, will now become the perception of agent-2. Agent-2's cognitive state will then lead the two agents to eat at home or go out to eat.

Similarly, the example in figure 13(c) shows other perceptive elements i.e. the perception of some guests that unexpectedly arrive, and the perception of weekdays and weekends. In the first case, the agent may have to go through the cooking process that it has not already planned or serve them with some other things. In the second case i.e. the perception of weekday/weekend, depending upon the agent's role in the house e.g. principle cook or not etc., it will start the cooking process based upon the availability of time. All of the above mentioned factors will either increase or decrease the agent's interactions with the household appliances e.g. cooker, fridge etc.

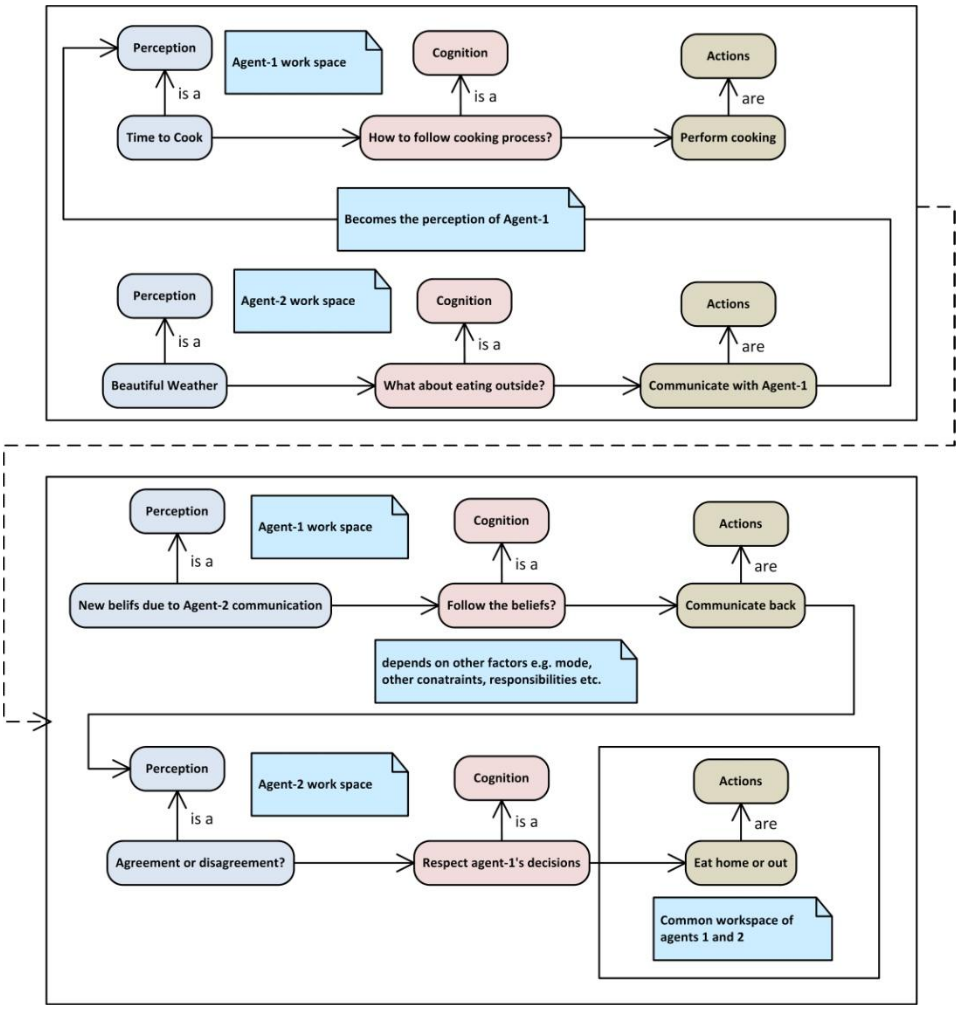


Figure 13 (b) – Social behaviour

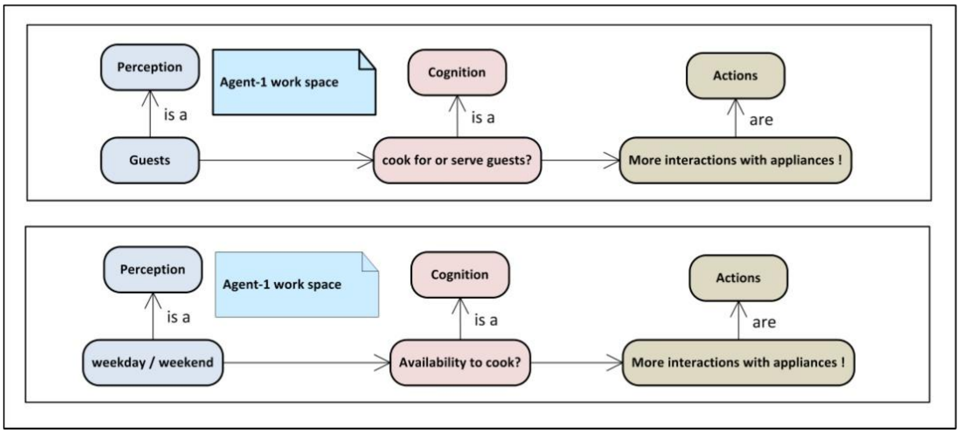


Figure 13 (c) – Other perceptive elements

The model of human behaviour has been implemented in the Brahms multi agent modelling and simulation environment [21]. Brahms provides a structure to model various elements that are relevant to the home situation: Agent model (for modelling inhabitants), Object model (for modelling inanimate objects such as appliances), Geography model (for modelling the physical home environment and the location of agents and objects), Activities model (for modelling the activities that can be performed by agents and objects.) Conceptual Object model (for modelling the concepts in people's mind) as well as facilities for modelling the time of performing some actions, the interactions and communication between agents and the way they adapt to perform certain actions [15, 16]. Note that we can also add an element of randomness, in timings for example, by giving different time ranges and durations for activities and different probabilistic values to control the frequency of activities.

3.1.4 Co-Simulation Approach and Results

In the co-simulation process, the dynamic behaviour of inhabitants is fed to the physical simulator containing the model of the fridge using an interface developed in Java. The physical simulator generates energy consumption cycles of the fridge and maintains the setpoint temperature. The physical simulator is implemented in Matlab and simulation results are monitored and analyzed with Simulink.

In order to perform certain activities, the inhabitants change their location, perform certain actions on appliances e.g. opening the fridge, putting food inside etc. As soon as these state changes happen, this information is sent to the physical simulator, where appliance behaviour is changed and its consumption is computed. The proposed co-simulation platform is presented in figure 14 showing 3 distinct elements (i) Brahms MAS, (ii) Brahms Java Interface and (iii) physical simulator (Matlab model of the fridge). The Brahms MAS element simulates the agent behaviour on the fridge. The Brahms java interface establishes the connection between Brahms and the physical model of the fridge by providing activities information generated during behavioural simulation to the physical simulator. This interface actually manages various aspects: it drives the Brahms virtual machine; it manipulates different attributes of the occupant's behaviour model to be simulated, by setting agents and objects attributes and handling the starting time of the simulation; and it keeps track of the current location of agents and of the current values of different attributes of objects. The physical simulator consists of the model of the fridge and the controllers for appliances. The model of the fridge is defined in a Matlab function file which uses the output of the Brahms simulation (such as opening the fridge, putting food in fridge) and based on the inside temperature of the fridge it turns the refrigeration cycles on or off. The inside temperature of the fridge is computed by the controller to maintain the setpoint temperature of the fridge.

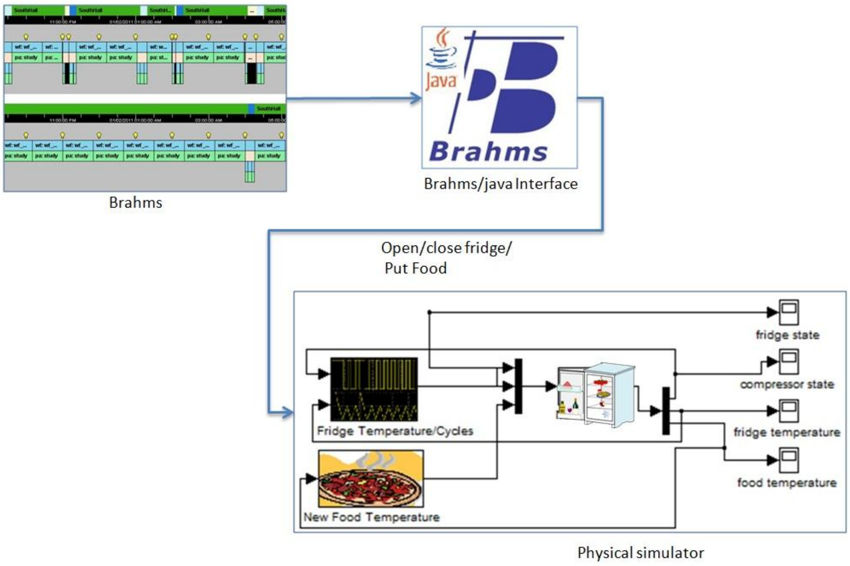
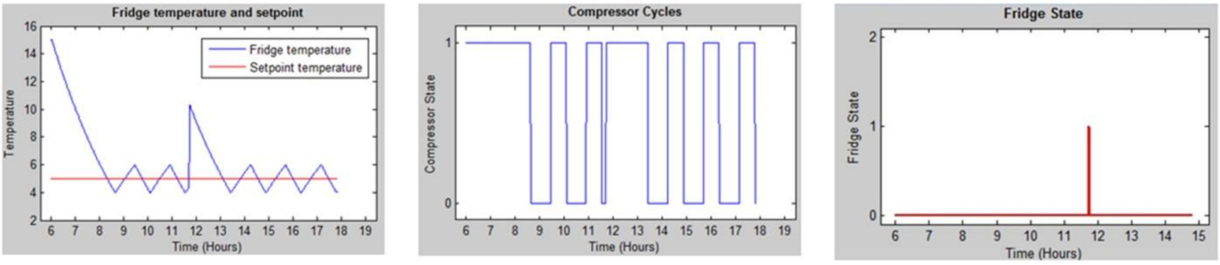
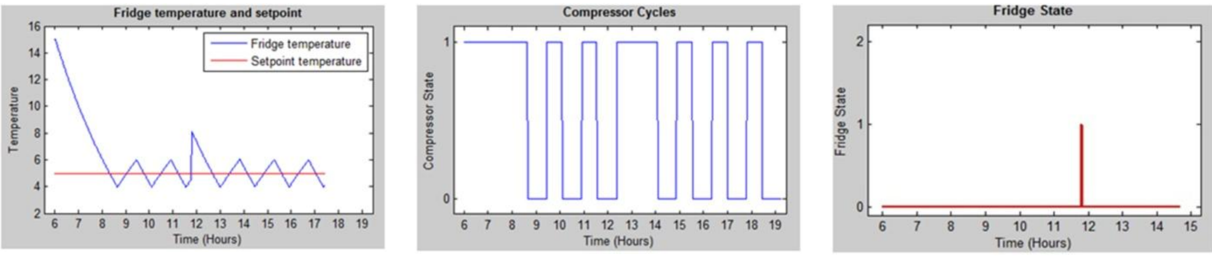


Figure 14 - Co-simulation platform to find high energy consuming activities

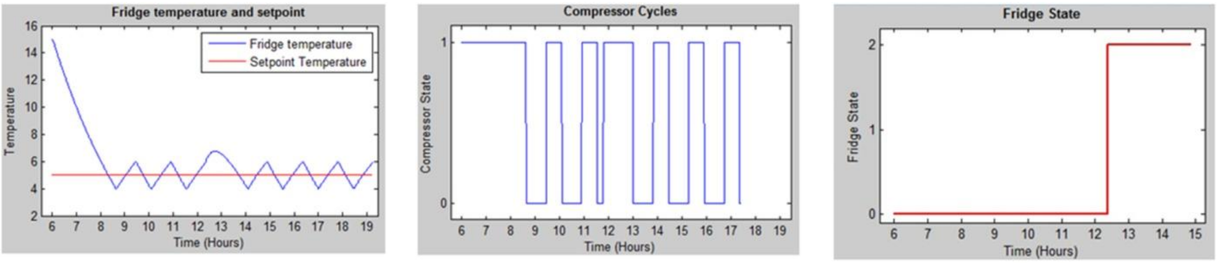
In the above figure, the first block represents the Brahms simulation environment. In the simulation the hunger level is perceived by the agents in Brahms. Based on this perception of hunger, the agents in Brahms perform different actions e.g, opening and closing the fridge to get the food, etc. The figures below show the actions of the agents on the fridge and the resulting effect on the inside temperature and the compressor cycles. Opening the fridge door for different durations affects the compressor cycles accordingly. In figure 15(a) the agent opened the door of the fridge for a long period, so the compressor worked longer and it consumed more energy than in figure 15(b) where the agent opened the door for a shorter period. Similarly in figure 15(c) an agent persuades another agent to eat at a restaurant, meaning that already cooked warm food is put inside the fridge. As a result, the inside fridge temperature increased causing the compressor to work longer than usual to bring the temperature back to the setpoint. The fridge states are represented by three levels 0,1,2 where 0 means that there is no action on the fridge, 1 means the door is opened and closed, and 2 means that new food is added.



a) Door opened for 100 seconds



b) Door opened for 60 seconds



c) New food introduced in the fridge

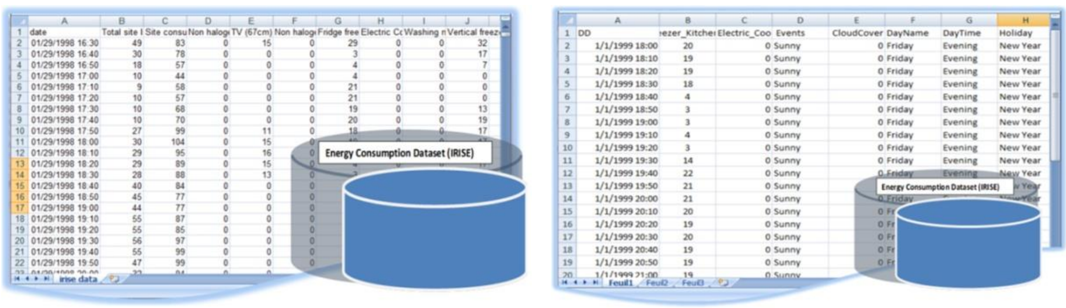
Figure 15 - Simulated inhabitants' behaviours affecting fridge temperature and compressor cycles

3.2 *IRISE Database Pre-Processing and Benchmarked Consumption Distributions (Step-2)*

The IRISE dataset is an excellent source of information for energy consumption however it cannot be effectively exploited due to missing activity data.

3.2.1 IRISE Dataset Pre-Processing

Figure 16(a) provides a glimpse of the IRISE dataset where the appliance consumption data is provided against the date/time stamp. We have supplemented the IRISE dataset with metrology information and energy consumption based activity patterns. This shift is presented in figure 16 as the events, cloud cover, day time and holiday as additional information figure 16(b).



(a) (b)

Figure 16 – IRISE dataset pre-processing

3.2.2 Benchmarked Fridge Cycle Distribution using Matlab

In this section we focus on calibrating the simulator by matching the fridge cycle distributions coming from our behaviour simulation with those computed from the IRISE database. We present the tuning parameters along with the computation of the fridge cycle distributions using Matlab from the IRISE dataset (figure 17). The duration in minutes of the fridge compressor cycle is shown on the x-axis and its probability density on the y-axis. The best fit of the probability densities is an inverse Gaussian distribution. This is the reference distribution computed from a house in the IRISE database which shall be used during the validation step.

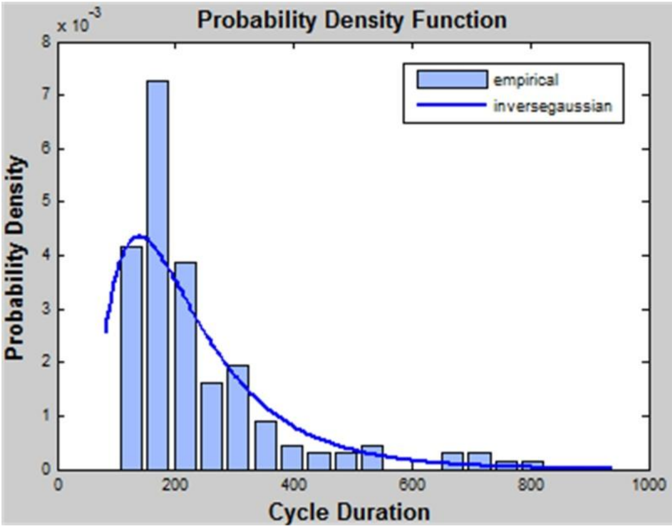


Figure 17 – Fridge cycles distribution from IRISE dataset

We have identified 4 tuning parameters that control the fridge cycle durations so that the simulated energy consumption's distribution fallows a similar pattern to the above benchmarked distribution. These parameters are selected because, after analyzing the IRISE database and field studies, they have a significant influence on the energy consumption cycles of the fridge. The proposed tuning parameters are (i) weekend and weekday, (ii) weather based cooking probabilities, (iii) communication based agreement/disagreement over cooking or eating out activities and (iv) guests parameter to conclude home cooking or non cooking fridge activities. The values of these tuning parameters fall between the probabilistic values of 0 and 1 and are randomly selected by the Brahms simulator during simulations. The goal is to find optimal values of these tuning parameters such that they generate the consumption distribution close to the benchmarked distribution.

Figure 18 explains how the choice of parameters, from simple to complex variables, has been made.

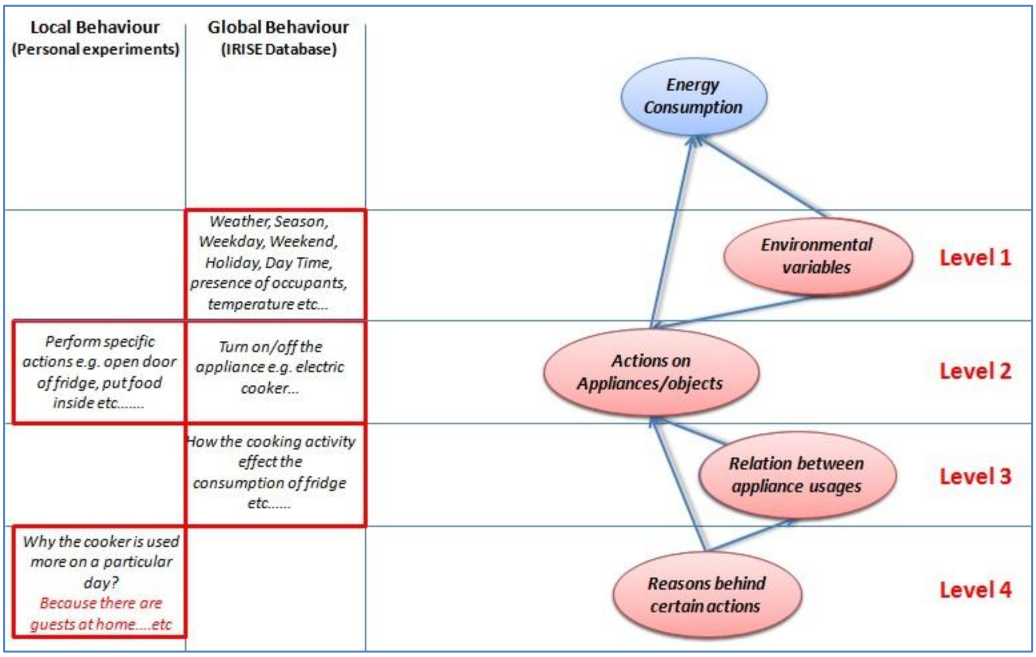


Figure 18 – Parameters considered as important for the model

Some variables can be identified from analyzing the IRISE database (global behaviour), others needs to be explored through empirical studies (local behaviours), while others can be chosen from both the global and local behaviours. The IRISE database only contains information about the consumption of electrical appliances and does not include any information about the activities behind those consumption patterns. Thus this database is used only to study the impact of more generic parameters, such as, when the cooker is on, the workday/weekday and the information about weather. However, this information is insufficient to find the impact of specific actions to which the compressor cycles are sensitive. These specific actions include, for example, the quantity of food introduced into the fridge, etc. These specific actions are related directly to the behaviour of occupants, who may have different behaviours for the achievement of same goal. Since, specific actions constitute these behaviours, it is important to take into account these types of actions and see the impacting results.

3.3 *Brahms Simulation with Initial Tuning Parameters (Step-3)*

We have used Brahms to implement a scenario of a husband and wife concerned with a cooking activity. The scenario is highly dynamic and random because of the probabilistic values of the tuning parameters presented in section 3.2.2. The objective is to run simulations, tuning the parameters, until the simulated consumption distribution becomes close to the benchmarked distribution from the IRISE database.

The tuning parameters are explained as follows:

- ***a)*** ***Weekend and weekday cooking probabilities:*** This defines the probability that the family cooks more during weekends or weekdays. While cooking, the agents interact more with the fridge. If we assign a higher probability to weekend cooking, then the family will interact more with the fridge during weekends compared to weekdays when they may eat out or use the food they have already cooked during weekends.
- ***b)*** ***Weather:*** This defines and controls the perception by agents about the outside weather. It means that if the weather is good, e.g. sunny and warm, then the family might prefer to eat out.
- ***c)*** ***Communication based agreement/disagreement over cooking or dining out:*** This involves the social interaction between agents where they agree or disagree on dining out or cooking at home. The purpose of introducing this parameter is to show how the social interactions of agents are interesting to include in simulations in order to make them closer to reality.
- ***d)*** ***Guests:*** This is a random parameter that increases the interactions with the fridge resulting in larger fridge cycles, hence large energy consumptions**.**

Different combinations of values for these parameters result in different consumption simulation results, one of which is shown in figure 19:

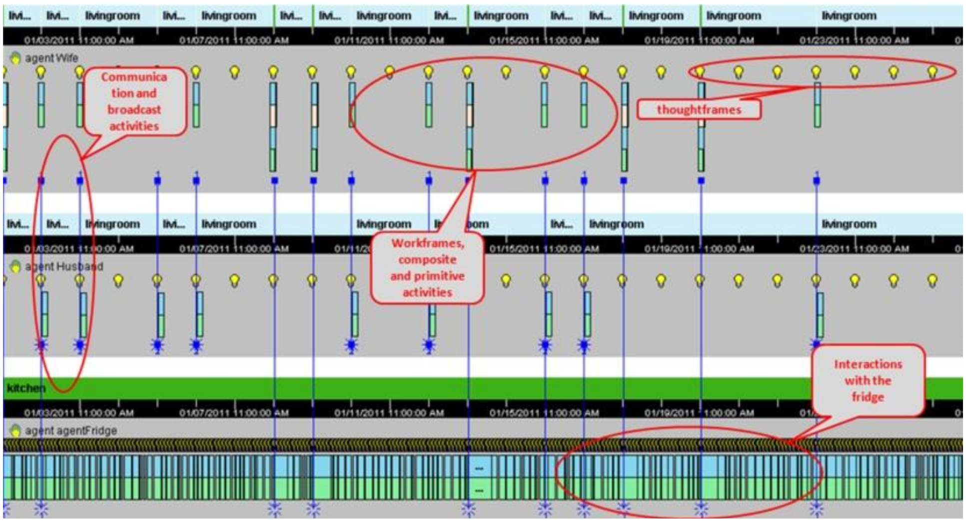


Figure 19 – Brahms scenario simulation results

Figure 19 shows a snapshot of a Brahms simulation over a 1-month period. The horizontal bar at the top shows that the agents move around the house, changing location from room to room (this change in location can be seen more clearly in figure 20 and 21). Below this is the simulation time in the agents' world; agents perceive the time for each time step of the simulation and based on this perception do different things. The bar with the light-bulb symbols shows the thoughtframes, where the agents reason based on different perceptions (such as time, day of the week, weather) coming from the environment. The colorful vertical bars in the area just behind the thoughtframes shows the workframes, where we have the activities of the agents, these may be composite activities or primitive ones. A composite activity is composed of primitive activities, e.g, the “prepare lunch” composite activity can be decomposed into the “open fridge”, “close fridge” and “cook food” primitive activities. An expended form of these workframes and thoughtframes is given in figures 20 and 21. The vertical bars going from one agent’s workframe area to another shows the communication between agents or the broadcasting of information (beliefs) that may in turn invoke actions in other agents.

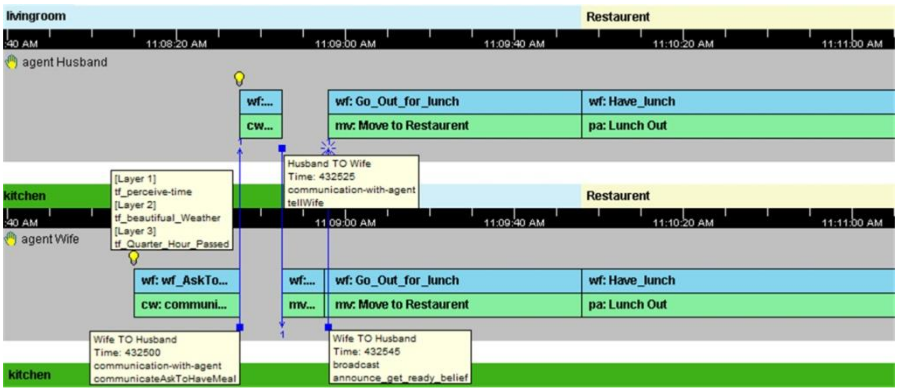


Figure 20 – Communication between agents

Figure 20 shows the expanded snapshot of one of the communications between the agents. Here we can see that the agent ‘Wife’ is perceiving certain facts (simulation time and outside weather) from the environment. As soon as she perceives that the weather outside is beautiful, she starts a communication with the agent ‘Husband’ about the idea of eating outside. If they agree, based on what the agent Husband replied to the agent Wife, they choose to go out or stay at home. If they agree, for example, they will go out as shown is figure 20, but if not, the agent Wife will cook at home and hence use the fridge as shown in figure 21, where sometimes she opens and closes the fridge, or introduces hot food.

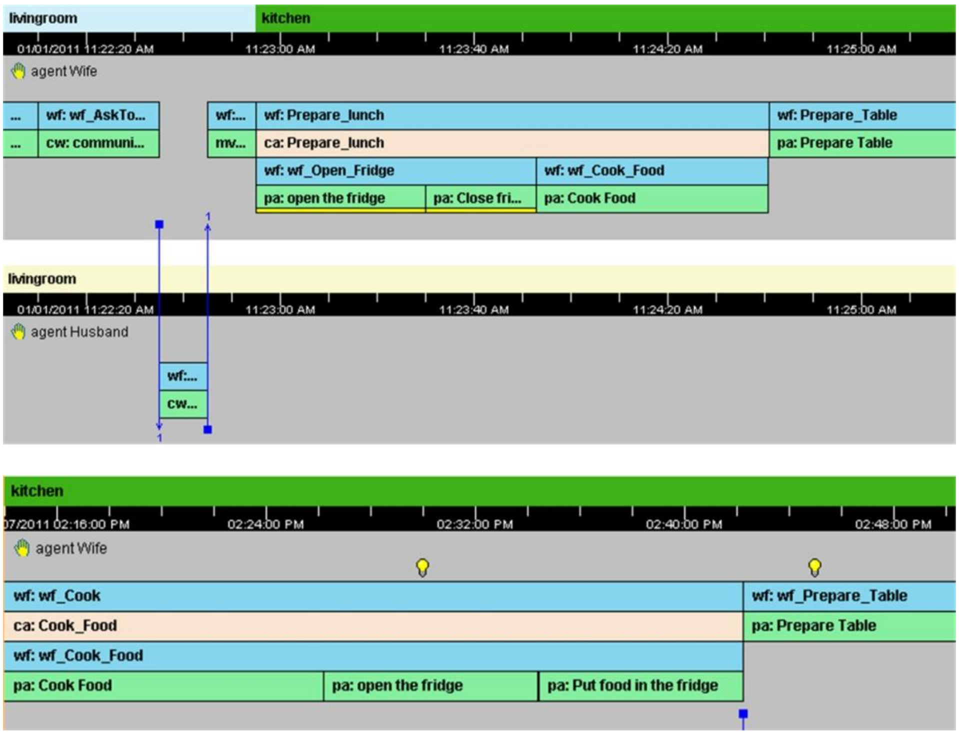


Figure 21 – Detailed cooking activity in Brahms simulation

The Brahms simulation results are combined into a text file. We have developed a parser to read these files and compute the energy consumption associated with the duration of fridge cycles. The initial results with the initial set of tuning parameters are presented in figure 23(a) for the reference.

The probabilities for each parameter are set at the start of the simulation. For example if the probability that the inhabitants will cook more on weekdays is set to 40%, they will cook on different days for each simulation run, but not for more or less than 40% of the time.

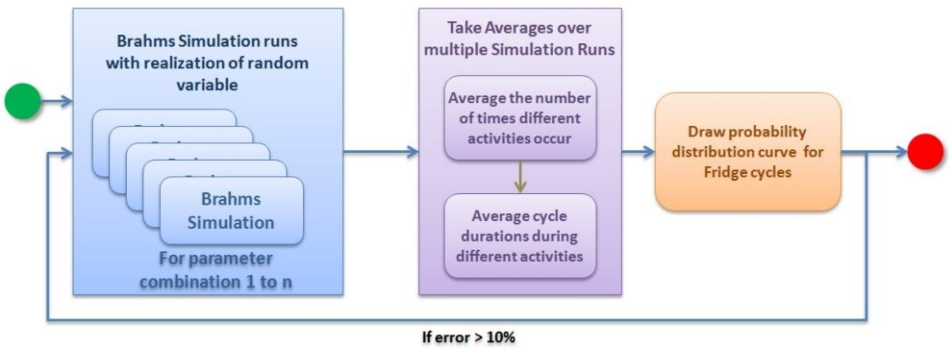


Figure 22 – How to get fridge cycle durations from simulations

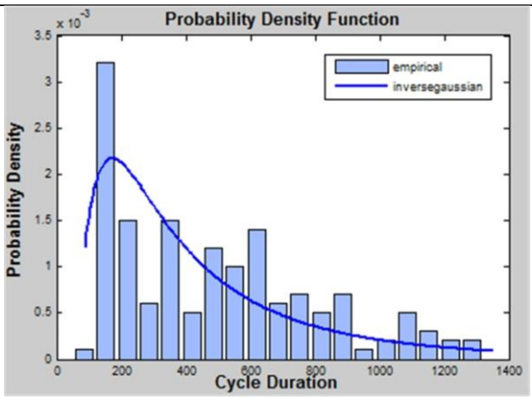
Figure 22 explains the process, where, for some particular probability values for each parameter, the simulation is run multiple times and then the results are averaged. Similarly, the probability values are changed for the next runs and the results are again averaged. The process of changing these probabilities continues until the selected probability values match with the observed behaviour of the people and the consumption trends starts matching with each other.

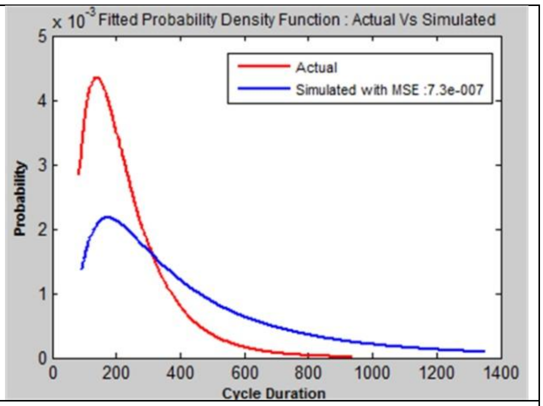
3.4 *Optimized Simulation Parameters (Step-4)*

In this section we present the optimization results found by adjusting the set of parameters (figure 23) and averaging the simulations over several runs. In order to capture the error between the actual and the simulated fitted distributions, we have used the standard mean squared error (MSE) function in Matlab. We have also computed the mean percentage error (MPE) in order to be as close as possible to our cut off criteria as mentioned in section 3, figure 2. The formula to calculate the mean percentage error is given below.

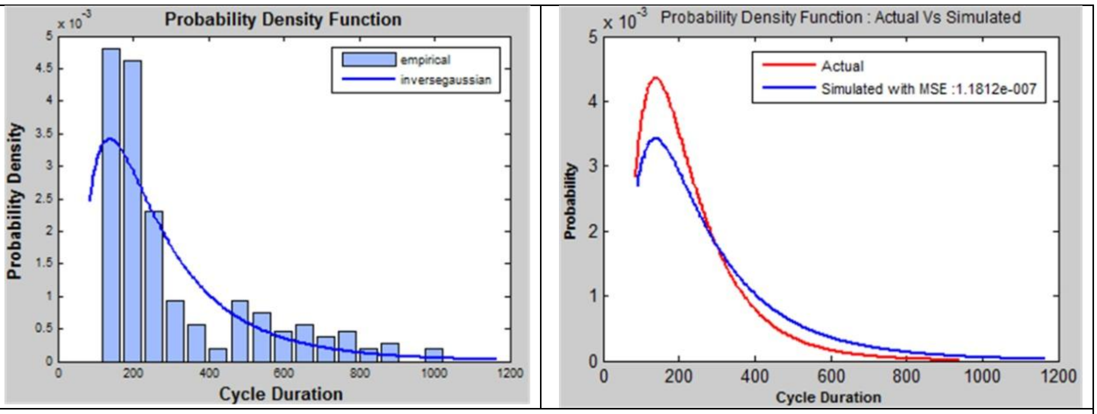
$$\text{MPE} = 1/\text{n} \sum_{i=1}^{n} \frac{ABS(S_i - A_i)}{A_i} * 100$$

where, Ai is the actual value and Si the simulated one.

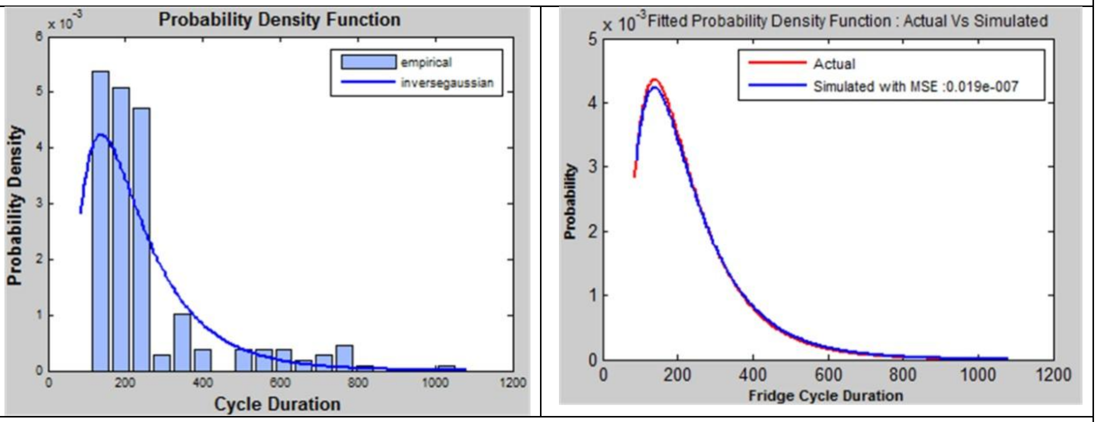




a)
Weekend = 20% chance of cooking activity
Weekday = 80% chance of cooking activity
Weather perception = 30% that weather is sunny
Guests on weekends (more interactions with fridge) = 20%
Social agreement to eat out = 20% chance that they agree



b)
Weekend = 80% chance of cooking activity
Weekday = 20% chance of cooking activity
Weather perception = 30% that weather is sunny
Guests on weekends (more interactions with fridge) = 20%
Social agreement to eat out = 50% chance that they agree



d)
Weekend = 80% chance of cooking activity
Weekday = 20% chance of cooking activity
Weather perception = 30% that weather is sunny
Guests anytime during month (more interactions with fridge) = 20% chances
Social agreement to eat out = 100% chance that they agree

Figure 23 – Optimized tuning parameters, simulated consumption patterns and comparison between actual and simulated fitted curves

If we analyze the above results from left to right and top to bottom we can see a convergence of the simulated distribution towards the benchmarked distribution by successively adjusting the tuning parameters. The final distribution is quite similar to the actual distribution curve.

It can be seen in figure 23 that the error is gradually reducing by adjusting the parameters such that they are closer to what is observed in the experiments (section 3). In figure 23(a), since the inhabitants have more chance to cook on weekdays, instead of weekends, and the weather is often not sunny, they tend to cook more often during the month. However, this is not close to the inhabitants' actual behaviour and is quite far from reality, hence the actual and simulated distributions do not match.

Figure 23(b) shows a particular case where the curves are very close, but the behaviours are not in line with what has been observed. Although the inhabitants cook more often during the weekends, the value for the social agreement is inconsistent with reality.

The parameter values for figure 23(c) are tuned according to the observations from the experiments (section 3). In this case the inhabitants cook more often during the weekends as compared to weekdays and there is a 30% chance that the weather will be sunny and warm. Also the parameter for the social agreement between agents to eat out is set to 100%, which seems to be more realistic compared to the previous cases. Here the statistical curves are not only in compliance with the reference distributions, but also the simulated behaviour is realistic.

4. Conclusions and discussions

We have proposed a 4-step methodology to accurately model and simulate how inhabitants' behaviours influence appliance consumptions, with the goal of accurately assessing energy consumption and reducing waste. Based on the simulation results from step-1 of the methodology, we selected the fridge, and cooking or non cooking activities as having a strong influence on energy consumption. The simulations highlighted that *(i)* frequently opening and closing the fridge door, and *(ii)* putting hot, uncovered, or large quantities of food inside the fridge results in the longer fridge cycles. We also noted that the cooking activity mostly includes, in parallel, the use of the fridge, resulting in high energy consumptions. Concerning non cooking activities, the frequency of the fridge usage is based on factors, such as whether it is a weekday or weekends, and the state of the weather; these result in variations in the fridge consumption cycles. These conclusions are used in the analysis of the IRISE database. Although this database contains energy consumption data per appliance, it does not contain activity and weather-based information. We have complemented the data in IRISE with metrological and activity information. The energy consumption distributions for the fridge against cooking and non cooking activities are computed (step-2).

The results from step-1 and step-2 are used to formulate 4 tuning parameters grouped into three classes; *(i)* cooking activity based tuning parameters, *(ii)* non cooking activity based tuning parameters and *(iii)* dual purpose tuning parameters. The cooking activity based tuning parameters include *(a)* weekend and weekday and *(b)* weather based cooking probabilities. These probabilities are directly linked and transformed into fridge cycles. The non cooking tuning parameters include food quantity based fridge cycles which are derived from the physical model of the fridge. Dual purpose parameters include (a) communication based agreement/disagreement over cooking or dining out activities and *(b)* the arrival or not of guests. These parameters have been incorporated into a scenario, implemented in the Brahms simulation environment in step-3 of the methodology. The parameter values were adjusted and simulations were run until the simulated energy consumptions distributions fall within 10% of the actual ones (step-4). We stated the requirements for a behavioural model at the beginning of this paper. We note that by using autonomous agents and co-simulation; taking into account the environmental perceptions and cognitive reasoning employed by inhabitants' (obtained through field studies); and by comparing simulation results with the complemented data from IRISE, the requirements for the model are satisfied.

In this paper, we have tried to emphasize how specific actions combine to constitute human behaviour and to take this into account in energy simulations. Further, to make these simulations more dynamic and resemble daily life, generic behaviours of inhabitants and social factors are introduced.

It should be noted that this methodology can be broadened by not only considering an example of a single house from database, but making clusters of houses having similar behaviours and using these clusters in simulations to get more generalized results. Our current work prepares for this and we hope that by showing that this methodology works on a specific example, it can be extended to obtain more generic results when applied to the whole population. So whilst we have modelled very low-level actions in this work, when we apply the cluster approach, it is possible to group behaviours and avoid the need for simulating the individual actions of every single inhabitant in a population.

The goal of this paper is to help give more accurate energy predictions by modelling human behaviours. We have focused on how these behaviours could be identified at different levels of details by identifying different parameters and how they can finally be introduced in physical simulations.

It should also be noted that we are not interested in merely differentiating between two activities, i.e., cooking and non cooking, since this information could be obtained from the IRISE database (giving results based on days, weeks, months or years). Our aim was to identify more specific actions that make up the cooking activity since combinations of these will lead to different consumption patterns for different houses or even for different inhabitants in the same house.

5. Future directions

The purpose of focusing on inhabitants' behaviour is so that it may be introduced into co-simulations. In terms of predicting energy consumption, these co-simulators already produce valuable results. If energy management systems are added to the co-simulator then we have an extremely powerful tool that can provide advice and guidance for inhabitants, designers and energy managers. The work in this paper is a step towards that direction. We are moving away from simply calculating total consumption towards a future where co-simulators and energy managements systems in smart homes will communicate directly with smart grids for energy demand prediction, forecasting and load estimation, etc.

The methodology and the developed co-simulator have a potentially wide range of applications for domain of energy load estimation and supply and demand predictions. The EMS may be used in smart homes so that users can be alerted to energy wastage and alternative behavioural activities suggested. This could result in economic benefits and help us to mitigate future energy crises. In addition, the identification of high energy consuming activities may be used for formulating education strategies for inhabitants' to reduce energy waste.

We have demonstrated that the methodology is feasible to identify the high energy consuming activities and it can easily be extended to other appliances. This methodology can be broadened by not only considering an example of a single house from database, but for clusters of houses having similar behaviours to obtain more generalized results from the simulations. Sampled clusters of houses from geographically segmented populations may be used and relevant parameters may be identified and assessed. The clustering of samples can be based on similar energy consumption distributions and be characterized by common characteristics, such as the number of people in the house and house location, etc. Once the optimal tuning parameters for each cluster have been identified, then simulations in proportion to its weighted membership in the population may be run. In addition, more sophisticated techniques, such as artificial intelligence based curve fitting algorithms may be used to find optimal tuning parameters with associated ranking of the most appropriate solutions.

In terms of validation, we can also consider two other methods: using data from another time period (e.g. the same season but a different year); and participative simulations where users are activity involved in the simulation at run-time [28].

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