BIRMINGHAM CITY UNIVERSITY

DOCTORAL THESIS

Agent-Based Models for Residential Energy Consumption and Intervention Simulation

Author:
Fatima ABDALLAH

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Abstract

The increase in energy consumption in buildings has gained global concern due to its negative implications on the environment. A major part of this increase is attributed to human behavioural energy waste, which has triggered the development of energy simulation models. These models are used to analyse energy consumption in buildings, study the effect of human behaviour and test the effectiveness of energy interventions. However, existing models are limited in simulating realistic and detailed human dynamics, including occupant interaction with appliances, with each other or with energy interventions. This detailed interaction is important when simulating and studying behavioural energy waste.

To overcome the limitations of existing models, this thesis proposes a **complete layered Agent-Based Model** (ABM) composed of three layers/ models. The **daily behaviour model** simulates realistic and detailed behaviour of occupants by integrating a Probabilistic Model (PM) in the ABM. The **peer pressure model** simulates family-level peer pressure effect on the energy consumption of the house. This model is underpinned using well-established human behaviour theories by Leon Festinger – informal social communication theory, social comparison theory and cognitive dissonance theory. The **messaging intervention model** implements and tests a novel messaging intervention that is proposed in the thesis along with the complete ABM. The intervention is a middle solution between the abstract data presented by existing energy feedback systems and the automated approach followed by existing energy management systems. Therefore, it detects and sends energy waste incidents to occupants who are allowed to take control of their devices. The proposed intervention is tested in the messaging intervention model, which takes advantage of the two other proposed models.

The undertaken experiments showed that the model is able to overcome the limitations of exiting models by simulating realistic and detailed human behaviour dynamics. Besides, the experiments showed that the model can be used by policy makers to decide how to target family members to achieve optimal energy saving, thus addressing the world's concern about increased energy consumption levels.

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Contents

List of Figures

List of Tables

Abbreviations

ABM Agent-Based Model

AI Artificial Intelligence

CDT Cognitive Dissonance Theory

DSM Demand Side Management

ECS Energy Consumption Survey

EFS Energy Feedback Systems

EMS Energy Management Systems

HVAC Heating Ventilation and Air Conditioning

IoT Internet of Things

ISCT Informal Social Communication Theory

MOA Motivation-Opportunity-Ability

NILM Non-Intrusive Load Monitoring

PDF Probability Distribution Function

PER Personal Energy Rating

PM Probabilistic Model

TM Threshold Model

TPB Theory of Planned Behaviour

TRA Theory of Reasoned Action

TUS Time-Use Surveys

WSN Wireless Sensor Networks

Dedicated to my parents who have always offered me limitless sacrifice and care

Chapter 1

Introduction

1.1 Preamble

The world is being increasingly concerned about environmental issues in the last couple of decades. This is due to the continuous increase in global electricity consumption especially electricity generated from fossil fuels [1]. Besides, with the expected increase in population by 2050 and improvements in life standards and economic conditions, energy consumption is still expected to increase rapidly [2]. This rapid and continuous growth of energy consumption has led to several world changes such as increased concentrations of greenhouse gases [3], and increased global temperature level [4].

These global changes are highly attributed to human actions rather than natural influences [3]. Specifically actions performed in buildings, knowing that the buildings sector is the world's largest energy consuming sector compared to industry, transport, and agriculture sectors [2]. It consumes more than one third of total worldwide energy consumption and half of its consumed electricity. Additional focus is necessary on the residential sector that is less understood than other sectors. The other sectors are centralised, highly regulated, and have expertise in reducing energy consumption, while the residential sector is highly affected by external factors, including the building structure and materials, human behaviour and privacy issues of data collection [5]. In this sense, several solutions have been proposed to improve energy efficiency in buildings, including [6], [7]:

- **building structural improvements** that aim to reduce heating, cooling, or ventilation consumption,
- **technological improvements** ranging from smart appliances to complete energy management systems, which help in controlling energy consumption, and

- **behavioural interventions** that aim to motivate occupants to change their energy consumption behaviour.

Among these solutions, the human behaviour factor is the most influential as it may reverse the effect of structural and technological improvements [8], [9]. Knowing that big part of energy consumption in buildings is caused by behavioural energy waste (e.g. leaving appliances and lights ON while not in use, or unnecessary heating/cooling in buildings), occupants have a great potential in reducing energy consumption in buildings [10], [11]. Besides, it has been proven that similar households (in terms of household composition, economic level, profession, and house structure) resulted in different energy consumption levels, which is mainly attributed to different human behaviour characteristics [12]. This necessitates the understanding of human behaviour aspects, including their effect on energy consumption, behaviour change and effectiveness of behavioural interventions.

1.2 Research Scope and Problem

In order to understand the effect of human behaviour and test solutions to reduce energy consumption in buildings, energy simulation models are designed and developed. The main aim of simulation models is to predict energy consumption at different levels (regional, national, building, household, etc.). In many cases, they are extended to predict changes in energy consumption when the affecting factors change (such as economic, atmospheric, technological, or behavioural). The results obtained through simulation models are highly beneficial for policy makers and governing bodies to assess energy consumption and decide the needed changes to control and reduce it [13].

Given the importance of studying the residential energy consumption sector and the human behaviour effect as presented in the previous section, this thesis looks into modelling the human behavioural aspect and assessing energy efficiency interventions through simulation models. Specifically simulating energy waste caused by occupants and testing interventions that help them avoid this waste in housheolds. As an alternative to simulation models, energy interventions and technological solutions can be tested through field experiments. Field experiments require launching the intervention system in a real environment, collecting data for a period of time, and observing the interaction of occupants with the system. This process can be challenging in terms of time, cost, and data access opposed to the simulation technique [14], which motivates the selection of simulation modelling in this research. Although field experiments allow to capture real user experience, they have limited experimental variation and can only be studied for a limited period of time [15]. However, computer simulations allow more varied scenarios and long time frame for the study. It cannot be denied that simulation models are limited in capturing all of the psychological aspect of energy interventions, however, we consider it as a first step for evaluating new ideas that could be implemented in the future. In this research, we use human behaviour theories in simulation models to capture psychological aspects at a high level of granularity.

Energy simulation models can be categorised into *top-down* and *bottom-up* approaches. Top-down approaches predict and study variations in energy consumption based on economic variables at a high-level (energy sector, city, region, nation, etc.) rather than low-level (household, individual energy use, appliance-level, etc.). Thus, this high level energy modelling does not allow the study of energy solutions, which are applied at the household/building level [16]. On the other hand, bottom-up approaches build up the energy consumption of a unit through simulating low-level consumption. One of the famous bottom-up methods are engineering models that focus on the physical heating behaviour of buildings. Engineering models are most suitable for assessing the effect of structural changes in buildings, but cannot be used to study the effect of changes in human behaviour. This is because they model human behaviour in a *deterministic* way through fixed and estimated schedules for occupancy (i.e. existence at home) and operation of appliances [5]. This does not only prevent energy interventions testing, but also leads to unrealistic human behaviour simulation.

Another bottom-up approach for energy simulation are *probabilistic* models, which may be used to overcome the limitation in engineering models [17]. Probabilistic Models (PMs) generate detailed energy consumption data (at appliance-level in small time steps) by simulating realistic daily occupants behaviour (presence in building, activities, and location). This is done by extracting probability distributions from Time-Use Surveys (TUS), which contain real and fine-grained individual activities in different days of the week. Detailed and activity-based energy modelling in PMs enables simulating energy waste and testing energy efficiency improvements, specifically Demand Side Management (DSM) that target end-users rather than utility providers or energy transportation [18], [19]. Although PMs are suitable for energy waste simulation and energy efficiency solutions, they are computationally not suitable for simulating human dynamics, which include interaction with appliances, with other individuals and with energy interventions. PMs follow a staged modelling process, which is capable of reproducing realistic and detailed occupant activities and energy consumption rather than simulating dynamic human behaviour that is affected by several personal and environmental factors. Besides, they assume that all occupants have the same and ideal energy consumption characteristic, while human behaviour is not ideal and may vary from one person to another [20].

Agent-Based Modelling is another technique used for energy simulation modelling. It is a bottom-up approach that can be either probabilistic or deterministic based on the way it models human behaviour. An Agent-Based Model (ABM) is composed of a group of interacting agents, which are autonomous software components. Each agent behaves based on its characteristics and a set of rules, and interacts with other agents in the environment [21]. ABM is used to simulate energy consumption where each agent represents an energy consumer that causes energy consumption in a building environment. The amount of consumed energy is then calculated based on the behavioural characteristics of the energy consumers. For example, one of the models represent each household as an agent that belongs to one consumer archetype [22]. The archetype determines the occupancy of the household and energy awareness level. Another approach is to model agents at occupant-level and characterise them using average energy consumption per year [13]. Modelling agents at household-level and using average energy consumption to characterise occupants lead to high-level energy data generation and do not allow the simulation of daily activities that cause energy consumption. This makes these models not suitable for human behavioural energy waste and occupant-appliance interaction simulation.

Another group of ABMs include occupant-level dynamics and generate detailed data that is useful for energy waste simulation [23], [24]. However, the occupancy and activities simulation in these models is extracted using a uniform distribution in fixed time intervals. This does not serve in simulating realistic human behaviour that can be more stochastic. Besides, the fact that these models use hypothetical/small case studies questions the generalisation of the results, especially the resulting effectiveness of energy interventions. Therefore, given the above problems presented in existing energy simulation models, there is a need for a model that can be used to assess energy interventions by simulating human behaviour energy wastage. This requires modelling realistic human behaviour and interaction with appliances.

Realistic occupant behaviour is not only modelled by simulating activities and interaction with appliances, but also by including the natural human-to-human interaction, which may affect individual's behaviour. This is referred to as peer pressure where individuals' communication and comparison lead to behaviour change in a community. This is highly applicable to environmental behaviour, for example, energy interventions proved more efficient when individuals discussed related issues with each other [25]. ABM has been used to simulate the peer pressure effect on energy consumption [13], [26]. The modelling of peer pressure is usually based on established human behaviour theories that explain the effect of social pressure on the behaviour of individuals, or may be calibrated using real data.

Existing models mainly focus on studying the effect of peer network structures on behaviour diffusion and energy consumption in commercial and residential communities. However, these models may not be used to model peer pressure in households because the used human behaviour theories and peer network structures/types are not applicable to family members interaction. In addition, these models do not model energy consumption behaviour change accurately because occupants are characterised by average energy consumption per day/year. Therefore the change in this attribute due to peer pressure may be explained by a change in daily behaviour, energy awareness (i.e. energy consumption behaviour), or both of them. Separating the daily behaviour aspect from the energy awareness aspect ensures more realistic study of peer pressure and energy interventions. Therefore, a new model that simulate peer pressure among family members is needed while separating occupants' daily behaviour from energy awareness. Besides, human behaviour change theories that are applicable to family environments need to be explored to obtain realistic occupants interaction.

In addition to energy consumption and peer pressure simulation, ABM has been used to test energy solutions, which include energy interventions. For example, the effect of energy training and workshops was studied in [13] where the affected individuals are randomly selected. The change in occupants' behaviour is based on an assumed effectiveness percentage for the intervention. Similarly, feedback interventions are modelled in [27] where an asymptotic equation is used with a specified rate of change. These models assume that the effect of interventions is always the same whatever the characteristics of the occupants and how often they are exposed to them. Whereas the interaction of occupants with the interventions differs from one individual to another. This makes the results of energy interventions not realistic enough, and does not allow the study of factors affecting them.

Energy Interventions can be applied in different forms, including commitment, goal setting, incentives, feedback. [28]. The most popular and used intervention approach these days is real-time feedback, especially with the development of sensing and communication technologies [29]. The purpose of feedback is to make occupants aware of their energy consumption to allow them to control and reduce it. Several research studies have been done to assess Energy Feedback Systems (EFS) and the interaction of occupants with them. These studies have shown that feedback systems can be effective in changing occupants awareness and encouraged them to reduce energy consumption [30]. However, in many cases, users found difficulty in understanding the displayed data and knowing what can be done to reduce consumption [31], because the data are abstract and not related to their daily practices. Many efforts also worked on supporting the energy consumption values with context data such as location context [32] or activities context [33]. Nevertheless, this still requires occupants to analyse the displayed data to identify the needed actions to conserve energy. Therefore, there is a need for an energy intervention that not only informs occupants about their energy consumption, but also guides them to which actions can be done to reduce it. This service requires sensing technologies and analysis techniques to identify the causes of high consumption, which is available in Energy Management Systems (EMS).

EMS provide the monitoring and control infrastructure to enable a central control of energy consumption in buildings. Most existing EMS use data related to occupants (e.g. presence and preferences) and the surrounding environment to control energy consuming devices on behalf of occupants [34], [35]. When testing the automated control approach with people, it was found that users lost the sense of control over their devices, which is proven to be uncomfortable [36]. Besides, the automation effect may be reversed or at least reduced by occupants if they are not comfortable with the system's decisions [9]. This highlights that a middle-point approach between automatic control and abstract feedback would be the best solution. In this case, technology and analysis techniques can be used to obtain actionable feedback by detecting and informing occupants about energy waste, and keeping the control for them.

To summarize the above body of literature, the following problems are identified in existing energy simulation models and energy solutions:

- PMs are not suitable for dynamic human behaviour simulation, and do not differentiate occupant energy consumption awareness. This makes it not possible to study energy waste and test energy interventions using PMs.
- Among existing ABMs, there are models that generate high-level data and are not activity-based, therefore, they cannot be used to simulate behavioural energy waste and occupant-appliance interaction.
- Another group of ABMs, are deterministic in simulating occupancy data, or use uniform distributions in fixed occupancy and activities time intervals, which may not generate realistic human behaviour.
- Existing ABMs that can simulate energy waste and probabilistic human behaviour use hypothetical or small case studies, which does not allow the study of varied scenarios and generalisation of results.
- ABMs that simulate peer pressure in residential and commercial communities cannot be used to simulate family-level peer pressure, and do not separate occupant daily behaviour simulation from the energy consumption behaviour.
- ABMs that test the effectiveness of energy interventions either assume the effect of the simulated intervention, or apply the same effect on all individuals regardless of their characteristics.
- EFS provide energy consumption data that are not enough to inform occupants' actions to conserve energy, and EMS follow the approach of automatic control, which is mostly uncomfortable for humans.

These identified research problems are used to scope the research contributions and aims of this dissertation.

1.3 Research Aims and Objectives

There are two aims of this research. The first aim is to develop an energy simulation model that can be used by policy makers to assess energy consumption in residential buildings and test the effectiveness of energy interventions. In order to do so, the model has to simulate human behavioural energy waste through modelling realistic occupant-level dynamics, including occupants' interaction with appliances, with each other (i.e. peer pressure) and with energy interventions. The other aim is to design a new energy intervention mechanism that notifies occupants about energy waste incidents and enables them to control their consumption. The proposed intervention is assessed using the developed energy simulation model.

In order to achieve these aims, the following objectives are outlined:

1. Review existing energy simulation models and assess their capability to simulate realistic human behaviour, energy waste, peer pressure, and energy interventions in households.

2. Develop and validate a model that simulates detailed energy consumption in residential buildings through simulating realistic human daily behaviour and energy waste.

3. Explore human behaviour theories that explain the peer pressure effect on behaviour change, and select the ones that can be used to model family peer pressure.

4. Develop and validate a model that simulates peer pressure effect on energy consumption behaviour among family members.

5. Review existing energy feedback and technological solutions (i.e. energy feedback systems and energy management systems) and assess their effectiveness in reducing households energy waste.

6. Design an energy messaging intervention that informs occupants about their energy waste and recommends actions to reduce the waste.

7. Develop a model that implements and assesses the proposed messaging intervention taking advantage of the previously developed models in objectives 2 and 4.

1.4 Contributions

The **first** contribution of this thesis is to conduct a thorough review of studies related to energy simulation modelling. This review includes: (1) top-down and bottom-up approaches, (2) probabilistic and deterministic approaches, (3) ABMs and PMs for energy simulation, (4) ABMs for peer pressure simulation, (5) human behaviour change theories that study the effect of peer pressure, (6) ABMs that simulate energy interventions (7) and the energy efficiency solutions EFS and EMS. These are the most related areas that need to be reviewed to show the addressed research gap.

In order to simulate realistic human behaviour and detailed energy consumption data, we propose to integrate PMs and ABMs. In this case, the PM provides the probability distributions that help in simulating realistic daily occupant behaviour, and the ABM simulates the detailed occupant interaction with appliances, with other occupants, and with energy interventions. This integration overcomes the limitations in PMs as they cannot be used for dynamic simulations as explained above. Besides, it supports the ABM with robust and realistic human behaviour simulations, which is the limitation in existing ABM as aforementioned in the previous section. Therefore, the **second** contribution of this thesis is a model that generates fine-grained and activity-based energy consumption data by integrating a PM in an ABM. Probability distributions of occupancy and activities data are obtained from an existing PM by Aerts [37]. The choice of this model is made after a review of existing PMs. In the ABM, every occupant is modelled as an agent that is characterised by its age and employment type. During the simulation, every agent selects its occupancy and activities based on the probability distributions from the PM. It also interacts with appliance agents that cause the energy consumption of the house. To model energy waste, we assign a personal energy consumption attribute to every occupant agent, which determines how often the occupant performs energy efficiency actions. A set of experiments are conducted to validate the model and show how it can be used to assess energy consumption in households. This is done by varying a number of social parameters such as employment type and household size.

The **third** contribution of this thesis is to develop a peer pressure model for family-level interaction. The model is built over the daily behaviour model, thus takes advantage of the separation of daily behaviour and energy consumption of occupants. To model realistic occupant interaction, we utilise Festinger's theories [38]–[40] that explain social group interaction and its effect on individual behaviour. These theories were selected as they are applicable for family-level peer pressure, and can lead to a usable and uncomplicated model while achieving realistic interaction of occupants. The formalisation of Festinger's theories is inspired by Granovetter's Threshold Model (TM) [41], which is basically aimed at simulating the diffusion of behaviour in a community. Therefore, the model is adapted to effectively simulate family-level peer pressure. The peer pressure model also includes the simulation of two types of interventions: (1) individual intervention and (2) social interventions [42]. These are included as abstract and general interventions to show how the model can be used to test interventions in different scenarios. The model is validated showing that it reflects the used human behaviour theories.

The developed daily behaviour and peer pressure models are used to assess a novel intervention mechanism, which represents the **fourth** contribution of this thesis. The intervention is considered a practical example of individual-level interventions simulated in the peer pressure model. It overcomes the limitations in existing EFS and EMS by informing occupants about energy waste incidents happening in their house, and allowing them to control their appliances instead of controlling them automatically. The incidents are suggested to be forwarded to occupants through their mobile devices. In order to make the messaging intervention non-intrusive (i.e. does not interrupt and annoy users), we propose a context-aware messaging strategy that controls the number and time of the messages to be sent. The proposed messaging intervention and strategy are implemented in a third model that is built upon the daily behaviour and peer pressure models, which represents the **fifth** contribution of this thesis. The fine grained and activity-based data generated by the daily behaviour model enables the testing of the proposed messaging intervention. A number of experiments are conducted to show how the model can be used to assess energy interventions. The experiments also show that the proposed messaging interventions is effective in reducing energy consumption.

The three models proposed in this thesis can be visualised as a complete layered 'onion-like' model. This is to emphasise that each layer (i.e. model) is built upon the other, and that extra layers can be added to the model whenever a new feature is needed. Figure 1.1 gives an illustration of the onion-like layered model. The daily behaviour model is placed in the core, and the other layers surround it. The last layer of the model (the messaging intervention model) is meant to be a customisable layer, where different types of energy interventions can be modelled, implemented and tested using the other two layers of the model. More than one intervention can also be added to test the effectiveness of multiple interventions.

Within the area of modelling, three roles of models can be defined: *predictor models*, *mediator models*, and *generator models* [43]. Predictor models are developed when there is a high level of understanding of the real system. In this case the model provides accurate predictions. When less is known

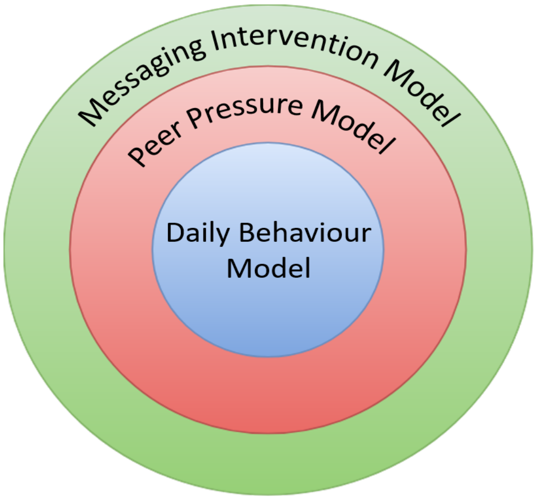


FIGURE 1.1: The Proposed Onion-like Layered Agent-based Model

about the system, the model can play the role of a mediator between theory and the real world. A mediator model does not reflect the exact behaviour of the system, but is used to gain insights into its characteristics and behaviour. The third category of models is generator, where hypotheses and theories are generated from the model, which are then experimented and validated in real world. The model developed in this thesis is considered a **mediator model**. This is because detailed real data about human interaction with each other and with interventions can be difficult to obtain. Therefore, the proposed model uses real data in the core daily behaviour model as it is available from TUS, and uses human behaviour theories to model occupants interaction. For the messaging intervention model, real statistics of smartphone possession and usage are used for the message reception simulation. Behaviour change due to the energy intervention is simulated based on the actual interaction of occupants with the messages and their compliance to it. Therefore, the proposed model can be used as a mediator to get a clear understanding of energy consumption in households and assess energy interventions affecting factors. In light of the obtained results, energy interventions can be deployed in reality, and real observations are recorded.

1.5 Thesis Outline

The rest of the thesis is organised as follows:

Chapter 2 provides an extensive literature review of energy simulation modelling. The chapter first gives a general overview of energy simulation approaches. Then a more detailed review is done on existing ABMs and PMs showing how the strengths of each of them overcome the limitations of the other. ABMs that model peer pressure effect are also reviewed in this chapter along with human behaviour change theories that explain the social effect on peoples' behaviour. The chapter also reviews the energy solutions EFS and EMS, and corresponding ABMs that are used to test these solutions. It presents the argument of automated and human controlled approaches to highlight the need for a middle-point energy intervention. The chapter is concluded by summarising all reviewed ABMs comparing their different features and showing the features of the proposed complete model. The review in this chapter covers **objectives 1, 3, and 5** outlined in section 1.3.

The core daily behaviour model is presented in Chapter 3. The rationale of selecting the existing PM is given first showing its unique features compared to other PMs. After that, the details of the proposed ABM are explained. The validation of the model is presented next and a number of experiments are conducted to show the effect of various social parameters on the consumption of households. The results of the experiments are discussed last giving the insights gained. Chapter 3 fulfils **objective 2** of the thesis.

Chapter 4 proposes the peer pressure model that is composed of two submodels: (1) the behaviour change sub-model, and (2) the energy intervention sub-model. The behaviour change sub-model formalises Festinger's theories and Granovetter's TM. The energy intervention sub-model simulates the occupant-level and family-level interventions. Experiments are presented in this chapter to validate the proposed model, and study the effect of peer pressure, energy interventions, and social parameters on the energy consumption of the house. **Objective 4** is covered in this chapter.

The new messaging intervention mechanism and the model that tests it are proposed in Chapter 5. The chapter includes an overview of appliance types that may be controlled using the intervention, the message pushing strategy and the factors that affect the energy consumption and messaging compliance. Then, technologies and technique needed to obtain the messaging intervention in reality are presented. Next, the messaging intervention model and the proposed strategy are formalised. At last, general intervention and detailed strategy results are presented after a set of experiments. This chapter satisfies **objectives 6 and 7**.

Finally, Chapter 6 concludes the thesis by summarising its contributions and highlighting future directions to go further with this research.

Figure 1.2 shows the structure of the thesis with the flow of output from each chapter to the other.

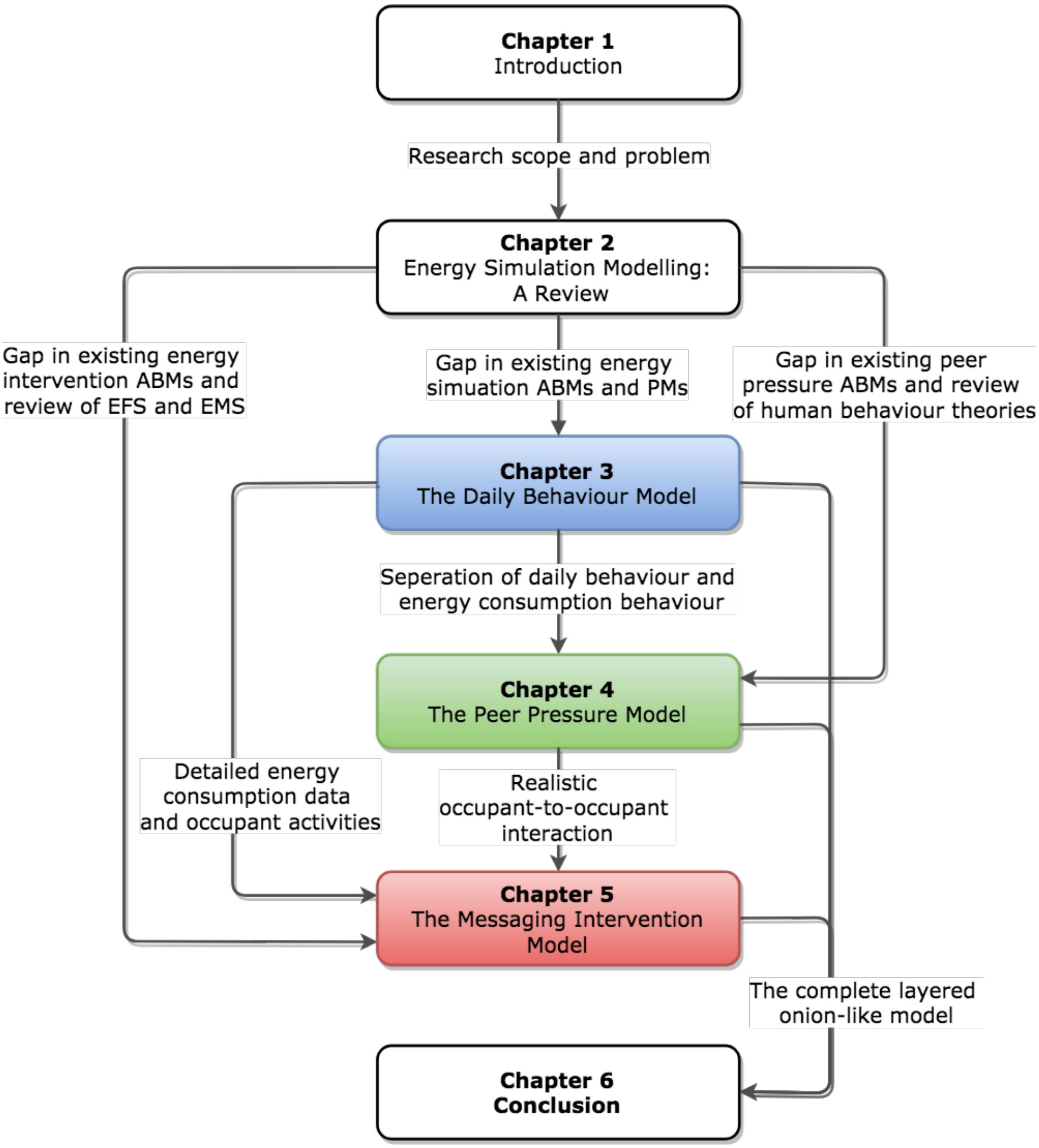


FIGURE 1.2: Thesis Structure

1.6 Publications

- F. Abdallah, S. Basurra, and M. M. Gaber, "A Non-intrusive Heuristic for Energy Messaging Intervention Modelled using a Novel Agent-based Approach,", *IEEE Access*. IEEE, 2019, vol. 7, no. 1, pp. 1627-1646 **[impact factor = 3.557]**

- F. Abdallah, S. Basurra, and M. M. Gaber, "An agent-based collective model to simulate peer pressure effect on energy consumption," in *Computational Collective Intelligence (ICCCI 2018)*. Springer, 2018, vol. 11055, pp. 283-296. **[Best Student Paper Award]**

- F. Abdallah, S. Basurra, and M. M. Gaber, "Cascading Probability Distributions in Agent-Based Models: An Application to Behavioural Energy Wastage," in *Artificial Intelligence and Soft Computing*. Springer, 2018, vol. 10842, pp. 489–503.

- F. Abdallah, S. Basurra, and M. M. Gaber, "A hybrid agent-based and probabilistic model for fine-grained behavioural energy waste simulation," in *IEEE 29th International Conference on Tools with Artificial Intelligence (ICTAI)*. IEEE, 2017, pp. 991–995.

Chapter 2

Energy Simulation Modelling: A Review

In light of the challenges presented in the previous chapter regarding existing energy simulation models and energy efficiency solutions (i.e. Energy Feedback Systems (EFS) and Energy Management Systems (EMS)), this chapter presents an in-depth literature review of energy consumption models, human behaviour change theories, EFS and EMS. The review of existing energy models is done to assess the capability of these models to simulate realistic human behaviour, study energy waste, model peer pressure and assess energy interventions. Human behaviour change theories that explain peer pressure are presented to select the ones suitable for family-level interaction simulation. In addition, EFS and EMS are reviewed to assess their capability to reduce energy consumption in households.

The structure of this chapter is driven by the main contributions of the thesis where each of the Sections 2.2, 2.3 and 2.4 are related to the chapters 3, 4 and 5, respectively. Section 2.1 presents a general review of existing approaches and technologies used for energy simulation modelling. It contextualises probabilistic and agent-based models in the wider categorisation of these approaches and explains the rationale of selecting them. Then, a thorough review of existing Agent-Based Models (ABMs) and Probabilistic Models (PMs) is presented in Section 2.2, which shows strengths and limitations of these modelling techniques, and shows how integrating them overcomes the limitations of others. Next, Section 2.3 refers to ABMs that model peer pressure, and shows the need for a new peer pressure ABM at the family members interaction level. A number of human behaviour theories are also presented to explain the rationale of selecting the theories that were adopted in the proposed model. Section 2.4 reviews a number of models that test the effectiveness of energy solutions that help in reducing/controlling energy consumption. Besides, it presents a review of existing EFS and EMS highlighting limitations in these systems and presenting the argument of automated and human controlled approaches.

In the review of existing ABMs, it will be noticed that most of the studies will be cited several times in different sections of this chapter. This is because every section tackles the models from a different perspective. More Specifically, section 2.2.1 focuses on the usage of ABM as a general technique for energy consumption simulation and compares the way of modelling energy consumption behaviour and the level of detail the model can produce. Section 2.3.1 focuses on ABMs that model peer pressure. Section 2.4.1 presents ABM that simulate the effect of policies, technologies and interventions on occupant behaviour and energy consumption. Finally, section 2.5 presents a summary of the previous sections and combines all referenced ABMs in one comparison table, which shows the features implemented in these models and how the proposed layered model combines the strengths of existing models.

2.1 Models for Energy Consumption Simulation

The purpose of energy simulation models is to predict energy demand at macro-level (national and regional), and/or determine the change in consumption at micro-level (household/appliance) after structural or technological improvements [5]. This information can inform policy makers' decisions to take actions in order to control/reduce energy consumption. Different approaches and techniques exist in the domain of building simulations, and each has its own purpose, strengths and limitations. Figure 2.1 shows the categories of existing approaches and models that will be discussed below.

Building energy simulation models are categorised into *top-down* and *bottom-up* approaches. This categorisation distinguishes the level of detail the model starts with to get the total energy consumption of the residential sector [5]. Top-down approaches study the effect of general variables that are mostly economic such as gross domestic progress, fuel prices, weather conditions, etc. [16]. They study the effect of these general variables to estimate the energy consumption of the sector as a whole, without studying energy consumption at occupant, household, or group of households level. The aim of top-down approaches is mainly to estimate energy supply. The strength of this type of modelling is that they require highly aggregated data, which can be easily obtained nationally and globally. However, this whole-sector level of study makes it difficult to identify the effect of household-level changes

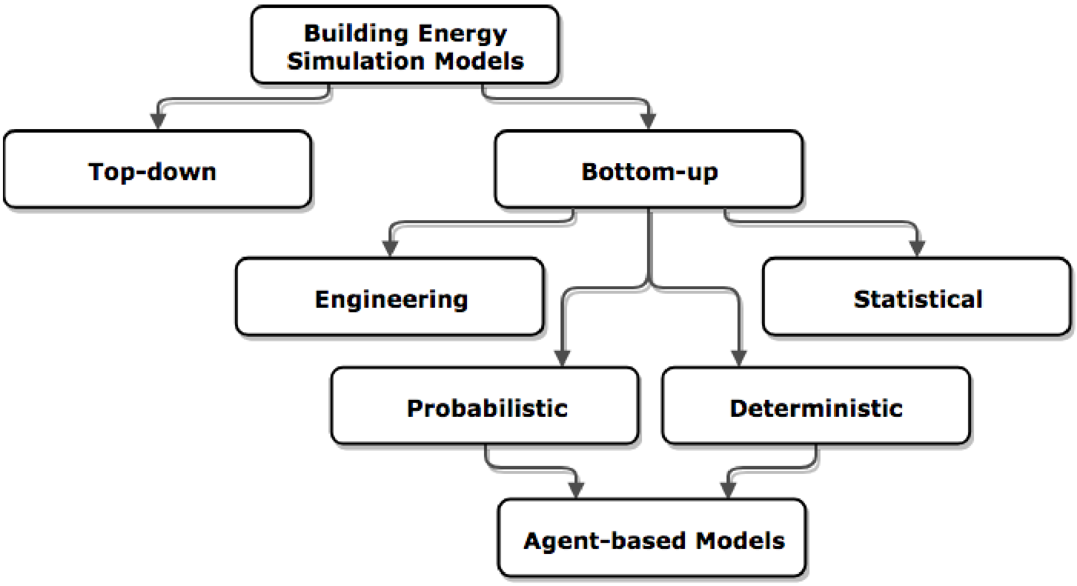


FIGURE 2.1: Energy Simulation Approaches and Models Categorisation

such as behavioural interventions, energy efficiency technologies and structural improvements [5], [16]. **This makes it infeasible to use top-down approaches for detailed energy consumption simulation and intervention studies.**

Bottom-up approaches obtain the energy consumption of a building or a city by calculating the consumption at appliance, individual end use, household, or group of households level, which are then aggregated to get the total consumption. Within bottom-up approaches, *statistical* and *engineering* methods are the most famous. Statistical methods use different machine learning techniques to predict the energy consumption based on historical data [6]. This is done by correlating different input variables with energy consumption [44]. These input variables are expected to affect energy consumption, and include weather data (temperature, humidity, solar radiation, wind speed, precipitation, etc.), occupancy data (occupant existence, time of day, calendars, etc.) and rarely building characteristics data [45]. Techniques that are usually used as statistical methods include regression, genetic algorithms, artificial neural networks, support vector machines [5], [6], [44], [45]. Although statistical methods are known to be simple to use, accurate and do not require detailed data, they **cannot be used to evaluate energy efficiency improvements and technologies** [16]. This is because they only aim to predict future consumption based on the input variables, and any change in other factors such as new technologies or occupant behaviour necessitates re-training the model [45]. One advantage of statistical models is that they incorporate the effect of occupant behaviour. They do so either implicitly through the historical data, which embed occupant behaviour [5], or explicitly by including behavioural variables like average usage time of appliances [46], or occupancy data [47]. However, statistical models still lack the flexibility to model the interaction between occupants and appliances, and activities of occupants that cause the energy consumption. Therefore, they **cannot serve in modelling energy waste due to occupant behaviour**.

The other group of bottom-up approaches are engineering (or building physics) models. Unlike statistical methods, engineering models do not depend on historical data, but define detailed thermodynamic equations to define the physical behaviour of heat transfer [5], [44]. The input variables for these models include weather conditions, building geometry and thermal characteristics, occupant schedules and the available Heating Ventilation and Air Conditioning (HVAC) systems, appliances and lighting used along with their operation schedules [16], [48]. Examples of software that use the engineering models are EnergyPlus, ESP-r, DOE-2, eQuest among others [44], [48]. The advantage of these models is that they are flexible enough to be used to assess the effectiveness of new technologies and energy efficiency improvements [5], [16]. This is because they define the equations that determine the consumption based on the input of the model and do not rely on historical data. The main purpose of these models is to predict thermal energy consumption and assess occupant comfort, however, appliances and lighting consumption is poorly represented and inaccurately predicted [49]. The main reason for this is that occupant behaviour, including occupancy and appliance usage, is modelled using simple and fixed estimates [5], [48]. This fixed representation **does not reflect the actual occupant behaviour and usage of appliances**. Therefore, there is a need for a bottom-up approach that defines the internal determinants of energy consumption, like engineering models, and represents realistic and detailed human behaviour.

The challenge in engineering models leads to another categorisation of energy models that simulate human behaviour. They can be either *deterministic* or *probabilistic* (stochastic). Deterministic models define the behaviour of the model components in a predictable and repeatable way, which is the method used in bottom-up engineering models. However, this does not reflect realistic human behaviour which can be stochastic and unpredictable [50]. To resolve this issue, probabilistic approaches were proposed to reflect realistic human behaviour. Probabilistic Models (PMs) are bottom-up models that simulate high resolution data (in terms of time, appliances and occupant activities and location) using probability distributions extracted from real data, which are then used to calculate the energy consumption of the household [51]. These detailed data are appropriate for modelling energy waste caused by human behaviour. However, some computational drawbacks in PMs exist, which make them **unsuitable for human interaction and intervention simulation** (these drawbacks will be detailed in the next section). Therefore we utilise *agent-based modelling* technique. ABMs are mainly used for dynamic human behaviour simulation where human agents can adjust their behaviour based on their characteristics and the surrounding environment. They can be categorised under the bottom-up approaches because they produce appliance/building-level consumption. In ABM, human behaviour can be modelled in a deterministic or probabilistic way.

In this research, we integrate ***probabilistic*** and ***agent-based modelling*** approaches combining the strengths of each of them. The next section reviews existing PMs and ABMs highlighting their limitations and showing how integrating them can overcome these limitations, which otherwise persist, when they work separately.

2.2 Agent-based and Probabilistic Models for Energy Consumption Simulation

2.2.1 Agent-based Models

Agent-based modelling started becoming popular in late 1990's as an alternative to typical simulation techniques (such as discrete-event simulation and differential equations) to explain interactive system dynamics [21], [43]. This is because of its ability to simulate the interaction of small units that compose a complex system in a simple way. ABM is defined as a computational technique, which models a group of autonomous software components called *agents* [21]. Agents are characterised by a set of states and rules, which determine the agent's behaviour [52]. Rules of behaviour are defined for agents that are allowed to act and interact in the environment in order to observe changes at the micro (low-level and individual) and macro-levels (high-level and environment) [52], [53]. In ABM, the agent has the following properties: (1) autonomy (not controlled externally but by its own rules), (2) social ability (interacts with other agents in the environment), (3) reactivity (responds to changes in the environment) and (4) pro-activity (uses the rules, interactions and reactions to reach a specific goal) [54]. ABM is best used (1) when the agent's behaviour is dynamic (i.e. affected by the surrounding environment), (2) when its location is not fixed and (3) when its characteristics are heterogeneous [21], [53]. These features of agents and agent-based models, make ABM the most appropriate technique to model human behaviour and study the factors that influence it [26]. This explains why ABM is chosen as the main modelling technique in this thesis. Besides, it is useful to simulate energy waste caused by human behaviour, occupant interaction and peer pressure and energy interventions. These features of the developed ABM will be detailed throughout this manuscript.

ABM has been applied in different application domains, including biology [55], economics [56], social sciences [57]. Energy consumption behaviour is an example of application domains where ABM have been used to model energy consumption in both residential, commercial and office buildings for different purposes. In such models, occupants are modelled as agents that spend time in a building/house environment, and cause the consumption of energy. In order to add the human behaviour aspect, the models characterise occupant agents by a personal attribute that determines its level of energy consumption. The way these models simulate the occupant agent behaviour and define their personal characteristics affects the level of details the model can generate.

Among existing ABM, Azar and Menassa [58] propose a model that adds occupants' energy consumption characteristics and interactions to engineering models. In their model, every occupant agent is characterised as a low, medium, or high consumer by which the occupant's level of energy consumption is determined. The energy consumption of the building is produced using the energy simulation tool *eQuest* based on the number of consumer types in the building. The consumer type attribute is used to determine the blinds position, periods for operating lights and equipment and hot water consumption. These values are derived based on some assumptions, existing studies on energy consumption patterns and suggestions from building standards. Although this work is among the first models that add occupant characteristics to energy simulation tools, it does not overcome the limitation in typical engineering energy simulation tools. This is because the model generates the agent occupancy and activities in a deterministic way through general and fixed schedules.

Another approach to characterise occupants' energy consumption in buildings is varying the average daily/weekly/yearly consumption per occupant. This is applied by Chen *et al.* [26] and Anderson *et al.* [7] who model occupants' interaction and behaviour change while varying the types and structures of peer networks. Similarly, Azar and Menassa [13], [59] and Anderson and Lee [14] study the effect of social networks on the results of interventions in office and residential buildings. Characterising occupants with average energy consumption per day/week/year does not only reflect the awareness of occupants, but also how long they spend in the building, what appliances they use and what activities they do. Hence, it is hard to distinguish if high energy consumption is due to low awareness or daily occupancy/activities. The energy consumption of the building in these models is calculated using the number of occupants and their energy consumption levels.

Jensen *et al.* [27] propose a framework, which is implemented in an ABM, for the assessment of behaviour change feedback devices. The framework combines the direct impact of feedback devices in households, the diffusion of devices to other households and the diffusion of behaviour change beyond these households. Focusing on the heating consumption, households are characterised by the heating set point temperature as an indication of household behaviour rather than the amount of energy consumed. Therefore, this model does not produce energy consumption data and cannot be used to produce appliance energy consumption.

The previously cited models [7], [13], [14], [26], [27], [59] may not be categorised into probabilistic or deterministic, because they do not simulate occupancy and activities of occupants (i.e. not activity-based). Therefore, these models do not produce detailed data (occupant activities and location and consumption data at appliance level), which are necessary to simulate, detect and determine the causes of energy waste.

Zhang *et al.* [22] develop an ABM to study households' interaction with smart meters and the experience of using them. In this model, every agent represents one household with one of four consumer archetypes. These archetypes are developed based on survey data to determine the occupancy of the household (time periods of leaving and getting back home), attitude toward the smart meter and energy saving awareness level. The occupancy of the household is simulated using a uniform distribution in the time periods of leaving the home and getting back. This kind of modelling imposes a number of limitations. First, representing agents as a whole household makes it impossible to model occupant-appliance interaction and study the effect of occupant behaviour on the consumption of the family. Second, it causes the loss of occupant-level dynamics in terms of occupancy, where it is assumed that all of the occupants leave home and get back at the same time. Third, although it may be considered that the occupancy of the house is modelled in a probabilistic way, it is based on fixed time periods. This affects the accuracy of the occupancy data and does not reflect the stochastic nature of human behaviour. These three limitations are added to the limitations mentioned for the aforementioned models [7], [13], [14], [26], [27], [59], where the model is not activity-based and does not produce detailed data.

Among the existing ABMs, there is a number of models that are activity-based, capture the occupant-appliance interaction and produce detailed data. For example, SMACH is a model that aims to simulate realistic behaviour of family members in households [60]. Its inputs are the duration of tasks, number of times they are repeated, preferred times to perform them, their type (individual or group task) and the location they take place in. The time of performing tasks can be affected by external factors, such as energy price change, thus affecting the energy consumption of the house. The model is capable of generating detailed energy consumption data based on occupant activity and capturing the occupant-appliance interaction. However, as the main aim of it is to produce reactive and realistic human agents, it does not explicitly define a personal energy consumption characteristic per agent. Thus, it cannot be used to simulate human behavioural energy waste. Besides, the model was validated with ergonomics experts and a small sample of data composed of 10 households [61], which may not be enough to prove the robustness of the model.

Other models define an explicit attribute to simulate the human behavioural aspect. For example, Zhang *et al.* [62] simulate occupant activities in a university building to test the effectiveness of an automated light management strategy opposed to a manual one. Every occupant agent has an energy awareness attribute between 0 and 100, which is determined by the stereotype that the agent belongs to among: (1) Environment champion, (2) Energy saver, (3) Regular user and (4) Big user. Similarly, Carmenate *et al.* [23] developed an ABM to determine the causes of behavioural energy waste in an office environment. The model simulates the complex interaction among occupants, building units and appliances. By including this interaction level, they highlighted the effect of both building structure and occupant awareness on the energy consumption of the building. The energy consumption of the office is generated based on the activities that occupant agents perform in the building and their energy literacy level. In the same vein, Lin *et al.* [24] and Lin *et al.* [63] simulate electricity consumption in a university office through an ABM to test the effect of pricing mechanisms on the behaviour of occupants and energy consumption. Similar to [62], four consumer types were defined to determine the probability that the occupants switch lights and computers OFF in response to the price change. The advantage of these models [23], [24], [62], [63] is that they simulate the detailed movement of occupants in the building and direct interaction between the occupants and appliances/lights. This enables the study of the factors that affect energy consumption within the building environment whether they are physical, social, or others. However, they hold the same limitation as in [22] where they simulate the occupancy, movement and activities of the occupants using a uniform distribution in specified time intervals.

One existing model proposed by Klein *et al.* [64] uses real and time-based probability distributions to generate occupant behaviour in the building. The authors propose an agent-based system to study the effect of multiple energy management and control strategies. The system controls both the building devices and occupants by changing meeting locations such that the energy consumption is reduced and occupant comfort is enhanced. Occupant agents are defined by temperature preferences, likelihood of turning devices ON and OFF, as well as the level of energy consciousness and intimacy. Although the probabilistic approach is used in this study, the model is built upon a small case study composed of 242 occupants between permanent and temporary employees. The same applies to the other models where [24] uses the data of 237 participants, [62] uses the data of 143 participants and [23] uses a hypothetical case study. This small number of participants used in these models raises questions about the accuracy of the results, limits the variation of parameters and offers energy efficiency strategies suited only for the studied environments. Otherwise, using large samples of data allows for generating more realistic data and enables more varied parameters, thus producing more generalised conclusions. This leads us to the necessity of PMs, which are used to reproduce realistic human behaviour from large samples of data and using highly dimensional and parametrised probability distributions. This type of modelling will be detailed in the next section (2.2.2) and section 2.2.3 compares both modelling techniques (PM and ABM) and shows how integrating them overcomes the corresponding limitations of the two techniques.

2.2.2 Probabilistic Models

Probabilistic modelling approach is a bottom-up approach that models residential demand profile by calculating the probability that an appliance is turned On or OFF at specific times of the day. The main purpose of PMs is to enhance the prediction of energy demand in residential buildings [17], as well as testing Demand Side Management (DSM) approaches [18]. This is because they can capture the variation of human behaviour, including unexplained emergent changes in actions [17] unlike the ABMs cited in the previous section that use fixed schedules for occupants [22]–[24], [62], [63]. Different techniques are used in PM such as Monte Carlo simulation [65], non-homogeneous first-order Markov chain [18], [66], [67], higher-order Markov chain [17], [51], logistic regression [50], [68], as well as hybrid approaches that combine more than one technique [19], [69]. PMs have been been used for several energy related applications and simulations, including occupancy [18], [66], windows opening [68], daily activities [67], [70], lighting consumption [71], disaggregated appliance consumption [19], [37], [70].

The most common approach in exiting models is simulating occupants' existence and activities to predict when appliances are turned ON/OFF [17], [51], [70], [72]. This is done with the help of Time-Use Surveys (TUS) which are 24-hour diaries filled-in by thousands of participants for a number of days. The participants record the activities they do throughout the day every period of time. Another approach that was proposed recently is generating appliance-level consumption directly from the consumption data without simulating occupancy and activities [19]. This approach is not useful when studying energy waste due to the fact that it is only possible to study energy waste when the information about the occupants' activities, location and schedule is available. Therefore, the PMs that we refer to in this thesis are those that generate occupant presence, activities and appliance-level consumption along with any other detail that may be produced or derived from TUS.

Using large amounts of data from TUS has several advantages that range from accuracy, variety and re-usability of the developed models. It is well known that higher amounts of input data used in simulations lead to more accurate models, thus more realistic simulated data. Besides, TUS offer a good representation of social, economic and demographic factors that influence energy consumption such as income, household size, occupant ages or employment types [17], [37], [73]. In addition, the level of granularity provided by TUS is useful to simulate and detect energy waste, and study the changes in occupant behavioural characteristics [51].

Although PMs produce detailed data, which are useful when modelling energy waste, the existing models only aim to reproduce realistic occupant activities and energy consumption. Therefore, they are not capable of capturing how occupants react to changes in their environment [74]. From the computational point of view, PMs follow a staged modelling process where occupancy and activity data are generated, and then used to generate the resulting electricity consumption in a following stage. This staged process cannot be used to model human behaviour, which is dynamic and can change based on several individual and environmental attributes [21]. For example, behavioural changes due to social interaction, communication and influence cannot be modelled using PMs.

Existing PMs assume that energy is consumed only when occupants are available at home or doing the activity [37], [70], [72]. They assume that all occupants are the same and consume energy in an rationale way. However, human behaviour is more complex and unlikely to be the same, which can be one of the most influential factors of energy consumption in buildings [13]. For example, more than 50% of energy consumption in commercial buildings is consumed during unoccupied hours, and even in occupied hours, lights and appliances are left ON when not in use [10]. In addition, the 'greenness' of household behaviour is considered one of the three dimensions when categorising residential energy consumers [20]. This dimension can be high or low, where low consumers are those who have high energy awareness and avoid energy waste. On the other hand, high consumers are those who have low energy awareness and waste energy. Ignoring the different levels of human energy awareness by PMs have caused an underestimation of the real energy consumption data in some existing models. Richardson *et al.* [70] noticed that there is more consumption during night in the real data compared to the simulated one, and attributed this to occupants leaving lights ON when they sleep. Similarly, Aerts [37] realised that their PM failed to produce high energy consumption levels, and explained that the reason could be behavioural energy waste.

2.2.3 Integrating Probabilistic and Agent-based Models

Since PMs utilise large samples of data from TUS, it is guaranteed that the produced data are realistic and possible to study the effect of social parameters on the energy consumption of the house. PMs also provide highly detailed data at the level of appliance (including different types and number of appliances) and at the level of occupants (including their activity, location, usage of appliances). Therefore, PMs can overcome the limitations that existed in some of the ABMs that use small case studies and generate high level data usually at building level. On the other side, ABMs overcome the staged approach in PMs by enabling dynamic human behaviour modelling where occupant agents take decisions based on their personal characteristics and the external state of the environment. Besides, occupants' peer pressure can be simulated in ABM, unlike PMs that do not provide the means by which peer pressure can be modelled. Furthermore, various energy awareness levels can be modelled at the occupant level in ABM, which enables the study of energy awareness in a family setting. Table 2.1 shows a comparison between PMs and ABMs, where the limitations and strengths of each technique are presented. The table motivates the need for an approach that cascades ABM and PM, thus overcoming limitations of both models when they are separated.

A similar methodology has been tested in Chapman *et al.* [75] who use a number of exiting PMs in an ABM. The used stochastic models include a presence model, activity model, windows usage model, lighting model and heat-gain model. The purpose of the developed ABM is to feed engineering models (such as EnergyPlus) with realistic human behaviour data, therefore, cannot generate detailed energy consumptin data. Although the model uses PMs in their ABM, they do not take advantage of the detailed activities data in PMs to simulate the operation of appliances. Besides, they do not differentiate between occupant energy consumption behaviour assuming that all individuals behave the same. However, in this thesis, we use the detailed activities and location data from PMs to simulate energy waste and test energy interventions. Similarly, the research group that developed SMACH [60], has recently suggested to calibrate their model through PMs [74]. However, the same limitation exists as in the previous model, where it cannot be used to simulate energy waste as mentioned in Section 2.2.1.

In this thesis, one of the existing PMs is selected to simulate the realistic daily behaviour data. The rationale behind this selection is detailed in Section 3.1 of Chapter 3. The methodology and probability distributions of

TABLE 2.1: Probabilistic and Agent-based Models Comparison

Probabilistic Models	**Agent-based Models**
+ Include large amounts of data	- Use small case studies
+ Produce detailed activity and energy consumption data	- Produce high level data
- Cannot simulate dynamic behaviour	+ Most suitable to model dynamic behaviour
- Assume same and ideal human behaviour	+ Enable having occupants with heterogeneous characteristics
- Cannot simulate social interaction and pressure	+ Suitable to simulate social interaction and pressure

the existing PM are cascaded in an ABM. Compared to existing ABMs, the cascaded model generates fine-grained data, including occupant daily occupancy, behaviour, location and interaction with appliances. The methodology of cascading ABMs and PM is presented in Chapter 3.

2.3 Peer Pressure

Peer pressure is the influence that members of the same community have on each other, which leads to change in behaviour. It is triggered by the existence of social norms, which represent the common accepted behaviour by a society, where disobeying this behaviour results in a social punishment [76]. In the domain of energy interventions, it has been proven that the reach and impact of energy interventions can be increased by spreading the individuals' knowledge in the community [25]. Besides, peer pressure effect is shown to be the most influential reason of environmental behaviour change [77]. This is because information received from personal relationships are better recognised and remembered than other sources of information [78]. Therefore, it is highly recommended that energy interventions take advantage of peer pressure to promote a desired behaviour.

In this thesis, we add the peer pressure effect to the simulation model as one of the factors that affect human behaviour and compliance to interventions. This helps make the model more realistic and reflects the normal human behaviour. The next section presents an overview of existing ABMs that simulate peer pressure and shows the need for a new peer pressure model for family environments. Peer pressure modelling has to be based on human behaviour theories, especially those that explain behaviour change due to social norms. Therefore, we select the theories that are compatible with peer pressure in families and lead to a usable model. Section 2.3.2 presents related human behaviour theories and explains the rationale of selecting the adopted theories.

2.3.1 Agent-based Models for Peer Pressure Simulation

As mentioned in Section 2.2.1, ABM is the most suitable technique for human behaviour simulation, especially when modelling social interaction [79]. This is because behaviour is defined at the individual level to observe the emergent collective behaviour at the group-level. ABMs have been used to study peer pressure effect on one-time decisions and/or continuous behaviour that need to be practised all the time [27], [80]. One-time decision models study the adoption of energy efficient appliances/technologies or renewable sources such as natural gas vehicles [81], electric vehicles [82] and efficient lighting [83]. The focus in this thesis is on simulating continuous behaviour rather than one-time decisions, where individual behaviour change rules are defined to study the emergent behaviour at a family level.

Among existing ABMs reviewed in Section 2.2.1, there is a number of models that simulate occupant behaviour change due to peer effect. Azar and Menassa [58] propose a model that simulate the effect of peer pressure and energy conservation workshops on the energy consumption of a commercial building. Occupant agents change their behaviour based on the level of influence of individuals and the number of occupants in each level of consumption (low, medium and high). However, the used behaviour change model is not theoretically grounded, but rather logically grounded. Models that involve human behaviour simulations need to be validated using huge amounts of real data, and if not available, need to be based on well established and accepted human behaviour theories [15].

Another ABM that simulates social influence is proposed by Chen *et al.* [26] who explore the effect of peer network structures on the energy consumption in a residential community. Their results evidenced that targeting individuals with strong relationships in peer networks is better to encourage energy savings than targeting those with more relationships. In their model, the occupant agent decreases its consumption when the consumption of connected occupants is less than that of the agent. On the other hand, increasing the agent's consumption is based on a constant probability that represents the percentage of occupants who increase their consumption with no effect from peers. However, it is more logical that peer effect happens in both directions– so that high energy consumers may affect others and cause them to increase their consumption in the same way low energy consumers may affect others. Network structures in an office environment were also studied by Azar and Menassa [13] where their model uses the *relative agreement theory*, which is applied in a community of heterogeneous culture and values. Thus, behaviour change starts between close individuals. However, in a family environment, which is the case in the current thesis, it is common that family members have similar culture and values. Therefore, other behaviour change theories need to be applied, which will be detailed in the next section. In addition, Anderson *et al.* [7] proved through an ABM that network types have an influence on the environmental behaviour change when using a feedback intervention and introducing an intervening environmental champion. The model in [7] was also used in [27] to implement a framework that combines technology diffusion, impact of feedback devices and behaviour diffusion in a neighbourhood. Peer networks were also studied by Anderson and Lee [14] to test the effectiveness of feedback interventions and identify best strategies of which occupants to target and when to target them.

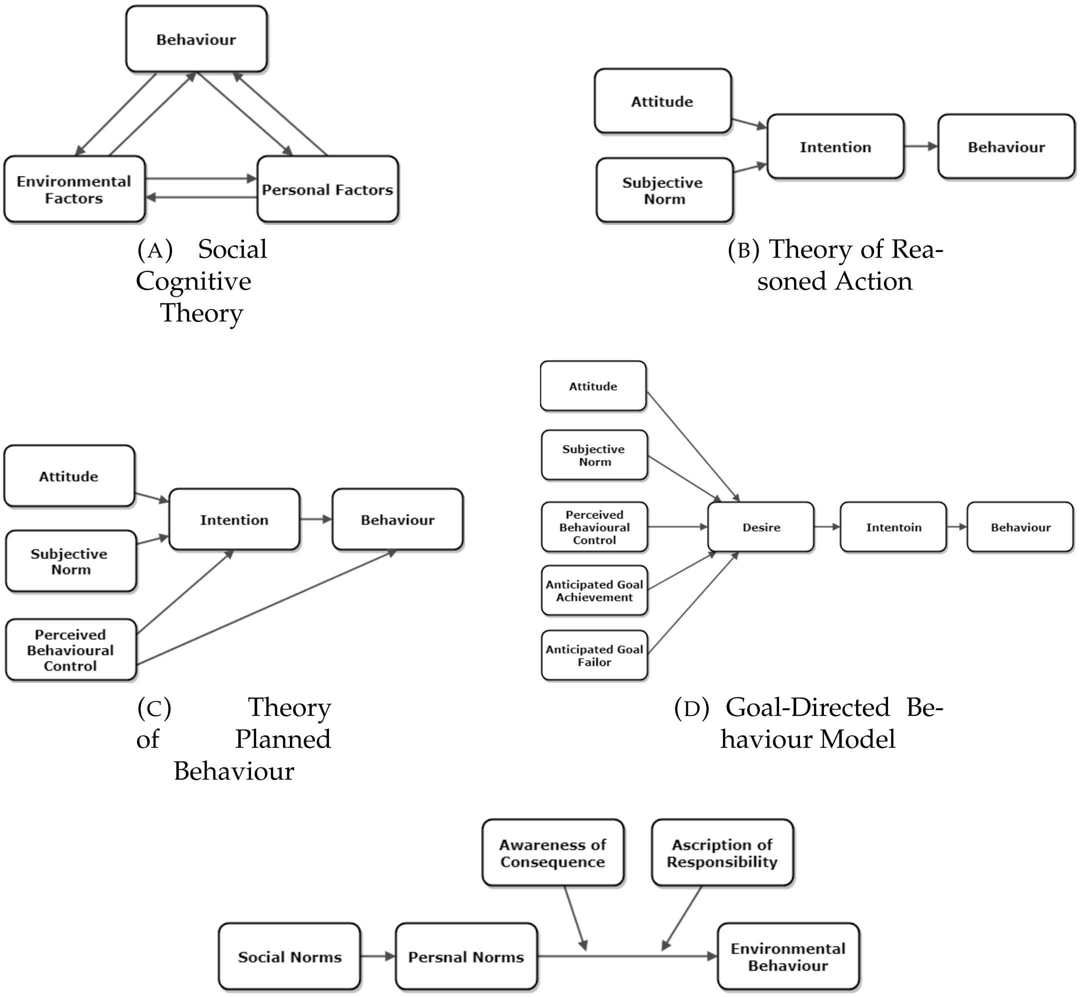
Studies in [7], [13], [14], [26], [27] vary the structure and type of peer networks based on the fact that not all individuals in a residential or office community are connected. While in a family environment, family members are always connected at least at night when they get back to the same house. Besides, these models characterise occupants by average daily/weekly/yearly energy consumption. As mentioned in Section 2.2.1, this attribute affects the time the occupants spend in the building, the appliances they use and the activities they do in the building, as well as their energy awareness. Therefore, when simulating peer effect and energy interventions, the change of this attribute does not always mean that the occupants are changing their energy awareness. To overcome this limitation, it is necessary to separate daily human occupancy and behaviour simulation, from occupant interaction with appliances and energy awareness. This separation can ensure a more realistic peer pressure simulation, because the detailed interaction of the occupants in the building can be extracted from occupant location and activities. It is worth to mention that this feature is very rarely implemented in existing models that simulate peer pressure, while most of the models that separate occupant daily behaviour and energy awareness do not simulate peer pressure. The layered model proposed in this thesis combines both features in one model. Details about the peer pressure model will be discussed in Chapter 4.

2.3.2 Human Behaviour Change Theories

Given that none of the models cited in the previous section are suited for simulating peer pressure at the family level, this section reviews human behaviour change theories and select the ones that will be used in our model. Several theories have been proposed in social related domains to explain human behaviour and human behaviour change. Due to the large number of theories, it would not be possible to make a comprehensive review of these theories. Therefore, we include well-established ones focusing on those that include the effect of social norms on the behaviour of individuals. The presented theories are assessed based on how much they focus on and explain the effect of peer pressure and whether they can be formalised in a computational model. Figure 2.2 shows illustrations of the presented theories.

The *social cognitive theory* [84] (see Figure 2.2a) is based on the idea that human beings learn by observation. This learning is a result of the interaction between personal and environmental factors and the behaviour itself. Personal factors include the individual's cognitive abilities such as belief, emotion and attitude. Environmental factors include external context attributes that affect behaviour such as social norms and physical resources. The theory includes an effect of observational learning when individuals adopt a behaviour by watching others performing an action and observing its consequences (positive or negative).

The *Theory of Reasoned Action* (TRA) [85] (see Figure 2.2b) points that the probability of performing a behaviour increases by the increase of the behaviour intention. Intention is in turn affected by the person's attitude, which represents the individual's perception toward the behaviour and subjective norms, which refer to the pressure performed by the surrounding society causing a perception of what is accepted and not accepted. In 1985, the TRA was extended and the *Theory of Planned Behaviour* (TPB) was created [86] (see Figure 2.2c). The TPB adds the effect of perceived behavioural control to attitude and subjective norms. Behavioural control is defined as the perception of how feasible the behaviour is, which affects both the behaviour intention and the behaviour itself.



(A) Social Cognitive Theory

(B) Theory of Reasoned Action

(C) Theory of Planned Behaviour

(D) Goal-Directed Behaviour Model

(E) Norm-Activation Theory

FIGURE 2.2: Illustrations of the Human Behaviour Theories

Based on the TRA and TPB, the model of *goal-directed behaviour* was created [87] (see Figure 2.2d). The model states that behaviour intention is not directly affected by attitude, subjective norms and behavioural control. Therefore, they introduce the concept of desire in between intention and the affecting factors. The model also adds the effect of anticipated goal achievement and goal failure as additional determinants of desire.

The *norm-activation theory* [88] (see Figure 2.2e) is mainly aimed at explaining environmental behaviour or any behaviour that benefits the society. It states that the environmental behaviour is triggered by activating personal norms, awareness of consequences, ascription of responsibility and social norms. Social norms usually affect personal norms which activate the behaviour when there is high attention for outcomes (awareness of consequences) for behaving pro-socially and responsibility for not behaving pro-socially.

Although all of the presented theories include the effect of social norms on the behaviour of individuals, embedding these theories in an ABM results in a highly parametrised and complex model. Complex models impose a number of challenges, including difficulty to relate external factors to the agent rules and difficulty to understand and validate the obtained results [15], which affect the usability of the model. For example, the *Consumat* model is a conceptual meta-model that formalises a number of human behaviour theories (some of which are briefly presented above) to determine consumer behaviour [15]. The model is based on the idea that consumers engage in one of four cognitive processes, including repetition, imitation, deliberation and social comparison. The choice of one of these processes depends on the micro and macro-level driving factors of human behaviour. Although this model formalises the theories using simple mathematical formulas (subtraction, weighted multiplication, asymptotic diminishing, etc.), the model includes at least 20 parameters that need to be initialised before starting the simulation. Besides, the model is targeted for consumer one-time behaviour such as product purchase rather than continuous consumption behaviour that is practised all days as the case in this thesis.

In order to overcome these challenges, we follow the approach of including a small number of parameters that encapsulate the factors that affect the behaviour. This is specially done because the aim of adding peer pressure effect is to make the simulation more realistic while achieving the main purpose of the simulation i.e. simulating energy waste and testing technological energy interventions. To achieve this, we explore theories developed by Leon Festinger [38]–[40] which are considered one of the classical pillars of social norm formation and social groups interaction [89]. The difference between Festinger theories and the theories presented above is that Festinger theories are generic enough to allow more space for testing and further development [38]. Therefore, these theories do not identify very specific factors for social group behaviour, however, they explain general informal interaction that happen in social groups. This makes them possible to formalise without using high number of parameters. In this case, it is necessary to keep a range of uncertainty by introducing some stochastic parameters to simulate the factors encapsulated in the parameters.

The first theory introduced by Festinger is the *Informal Social Communication Theory* (ISCT) [38]. The theory postulates that the need for uniformity is a major source for communication in a social group. The communication occurs about conflicting opinions, beliefs and attitudes within the group and is an intermediary action that influences the opinion or behaviour of the group members to achieve uniformity. Festinger also identifies that the the pressure towards communication increases when (1) the magnitude of the conflict increases; (2) the relevance of the topic — to be discussed — to the functioning of the group increases; and (3) the connection between the group members increases, which makes it difficult for a member who holds a different opinion than the others to simply leave the group.

These factors are highly applicable to family environments as it is expected that family members are strongly connected and hold the same group goals. The ISCT was then developed further to obtain the *social comparison theory* [39]. The theory states that humans, in their nature, tend to evaluate their opinions and abilities by comparing them to those of others. Festinger also discussed that the factors that increase the communication in a social group identified in the ISCT also increase the comparison in the group, and thus lead to behaviour change.

Another theory that Festinger developed is the the *Cognitive Dissonance Theory* (CDT) is mainly focused on the explanation of individuals' behaviour when their cognitive elements are inconsistent or dissonant. These cognitive elements, such as knowledge, opinions, beliefs, or attitudes, are the factors that drive the individual's behaviour. Based on the fact that dissonance is psychologically uncomfortable, the theory proves that humans try to reduce it by adapting their behaviour or changing one or more of the cognitive elements. What makes this theory applicable to the case of peer pressure is that one of the major sources of dissonance is social groups. Therefore, observing others doing a behaviour that is very different from the individual's behaviour or spreading a general belief that a specific behaviour is not accepted, drives members of a social group to adapt their behaviour, thus reducing the uncomfortable dissonance. Festinger considers that as the magnitude of dissonance increases, it is expected that the tendency to reduce it will increase, which is compatible with the ideas in the previously mentioned theories [38], [39]. The magnitude of dissonance is affected by (1) the number of others who hold a different behaviour; and (2) the level of difference between the individuals' behaviours.

In order to formalise Festinger theories, we use an approach similar to Granovetter's *Threshold Model* (TM) [41] which is one of the collective behaviour models. Threshold modelling is one of the common approaches used to simulate consumer adoption behaviour [90]. Granovetter uses threshold modelling to explain the diffusion of a behaviour due to social contagion.

Contagion is defined as the diffusion of a behaviour in a group due to the imitation of actions of others. The model follows a simple decision rule, where individuals choose to adopt a behaviour when the percentage of others in the same group/community doing the behaviour exceeds a threshold. This threshold represents a complex combination of norms, values, motives, beliefs, etc. Once the threshold is exceeded, it is considered that the net benefit of the behaviour exceeds the perceived costs. Bearing in mind that the main idea of collective behaviour does not contradict Festinger theories, and in order to keep the model simple, Granovetter's TM is adopted to formalise Festinger's theories. The formalisation of these theories and the details of the peer pressure model are presented in Section 4.1 of Chapter 4.

2.4 Energy Interventions

Having discussed ABMs that simulate energy consumption and peer pressure effect, this section focuses on energy interventions, which aim to reduce energy consumption, and ABMs that test energy interventions.

One of the approaches to address the energy consumption problem in buildings is to influence energy consumption behaviour through interventions. Interventions are defined as the interruption of peoples' normal behaviour [91] by changing their values, attitudes, beliefs and knowledge to motivate them to adopt an energy efficient behaviour. Existing interventions include commitment, goal setting, information (workshops, mass media campaigns and home audits), modelling, incentives and feedback [28]. The effect of these methods on peoples' knowledge and energy consumption varies based on the intervention mechanism, and combining them can result in even more reduction [28].

Energy interventions may directly or indirectly affect occupant behaviour, while the resulting behaviour can be a one-time action/decision, or a continuous behaviour that needs to be practised all the time. Therefore, targets of interventions include (1) raising awareness and pro-environmental motivation of energy consumers, (2) encouraging one-time energy efficiency practices such as buying energy efficient appliances, (3) using renewable energy, (4) encouraging energy conservation (turn off appliances, line drying, etc.), (5) eliminating stand-by consumption and (6) applying demand side response, which involves reducing consumption during peak-times [42]. The intervention introduced and tested in this thesis targets continuous direct behaviour, including energy conservation and demand side management practices. Furthermore, it is considered an enhancement of feedback systems among the different intervention types. The proposed messaging intervention is tested in an ABM, therefore, we present a comparison of existing ABMs that evaluate energy interventions in the next section. Then, we explain in details the purpose, types and limitations of existing Energy Feedback Systems (EFS) and Energy Management Systems (EMS) showing the need for an approach that provides more sensible information for occupants while keeping the control for them.

2.4.1 Agent-Based Models for Energy Intervention Simulation

ABM has been used to simulate the effect of external factors on the behaviour and energy consumption of occupants. These external factors may include energy management policies, technologies and interventions. For example, Zhang *et al.* [62] compare the effectiveness of energy solutions, including an automated lighting strategy and a human-controlled one. Although this model includes an energy awareness attribute to simulate realistic lighting behaviour, the energy solution they propose and test is not aimed at enhancing the energy awareness of the occupants, but only testing the automated strategy. Therefore, it may not be categorised as an energy intervention. An energy intervention approach is proposed in [64], where the research aims to test a number of building management and control approaches. One of the tested approaches includes a proactive meeting relocation capability. It suggests changing meeting rooms to smaller rooms or rooms that were previously occupied (i.e. previously heated) to save energy consumption in a university building. The occupant agents may or may not accept the relocation suggestion based on the meeting constraints and their energy consciousness. However, the model does not capture the change of occupant energy consciousness/behaviour in effect of the proactive approach after several incidents of relocation. This contradicts the aim of energy interventions, which is changing occupant actions and decisions to reduce their consumption.

Zhang *et al.* [22] simulate the learning experience of household agents as a result of smart meters usage in the United Kingdom. For this purpose, they use the behavioural learning theory where households learn through repetition and conditioning. The formula is used to determine when the agents change from inexperienced to experienced smart meter users. In this model, energy consumer agents are modelled as a whole household that owns and uses the smart meter. This type of modelling not only affects the realistic occupancy and behaviour simulation as mentioned in Section 2.2.1, but also causes the loss of individual level dynamics where the intervention may affect household members in different ways.

The ABMs in [13], [58] study the effect of discrete interventions such as energy training and workshops along with peer pressure effect, which helps the diffusion of the green behaviour in office buildings. As mentioned in Section 2.2.1, these models do not generate detailed occupancy and activities of occupants. Therefore, the only way to simulate the discrete intervention is by randomly selecting the affected individuals, and changing the energy consumption level based on the assumed success percentage of the intervention. Besides, it is not possible to simulate accurately the effect of continuous interventions such as feedback or messaging interventions.

One of the models that simulate continuous interventions is proposed by Anderson and Lee [14], who compare the effect of individual and comparative – to neighbours for example – feedback. The model stochastically determines the possibility of checking the feedback, which causes change in occupants' behaviour. Feedback interventions are also studied in Jensen *et al.* [27], where the intervention effect is modelled using an asymptotic equation. The behaviour level is changed toward an incentivised target with a specific rate, which represents the intensity of the intervention. Similarly, Lin *et al.* [24] and Lin *et al.* [63] evaluate the effectiveness of tiered pricing in office buildings. The change of the energy awareness of occupants depends on the level of change in the price. Although these models [14], [24], [27], [63] simulate continuous interventions at occupant level, the used behaviour change equations assume the same effect of the intervention in all cases. However, the effectiveness of interventions may vary based on how often the occupant uses the intervention, whether he/she is interested in it and his/her social and psychological characteristics. The ABM proposed in this thesis simulates realistic interaction of occupants with the energy intervention based on their social characteristics and interest in it, and changes the awareness of the occupants based on how often they complied to it.

2.4.2 Energy Feedback Systems

As mentioned previously, feedback is one of the interventions that aims to help occupants save energy. Consuming energy is considered abstract and invisible as it is used indirectly to perform daily tasks [92]. Therefore, it is agreed that giving people information about the amount they are using makes them aware of their consumption and ultimately allows them to control it. Direct feedback is available in various forms, including meter reading, direct and interactive feedback via monitors, pay-as-you go meters and plug/ appliance meters [91]. However, with the advancements in sensor and communication technologies, direct and interactive feedback is now the most common [29]. For example, in response to the European Commission plan to reduce 20% of the Union's energy consumption [93], the United Kingdom has installed 8.5 million smart meters (along with feedback displays) up to 2017 [94].

Energy Feedback Systems (EFS) have been widely researched to study their effectiveness and users' interaction with them. For example, the effectiveness of simple energy displays (stationary and portable) was investigated in [30]. The study shows that energy displays resulted in an average of 11% energy reduction and increased the energy awareness of occupants. Besides, commercial feedback systems were assessed qualitatively in [95] by asking people about the motivation of owning display systems, ways of usage, observed behaviour change and limitations of usage. Along the same lines, Karjalainen [96] systematically reviewed the different ways of presenting feedback. Several user interface prototypes were developed with varied comparison types, units of display, disaggregation levels, presentation types and time scales. They found that presentation of energy costs, appliance consumption and historical comparison are the most preferred by users.

Although these studies showed that EFS play a role in increasing occupant awareness, many studies highlighted a number of limitations. For example, Strengers [31] observed that a considerable number of users struggled in understanding the displayed data and converting them to meaningful information. This is because the displayed data are absolute and not related to the surrounding context. The same conclusion was reported in [97] where people wanted more context, such as occupancy and temperature to interpret high/low consumption levels. In response to this challenge, a number of studies suggest to relate energy consumption to daily activities either by annotating consumption graphs with activities [33], or using calendars as an artefact to help understand consumption [98]. Similarly, Castelli *et al.* [32] propose to use the location of appliances and occupants, which they call 'room context'. This helps identify energy wastage, match consumption with occupant presence and link consumption with everyday activities.

Despite that these efforts make more meaningful information, they still view users as micro-resource managers [31], [99] who are expected to analyse the displayed data and change their behaviour– such that it meets their preferences, everyday needs and financial and environmental goals. Based on this, Pullinger *et al.* [99] identify one more specification for EFS, which is explaining what the information means in terms of behaviour change. In addition to detailed energy consumption data, this service requires collecting environmental data and Artificial Intelligence (AI) analysis techniques, which are not provided by existing EFS. In this thesis, we try to fill-in this gap by proposing the idea of an energy messaging intervention, which provides occupants with sensible messages that tell them what to do to reduce their consumption, instead of only giving them the amount of energy they are using. We identify the technologies and techniques available to collect and analyse the required data, and test the effectiveness of this approach in an energy simulation model in Sections 5.1.4 and 5.2 of Chapter 5.

2.4.3 Energy Management Systems

Another approach to help understand and handle energy consumption in buildings are Energy Management Systems (EMS), which provide the infrastructure to monitor and control energy consumption. They are defined as the monitoring software, data collection hardware and communication systems for the purpose of storing, analysing and displaying the energy data of buildings [100]. These systems are often integrated with smart homes and home automation systems for the purpose of energy efficiency [101]. As an example, Kim *et al.* [102] propose a home energy management system based on universal plug-and-play architecture. The main purpose of the system is to connect home appliances and mobile devices in one platform for the purpose of adjusting energy consumption based on real-time prices. The system automatically controls the activity or quality of service of appliances based on electricity price and a policy agreed on between the customer and the provider. The presented architecture allows users to control appliances using mobile devices. Similarly, Jahn *et al.* [103] present a smart home that embeds energy efficiency. It provides an intuitive interface that shows appliance usage, accumulated usage and cost on mobile devices and allows remote control of appliances by the users. These two systems are good examples of the available platforms that help connect appliances and remote control services, however, they do not depend on any environmental data to ensure occupant comfort and understanding of the displayed consumption data.

To overcome this limitation, a number of EMS were proposed taking advantage of Wireless Sensor Networkss (WSN) [104] and Internet of Things (IoT) [105]. These systems utilise data collected from environmental sensors (temperature, humidity, illuminance, etc.), user input (activities, preferences, etc.) and appliance-level energy consumption. We refer to these types of data as context data. AI algorithms are used to infer and analyse these data to detect the situation of the occupants and help them make decisions that comply with their comfort. An example of these approaches is by Dong and Andrews [34] who propose an algorithm to model and predict occupant presence using rich data patterns, including motion, illuminance, temperature, humidity. The predicted occupancy data are then used to set a dynamic schedule for cooling temperature while maintaining occupant comfort. Similarly, Agarwal *et al.* [35] provide the specifications of an accurate, low-cost and easily deployable wireless sensor system, which is also used to control the Heating Ventilation and Air Conditioning (HVAC) system of buildings.

EMS are not only designed to monitor and control HVAC systems, but also for other everyday appliances. One of these systems is GreenBuilding [106], [107], which combines monitoring and control of energy consumption. GreenBuilding provides a sensor-based infrastructure to reduce standby consumption, schedule flexible tasks and control appliances to eliminate energy waste. These services are done based on rules set by the user and data collected by environmental sensors. A general architecture of an EMS that makes use of WSN is Sensor9K [104], the aim of which is to ease the development of energy efficiency applications. The architecture is composed of two layers: (1) a physical layer that contains the sensors/actuators and ensures the communication among the components of the system, and (2) a middleware layer that offers the basic functionalities of an EMS (such as monitoring consumption, detecting user presence and profiling preferences), which can then be used by application developers. The architecture was tested with a temperature control case study. Within the effort to test the applicability of smart grids, PowerMatching City [108] was established as a living lab demonstration project. Smart grids refer to the infrastructure that ensures two way communication between providers and end-users to balance the supply and demand of energy. PowerMatching City project includes an energy management system that automatically controls the operation of appliances to minimise costs and take advantage of renewable energy. More recently, an energy aware smart home system was proposed in [105]. The system controls lighting and appliance consumption automatically based on occupant presence and natural lighting. The system ensures efficient communication among the system components through IoT technologies.

In relation to the messaging intervention proposed in this thesis, existing EMS provide evidence of enabling technologies and algorithms necessary to produce the real-time sensible feedback. However, the main approach in most of these systems is to utilise the collected data to act on behalf of the occupant. They follow the school of thought that considers that smart home control systems should be fully-automated, hence, it should predict user's changing preferences while maintaining comfort and achieving savings [109]. Another school of thought considers a smart home as a system that engages its users in the energy management process, thus having well-informed and aware occupants. The argument of these two schools is detailed in the next section.

2.4.4 Automated vs. Human Controlled Approaches

While reviewing existing literature on energy management, it has been noticed that most EMS approaches utilise AI and sensor technologies to automate the control of energy consumption of the house/building. The development of such systems is stimulated based on the fact that encouraging people to adopt energy efficient behaviour is not an easy job, therefore, acting on behalf of them, while maintaining their comfort and minimising costs, will improve user experience. However, automatic control has been proven to take-off the sense of control from people, which is mostly uncomfortable for humans [36]. For example, when asking users about their experience when using PowerMacthing City EMS [108], they reported the lack of control over the system. Participants preferred to interact with the system and actively participate in its decisions. Based on this feedback, the PowerMactching City project designers added semi-automatic and manual appliances control in its second phase [110]. They gave people advice on the best time to turn on appliances. In this case, users reported that they gained back the sense of control over appliances, and with time they learned how to achieve their energy efficiency goals. Thus, empowering users with information of how to reduce their consumption maintains their feel of comfort.

Apart from losing the sense of control, automation is not always the best solution for energy efficiency. For example, Zhang *et al*. [62] found that increasing the awareness of occupants is more efficient than applying an automated light management strategy. In addition, human behaviour may sometimes oppose the automation like opening windows and doors when the heating is ON, or manually putting heavy appliances ON in peak times [111]. This is especially true if it happens that automatic actions interfere with occupants' important life functions [109]. Besides, installing technologies without informing users how to take advantage of them causes the limitation of energy reduction [112]. This applies specifically when the technology does not require user involvement and is usually referred to as rebound effect. When people perceive that a technology has the potential to save energy, it is proven that they change their behaviour to achieve more comfort, which leads to less energy saving than expected [9], [111]. Therefore, giving occupants enough information of how to use the technologies and raising their awareness is more reliable than having a fully automated system.

Along these lines, Leake *et al.* [113] suggest a human centred computing paradigm to design smart homes, which uses a simple and transparent learning process. Therefore, in order to maintain human trust in the system and obtain informed and capable occupants, the system will need to interact with the occupants and provide explanations of its decisions. In addition, Geelen *et al.* [112] recommends to provide feedback that shows the occupants which behaviours need to be changed.

In this thesis, we highlight the need for an intervention that takes advantage of technologies used in exiting EMS to trigger occupants' actions to reduce energy consumption. We suggest not to automatically control appliances, but rather to detect energy wastage and inform users about it. In this case, users are supported with information about what and when actions are needed to control and reduce their consumption. The details of this intervention and its simulation in the proposed ABM are presented in Chapter 5.

2.5 Summary

This chapter has presented a review of existing approaches for simulating energy consumption. It showed the need for a probabilistic bottom-up approach, which can be used to simulate realistic and detailed energy consumption of occupants in residential buildings. Since PMs has a number of computational limitations that prevents dynamic human behaviour simulation, we suggest that integrating them with ABMs overcomes these limitations. Besides, using PMs fills-in the gap that existed in some ABMs in terms of detailed data generation and using small samples of data.

A thorough review of existing ABMs was also presented in different sections of this chapter. Table 2.2 summarises the features of these models and compares them among each other. Based on the performed literature review, we propose an ABM that combines the strengths of existing models and structures them in a three layered model: the *Daily Behaviour Model*, the *Peer Pressure Model* and the *Messaging Intervention Model* (see Figure 1.1 of Chapter 1).

The daily behaviour model is the core model that generates occupant daily behaviour. This model is activity-based and produces detailed individual occupancy, activities and energy consumption (every 10 minutes at appliance level) opposed to [7], [13], [14], [22], [26], [27], [58], [59], which generate high level data (at building/household level, every day, week, or year) and are not activity-based. This is possible because the core layer of the ABM is integrated with a PM while some other models [22]–[24], [58], [62], [63] generate occupancy and activity data in fixed time intervals. The used PM is based on large amounts of data from TUS, which overcome the limitations in ABMs that use small or hypothetical case studies [23], [24], [62], [64]. The detailed data generated by the core model enable real-time detection of energy waste and identification of its causes. Besides, the energy behaviour attribute is modelled at the occupant-level rather than household-level as in [22].

Another layer included in this model is a family level peer pressure model. The model simulates the social pressure among family members compared to exiting models [7], [13], [14], [26], [27], which focus on office and residential communities rather than family level interaction. The proposed model characterises occupants using a personal energy behaviour attribute that is separated from daily behaviour simulation. This ensures that the change in this attribute due to peer pressure or energy interventions does not affect the individual's daily occupancy and activities compared to existing models that do not make this separation [7], [13], [14], [26], [27]. The peer pressure model is based on well established human behaviour theories by Leon Festinger [38]–[40], which explain the effect of social norms on individual interaction and behaviour. These theories were chosen as they are applicable to family-level environments, and lead to a usable model (i.e. a model with small number of parameters) while ensuring realistic simulation of pressure effect.

This chapter also presented the argument of automated vs. human controlled energy solutions by exploring limitations in energy feedback systems and energy management systems. Based on this review, we highlighted the need for actionable energy interventions. Instead of just displaying abstract data as in typical EFS or taking action on behalf of occupants as in EMS, these interventions are preferred to be in a middle-point position. This is done by taking advantage of existing technologies/techniques (i.e. monitoring, controlling and analysing energy consumption and context data) for informing occupants about actions they can take to reduce their energy consumption, while keeping the control for them. In Chapter 5, we present technologies and techniques that enable the implementation of a messaging intervention, which detects energy waste incidents and forward them to occupants in real-time allowing them to take action to avoid energy waste. Besides, a strategy is proposed in this chapter to ensure that the occupants are not annoyed and interrupted by the energy messages. This strategy is context-aware and based on the data produced by the core daily behaviour model. Then, we use the developed ABM to asses the proposed intervention and strategy in the family environment.

Therefore, the third layer of the model is a messaging intervention model. This layer is considered a customisable layer where different types of interventions can be plugged in to test their effectiveness. Comparing the messaging intervention model with existing ABMs, our simulated intervention is considered a continuous intervention opposed to other peer pressure models that model discrete interventions [13], [58], where the effect of the intervention needs to be determined beforehand and applied randomly. With the level of details of data generated by the core model, it is possible to model a realistic effect of continuous interventions. This is based on how often the occupants have used the intervention and their energy awareness about using it. The result of the intervention is also affected by the occupant age, employment type and family composition, which in turn affect their interaction with it. This is unlike existing ABMs [14], [24], [27], [63] that assume the same effect in all cases.

The last row of Table 2.2 shows that the proposed layered ABM combines the strengths of existing models. Bringing these feature in one model has not been attempted in any of the previous models. The following three chapters address each of the layers of the model as follows : Chapter 3 proposes the Daily Behaviour Model, Chapter 4 presents the Peer Pressure Model and

Chapter 5 discusses the Messaging Intervention Model.

TABLE 2.2: Exiting Agent-Based Models Comparison and Features

Authors [Reference]	**Activity-based**	**Probabilistic (P) / Deterministic (D) / Not Applicable (-)**	**Captures the occupant-appliance interaction**	**Generates detailed data**	**Models human energy consumption behavioural aspect**	**Simulates peer pressure**	**Evaluates energy interventions**
Azar and Menassa [58]	✗	(D)	✗	✗	✓	✓	✓
Azar and Menassa [13]; Azar and Menassa [59]	✗	-	✗	✗	✓	✓	✓
Anderson *et al.* [7]; Anderson and Lee [14]	✗	-	✗	✗	✓	✓	✓
Jensen *et al.* [27]	✗	-	✗	✗	✓	✓	✓
Chen *et al.* [26]	✗	-	✗	✗	✓	✓	✗
Zhang *et al.* [22]	✗	(D)	✗	✗	✓	✗	✓
Zhang *et al.* [62]	✓	(D)	✓	✓	✓	✗	✗
Carmenate *et al.* [23]	✓	(D)	✓	✓	✓	✗	✗

Lin *et al.* [63]; Lin *et al.* [24]	✓	(D)	✓	✓	✓	✗	✓
Klein *et al.* [64]	✓	(P)	✓	✓	✓	✗	✓
Amouroux *et al.* [60]; Quentin *et al.* [61]; Quentin *et al.* [74]	✓	(P)	✓	✓	✗	✗	✓
Chapman *et al.* [75]	✓	(P)	✗	✗	✗	✗	✗
The Proposed Layered ABM	✓	***(P)***	✓	✓	✓	✓	✓

Chapter 3

The Daily Behaviour Model

This chapter proposes the first model – the core daily behaviour model – of the complete Agent-Based Model (ABM) proposed in this thesis (Figure 3.1). The daily behaviour model simulates realistic and detailed daily human behaviour data, which enable studying energy waste.

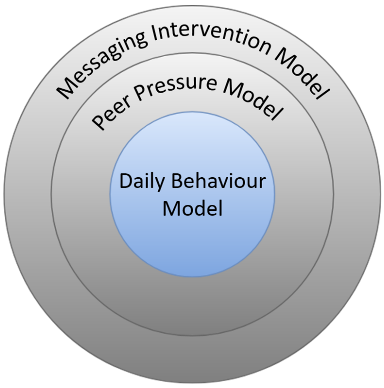


FIGURE 3.1: The Core Daily Behaviour Model from the Layered ABM

The proposed model integrates a Probabilistic Model (PM) in an ABM. To design this process of integration, we model it as a cascaded process where the first stage is obtaining probability distributions from realistic data to simulate the occupant daily behaviour, and the second stage is using these distributions in an ABM to simulate the dynamic interaction of occupants and appliances as shown in Figure 3.2. The inputs to this model are the occupants' employment type, age and personal energy rating, which are going to be explained in the following sections.

The following section presents the PM that was selected from existing literature to be used in the developed ABM. Next, the ABM formalisation and design are discussed, followed by the experiments and discussion sections. Findings reported in this chapter are published in [114] and [115].

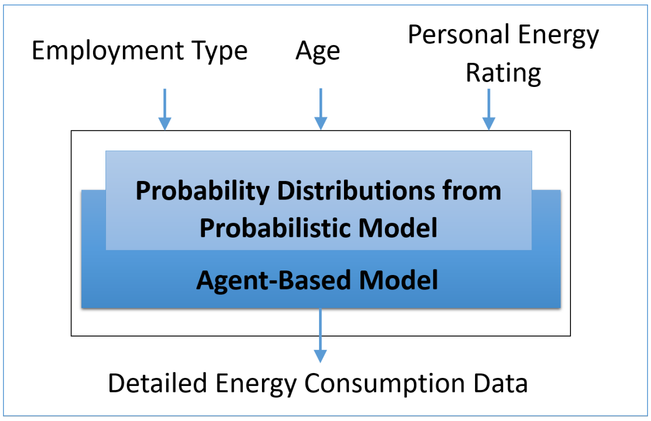


FIGURE 3.2: Cascaded Probabilistic Model and Agent-based Model

3.1 The Selected Probabilistic Model

To get the realistic probability distributions, we take advantage of an existing PM that is developed by *Aerts* [17],[37]. Aerts model is one of the recent models that has advantages over other PMs and satisfies the requirements of modelling energy waste. The model was selected because it includes the following features:

- obtains more realistic duration of activities and occupancy states (opposed to [70] and [72]) by separating the transition and duration probabilities of a state/activity;
- enables multitasking where occupants can be doing more than one activity at a time (opposed to [72]);
- includes nine activities that are linked to energy usage opposed to [51] that includes activities that may not be connected to energy consumption;
- simulates household dynamics by distinguishing between household tasks that are done by one member of the family, and personal activities that can be done and shared by more than one occupant at a time;
- uses seven patterns of typical occupancy behaviour based on age and employment type, which results in more realistic occupancy data;
- models daily occupancy and activities depending on time, previous state, occupant's age, employment type, work routine and day type (Weekday/Saturday/Sunday) opposed to [18], [67], [70], which are based on time and previous state only; and

- assigns different types and number of appliances to households based on income level and household composition (used interchangeably with household type), which includes the number of occupants, their ages and employment type.

Aerts [37], [116] model generates realistic occupancy and activity data using higher order Markov Process. The process is based on transition probability from one state to another, and the probability distribution for the duration of the state. Probability Distribution Functions (PDFs) were extracted from Belgian time-use survey and household budget survey collected in 2005, which include 6400 respondents from 3455 households, and the Energy Consumption Survey (ECS) collected in 2012 for households energy consumption and appliances ownership. Table 3.1 shows the size of the sample that was selected from the surveys grouped by household composition.

TABLE 3.1: Data Sample Grouped by Household Composition

Household Composition	**Sample Size**
1 Adult	1276
1 Adult with Children	179
2 Adults	366
2 Adults with Children	721
Total	*2542*

The PDFs are generated based on several social and environmental parameters such as occupant ages and employment types, household composition and day of week. The model is composed of three stages (1) occupancy model, (2) activity model, (3) and electricity model.

The occupancy and activity models with their associated PDFs are used in the ABM to produce realistic human behaviour. The PM by Aerts [17], [37], [117] was re-implemented to be embedded in the agent-based platform. The three models in the existing PM are implemented consecutively such that one-year data is generated from the occupancy model, which are passed as the input to the activity model. Then, the activity model generates one-year data for the electricity model, which generates the electricity consumption of the house. This is the process referred to as the staged modelling process in Section 2.2.2, which is not suitable for intervention testing. This process is broken down in the implemented ABM where the activities and energy consumption behaviour of occupants are simulated per time step (10 minutes).

This allows for intervention modelling where changes in the occupant energy consumption behaviour and activities should be simulated as a result of the intervention.

In order to model behavioural energy waste, modifications were made mainly to the electricity model. Two attributes were added to the model: (1) an attribute that determines the personal energy consumption behaviour of occupants, and (2) a location attribute that determines the rooms that the occupants are using. These attributes affect when occupants turn appliances and lights ON or OFF. Thus, behavioural energy waste is modelled by combining data about which appliances are ON, what activities are being performed and what locations/rooms are occupied, along with other environmental factors that will be explained in Section 3.2.3.

The following section discusses the components of the proposed ABM (i.e. 'Occupant Agents', 'Appliance Agents' and the 'Environment' that the agents act in). Details about the usage of the probability distributions in the ABM are presented where necessary.

3.2 Model Formalisation and Design

3.2.1 Appliance Agents

Electric appliances in the house are modelled as dummy agents that react to occupant agents. The types and number of appliances in the house are obtained from appliances PDFs in the PM. During the simulation initialisation, the household is assigned a number of appliances along with their types based on the household composition and income. The appliance type identifies the amount of energy that the appliance consumes, which is represented using the variable *inUseConsumption* measured in Watt (W).

Every appliance is located in a room (r) of the house environment that is defined in the next section. Lights are assigned to every room, and computers and televisions are assigned to living rooms and bedrooms. Occupant agents change appliances state from ON to OFF or vice versa based on the activities they perform in the house. Therefore, every appliance (a) has a set of occupants using it (denoted O_a). The appliance agent is implemented as a state chart as shown in Figure 3.3. Occupant agents communicate with appliance agents through messages that are received by the state chart. The state chart is executed every time step by processing the received messages. It changes

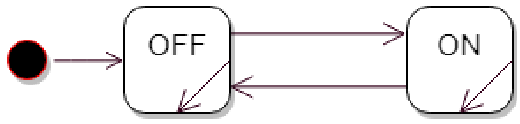


FIGURE 3.3: Appliance Agent State chart

the state of the appliance (ON or OFF) accordingly and assigns the amount of energy the appliance is consuming ($c_{t,d}$) every time step t and day d.

The set of appliance agents **A** in the house can be formalised as follows:

- **A** is the set of appliances in the house: For every appliance $a \in \mathbf{A}$, a is defined by the tuple <*inUseConsumption*, r, O_a, C>, where *inUseConsumption* is the amount of energy used when the device is ON, r is the room that the appliance is in, O_a is the set of occupants using the appliance and C is the consumption array of the appliance over a whole year, where every $c_{t,d} \in C = \{0, inUseConsumption\}$ based on its ON-OFF state.

3.2.2 The House Environment

Occupant agents live and interact in a house environment composed of a number of rooms, each having a set of appliances (A_r) and occupants using the room (O_r). The number of rooms affects the mobility and number of locations that the occupants can be in, and consequently the energy consumption. Therefore, the number of rooms was obtained from the 'Income and Living Conditions Database' by Eurostat [118]. The database contains data about the average number of rooms per person by household composition and income group. Table 3.2 [1] was obtained after extracting the Belgian data in year 2012 [2]. Every household was assigned one kitchen, one living room, at least one bedroom and at least one bathroom. Dining and laundry/utility rooms were added in high income houses when necessary. The size of basic rooms was set to 20 m^2 based on the average room size in Belgium [119]. The room size was used to calculate the amount of light consumed in the every room as the lights consumption is expressed in W/m^2.

In terms of the day and time, occupant agents are aware of the day of the week (d) distinguishing between weekdays, Saturdays and Sundays, time of

[1] The number of rooms refers to separate spaces intended for habitation, including kitchens, bedrooms, living rooms, dining rooms. Therefore, other spaces such as bathrooms, toilets and passageways are not counted as rooms

[2] The year 2012 was selected because the probabilistic model used the 2012 Belgian ECS to get the income and appliances data

TABLE 3.2: Average number of rooms as function of household type and income group

Household Type/Income	<€1000	>€1000
One adult younger than 65 years	3	4
One adult older than 65 years	4	5
One adult with one or two children	4	4
Two adults younger than 65 years	5	5
Two adults older than 65 years	5	6
Two adults with one child	4	5
Two adults with two children	5	6

day in a 10-minute time step (t) and the amount of external daylight ($daylight_{t,d}$) measured in lux (lx).

The simulation environment **E** can be defined using the two sets **T** and **R**, where:

- **T** is a one-year simulation time defined by the triplet $<t, d, daylight_{t,d}>$ where $t \in [1\text{-}144]$ is a 10-minute time step in 24 hours, d is the day of the week, which is defined by its number (1 to 7) and type (weekday, Saturday and Sunday) and $daylight_{t,d}$ is the amount of external daylight at every time step and day.
- **R** is the set of rooms in the house: For every room $r \in$ **R**, r is defined by the triplet $<size, A_r, O_r>$, where *size* is the size of the room, A_r is the set of appliances in the room and O_r is the set of occupants that are in the room.

3.2.3 Occupant Agents

Initially, occupant ages and employment types are given as input for the model. Employment types include: *full time job*, *part time job*, *unemployed*, *retired* and *school*. Occupants whose age is between 12 and 17 are given the employment type *school* by default, and similarly those who are 65 and above are given the employment type *retired*. Another input attribute of the model is the Personal Energy Rating (PER) attribute, which determines how often occupants follow energy saving actions. The income group of the household is assigned using the income PDF in the PM. Next, the appliances and rooms of the house are determined as functions of the household composition and income group. At this stage, all occupant agents are initialised and start doing activities in the house. At every time step, the occupant agents change the state of the environment by performing activities, changing their location and using the electric appliances.

Occupant Daily and Weekly Behaviour

In order to simulate occupancy of members, two parameters are needed before starting to generate detailed data: (1) work routine, and (2) occupancy pattern. Working occupants (full time and part-time) can belong to one of ten work routines (*wr*) to decide working days and duration of work per day. The work routines include different forms of standard, extended and part-time work weeks (for more details about work routines refer to [37]). The selection of the work routine depends on the age and employment type of the working occupant. Every day, and based on the occupant age, employment type, day type and work routine for working occupants, the occupant agent chooses one occupancy pattern op_d for the day. The PM includes seven occupancy patterns which were used in [37], [116].

Every time step, the occupant agent either selects a new occupancy state $os_{t,d}$ and a duration (*dr*) for the state based on the PDF in the PM, or decrements the duration of an already running occupancy state. The occupant agent's action to select new occupancy state is defined by Formulae (3.1)

$$\begin{aligned} OS : op_d, os_{(t-1),d}, t &\rightarrow os_{t,d} \\ op_d, os_{t,d}, t &\rightarrow dr \ , \end{aligned} \tag{3.1}$$

where $os_{t,d}$ is the new occupancy state, $os_{t,d} \in \{Away, Sleeping, Active\}$ (*Away*: when the occupant is not at home, *Sleeping*: when the occupant is at home but sleeping and *Active*: when the occupant is at home and not sleeping). The agent first selects a new state as function of its occupancy pattern op_d, previous state $os_{(t-1),d}$ and time of day t, then decides the duration dr of the state based on its occupancy pattern, current occupancy state and time of day.

The PM distinguishes between tasks and personal activities, where tasks are performed by one occupant at a time, while personal activities can be performed by more than one occupant at a time and can be shared. When the occupant agent is in the *Active* occupancy state, it can do several tasks (*tk*) or personal activities (*ac*). The agent can either select to start the activity, or decrement the duration (*dr*) of an ongoing activity. The action of selecting new activities is defined by Formulae (3.2).

$$AC_{ac|tk} : age, emp, t, d \rightarrow \{0, 1\}_{ac|tk}, dr \tag{3.2}$$

This function is performed by the occupant agent for every personal activity $ac \in$ {*Using the computer*, *Watching television*, *Listening to music*, *Taking shower/bath*} and task $tk \in$ {*Preparing food*, *Vacuum cleaning*, *Ironing*, *Doing dishes*, *Doing laundry*}. The equation returns a boolean value {0,1} to distinguish whether the action will take place or not. This way of modelling enables multitasking (i.e. the occupant can perform more than one activity at a time given that the activities are compatible). The decision of doing an activity is based on the occupant's *age*, employment type (*emp*), time of day (t) and day type (d). Once a new activity is selected to be performed, the agent selects the duration dr of the activity based on the same input variables.

The decision of which factors affect the prediction of individual's occupancy and activities is adapted from the PM by Aerts [37]. The author proved through detailed analysis of the data from the Belgian time-use survey that the age, employment type, time of the day and day of week are the most affecting factors.

Algorithm 1 generalises the process of extracting occupant states (weekly work routine, occupancy state, occupancy, activities, duration of occupancy /activities) from PDFs.

Algorithm 1: Select New State

```
rand ← Rand(0,1) // Rand(0,1) is a uniform random generator
    between 0 and 1

foreach state ∈ States do
    p ← P(state, a1, a2, ..., an)
    if rand ≤ p then
        return state
```

P is a cumulative PDF, where its last value is always equal to 1, of $n+1$ parameters. One of the parameters of P is *state* that will be selected from the set of available *States*. The rest of the parameters $(a_1, a_2, ..., a_n)$ are n factors that affect the choice of *state*. For example, if it is required to select a new occupancy *state* ($os_{t,d}$), then *States* is the set of possible states {*Away*, *Sleeping*, *Active*} and $P(os_{t,d}, op_{t,d}, os_{(t-1),d}, t)$ is the cumulative PDF of occupancy states that has 4 parameters, where $os_{t,d}$ is the state to be selected, and $op_{t,d}$,$os_{(t-1),d}$ and t are the factors that affect the choice of $os_{t,d}$.

Occupant Location

Whenever the occupant agent is at home, it needs to be in one of the house rooms (r). Every activity is assigned to a room or a set of possible rooms as shown in Table 3.3.

TABLE 3.3: Location where Activities and Tasks Take Place

Activity/Task	**Location/s**
Using the Computer	Computer Location (Living Room/Bedroom)
Watching Television	Television Location (Living Room/Bedroom)
Listening to Music	Random
Taking Shower/Bath	Bathroom
Preparing Food	Kitchen
Vacuum Cleaning	Random
Ironing	Bedroom/Television Location
Doing Dishes	Kitchen
Doing Laundry	Kitchen
None	Random

The occupant agent determines its location using Formulae (3.3).

$$OL : os_{t,d}, AC_{t,d}, TK_{t,d} \rightarrow r_{t,d} \tag{3.3}$$

The occupant agent decides its location $r_{t,d}$ based on its occupancy state $os_{t,d}$, the set of ongoing personal activities $AC_{t,d}$ and the set of ongoing tasks $TK_{t,d}$. Sleeping occupant agents are assigned to bedrooms by default. The occupant agent can have a set of possible rooms when doing more than one activity at a time. In this case, the agent alternates randomly between the possible rooms. If the agent is *Active* at home and not performing any of the activities or tasks, its locations is selected randomly among the basic house rooms.

Occupant Energy Awareness and Energy Usage

In addition to the occupant's age and employment type, the ABM characterises occupants based on their personal energy consumption behaviour. This is because energy consumption behaviour is different from one occupant to another. Occupants' energy awareness has been modelled in existing literature in different ways. For example, Carmenate *et al.* [23] distinguish between energy literate and energy illiterate occupants. Similarly, Zhang *et al.* [20] categorise occupants into high and low consumers and Azar and Menassa [58] divide occupants into high, medium and low consumers. Another way is using average yearly/daily consumption as a characteristic of the occupant [26], [13]. The most detailed and flexible definition of energy awareness was proposed by Zhang *et al.* [22] where energy consumers can belong to one of four consumer types: '*Follower Green*', '*Concerned Green*', '*Regular Waster*' and '*Disengaged Waster*'. Based on the consumer type, the agent's energy awareness attribute is assigned a value between 0 and 100. This attribute is used to decide the probability that an occupant follows energy saving actions such as turning OFF devices when they are not in use or avoiding putting heavy appliances ON in peak times. The value is calculated based on a normal distribution for every consumer type (Table 3.4).

TABLE 3.4: Mean and Standard Deviation of Consumer Types from Zhang *et al.* [22]

Consumer Types	**Mean μ**	**Standard Deviation σ**
Follower Green	0.74	0.041
Concerned Green	0.72	0.043
Regular Waster	0.41	0.033
Disengaged Waster	0.25	0.057

In the current model, the consumer types defined in [22] are adopted to model energy awareness of occupant agents. The consumer types are reflected in the model by the PER attribute, which is assigned using the normal distributions in Table 3.4 during the simulation initialisation. PER is also used to determine how often occupants comply to the recommendations forwarded by the messaging intervention that is proposed and modelled in Chapter 5 of this thesis.

The action of turning appliances ON/OFF is related to the occupants' activities and their energy awareness defined by the attribute PER. Every activity that the occupant performs is associated to an appliance a. The actions of turning appliances ON and OFF ($turnOn_a$, $turnOff_a$) are shown in Formulae (3.4).

$$\begin{aligned} TO_a : ac_{t,d} \rightarrow turnOn_a \quad & | \\ ac_{t,d}, PER, O_a \rightarrow \{keepOn, turnOff\}_a & \end{aligned} \tag{3.4}$$

When the occupant agent starts an activity ($ac_{t,d}$), it turns ON the appliance associated to this activity. When the activity ends and based on the agent's *PER* attribute, it may turn OFF the appliance or keep it ON. The occupant may also communicate with other occupant/s (O_a) who may be using the same appliance at the same time to decide whether to turn OFF the appliance. The action of turning OFF appliances is also executed every time an occupant agent visits a room and finds appliances that are ON but unused, taking into consideration its PER.

The action of turning lights ON/OFF is different from using appliances since using lights depends on the amount of natural daylight and the location of occupants. The actions of turning lights ON and OFF is shown in Formulae (3.5).

$$\begin{aligned} TO_r : r_{t,d}, daylight_{t,d} \rightarrow \{turnOn, keepOff\}_r \quad & | \\ r_{t,d}, PER, O_r \rightarrow \{keepOn, turnOff\}_r \end{aligned} \tag{3.5}$$

Every time the occupant agent is in a room $r_{t,d}$, it may decide to turn ON the light in this room based on the amount of natural daylight ($daylight_{t,d}$). The agent chooses to turn ON the lights when $daylight_{t,d} \times 0.02 < 200\ lx$ as modelled in [37], which was also used to obtain real daylight data. When the occupant leaves the room, it decides whether to turn OFF the light based on its PER attribute and other occupant agents (O_r) that may be using the room.

In summary, the occupant agent **OA** is defined using the tuple <age, emp, wr, op_d, os_{td}, PER, AC_{td}, TK_{td}, r_{td} > and can perform the actions in the tuple <OS, $AC_{ac|tk}$, OL, TO_a, TO_r>.

3.3 Model Implementation Environment

The model was implemented in Repast Simphony [120] version 2.4 (2016), which is an agent-based platform, using Java version 8. Using a software platform (i.e. Repast Simphony) instead of a plain programming language helps in overcoming challenges of agents memory and simulation time management [121]. Among several platforms for agent-based simulation, Repast Simphony is one of the top used software platforms [122], it is free, open-source and fully object-oriented. It includes an embedded scheduler of methods, which automatically executes concurrent multi-threaded events. The choice of object-oriented programming (Java) is driven by the nature of agents, which are autonomous. Therefore, agents can be easily implemented as objects that have a set of attributes representing the agent characteristics, and methods representing the agent rules and behaviour [121], [122].

The experimental scenarios are run on a remote server hosted by Microsoft Azure. The server has 140 GB of RAM and 20 CPU processors. These high specifications of the server where selected to speed up the simulation, where multiple scenarios were run using the batch service in Repast Simphony.

Three appliances were implemented as a proof-of-concept: (1) lights, (2) televisions and (3) computers. These appliance are clearly affected by the energy awareness of occupants like leaving lights ON when leaving a room or leaving the television/computer ON when the activity ends.

3.4 Experiments and Results

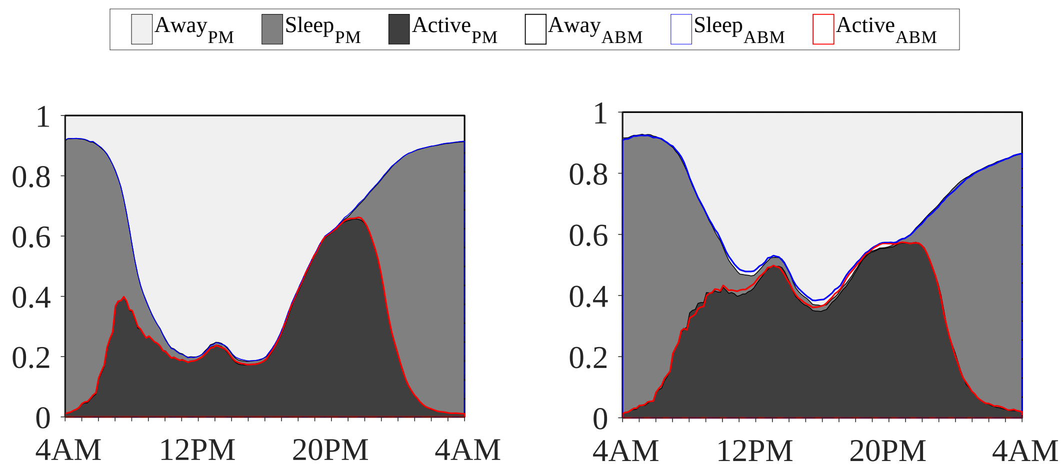
This section presents a set of experiments to test the validity of the model and study the effect of social parameters on the energy consumption of the house with varied consumer types of occupants. Every simulation run (or scenario) calculates the average energy consumption of 100 simulated households of the same composition, but different work routines for occupants, income levels, appliances number and types and house rooms.

3.4.1 Model Validation

In order to validate and verify the developed model, we use a number of common techniques, including tracing, graphical representation, model-to-model comparison and statistical significance. More details about these techniques will follow.

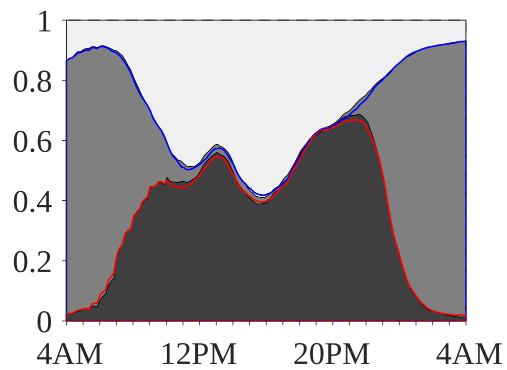
Predictive Validity

For the predictive validation of the daily behaviour data (occupancy and activities), we refer to TAPAS (Take A Previous Model and Add Something) principle [123], which is one of the startegies to validate simulation models. This incremental strategy is one of the most successful strategies for model creation, where a new model is built upon a previously validated model. In this case, the predictive validity of the previous model (the PM in our case) is passed to the new one (the developed ABM). In order to verify that the implemented ABM actually generates the same data as the previous PM, we use the Model-to-Model comparison technique [124]. In this technique the outputs of each of the models are compared and the difference is calculated and/or graphically represented. Figures 3.4 and 3.5 show the plots for occupancy data and activities data (watching television and using the computer) generated by the PM and the implemented ABM. The shown data represent the average of 100 simulations of the scenario "one adult aged 25-39 with a full-time job" given that the two models use uniform random number generators with different seeds. The figures clearly show that the implemented ABM is able to generate identical data to the one generated by the existing PM [37]. To statistically prove that the data sets generated by the two models come from the same distribution, we perform Kolmogorov-Smirnov test [125]. The results of the test are shown in table 3.5, which shows that the p-value is close to 1. This indicates that the models produce the same distribution of data, thus the predictive validity of the occupancy and activities data is passed from the existing PM to our developed ABM.



(A) Weekdays Occupancy

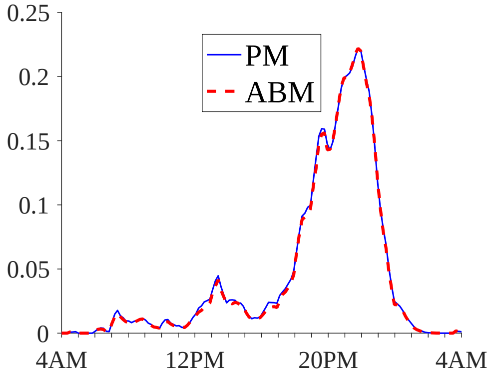
(B) Saturdays Occupancy



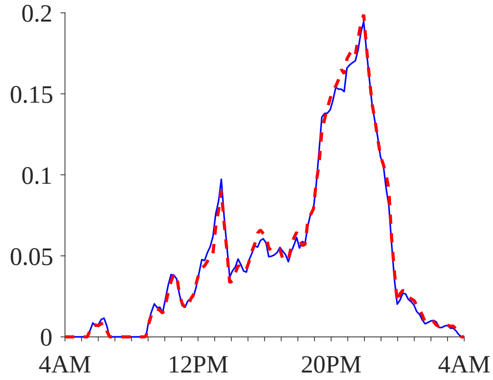
(C) Sundays Occupancy

FIGURE 3.4: Average Occupancy Data Comparison between the developed ABM and the existing PM

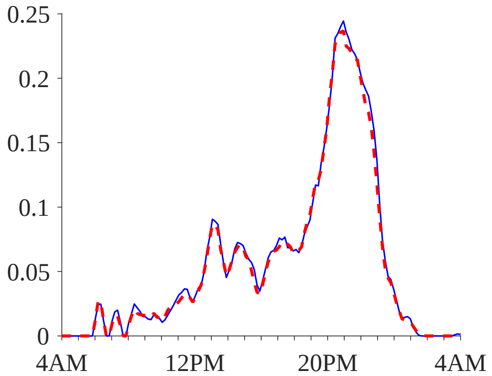
As the PER attribute is added in the developed ABM to simulate energy waste, the energy consumption data generated by the existing PM was different from the one generated in the ABM. Therefore, testing the predicitive validity of energy consumption data requires knowing the distribution of the



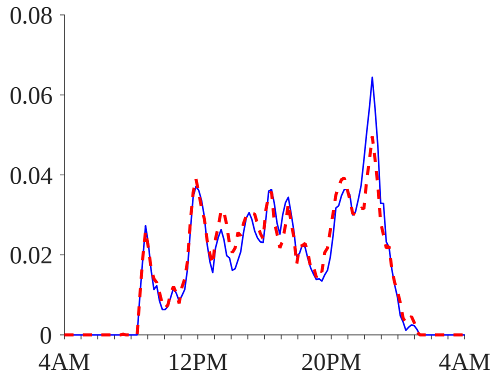
(A) Weekdays Watching Television Activity



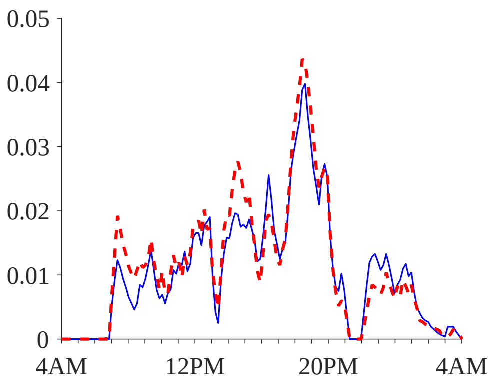
(B) Saturdays Watching Television Activity



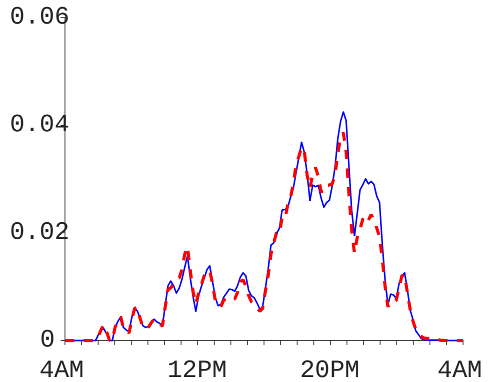
(C) Sundays Watching Television Activity



(D) Weekdays Using the Computer Activity



(E) Saturdays Using the Computer Activity



(F) Sundays Using the Computer Activity

FIGURE 3.5: Average Activities Data Comparison between the developed ABM and the existing PM

PER attribute in the Belgian community where the time-use survey was collected, and comparing the simulated energy consumption data with the real

TABLE 3.5: Daily Behaviour Predictive Validity: Kolmogorov-Smirnov Test Results

Tested Dataset	p-value
Occupancy	0.999
Watching television activity	0.988
Using the computer activity	0.975

ones. Obtainig this distribution was not possible since the survey took place in 2005. Therefore, predictive validation of the energy consumption data was not possible. Taking this limitation into account, we follow the approach of comparative analysis experiments by observing the changes in results when the inputs of the model change. This approach is common among ABMs that simulate energy cosumption, as the collection of data is not always possible [59]. Besides, this is also compatible with the mediator role of the model that we described in Chapter 1. Mediator models are developed when a high level of understanding of the system is not possible, where the model is used to gain insights that are then tested in reality.

Internal Validity

To prove the internal validity of the model, we compare the data generated by the model when using different seeds. If the replicated scenarios with different seeds generate the same distribution of data, then the model is internally valid [124]. For this purpose, we run 5 pairs of 5 different household types each with different random seed and calculate the p-value using Kolmogorov-Smirnov test [125]. The results of the test are reported in Table 3.6. The table shows that the p-value for all the simulated scenarios is close/equal to 1, which indicates that each tested pair of datasets come from the same distribution. This proves the internal validity of the model.

Structural Validity

The structural validity of the occupancy and activities modelling is done using the tracing technique [59]. The agent behaviour is followed per time step to ensure that it is behaving as designed. We start by observing one occupant agent in a household, and proceed to observe the collective behaviour of several family members who may be sharing activities and appliances. A rule-based method has been followed to observe whether the agents are logically behaving based on values of parameters in the model. An abstraction

TABLE 3.6: Internal Validity: Kolmogorov-Smirnov Test Results

Household Type	**p-value**
One adult 25-39 years old with full-time job	0.968
One adult 40-54 years old with full-time job, and one child 12-17 years old	1
Two adults 40-54 years old one with full-time job and the other is unemployed, and one child 12-17 years old	1
Two adults 55–64 years old both with full-time job	1
One elderly 65-75 years old who is retired	0.999

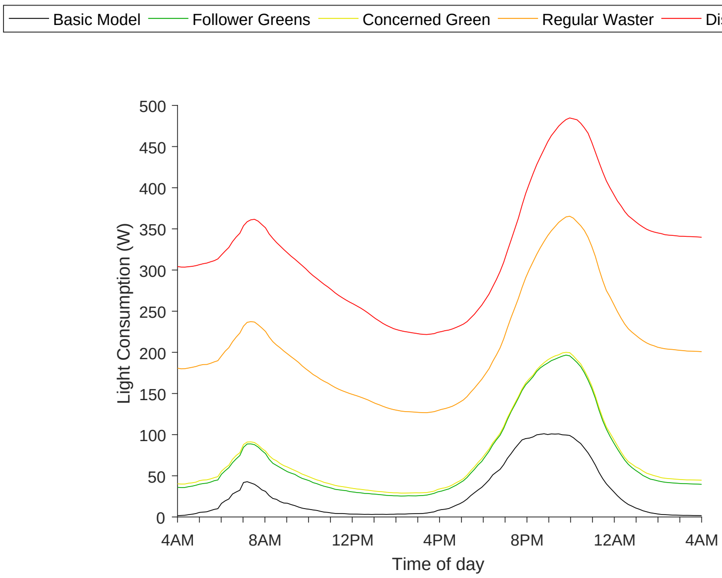
of these rules is presented in Relation (3.6)

$$c_1 \wedge c_2 \wedge \cdots \wedge c_n \rightarrow B \,, \tag{3.6}$$

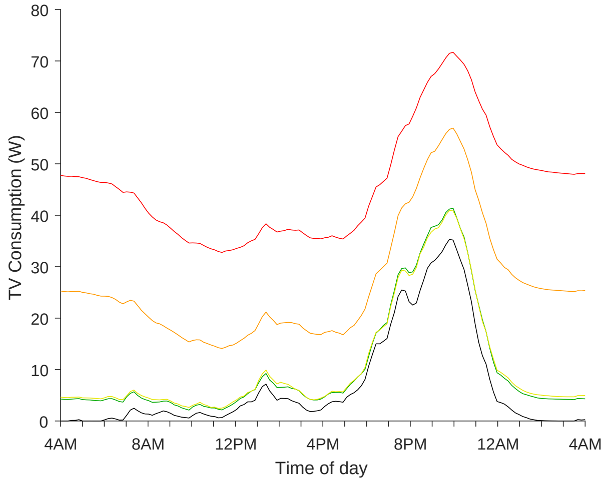
where $c_1, c_2, \ldots c_n$ are the rule conditions, and B is the expected behaviour if the conditions are true. For example, when the occupant finishes the *watching television* activity, it is not supposed to turn OFF the television if another occupant is still watching television. All the rules that affect the agent behaviour and reaction have been tested and approved, thus validity by tracing is confirmed.

To prove the structural validity of the electricity model, we run experiments of a single occupant household and observe the results graphically. This is done by studying how the occupant consumer type affects the energy consumption of the house. Households with one occupant were simulated varying ages and employment of occupants. Figure 3.6 represents the resulting weekday average energy consumption of lights, TV and PC for an occupant who is 25-39 years old in a full-time job. Each of the sub-figures in Figure 3.6 includes the results of 5 scenarios: the basic model that is the ideal scenario with 100% PER (referring to the existing PM [37]), and four scenarios, each having a different consumer type.

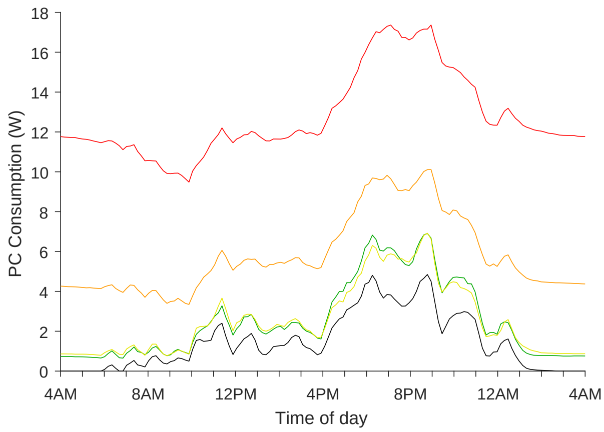
In the basic model (i.e. ideal scenario), it is observed that every time the occupant is sleeping or away, the energy consumption is very low or almost zero. For the other four scenarios, it is observed that the implemented model produces similar trend of daily energy consumption. The only difference is due to the addition of the PER attribute, which has caused the line graph to level up in a proportional way based on the percentages in Table 3.4.



(A) Lights Consumption



(B) TV Consumption



(C) PC Consumption

FIGURE 3.6: Appliances energy consumption of one occupant (25-39 years old / full-time job)

The energy consumption of *Follower Green* and *Concerned Green* occupants are almost similar because their mean PER is very close (74% and 72% respectively). While the other two waster occupants are much higher with the *Regular Waster* being more efficient than the *Disengaged Waster* who turns off appliances and lights only 25% of the time. Same observations were noticed for Saturdays and Sundays and for all age groups and employment types. These results prove the structural validity of the implemented model, which produces energy consumption trends similar to the basic model, and reflects the various consumer types levels of occupants.

3.4.2 Effect of Social Parameters

These experiments study the effect of social parameters on the energy consumption of households. In order to limit the number of scenarios, while achieving the objectives of the study, the consumer types of occupants is reduced to the two extreme types: *Follower Green* (G) and *Disengaged Waster* (W). Table 3.7 shows the simulated household types. The last column of the table shows the number of simulated scenarios for each household type with all possible combinations of consumer types. For example, a 4 occupant family has 16 $(= 2^4)$ possible combinations where every occupant can be either a *Follower Green* or a *Disengaged Waster*. The total of these scenarios is 214 as shown in Table 3.7. Besides, 30 scenarios were simulated (equal to the number of available household types) for the basic model (100% PER value) to calculate the rate of energy waste. Therefore, a total of 244 (= 214 + 30) scenarios were simulated. Out of these 244 scenarios a diverse set of scenarios are selected to be presented and discussed in this section as a proof-of-concept.

For every simulated scenario the total yearly consumption for three appliances (lights, TV and PC) is calculated using Equation (3.7),

$$C_n = \sum_{t=1}^{144} \sum_{d=1}^{7} \sum_{a \in A} \bar{c}_{t,d,a} \,, \tag{3.7}$$

where C_n is the total energy consumption of scenario n and $\bar{c}_{t,d,a}$ is the average energy consumption for appliance a at time step t and day d. In order to calculate the energy efficiency of each scenario, the energy waste rate W_n is calculated using the equation (3.8),

$$W_n = \frac{C_n}{C_{n,base}} \,, \tag{3.8}$$

TABLE 3.7: Simulated Household Types and Number of Scenarios

Age of adults	**Number and employment types of adults**	**Number of children**	**Total number of occupants (N)**	**Number of simulated scenarios ($= 2^N$)**
23-39	One adult with full-time job	0	1	2
		1	2	4
		2	3	8
	Two adults both with full-time job	0	2	4
		1	3	8
		2	4	16
	Two adults one with full-time job and one with part-time job	0	2	4
		1	3	8
		2	4	16
	Two adults one with full-time job and one unemployed	0	2	4
		1	3	8
		2	4	16
40-54	One adult with full-time job	0	1	2
		1	2	4
		2	3	8
	Two adults both with full-time job	0	2	4
		1	3	8
		2	4	16
	Two adults one with full-time job and one with part-time job	0	2	4
		1	3	8
		2	4	16
	Two adults one with full-time job and one unemployed	0	2	4
		1	3	8
		2	4	16
55-64	One adult with full-time job	0	1	2
	One retired adult	0	1	2
	Two adults both with full-time job	0	2	4
	Two adults both retired	0	2	4
65-75	One retired adult	0	1	2
	Two adults both retired	0	2	4
Total				*214*

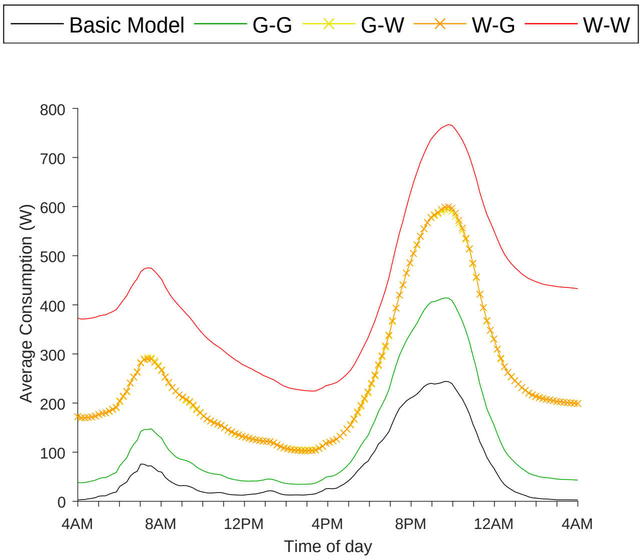
where $C_{n,base}$ is the ideal energy consumption for scenario n where devices are only ON when they are being used (i.e. all occupants of the house are 100% energy aware). Analytically, $W_n \geq 1$ as the nominator is always more than the denominator that represents the ideal consumed energy. As much as W_n is closer to 1 it means that the household is closer to the ideal scenario i.e. causes less energy waste.

Effect of Energy Awareness

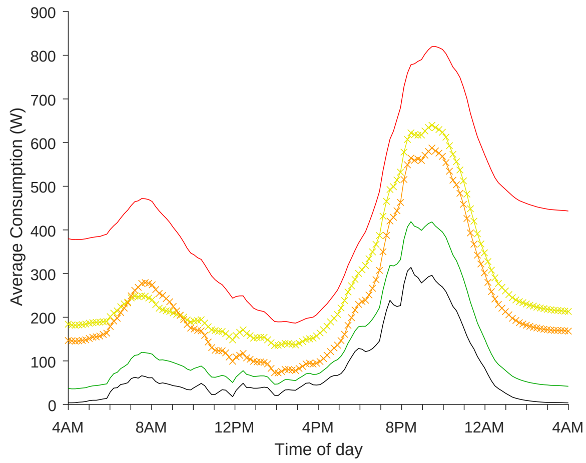
This experiment studies the effect of energy awareness on the consumption of multiple occupant households. Figure 3.7 shows the consumption of two 25-39 year old occupants (Figure 3.7a where both are in full-time job, and Figure 3.7b where one is in full-time job and the other is unemployed). The legend of the figure encodes the consumer type of the household, where the sequence of the letters (G and W) has the same sequence as the description of the household type in the captions of the sub-figures.

It is noticed that the observation in the previous section for a single occupant household (Figure 3.6) still applies on two-occupant households, which proves that the model reflects consumer types of occupants with multiple occupancy. Both Figures (3.7a and 3.7b) show the two extremes of energy consumption when there are two *Follower Green* (G) occupants or two *Disengaged Waster* (W) occupants at home. In-between scenarios in Figure 3.7a resulted in the same energy consumption (crossed yellow and orange lines) even when reversing the consumer types of the two occupants. However, this observation does not hold when having different employment types (Figure 3.7b). It is observed that the household consumes less energy when the unemployed occupant is a *Follower Green*. This is observed during the whole 24 hours except few hours in the morning (7:00 am and 9:30 am) when it is more probable that the *Disengaged Waster* full-time occupant is awake and the *Follower Green* unemployed occupant is sleeping. A similar observation is noticed when the unemployed occupant is a *Disengaged Waster*, where the household consumes more energy. This is explained by the fact that unemployed occupants spend more time in the house which makes their effect more obvious than full-time employed occupants.

These observations show that employment type is a factor that affects the energy consumption of the house when varying occupants' consumer types. However, further investigation is needed to quantify this effect and test it on other age groups and household types, which is the focus of the coming experiments.



(A) Two occupants both in full-time job



(B) Two occupants: the first in full-time job and the second is unemployed

FIGURE 3.7: Total energy consumption of two occupant households both 25-39 years old

Effect of Family size

This experiment is intended to study the effect of the number of occupants in the house. As a proof of concept, scenarios of the age group 25-39 in full-time job that are studied in this experiment are presented in Table 3.8. The table consists of two groups of scenarios; each group has the same age and employment type for adults, same consumer type, but different number of occupants.

TABLE 3.8: Scenarios and Results for the Effect of Family Size

<table>
<tr><th>Adults Age Group/ Empl. Type / Consumer Types</th><th>N. of Occupants</th><th>Household Composition</th><th>W_n</th></tr>
<tr><td rowspan="6">25-39/ Full-time Job/ All Green Occupants</td><td>1</td><td>One adult</td><td>2.31</td></tr>
<tr><td>2</td><td>One adult, one child</td><td>1.97</td></tr>
<tr><td>2</td><td>Two adults</td><td>1.99</td></tr>
<tr><td>3</td><td>One adult, two children</td><td>1.42</td></tr>
<tr><td>3</td><td>Two adults, one child</td><td>1.58</td></tr>
<tr><td>4</td><td>Two adults, two children</td><td>1.59</td></tr>
<tr><td rowspan="6">25-39/ Full-time Job/ All Waster Occupants</td><td>1</td><td>One adult</td><td>10.49</td></tr>
<tr><td>2</td><td>One adult, one child</td><td>6.13</td></tr>
<tr><td>2</td><td>Two adults</td><td>6.66</td></tr>
<tr><td>3</td><td>One adult, two children</td><td>3.92</td></tr>
<tr><td>3</td><td>Two adults, one child</td><td>4.18</td></tr>
<tr><td>4</td><td>Two adults, two children</td><td>4.17</td></tr>
</table>

In the first group of scenarios, where all family members are green occupants, it is observed that as the number of occupants increases, the waste rate W_n decreases. This means that more green occupants causes less energy waste. For the second group of scenarios, where all occupants are energy wasters, it could be expected that when the number of wasters increases, W_n should increase. However, it is observed that as the number of wasters increases, W_n decreases (i.e. the family becomes closer to the ideal scenario – $C_{n,base}$). This indicates that more occupants in the house causes energy waste to decrease, regardless of the consumer types of the occupants.

Effect of Employment Type

The purpose of this experiment is to test the effect of employment type on the energy consumption of the house. In order to do that, it is important to fix occupant ages and number of occupants while varying the employment types. Therefore, based on the household compositions available in the data of the PM, it is only possible to study the effect of full-time, part-time and unemployed occupants. Table 3.9 represents the scenarios for age group 40-45 involved in this experiment.

The 'Consumer Types' column encodes the energy awareness of occupants. The sequence of letters (G and W) in this column has the same sequence of occupants defined in the previous columns of the same table. For every household composition, the first two occupants (which are full-time/

part-time or full-time/unemployed) are involved in the consumer types variation, while the rest are put all green or all waster occupants in order to observe the effect. The difference between the waste rate of every two varied scenarios is calculated in the last column.

TABLE 3.9: Scenarios and Results for the Effect of Employment Type

Occupants Age Group/ Employment Type				Consumer Types	W_n	Diff.
Occ. 1	Occ. 2	Occ. 3	Occ. 4			
40-54/ Full-time	40-54/ Part-time			GW	3.89	0.23
				WG	3.66	
40-54/ Full-time	40-54/ Part-time	12-17/ School		GWG	2.34	0.11
				WGG	2.23	
				GWW	3.14	0.07
				WGW	3.07	
40-54/ Full-time	40-54/ Part-time	12-17/ School	12-17/ School	GWGG	1.88	0.05
				WGGG	1.83	
				GWWW	3.10	0.09
				WGWW	3.01	
40-54/ Full-time	40-54/ Unemployed			GW	3.05	0.37
				WG	2.68	
40-54/ Full-time	40-54/ Unemployed	12-17/ School		GWG	2.12	0.24
				WGG	1.88	
				GWW	2.75	0.14
				WGW	2.61	
40-54/ Full-time	40-54/ Unemployed	12-17/ School	12-17/ School	GWGG	1.69	0.03
				WGGG	1.66	
				GWWW	2.62	0.15
				WGWW	2.47	

Among the total number of simulated scenarios, there are cases when two occupants belong to the same age group and have the same employment type. It was observed that swapping the consumer types between these occupants resulted in similar amounts of energy consumption with very slight differences. This difference is expected to be due to random numbers generation. The average difference between these scenarios was calculated and denoted by $\epsilon = 0.1$, which is the error due to randomisation. Therefore, whenever the difference between two scenarios is greater than ϵ, it is considered a significant difference and further analysis is made to identify the cause of the difference.

The first three household types in Table 3.9 are for comparing full-time and part-time employment types. It is observed in all of these scenarios that whenever the part-time occupant is the green occupant, the energy consumption of the house is closer to the ideal scenario. This means that green part-time occupants are responsible for improving the house energy consumption when compared to full-time occupants. A similar observation is noticed when comparing full-time and unemployed occupants in the other three household types. This observation was noticed in the previously discussed experiment that studied the effect of energy awareness in multiple occupant household, and is further supported in this experiment.

Looking at the difference values, part-time occupant efficiency effect is significant ($> \epsilon$) in two cases: (1) the two-occupant families and (2) the three-occupant families when the third occupant is a green occupant. This indicates that part-time occupants can make an energy saving effect in small families (a small family is a family less than 4 occupants) and when there are more green occupants in the house, but not in big families where the difference is $0.05 \leq \epsilon$ and $0.09 \leq \epsilon$. However, for unemployed occupants, the efficiency effect is significant in most of the cases except for the four-occupant family when all of the other occupants are green occupants. It is also observed that unemployed occupants, in general, have higher efficiency effect than part-time occupants. These observations show that unemployed occupants are more efficient than part-time occupants, and the latter are more efficient than full-time occupants in small families.

Effect of Occupant Ages

In order to study age groups for adults, households that have the same employment type and number of occupants with no children were considered (Table 3.10). As for the children effect, households with an equal number of adults and children, with the same employment type for adults were studied (Table 3.11).

Table 3.10 shows that as the age of adults in small families increases, the household becomes less efficient (both for waster and green households). And for children, it is observed in Table 3.11 that children were more efficient than adults in small families ($0.26 > \epsilon$ and $0.11 > \epsilon$), but not in big families where adults were more efficient in some of the cases ($-0.17 \leq \epsilon$). These observations imply that younger occupants, including children, can make more efficiency effect in small families but not in big families.

TABLE 3.10: Scenarios and Results for the Effect of Adults Ages in Full-time Job

Consumer Types	**Occupant 1 Age Group**	**Occupant 2 Age Group**	$\mathbf{W_n}$
All Green Occupants	25-39		2.31
	40-54		2.47
	55-64		2.78
All Waster Occupants	25-39		10.49
	40-54		11.35
	55-64		13.29
All Green Occupants	25-39	25-39	1.99
	40-54	40-54	1.87
	55-64	55-64	1.85
All Waster Occupants	25-39	25-39	6.66
	40-54	40-54	6.68
	55-64	55-64	6.75

TABLE 3.11: Scenarios and Results for Studying the Effect of Children

Adults Age Group	**Household Type**	**Occupant Types**	W_n	**Difference**
25-39	One adult, one child	GW	3.94	0.26
		WG	3.68	
40-54	One adult, one child	GW	3.11	0.11
		WG	3.20	
25-39	Two adults, two children	WWGG	2.41	0.04
		GGWW	2.45	
40-54	Two adults, two children	WWGG	2.57	-0.17
		GGWW	2.74	

3.5 Discussion and Insights

This chapter proposed a model to combine ABM and PM to produce fine grained data. The implemented model simulates the dynamic interaction of occupants with appliances to produce detailed activities and energy consumption of houses. Opposed to exiting PMs [17], [37], [51], [70], [72] the cascaded model simulates dynamic occupant behaviour, which is affected by occupant personal characteristics and surrounding environment. In addition, a personal energy rating attribute can be assigned at occupant-level, which varies based on the occupant's greenness level, while PMs assume the same and ideal energy consumption behaviour of occupants.

The proposed model simulates energy waste caused by human behaviour. Existing ABMs that simulate the effect of human behaviour [13], [14], [22],

[26], [27], [58], [59] produce the consumption data at household or building level. This is because these models either represent consumer agents at household level or characterise occupant agents by yearly/monthly/daily consumption. The daily behaviour model developed in this chapter generates energy consumption data at appliance level as shown in the structural validity experiment, and models the detailed occupant-appliance interaction. These detailed data and simulated interaction enabled the study of energy waste in households as shown in the experimental results. Another group of ABMs produce appliance-level consumption, model energy awareness at occupant level, and simulate the occupant appliance interaction. Thus, they are able to simulate energy waste [23], [24], [62]–[64]. However, these models use small case studies and/or generate occupant behaviour using uniform distributions in fixed schedules for occupancy and activities. On the other hand, the proposed ABM uses a PM (with embedded Markov Process technique) to get the realistic occupant activities. In addition, using PMs enables the inclusion of data for a whole city (thousands of respondents vs. few hundreds of respondents), which leads to more varied scenarios and generalised conclusions.

Additionally, the integration of PM with ABM has given the advantage of studying the effect of social parameters on the energy consumption of families. These conclusions are important as they give insights for policy makers and governments about how to target family members to achieve higher energy saving. In section 3.4.2, the experiment that studied the effect of family size showed that as the number of occupants increases, the household wastes less energy even if all of the occupants are not energy aware. Although the implemented model that was used for these experiments does not model family pressure, which means that family members do not affect the energy awareness of each other, we have shown that merely having more occupants in the house causes less energy waste even though they actually consume more. This is explained by the fact that more occupants in the house means higher probability that somebody turns OFF appliances/lights that are not currently in use (knowing that occupant agents can know if a device is being used or a room is being occupied by other occupants). For example, if one occupant, who lives alone, leaves the house/room while the lights are ON, the lights will never be OFF until s/he returns back to the location. However, in a four-occupant family, if a member leaves an appliance ON and goes away, there is still a probability that somebody will turn it OFF or use it before s/he returns back. This conclusion implies that high intensity and focused interventions are needed in small families, because they cause high rates of energy waste. Whereas, interventions in big families can have lower intensity and can be distributed on the family members since they help each other in avoiding the energy waste as proved in this chapter.

The experiments that studied the effect of employment type proved that unemployed occupants have the most efficiency effect in small families compared to part-time and full-time occupants. Whereas part-time occupants are more efficient than full-time occupants, again in small families. This is mainly explained by the occupancy pattern of each employment type, where unemployed and part-time occupants are available at home more than full-time occupants. This enables unemployed and part-time occupants to reduce the waste in small families. However, in big families, this effect is reduced due to the existence of more occupants in the house who may cancel the effect of the green occupant. A similar conclusion was obtained concerning ages of occupants, where younger occupants made the household more efficient in small families of the same size. It is important here to note that this conclusion does not imply that younger occupants are more aware than older occupants. However, with the same energy awareness levels, the longer existence or longer active durations of younger occupants at home causes less energy waste than older occupants. These conclusion can imply similar insights as those implied from the family size experiment. Occupants with full-time jobs and elder ones in small families need to be targeted by high intensity interventions as they have high energy waste rate. However, children and adults who are housewives, unemployed, carers, or part-time employees in small families can be targeted with lower intensity interventions. This is because these occupants are more efficient than full-time and elder occupants. For big families, and since the effect of employment type and age was not significant, the same implication as the family size experiment can be concluded, which is the need for an intervention that is distributed on all the members of the family.

3.6 Summary

This chapter presented a model for energy consumption simulation. The model produces appliance energy consumption data by simulating occupant daily behaviour (occupancy, activities and location) in a house. This is done with the help of a PM that is integrated with an ABM. The integration process has shown efficient as each of the models shows its strengths in the developed model. The PM provides highly dimensional probability distributions that help in producing realistic occupant daily behaviour, and the ABM enables simulating dynamic human behaviour and interaction with appliances. These features provided by each of the models enable the study of energy waste caused by human behaviour. The PM by Aerts [37] was chosen among existing PMs as it includes the requirements of energy waste simulation. The probability distributions from this PM were used in the developed ABM to initialise the characteristics of the household and simulate the daily behaviour of the occupants. The ABM also distinguishes between occupant energy consumption behaviour through a PER attribute, which helps in simulating energy waste. The model validity (predictive, structural and internal) was tested using a number of techniques, and a set of experiments were conducted to show what insights can be gained when using the model. Through parameter variation, we found that the social characteristics (employment type, age and family size) are factors that affect the energy efficiency of the house. We found that the employment types retired, part-time job and full-time job have different efficiency effect on households, with the retired type being the most efficient and the full-time job being the least efficient. Similarly, bigger families cause less energy waste than smaller families. Regarding occupant ages, we found that younger occupants are more efficient than elder ones. These conclusions are mainly explained by the fact that these factors affect the movement and activity of occupants in the house. Thus, they may give more/less chance for occupants to control their appliances. The experiments have also shown that the developed model can be used by policy makers as an effective tool for studying energy consumption, and giving insights of which family members to target with energy interventions of various intensities.

The PER attribute used in this model can be affected by peer pressure where occupant behaviour may change based on the behaviour of others. This effect is going to be modelled in the next chapter. Besides, the level of details provided by the model is required to test energy interventions, which will be demonstrated in Chapter 5.

Chapter 4

The Peer Pressure Model

Having discussed the daily behaviour model in the previous chapter, this chapter presents a family-level peer pressure model that is the second model of the complete Agent-Based Model (ABM) proposed in this thesis (Figure 4.1). The model adds a more realistic layer of human behaviour and interaction.

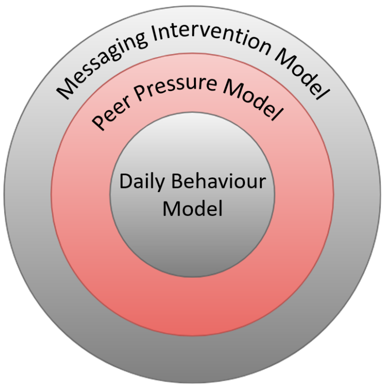


FIGURE 4.1: The Peer Pressure Model from the Layered ABM

The model is implemented in a family setting, therefore we may refer to it as the family pressure model. It is composed of two sub-models: (1) behaviour change sub-model, which formalises the behaviour change theories; and (2) energy efficiency intervention sub-model, which is intended to study the effect of peer pressure on the results of energy interventions. The coming sections formalise and design the two sub-models, then the experiments and discussion are presented. Findings reported in this chapter are published [126].

4.1 Behaviour Change Sub-Model

The occupant behaviour change is based on Festinger theories, namely, informal social communication theory, social comparison theory and cognitive dissonance theory [38]–[40]. The formalisation of Festinger theories uses Granovetter's Threshold Model (TM) [41] – such that the occupant agents change their behaviour when a threshold is exceeded as expalined in Section 2.3.2. In our model, the threshold is a combination of norms, values, motives and beliefs that trigger social comparison, communication and behaviour change as in Festinger theories. Although Granovetter's model simualtes collective behaviour which is compatible with social pressure, it does not fit the family pressure effect on energy efficient behaviour for two reasons. First, the model is applied in a public community, which has different values and motives, therefore different thresholds for individuals. However, in a family setting, we consider that family members have similar values and motives based on the fact that they have chosen to live together or were raised together. Therefore, when adapting Granovetter's TM to the application at hand, we consider one global threshold for the whole family. This does not revoke the fact that people react differently, therefore, we have set the global threshold as a probabilistic one [90] – so once the threshold is exceeded the individuals adopt the behaviour with a probability. Second, Granovetter's TM considers binary decisions while energy consumption behaviour is a continuous behaviour that is performed at different levels. This point is addressed by applying one of the main principles in Festinger theories. Knowing that social communication, social comparison and tendency to reduce cognitive dissonance increase with the increase in the magnitude of opinion/behaviour difference as outlined in Section 2.3.2, we adapt the definition of the threshold to fit the continuous energy consumption behaviour. Therefore, we formalise the threshold as the difference between the individual's consumer type and the average of other's consumer types.

In terms of network type, the occupant agents are structured in a fully connected network because in a family environment we can assume that every occupant can communicate with all other occupants unlike office, commercial and residential communities. Figure 4.2 shows an illustration of a fully connected network composed of 5 agents. The time step in this model is set to 4 weeks of simulation time (hereafter time period (T)), given that behaviour change is a process that does not happen instantly [127]. In order to express consumer types in numerical values, every type is given an integer value as shown in the second column of Table 4.1.

For a family composed of N occupants, every time period T, each occupant agent i calculates the difference $diff_{T,i}$ between its consumer type a_i and

FIGURE 4.2: Fully Connected Network Illustration

TABLE 4.1: Value and Abbreviations of Consumer Types

Consumer Type	**Value (a)**	**Abbreviation**
Follower Green	1	F
Concerned Green	2	C
Regular Waster	3	R
Disengaged Waster	4	D

the average consumer types of others a_j, where $j \in [1, N] : j \neq i$ using equation (4.1).

$$diff_{T,i} = a_i - \frac{\sum\limits_{j=1, j\neq i}^{N} a_j}{N-1} \tag{4.1}$$

Behaviour change happens if $|diff_{T,i}|$ exceeds the global threshold d where $d \in \mathbb{R}$. If $d \leq 3$, then there is a possibility for behaviour change, while if $d > 3$, then behaviour change is not possible as $diff_{T,i}$ can be maximum 3. The latter case is included to cover all possible types of people, where it is possible that an extreme person does not change her/his behaviour in any case. Within the range $[0, 3]$, a high threshold implies low sensitivity to social communication, comparison and cognitive dissonance, and a low threshold implies high sensitivity to social communication, comparison and cognitive dissonance. The global threshold d is a probabilistic threshold such that the occupant changes behaviour with probability p where $p \in [0, 1]$. This attribute is referred to as threshold lag [128], which explains the stochastic nature of human behaviour due to uncertainty and differences in the speed of reaction, where a high value of p means a high rate of change.

Once behaviour change is decided, the consumer type of the occupant changes towards the average of others' consumer types assuming that the occupant agent adapts its behaviour to be similar to others. Behaviour change is done by stepping between the consumer types one step at a time either to the green side (green effect) or the waster side (waster effect) as shown in Figure 4.3. The occupant agent is then assigned a new Personal Energy Rating (PER) value based on the mean and standard deviation of the new consumer type as in Table 3.4.

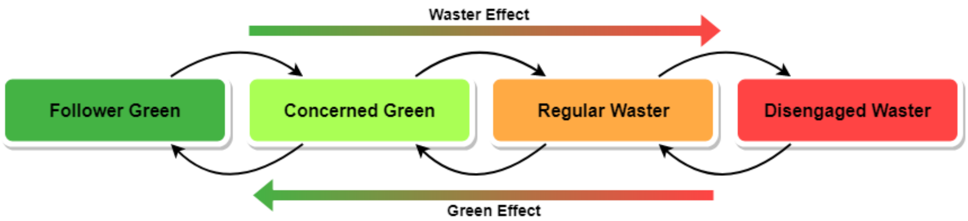


FIGURE 4.3: Behaviour Change Steps between Consumer Types

The behaviour change step is outlined in Algorithm 2, which is repeated for every agent i at every time period T. Figure 4.4 shows a flow chart of the behaviour change decision.

Algorithm 2: Behaviour Change Step

```
calculate diff_{T,i} using Equation (4.1)
if |diff_{T,i}| ≥ d then
    rand ← Rand(0,1) // Rand(0,1) is a uniform random
        generator between 0 and 1

    if rand ≤ p then
        if diff_{T,i} > 0 then
            if a_i > 1 then
                a_i ← a_i − 1
        else
            if a_i < 4 then
                a_i ← a_i + 1
```

4.2 Energy Efficiency Intervention Sub-Model

Energy interventions can be categorised into individual or social interventions among a range of categories as presented in [42]. Individual interventions are those that consider specific consumers as targets of the intervention regardless of their community context, while social interventions target the group of individuals as a whole, affecting the social norms within the group.

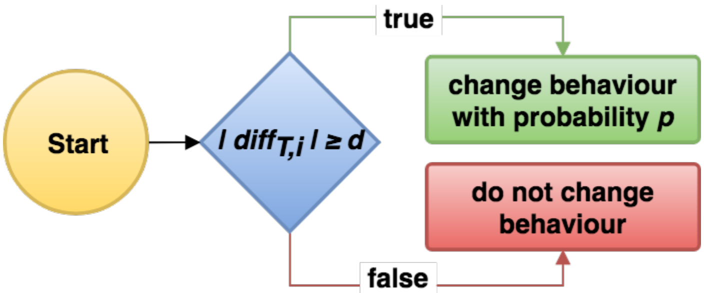


FIGURE 4.4: Behaviour Change Flowchart

Therefore, in this model we distinguish between family-level interventions and occupant-level interventions. Each of these interventions can be of any form as outlined in Section 2.4, but they differ in the number of occupants to target. The family-level intervention targets the family in general by changing its overall norms, values and beliefs. It can be applied by promoting the energy efficient behaviour such as giving financial incentives or repressing the wasting behaviour such as incurring charges [129]. The occupant-level intervention targets specific occupant/s in the family and leads to increasing their awareness levels. These two types of interventions are considered to observe how the collective family pressure can help in achieving more aware occupants and less energy consumption. It also allows policy makers to decide the needed combination and intensity of interventions based on each family composition (in terms of energy awareness levels and social parameters).

When the family-level intervention is applied, the overall norms, values and beliefs of the family change. The family-level intervention has two intensities, which represent the efficiency or effort made to achieve better results. Therefore, $I_p \in [1, 4]$ is defined as the promotion intensity and $I_r \in [1, 4]$ as the repression intensity. These two types of family-level interventions are reflected by two thresholds: one that affects the promotion of green effect $d_g \in \mathbb{R}$ and another that affects the repression of waster effect $d_w \in \mathbb{R}$. Therefore, the intervention increases d_w by I_r, thus increasing the cost to adopt waster behaviour and/or decreases d_g by I_p, thus increasing the benefit of adopting the green behaviour as outlined in Granovetter [41]. d_g and d_w change in effect of the intervention based on equations (4.2) and (4.3) given the initial threshold d.

$$d_g = d - I_p \tag{4.2}$$

$$d_w = d + I_r \tag{4.3}$$

For deciding behaviour change, d_g is checked when there is a possibility to change towards the green side ($diff_{T,i} > 0$), and d_w is checked when there is a possibility to change towards the waster side ($diff_{T,i} < 0$) as shown in Algorithm 3. The flowchart for behaviour change due to intervention is shown in Figure 4.5.

Algorithm 3: Intervention Behaviour Change Step

```
calculate diff_{T,i} using Equation (4.1)
if diff_{T,i} > 0 then
    if |diff_{T,i}| ≥ d_g then
        rand ← Rand(0,1) // Rand(0,1) is a uniform random
            generator between 0 and 1

        if rand ≤ p then
            if a_i > 1 then
                a_i ← a_i − 1
if diff_{T,i} < 0 then
    if |diff_{T,i}| ≥ d_w then
        rand ← Rand(0,1)
        if rand ≤ p then
            if a_i < 4 then
                a_i ← a_i + 1
```

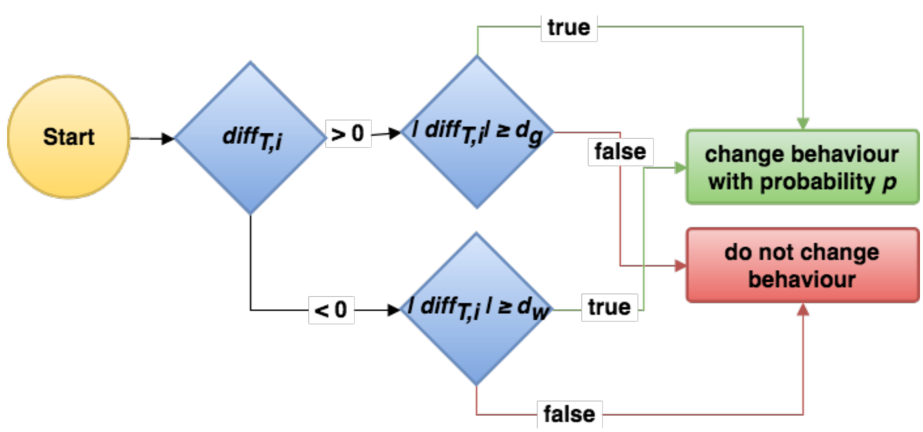


FIGURE 4.5: Intervention Behaviour Change Flowchart

The occupant-level intervention does not change the threshold of the family because it targets specific occupants. It aims to change the awareness of occupants while the regular behaviour change step represented by Algorithm 2 is applied. The intervention can have an intensity $I_o \in [1,3]$ and can be applied to a member of the family i at a specific time period T according to Equation (4.4).

$$a_{i,(T+1))} = \begin{cases} a_{i,T} - I_o & : \quad a_{i,T} > 1 \\ a_{i,T} & : \quad a_{i,T} = 1 \end{cases} \tag{4.4}$$

The messaging intervention proposed and tested in the next chapter is considered an application of the occupant-level intervention. Occupants may change their behaviour by changing their consumer type in effect of the messaging intervention. The messaging intervention simulation and behaviour change step as a result are detailed in Chapter 5.

4.3 Experiments and Results

This section presents a number of experiments with different input parameters to show how varying these inputs can result in different intervention outcomes. It is worth to mention that these experiments only present a number of significant scenarios as a proof-of-concept to show how the model can be used to analyse different cases, while achieving the purpose of the study. Abbreviations of consumer types (third column of Table 4.1) are used to identify the initial awareness of the family. For example, a four occupant family with one '*Follower Green*' and three '*Disengaged Wasters*' is denoted by *FDDD*. In every simulation run, 100 households were simulated to capture the stochastic effect of the threshold lag. The scenarios are run for a year and the resulting average yearly consumption and converged consumer types are recorded. These types were categorised based on the number of *Green* occupants in the family (represented in the figures by different colours in the bars). The threshold lag p is set to 0.5 as a middle point between high and low rate of change [13] throughout the simulations in this chapter. The same hardware specifications mentioned in Section 3.3 of Chapter 3 have been used for these experiments.

4.3.1 Family Pressure Convergence

The aim of this experiment is to observe the resulting consumer types as an effect of family pressure based on different thresholds. Since the threshold $d \in \mathbb{R}$ (i.e. it can have infinite number of values), we limit the values of d with the significant values {0,1,2,3,4}. This is because $|diff_{T,i}| \in [0, 3]$, therefore, if $d = 4$, then the change in the family will not be possible, and as the value of d decreases, the change in the family will be easier. Figure 4.6 shows the results of four scenarios: (a) *FFFD*, (b) *FCRD*, (c) *FFDD* and (d) *FDDD*. The colours in the bars refer to the number of *Green* occupants in the family after convergence. The last bar of every graph when $d = 4$ shows the initial category of the family before convergence.

In scenarios (b) and (c), the family remained with two green occupants at thresholds 2 and 3, besides, in (a) and (d), the family remained the same at threshold 3 and only one occupant was changed at threshold 2. This indicates that the family does not change significantly when the threshold is high ($d = 2$ and $d = 3$). However, at low thresholds ($d = 0$ and $d = 1$), the family converged mainly toward the dominant consumer type. For example, in (a) the convergence was mostly toward '4 green occupants', because initially there were three green occupants. A similar observation was noticed in (d). In scenario (b) and (c) where there is no dominant awareness type, the convergence was with equal probabilities either to all green occupants or all waster occupants ('no green occupants' category) with higher convergence to the extremes at threshold 0. These results indicate that the proposed model is conceptually valid as it reflects Festinger theories and collective behaviour, which agree that people tend to change their behaviour to conform with the behaviour of others.

It is worth noting that in (a) and at threshold 0, around 20% of the households converged to 'no green occupants'. This means that the only waster occupant succeeded to change the behaviour of the other three green occupants. This phenomenon is explained in the cognitive dissonance theory, which states that dissonance can be reduced by either adapting with others, or convincing the others to adapt with the individual. This explains how the three green occupants converged to wasters in effect of one waster occupant as in (a) and vice versa in (d). Festinger [40] mentions that in this case, the overall cognitive elements of the surrounding environment change, but this is easy when the individual can find others who follow the same behaviour,

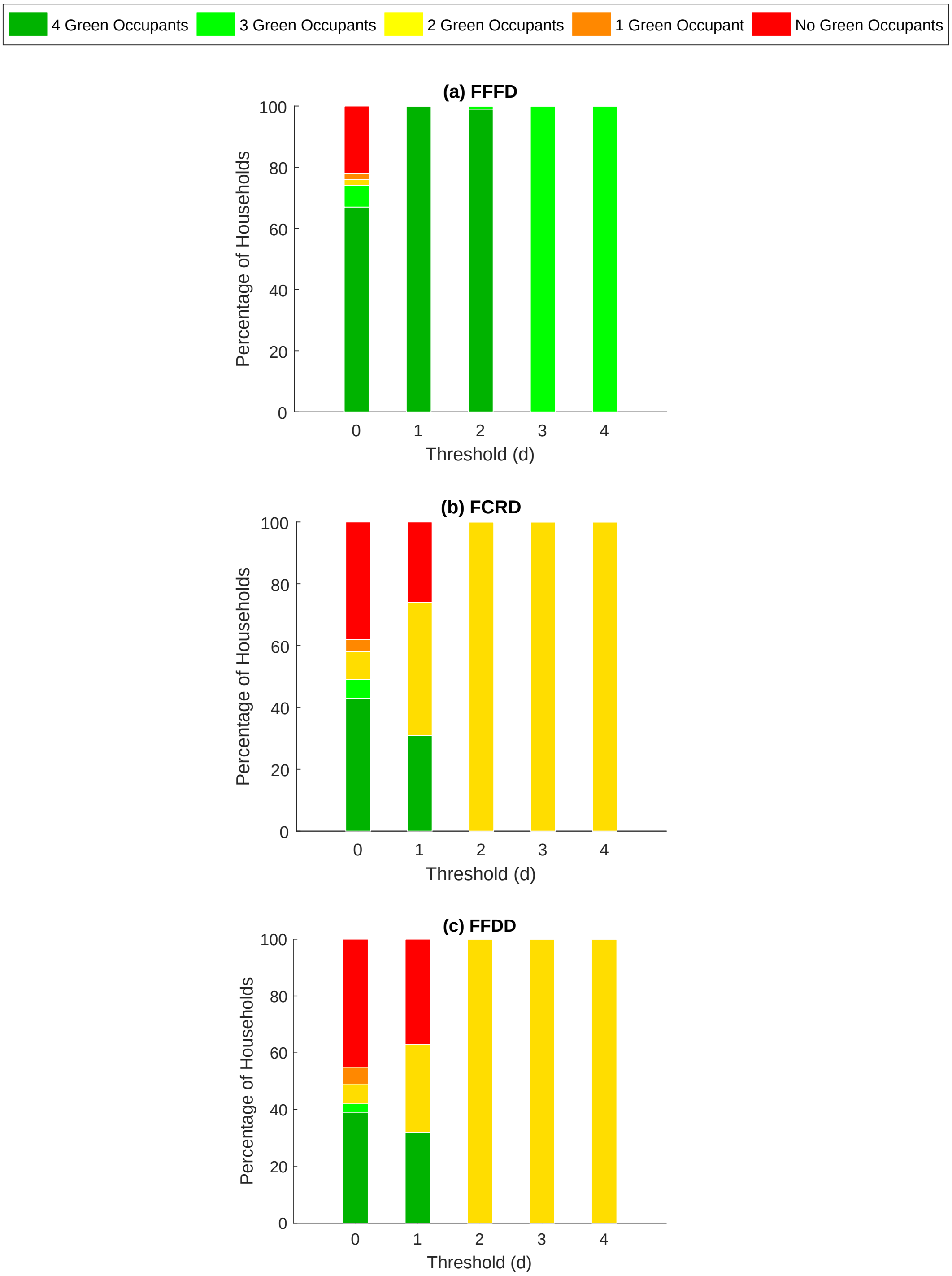


FIGURE 4.6: Family Consumer Types Convergence (Continued in the next page)

which explains the low percentage of this convergence (20% in our experiment). Scenarios with no green occupants are usually targets for interventions to repress the waster effect and achieve more energy efficiency, which are the focus of the next two experiments.

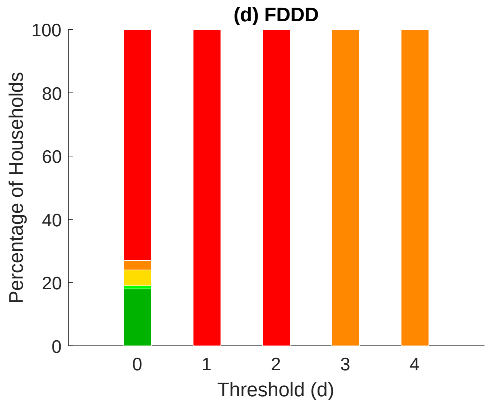


FIGURE 4.6: Family Consumer Types Convergence

4.3.2 Family-level Intervention

In this experiment, family-level interventions are applied to scenario (d) of the previous experiment (*FDDD*) as it has the most waster occupants after convergence. For each threshold, the possible intensities of family-level interventions are applied keeping the thresholds d_g and d_w within the the significant values {0,1,2,3,4}. The aim of this experiment is to show the effect of promotion and repression interventions when varying their intensities. Figure 4.7 shows the results with initial thresholds $d = \{0, 1, 2, 3, 4\}$.

It is noticed that in all the scenarios, when the promotion and repression intensities are the maximum, the category '4 green occupants' dominates. Looking at the scenarios in-between when varying the intervention intensities, we can observe that the number of green occupants increases as the promotion intensity (I_p) increases, which is not the case with repression intensity (I_r) where most of the occupants stayed wasters. For example, at threshold 2, applying promotion intervention ($I_p = 2$) resulted in around 100% '4 green occupants', while applying repression intervention ($I_r = 2$) resulted in 100% '1 green occupants'. This indicates that repression intervention is less effective than the promotion intervention. This is attributed to the high number of waster occupants that existed in the family (*FDDD*), such that encouraging them to adopt the green behaviour is more effective than repressing the only green occupant from getting affected by waster occupants.

Another indication from varying intervention intensities is inferring the minimum intensity needed to increase the possibility of getting 4 green occupants. For example, at threshold 0, applying repression intervention ($I_r = 2$) is enough to get '4 green occupants' with probability more than 0.95. This allows to identify the minimum effort needed while achieving the maximum number of green occupants.

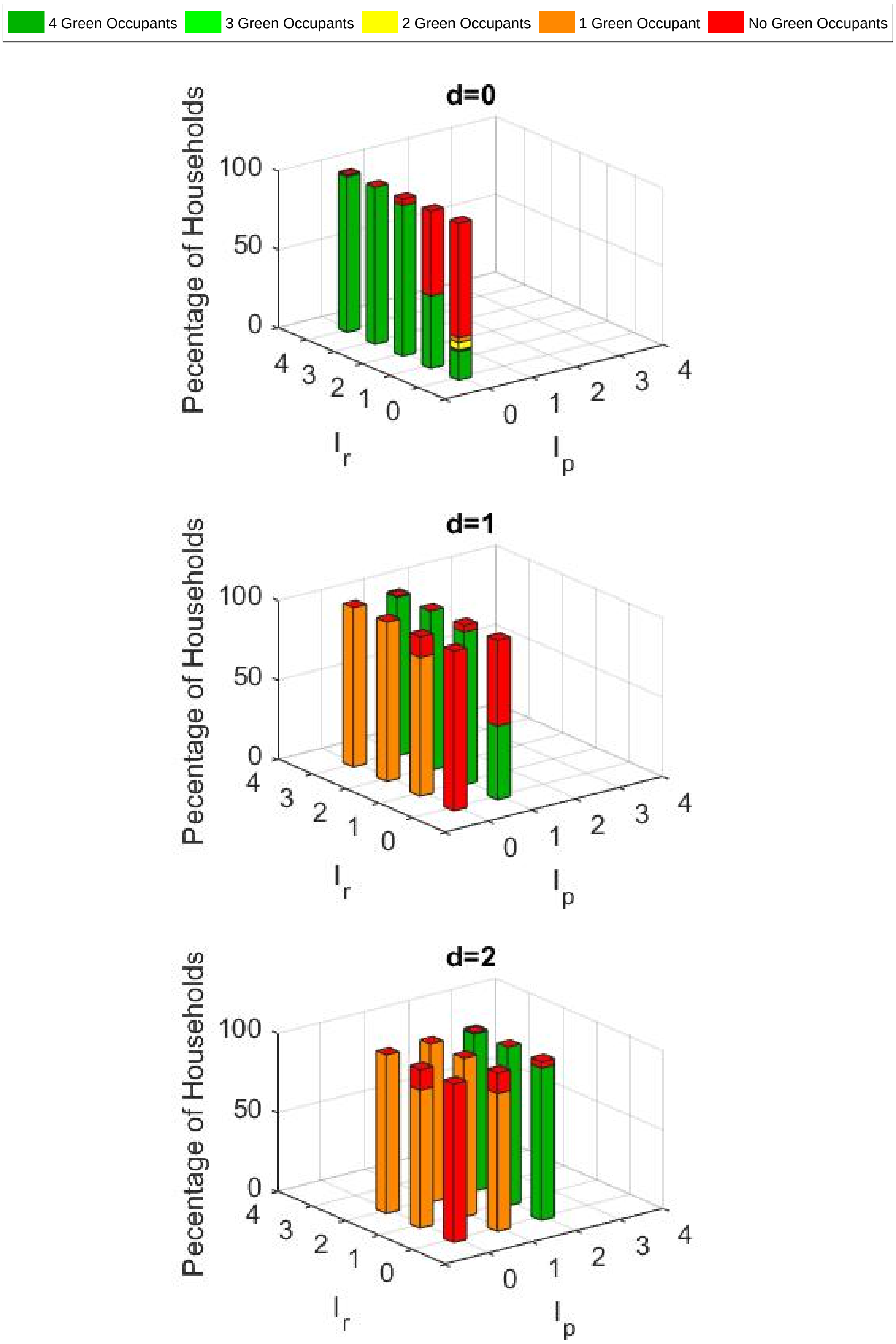


FIGURE 4.7: Family-level Intervention Convergence – Scenario FDDD (Continued in the next page)

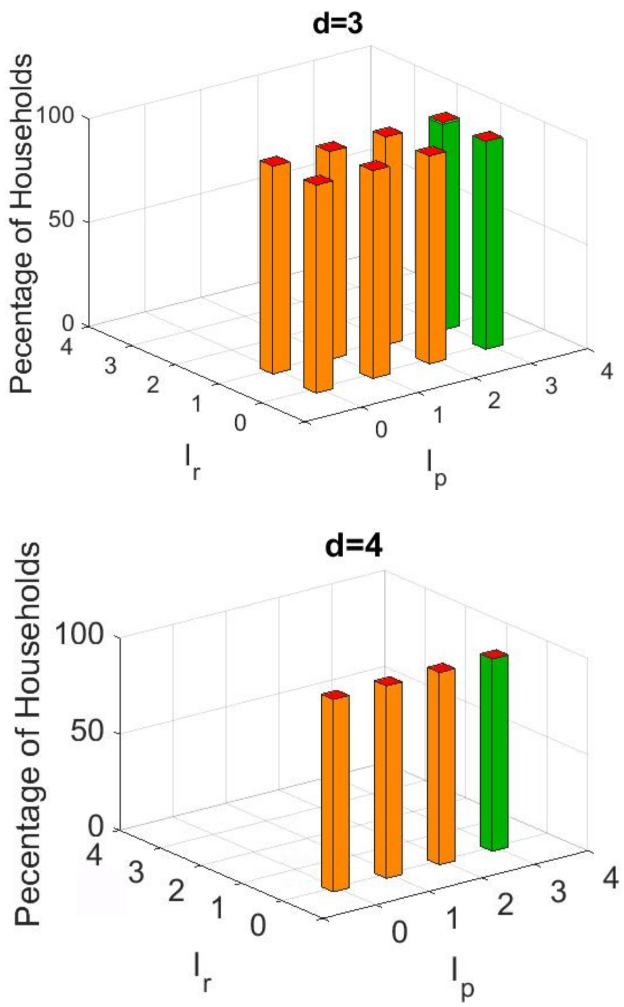


FIGURE 4.7: Family-level Intervention Convergence – Scenario FDDD

4.3.3 Occupant-level Intervention

This experiment studies the effect of occupant-level intervention, which directly changes the awareness of specific occupants. For this experiment, we choose to target the least aware occupant of the family. The intervention can be applied at specific times of the year, therefore we set 3 times for it: (1) 'early intervention' at $T = 2$, (2) 'mid-year intervention' at $T = 6$, or (3) 'late intervention' at $T = 9$. Scenario *FFFD* with threshold $d = 0$ is selected to get the minimum intensity required to prevent the 'no green occupants' convergence (as shown in scenario (a) in the experiment reported in Section 4.3.1). Besides, it can be used to determine the best intervention time just before the waster occupant affects other green occupants. Figure 4.8 shows the results while varying the intervention time and intensity.

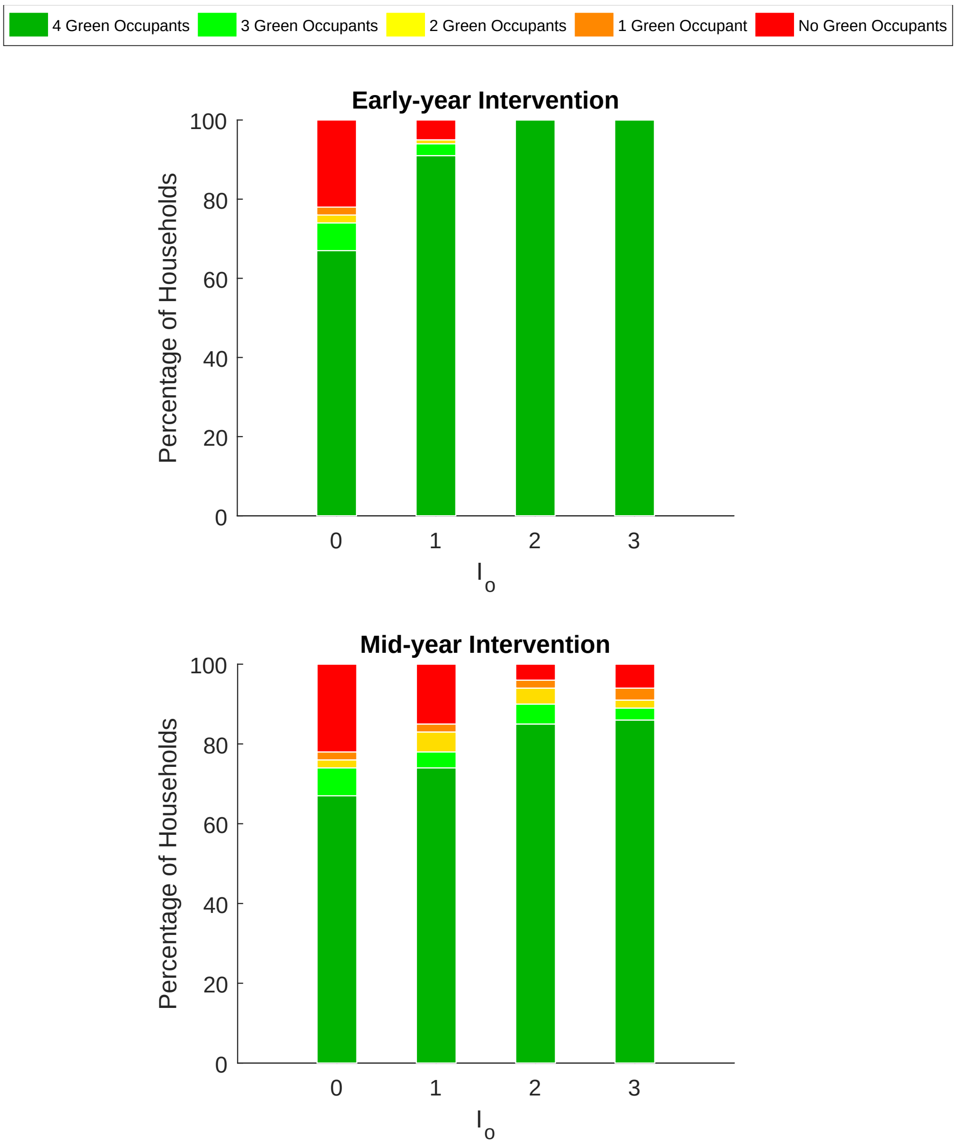


FIGURE 4.8: Occupant-level Intervention Convergence – Scenario FFFD, d = 0 (Continued in the next page)

It is observed that as earlier the intervention is and as its intensity increases, more green occupants are obtained. The early interventions with intensities 2 and 3 are the most effective with no waster occupants after a year. This is expected because the waster occupant is affected by the occupant-level intervention at an early stage, thus leading to 4 green occupants. However, in all other scenarios, waster occupants are observed even at high intensities. This shows that one intervention per year is not enough to make an impact on families with only one waster occupant. This suggests to perform continuous interventions to maintain the green effect and combine them with family-level interventions. Note the this experiment was performed with very low threshold of the family ($d = 0$) – so occupants can easily influence

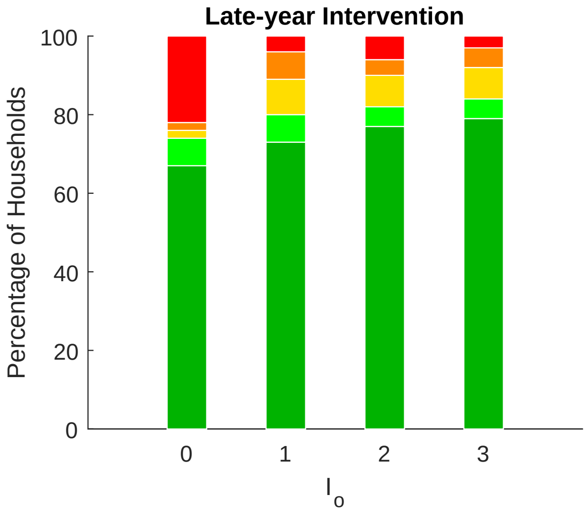


FIGURE 4.8: Occupant-level Intervention Convergence – Scenario FFFD, d = 0

each other.

4.3.4 Effect of Interventions on Families with Varied Social Parameters

In the previous chapter, it was shown that social parameters affect the energy efficiency of the family. Although the previous model does not simulate family pressure, we showed that energy waste in large families is less than small families. On the basis of this conclusion, the current experiment tests whether the repression family-level intervention is more effective in big or small families. For this purpose, the family-level intervention is applied on (a) a two-occupant family (two adults 25-39 years old both with full-time job), and (b) a four-occupant family (two adults 25-39 years old both with full-time job, and two children). The initial threshold d of both families is 0, and the initial number of green and waster occupants is equivalent ((a) FD and (b) FFDD). Figures 4.9a and 4.9b show the consumer types convergence of scenarios (a) and (b), respectively. Figure 4.9c shows the resulting energy saving percentage when compared to the no-intervention scenario ($I_r = 0$) and the *convergence time*, which is the time it takes the family to reach a stable state where the occupants are no more affected by each other.

In Figure 4.9c, at intervention intensities 1 and 2, the percentages of saving for big families are 9% and 16% respectively, which are more than that of small families (i.e. 1% and 11%). This is also observed in the awareness type convergence (Figures 4.9a and 4.9b) where the '4 green occupants' category is

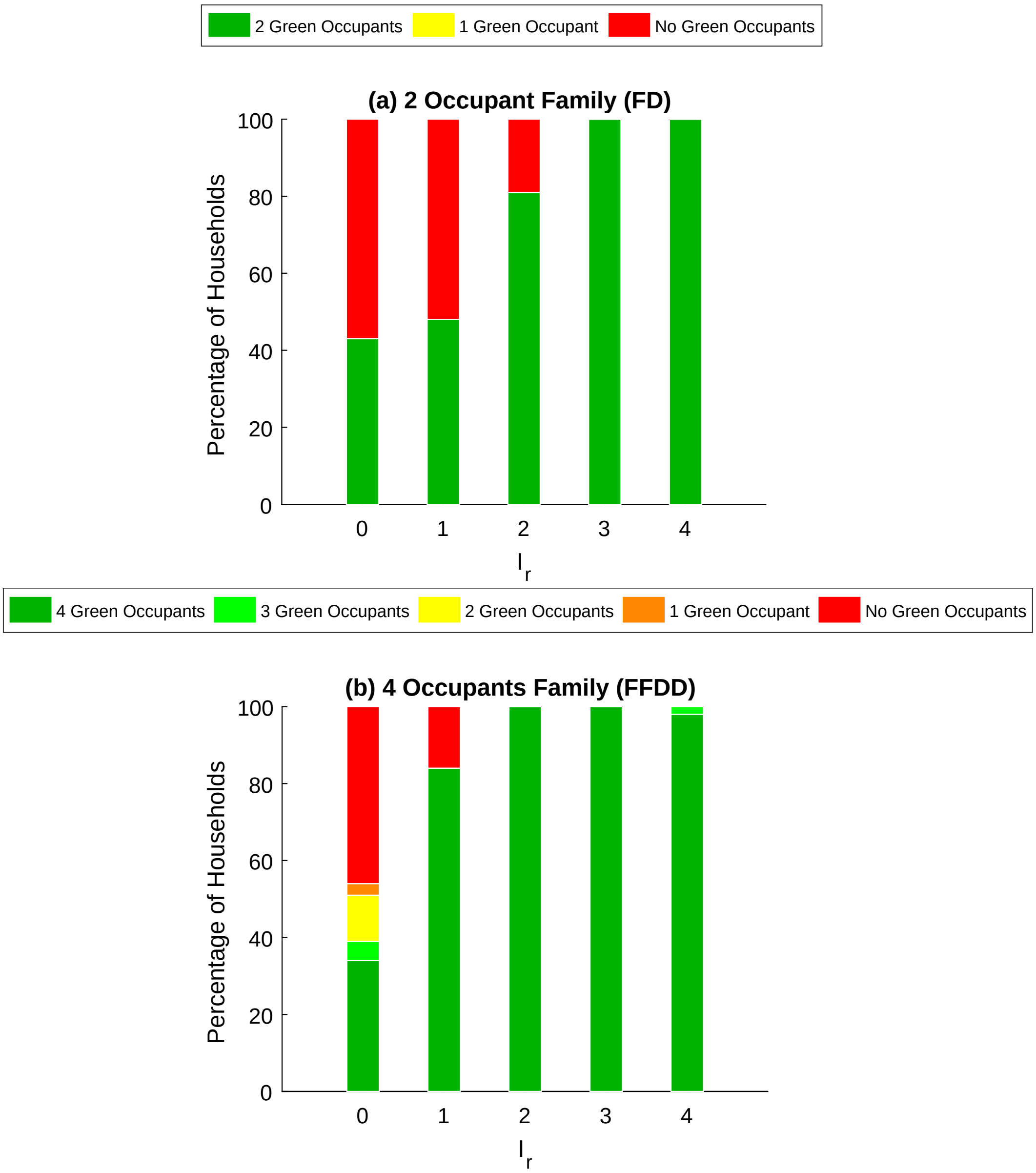


FIGURE 4.9: Effect of Family-level Intervention on Two- and Four-Occupant Families – d = 0 (Continued in the next page)

more dominant in (a) than the '2 green occupants' category in (b). However, at intensities 3 and 4, the savings of small families are 21% and 25% respectively, which dominates that of big families (i.e. 16% and 15%)(Figure 4.9c). Besides, all of the occupants in scenarios (a) and (b) converged to green occupants as shown in Figures 4.9a and 4.9b. This is explained by the lower convergence time of small families (Figure 4.9c). This means that a higher intensity intervention converges small families quicker than big families, which consequently leads to higher saving. Besides, low intensity interventions can lead to maximum saving in big families.

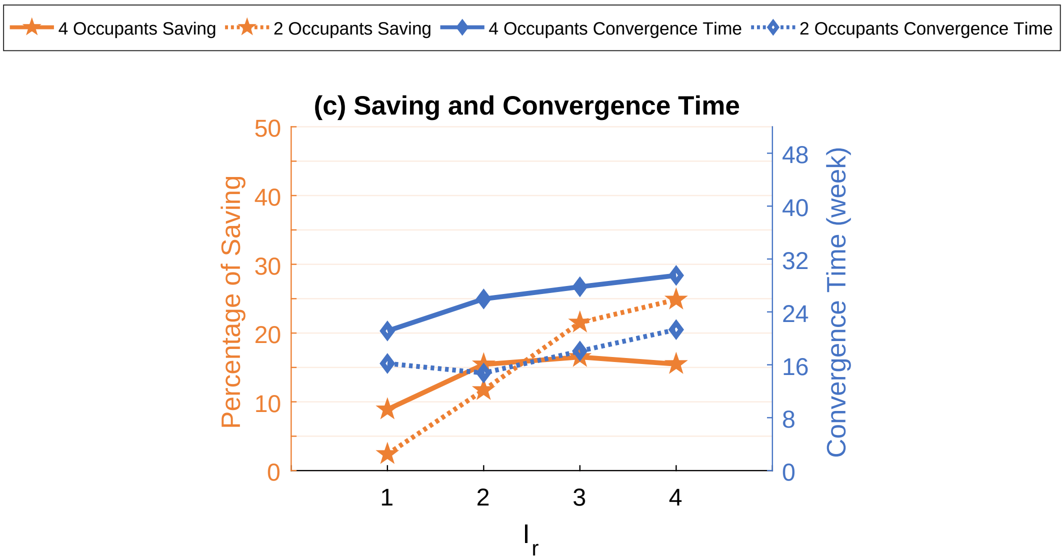


FIGURE 4.9: Effect of Family-level Intervention on Two- and Four-Occupant Families – d = 0

4.4 Discussion and Insights

The model proposed in this chapter simulates peer pressure effect on energy awareness levels and consumption of families. The peer effect behaviour of occupants is underpinned by the well-established human behaviour theories by Festinger[38]–[40] opposed to other models that do not use existing theories [58]. Besides, the existing models [7], [14], [26], [27], which are developed for residential and commercial communities vary the structure and type of peer networks, which is not applicable for families. The developed peer pressure model uses behaviour theories that are adapted to comply with family pressure effect on energy consumption in households. In addition, as the model is built upon the daily behaviour model, it separates the change in energy use behaviour attribute from the daily activities of occupants.

The experiments presented in this chapter showed how the model can be used to analyse the effect of interventions in a number of significant scenarios. We proved that the promotion family-level intervention is more effective than the repression intervention in a family where the waster occupants dominate. This implies that it is better to give incentives and rewards for members of waster families to encourage them to adopt the green behaviour. For the occupant-level intervention, we showed that even when green occupants dominate in a family, one intervention per year is not enough to prevent the waster occupant from affecting the green occupants. This indicates that occupants need to be continuously targeted by interventions even if the number of green occupants is high in the family.

In the last experiment, we showed that the family-level intervention can result in maximum saving at low intensity in big families as opposed to small families. While a high intensity intervention is more effective in small families as it leads to a larger and quicker saving than big families. This indicates that more effort is needed when targeting small families, while big families can reach their maximum saving with lower effort. These implications are compatible with the ones obtained from the experiment that studied family size in Section 3.4.2 of Chapter 3 and discussed in Section 3.5. The recommendation in Chapter 3 was to target small families with focused and high intensity interventions, and big families with low intensity and distributed interventions. This is because small families waste more energy as proved in in Chapter 3, and save more when targeted with high intensity interventions as shown in this chapter, and big families waste less and save the maximum when targeted with low intensity interventions.

The developed model can be used to repeat these experiments with varied social parameters, thresholds and intervention types to obtain the most effective intervention in every case.

4.5 Summary

This chapter has presented a model that simulates the effect of peer pressure on the energy consumption of households. Behaviour change due to peer pressure is modelled using Festinger theories (informal soaicl communication theory, social comparison theory and cognitive dissonance theory), which are compatible to a family setting and lead to an uncomplicated model. Besides, these theories are formalised by adapting Granovetter's Threshold Model. The occupant agents change their energy behaviour every period of time based on the observed behaviour of other occupant agents around it. The model also includes an abstraction of two types of energy interventions (occupant-level, and family-level interventions). This is done to study the effect of peer pressure on the results of interventions. The presented experiments prove the conceptual validity of the model – such that it reflects the used theories. In addition, they show how the model offers an analytical tool for governing bodies to analyse the effect of interventions and decide how to target different families to get the best desired results.

The next chapter presents an energy messaging intervention, which is categorised as an occupant-level intervention. The intervention will be tested using a third model that is built over the daily behaviour model presented in the previous chapter and the peer pressure model presented in this chapter.

Chapter 5

The Messaging Intervention Model

After presenting the peer pressure model that simulate realistic occupant-to-occupant interaction, this chapter models the occupant-intervention interaction. The chapter also proposes a messaging intervention that combines the technologies used for automated control and the service of providing energy feedback. The proposed intervention is implemented in a third layer of the proposed complete Agent-Based Model (ABM) (Figure 5.1). The messaging intervention model is built upon the daily behaviour model and the peer pressure model.

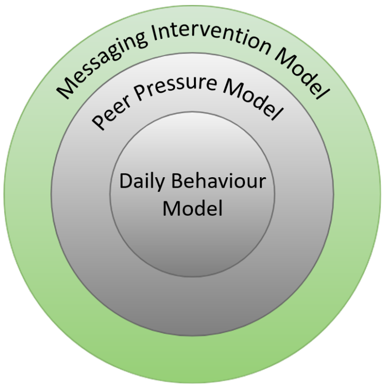


FIGURE 5.1: The Messaging Intervention Model from the Layered ABM

In this chapter, we show the strengths of designing the complete model in a layered onion-like structure for the following reasons:

- The messaging intervention model takes advantage of the detailed daily behaviour and energy consumption data generated by the core model, and the realistic family pressure simulated in the peer pressure model. The previously developed models enable the simulation and detection of energy waste incidents, which are used to test the messaging intervention. Besides, they are necessary to simulate realistic interaction of occupants with the intervention.

- The layered onion-like structure enables plugging and unplugging various intervention types and mechanisms taking advantage of the data generated by the models. This makes the complete model a useful tool for policy and decision makers to design customised energy interventions.

The following section presents the proposed intervention, then, the model formalisation and design are presented. Next, a number of experiments that assess the intervention are presented and discussed. Findings reported in this chapter are published in [130].

5.1 The Proposed Messaging Intervention

Based on the literature reviewed in Section 2.4, we present a messaging intervention that is a middle solution between Energy Feedback Systems (EFS) and Energy Management Systems (EMS). Therefore, instead of providing the amount of energy being consumed or comparing the household consumption with similar ones as in EFS, the intervention provides the occupant with real-time messages about their current energy wastage and recommends actions to reduce their consumption. This is done by relating the energy consumption of appliances with the context of the house, including occupant presence, activities and schedule, as well as environmental data. This enables the detection of energy waste incidents in which the intervention can recommend to reduce this waste based on the occupant state. The approach in this intervention is to avoid taking automatic actions opposed to the general approach in EMS. This is done to maintain the occupants' comfort allowing them to take decisions whether to comply with the messages or not. An example of real-time messages would be: "*Your television in the master bedroom is now ON while nobody is there, it is recommended that you turn OFF devices while not in use*", or "*The lights in the living room are now ON while there is enough daylight in the room, you can take advantage of natural daylight to reduce your energy consumption*".

The following sections (1) detail the type of appliances that was implemented in the simulation model, (2) define a messages pushing strategy/ heuristic to control the rate and number of messages to be sent to occupants, (3) present the factors that affect occupants energy consumption behaviour, including compliance to the waste messages and (4) present different enabling technologies and techniques that may be used to obtain and forward the messages in reality.

5.1.1 Appliance Types

Energy waste incidents involve different appliances and reasons for the waste, and consequently different suggestions to minimise or avoid the waste. In this sense, three general types of appliances can be identified based on the type of waste that may occur:

- Presence-dependent appliances (televisions, computers, game consoles, fans, lights, etc.), which are not supposed to be ON if they are not being used.
- Presence-independent and heavy appliances (washing-machine, tumble dryer, dishwasher, etc.), which are not recommended to be ON in peak-times, therefore can be scheduled as they do not depend on the occupant presence.
- Heating/cooling related devices where the waste may happen if windows/doors are opened while they are ON, or over-heating/cooling is detected in some areas of the house.

Detecting energy waste incidents of each of these types requires a different set of context data. The context data needed to obtain meaningful energy feedback for occupants include: *occupant context*, *appliance context* and *environment context* [131]. This thesis focuses mainly on the presence-dependent appliances, namely, *televisions, computers and lights* as a proof-of-concept. Energy waste from presence-dependent appliances is detected when they (1) are switched ON while occupants are not in the location of the appliance, (2) are not being used, or (2) are not needed to be ON (e.g. keeping the lights ON while there is enough daylight in the room). This requires data about the occupant context (occupant location and ongoing activities), environment context (amount of natural daylight depending on the time of the day and weather conditions) and appliance context that is used to identify appliances that are turned ON.

5.1.2 Message Pushing Strategy

Forwarding messages to the occupants is done by pushing notifications to the occupants' mobile devices taking advantage of the wide availability of mobile technologies these days. However, in order to ensure that occupants are not continuously interrupted by the messages, a message pushing strategy needs to be defined. This is because notifications sent in high numbers, at a high rate and/or in inappropriate times can affect the users' ongoing-tasks, hence causing frustration [132]. In addition, it may lead ultimately to un-installing the application [133]. Therefore, we propose a non-intrusive message pushing strategy that minimises the annoyance level of occupants, whilst ensuring that the family reaches the saving target set by governmental bodies and policy makers. The strategy is implemented in the simulation model by a heuristic, which will be detailed in Section 5.2.

In order to define this strategy, we explore studies that aim to study user's notification-interaction behaviour and build interruptibility management mechanisms. These studies aim to determine the most appropriate times and contextual situations to send notifications, and identify the factors that affect the interruptibility and receptivity of notifications. The aim is to reduce users' interruptibility (i.e. interruption of ongoing activities) and increase receptivity (i.e. the probability that the user receives the notification and reacts to it). One study found that sending a notification when the user transits from one activity to another reduces interruptibility [134]. Other studies, such as [135]–[137], develop machine learning models that use contextual data to predict the appropriate times for sending notification messages. These context data include time of the notification, type and the sender of information, location, emotional state, level of engagement in the activity, response time to notifications and phone lock/unlock times. Another study found that the content factors of the message (including interest, entertainment, relevance and actionability) affect the receptivity of the message more than the time of delivery [138].

Based on these studies, the proposed strategy aims to minimise occupant annoyance level caused by the feedback messages. This is achieved by the following:

- sending messages only in appropriate times based on the occupants location and activity;
- limiting the number of messages sent to occupants per day based on the occupants' interest in the information,
- distributing the messages over the time of the day,
- giving priority for high wastage incidents and
- adjusting the number of occupants to be targeted by the intervention based on the saving target

5.1.3 Effective Energy Consumption Behaviour Factors

The possibility of receiving the message does not mean that the occupants will comply to the messages anyway. There are several factors that determine whether the occupant will accept the suggestion of the intervention. These factors are outlined by Li *et al.* [139] who adapt the Motivation-Opportunity-Ability (MOA) model to the energy consumption behaviour. The MOA model is initially developed to explain consumers purchasing behaviour. The following points map the factors that affect occupant energy consumption behaviour and compliance to the feedback messages with motivation, opportunity and ability.

- **Motivation** is defined as the needs, goals and values that affect the level of interest and willingness to adopt the energy conservation behaviour. It represents the level of concern about personal energy consumption and personal relevance of the presented feedback information.

- **Opportunity** includes the relevant resources (external and environmental factors not in control of the person) that enable or prevent the behaviour. In terms of energy feedback, it represents understandable and accessible feedback and easily accessible controls. It also includes social opportunity such as peer pressure from other individuals in the environment.

- **Ability** is defined as the personal capabilities that enable the behaviour. It includes the knowledge capacity of interpreting energy related information, consequences of energy use, as well as the ways for saving energy.

The messaging intervention proposed in this chapter enhances occupant *ability* and *opportunity* of control by exposing occupants to understandable information and making the information accessible through mobile devices. However, other parts of the MOA model are not affected by the messaging intervention. Therefore, we use the Personal Energy Rating (PER) attribute in the simulation model to determine how often occupants comply to the messages, and assume that these factors are embedded in the PER. This PER value is also affected by peer pressure as presented in the previous chapter.

5.1.4 Messaging Intervention Enabling Technologies

In order to realise the sensible real-time messages, several enabling technologies and techniques exist in research and in industry. These technologies and techniques are presented in the following points to help practitioners provide the intervention in reality. Note that the enabling technologies presented in this section serve in detecting energy waste for all appliance types not just presence-dependent appliances implemented in this thesis.

- **Energy monitoring at appliance level**: This can be achieved using smart plugs, which detect when the appliance is turned ON and monitor the amount of energy being used. For more information about commercial smart plugs, Ford *et al.* [140] provide a comprehensive review of smart plugs available these days. Another way of detecting appliance consumption is through smart appliances, which allow the monitoring of their energy consumption and status, as well as control and communication with the user [109], [112], [140]. Appliance consumption can also be obtained from aggregated consumption data through Non-Intrusive Load Monitoring (NILM) techniques [141]. Beside these direct energy monitoring methods, some appliances can be monitored indirectly through environmental sensors such as temperature, noise, vibration, etc. [142].

- **Environment monitoring**: The surrounding environment inside and outside the house can be monitored through different sensors such as temperature, humidity, illuminance, motion, presence, body detection (e.g. smart watches), doors/windows detectors, among others. In addition, virtual/software sensors can provide useful information such as occupants' schedules and calendars, or live and forecast weather data.

- **AI techniques**: These techniques may be used for different purposes to analyse the collected context data. For example, Bayesian Networks [143] and Ontological and Probabilistic Reasoning [144] are used for activity recognition in households. Sleeping detection is also possible by utilising data from smart watches [145] which are considered as permanent monitoring devices. Other activity recognition, learning and prediction techniques can be found in [142]. Another application of AI techniques is NILM which is usually based on Hidden Markov Models and artificial neural networks [141]. Optimisation algorithms are also used for appliance scheduling [146] in order to minimise energy costs and peak demand, and maximise user preferences and comfort.

- **Platforms for communication**: As energy waste detection requires the communication of different elements, communication platforms need to be in place to provide the connection among them. The most common way for this purpose are Wireless Sensor Networks (WSN) which are used in [103] and [104]. In these approaches, sensors and actuators are set to communicate with each other in a single network. More recently, the Internet of Things (IoT) paradigm was established where appliances and objects (e.g. smart appliances and smart plugs) can communicate and exchange data [147]. IoT technologies are proposed to ensure reliable communication in a complex environment [105].

- **System Architecture**: The general architecture of EMS, including the messaging intervention proposed in this chapter, is outlined by De Paola *et al.* [142]. The system is composed of different components, each having a specific functionality.
  - *Sensory and actuation infrastructure*: includes the energy and environment monitoring devices, as well as actuators, which allow to control the appliances.
  - *Middleware*: deals with the heterogeneous devices and sensors in the home, and provides a common interface for processing.
  - *Processing engine*: performs the analysis of the collected context data such as activity recognition and detection of energy waste.
  - *User interaction interface*: provides the occupants of the house with notifications about the energy waste, and collects their feedback and preferences about the system suggestions. This is suggested to be provided through mobile devices such as smartphones and smart watches.

The components that provide the proposed intervention can be centralised such that all communication and processing passes through a central server, or distributed – so that the components communicate directly and the processing is done in distributed processing units [142]. Figure 5.2 provides a general illustration of the system that can provide the messaging intervention.

5.2 Model Formalisation and Design

The approach proposed in this intervention is to detect energy waste and forward the messages to occupants. This layer models the energy detection feature, and implements a heuristic to simulate the message pushing strategy

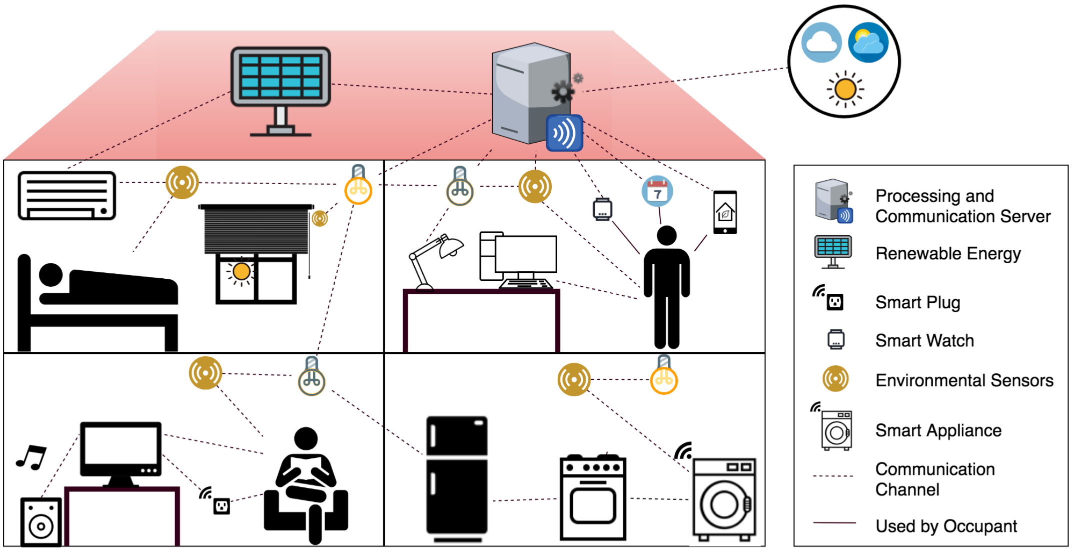


FIGURE 5.2: Messaging Intervention Technologies Illustration

defined in 5.1.2. Then, it simulates the message reception, compliance and behaviour change of occupants in effect of the messaging intervention.

5.2.1 Energy Waste Detection

As the ABM simulates presence-dependent appliances, the energy waste incidents detected are related to the occupant location in the house, ongoing activities and natural daylight as follows:

- Televisions and computers are detected as wasting energy when they are turned ON but not being used. The appliance is identified to be used when the activity associated to it (watching television and using the computer) is being performed regardless of the location of the occupant in the house, because the ABM enables multitasking. For example, the occupant can be watching television and preparing food in the kitchen. In this case, the television located in the living room is not detected to be wasting energy.

- Lights are detected to be wasting energy when the light is on and (1) the room is not in use,(2) the room is in use but natural daylight is enough to light the room, or (3) the room is in use but all the occupants in the room are sleeping. The room is considered to be in use if there is an occupant using it even if s/he is not in the room due to multitasking as explained above. This covers the case when people leave the lights ON when they are returning to the room in a short while.

The above mechanism is provided as an example for energy waste detection. Any other detection mechanism can be implemented and tested, including mechanisms that utilise predicted activities and energy consumption of occupants or customise the waste detection to the occupant preferences.

5.2.2 Message Pushing Strategy Simulation

The energy waste incidents are detected and updated every time-step based on the mechanism determined in the previous section. However, it is not possible to send the occupants a group of messages about their energy waste every 10 minutes (the time step in the daily behaviour model) asking them to turn OFF appliances and change their behaviour. Using the studies presented in Section 5.1.2, we implement a non-intrusive strategy that selects to forward messages at appropriate times, and limits and distributes the messages to be sent to occupants in order to reduce interruptibility and increase receptivity. The strategy is implemented based on a heuristic defined in the following 4 steps:

(1) Send messages in appropriate times

As shown by Ho and Intille [134], the appropriate time to send notifications to users is when they are transiting from one activity to another, which reduces interruptibility. Applying this factor to the messaging intervention, the messages are only sent to occupant agents when they transit from one occupancy state to another, from one activity to another, or from one location to another (inside the house).

(2) Set a frequency cap per day

Many studies identify that the user's level of interest in the information is one of the influential factors that affect receptivity of notifications. Therefore, we use this factor to limit the number of messages to be sent to occupant agents. Consequently, we define a frequency cap fc that determines the number of messages that can be sent per day. fc is determined based on the number of transitions the occupant agent performs during the day and its interest in the information, which is determined by the consumer type. Every consumer type is given a weight to determine the level of interest, setting the maximum for the 'Follower Green' type and the minimum for the 'Disengaged Waster' type with an arbitrary equal difference between any two consecutive consumer types as shown in Table 5.1.

TABLE 5.1: Weighting of Consumer Types used in the Messaging Intervention Strategy

Consumer Type	**Weight (w_a)**
Follower Green	1.00
Concerned Green	0.75
Regular Waster	0.50
Disengaged Waster	0.25

Every time period T (set to 4 weeks – the same as the peer pressure model), the frequency cap $fc_{i,T}$ of every occupant agent i is calculated using Equation (5.1).

$$fc_{i,T} = nTran_{(T-1)} \times w_a \tag{5.1}$$

where $nTran_{(T-1)}$ is the number of transitions the occupant agent performed in the previous time period *T-1*, and w_a is the weighting of the agent's consumer type.

The frequency cap $fc_{i,T}$ is then divided on the number of days in the period T ($n_T = 28 = 4 \quad weeks \times 7 \quad days \quad per \quad week$) to ensure that the messages are distributed over the days. The frequency cap per day $fc_{i,d}$ is calculated using Equation (5.2).

$$fc_{i,d} = \frac{fc_{i,T}}{n_T} \tag{5.2}$$

The messaging intervention strategy keeps the number of messages sent to the occupant agent less than or equal the frequency cap per occupant.

(3) Adjust the number of messages per occupant per time step

In order to guarantee that the messages are distributed over the day, the strategy adjusts the number of messages to be sent to the occupant agent per time step while focusing on high energy wastage. This is done based on the remaining number of messages that can be sent to the occupant (hereafter occupant's messaging capacity) and the expected number of waste incidents until the end of the day.

Every time step t, the number of messages to be sent to the occupant agent i is set using Equations (5.3), (5.4) and (5.5).

$$nMsg_{i,t} = \left\lceil \frac{c_{i,t}}{nExp_t} \right\rceil \tag{5.3}$$

$$c_{i,t} = fc_{i,d} - NMsg_{i,t} \tag{5.4}$$

$$nExp_t = nDet_t - NExp_d \tag{5.5}$$

where $nMsg_{i,t}$ is the number of messages to be sent to the occupant agent i at time step t, $c_{i,t}$ is the occupant's messaging capacity, $nExp_t$ is the remaining number of incidents expected at time step t until the end of the day, $NMsg_{i,t}$ is the total number of messages received by the occupant agent i so far, $nDet_t$ is the number of detected incidents so far and $NExp_d$ is the total number of incidents expected per day. In this model, $NExp_d$ is calculated from the last time period (4 weeks) then divided over the days. It was possible to calculate $NExp_d$ in the ABM, however, in reality various machine learning algorithms can be applied to identify the expected incidents throughout the day.

(4) Adjust the number of occupants per time period

Every period of time, the strategy adjusts the the number of occupants to be targeted by the intervention. The family is set an energy saving target (in percentage) to be achieved after one year of applying the intervention. This target is supposed to be set by policy makers and governmental bodies. Therefore, based on whether the percentage of saving is more or less than the target, the number of occupants is decided in a way that reduces the annoyance of occupants if they have already reached the target. This process is shown in Algorithm 4, which is repeated every time period T, where $nTar_T$

Algorithm 4: Adjust Number of Occupants

```
Ensure: nTar_T ≥ 0 and nTar_T ≤ N
  if first time period T then
  |  nTar_T ← N
  else
  |  if s_T > tar + 1 then
  |  |  nTar_(T+1) ← nTar_T − 1
  |  if s_T ≥ tar − 1 and s_T ≤ tar + 1 then
  |  |  nTar_(T+1) ← nTar_T
  |  if s_T < tar − 1 then
  |  |  nTar_(T+1) ← nTar_T + 1
```

is the number of targeted occupants at time period T, N is the total number of occupants in the family, s_T is the energy saving percentage before time period T and tar is the energy saving target (in percentage) set for the family to reach. Occupants with the highest frequency cap are selected to be targeted by the intervention. The simulation is run for one year without the messaging intervention in order to calculate the energy saving percentage.

5.2.3 Message Reception Simulation

The energy waste incidents are forwarded to the occupant agents' mobile device (smartphone, tablet, etc.) if they possess any. In this thesis, we simulate the case of smartphones as they are the most widely used types of mobile devices these days [148]. Real statistical figures were obtained for the possession and usage of smartphones from Deloitte Global Mobile Consumer Survey (Belgian edition)[1] [148]. Table 5.2 shows the possibility of owning a smartphone based on the occupant's age. Therefore, it is decided in the initialisation phase whether the occupant agent possesses a smartphone or does not.

TABLE 5.2: Smartphone Possession Probability by Age Group

Age Group	Smartphone Possession Probability (%)
12-17 [2]	86.1
18-24	90.0
25-39	92.0
40-54	83.0
55-64 [3]	83.0
65-75	56.0

Possessing a mobile device does not mean that the occupant will always receive the message. To determine the mobile device check probability, the Global Mobile Consumer Survey was used. The survey includes data about how often people check their smartphone per day by age group (Table 5.3), and the percentage of people who check their phone while doing different activities during the day (Table 5.4).

[1]The Belgian edition of the survey was selected since the probability distributions used in the ABM are calibrated using the Belgian time-use surveys.

[2]The age group 12-17 is not included in the Global Mobile Consumer Survey [148]. Instead, we used a survey by IVox and Wiko who found that 86.1% of children aged 13-16 possess smartphones in 2015. **Reference**: `http://be-nl.wikomobile.com/a4342-Wat-is-de-ideale-leeftijd-om-een-smartphone-te-bezitten` (Accessed 2 May 2018). For the smartphone usage we used the data of the closest age group 18-24 as shown in Table 5.3

[3]Results for age group 55-64 are not reported in the Global Mobile Consumer Survey report. Therefore, we used the data of the closest age group 40-54 instead. This also applies for smartphone usage percentages in table 5.3.

TABLE 5.3: Frequency of Checking the Smartphone by Age Group

Age group (age)	**Frequency of checking the smartphone per day**
12-17	70
18-24	70
25-39	46
40-54	28
55-64	28
65-75	11

TABLE 5.4: Percentage of Checking the Smartphone while Doing Different Activities

Day Period	**Activity**	**Percentage (%)**
Morning (7am-9am)	Within 5 minutes after waking-up	31
	While on road	26
Daytime/ Work Time (9am-5pm)	While working	66
	In a meeting	22
	While Shopping	33
Evening (5pm-11pm)	While on road	26
	While Watching TV	52
	While spending time with friends/family	33
Sleep (11pm-7am)	Within 5 min before sleeping	28
	If sleeping was interrupted	40

Based on these data, we calculate the percentage of checking the smartphone for every age group and day period, which is mapped to the corresponding age groups and periods in the model, and assume that the message is received once the phone is checked. The action of smartphone checking ($sc_{t,d}$) depends on the time of the day (t), day type –workday or weekend– (d), occupant *age* and occupancy state ($os_{t,d}$) as shown in Formulae (5.6).

$$SC : age, os_{t,d}, t, d \rightarrow sc_{t,d} \tag{5.6}$$

5.2.4 Message Compliance Simulation

Whenever the occupant agent receives a message, it may comply to it by turning OFF the appliance that is causing the waste. This action happens based on the agent's PER attribute, which embeds different personal and external factors that either allow or prevent the action from happening.

When the message is sent to the occupant's mobile device, the agent's smartphone check probability ($sc_{t,d}$) is used along with its occupancy state ($os_{t,d}$), location/room ($r_{t,d}$) and PER to determine the reaction towards the message as in Equation (5.7).

$$MC : sc_{t,d}, os_{t,d}, r_{t,d}, PER \rightarrow \{keepOn, turnOff\} \tag{5.7}$$

5.2.5 Behaviour Change Due to Messaging Intervention

The occupant agents may change their consumer type, and consequently their PER assuming that they are becoming more energy aware as a result of the messaging intervention. This is decided by comparing the actual behaviour of the occupant agent and the mean value of the consumer types shown in Table 3.4. The actual behaviour of the agent is calculated using Formulae (5.8)

$$aB = \frac{nOFF}{supNOFF}, \tag{5.8}$$

where aB is the ratio of the number of times the occupant agent turned the appliance OFF ($nOFF$) and the number of times it was supposed to turn the appliance OFF ($supNOFF$). If aB exceeds the mean of the more-green consumer type (see Table 3.4), the agent changes its consumer type to the green side, thus increases its PER attribute. This step is executed every time period T, then the peer pressure behaviour change step (Algorithm 2) is executed such that the occupant agent may affect others' behaviour or the others may affect it.

5.3 Experiments and Results

The aim of these experiments is to show how the proposed simulation model can be used to test energy interventions. The family simulated in these experiments is composed of four occupants: two adults who are 25-39 years old in a full-time job, and two children 12-17 years old who go to school. For this family type, we simulate two scenarios by varying the consumer types and PER values (all follower green families, and all disengaged waster families) to test the effect of energy awareness on the effectiveness of the intervention. In order to test the effectiveness of the proposed message pushing strategy, we run two types of scenarios, one where the *proposed strategy* is applied at its entirety as outlined in the previous section, and another where messages are sent whenever the occupants are active at home (hereafter *naive strategy*). With the naive strategy, it is assumed that occupants stop complying to messages when their frequency cap is reached, while the messages continue to be sent by the messaging intervention in response to energy waste incidents. This follows the conclusion reached in [133], where users stop using the application when they receive a high number of notifications. Besides, we vary the saving target of the proposed strategy to get the maximum percentage of saving that can be achieved when applying it.

For every scenario, 100 households were simulated to capture the probabilistic nature of the model. Each household has the same composition but different income levels, work routines for employed occupants, ages, appliance number and types and number of rooms in the house, all drawn based on the probability distributions from the real data. Every household is run for one year without any intervention to get the baseline consumption of the house, then for another year while applying the proposed strategy or the naive strategy. The percentage of saving of every scenario is calculated using Equation (5.9),

$$S = \frac{(C_0 - C)}{C_0 \times 100}, \tag{5.9}$$

where S is the percentage of saving, C is the yearly consumption when applying the messaging intervention, and C_0 is the yearly consumption when no intervention is applied.

In order to measure the level of annoyance that occurs as a result of the feedback messages, we calculate the percentage of messages sent in comparison to the frequency cap of the occupants (5.10).

$$A = \frac{NMsg_{total}}{fc_{total}} \times 100, \tag{5.10}$$

where A is the level of annoyance of occupants, $NMsg_{total}$ is the total number of messages sent to the occupants in the whole year and fc_{total} is the summation of frequency caps of all the occupants in the whole year. A value of annoyance less than 100 means that the occupants were not annoyed by the messages, and a value more than 100 means that they are annoyed by the messages, which indicates high probability of switching off the notifications. Annoyance level may exceed 100 when the messages are sent even if the frequency cap is exceeded as in the naive strategy.

First, we show some general results (average savings and annoyance) of the simulated scenarios, then we present detailed results of the messaging intervention to show how the model can be used to test the performance of the proposed strategy. The same hardware specifications mentioned in Section 3.3 of Chapter 3 have been used to run these experiments.

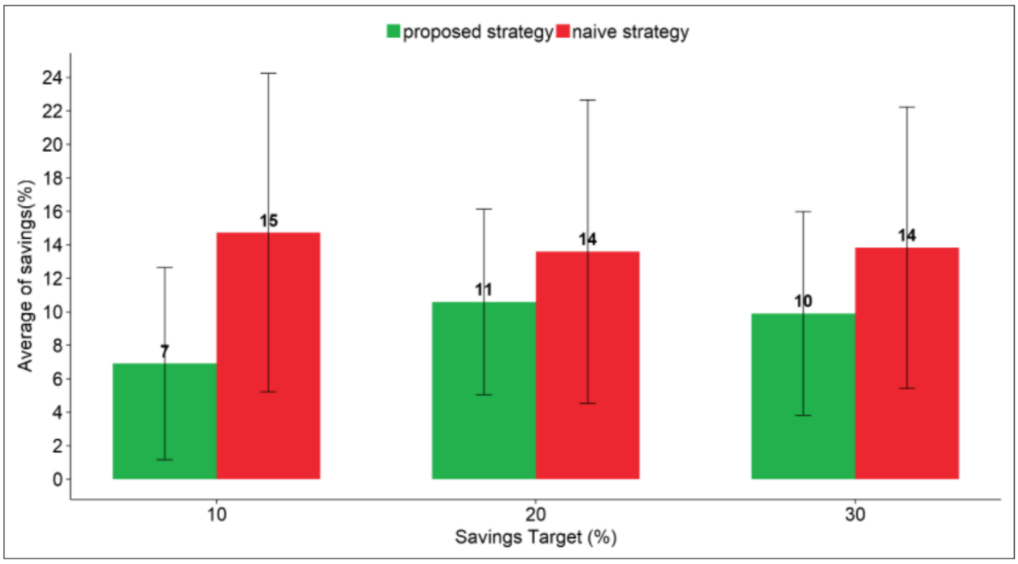
5.3.1 General Results

Figures 5.3 and 5.4 show the average and standard deviation of energy saving and annoyance level of the simulated 100 households in each scenario.

Scenarios that run with the naive strategy have the same indication when varying the energy saving target, because the target does not affect the way of sending the messages. In order to get the maximum saving result of the messaging intervention when applying the proposed strategy, we start by simulating scenarios with low targets (10%) and increase it until we noticed that the average saving is not changing. When the average saving does not increase as the target increases, then this means that the proposed strategy is targeting the maximum number of occupants, but the household could not achieve more saving. This is noticed when increasing the target from 20% to 30% where the saving increased only 1% with the green occupants and decreased 1% with waster occupants. Therefore, with the proposed strategy, the maximum average saving for green occupants is 13% and for waster occupants is 11%.

The energy saving of the intervention with the naive strategy ranges between 13-15% for both green and waster families, while the savings achieved when applying the proposed strategy is between 7-13%. However, when looking at the annoyance levels, we notice that the proposed strategy is able to achieve these savings with low levels of annoyance (21-52% for green occupants, and 45-75% for waster occupants). While the annoyance level of all waster families with the naive strategy exceeds the frequency cap of the occupants by almost three times (287-294%). This indicates that the saving percentage 14-15% resulting from using the naive strategy could not be achieved in reality because of the high annoyance level. Besides, for green occupants, the proposed strategy achieved the same amount of savings (12-13%) with annoyance level 48-52% compared to 96% annoyance level when the naive strategy is applied. This indicates that the proposed strategy succeeded to keep occupants unannoyed while achieving reasonable savings. This is because it reduces the number of occupants to target when the saving target is

(A) All Green Scenario

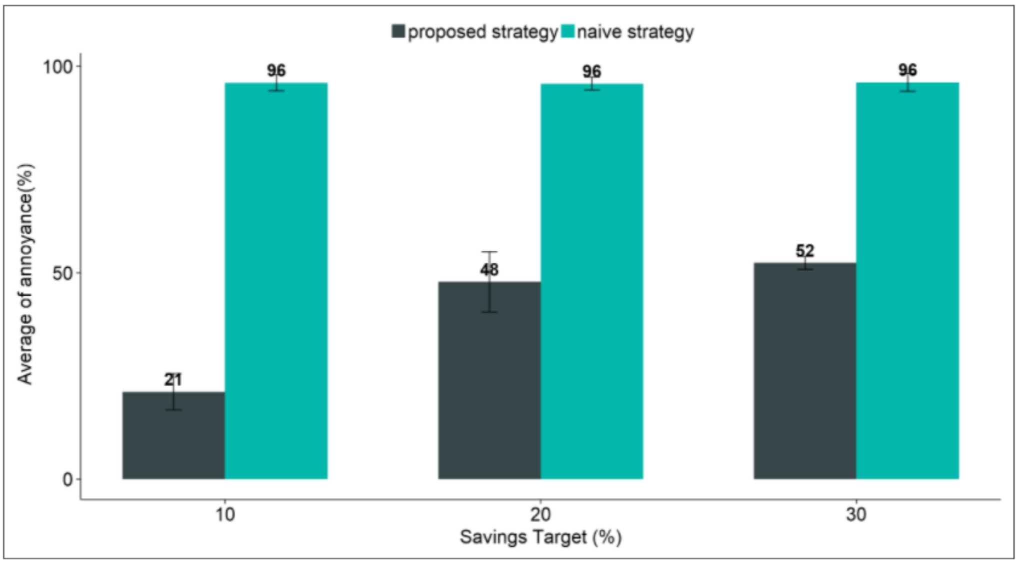


(B) All Waster Scenario

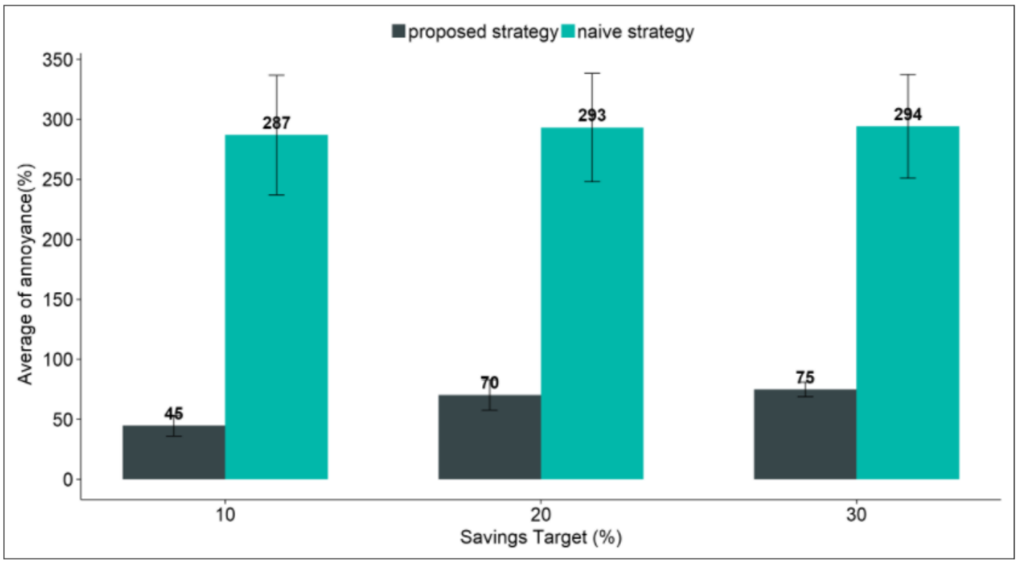
FIGURE 5.3: Average of Savings When Applying the Proposed Strategy and the Naive Strategy

reached, and distributes the messages over the day while focusing on high wastage. These results indicate that the proposed intervention strategy is more affective than the naive one. The details of the proposed strategy will be presented in the next experiment.

Looking at the standard deviation of the reported results, we notice that results of all waster families are more scattered than green families. This is because waster occupants have the chance to change their consumer type and become more aware, thus achieving different energy savings. An example of two different scenarios will be presented in the next section to show



(A) All Green Scenario



(B) All Waster Scenario

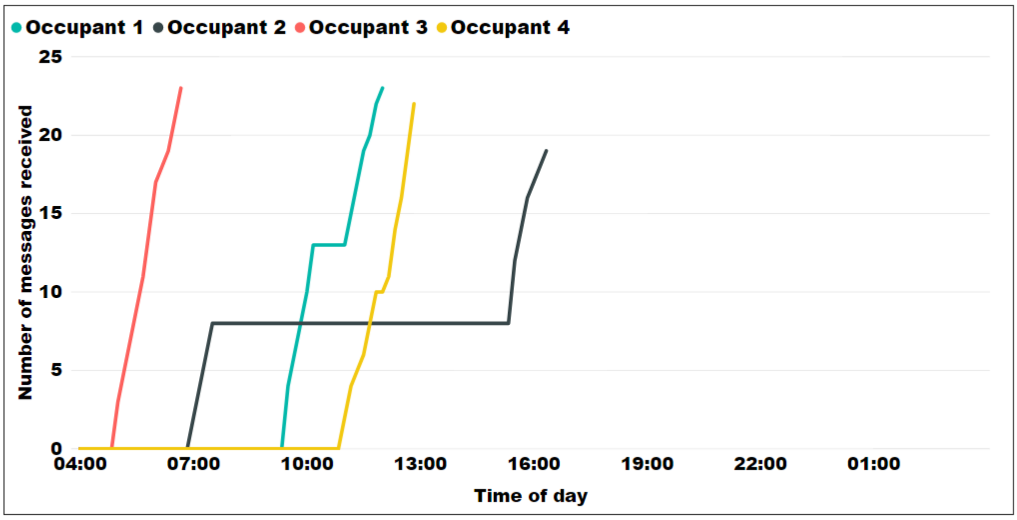
FIGURE 5.4: Average of Annoyance When Applying the Proposed Strategy and the Naive Strategy

the reason of these scattered results. In terms of achieving the saving target, the proposed strategy did not succeed to achieve the targets in average. The percentage of successful scenarios among the simulated households is 14%, 3% and 1% for the targets 10%, 20%,and 30%, respectively. This reveals that policy makers will need to adjust the message pushing strategy and/or apply a combined intervention approach – such that targets are achieved while minimising the annoyance level of the occupants. The proposed model can help to evaluate these strategies and interventions before implementing them in reality. Note that these results are specific for the family type tested in this experiment. Different results may be obtained when changing the inputs to the model. City level results can be obtained by feeding the model with the demographic distribution of the city to obtain the effectiveness of the intervention and strategy.

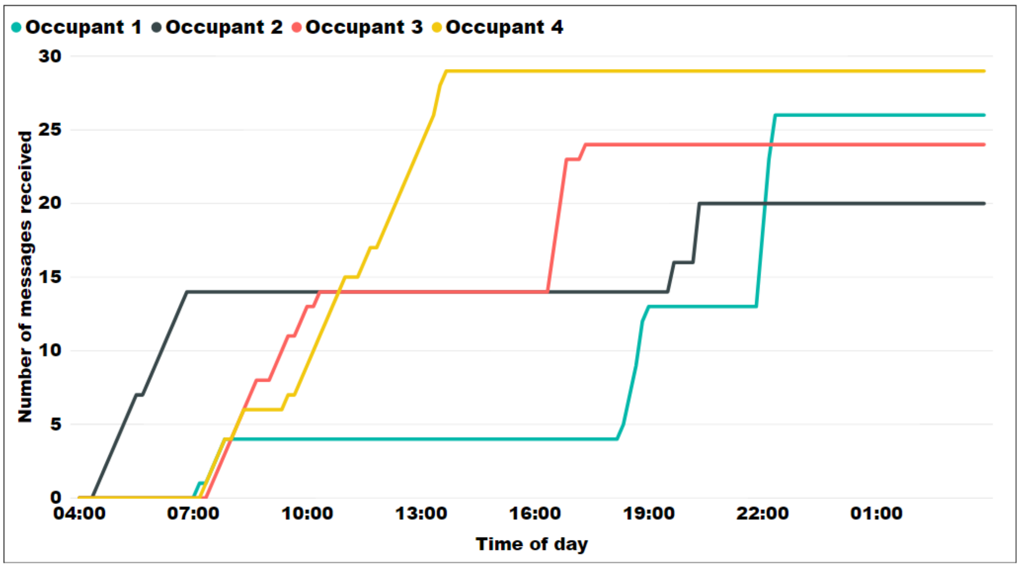
5.3.2 Detailed Strategy Results

This section presents detailed examples to show how the proposed strategy works. Figure 5.5 compares how the messages are sent over the 24 hour period using the proposed strategy and the naive one. In Figure 5.5a where the naive strategy is applied, messages are sent to occupants whenever they are active at home. It is noticed that most of the messages are sent once the occupants wake up in the morning, and the occupants stop complying to the messages at the middle of the 24 hour period (at 04:00 pm). After this time, the intervention system continues sending the messages, but it is assumed that the occupants stop complying to them when the number of messages received reaches their frequency cap. Figure 5.5b shows how the messages are sent when the proposed strategy is applied. It is clear that the messages continue to be sent until the end of the day (at 10:00 pm), and no messages are sent after the frequency cap of each occupant is reached. This ensures that the messages are distributed over the day while focusing on high waste incidents.

Figure 5.6 shows how the energy saving changes over the year (tracked every 4 weeks) and how the proposed strategy changes the number of occupants to target accordingly (the left y-axis refers to the saving percentage, and the right y-axis refers to the number of occupants to target). Figure 5.6a presents a scenario where the family succeeded to reach the energy saving target (30%) at week 28. As a result, the proposed strategy started to decrease the number of occupants to target from 4 until it reaches 0 at week 44. By the end of the year, the family had 30 % of energy saving. This saving percentage was possible, because the occupants changed their consumer types from “4 disengaged wasters” to “3 regular wasters and one follower green”. This is due to both peer pressure and the effect of the messaging intervention. Figure 5.6b shows a family that did not succeed to reach the saving target during the whole year. As a result, the number of occupants to target remained equal to the maximum that is 4 occupants. Concerning the consumer types of this family, all of the occupants remained disengaged



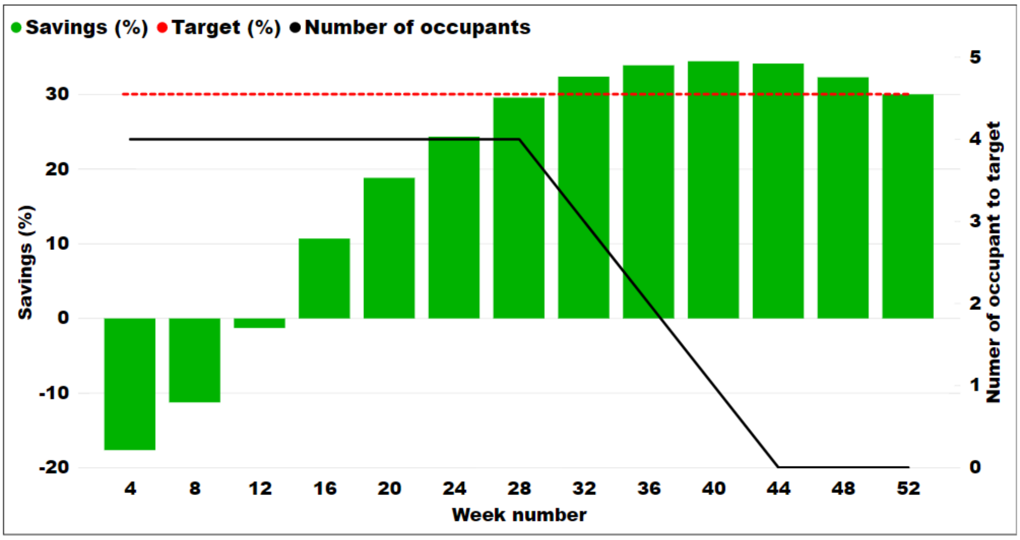
(A) Proposed Strategy



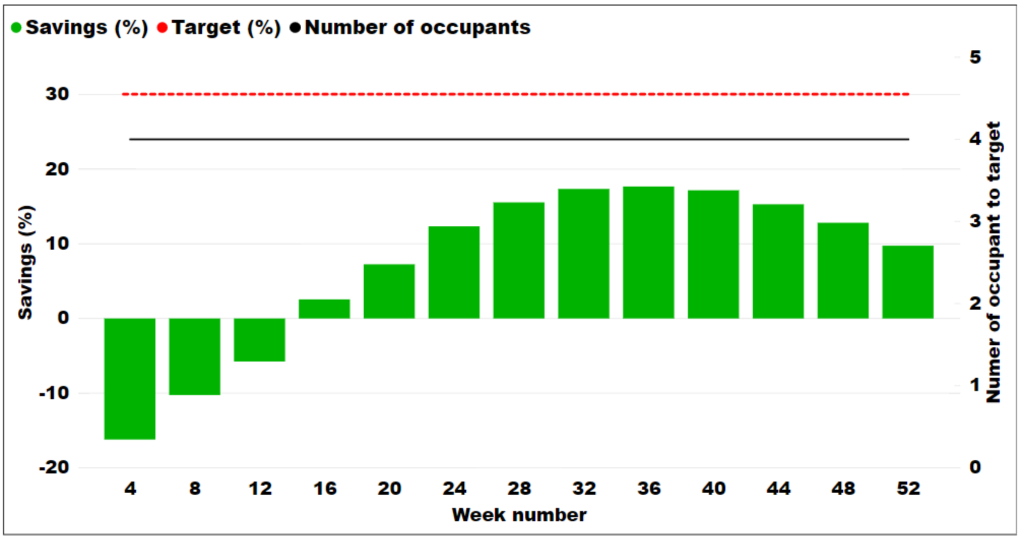
(B) Naive Strategy

FIGURE 5.5: Messages Distribution over the Day when using the Proposed Strategy and the Naive Strategy

wasters by the end of the year. This shows one of the reasons why interventions work in some cases but not in others. In addition, it indicates that in some cases, the messaging intervention is not enough to achieve the saving target. In this case, another type of intervention needs to be combined with it to change occupant awareness and save more energy.



(A) Successful Scenario



(B) Unsuccessful Scenario

FIGURE 5.6: Change of Energy Saving over the year and Adjustment of Occupants to Target

5.4 Discussion and Insights

This chapter introduced an energy messaging intervention. Most existing energy feedback systems display abstract or contextualised energy consumption data [32], [33], [97], [98]. However, these data still need to be further analysed by occupants to determine energy waste causing activities/actions and minimise their consumption [31], [99]. In this chapter, we identified the specifications and enabling technologies and techniques that can be used to realise the messaging intervetntion in reality. The intervention supports occupants to reduce their energy consumption using sensible feedback; a feedback that tells occupants what appliances are causing high energy waste. Instead of controlling appliances on behalf of occupants, like most existing EMS do [34], [35], [102], [105], [108], we propose to keep occupants in control. Therefore, we suggest that the energy wastage messages are forwarded to occupants' mobile devices giving them the choice whether to comply to the feedback messages or not.

One challenge that exists when dealing with applications that forward messages to users is the intrusiveness of the messages – such that the pushed notifications may be sent at the wrong times or in high number/rate. In order to overcome this challenge, we presented a heuristic approach that sends messages only when the occupants transit from one location/activity to another, sets a frequency cap to limit the number of messages, distributes them over the day and reduces the number of occupants to be targeted when a saving target is reached.

We use the daily behaviour and peer pressure models developed in the previous two chapters to implement a model that tests the proposed messaging intervention. The model uses real statistical figures of the possession and usage of smartphones by occupants to simulate the occupants' interaction with the intervention. Therefore, unlike existing models [13], [14], [24], [27], [58], [63], the developed model simulates realistic interaction of occupants with energy interventions, where the result of the intervention can be affected by the occupant daily behaviour and social characteristics. The experiments presented in the chapter showed that the proposed intervention strategy was effective as it achieves reasonable saving and keeps the occupants not annoyed when compared to a naive strategy. The presented scenarios also showed that the intervention may be effective in one family but not in another. Therefore, the developed model enables policy makers to determine the effectiveness of interventions and the factors that affect it.

5.5 The Complete Model: Putting Things Together

In order to present the steps in all of the three models together, Figure 5.7 shows a flowchart of the occupant agent behaviour. The colors of the steps refer to the model that the step is executed in. The chart also shows the associated equation/algorithm used in each step. The steps are repeated until the simulation time – set to one year – is finished.

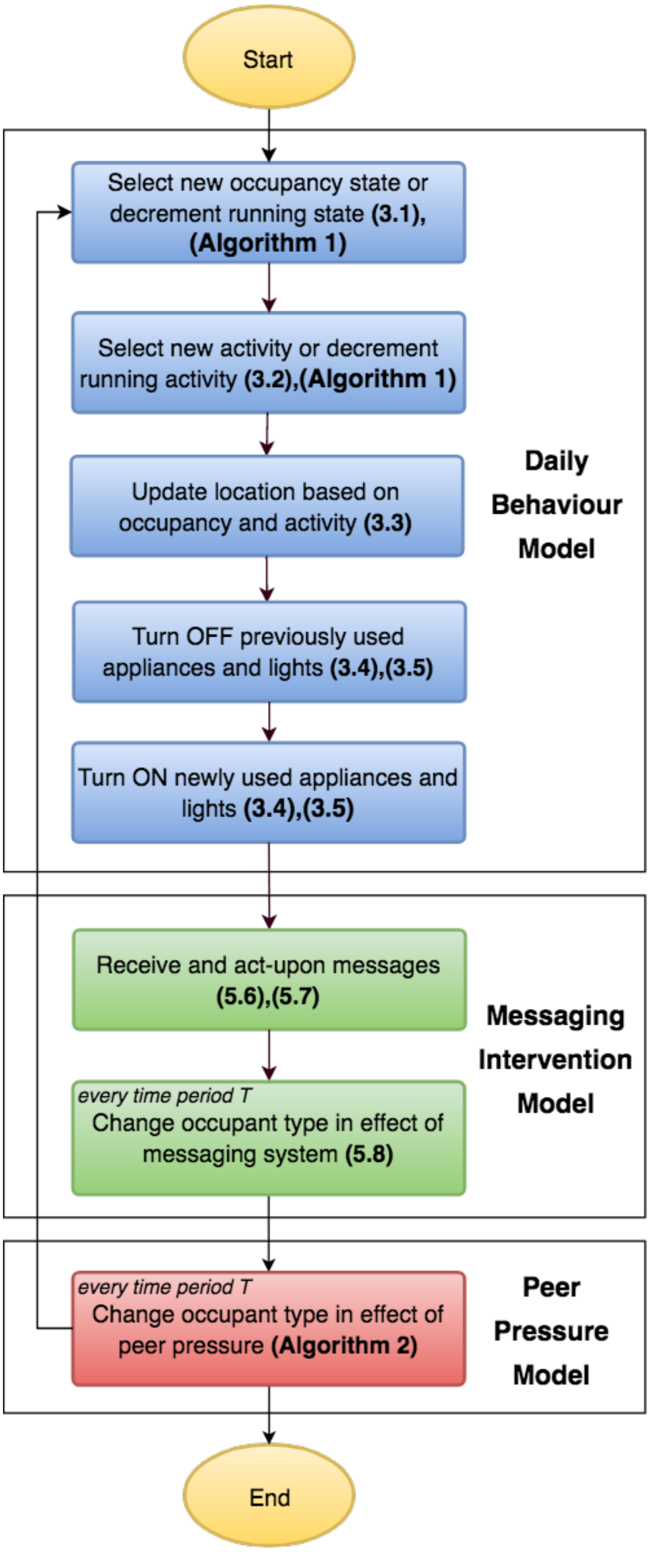


FIGURE 5.7: Occupant Agent Execution steps

5.6 Summary

This chapter has presented a messaging intervention that helps occupants to reduce their energy consumption by informing them about real-time energy waste incidents. Unlike existing EFS, the intervention does not only provide the amount of energy being consumed, but provides actionable feedback, which tells them how to avoid energy waste. Besides, compared to existing EMS, which control appliances automatically, the messaging intervention allows occupants to control their appliances, thus making them feel comfortable. The chapter has also presented the enabling technologies and techniques that are needed to realise the messaging intervention in reality. In order to avoid occupants annoyance from the notifications (which are suggested to be sent to their mobile devices), we have proposed a strategy that controls the number of occupants to target, the number of messages to send per occupant and the time of sending the messages.

The proposed messaging intervention and strategy were implemented in a model that is built upon the daily behaviour and peer pressure models. The developed model takes advantage of the fine-grained data generated in the daily behaviour model to detect energy waste and simulate realistic interaction of occupants with the intervention. The occupant agents in the model can then decide to comply to the messages or to ignore them based on their PER. They may also change their PER to simulate that they have been affected by the intervention. The model has been used to run a set of experiments. The experiments showed that the proposed intervention and strategy can result in acceptable energy saving while keeping the occupants comfortable (not annoyed by the messages). It also showed how the model can be used as an analytical tool to explain how interventions can be effective in some families but not in others.

Chapter 6

Conclusion and Future Directions

6.1 Summary of Contributions

Human behaviour is one of the most influential factors that are causing global energy consumption to increase, specifically in buildings. Therefore, it is important to study the factors that affect it and suggest the needed actions to change occupant behaviour, thus reducing energy consumption. Therefore, this thesis has looked into energy simulation models that aim to predict and assess energy consumption in buildings. As the human behaviour aspect is very important, we focused on behavioural energy waste and interventions to help occupants reduce it.

The *first* contribution of this thesis is an extended literature review of exiting energy simulation models. The review started by identifying the main categories for energy simulation approaches: top-down and bottom-up approaches, which differ in the level of detailed data the model generates. Another categorisation of energy simulation models that has been reviewed is deterministic and probabilistic approaches, which differ in the process of human behaviour data generation (occupancy and activities). From this general review of energy simulation approaches, we concluded that a **bottom-up probabilistic** approach is needed to allow the study of the human behaviour factor on the energy consumption of households. This approach is also important for the assessment of energy efficiency interventions.

The dynamism of agent-based modelling, which is one of the techniques for energy simulation, makes it the most suitable for human behaviour simulation. An Agent-Based Model (ABM) is a bottom-up approach that can be used in a deterministic or probabilistic way. The review of existing ABMs that simulate energy consumption highlighted a number of challenges, including: (1) deterministic human behaviour simulation [58], (2) generation of high level data (that is not activity-based and/or at building or household level) [7], [13], [14], [26], [27], [59], (3) lack of human behavioural aspect simulation [60], [61], [74], [75], (4) lack of occupant-appliance interaction simulation [22] and (5) usage of small case studies [23], [24], [62], [64]. These limitations do not allow the simulation of realistic human behaviour and the caused energy waste in households. When reviewing existing Probabilistic Models (PMs), we found that the level of details they generate (appliance level energy consumption and activity-based) and the large amounts of data they use are suitable for realistic human behaviour and energy waste simulation. However, they are not capable of simulating dynamic human behaviour, which may be affected by external factors (e.g. energy interventions) [74]. Therefore, the integration of probabilistic and agent-based models was proposed as a solution to overcome the limitations in both models.

The review then discussed the applicability of existing ABMs that simulate peer pressure effect on energy consumption of individuals to family environments. Existing models usually study commercial, office and residential communities [7], [13], [14], [26], [27]. We found that the used human behaviour theories and network structures/types are not applicable to simulate peer pressure among family members. Besides, occupants' daily behaviour and energy consumption behaviour are simulated and controlled using the same attribute. This leads to unrealistic simulation of peer pressure. Therefore, we identified that a new model that simulates family peer pressure is needed. In relation to energy interventions, ABMs that test energy interventions were also reviewed. The main limitation of these models is that they either select affected individuals randomly or assume the same effect for the intervention on all occupants regardless of their characteristics and interaction with it [13], [14], [24], [27], [58], [63]. This leads to unrealistic assessment of energy interventions, and prevents studying the factors that affect its results. This review of energy simulation models achieves **objective 1** outlined in Chapter 1.

Based on the review of energy simulation models, this thesis has proposed a **complete agent-based model** that combines (1) a **daily behaviour model**, (2) a **family-level peer pressure model** and (3) an **energy intervention model**. The complete model is designed in a layered 'onion-like' structure, where the daily behaviour model is in the core, the peer pressure model is built upon the core model and the energy intervention model is the outermost layer. This structure emphasises that each upper layer model takes advantage of the model underneath to achieve its aim. The peer pressure model changes the energy consumption attribute of occupants without changing the occupant daily behaviour that is simulated in the core model, and the intervention model uses the detailed data in the core model to detect energy waste and simulate detailed and realistic interaction of occupants with the intervention. Besides, the structure of the complete model allows plugging various energy interventions for testing and comparing among them, in order to decide the most efficient ones for every scenario. This complete model encompasses three contributions of this thesis each representing one model as summarised below.

The core daily behaviour model is developed by integrating an existing PM in an ABM. The model simulates realistic human behaviour and detailed energy consumption data with the help of the PM developed by Aerts [37]. The ABM characterises occupants with a Personal Energy Rating (PER) attribute that indicates how often they apply energy efficiency actions, and helps simulating the detailed occupant-appliance interaction. These features allow for energy waste simulation and energy intervention assessment, which are used by the other models developed in this thesis. The model was validated using a number of techniques, including: (1) model-to-model comparison (predictive validity of daily behaviour data), (2) graphical representation and tracing (structural validity) and (3) seed variation (internal validity). Experiments were conducted by varying social parameters (employment type, family size and occupant age) to assess the effect of these factors on the energy consumption of the house. It was concluded that bigger families cause less energy waste than small families due to the higher probability of somebody to turn OFF unneeded consumption. Besides, young, unemployed and part-time occupants can make more efficiency effect in small families than full-time and older occupants, because they are more active at home. This efficiency is calculated by the amount of wasted energy in the house. These conclusions prove that the developed model is effective in assessing energy consumption and energy waste in households, therefore, it fulfils **objective 2** of the thesis. The daily behaviour model is the *second* contribution of the thesis.

The second developed model is a family-level peer pressure model. Since none of the reviewed ABMs use human behaviour change theories that are applicable to family interaction, a review of human behaviour theories was conducted. Theories that explain the effect of social interaction on the behaviour of individuals were reviewed. The review resulted in choosing Festinger theories (i.e. informal social communication theory [38], social comparison theory [39] and cognitive dissonance theory [40]) to be used in the model as they are applicable to family environments. Besides, Granovetter's threshold model was identified to formalise Festinger theories in a usable model that has a small number of encapsulated parameters. This review of human behaviour theories satisfies **objective 3** of the thesis. The peer pressure model was developed by adapting Granovetter's threshold model and formalising Festinger theories where every occupant agent may change its PER when it is affected by the behaviour of other occupant agents. The model also includes the simulation of two abstract types of interventions: (1) individual-level intervention, (2) and family-level intervention. Experiments were conducted to prove the conceptual validity of the model, which has shown that the model reflects the used theories. The experiments has also given examples of how the model can be used to assess energy interventions and decide the needed intervention types and intensities in different scenarios. The developed and validated peer pressure model achieves **objective 4** of the thesis, and is the *third* contribution of it.

As an example of the individual-level energy intervention, we proposed an intervention that can be tested using the proposed models. Therefore, we reviewed the energy efficiency solutions Energy Feedback Systems (EFS) and Energy Management Systems (EMS) and highlighted their limitations. On the one hand, EFS, which aim to inform occupants about their energy consumption, display either abstract or contextualised energy data [32], [33], [97], [98]. These data need to be analyses by users to decide what actions are needed to reduce their house consumption. On the other hand, EMS use technological and analytical tools to infer the surrounding context (occupant presence, preferences, environmental data, etc.), and control appliances on behalf of occupants to reduce their consumption [34], [35], [102], [105], [108]. However, it was proven that this automated approach makes the users feel uncomfortable, and may be reversed by their actions. Therefore, we found that a middle solution is needed – such that occupants maintain their control, and at the same time get informed and know what is needed to reduce their consumption. This review satisfies **objective 5** of the thesis.

Based on these limitations in existing energy efficiency solutions, we proposed an intervention that detects energy waste incidents, and informs occupants about the incidents recommending actions to avoid them. The incidents are suggested to be sent to occupants' mobile devices. Since mobile messages can be annoying, we designed a messaging strategy where the time of the notifications is based on the context of the occupant, and the number of notifications is controlled based on the occupant's interest in the message.

We also identified all necessary technologies and techniques needed to realise the messaging intervention in reality. This proposed intervention and strategy achieves **objective 6** of the thesis.

The messaging intervention and strategy were implemented and assessed in a third simulation model of the complete ABM. This model uses the detailed data produced by the core model to detect energy waste. Once the occupant agents receive the messages based on the designed strategy, they have the choice to comply to it or not. The intervention may also cause the occupants to change their PER attribute indicating that they are learning and changing their behaviour because of it. The occupant interaction with the intervention is simulated by real statistical figures of the possession and usage of smartphones. A set of experiments were conducted to test the proposed intervention and strategy in specified scenarios. The experiments showed that the strategy is effective in keeping occupants not annoyed and achieving acceptable saving. The detailed results of the experiments showed that the intervention can be effective in some scenarios but not others. Therefore, the developed model can be used to simulate these cases and test various interventions. The messaging intervention model fulfils **objective 7** of the thesis, and together with the proposed intervention are the *fourth* and *fifth* contributions of this thesis.

The complete layered ABM developed in this thesis is capable of simulating realistic and detailed human behaviour dynamics, thus overcoming the shortcomings of existing models. It offers an effective tool for policy makers and governing bodies to (1) study the effect of human behaviour on energy consumption in buildings, and (2) assess energy interventions. In addition, the proposed messaging intervention makes the consumers informed about needed energy efficiency actions. Therefore, the developed model and intervention play a role in resolving the global concern of reducing energy consumption.

6.2 Future Directions

After the development of the complete ABM and the assessment of the messaging intervention in the model, the following future directions can be identified.

In terms of daily behaviour modelling, individual's occupancy and activities can be modelled in an interactive way where the behaviour of one occupant may be dependent on the other (e.g. going out of the house together, choosing to do a shared activity, etc.). This aspect is implicitly included in TUS used in this research. Besides, the chosen PM [37] simulates part of this interaction by distinguishing between household tasks and personal activities, where household tasks are modelled at household-level then assigned to individuals. This aspect can be simulated explicitly either by modelling the occupant deliberative process using Belief-Desire-Intention models as in [149], or by modelling reactive occupants as in SMACH [60].

The model developed in this thesis has concentrated on household-level simulation for the purpose of studying energy waste. However, making policy decisions may require studying a group of buildings or cities. Therefore, the same model can be used to obtain city-level data by feeding the model with the demographic composition of the city and the distribution of awareness levels of the occupants. In this case, peer pressure interaction may occur between families or members of different families in addition to peer pressure among family members. This emphasises the strength of the onion-like layered structure of the proposed model, where an extra layer can be added to implement peer pressure between families. This is implemented in existing models such as [26] and [14], which simulate peer pressure in residential communities.

Besides, further calibration of the generated energy consumption data can be conducted to represent real energy consumption. This requires the availability of real energy consumption data to validate the output of the model. In addition, the accuracy of the messaging intervention model, as well as the complete model, can be measured by implementing the intervention in reality and observing the results. This will help obtain the ground truth data that can be used to calculate the exact accuracy of the model. This will move the model from the mediator role to the predictor role by introducing the predictive validation of it. The required data set would include occupants' daily activities, appliance level energy consumption, and data about the interaction of occupants with the messaging intervention. Such data sets are currently not publicly available. Governing bodies and researchers with interest can gather such data sets, which in turn would enable them to use the model proposed in this thesis.

For the peer pressure model, the behaviour change equation is designed at the consumer type level rather than the PER attribute value. A variation of this approach is to design it at the PER value level. This can enhance model's capability to simulate more fine-grained behaviour change. Besides, the equation is calculated every time period regardless of how much the occupant has made contact with the other occupants. Otherwise, this can be done by relating the effect of members with the total time they are in contact in the house, which makes the interaction more realistic. This can be easily achieved in the current model as the core daily behaviour model simulates individual daily availability at home in a 10-minute time step. Therefore, it will be easy to track how often occupants exist at home together, occupy the same room, or make a shared activity. Another enhancement of the peer pressure model is to add a weighting attribute, which determines the level of relation between the occupants, thus affecting the peers level of influence [7]. This attribute can be added in the future where the intervention may be targeted at specific relationships if it proves efficient as in [26]. These enhancements are expected to produce an even more realistic model that reflects the quality and rate of daily interactions among the family members.

The current peer pressure model includes a number of human-related parameters that are abstracted using numerical values such as the threshold and the threshold lag. These attributes need to be concretely related to human characteristics and behaviour. This can be done by conducting a survey/questionnaire, which matches between the actual human characteristics and the values of the parameters, such as the questionnaire performed in [150]. The peer pressure model offers different options of inputs, including social parameters (family size, employment types, ages), awareness levels, values and beliefs that affect the energy consumption behaviour and intervention options. Through a number of simulated scenarios, we proved in the experiments that these inputs affect the outcome of interventions. The experiments focused on demonstrating the application of the model in prespecified scenarios. The model can ideally be used to study the impact of any intervention planned by governing bodies on the outcome (i.e. energy saving). This can be done by estimating unknown parameters, running the model with initial parametrisation of known and unknown parameters. Then a search mechanism (e.g. grid search) can be applied to best estimate the unknown parameters, minimising the difference between the model's synthesised data and the observed real data. If the search space is large, in case of having too many unknown parameters, computational intelligence methods like *Genetic Algorithm* [151] can be applied. Revealing these unknown parameters can help in determining the reason why interventions are effective in some cases, but not in others.

Concerning the proposed messaging intervention, a number of challenges may be observed when applying a human controlled approach. The first challenge is the possibility that the occupants do not comply to the messages. This may be affected by several internal barriers (e.g. personal motivation), and external barriers (e.g. inaccessibility to control the appliances). Therefore, it is important to identify and overcome these barriers through field testing. The second challenge is the users' trust in the system, which may be breached if the forwarded energy waste incidents are not accurately predicted. This challenge can be addressed by developing and using accurate sensing devices and analysis techniques, and taking the users' feedback about the provided messages.

It is worth to mention that in a behaviour change type of problems, there is no "*silver-bullet type of solution*" [42]. Therefore, it cannot be assumed that the proposed intervention will work in any case and type of household where a combination of interventions may be needed. Therefore, one of the future directions to further develop such interventions is to study it from the social psychological point of view. This is done to determine the most effective way of presenting the information – so that occupants are encouraged to take action. This can be done by field experiments as well as agent-based modelling. One of the models that study the needed persuasive mechanisms to encourage occupants to adopt energy efficient actions and tailor energy messages based on the occupants' characteristics is developed by Mogles *et al.* [152]. Their model is considered a complementary model to the complete ABM developed in this thesis. The model developed in this thesis focuses on implementing the detailed energy consumption and activities of occupants in households, and the used PER attribute represents a black box formalisation of the occupant's energy consumption decisions. Mogles *et al.* [152] model simulates the human cognitive process by formalising the determinants of energy consumption behaviour, which enables a more detailed study of energy interventions.

The complete model proposed in this thesis is now implemented for lights, televisions and computers which are presence-dependent appliances. The model can be extended to simulate other types of appliances, thus testing other types of interventions or actions to control energy consumption. These appliance types include presence-independent and heavy appliances (washing machine, tumble dryer, dishwasher, etc.), which are not recommended to be switched ON in peak-times. This is called demand response, which is applied when the price of electricity unit varies based on the time of the day. Demand response benefits both consumers (by reducing their energy bill), and providers (by reducing the generation cost and operating the electricity system more efficiently) [100]. In this case, the messaging intervention could suggest to reschedule the heavy appliance to a non-peak time that is convenient for the occupants' schedule and preference, or use an alternative such as using line drying instead of using tumble dryer, renewable energy instead of electricity, etc. The other type of energy waste that can be tested is heating/cooling energy waste. This could happen when (1) heating/cooling devices are ON when occupants are not present and pre-cooling/heating is not scheduled, (2) windows/doors are opened while the devices are ON, or (3) over-heating/cooling is detected. The suggestions in these cases are to turn the device OFF or adjust the temperature set point of heating/cooling. In order to test these interventions, all the necessary context data will need to be added to the simulation model (specifically the core daily behaviour model) such as occupant schedules, occupant preferences and internal and external temperature. Then, the interventions related to these appliances can be modelled and tested. Besides, various strategies for sending messages out to occupants may be defined, implemented and tested using the same model. This emphasises the applicability of the customisable energy intervention testing feature of the complete model proposed in this thesis.

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Appendix A

Publications

A Hybrid Agent-Based and Probabilistic Model for Fine-grained Behavioural Energy Waste Simulation

Fatima Abdallah, Shadi Basurra, and Mohamed Medhat Gaber
School of Computing and Digital Technology, Birmingham City University, Birmingham, UK
Email: fatima.abdallah@bcu.ac.uk, shadi.basurra@bcu.ac.uk, mohamed.gaber@bcu.ac.uk

***Abstract*—Several agent-based and probabilistic models were proposed to simulate human behaviour, which is an important cause of high energy consumption in buildings. However, some of these models ignore behavioural energy waste at occupant level, and when they model it, they are based on small case studies and produce high level energy consumption data. This paper proposes a hybrid approach that integrates agent-based and probabilistic models to simulate behavioural energy waste at occupant level. The combination of the two approaches helps produce fine-grained data, and is based on large real data samples. The developed model was validated against realistic data. The results show that employment type have an effect on the energy consumption of households, which needs further investigation to quantify the effect and test other social parameters.**

I. Introduction

More than half of the energy consumption of buildings is caused by human behavioural energy waste (e.g. leaving appliances and lights on while not in use) [1]. Therefore, it is crucial to study human behaviour especially with the recent research in zero carbon buildings design where human behaviour is important [2].

To analyse buildings energy performance and study the effect of human behaviour, several energy simulation models have been proposed. Among these are Probabilistic Models (PM) and Agent-Based Models (ABM) that simulate energy consumption human behaviour. PM simulate the activities of occupants through probability distributions then get the resulting energy consumption of appliances [2], [3]. However, these models do not simulate occupants behavioural energy waste. They assume ideal human behaviour [4] and consider that occupants have identical behavioural characteristics, while in fact, occupants may have different consumption habits [5]. ABM approaches have been proposed to model behavioural energy waste in both commercial [6] and residential buildings [7]. In these models, occupants/energy consumers are modelled as separate computational entities that change their state and make decisions by interacting with their environment (electric appliances) and other occupants [8]. However, most of these models do not model the low level interaction between occupants and appliances thus produce high level data. Modelling this interaction at a fine-grained level is important to determine the causes of energy waste in buildings [9].

This paper proposes a hybrid approach that takes advantage of both probabilistic and agent-based models to overcome their limitations when they work separately. Thus, obtaining a model that simulates various levels of energy awareness of occupants and produces more detailed data at occupant and appliance level. This helps in understanding the impact of occupant's energy awareness levels in family settings. The results of this paper set the way for more experiments to study the effect of social parameters on the energy consumption of a family. The paper is divided into the following sections: the next section presents part of the existing probabilistic and agent-based models highlighting their limitations and showing how integrating them in one model overcomes these limitations. Section III presents the integration methodology. Section IV illustrates the resulting energy consumption of different types of households. Finally, conclusion and future work are presented in section V.

II. Related Work

A. Probabilistic Models

Probabilistic Models (PM) have been widely proposed to predict energy demand in residential buildings. They utilise time-use surveys to calculate the probability that an action occurs and simulate occupant activities and energy consumption at home. These models are considered as bottom-up approaches that build up the energy consumption of the building from high resolution data at activity and appliance level [3]. Bottom-up approaches make it possible to detect energy waste when having information about what the occupant is doing, what is his/her location, which appliances are turned on, etc. In addition, this level of granularity is useful to study the changes in occupant behavioural characteristics [10].

Although PM produce high resolution data which is useful when modelling energy waste, existing models only aim to reproduce realistic occupant activities and energy consumption. This is because these models follow a linear data generation process where occupancy and activity data are generated and then used to generate the resulting electricity consumption. This linear process cannot be used to model dynamic behaviour because human behaviour is non-linear and can change based on several individual and environmental attributes [8].

Existing PM assume that all occupants are the same and consume energy in an ideal way; That is, energy is consumed only when occupants are available at home or doing the activity [3], [4], [11]. However, human behaviour is more complex and is unlikely to be the same. For example, more than 50% of energy consumption in commercial buildings is consumed during unoccupied hours [1]. In addition, residential occupants can be categorised into high, medium, and low consumers [6]. Ignoring the different levels of human energy awareness have

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caused an underestimation of energy consumption compared to the real data in some existing PM. Richardson et al. [4] noticed that there is more consumption during night in the real data compared to the simulated one, and attributed this to occupants leaving lights on when they sleep. Similarly, Aerts [11] realised that the developed model failed to produce high energy consumption levels, and explained that the reason could be behavioural energy waste.

B. Agent-based Models

Besides PM, Agent-Based Models (ABM) simulate human actions in dynamic environments. In ABM, agents are defined as autonomous software components that take decisions based on their state and rules of behaviour. ABM is best used when agents behaviour is non-linear and affected by the surrounding environment, when agents location is not fixed, and when agents characteristics are heterogeneous [8].

Existing ABM approaches have been proposed for both residential and commercial buildings and for different purposes. For example, Azar and Menassa [5], [6] used ABM to study the effect of peer pressure and energy conservation workshops on the energy consumption of a commercial building. This model differentiates between occupants by varying the average yearly consumption. This factor is not only affected by how aware the occupants are, but also how long they spend in the building or what appliances they use. In addition, it does not produce high resolution data like location and activity of occupants which are important attributes when studying behavioural energy waste. In a similar way, Zhang et al. [7] represented energy-consumer agents at household level to study the experience development of households when using smart meters. Taking the household as a whole entity which has one energy awareness level makes it difficult to model occupants-appliances interaction and study the effect of occupants energy awareness on the consumption of the family.

Among existing ABM a few of them model the occupant-appliance interaction and vary the energy awareness at occupant level. For instance, Carmenate et al. [9] developed an ABM that models the human-appliance-building interaction, and highlighted the effect of both building structure and occupants awareness on energy consumption of the building. The advantage of such models is that they simulate the detailed movement of occupants in the building and study the factors that affect energy consumption whether they are physical, social or others. However, the limitation of these models is that they are implemented for specific case studies which offers energy efficiency strategies specific for these environments, whereas using large samples allows for studying more varied scenarios which results in wider conclusions.

C. Integrating Probabilistic and Agent-based models

PM utilise large samples of data which guarantees that the produced data are realistic. They also provide high resolution data at appliance and occupant level. Therefore, PM can overcome the limitations in some of the ABM models presented above. On the other hand, ABM overcomes the linear approach in PM by enabling dynamic human behaviour modelling where occupant agents take decisions based on their personal characteristics and the external state of the environment. Furthermore, various energy awareness levels can be modelled at the occupant level in ABM which enables the study of energy awareness in a family setting. Therefore, a hybrid approach that combines ABM and PM overcomes limitations of both models when they are separated. This idea of using PM in ABM was recently proposed in Reynaud et al. [12] who propose to calibrate an ABM model with PM to gain reactivity and coordination of occupant agents. Despite the fact that the integration has not been implemented yet, the ABM they proposed do not model behavioural energy waste.

III. The Agent-Based and Probabilistic Model Integration Methodology

The ABM model proposed in this paper obtains realistic behaviour of occupants from Aerts PM [2], [11]. Aerts model is one of the recent models which has advantages over other models [3], [4], [10] and satisfies the requirements of modelling energy waste. The model was selected because it (1) produces more realistic occupancy and activities data, (2) enables doing more than one activity at a time, (3) includes nine activities that are linked to energy usage, and (4) distinguishes between household tasks and personal activities.

Aerts model generates realistic occupancy and activity data through probability distribution functions (PDF) extracted from Belgian Time-Use Survey and Household Budget Survey which include 6400 respondents from 3455 households. The PDFs are generated based on several parameters such as occupant ages and employment types, household types, and days of week. The model is composed of three stages: (1) occupancy modelling and (2) activity modelling which were used in the ABM to produce realistic human behaviour, and (3) electricity modelling. In order to model behavioural energy waste, modifications were made mainly on the electricity model by adding an energy awareness and location attribute for occupant agents. These attributes, along occupants activity and time of day, are used to control when occupants turn appliances and lights on or off. The ABM consists of: 'Occupants Agents', 'Appliances Agents', and the 'Environment' that the agents act in.

A. The Environment and Appliances Agents

Occupants and appliances agents act in a house environment composed of a number rooms. The house rooms affect the mobility and number of locations that the occupants can be in, and consequently their energy consumption. Therefore, the number of rooms in the house was obtained from the Eurostat income and living conditions database [13] which contains the average number of rooms per person by type of household and income group. The data was normalized and fitted to the household types included in the PM. Every household was assigned one kitchen, one living room, at least one bedroom and at least one bathroom. Dining and laundry/utility rooms were added in high income houses when necessary. The size of basic rooms was set to 20 m^2 based on the average room size in Belgium [14] which was used to calculate lights consumption. In terms of the day and time, the occupant agent is aware of the day type (Weekday, Saturday, or Sunday), time of day (10-minute time step), and the amount of external daylight.

Electric appliances in the house are modelled as dummy agents that are controlled by occupant agents. They only respond to actions from occupants to change their state from on to off or vice versa. At every time step, each appliance records the amount of consumed energy based on its state. Before initialising the simulation, every household is assigned a number and types of appliances based on the household type and income as modelled in the PM. The type of appliance identifies the amount of energy that the appliance consumes when it is on.

Therefore, the simulation environment **E** can be define using the triplet <**T**, **R**, **A**>, where:

- **T** is a one-year simulation time defined by the triplet <*t*, *d*, $daylight_{td}$>where *t* ∈ [1-144] is a 10-minute time step in every day *d*, and $daylight_{td}$ is the amount of external daylight at every time step *t* and day *d*.
- **R** is the set of rooms in the house. For every room $r \in$ **R**, *r* is defined by the triplet <*size*, A_r, O_r>, where *size* is the size of *r*, A_r is the set of appliances in *r*, and O_r is the set of occupants that are in *r*.
- **A** is the set of appliances. For every appliance $a \in$ **A**, *a* is defined by the set <*inUseConsumption*, *r*, O_a, C_{td}>, where *inUseConsumption* is the amount of energy used when the device is on, *r* is the room that the appliance is in, O_a is the set of occupants using the appliance, and C_{td} is the consumption array of the appliance over a whole year, where every $c_{td} \in C_{td}$ can be either *inUseConsumption* or 0 based on the appliance state.

B. The Occupant Agent

Initially, occupants' ages and employment types are given as input for the model. Employment types include: full time job, part time job, unemployed, retired and school, where under 18 occupants are school children and above 65 are retired. Based on the household type (occupants' ages and employment types) the income of the household is assigned using the income PDF in the PM. Next, the appliances and rooms of the house are determined as detailed above. At every time step, the occupants change the state of the environment by changing their location and using the electric appliances.

1) Occupant Daily and Weekly Behaviour: Before simulating occupancy, work routines and occupancy patterns are assigned to each occupant. Details of these attributes can be found in Aerts et al. [11]. At every time step, the occupant either selects a new occupancy state os_{td} based on PDFs in the PM, or decrements the duration of an already running occupancy state. The occupant action to select new occupancy state is defined by the function $\mathbf{OS} : \mathbf{op_d}, \mathbf{os_{(t-1)d}}, \mathbf{t} \rightarrow \mathbf{os_{td}}$

$$\mathbf{op_d}, \mathbf{os_{td}}, \mathbf{t} \rightarrow \mathbf{dr}$$

where, os_{td} is the new occupancy state, $os_{td} \in$ {*Away*, *Sleeping*, *Active*} (*Away*: when the occupant is not at home, *Sleeping*: when the occupant is at home but sleeping, and *Active*: when the occupant is at home and not sleeping). The agent first selects a new state as function of his occupancy pattern op_d, previous state $os_{(t-1)d}$, and time of day *t*, then decides the duration *dr* of the state.

The PM distinguishes between tasks which can be performed by one occupant at a time and personal activities that can be shared by some/all occupants and can be shared. When the occupant is in the *Active* state, he/she can either select to start a task or personal activity, or decrement the duration of an ongoing activity. The action of selecting new activities is defined by the function $\mathbf{AC} : \mathbf{age}, \mathbf{emp}, \mathbf{t}, \mathbf{d} \rightarrow \{\mathbf{0}, \mathbf{1}\}_{\mathbf{ac/tk}}, \mathbf{dr}$ which is performed by the occupant agent for every personal activity $ac \in$ {*Using_the_computer*, *Watching_television*, *Listening_to_music*, *Taking_shower/bath*} and task $tk \in$ {*Preparing_food*, *Vacuum_cleaning*, *Ironing*, *Doing_dishes*, *Doing_laundry*}. The function returns a Boolean value {0,1} to distinguish if the action will take place or not. This way of modelling enables the occupant to perform more than one activity at a time. The decision of doing an activity is based on the occupant *age*, employment type (*emp*), time of day *t*, and day type *d*. If a new activity is selected to be performed, the agent selects the duration *dr* of the activity.

2) Occupant Location: Whenever the occupant agent is in the *Active* or *Sleeping* state, it means he/she should be in one of the house rooms. Every activity is assigned a set of possible rooms. The occupant agent determines his/her location r_{td} using the function $\mathbf{OL} : \mathbf{os_{td}}, \mathbf{AC_{td}}, \mathbf{TK_{td}} \rightarrow \mathbf{r_{td}}$, where AC_{td} are ongoing personal activities, and TK_{td} are ongoing tasks. If the occupant is doing more than one activity at a time, he/she may have a set of possible rooms and his/her location alternates among these rooms at every time step.

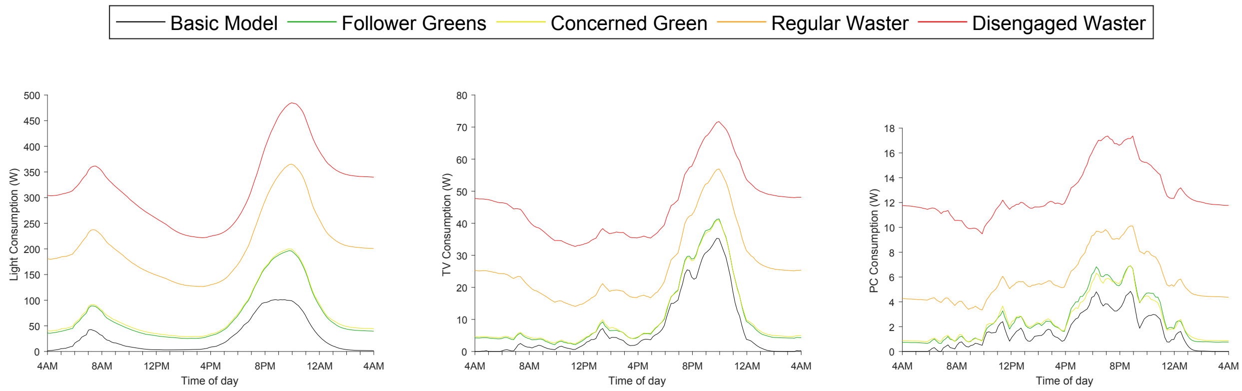
3) Occupant Energy Awareness and Energy Usage: Occupants' energy awareness have been modelled in existing literature in different ways. For example, Carmenate et al. [9] distinguishes between energy literate and energy illiterate occupants. Similarly, Azar and Menassa [6] divided occupants into high, medium, and low consumers. Another way is using average yearly/daily consumption as a characteristic of the occupant [5]. The most detailed and flexible definition of energy awareness was proposed in Zhang et al. [7] where energy consumers can belong to one of four consumer types: 'Follower Green', 'Concerned Green', 'Regular Waster', and 'Disengaged Waster'. Based on the consumer type, the agent's energy awareness attribute is assigned a value between 0 and 100. This attribute is used to decide the probability that an occupant follows energy saving actions such as turning off devices when they are not in use. The value is calculated based on a normal distribution for every consumer type (Table I). In the current ABM, the energy awareness of occupant agents is defined based on occupant types in Zhang et al. [7].

TABLE I: Mean and Standard Deviation of Consumer Types

Consumer Types	**Mean μ**	**Standard Deviation σ**
Follower Green	0.74	0.041
Concerned Green	0.72	0.043
Regular Water	0.41	0.033
Disengaged Waster	0.25	0.057

The action of turning appliances on/off is defined by the function $\mathbf{TO_a} : \mathbf{ac_{td}} \rightarrow \mathbf{turnOn_a}$

$$\mathbf{ac_{td}}, \mathbf{O_a}, \mathbf{ea} \rightarrow \{\mathbf{keepOn}, \mathbf{turnOff}\}_\mathbf{a}.$$



(a) Lights Consumption

(b) TV Consumption

(c) PC Consumption

Fig. 1: Appliances energy consumption of one occupant (25-39 years old / full-time job)

When the occupant starts an activity ac_{td}, he/she turns on the appliance a associated to this activity. When the activity ends and based on the occupants energy awareness ea, he/she may turn off the appliance or keep it on. The occupant may also communicate with other occupant/s O_a who may be using the same appliance at the same time to decide whether to turn off the appliance. The action of turning off appliances is also executed every time an occupant visits a room and finds appliances that are on but unused. The action of turning lights on/off is different from using appliances, because using lights depends on the amount of daylight and the location of occupants. $\mathbf{TO_r} : \mathbf{r_{td}}, \mathbf{daylight_{td}} \rightarrow \{\mathbf{turnOn}, !\mathbf{turnOn}\}_\mathbf{r}$

$$\mathbf{r_{td}}, \mathbf{O_r}, \mathbf{ea} \rightarrow \{\mathbf{turnOff}, !\mathbf{turnOff}\}_\mathbf{r}$$

Every time the occupant is in a location r_{td} he may decide to turn on the light in this room based on the amount of daylight at the timestep ($daylight_{td}$) [11]. When the occupant leaves his/her location, he/she checks if there is more occupants in the room O_r, and based on his energy awareness (*ea*) he/she may decide to turn off the light or not.

In summary, the occupant agent **OA** is defined using the set $<$*age*, *emp*, op_d, os_{td}, *ea*, AC_{td}, TK_{td}, r_{td} $>$and can perform the actions $<\mathbf{OS}, \mathbf{AC}, \mathbf{OL}, \mathbf{TO_a}, \mathbf{TO_r}>$. The model was implemented in Repast Simphony (https://repast.github.io), a Java-based agent-based platform. The implementation of the occupancy and activity behaviour in ABM was tested and found to be generating the same occupant behaviour as the original PM [11]. Three appliances were implemented: Lights, TV, and PC, which are clearly affected by the energy awareness of occupants like leaving lights on when leaving a room or leaving the TV/PC on when the activity ends.

IV. Simulation Results and Discussion

This section presents a set of experiments to test the validity of the model and study the effect of energy awareness on household consumption. In each scenario, the average energy consumption of 100 simulated households (with the same type and energy awareness, but different income, appliances number and types, and house rooms) is calculated.

A. Experiment 1: Single Occupant Household

The purpose of this experiment is to demonstrate the validity of the developed model. In order to study the effect of energy awareness, single occupant households were simulated varying ages and employment of occupants. Fig. 1 represents the resulting weekday average consumption of lights, TV, and PC for a 25-39 years old occupant in full-time job. Each of the sub-figures in Fig. 1 includes 5 scenarios: the basic model which is the ideal scenario with 100% energy awareness (referring to Aerts PM [11]), and four scenarios each with a different occupant type.

In the basic model, it is observed that when the occupant is sleeping or away the energy consumption is very low or almost zero. For the other four scenarios, it is observed that the implemented model produces very similar trend of daily energy consumption. The observed difference in energy consumption is due to the energy awareness attribute which has caused the line graph to level up in a proportionally based the energy awareness percentages in Table I. The energy consumption of *Follower Green* and *Concerned Green* occupants are almost similar because their mean energy awareness is very close (74% and 72% respectively). While the two waster occupants are much higher with the *Regular Waster* being more efficient than the *Disengaged Waster* (41% and 25% respectively). Same observations were made for other day types, age groups, and employment types.

These results prove the validity of the implemented model that produces energy consumption trends similar to the basic model which was constructed from real data in the PM, and reflects the various energy awareness levels of occupants.

B. Experiment 2: Two Occupant Household

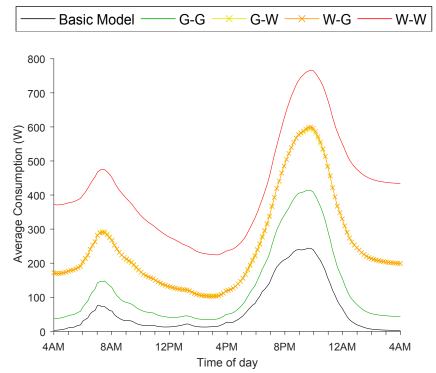
In order to study the effect of energy awareness on multiple occupant households, the energy awareness of occupants is reduced to the two extreme types: *Follower Green* (G) and *Disengaged Waster* (W) which limits the number of scenarios while achieving the objectives of this study. The total energy consumption per day for the three appliances (lights, TV, and PC) was calculated and shown in Fig. 2 which shows the consumption of two 25-39 year old occupants (Fig. 2a where both are in full-time job, and Fig. 2b where one is in full-time job and the other is unemployed). The legend of the figure encodes the energy awareness of the household, where the sequence of the letters (G and W) has the same sequence as the description of the household type in the captions of the sub-figures.

It is noticed that the observation in the previous experiment (one occupant household) still applies on two occupant households which proves that the model reflects energy awareness of occupants with multiple occupancy. Both Figures (2a and 2b) show the two extremes of energy consumption when there are two *Follower Green* occupants or two *Disengaged Waster* occupants at home. In-between scenarios in Fig. 2a resulted in the same energy consumption (yellow and orange crossed lines) even when reversing the energy awareness of the two occupants. However, this observation doesn't hold when having different employment types (Fig. 2b). It is observed that the household consumes less energy when the unemployed occupant is a *Follower Green*. This is observed during the whole 24 hours except few hours in the morning (7:00 am and 9:30 am) when it is more probable that the *Disengaged Waster* full-time occupant is awake and the *Follower Green* unemployed occupant is sleeping. Similar observation is noticed when the unemployed occupant is a *Disengaged Waster* where the household consumes more energy. This is explained by the fact that unemployed occupants spend more time in the house which makes their effect more obvious than full-time employed occupants.

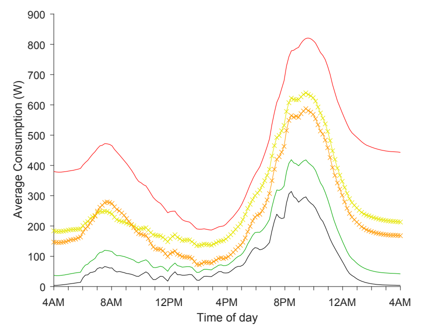
These observations show that employment type is a factor that affects the energy consumption of the house when varying occupants energy awareness. However, further investigation is needed to quantify this effect and test it on other age groups and household types.

V. Conclusion and Future Work

This paper presented a methodology to integrate agent-based and probabilistic models to overcome limitations of existing models. The proposed hybrid model incorporates energy awareness at occupant level and produces fine-grained data to model behavioural energy waste. It was shown that the developed model produces valid consumption data compared to the real data and reflects various energy awareness levels of occupants. The experiments also showed that there is an effect for employment type on the energy consumption of the house. This conclusion needs to be quantified in future research, and other social parameters such as occupants ages and household types can also be studied to gain insights towards energy efficiency plans for families. Furthermore, the model opens the way for more experiments to study the effect of intervention technologies (e.g. customized energy waste messages) and family members pressure on the energy consumption of household.



(a) Two occupants both in full-time job



(b) Two occupants: the first in full-time job and the second is unemployed

Fig. 2: Total energy consumption of two occupant households both 25-39 years old

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Cascading Probability Distributions in Agent-Based Models: An Application to Behavioural Energy Wastage

Fatima Abdallah, Shadi Basurra(✉), and Mohamed Medhat Gaber

School of Computing and Digital Technology, Birmingham City University, Birmingham, UK
{fatima.abdallah,shadi.basurra,mohamed.gaber}@bcu.ac.uk

Abstract. This paper presents a methodology to cascade probabilistic models and agent-based models for fine-grained data simulation, which improves the accuracy of the results and flexibility to study the effect of detailed parameters. The methodology is applied on residential energy consumption behaviour, where an agent-based model takes advantage of probability distributions used in probabilistic models to generate energy consumption of a house with a focus on energy waste. The implemented model is based on large samples of real data and provides flexibility to study the effect of social parameters on the energy consumption of families. The results of the model highlighted the advantage of the cascading methodology and resulted in two domain-specific conclusions: (1) as the number of occupants increases, the family becomes more efficient, and (2) young, unemployed, and part-time occupants cause less energy waste in small families than full-time and older occupants. General insights on how to target families with energy interventions are included at last.

1 Introduction

The building sector accounts for more than one-third of the total worldwide energy consumption which is also expected to increase with the increase in population [1]. From this high percentage, more than a half is caused by human behavioural energy waste (e.g. leaving appliances ON while not in use) [2]. Beisdes, human behaviour is gaining more interest in the zero carbon design as it is considered one of the barriers against the efficiency of zero carbon buildings [3].

This concern about the effect of human behaviour on energy consumption has been considered in several energy simulation models which are used to analyse buildings energy performance. One approach of simulation models are *Probabilistic Models* (PM) whose aim is to add the human behaviour factor to building simulation tools. These models simulate the activities of occupants, and as a result the energy consumption of the house. Furthermore, PM enable modelling different household characteristics such as occupants' ages, employment types, and household income [3,4]. However, these models do not simulate behavioural

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energy waste because they assume ideal and identical behaviour among occupants [5]. While in fact, occupants may have different energy awareness levels thus different energy consumption habits [6]. Another emerging trend of energy simulation models are *Agent-Based Models* (ABM). Several ABM approaches have been used to model behavioural energy waste in both residential [7] and commercial buildings [8]. In these models, occupants/energy consumers are modelled as agents that change their state and make decisions by interacting with their environment (electric appliances) and other occupants [9]. However, most of these models do not capture the low level interaction between occupants and appliances which is important to determine the causes of energy waste in buildings [10], and to produce high level data. These limitations in existing PM and ABM in simulating energy consumption motivates the approach of this paper, where the integration process can overcome their limitations when they work separately. The ABM takes advantage of probability distributions used in PM to produce more detailed data at occupant and appliance level, and simulates various levels of energy awareness of occupants. The same cascading approach can be used in other human behaviour models such as transport modelling and human communications to ensure the accuracy and flexibility of the results. The energy simulation model has been validated in [11] and proved that there is an effect of employment type on the energy efficiency of the house. Therefore, beside proposing the integration approach, detailed results of the effect of varied social parameters are presented to gain insights towards energy efficiency plans.

The paper is organised as follows. The next section presents existing PM and ABM highlighting their limitations and advantages of integrating them. Section 3 presents the proposed cascading approach. Section 4 illustrates how the proposed model can be used to analyse energy consumption based on occupants energy awareness and varied social parameters. Based on the results, the model is compared with existing PM and ABM in Sect. 5 and the results of the experiments are discussed providing general recommendations for policy makers on how to target family members to achieve less energy waste in buildings. Finally, conclusion and future work are presented in Sect. 6.

2 Related Work

2.1 Probabilistic Models

Probabilistic (or stochastic) Models (PM) have been widely proposed to enhance the prediction of energy demand in residential buildings by simulating occupant activities. They utilise time-use surveys, where occupants record the activities they do throughout the day, to calculate the probability that an action occurs. Using large amounts of data from time-use surveys enables generating the data based on different socio-economic factor like income, household size, occupants ages or employment types [3,4]. These models are considered as bottom-up approaches because they use highly detailed data (at activity and appliance level) to build up the energy consumption of the house [12]. Bottom-up approaches make it possible to detect energy waste when having information about what the occupant is doing, what is her/his location, which appliances are turned ON, etc. In addition, this level of granularity is useful to study the changes in occupant behavioural characteristics [13].

Although PM produce detailed data which is useful when modelling energy waste, the existing models only aim to reproduce realistic occupant activities and energy consumption. Therefore, they are not capable of capturing how occupants react to changes in their environment [14]. From the computational view, PM follow a linear modelling process where occupancy and activity data are generated, then the resulting electricity consumption. This linear process cannot be used to model dynamic humna behaviour which is non-linear and can change based on several individual and environmental attributes [9]. Existing PM assume that all occupants are the same and consume energy in an ideal way, i.e. energy is consumed only when occupants are active at home or doing an activity [4,5,12]. However, human behaviour is more complex and is unlikely to be always the same, which can be one of the most influential factors of energy consumption in buildings. For example, more than 50% of energy consumption in commercial buildings is consumed during unoccupied hours, and sometimes even in occupied hours [2]. In addition, occupants can be categorised based on their greenness of behaviour [6]. Assuming that no energy is wasted have caused an underestimation of the real data in some existing models. For example, Aerts [4] realised that the developed model failed to produce high energy consumption levels, and explained that the reason could be behavioural energy waste.

2.2 Agent-Based Models

Besides PM, buildings energy consumption can be generated using Agent-Based Models (ABM). In ABM, agents are defined as autonomous software components that take decisions based on their state and rules of behaviour [9]. ABM are widely used in social sciences to study dynamic human behaviour and its influential factors [8]. Azar and Menassa [15] developed an ABM that represents social network structures in commercial buildings to study the effectiveness of energy interventions. Similarly, Chen et al. [8] studied structural properties of peer networks in residential buildings. These models differentiate between occupants by varying the average daily/yearly consumption. This factor is not only affected by how aware the occupants are, but also how long they spend in the building or what appliances they use. Therefore, no consideration was made whether high energy consumption is a result of occupant behaviour. In another way, Zhang et al. [7] represented energy-consumer agents at household level to study experience development of households when using smart meters. Modelling the household as a whole entity with one energy awareness level makes it difficult to model occupants-appliances interaction and study the effect of occupants behaviour on the consumption of the family. Therefore, the aforementioned models [7,8,15] do not produce detailed data like location and activity of occupants which are important attributes when studying behavioural energy waste.

Among the existing ABM, only a few capture the occupant-appliance interaction and produce detailed data that is useful in energy waste analysis. Zhang et al. [16] tested the effectiveness of automated lighting strategy against manual lighting strategy in a university building. They found that the manual strategy is more effective when occupants have high energy awareness level, and the automatic one is better when occupants have low awareness level. Similarly, Carmenate et al. [10] developed an ABM that models the human-appliance-building interaction to understand determinants of energy waste in an office environment. By including this interaction level they highlighted the effect of both building structure and occupants awareness on energy consumption of the building. The advantage of these models is that they simulate the detailed movement of occupants in the building and study the factors that affect energy consumption within the building environment (physical, social or others). However, the limitation of these models is that they are implemented from hypothetical [10] and small [16] case studies which questions the accuracy of the results, limits the variation of parameters, and offers energy efficiency strategies specific for these environments, while using large samples allows more realistic data, more varied parameters, and more generalised conclusions.

2.3 Cascading Probabilistic and Agent-Based Models

PM utilise large samples of data, therefore, it is guaranteed that the produced data are realistic and possible to study the effect of social parameters on energy consumption of the house. PM also provide detailed data at appliance and occupant level. Therefore, cascading PM with ABM overcomes the limitations that existed in some of the ABM presented above. Besides, ABM overcome the linear approach in PM by enabling dynamic human behaviour modelling where occupant agents take decisions based on their personal characteristics and the state of the environment. Furthermore, various energy awareness levels can be modelled at occupant level in ABM which enables the study of energy awareness in a family setting. Therefore, an approach that combines ABM and PM overcomes limitations of both models when they are separated.

3 The Agent-Based and Probabilistic Model Cascading Methodology

The model proposed in this paper cascades PM and ABM, where the first stage is obtaining probability distributions from realistic data to simulate the occupants daily behaviour, and the second stage is using these distributions in an ABM to simulate the dynamic interaction of occupants and appliances. To get the probability distributions, we take advantage of an existing PM which is developed by *Aerts* [3,4]. Aerts model is one of the recent models which has advantages over other models and satisfies the requirements of modelling energy waste. The model was selected because it includes the following features: (1) Obtains more realistic duration of activities and occupancy states (opposed to [5,12]); (2) enables multitasking where occupants can be doing more than one activity at a time (opposed to [12]); (3) includes nine activities that are linked to energy usage opposed to [13] that includes activities that may not be connected to energy consumption; (4) simulates household dynamics by distinguishing between household tasks and personal activities; and (5) uses 7 patterns of typical occupancy behaviour based on age and employment type, which results in more realistic occupancy data. The main approach followed in Aerts model is generating realistic occupancy and activity data using higher order Markov Process. The process is based on transition probability from one state to another, and the probability distribution for the duration of the state. Probability Distribution Functions (PDF) were extracted from Belgian Time-Use Survey and Household Budget Survey which include 6400 respondents from 3455 households. The PDFs are generated based on several social and environmental parameters such as occupants ages and employment types, household type, and day of week. The model is composed of three stages: (1) occupancy model, (2) activity model and (3) electricity model. The occupancy and activity models with their associated PDFs are used in the ABM to produce realistic human behaviour. However, in order to model behavioural energy waste, modifications were made mainly on the electricity model by adding an energy awareness and location attributes for occupant agents. These attributes control when occupants turn appliances and lights ON or OFF. Thus, behavioural energy waste is modelled by combining data about occupants activity, location, energy awareness, and time of day.

The following subsections explain the components of the agent-based model: 'Occupants Agents', 'Appliances Agents', and the 'Environment' that the agents act in. Details about the usage of the probability distributions in the ABM is explained where necessary.

3.1 The Environment and Appliances Agents

Occupant agents live and interact in a house environment composed of a number rooms, each having a set of appliances. The number of rooms affects the mobility and number of locations that the occupants can be in, and consequently the energy consumption. Therefore, the number of rooms was obtained from the Income and Living Conditions Database by Eurostat [17]. The database contains data about the average number of rooms per person by household type and income group. The data were normalised and fitted to the included household types. Every household is assigned a kitchen, a living room, at least one bedroom and at least one bathroom, in addition to dining and laundry rooms when necessary. The size of basic rooms was set to $20\,\mathrm{m}^2$ based on the average room size in Belgium [18] (the room size was used to calculate the amount of lights consumed in every room). In terms of the day and time, occupant agents are aware of the day of the week, time of day in a 10-min time step, and the amount of external daylight. Electric appliances in the house are modelled as dummy agents that react to occupant agents. Occupants change appliances state from ON to OFF or vice versa. The types and number of appliances in the house are obtained from appliances PDFs in the PM. Before initialising the simulation and based on the household type and income, the household is assigned a number and types of appliances which identifies the amount of energy that the appliance consumes.

The simulation environment **E** can be defined using the triplet $<\mathbf{T}, \mathbf{R}, \mathbf{A}>$, where:

- **T** is a one-year simulation time defined by the triplet $<t, d, daylight_{td}>$ where, $t \in$ [1–144] is a 10-min time step in 24 h, d is the day of the year, and $daylight_{td}$ is the amount of external daylight at every time step and day.
- **R** is the set of rooms in the house: For every room $r \in \mathbf{R}$, r is defined by the triplet $<size, A_r, O_r>$, where *size* is the size of the room, A_r is the set of appliances in the room, and O_r is the set of occupants that are in the room.
- **A** is the set of appliances in the house: For every appliance $a \in \mathbf{A}$, a is defined by the set $<inUseConsumption, r, O_a, C_{td}>$, where *inUseConsumption* is the amount of energy used when the device is ON, r is the room that the appliance is in, O_a is the set of occupants using the appliance, and C_{td} is the consumption array of the appliance over a whole year, where every $c_{td} \in C_{td}$, $c_{td} = \{0, inUseConsumption\}$ based on its ON-OFF state.

3.2 The Occupant Agent

Initially, occupants' ages and employment types are given as input for the model. Employment types include: full time job, part time job, unemployed, retired and school, where under 18 occupants are school children and above 65 are retired. Another input attribute of the model is the energy awareness which will be explained in this section. Based on the defined household type (occupants' ages and employment types) the income group of the household is assigned using the income PDF in the PM. Next, the appliances and rooms of the house are determined as functions of the household type and income group. At this stage, all occupant agents are initialised and start doing activities in the house. At every time step, the occupants change the state of the environment by changing their location and using the electric appliances.

Occupant Daily and Weekly Behaviour. In order to simulate occupancy of members, work routines and occupancy patterns are needed. Working occupants can belong to one of ten work routines (wr) to decide working days and duration of occupants. Every day, and based on the occupant's age, employment and day type, the occupant chooses one occupancy pattern op_d for the day. The PM includes 7 occupancy patterns which could be referred to in Aerts et al. [3].

At every time step, the occupant either selects a new occupancy state os_{td} based on PDFs in the PM, or decrements the duration of an already running occupancy state. OS is the function to select a new occupancy state.

$$OS : op_d, os_{(t-1)d}, t \rightarrow os_{td} \quad (1)$$

$$op_d, os_{td}, t \rightarrow dr \quad (2)$$

where, os_{td} is the new occupancy state, $os_{td} \in \{Away, Sleeping, Active\}$ (*Away*: out of home, *Active*: at home and not sleeping, *Sleeping*: at home but sleeping). The agent first selects a new state as function of his/her occupancy pattern op_d, previous state $os_{(t-1)d}$, and time of day t, then decides the duration dr of the state based on his occupancy pattern, current occupancy state, and time of day.

The PM distinguishes between household tasks which are performed by one occupant at a time, and personal activities that can be performed and shared by all occupants. When the occupant is in the *Active* occupancy state, he/she can do several tasks or personal activities. The occupant can either select to start the activity, or decrement the duration of an ongoing activity. The action of selecting new activities is defined by the function AC

$$AC : age, emp, t, d \rightarrow \{0, 1\}_{ac/tk}, dr \tag{3}$$

This function is performed by the occupant agent for every personal activity $ac \in \{$*Using the computer*, *Watching television*, *Listening to music*, *Taking shower/bath*$\}$ and task $tk \in \{$*Preparing food*, *Vacuum cleaning*, *Ironing*, *Doing dishes*, *Doing laundry*$\}$. The function returns a Boolean value {0,1} to distinguish if the action will take place or not. This way of modelling enables the occupant to perform more than one activity at a time. The decision of doing an activity is based on the occupant *age*, employment type (*emp*), time of day t, and day type d; and similarly the duration dr of the activity.

Occupant Location. Whenever the occupant is at home, he/she needs to be in one of the rooms. Every activity is assigned to a room or a set of possible rooms. The occupant agent determines his/her location using the function OL

$$OL : os_{td}, AC_{td}, TK_{td} \rightarrow r_{td} \tag{4}$$

The occupant decides his/her location r_{td} based on his occupancy state os_{td}, ongoing personal activities AC_{td}, and ongoing tasks TK_{td}. If the occupant is doing more than one activity at a time, he/she may have a set of possible rooms and his/her location alternates among the rooms of this set at every time step.

Occupant Energy Awareness and Energy Usage. Occupants' energy awareness have been modelled in existing literature in different ways. For example, Carmenate et al. [10] distinguishes between energy literate and energy illiterate occupants. Similarly, Zhang et al. [6] categorises occupants into high and low consumers. Another way is using average yearly/daily consumption as a characteristic of the occupant [8,15]. The most detailed and flexible definition of energy awareness was proposed in Zhang et al. [7] where energy consumers can belong to one of four consumer types: 'Follower Green', 'Concerned Green', 'Regular Waster', and 'Disengaged Waster'. Based on the consumer type, the agent's energy awareness attribute is assigned a value between 0 and 100. This attribute is used to decide the probability that an occupant follows energy saving actions such as turning off devices when they are not in use. The value is calculated based on a normal distribution for every consumer type (Table 1). In the current model, the occupant types and energy awareness attribute defined in Zhang et al. [7] are used to model energy awareness of occupant agents.

Table 1. Mean and standard deviation of consumer types

Consumer types	Mean μ	Standard deviation σ
Follower green	0.74	0.041
Concerned green	0.72	0.043
Regular waster	0.41	0.033
Disengaged waster	0.25	0.057

The action of turning appliances ON/OFF is defined by the function TO_a

$$TO_a : ac_{td} \rightarrow turnOn_a \tag{5}$$

$$ac_{td}, O_a, ea \rightarrow \{keepOn, turnOff\}_a \tag{6}$$

Every activity ac_{td} that the occupant performs is associated to an appliance a. When the occupant starts an activity, he/she turns ON the appliance associated to this activity. When the activity ends and based on the occupants energy awareness attribute, he/she may turn OFF the appliance or keep it ON. The occupant may also communicate with other occupant/s O_a who may be using the same appliance at the same time to decide whether to turn the appliance OFF. The action of turning OFF appliances is also executed every time an occupant visits a room and finds appliances that are ON but unused.

The action of turning lights ON/OFF is different from using appliances, because using lights depends on the amount of daylight and the location of occupants.

$$TO_r : r_{td}, daylight_{td} \rightarrow \{turnOn, !turnOn\}_r \tag{7}$$

$$r_{td}, O_r, ea \rightarrow \{turnOff, !turnOff\}_r \tag{8}$$

Every time the occupant is in a room r_{td} he may decide to turn ON the light in this room based on the amount of daylight ($daylight_{td}$) [4]. When the occupant leaves the room, he/she checks other occupants in the room O_r, and based on his energy awareness (ea) he/she may decide whether to turn off the light.

In summary, the occupant agent **OA** is defined using the set $<age, emp, wr, op_d, os_{td}, ea, AC_{td}, TK_{td}, r_{td}>$ and can perform the actions $<OS, AC, OL, TO_a, TO_r>$ to act in the house environment.

The model was implemented in Repast Simphony (https://repast.github.io), a Java-based agent-based platform. For validation of the model refer to [11]. Three appliances were implemented: Lights, TV, and PC. These appliance are clearly affected by the energy awareness of occupants like leaving lights ON when leaving a room or leaving the TV/PC ON when the activity ends.

4 Simulation Experiments and Results

This section presents a set of experiments that were done to study the effect of social parameters on the energy consumption of the house with various occupants energy awareness. Every simulation run (or scenario) calculates the average energy consumption of 100 simulated households of the same type, but different work routines, income, appliances number and types, and house rooms.

The energy awareness of occupants is reduced to two types: *Follower Green* and *Disengaged Waster* in order to limit the number of scenarios, while achieving the objectives of this study. The validation of the model which includes all occupant types can be found in [11]. A total of 244 scenarios were tested; for every simulated scenario the total amount of energy per day for three appliance types (lights, TVs, and PCs) is calculated using the formula:

$$C_n = \sum_{t,d,a} \overline{c}_{td} \tag{9}$$

where C_n is the total energy consumption of scenario n and $\overline{c}_{td}$ is the average energy consumption at time step t and day d. In order to calculate the energy efficiency of each scenario, the distance to the ideal energy saving behaviour D_n is calculated using the formula:

$$D_n = \frac{C_n}{C_{base}} \tag{10}$$

where, C_{base} is the total energy consumption in the ideal scenario where devices are only ON when they are being used. As much as D_n is closer to 1 means that the household is closer to the ideal scenario, thus more efficient. In the below experiments, family size, employment type, and occupants' ages are the tested social parameters. These parameters were selected, because they are available in the real data provided in the PM. Other social parameters can be included if the corresponding real data are available.

4.1 Experiment 1: Effect of Family Size

This experiment is intended to study the effect of number of occupants in the house. Scenarios of the age group 25–39 in full-time job are presented in Table 2. The table consists of two groups of scenarios, each group has the same age and employment type for adults, same energy awareness type, but different number of occupants. In the first group of scenarios, where all family members are green occupants, it is observed that as the number of occupants increases, D_n decreases. This means that more green occupants in the house makes the family more energy efficient. For the second group of scenarios, where all occupants are energy wasters, it could be expected that when the number of wasters increases, D_n should increase. However, it is observed that as the number of wasters increases, D_n decreases and the family is closer to the ideal scenario. This indicates that more occupants in the house, whether they are green or waster occupants, causes the house to be more efficient. Similar observations were noticed for other age groups and employment types.

Table 2. Scenarios and results for the effect of family size

Adults age group/empl. type/energy awareness	No. of occupants	Household type	D_n
25–39/full-time job/All *Green* occupants	1	One adult	2.31
	2	One adult, one child	1.97
	2	Two adults	1.99
	3	One adult, two children	1.42
	3	Two adults, one child	1.58
	4	Two adults, two children	1.59
25–39/full-time job/all *Waster* occupants	1	One adult	10.49
	2	One adult, one child	6.13
	2	Two adults	6.66
	3	One adult, two children	3.92
	3	Two adults, one child	4.18
	4	Two adults, two children	4.17

4.2 Experiment 2: Effect of Employment Type

The purpose of this experiment is to test the effect of employment type on the energy consumption of the house. In order to do that, it is important to fix occupants ages and number of occupants while varying the employment types. Therefore, based on the household types available in the PM, it is only possible to study the effect of full-time, part-time, and unemployed occupants. Table 3 represents the scenarios for age group 40–45. The Occupant Types column encodes the energy awareness of occupants where G refers to green occupants and W refers to waster occupants. The sequence of letters (G and W) has the same sequence of occupants defined in the previous columns.

For every household type, the first two occupants (which are full-time/part-time or full-time/unemployed) are involved in the energy awareness variation, while the rest are put all green or all waster occupants in order to observe the effect. The difference between every two varied scenarios is calculated in the last column. Among the total number of simulated scenarios, there are cases when two occupants belong to the same age group and have the same employment type. It was observed that swapping the energy awareness between these occupants resulted in similar amounts of energy consumption with very slight differences. This difference is expected to be due to random numbers generation. The average difference between these scenarios was calculated and found to be 0.1. Therefore, whenever the difference between two scenarios is more than 0.1, it is considered a significant difference and further analysis is made to identify the cause of the difference. The first three household types in Table 3 are for comparing full-time and part-time employment types. It is observed in all of these scenarios that whenever the part-time occupant is the green occupant, the energy consumption of the house is closer to the ideal scenario. This means

Table 3. Scenarios and results for the effect of employment type

Occupants age group/employment type				Occ. types	D_n	Difference
Occ. 1	Occ. 2	Occ. 3	Occ. 4			
40–54/full-time	40–54/part-time			GW	3.89	0.23
				WG	3.66	
40–54/full-time	40–54/part-time	12–17/school		GWG	2.33	0.1
				WGG	2.23	
				GWW	3.14	0.07
				WGW	3.07	
40–54/full-time	40–54/part-time	12–17/school	12–17/school	GWGG	1.88	0.05
				WGGG	1.83	
				GWWW	3.10	0.09
				WGWW	3.01	
40–54/full-time	40–54/unemployed			GW	3.05	0.37
				WG	2.68	
40–54/full-time	40–54/unemployed	12–17/school		GWG	2.12	0.24
				WGG	1.88	
				GWW	2.75	0.14
				WGW	2.61	
40–54/full-time	40–54/unemployed	12–17/school	12–17/school	GWGG	1.69	0.03
				WGGG	1.66	
				GWWW	2.62	0.15
				WGWW	2.47	

that green part-time occupants are responsible for improving the house energy consumption when compared to full-time occupants. A similar observation is noticed when comparing full-time and unemployed occupants in the next three household types. This observation was noticed in our previous paper [11] and is further supported in Table 3. Looking at the difference values, part-time occupants efficiency effect is significant (>0.1) in two cases: (1) the two-occupant family and (2) the three-occupant family when the third occupant is a green occupant. This indicates that part-time occupants can make an energy saving effect in small families (a small family is a family less than 4 occupants) and when there are more green occupants in the house, but not in big families where the difference is 0.05 and 0.09. However, for unemployed occupants, the efficiency effect is significant in most of the cases except for the four-occupant family when all of the other occupants are green occupants. It is also observed that unemployed occupants, in general, have higher effect than part-time occupants. These observations show that unemployed occupants are more efficient than part-time occupants, and the latter are more efficient than full-time occupants in small families.

4.3 Experiment 3: Effect of Occupants Ages

In order to study age groups for adults, households that have the same employment type and number of occupants with no children were considered (Table 4). As for the children effect, households with an equal number of adults and children, with the same employment type for adults were studied (Table 5). Table 4 shows that as the age of adults in small families increase, the household is becoming less efficient (both for waster and green households). And for children, it is observed in Table 5 that children were more efficient than adults in small families (0.26 and 0.1), but not in big families where adults were more efficient in some of the cases (−0.17). These observations imply that younger occupants including children can make more efficiency effect in small families but not in big families.

Table 4. Scenarios and results for the effect of adults ages in full-time job

Energy awareness	Occupant 1 age group	Occupant 2 age group	D_n
All green occupants	25–39		2.31
	40–54		2.47
	55–64		2.78
All waster occupants	25–39		10.49
	40–54		11.35
	55–64		13.29
All green occupants	25–39	25–39	1.99
	40–54	40–54	1.87
	55–64	55–64	1.85
All waster occupants	25–39	25–39	6.66
	40–54	40–54	6.68
	55–64	55–64	6.75

Table 5. Scenarios and results for studying the effect of children

Adults age group	Household type	Occupant types	D_n	Difference
25–39	One adult, one child	GW	3.94	0.26
		WG	3.68	
40–54	One adult, one child	GW	3.10	0.10
		WG	3.20	
25–39	Two adults, two children	WWGG	2.41	0.04
		GGWW	2.45	
40–54	Two adults, two children	WWGG	2.57	−0.17
		GGWW	2.74	

5 Discussion and Insights

This study proposes a methodology to combine ABM and PM to produce fine grained data. The implemented model simulates the dynamic interaction of occupants with appliances to produce detailed activities and energy consumption of houses. Opposed to exiting PM [3–5,12,13] the cascaded model simulates dynamic occupants behaviour which is affected by occupants personal characteristics and surrounding environment. In addition, an energy awareness level can be assigned at occupant level which varies based on the occupant's greenness level, while PM assume same and ideal energy consumption behaviour of occupants. The proposed model simulates energy waste caused by human behaviour. Existing ABM that simulate the effect of human behaviour [7,8,15] produce the consumption data at household or building level, however, the proposed model generates energy consumption data at appliance level as shown in our previous paper [11]. This is because exiting models either model consumer agents at household level or characterise occupant agents by yearly/monthly consumption. The most similar ABM in terms of output are Carmenate et al. [10] (hypothetical case study) and Zhang et al. [16] (real case study). These models can produce appliance level consumption and model energy awareness at occupant level. The difference is that the proposed model uses PM (embedded Markov Process technique) to get the realistic occupants activities as a preprocessing stage to ABM, while existing models use the real data directly in the ABM to simulate human activity. Using PM ensures that the produced data are realistic and enables the inclusion of data for a whole city (6400 respondent vs. 143 respondent in Zhang et al. [16]) which leads to more varied scenarios and generalised conclusions.

Besides the above discussions, the integration of PM with ABM has given the advantage of studying the effect of social parameters on the energy consumption of families. Experiment 1 showed that as the number of occupants increases, the household becomes more energy efficient even if all of the occupants are unaware of energy consumption. Although the implemented model does not model family pressure, which means that family members do not affect the energy awareness of each other, we have shown that merely having more occupants in the house makes the family more efficient (by more efficient we mean that big families waste less than small ones even though they actually consume more). This is explained by the fact that more occupants in the house means more probability that somebody turns off unneeded appliances/lights (knowing that occupant agents can know if a device is being used or a room is being occupied). For example, if one occupant, who lives alone, leaves the house/room while the lights are ON, the lights will never be OFF until he/she returns back to the location. However, in a four-occupant family, if a member leaves something ON and goes away, there is still a probability that somebody will turn it OFF before he/she returns back. The second experiment proved that unemployed occupants have the most efficiency effect in small families compared to part-time and full-time occupants. Whereas part-time occupants are more efficient than full-time occupants, again in small families. This is mainly explained by the occupancy pattern of each employment type, where unemployed and part-time occupants are available at home more than full-time occupants. This enables unemployed and part-time occupants to reduce the waste in small families. However, in big families, this effect is reduced due to the existence of more occupants in the house who may cancel the effect of the green occupant. A similar conclusion was obtained concerning ages of occupants, where younger occupants made the household more efficient in small families. It is important here to note that this conclusion does not imply that younger occupants are more aware than older occupants, but with the same energy awareness levels younger occupants' longer existence at home or longer active durations causes less energy waste than older occupants.

These conclusions are important as they give insights for policy makers and governments about how to target family members to achieve higher energy efficiency. The developed model shows that it is important to target all members of big families with energy efficiency interventions and technologies – not just because big families consume more energy in general, but also because increasing the energy awareness of all members of big families makes more effect than small families. Concerning small families, it is important to concentrate on younger occupants including children, and adults who are housewives, unemployed, carers, or those who work in part-time jobs, because we have shown that these types of people can make more efficiency effect than older occupants and full-time employees.

6 Conclusion and Future Work

This paper presented a methodology to cascade ABM and PM in order to generate detailed and accurate data. The proposed approach was applied on the energy consumption domain, however, it can be used to simulate other human behaviour applications. The energy consumption model incorporates energy awareness at occupant level and produces fine-grained data to simulate behavioural energy waste. The paper have shown that the cascading approach overcomes limitations of exiting PM and ABM when they work separately. Social parameters were varied to gain insights towards energy efficiency plans for families. It was concluded that bigger families cause less energy waste than small families due to the higher probability of somebody to turn OFF unneeded consumption. Besides, young, unemployed and part-time occupants can make more efficiency effect in small families than full-time and older occupants because they are more active at home. The model can be used in the future to study the effect of intervention technologies (e.g. energy waste notifications) or family pressure when varying social parameters. This will give insights about how to target and customise interventions for different types of occupants/households.

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An Agent-Based Collective Model to Simulate Peer Pressure Effect on Energy Consumption

Fatima Abdallah, Shadi Basurra(✉), and Mohamed Medhat Gaber

School of Computing and Digital Technology,
Birmingham City University, Birmingham, UK
{fatima.abdallah,shadi.basurra,mohamed.gaber}@bcu.ac.uk

Abstract. This paper presents a novel model for simulating peer pressure effect on energy awareness and consumption of families. The model is built on two well-established theories of human behaviour to obtain realistic peer effect: the collective behaviour theory and the theory of cognitive dissonance. These theories are implemented in a collective agent-based model that produces fine-grained behaviour and consumption data based on social parameters. The model enables the application of different energy efficiency interventions which aim to obtain more aware occupants and achieve more energy saving. The presented experiments show that the implemented model reflects the human behaviour theories. They also provide examples of how the model can be used as an analytical tool to interpret the effect of energy interventions in the given social parameters and decide the optimal intervention needed in different cases.

1 Introduction

Increased energy consumption generated from fossil fuels is causing high carbon emissions and increased global temperature which is mainly attributed to human actions rather than nature [1]. A significant part of the human effect is accounted for the residential sector which consumes high percentages of the world's electricity consumption (23–31%) [2]. Although many technological and structural improvements are suggested to decrease energy consumption, occupants' behaviour plays an important role in this matter [3]. A human solution is based on peer pressure, knowing that human actions are mostly affected by the behaviour of others [4]. Hence, it is suggested that policy makers work on stimulating peer pressure to encourage energy efficient behaviour.

This paper presents an Agent-Based Model (ABM) that studies the collective peer pressure effect on energy consumption in a family environment (hereafter family pressure). The occupant agent's peer effect behaviour is inspired by two theories of human social behaviour: *collective behaviour* by Granovetter [5] and *cognitive dissonance* by Festinger [6]. The model then adds two types of interventions that aim to enhance the occupants' energy awareness and thus reduce their

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consumption. The presented model offers a tool that enables analysing the outcomes of energy efficiency interventions in different social conditions. The paper is organised as follows. The next section presents related work including similar ABMs. The used human behaviour theories and available energy interventions are presented in Sect. 3.1. Section 4 presents the ABM that simulates family pressure and energy efficiency interventions, and explains how the behaviour theories were adapted to the application at hand. Section 5 presents the results of simulating a number of scenarios showing how the model can be used to determine the efficiency of interventions in these scenarios. Finally, Sect. 6 concludes the paper with a summary and pointers for future directions.

2 Related Work

Agent-based modelling is considered the most suitable technique to simulate social interaction [7]. An agent-based model is composed of a group of autonomous software components, called agents, which take decisions based on their state and rules of behaviour. The collective agents' decisions cause changes in the environment which is observed and analysed [8]. The technique has been widely used to study occupants energy consumption behaviour.

Among existing ABMs, there are few that simulate occupants' behaviour change due to peer effect. Azar and Menassa [9] propose a model that adds occupants' energy consumption characteristics and interaction to traditional energy simulation tools. The peer effect model is based on the level of influence of individuals and the number of occupants in each level of consumption. However, the used behaviour change model is not theoretically grounded. Models that involve human behaviour simulations need to be validated using huge amounts of real data, and if not available, need to be based on well established and accepted human behaviour theories. Another ABM that simulates social interactions is Chen et al. [10] who explore the effect of peer network structures on the energy consumption in a residential community. The occupant agents decrease their consumption when the consumption of connected occupants is less than that of the agent. On the other hand increasing the agent's consumption is based on a constant probability that represents the percentage of occupants who increase their consumption with no effect from peers. However, it is more logical that peer effect happens in both directions so that high energy consumers may affect others and cause them to increase their consumption in the same way low energy consumers may affect others. Network structures were also studied in Azar and Menassa [11] which is applied in an office environment. The model uses the relative agreement theory which is applied in a community of heterogeneous culture and values. Thus, behaviour change starts between close individuals. However, in a family environment, which is the case in the current paper, it is common that family members have similar culture and values. Therefore, other behaviour change theories need to be applied which will be detailed in Sect. 3.1.

Studies in [10,11] vary the structure of peer networks based on the fact that not all individuals in a community are connected. While in a family environment, family members are always connected at least at night. Therefore, in the current model, the agents are structured in a fully connected network. Another difference between the currently proposed model and existing models [9–11] is related to the occupant awareness modelling. Existing models characterise occupants by one attribute which is the average yearly/monthly consumption. This attribute does not only reflect the awareness of occupants, but also the time they spend in the building. Hence, it is hard to distinguish if high energy consumption is due to low awareness or daily occupancy. However, the proposed model separates daily human behaviour of occupants (which is based on social parameters) from their energy awareness. More details will follow in Sect. 4.

3 Background: Behaviour Change Theories and Energy Interventions

3.1 Behaviour Change Theories

Humans beings can be highly affected by the behaviour of others. Based on this observation, the theory of collective behaviour was formalised in Granovetter's threshold model [5] to explain the diffusion of a behaviour due to social contagion. The model follows a simple decision rule, where individuals choose to adopt a behaviour when the percentage of others doing the behaviour exceeds a threshold. This threshold represents a complex combination of norms, values, motives, beliefs, etc. Once the threshold is exceeded, it is considered that the net benefit of the behaviour exceeds the perceived costs. The threshold model has been widely used in several applications such as effective targets to influence collective behaviour [12]. The other human behaviour theory used in this model is cognitive dissonance by Festinger [6]. Dissonance is defined as the inconsistency that happens between the individual's knowledge, opinion, beliefs, or attitudes, which are the cognitive factors that drive behaviour. Based on the fact that dissonance is uncomfortable, Festinger [6] proves that humans try to reduce it by adapting their behaviour or changing one or more of the cognitive factors. One of the major sources of dissonance are social groups. Therefore, observing others doing a behaviour that is very different from the individual's behaviour or spreading a general belief that a specific behaviour is not accepted, drives members of a social group to adapt their behaviour, thus reducing the uncomfortable dissonance. Besides, as the magnitude of dissonance increases, it is expected that the tendency to reduce it will increase. The magnitude of dissonance is affected by (1) the number of others who hold a different behaviour, and (2) the level of difference between the individuals' behaviours.

3.2 Energy Efficiency Interventions and Peer Pressure

Given the high percentage of energy consumption in residential buildings, research and policy makers efforts have been focused on promoting energy efficient behaviour, technologies, and structural improvements. This paper is focused on the behavioural aspect by modelling energy efficiency interventions. The target of interventions is to motivate occupants to adopt energy efficiency behaviour by working on their values, attitudes, beliefs, and knowledge [13]. Interventions can be of many forms such as goal setting, information (workshops, mass media campaigns, and home audits), rewards, and feedback [13]. In many occasions, these interventions take advantage of the peer pressure effect by comparing ones behaviour with the behaviour of others. Peer pressure is the influence that members of the same community have on each other which leads to change in behaviour. This effect is shown to be the most influential reason of environmental behaviour change [4]. This is because information received from personal relationships are better recognised and remembered than other sources of information [14].

4 Methodology

4.1 The Agent-Based Model

The proposed family pressure model is based on the ABM developed in Abdallah et al. [15,16]. The model simulates energy consumption behaviour of families. Every occupant is represented by an agent that acts in a house environment and interacts with appliances. The inputs of the model are the social parameters including family size, ages, and employment types (full/part-time job, unemployed, retired and school). Besides, the energy awareness type of occupants determines the probability of performing energy saving actions (e.g. turning off devices when not in use). This can be one of four types: ‘Follower Green’, ‘Concerned Green’, ‘Regular Waster’, and ‘Disengaged Waster’. Each of these types is reflected in the model as a continuous attribute called ‘energy awareness’ between 0 and 100 based on a normal distribution as shown in the 2^{nd} and 3^{rd} column of Table 1.

Table 1. Mean and standard deviation of awareness types

Awareness type	Mean μ	Standard deviation σ	Value (a)	Abbreviation	Category
Follower Green	0.74	0.041	1	F	Green
Concerned Green	0.72	0.043	2	C	Green
Regular Waster	0.41	0.033	3	R	Waster
Disengaged Waster	0.25	0.057	4	D	Waster

The ABM is supported by probability distributions from an integrated probabilistic model based on large sets of real data. The distributions are used to generate realistic occupancy and activities based on the given social parameters. The simulation time is determined by the day of the week (d) and 144 time steps per day (t) each representing 10 min. During the simulation, the occupant agent selects an occupancy state (os_{td}) which can be *away*, *active* at home, or *sleeping*, for a duration (dr). The occupancy state is selected based on the occupant's previous state $os_{(t-1)d}$, *age*, employment type (*emp*), day (d), and time (t) as shown in functions (1) and (2). When the occupant agent is *active* at home, it performs activities from the following set {*Using the computer, Watching television, Listening to music, Taking shower, Preparing food, Vacuum cleaning, Ironing, Doing dishes, Doing laundry*}. The decision of doing an activity for a specific duration (dr) depends on the occupant's *age*, employment type (*emp*), day (d), and time (t) as shown in function (3).

$$OS : age, emp, os_{(t-1)d}, t, d \rightarrow os_{td} \tag{1}$$

$$age, emp, os_{td}, t, d \rightarrow dr \tag{2}$$

$$AC : age, emp, t, d \rightarrow ac_{td}, dr \tag{3}$$

Every activity that the occupant performs is associated to an appliance a. Appliances are modelled as dummy agents that only react to occupant agents actions (turn ON and OFF). When the occupant agent starts an activity, it turns the associated appliance ON. When the activity ends, it chooses to turn the appliance ON or OFF based on its energy awareness attribute (ea) and any other occupant (O_a) who is sharing the same appliance according to functions 4 and 5. For more details about the previous model, readers are referred to [15,16].

$$TO_a : ac_{td} \rightarrow turnOn_a \tag{4}$$

$$ac_{td}, O_a, ea \rightarrow \{keepOn, turnOff\}_a \tag{5}$$

4.2 The Family Pressure Model

The family pressure model is composed of two sub-models: behaviour change sub-model, and energy efficiency interventions sub-model.

Behaviour Change Sub-Model. The occupants behaviour change is motivated by Granovetter's threshold model [5] such that the occupant agents change their behaviour when a threshold is exceeded. Although Granovetter's model explains the effect of social pressure on behaviour, it does not fit to the family pressure effect on energy efficient behaviour for two reasons. First, the model is applied in a public community which has different values and motives, therefore different thresholds. However in a family setting, we consider that family members have similar values and motives based on the fact that they have chosen to live together or were raised together. Therefore, when adapting Granovetter's model to the application at hand, we consider one global threshold for the whole family. This does not revoke the fact that people react differently because we have set the global threshold as a probabilistic one [17] – so once the threshold is exceeded the individuals adopt the behaviour with a probability. Second, the threshold model considers binary decisions. However, energy consumption behaviour is a continuous behaviour that is performed at different levels.

This difference led us to explore the well-established theory of cognitive dissonance by Festinger [6] which is used to adapt the threshold model to the energy consumption application. Based on the two factors that affect the magnitude of dissonance outlined in Sect. 3.1, we adapt the definition of the threshold to fit the energy consumption behaviour. The first factor goes along with Granovetter's threshold definition such that more adopters of a given behaviour leads to changing others' behaviour. The second factor is used to overcome the inapplicability of the threshold model with the energy efficiency behaviour being continuous. Therefore, we define the threshold as the difference between the individual's awareness type and the average of other's awareness types.

The time step in this model is set to 4 weeks of simulation time since individuals usually take time to observe the behaviour of others. In order to express awareness types in numerical values, every awareness type is given an integer value as shown in the 4^{th} column of Table 1. For a family composed of N occupants, every time step T, each occupant agent i calculates the difference $diff_{Ti}$ between its awareness type a_i and the average awareness types of others a_j, where $j \in [1, N] : j \neq i$ using Eq. (6).

$$diff_{Ti} = a_i - (\sum_{j=1, j\neq i}^{N} a_j)/(N-1) \tag{6}$$

Behaviour change happens if $|diff_{Ti}|$ exceeds the global threshold d where $d \in [0, 4]$. A high threshold implies low sensitivity to cognitive dissonance and a low threshold implies high sensitivity to cognitive dissonance. The global threshold d is a probabilistic threshold such that the occupant changes behaviour with probability p where $p \in [0, 1]$. This attribute is referred to as threshold lag [18] which explains the stochastic nature of human behaviour due to uncertainty and differences in the speed of reaction, where a higher value of p means a higher rate of change. p is set to 0.5 as a middle point between high and low rate of change throughout the simulations in this paper. Once behaviour change is decided, the awareness type of the occupant changes towards the average of other's awareness types assuming that the occupant is adapting her/his behaviour to be similar to others. Behaviour change is done by stepping between the awareness types one step at a time either to the green side (green effect) or the waster side (waster effect). The behaviour change process step is outlined in Algorithm 1 which is repeated for every agent i at every time step T.

Energy Efficiency Interventions Sub-Model. This paper distinguishes between family-level interventions, and occupant-level interventions. Each of these interventions can be of any form as outlined in Sect. 3.2, but they differ in the number of occupants to target. The family-level intervention targets the family in general by changing its overall norms, values and beliefs. It can be applied by promoting the energy efficient behaviour such as giving financial incentives or repressing the wasting behaviour such as incurring charges [12]. The occupant-level intervention targets the least aware occupant/s in the family

Algorithm 1: Behaviour Change Step

```
calculate diff_Ti using equation (6)
if |diff_Ti| ≥ d then
    select random number rand
    if rand ≤ p then
        if diff_Ti > 0 then
            a_i = a_i − 1
        else
            a_i = a_i + 1
```

Algorithm 2: Intervention Behaviour Change Step

```
calculate diff_Ti using equation (6)
if diff_Ti > 0 then
    if |diff_Ti| ≥ d_g then
        select random number rand
        if rand ≤ p then
            a_i = a_i − 1
if diff_Ti < 0 then
    if |diff_Ti| ≥ d_w then
        select random number rand
        if rand ≤ p then
            a_i = a_i + 1
```

and leads to increasing their awareness levels. These two types of interventions are considered to observe how the collective family pressure can help in achieving more aware occupants, thus less energy consumption. It also allows policy makers to decide the needed combination and intensity of interventions based on each family composition (in terms of awareness levels and social parameters).

When the family-level intervention happens, the overall norms, values and beliefs of the family change. The family-level intervention has two intensities which represent the efficiency or effort made to achieve better results. Therefore, $I_p \in [1, 4]$ is defined as the promotion intensity and $I_r \in [1, 4]$ as the repression intensity. These two types of family-level interventions are reflected by two thresholds: one that affects the promotion of green effect $d_g \in [0, 4]$ and another that affects the repression of waster effect $d_w \in [0, 4]$. Therefore, the intervention increases d_w by I_r thus increasing the cost to adopt waster behaviour and/or decreases d_g by I_p thus increasing the benefit of adopting the green behaviour as outlined in Granovetter [5]. d_g and d_w change in effect of the intervention based on Eqs. (7) and (8) given the initial threshold d. For deciding behaviour change, d_g is checked when there is a possibility to change towards the green side ($\mathit{diff}_{Ti} > 0$), and d_w is checked when there is a possibility to change towards the waster side ($\mathit{diff}_{Ti} < 0$) as shown in Algorithm 2. The occupant-level intervention does not change the threshold of the family because it targets specific occupants. It aims to change the awareness of occupants while the regular behaviour change step in Algorithm 1 is applied. The intervention can have an intensity $I_o \in [1, 3]$ and can be applied to a member of the family i at a specific time step T according to Eq. (9).

$$d_g = d - I_p \quad : \quad d_g \in [0, 4] \tag{7}$$

$$d_w = d + I_r \quad : \quad d_w \in [0, 4] \tag{8}$$

$$a_{i(T+1)} = a_{iT} - I_o \quad : \quad a_{iT} \in [0, 4] \tag{9}$$

5 Experiments and Discussion

This section presents a number of experiments with different input parameters to show how varying these inputs can result in different intervention outcomes. It is worth to mention that this paper only presents a number of significant scenarios as a proof-of-concept while achieving the purpose of the paper. Abbreviations of awareness types (5^{th} column of Table 1) are used to identify the initial awareness of the family, such that a four occupant family with one 'Follower Green' and three 'Disengaged Wasters' is denoted by *FDDD*. In every simulation run, 100 households were simulated to capture the stochastic effect of the threshold lag[1]. The scenarios are run for a year and the resulting average yearly consumption and converged awareness types are recorded. These types were categorised based on the number of *Green* occupants in the family (represented in the figures by different colours in the bars). The categories of the awareness types are determined by the last column of Table 1.

5.1 Family Pressure Convergence

The aim of this experiment is to observe the resulting awareness types as an effect of family pressure based on different thresholds. Figure 1 shows the results of three scenarios: (a) *FFFD*, (b) *FCRD*, and (c) *FDDD*. The last scenario of every bar graph (d = 4) shows the initial category of the family because $diff_{Ti}$ can be maximum 3, thus no change in awareness types.

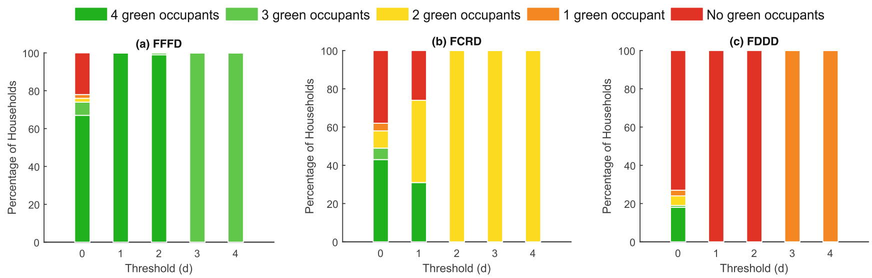

Fig. 1. Family awareness types convergence (Color figure online)

In scenario (b), the family remained with two green occupants at thresholds 2 and 3, besides, in (a) and (c) the family remained the same at threshold 3 and changed only one occupant at threshold 2. This indicates that the family does not change significantly when the threshold is high (d = 2 and 3). However, at low thresholds (d = 0 and 1), the family converged mainly towards the dominant awareness type. For example, in (a) the convergence was mostly towards '4

[1] The model was validated by running a number of scenarios with different random numbers seed where the results came out to be similar.

green occupants', because initially there were three green occupants. A similar observation was noticed in (c). In scenario (b) where there is no dominant awareness type, the convergence was with equal probabilities either to all green occupants or all waster occupants ('no green occupants' category) with higher convergence to the extremes at threshold 0. These results indicate that the proposed model reflects the theory of cognitive dissonance and collective behaviour which agree that people tend to change their behaviour to conform with the behaviour of others. It is worth noting that in (a) and at threshold 0, around 20% of the households converged to 'no green occupants'. This means that the only waster occupant succeeded to change the behaviour of the other three green occupants. This phenomenon is explained in the cognitive dissonance theory which states that dissonance can be reduced by either adapting with others, or convincing the others to adapt with the individual. This explains how the three green occupants converged to wasters in effect of one waster occupant as in (a) and vice versa in (c). Festinger [6] mentions that in this case, the overall cognitive elements of the surrounding environment change, but this is easy when the individual can find others who hold the same behaviour, which explains the low percentage of this convergence (20% in our experiment).

5.2 Family-Level Intervention

In this experiment, family-level interventions are applied to scenario (c) of the experiment 1 (FDDD) as it has the most waster occupants after convergence. For each threshold, the possible intensities of family-level interventions are applied keeping the thresholds d_g and d_w in their limits $[0, 4]$. The aim of this experiment is to show the effect of promotion and repression interventions when varying their intensities. Figure 2 shows the results with initial thresholds 0, 1 and 2.

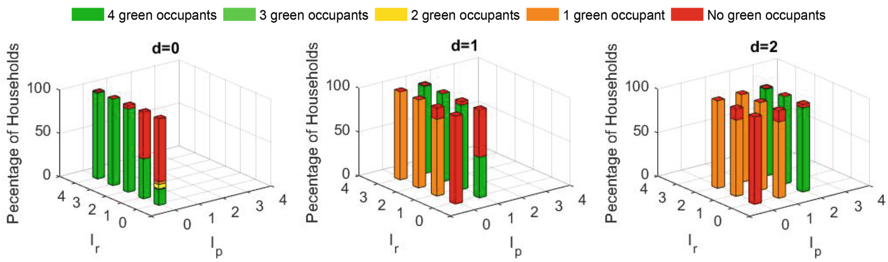

Fig. 2. Family-level intervention convergence (Scenario FDDD)

It is noticed at thresholds 1 and 2 that the number of green occupants increases as the promotion intensity (I_p) increases, which is not the case with repression intensity (I_r) where most of the occupants stayed wasters. This indicates that repression intervention is less efficient than the promotion intervention. This is attributed to the high number of waster occupants, such that encouraging them to adopt the green behaviour is more effective than repressing the only green occupant from getting affected by waster occupants. Another indication from varying intervention intensities is inferring the minimum intensity needed to increase the possibility of getting 4 green occupants. For example at threshold 0, repression intensity 2 is enough to get '4 green occupants' with probability more than 0.95. This allows to identify the minimum effort needed while achieving the maximum number of green occupants.

5.3 Occupant-Level Intervention

This experiment studies the effect of occupant-level interventions which directly change the awareness of least aware occupants. Scenario FFFD with threshold 0 is selected to get the minimum intensity required to prevent the 'no green occupants' convergence (as shown in scenario (a) in Sect. 5.1). As the family initially has one waster occupant, the intervention is applied for one occupant with different intensities. Besides, the intervention can be applied at specific times of the year, therefore it can be an 'early intervention' at $T = 2$, 'mid-year intervention' at $T = 6$ or 'late intervention' at $T = 9$. This determines the best intervention time just before the waster occupant affects other green occupants. Figure 3 shows the results while varying the intervention time and intensity.

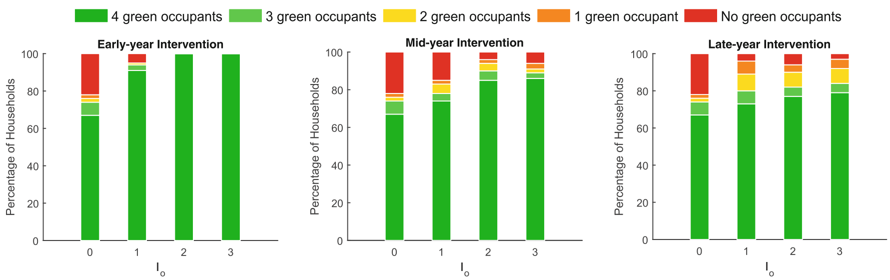

Fig. 3. Occupant-level intervention convergence (Scenario FFFD d = 0) (Color figure online)

It is observed that as earlier the intervention and as higher its intensity, as more green occupants are obtained. The early interventions with intensities 2 and 3 are the most effective with no waster occupants after a year. This is expected because the waster occupant is affected by the external intervention at an early stage, thus leading to 4 green occupants. However, in all other scenarios, waster occupants are observed even at higher intensities. This shows that one intervention per year is not enough to make an impact on families with only one waster occupant. This suggests to perform continuous interventions to maintain the green effect and combine them with family-level interventions. Note the this experiment was performed with very low threshold of the family ($d = 0$) so occupants can easily influence each other.

5.4 Effect of Interventions on Families with Varied Social Parameters

In our previous paper [16], it was concluded that social parameters affect the energy waste of the family. Although the previous model does not simulate family pressure, we showed that energy waste in large families is less than small families. On the basis of this conclusion, the current experiment tests if a family-level intervention is more efficient in big families than small families. For this purpose, the family-level intervention is applied on (a) a two-occupant family and (b) a four-occupant family. Figures 4a and b show the awareness types convergence of scenarios (a) and (b) respectively with an equivalent initial numbers of green and waster occupants (FD and FFDD) and threshold $d = 0$. Figure 4c shows the resulting energy saving percentage when compared to the no-intervention scenario ($I_r = 0$) and the convergence time which is the time it takes the family to reach a stable state where the occupants are no more affected by each other.

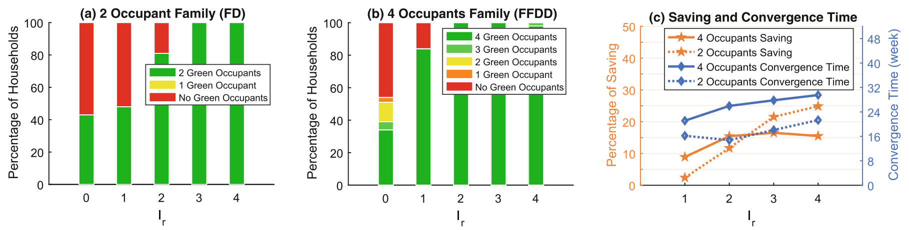

Fig. 4. Effect of Family-level intervention on two and four occupant families (d = 0) (Color figure online)

In Fig. 4c at intervention intensities 1 and 2, the percentages of saving for big families are 9% and 16% respectively, which are more than that of small families (i.e. 1% and 11%). This is also observed in the awareness types convergence (Figs. 4a and b) where the '4 green occupants' category is more dominant in (a) than the '2 green occupants' category in (b). However, at intensities 3 and 4, the savings of small families are 21% and 25% respectively, which dominates that of big families (i.e. 16% and 15%) (Fig. 4c). Besides, all of the occupants in scenarios (a) and (b) converged to green occupants as shown in Figs. 4a and b. This is explained by the lower convergence time of small families (Fig. 4c). This means that a higher intensity intervention converges small families quicker than big families which consequently leads to higher saving. Thus, the family-level intervention can result in maximum saving at low intensity in big families as opposed to small families. While a high intensity intervention is more efficient in small families as it leads to a larger and quicker saving than big families. This experiment can be repeated with varied social parameters, thresholds, and intervention types to obtain the most efficient intervention in every case.

5.5 Discussion

The model proposed in this paper simulates peer pressure effect on energy awareness levels and consumption of families. The peer effect behaviour of occupants is based on two human behaviour theories opposed to other models that do not use existing theories [9]. The behaviour theories were adapted to comply with the energy consumption behaviour and family environment, while other models use different theories that simulate office environments [11]. Beside, the current model offers different options of input including social parameters (family size, employment types, ages), awareness levels, values and beliefs that affect the energy consumption behaviour, and intervention options. We proved in the experiments that these inputs affect the outcome of interventions. The experiments focused on demonstrating the application of the model in pre-specified scenarios. The model can ideally be used to study the impact of any intervention planned by governing bodies on the outcome (i.e. energy saving). This can be done by estimating unknown parameters, running the model with initial parametrisation of known and unknown parameters. Then a search mechanism (e.g. grid search) is applied to best estimate the unknown parameters, minimising the difference between the model's synthesised data and the observed real data. If the search space is large, in case of having too many unknown parameters, computational intelligence methods like *Genetic Algorithm* can be applied. Revealing these unknown parameters can help in determining the reason why interventions are effective in some cases, but not in others.

6 Conclusion and Future Work

This paper presented an ABM that simulates energy awareness peer pressure in a family setting. The model uses the *collective behaviour theory* and the *theory of cognitive dissonance* to reflect realistic peer effect. Different energy efficiency interventions can be applied and the resulting awareness types and savings are observed. The presented experiments show that the human behaviour theories are well-reflected in the model. Besides, they show how the model can offer an analytical tool for governing bodies to analyse the effect of interventions and make decisions of how to target different families to get the best results.

A variation of this model is to make the effect of members depend on how often they are in contact in the house, which makes the interaction more realistic. This can be easily achieved because the ABM simulates individuals' daily availability at home in a 10-minute time step. The current model have not considered a weighting attribute which determines the level of relation between the occupants which affects the level of influence. This attribute can be added in the future where the intervention may be targeted at a specific relationship if it proves efficient. Also the modelling of behaviour change can be done at the energy awareness level, not at the awareness type level. This can enhance model's capability to simulate more fine-grained behaviour change. These enhancements are expected to produce an even more realistic model that reflects the quality and rate of daily interactions among the family members.

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A Non-Intrusive Heuristic for Energy Messaging Intervention Modeled Using a Novel Agent-Based Approach

FATIMA ABDALLAH, SHADI BASURRA, AND MOHAMED MEDHAT GABER
School of Computing and Digital Technology, Birmingham City University, Birmingham B4 7XG, U.K.

Corresponding author: Fatima Abdallah (fatima.abdallah@bcu.ac.uk)

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ABSTRACT In response to the increased energy consumption in residential buildings, various efforts have been devoted to increase occupant awareness using energy feedback systems. However, it was shown that the feedback provided by these systems is not enough to inform occupant actions to reduce energy consumption. Another approach is to control energy consumption using automated energy management systems. The automatic control of appliances takes out the occupant sense of control, which is proved to be uncomfortable in many cases. This paper proposes an energy messaging intervention that keeps the control for occupants while supporting them with actionable messages. The messages inform occupants about energy waste incidents happening in their house in real time, which enables occupants to take actions to reduce their consumption. Besides, a heuristic is defined to make the intervention non-intrusive by controlling the rate and time of the messages sent to occupants. The proposed intervention is evaluated in a novel layered agent-based model. The first layer of the model generates the detailed energy consumption and realistic occupant activities. The second layer is designed to simulate the peer pressure effect on the energy consumption behavior of the individuals. The third layer is a customizable layer that simulates energy interventions. The implemented intervention in this paper is the proposed non-intrusive messaging intervention. A number of scenarios are presented in the experiments to show how the model can be used to evaluate the proposed intervention and achieve energy efficiency targets.

INDEX TERMS Agent-based modeling, energy consumption, energy efficiency, energy feedback system, energy interventions, energy management system.

I. INTRODUCTION

Global electricity consumption is experiencing a continuous increase over the past decades with a focus on electricity generated from fossil fuels [1]. This increase in energy consumption is leading to climate change effects, which are highly attributed to human activities [2]. In response to this human effect, the European Commission recommended that end-users will need to play a major role in reducing energy consumption in buildings [3]. Therefore, many efforts have been made to make energy consumption in buildings tangible using energy consumption feedback systems. These systems are considered one of the energy interventions that aim to change occupants energy consumption behavior. Existing feedback systems suffer from abstract data, which is not usually understood by occupants and does not inform their actions to reduce consumption [4]. Besides, technological advancements enabled the development of smart energy management systems that provide the infrastructure to monitor and control consumption. The main approach of these systems is to control appliances on behalf of occupants, which was proven to breach their comfort [5]. This paper introduces a non-intrusive messaging intervention that takes advantage of exiting sensing and analysis technologies to send real-time sensible messages to occupants. The messages help occupants to be informed about energy waste incidents happening in the house, and thus take actions to reduce it. The intervention is designed to be non-intrusive by proposing a context-aware heuristic that control the time of the messages and their number per day based on the occupants location, activity and interest in the information.

In order to test the effectiveness of the intervention, we propose a novel layered Agent-Based Model (ABM). The model generates consumption data based on occupant activities, which makes the data more realistic and enables the detection of waste incidents. It also includes a layer that simulates the effect of peer pressure on the energy consumption behavior of occupants. In addition, a customizable layer for simulating and evaluating energy interventions is included. The messaging intervention is considered an example of these interventions, where any other intervention can be introduced and tested.

The paper is outlined as follows. The next section presents literature review related to energy efficiency including energy interventions, energy feedback systems and energy management systems. It highlights limitation in these approaches and presents the argument of automated and human controlled approaches. Section III presents existing ABM's showing the advantage of the layered ABM proposed in this paper. The details of the non-intrusive messaging intervention are presented in Section IV along with the technologies & techniques that enable its implementation in reality. Next, Section V details the layered ABM, which simulates the occupants daily behavior, peer pressure, and the messaging intervention. Section VI presents the results of simulating a number of scenarios to show how the model can be used to evaluate energy interventions. The results discussion is presented in section VII, and finally, section VIII concludes the paper and suggests future directions.

II. RELATED WORK: ENERGY EFFICIENCY

A. ENERGY EFFICIENCY INTERVENTIONS TO CHANGE OCCUPANT BEHAVIOUR

One of the approaches to address the energy consumption problem in buildings is to influence occupants' energy consumption behavior through interventions. Interventions are defined as the interruption of peoples' normal behavior [6] by changing their values, attitudes, beliefs, and knowledge to motivate them to adopt an energy efficient behavior. Existing interventions include commitment, goal setting, information (workshops, mass media campaigns, and home audits), modeling, incentives, and feedback [7]. The effect of these methods on peoples' knowledge and energy consumption vary based on the intervention mechanism, and combining them can result in more reduction [7].

Energy interventions may directly or indirectly affect occupant behavior, while the resulting behavior can be a one-time action/decision, or a continuous behavior that needs to be practiced all the time. Therefore, targets of interventions include raising awareness and pro-environmental motivation of energy consumers, encouraging one-time energy efficiency practices such as (1) buying energy efficient appliances, (2) using renewable energy, (3) encouraging energy conservation (turn off appliances, eliminate stand-by consumption, line drying, etc.), and (4) applying demand side response that involves reducing consumption during peak-times [8]. The intervention introduced and tested in this paper targets continuous direct behavior including energy conservation and demand side management practices. Furthermore, it is considered an enhancement of feedback systems among the different intervention types. The next section explains in details the purpose, types, and limitations of existing feedback systems.

In many occasions, energy interventions take advantage of the peer pressure effect knowing that human behavior is highly affected by the behavior of others [9]. Peer pressure is the influence that members of the same community have on each other, which leads to change in behavior when comparing ones behavior with the behavior of others. This effect is shown to be the most influential reason of environmental behavior change [9]. This is because information received from personal relationships are better recognized and remembered than other sources of information [10]. In this paper, we add the peer pressure effect to the simulation model used to test the messaging intervention as one of the factors that affect human behavior. This helps make the model more realistic and reflects the normal human behavior.

B. ENERGY CONSUMPTION FEEDBACK SYSTEMS

As mentioned in the previous section, feedback is one of the interventions that aims to help occupants save energy. Consuming energy is considered abstract and invisible because it is used indirectly to perform daily tasks [11]. Therefore, it is agreed that giving people information about the amount they are using makes them aware of their consumption and ultimately allows them to control it. Direct feedback is available in various forms including meter reading, direct and interactive feedback via monitors, pay-as-you go meters, plug/appliance meters [6]. However, with the advancements in sensor and communication technologies, direct and interactive feedback is now the most common [12]. For example, in response to the European Commission plan to reduce 20% of the Union's energy consumption [3], the UK has installed 8.5 million smart meters (along with feedback displays) so far up to 2017 [13].

Energy feedback displays have been widely researched to study their effectiveness and users interaction with them. For example, the effectiveness of simple energy displays (stationary and portable) was investigated in [14]. The study shows that energy displays resulted in an average of 11% energy reduction and increased the energy awareness of occupants. Besides, commercial feedback systems were assessed qualitatively in Hargreaves *et al.* [15] by asking people about the motivation of earning display systems, ways of usage, observed behavior change, and limitations of use. Along the same lines, Karjalainen *et al.* [16] systematically reviewed the different ways of presenting feedback. Several user interface prototypes were developed with varied comparison types, units of display, disaggregation levels, presentation types, and time scales. They found that presentation of energy costs, appliances consumption, and historical comparison are the most preferred by users.

Although these studies showed that feedback systems play a role in increasing occupants' awareness, many studies highlighted a number of limitations. For example, Strengers [4] observed that a considerable number of users struggled in understanding the displayed data and converting them to meaningful information. This is because the displayed data are absolute and not related to the surrounding context. The same conclusion was reported in [17] where people wanted more context such as occupancy and temperature to interpret high/low consumption levels. In response to this challenge, a number of studies suggest to relate energy consumption to daily activities either by annotating consumption graphs with activities [18], or using calendars as an artefact to help understand consumption [19]. Similarly, Castelli *et al.* [20] propose to use the location of appliances and occupants, which they call room context. This helps identify energy wastage, match consumption with occupant presence, and link consumption with everyday activities.

Despite that these efforts make more meaningful information, they still view users as micro-resource managers [4], [21] who are expected to analyze the displayed data and change their behavior such that it meets their preferences, everyday needs, and financial & environmental goals. Based on this, Pullinger *et al.* [21] identify one more specification for feedback displays, which is explaining what the information means in terms of behavior change. In addition to detailed energy consumption data, this service requires collecting environmental data and Artificial Intelligence (AI) analysis techniques, which are not provided by existing feedback systems. In this paper, we try to fill-in this gap by proposing the idea of an energy messaging intervention, which provides occupants with sensible messages that tell them what to do to reduce their consumption, instead of only giving them the amount of energy they are using. We identify the technologies and techniques available to collect and analyze the required data, and test the effectiveness of this approach in an innovative layered simulation model.

C. ENERGY MANAGEMENT SYSTEMS

Another approach to help understand and handle energy consumption in buildings are Energy Management Systems (EMS), which provide the infrastructure to monitor and control energy consumption. They are defined as the monitoring software, data collection hardware, and communication systems for the purpose of storing, analyzing and displaying the energy data of buildings [22]. These systems are often integrated with smart homes and home automation systems for the purpose of energy efficiency [23]. As an example, Kim *et al.* [24] propose a home EMS based on universal plug-and-play architecture. The main purpose of the system is to connect home appliances and mobile devices in one platform for the purpose of adjusting energy consumption based on real-time prices. The system automatically controls the activity or quality of service of appliances based on electricity price and a policy agreed on between the customer and the provider. The presented architecture allows users to control appliances using mobile devices. Similarly, Jahn *et al.* [25] present a smart home that embeds energy efficiency. It provides an intuitive interface that shows appliances usage, accumulated usage and cost on mobile devices, and allows remote control of appliances by the users. These two systems are good examples of the available platforms that help connect appliances and remote control services, however, they do not depend on any environmental data to ensure occupant comfort and understanding of the displayed consumption data.

To overcome this limitation, a number of EMS were proposed taking advantage of Wireless Sensor Networks (WSN) [26] and Internet of Things (IoT) [27]. These systems utilize data collected from environmental sensors (temperature, humidity, illuminance, etc.), user input (activities, preferences, etc.), and appliance-level energy consumption. We refer to these kinds of data as context data. AI algorithms are used to infer and analyze these data to detect the situation of the occupants and help them make decisions that comply with their comfort. An example of these approaches is by Dong and Andrews [28] who propose an algorithm to model and predict occupants presence using rich data patterns including motion, illuminance, temperature, humidity, etc. The predicted occupancy data are then used to set a dynamic schedule for cooling temperature while maintaining occupant comfort. Similarly, Agarwal *et al.* [29] provide the specifications of an accurate, low-cost, and easily deployable wireless sensor system which is also used to control the HVAC (Heating Ventilation and Air Conditioning) system of buildings.

EMS are not only designed to monitor and control HVAC systems, but also for other everyday appliances. One of these systems is GreenBuilding [30], [31], which combines monitoring and control of energy consumption. GreenBuilding provides a sensor-based infrastructure to reduce standby consumption, schedule flexible tasks, and control appliances to eliminate energy waste. These services are done based on rules set by the user and data collected by environmental sensors. A general architecture of an EMS that makes use of WSN is Sensor9K [26], the aim of which is to ease the development of energy efficiency applications. The architecture is composed of two layers: a physical layer that contains the sensors/actuators and ensures the communication between the components of the system, and a middleware layer that offers the basic functionalities of an EMS (such as monitoring consumption, detecting user presence, and profiling preferences), which can then be used by application developers. The architecture was tested with a temperature control case study. Within the effort to test the applicability of smart grids, PowerMatching City [5] was established as a living lab demonstration project. Smart grids refer to the infrastructure that ensures two way communication between providers and end-users to balance the supply and demand of energy. PowerMatching City project includes an EMS that automatically controls the operation of appliances to minimize costs and take advantage of renewable energy. More recently, an energy aware smart home system was proposed in [27]. The system controls lighting and appliances consumption automatically based on occupant presence and natural lighting. The paper ensures efficient communication among the system components through IoT technologies.

In relation to the messaging intervention proposed in this paper, existing EMS provide evidence of enabling technologies and algorithms necessary to produce the real-time sensible feedback. These details will be explored in details in section IV. However, the main approach in most of these systems is to utilize the collected data to act on behalf of the occupant. They follow the school of thought that considers that smart home control systems should be fully-automated, hence, it should predict user's changing preferences while maintaining comfort and achieving savings [32]. Another school of thought considers a smart home as a systems that engages its users in the energy management process, thus having well-informed and aware occupants. The argument of these two schools is detailed in the next section.

D. AUTOMATED VS. HUMAN CONTROLLED APPROACHES

While reviewing existing literature on energy management, it has been noticed that most EMS approaches utilize AI and sensors technologies to automate the control of energy consumption of the house/building. They explain this by the fact that encouraging people to adopt energy efficient behavior is not an easy job, therefore, acting on behalf of them, while maintaining their comfort and minimizing costs, will improve user experience. However, automatic control has been proven to take off the sense of control from people, which is mostly uncomfortable for humans [33]. For example, when asking users about their experience when using PowerMacthing City EMS [5], they reported the lack of control over the system. Participants preferred to interact with the system and actively participate in its decisions. Based on this feedback, the PowerMactching City project designers added semi-automatic and manual appliances control in its second phase [34]. They gave people advice of when is the best time to turn on appliances. In this case, users said that they gained back the sense of control over appliances, and with the time they learned how to achieve their energy efficiency goals. Thus, empowering users with information of how to reduce their consumption maintains their feel of comfort.

Apart from losing the sense of control, automation is not always the best solution for energy efficiency. For example, Zhang *et al*. [35] found that increasing the awareness of occupants is more efficient than applying an automated light management strategy. In addition, human behavior may sometimes oppose the automation like opening windows and doors when the heating is ON, or manually putting heavy appliances ON in peak times [36] especially if it happens that automatic actions interfere in occupants' important life functions [32]. Besides, installing technologies without informing users how to take advantage of them causes the limitation of energy reduction [37]. This applies specifically when the technology does not require user involvement and is usually referred to as rebound effect. When people perceive that a technology has the potential to save energy, it is proven that they change their behavior to achieve more comfort, which leads to less energy saving than expected [36], [38]. Therefore, giving occupants enough information of how to use the technologies and raising their awareness is more reliable than having a fully automatic system.

Along these lines, Leake *et al.* [39] suggest human centered computing paradigm to design smart homes, which uses a simple and transparent learning process. Therefore, in order to maintain human trust in the system and obtain informed and capable occupants, the system will need to interact with the occupants and provide explanations of its decisions. In addition, Geelen *et al.* [37] recommends to provide feedback that shows the occupants what behaviors need to be changed.

In this paper, we introduce an intervention that takes advantage of technologies used in existing EMS to trigger occupants' actions to reduce energy consumption. We suggest not to automatically control appliances, but rather to detect energy wastage and inform users about it. In this case users are supported with information about what and when actions are needed to control and reduce their consumption.

III. RELATED WORK: AGENT-BASED MODELS

This paper examines the effectiveness of the messaging intervention in a simulation model. The simulation approach was selected as an alternative to field experiments, which require launching the system in a real environment, collecting data for a period of time, and observing the interaction of occupants with the system. Although field experiments allow to capture real user experience, they have limited experimental variation and can only be studied for a limited period of time [40]. However, computer simulations allow more varied scenarios and long time frame for the study. It cannot be denied that simulation models are limited in capturing all the psychological aspect of the messaging intervention, however, we consider it as a first step for evaluating new ideas that could be implemented in the future. In this research, we use human behavior theories in simulation models to capture psychological aspects at a high level of granularity.

Agent-Based Models (ABM) is a computational system in which a group of autonomous software components, called *agents*, interact in an environment based on their rules of behavior, other agents around them and the state of the environment [41]. Rules of behavior are defined for agent,s which are allowed to act and interact in the environment in order to observe changes at the macro and micro-levels. In ABM, the agent has the following properties: (1) autonomy (not controlled externally but by its own rules), (2) social ability (interacts with other agents in the environment), (3) reactivity (responds to changes in the environment), and (4) pro-activity (uses the rules, interactions, and reactions to reach a specific goal) [42]. ABM is best used when agents' behavior is nonlinear (i.e affected by the surrounding environment), when agents' location is not fixed and when agents are heterogeneous [43]. These features of agents and ABM, make it the most appropriate technique to model human behavior and study the factors that influence it, and provides the rationale of selecting ABM compared to typical simulation techniques (such as discrete-event simulation and differential equations) which cannot model interactive systems [43], [44].

One of the applications of human dynamic behavior is energy consumption behavior in buildings. In such models, occupants are modeled as agents responsible for energy consumption in a building/house environment over a period of time. In order to add the human behavior aspect, the models characterize occupant agents by a personal attribute that determines its level of energy consumption. The way these models simulate the occupant agents behavior and define their personal characteristic affects the level of details the model can generate. Besides, some models aim to evaluate energy interventions, which change occupants characteristics. These models often focus on the peer pressure effect, which is a natural human behavior change factor.

A group of existing models generate the energy consumption data based on activities that the occupant agents perform in the building. For example, Carmenate *et al.* [45] developed an ABM to determine the causes of behavioral energy waste in an office environment. The model simulates the complex interaction between occupants, building units and appliances. The energy consumption of the office is generated based on the activities occupant agents perform in the building and their energy literacy level. Similarly, Zhang *et al.* [35] simulate occupant activities in a university building to test the effectiveness of an automated light management strategy opposed to the manual strategy. They categorize occupant agents into 4 agent types, which determine their energy saving awareness, and found that the manual strategy can be more efficient when increasing occupants awareness. This activity-based type of modeling ensures that the resulting energy consumption is accurate in comparison to other modeling techniques, which are based on fixed schedules and activities of occupants. Besides, it enables generating detailed data (occupants activities and location, and consumption data at appliance level), which facilitates detecting energy waste and determining its causes. Although these two models ([35], [45]) are activity-based and generate detailed data, they lack the peer pressure aspect and do not include any intervention modeling and evaluation. An ABM that simulates an energy intervention approach is proposed in [46]. The research aims to test a number of building management and control approaches. One of the tested approaches includes a proactive meeting relocation capability. It suggests changing meeting rooms to smaller rooms or rooms that were previously occupied (i.e. previously heated) to save energy consumption. The occupant agents may or may not accept the suggestion based on the meeting constraints and their energy consciousness. However, the model does not capture the change of occupants energy consciousness/behavior in effect of the proactive approach, which is usually the aim of energy interventions. Besides, similar to the previous models, the model does not simulate the peer pressure effect.

Another group of ABMs that simulate human energy consumption behavior focuses on the effect of peer pressure in communities. For instance, Azar and Menassa [47] introduced human characteristics and interaction to typical energy simulation tools through an ABM. The occupant agents are characterized as low, medium or high consumers by which the occupant's level of energy consumption is determined. Besides, the model simulates peer pressure, where occupant agents change their behavior based on the level of influence of other agents and the number of agents in each level of consumption. A behavior change is also triggered by discrete interventions (training or workshops), which are simulated by randomly selecting the affected individuals based on the success percentage of the intervention. Moreover, the same authors (Azar and Menassa [48]) developed an ABM to help identify the social network characteristics that lead to the most energy savings when applying discrete interventions. The effect of peer networks was also studied in [49], which varies the structure of peer networks. The authors found that targeting individuals with strong relationships in peer networks is better to encourage energy savings than targeting those with more relationships. However, their model does not simulate energy interventions. Energy Interventions and peer networks were also studied in Anderson and Lee [50] through an ABM. The model tests the effectiveness of individual and comparative to neighbors for example feedback while varying the network types and strategies of which occupants to target and when to target them. As a result of occupants' interaction and feedback intervention, the occupants change their energy use behavior, which is measured by average consumption per week. All of these models that focus on peer networks, such as those discussed in ([47]–[50]), are not activity-based and do not produce detailed occupants activities and energy consumption data. This is because they characterize occupants by average daily/weekly/yearly consumption [48]–[50] or generate the occupancy of the agents through general fixed schedules [47].

The ABM proposed in this paper combines strengths of these previous models and structures them in a layered model. The core layer generates occupant daily behavior. It is activity-based and produces detailed occupants activities and energy consumption (every 10 minutes at appliance-level). This is possible because the core layer of the ABM is integrated with a probabilistic model based on big amounts of data. These detailed data enable real-time detection of energy waste and identification of its causes. Besides, the core layer characterizes occupants by their personal energy consumption behavior, which is changed due to peer pressure and energy interventions. Another layer included in this model is a family level peer pressure model, which is not usually implemented in ABMs that are activity-based. The model includes a customizable energy intervention layer where different types of interventions can be plugged and unplugged to test their effectiveness. The intervention implemented in this model is a messaging intervention that sends sensible feedback to occupants about energy waste incidents occurring in real-time. This is considered a continuous intervention opposed to other peer pressure models that model discrete interventions only [47], [48]. In these models, the effect of

TABLE 1. Exiting models comparison and features.

Paper (authors, year)	Activity-based	Generates detailed data	Simulates occupant behaviour	Simulates peer pressure	Evaluates energy interventions
Carmenate *et al.*, 2016	✓	✓	✓	✗	✗
Zhang *et al.*, 2011	✓	✓	✓	✗	✗
Klein *et al.*, 2012	✓	✓	✓	✗	✓ (occupants do not change behaviour due to intervention)
Azar and Menassa, 2012	✗	✗	✓	✓	✓ (discrete intervention)
Azar and Menassa, 2014	✗	✗	✓ (through average energy consumption per year)	✓	✓ (discrete intervention)
Chen *et al.*, 2012	✗	✗	✓ (through average energy consumption per day)	✓	✗
Anderson and Lee, 2016	✗	✗	✓ (through average energy consumption per week)	ding51	✓ (stochastic interaction between the occupants and the intervention)
Layered agent-based model	✓	✓	✓	✓	***✓ (enables realistic continuous interventions simulation)***

discrete interventions needs to be assumed and applied randomly. Similarly, the model in [50] stochastically determines the possibility of checking the feedback, which is considered a continuous intervention. However, with the level of details generated in the core model, it is possible to model a realistic effect of continuous interventions. This is based on how much the occupants are exposed to the intervention and their compliance to it. The details of the layered model will be explained in Section V. Table 1 shows the differences among existing ABMs and the last row of it shows the features included in the layered model proposed in this paper.

IV. THE PROPOSED ENERGY MESSAGING INTERVENTION

In this paper, we propose a messaging intervention that combines the technologies used for automated control and the service of providing energy feedback. Instead of providing the amount of energy being consumed or comparing the household consumption with similar ones, the intervention provides the occupants with real-time messages about their current energy wastage and recommends actions to reduce their consumption. This is done by relating the energy consumption of appliances with the context of the house including occupant presence, activities, and schedule, as well as environmental data. The approach in this paper is to avoid taking automatic actions in order not to breach the occupants' comfort, but to allow the occupants to take decisions whether to comply with the messages or not. An example of real-time messages would be : "*Your television in the master bedroom is now ON while nobody is there, it is recommended that you turn off devices while not in use*", or "*The lights in the living room are now ON while there is enough daylight in the room, you can take advantage of natural daylight to reduce your energy consumption*".

The following sections (1) detail the type of appliances that was implemented in the simulation model, (2) define a messages pushing strategy/heuristic to control the rate and number of messages to be sent to occupants, (3) present the factors that affect occupants energy consumption behaviour including compliance to the waste messages, and (4) present different enabling technologies and techniques that may be used to obtain and forward the messages in reality.

A. APPLIANCES TYPES

Detecting energy waste incidents involves different appliances and reasons for the waste, and consequently different suggestions to minimize or avoid the waste. In this sense, three general types of appliances can be identified based on the type of waste that may occur:

- Presence-dependent appliances (televisions, computers, game consoles, fans, lights, etc.), which are not supposed to be ON if they are not being used.
- Presence-independent and heavy appliances (washing-machine, tumble dryer, dishwasher, etc.), which are not recommended to be ON in peak-times, therefore can be scheduled as they do not depend on the occupants presence.
- Heating/cooling related devices where the waste may happen if windows/doors are opened while they are ON, or over-heating/cooling is detected in some areas of the house.

Detecting energy waste incidents of each of these types requires a different set of context data. In a previous paper [51], we identified the context data needed to obtain meaningful energy feedback for occupants, which include: *occupant context*, *appliances context*, and *environment context*. This paper focuses mainly on the presence-dependent appliances: *televisions, computers and lights* as a proof-of-concept. Energy waste from presence-dependent appliances is detected when they (1) are switched ON while occupants are not in the location of the appliance, (2) are not being used, or are not needed to be ON (e.g. keeping the lights ON while there is enough daylight in the room). This requires data about the occupant context (occupant location and ongoing activities), environment context (amount of natural daylight depending on the time of the day and weather conditions), and appliances context that is used to identify appliances that are turned ON.

B. MESSAGES PUSHING STRATEGY

Forwarding messages to the occupants is done by pushing notifications to the occupants' mobile devices taking advantage of the wide spread of mobile technologies these days. However, in order to ensure that occupants are not continuously interrupted by the messages, a messages pushing strategy need to be defined. This is because notifications sent in high numbers, at a high rate, and/or at an inappropriate times can affect the users' ongoing-tasks, hence causing frustration [52]. In addition, it may lead ultimately to un-installing the application [53]. Therefore, we propose a non-intrusive message pushing strategy that minimizes the annoyance level of occupants, whilst ensuring that the family reaches the savings target set by the governmental bodies and policy makers. The strategy is implemented in the simulation model by a heuristic, which will be detailed in section V-C.

In order to define this strategy, we explore studies that aim to study user's notification-interaction behaviour and build interruptibility management mechanisms. These studies aim to determine the most appropriate times and contextual situations to send notifications, and identify the factors that affect the interruptibility and receptivity of notifications. The aim is to reduce users' interruptibility (i.e. interruption of ongoing activities) and increase receptivity (i.e. the probability that the user receives the notification and reacts to it). One study found that sending a notification when the user transits from one activity to another reduces interruptibility [54]. Other studies, such as [55]–[57], develop machine learning models that use contextual data to predict the appropriate times for sending notification messages. These context data include time of the notification, type and the sender of information, location, emotional state, level of engagement in the activity, response time to notifications, and phone lock/unlock times. Another study found that the content factors of the message including interest, entertainment, relevance, and actionability affect more the receptivity of the message than the time of delivery [58].

Based on these studies, the proposed strategy aims to minimize occupant annoyance level caused by the feedback messages. This is achieved by the following:

- Sending messages only in appropriate times based on the occupant location and activity
- Limiting the number of messages sent to occupants per day based on their interest in the information
- Distributing the messages over the day
- Giving priority for high wastage incidents
- Adjusting the number of occupants to be targeted by the intervention based on the saving target

C. EFFECTIVE ENERGY CONSUMPTION BEHAVIOUR FACTORS

The possibilities of receiving the message does not mean that the occupants will comply to the messages anyway. There are several factors that determine whether the occupant will accept the suggestion of the intervention. These factors are outlined in Li *et al.* [59] who adapt the Motivation-Opportunity-Ability (MOA) model to the energy consumption behaviour. The MOA model is initially developed to explain consumers purchasing behaviour. The following points map the factors that affect occupant energy consumption behaviour and compliance to the feedback messages with motivation, opportunity, and ability.

- **Motivation** is defined as the needs, goals, and values that affect the level of interest and willingness to adopt the energy conservation behaviour. It represents the level of concern about personal energy consumption and personal relevance of the presented feedback information.
- **Opportunity** includes the relevant resources (external and environmental factors not in control of the person) that enable or prevent the behaviour. In terms of energy feedback it represents easily accessible controls, more understandable and accessible feedback. It also includes social opportunity such as peer pressure from other individuals in the environment.
- **Ability** is defined as the personal capabilities that enable the behaviour. It includes the knowledge capacity of interpreting energy related information, consequences of energy use, as well as the ways for saving energy.

The messaging intervention proposed in this paper enhances occupant *ability* and *opportunity* of control by exposing occupants to understandable information and making the information accessible through mobile devices. However, other parts of the MOA model are not affected by the messaging intervention. Therefore, we use the Personal Energy Rating (PER) attribute in the simulation model to determine how often occupants comply to the messages, and assume that these factors are embedded in the PER. The details of implementation of the PER attribute will be detailed in section V.

D. ENABLING TECHNOLOGIES

In order to realize the sensible real-time messages, several enabling technologies and techniques exist in research and in industry. These technologies and techniques are presented in the following points to help practitioners provide the intervention in reality. Note that the enabling technologies presented in this section serve in detecting energy waste for all appliances types not just presence-dependent appliances implemented in this paper.

- **Energy monitoring at appliance level**: This can be achieved using smart plugs, which detect when the appliance is turned ON and monitor the amount of energy being used. For more information about commercial smart plugs, Ford *et al.* [60] provide a comprehensive review of smart plugs available today. Another way of detecting appliances consumption is through smart appliances, which allow the monitoring of their energy consumption and status as well as control and communication with the user [32], [37], [60]. Appliance consumption can also be obtained from aggregated consumption data through NILM (Non-Intrusive Load Monitoring) techniques [61]. Beside these direct energy monitoring methods, some appliances can be monitored indirectly through environmental sensors such as temperature, noise, vibration, etc. [62].

- **Environment monitoring**: The surrounding environment inside and outside the house can be monitored through different sensors such as temperature, humidity, illuminance, motion, presence, body detection (e.g smart watches), doors/windows detectors, among others. In addition, virtual/software sensors can provide useful information such as occupant schedules and calendars, or live & forecast weather data.
- **AI techniques**: These techniques may be used for different purposes to analyze the collected context data. For example, Bayesian Networks [63] and Ontological & Probabilistic Reasoning [64] are used for activity recognition in households. Sleeping detection is also possible by utilizing data from smart watches [65], which are considered as permanent monitoring devices. Other activity recognition, learning and prediction techniques can be found in [62]. Another application for AI techniques is NILM, which is usually based on Hidden Markov Models and artificial neural networks [61]. Optimization algorithms are also used for appliances scheduling [66] in order to minimize energy costs and peak demand, and maximize user preferences and comfort.
- **Platforms for communication**: As energy waste detection requires the communication of different elements, communication platforms need to be in place to provide the connection among them. The most common way for this purpose are WSNs, which are used in references [25] and [26] cited in section II-C. In these approaches, sensors and actuators are set to communicate with each other in a single network. However, more recently the IoT paradigm was established where appliances and objects (e.g. smart appliances and smart plugs) can communicate and exchange data [67]. IoT technologies are proposed to ensure reliable communication in a complex environment [27].
- **System Architecture**: The general architecture of any EMS, including the messaging intervention tested in this paper, is outlined by De Paola *et al.* [62]. The system is composed of different components each having a specific functionality.
  - *Sensory and actuation infrastructure*: includes the energy and environment monitoring devices, as well as actuators, which allow to control the appliances.
  - *Middleware*: deals with the heterogeneous devices and sensors in the home and provides a common interface for processing.
  - *Processing engine*: performs the analysis of the collected context data such as activity recognition and detection of energy waste.
  - *User interaction interface* provides the occupants of the house with notifications about the energy waste and collects their feedback and preferences about the system suggestions. This is suggested to be provided through mobile devices such as smartphones and smart watches.

The components that provide the proposed intervention can be centralized such that all communication and processing passes through a central server, or distributed so that the components communicate directly and the processing is done in distributed processing units [62]. Fig. 1 provides a general illustration of the system that can provide the messaging intervention.

V. THE LAYERED AGENT-BASED MODEL

The ABM proposed in this paper is designed using an innovative layered structure, which includes realistic and detailed occupant behaviour, peer pressure social aspect, and customizable interventions modeling. Fig. 2 shows the three layers of the model:

- **Layer One: Daily Behaviour sub-model**, which is the core model that simulates detailed and realistic occupants daily occupancy, activities, and energy consumption.
- **Layer Two: Peer Pressure sub-model**, which adds a more realistic human behaviour aspect by simulating the peer pressure effect on occupants' energy consumption behaviour.
- **Layer Three: Messaging Intervention sub-model**, which detects energy waste and simulates the messages reception and compliance by occupants.

The last layer of the model (the messaging intervention submodel) is a customizable layer where any type of intervention can be modeled, implemented and tested using the other two layers of the model. More than one intervention can also be added to test the effectiveness of multiple interventions. Here, the messaging intervention is implemented and applied as an enhancement to the existing EMS and feedback displays.

A. LAYER ONE: DAILY BEHAVIOUR SUB-MODEL

The messaging intervention is simulated in an ABM that was developed in Abdallah *et al.* [68], [69]. The ABM is implemented in Repast Simphony (https://repast.github.io) – a Java-based agent-based platform. The model simulates energy consumption behaviour of families and allows the simulation and detection of energy waste incidents caused by occupants behaviour. This is because the generated data are fine-grained (generated every 10 minutes at appliance-level) and activity-based where the appliances consumption is generated based on occupant presence and activities. Every occupant is represented by an agent that resembles an individual in a household environment and interacts with other occupants and appliances. Occupant agents are characterized by the social parameters such as age and employment type (full-time job, part-time job, unemployed, retired and school), while the house is characterized by the total number of occupants, income, number of rooms, and number and types

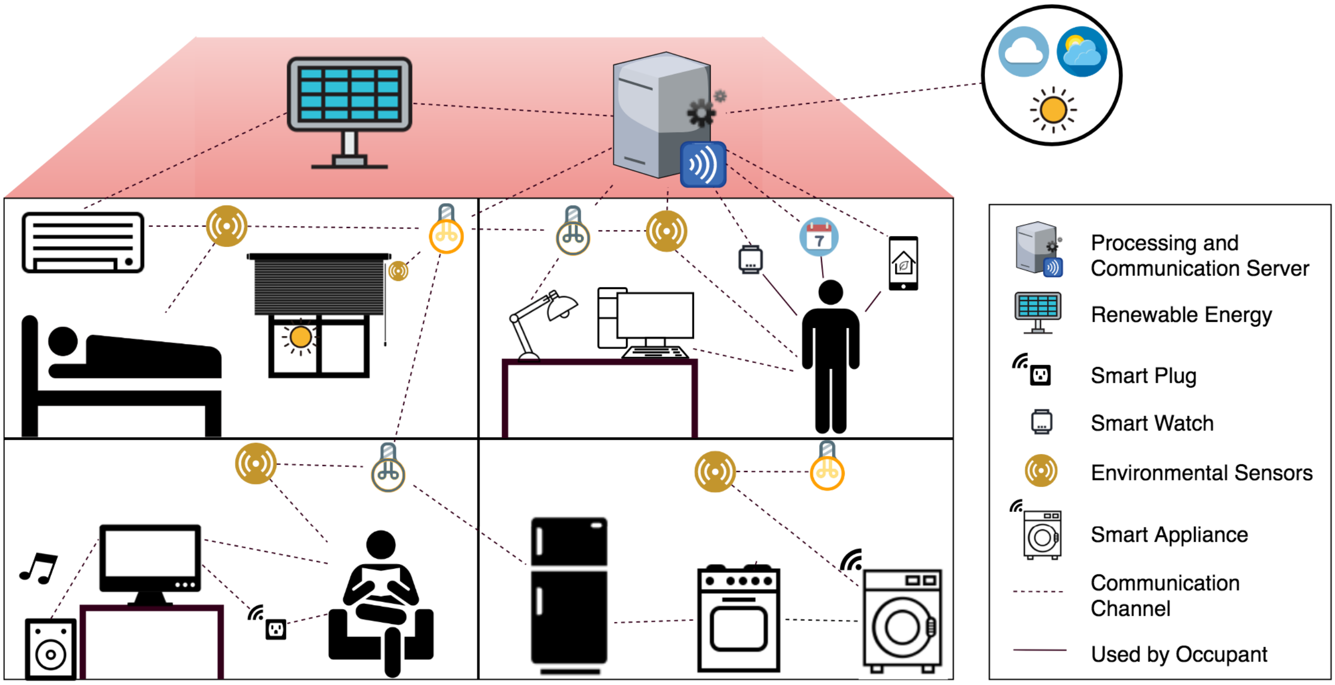


FIGURE 1. Messaging intervention technologies illustration.

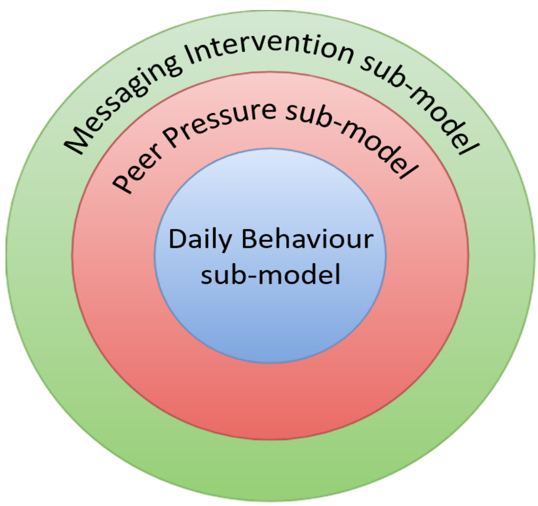


FIGURE 2. The layered agent-based model.

of appliances. The ABM generates realistic occupancy and activities based on the given occupants characteristics, then appliances consumption is generated as a result of occupants interaction with appliances agents.

The ABM was validated by incorporating probability distributions from an existing Probabilistic Model (PM) [70], which uses higher-order Markov Process. The PM is calibrated using Belgian Time-Use Survey (TUS) and the Household Budget survey. The surveys include real data from 6400 occupants in 3455 households. Table 2 shows the size of the sample that was selected from the surveys grouped by household composition with different employment types.

TABLE 2. Data sample grouped by household composition.

Household Composition	Sample Size
1 Adult	1276
1 Adult with Children	179
2 Adults	366
2 Adult with Children	721
Total	*2542*

1) OCCUPANCY AND ACTIVITIES SIMULATION

The simulation time is determined by the day of the week (d), which is distinguished between a workday or a weekend, and 144 time-steps per day (t) each representing 10 minutes. Every time step, the occupant agent either selects a new occupancy state and activity based on the probability distributions, or decrements the duration of an already running occupancy state/activity. The occupant agent selects an occupancy state ($os_{t,d}$), which can be *away*, *active* at home, or *sleeping*, for a duration (dr). The occupancy state and its duration are selected based on the occupant's previous state $os_{(t-1),d}$, age, employment type (emp), day (d), and time (t) as shown in (1).

$$\begin{aligned} OS: age, emp, os_{(t-1),d}, t, d &\rightarrow os_{t,d} \\ age, emp, os_{t,d}, t, d &\rightarrow dr \end{aligned} \tag{1}$$

When the occupant agent is active at home, it performs activities from the following set {*Using the computer, Watching television, Listening to music, Taking shower, Preparing food, Vacuum cleaning, Ironing, Doing dishes, Doing laundry*}. The decision of doing an activity ($ac_{t,d}$) for a specific duration (dr) depends on the occupant's age, employment type (emp), day (d), and time (t) as shown in (2). This step

TABLE 3. Mean and standard deviation of occupant types.

Occupant Types	Mean (μ)	Standard Deviation (σ)	Value (a)	Weight (w_a)
Follower Green	0.74	0.041	1	1
Concerned Green	0.72	0.043	2	0.75
Regular Water	0.41	0.033	3	0.50
Disengaged Waster	0.25	0.057	4	0.25

Away_{PM} Sleep_{PM} $\text{Active}_{\text{PM}}$ Away_{ABM} $\text{Sleep}_{\text{ABM}}$ $\text{Active}_{\text{ABM}}$

is repeated for every activity to allow multitasking where the occupant can be performing more than one activity at a time given that the activities are compatible i.e can be performed together.

$$AC : age, emp, t, d \rightarrow ac_{t,d}, dr \tag{2}$$

The decision of which factors affect the prediction of occupants' occupancy and activities is adapted from Aerts research [70]. The author proved through detailed analysis of the data from the Belgian TUS that the age, employment type, time of the day and day of the week are the most affecting factors.

The occupant agent's location in the house is determined by the activity being performed every time-step. Each activity is assigned to a room or a set of possible rooms. The agent decides its location $r_{t,d}$ based on its occupancy state $os_{t,d}$ and the set of ongoing activities ($AC_{t,d}$) as shown in (3). The occupant agent can have a set of possible rooms when doing more than one activity at a time. In this case, the agent alternates randomly between the possible rooms.

$$OL : os_{t,d}, AC_{t,d} \rightarrow r_{t,d} \tag{3}$$

2) ENERGY CONSUMPTION BEHAVIOUR SIMULATION

In addition to the occupant age and employment type, the ABM characterizes occupants based on their personal energy consumption behaviour. This is because energy consumption behaviour is different from one occupant to another. Therefore, the *occupant type* attribute is added to determine how often the occupant applies energy saving actions such as turning OFF appliances when they are not in use or avoiding putting heavy appliances ON in peak times. For this purpose, the ABM utilizes the categorization introduced by Zhang *et al.* [71] who divide occupants to four types: 'Follower Green', 'Concerned Green', 'Regular Waster', and 'Disengaged Waster'. Each of these types is reflected in the model by the Personal Energy Rating (PER) attribute between 0 and 100 based on a normal distribution as shown in the 2^{nd} and 3^{rd} columns of Table 3. PER is also used to determine how often occupants comply to the recommendations forwarded by the messaging intervention, therefore embeds the MOA factors identified in section IV.

Appliances are modelled as dummy agents that only react to occupant agents actions (turn ON and OFF). Every activity ($ac_{t,d}$) that the occupant performs is associated to an appliance a. When the occupant agent starts an activity, it turns ON the appliance associated to this activity. When the activity ends and based on the agent's *PER* attribute and other occupant agents (O_a) that may be using the same appliance, the agent decides whether to turn OFF the appliance or keep it ON. The actions of turning appliances ON and OFF is shown in (4).

$$\begin{aligned} TO_a : ac_{t,d} &\rightarrow turnOn_a \mid \\ ac_{t,d}, PER, O_a &\rightarrow \{keepOn, turnOff\}_a \end{aligned} \tag{4}$$

Turning lights ON/OFF is different from using appliances, because using lights depends on daylight and location. Every time the occupant agent is in a room $r_{t,d}$, it may decide to turn ON the light in this room based on the amount of natural daylight ($daylight_{t,d}$). The agent chooses to turn ON the lights when $daylight_{t,d} \times 0.02 < 200\ lx$ as modelled in [70], which was also used to obtain real daylight data measured in lux (lx). When the agent leaves the room, it decides whether to turn OFF the light based on its *PER* attribute and other occupants (O_r) in the room. The actions of turning lights ON and OFF is shown in (5).

$$\begin{aligned} TO_r : r_{t,d}, daylight_{t,d} &\rightarrow \{turnOn, keepOff\}_r \mid \\ r_{t,d}, PER, O_r &\rightarrow \{keepOn, turnOff\}_r \end{aligned} \tag{5}$$

The ABM simulates presence-dependent appliances (televisions, computers, and lights), which are related to the agents occupancy state, location, and the activities: *watching television* and *using the computer*.

For the predictive validation of the implemented daily behaviour data, we refer to TAPAS (Take A Previous Model and Add Something) principle [72], which is one of the strategies to validate simulation models. This incremental strategy is one of the most successful strategies for models creation, where a new model is built upon a previously validated model. In this case, the predictive validity of the previous model (the PM in our case) is passed to the new one (the ABM). In order to verify that the implemented ABM actually generates the same data as the previous PM, and the generated data were plotted on the same graph for comparison. Fig. 3 shows the plot for occupancy data for three day types generated by the PM and the implemented ABM. The shown data is the average occupancy for 100 simulations of the scenario "one adult aged 25-39 with a full-time job" given that the two models are fed with the different random numbers generator. The figure clearly shows that the implemented ABM was able to generate identical data to the one generated by the existing

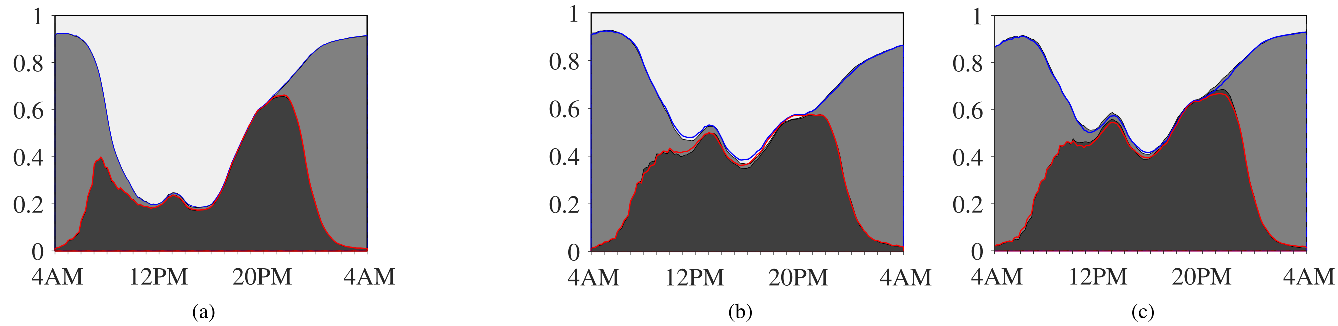


FIGURE 3. Average occupancy data comparison between the developed ABM and the existing PM. (a) Weekdays occupancy. (b) Saturdays occupancy. (c) Sundays occupancy.

PM [70]. To statistically prove that the data sets generated by the two models come from the same distribution, we perform Kolmogorov-Smirnov test. The results of the test are shown in Table 4, which shows that the p-value is close to 1. This indicates that the models produce the same distribution of data, thus the predictive validity of the occupancy and activities data is passed from the existing PM to our developed ABM. For further validation, the reader is referred to [68] and [69].

TABLE 4. Kolmogorov-Smirnov test results.

Tested Dataset	p-value
Occupancy	0.999
Watching television activity	0.988
Using the computer activity	0.975

B. LAYER TWO: PEER PRESSURE SUB-MODEL

The peer pressure sub-model used in this research is based on the approach proposed in [73], which models the effect of peer pressure on the energy consumption of family members. The model is based on two well-established human behaviour theories: the *collective behaviour theory* [74] and the *theory of cognitive dissonance* [75]. The collective behaviour theory was formalized in Granovetter's threshold model [74] to explain the diffusion of a behaviour due to social contagion. The model follows a simple decision rule, where individuals choose to adopt a behaviour when the percentage of others doing the behaviour exceeds a threshold. This threshold represents a complex combination of norms, values, motives, beliefs, etc. Once the threshold is exceeded, it is considered that the net benefit of the behaviour exceeds the perceived costs, which means that the individual will adopt the behaviour of others. The other human behaviour theory used in the model is the theory of cognitive dissonance [75]. Dissonance is defined as the inconsistency that happens between the individual's cognitive factors (e.g. knowledge, opinion, and beliefs) that drive behaviour. Based on the fact that dissonance is uncomfortable, Festinger [75] proves that humans try to reduce it by adopting the behaviour of others. One of the major sources of dissonance are social groups. Therefore, observing others doing a behaviour that is very different from the individual's behaviour or spreading a general belief that a specific behaviour is not accepted, drives members of a social group to adopt the behaviour of the majority, thus reducing the uncomfortable dissonance. The two theories were adapted – so they can be applied to simulate the effect of peer pressure on energy consumption in families. Accordingly, the threshold for behaviour change is define as the difference between the individual's occupant type and the average of others' occupant types, knowing that the occupant type is what determines the energy efficiency behaviour of individuals.

The time step in this model is set to 4 weeks of simulation time (hereafter time period) since individuals usually take time to observe the behaviour of others to change their behaviour. In order to express occupant types in numerical values, every occupant type is given an integer value as shown in the 4^{th} column of Table 3. For a family composed of N occupants, every time period T, each occupant agent i calculates the difference $diff_{T,i}$ between its occupant type a_i and the average occupant types of others a_j, where $j \in [1, N] : j \neq i$ using (6).

$$diff_{T,i} = a_i - \frac{\sum_{j=1, j\neq i}^{N} a_j}{N-1} \tag{6}$$

Behaviour change happens if $|diff_{T,i}|$ exceeds the threshold d where $d \in [0, 4]$. A high threshold implies low sensitivity to cognitive dissonance and a low threshold implies high sensitivity to cognitive dissonance. The model simulates the stochastic nature of human behaviour due to uncertainty and differences in the speed of reaction by using a threshold lag attribute such that the occupant changes behaviour with probability $p \in [0, 1]$ (a higher value of p means a higher rate of change). p is set to 0.5 as a middle point between high and low rate of change throughout the simulations in this paper. Once behaviour change is decided, the occupant type of the individual changes towards the average of others occupant types assuming that the occupant agent is adapting its behaviour to be similar to others. Behaviour change is done by stepping between the occupant types one step at a time either to the green side or the waster side. The behaviour change process step is outlined in algorithm 1, which is repeated for every agent i at every time step T.

Algorithm 1 Behaviour Change Step

```
calculate diff_{T,i} using Equation (6)
if |diff_{T,i}| ≥ d then
    rand ← Rand(0, 1) // Rand(0,1) is a
        uniform random generator between
        0 and 1

    if rand ≤ p then
        if diff_{T,i} > 0 then
            if a_i > 1 then
                a_i = a_i − 1
        else
            if a_i < 4 then
                a_i = a_i + 1
```

The peer pressure sub-model was conceptually validated in [73] proving that the model generates data that conforms to the used human behaviour change theories. The paper also defines interventions that change the occupant type of specific individuals (called occupant-level interventions), then uses the model to study the effect of the intervention and peer pressure on the occupant types of the family members and their energy consumption. The feedback messaging intervention proposed and tested in this paper is considered an application of the occupant-level intervention. Occupants may change their behaviour by changing their occupant type in effect of the messaging intervention. The messaging intervention simulation and behaviour change step as a result are explained in the next section.

C. LAYER THREE: MESSAGING INTERVENTION SUB-MODEL

As outlined in section IV, the approach proposed in this paper is detecting energy waste and forwarding the messages to the occupants. This layer models the energy detection feature and implements a heuristic to simulate the messages pushing strategy defined in IV. Then, it simulates the messages reception and compliance of occupants.

Energy Waste Detection: As the ABM simulates presence-dependent appliances, the energy waste incidents detected are related to the occupants location in the house, ongoing activities, and natural daylight as follows:

- Televisions and computers are detected as wasting energy when they are turned ON but not being used. The appliance is identified to be used when the activity associated to it (watching television and using the computer) is being performed regardless of the location of the occupant in the house, because the ABM enables multitasking. For example, the occupant can be watching television and preparing food in the kitchen. In this case the television located in the living room is not detected to be wasting energy.
- Lights are detected to be wasting energy when the light is on and (1) the room is not in use, (2) the room is in use but natural daylight is enough to light the room, or (2) all the occupants in the room are sleeping. The room is considered to be in use if there is an occupant using it even if he/she is not in the room due to multitasking as explained above. This covers the case when people leave the lights on when they are returning to the room in a short while.

The above mechanism is provided as an example for energy waste detection. Any other detection mechanism can be implemented and tested, including mechanisms that utilize predicted activities and energy consumption of occupants or customize the waste detection to the occupant preferences.

Messages Pushing Strategy Simulation: The energy waste incidents are detected and updated every time-step based on the mechanism determined in the previous section. However, it is not possible to send the occupants a group of messages about their energy waste every 10 minutes asking them to turn off appliances and change their behaviour. Using the studies cited in section IV, we implement a non-intrusive strategy that selects to forward messages at appropriate times, and limits and distributes the messages to be sent to occupants in order to reduce annoyance and frustration. The strategy is implemented based on a heuristic defined in the following 4 steps:

1) SEND MESSAGES IN APPROPRIATE TIMES

As shown in [54], the appropriate time to send notifications to users is when they are transiting from one activity to another, which reduces interruptibility. Applying this factor to the messaging intervention, the messages are only sent to occupant agents when they transit from one occupancy state to another, from one activity to another, or from one location to another (inside the house).

2) SET A FREQUENCY CAP PER DAY

Many studies identify that the user's level of interest in the information is one of the influential factors that affect receptivity of notifications. Therefore, we use this factor to limit the number of messages to be sent to occupant agents. Consequently, we define a *frequency cap* that determines the number of messages that can be sent per day. The frequency cap is determined based on the number of transitions the occupant agent performs during the day and its interest in the information, which is determined by the occupant type. Every occupant type is given a weight to determine the level of interest, setting the maximum for the 'Follower Green' type and the minimum for the 'Disengaged Waster' type with an arbitrary equal difference between any two consecutive consumer types as shown in the 4^{th} column of Table 3.

Every time period T (set to 4 weeks – the same as the peer pressure sub-model), the frequency cap $f_{i,T}$ of every occupant agent i is calculated using (7).

$$f_{i,T} = nTran_{(T-1)} \times w_a \tag{7}$$

where $nTran_{(T-1)}$ is the number of transitions the occupant agent performed in period T-1, and w_a is the weighting of the agent's occupant type.

The frequency cap $f_{i,T}$ is then divided on the number of days in the period T ($n_T = 28 = 4\ weeks * 7\ days\ per\ week$) to ensure that the messages are distributed over the days. The frequency cap per day $f_{i,d}$ is calculated using (8).

$$f_{i,d} = \frac{f_{i,T}}{n_T} \tag{8}$$

The messaging intervention strategy keeps the number of messages sent to the occupant agent less than the frequency cap per occupant.

3) ADJUST THE NUMBER OF MESSAGES PER OCCUPANT PER TIME STEP

In order to guarantee that the messages are distributed over the day, the strategy adjusts the number of messages to be sent to the occupant agent per time step while focusing on high energy wastage. This is done based on the remaining number of messages that can be sent to the occupant (hereafter occupant's messaging capacity) and the expected number of waste incidents until the end of the day.

Every time step t, the number of messages to be sent to the occupant i is set using (9), (10), and (11).

$$nMsg_{i,t} = \lceil \frac{c_{i,t}}{nExp_t} \rceil \tag{9}$$

$$c_{i,t} = fc_{i,d} - NMsg_{i,t} \tag{10}$$

$$nExp_t = nDet_t - NExp_d \tag{11}$$

where $nMsg_{i,t}$ is the number of messages to be sent to the occupant at time step t, $c_{i,t}$ is the occupant's messaging capacity, $nExp_t$ is the remaining number of incidents expected at time step t until the end of the day, $NMsg_{i,t}$ is the number of messages received by the occupant so far, $NDet_t$ is the number of detected incidents so far, and $NExp_d$ is the total number of incidents expected per day. In this model $NExp_d$ is calculated from the last time period (4 weeks) then divided over the days. It was possible to calculate $NExp_d$ in the ABM, however in reality various machine learning algorithms can be applied to identify the expected incidents throughout the day.

4) ADJUST THE NUMBER OF OCCUPANTS PER TIME PERIOD

Every period of time, the strategy adjusts the number of occupants to be targeted by the intervention. The family is set an energy saving target (in percentage) to be achieved after one year of applying the intervention. This target is supposed to be set by policy makers and governmental bodies. Therefore, based on whether the percentage of saving is more or less than the target, the number of occupants is decided in a way that reduces the annoyance of occupants if they have already reached the target. This process is shown in Algorithm 2, which is repeated every time period T.

Algorithm 2 Adjust Number of Occupants

```
Ensure: nTar_T ≥ 0 and nTar_T ≤ N
  if first time period T then
    nTar_T ← N
  else
    if s_T > tar + 1 then
      nTar_(T+1) ← nTar_T − 1
    if s_T ≥ tar − 1 and s_T ≤ tar + 1 then
      nTar_(T+1) ← nTar_T
    if s_T < tar − 1 then
      nTar_(T+1) ← nTar_T + 1
```

$nTar_T$ is the number of targeted occupants at time period T, N is the total number of occupants in the family, s_T is the energy saving percentage before time period T, and tar is the energy saving target (in percentage) set for the family to reach. Occupants with highest frequency cap are selected to be targeted by the intervention. The simulation is run for one year without the messaging intervention in order to calculate the energy saving percentage.

Messages Reception Simulation: The energy waste incidents are forwarded to the occupant agents' mobile device (smartphone, tablet, smart watches, etc.) if they possess any. In this paper, we simulate the case of smartphones as they are the most spread and used types of mobile devices these days [76]. Real statistics were obtained for the possession and usage of smartphones from Deliotte Global Mobile Consumer Survey (Belgian edition)[1] [76]. Table 5 shows the possibility of owning a smartphone based on the occupant's age. Therefore, it is decided in the initialization phase whether the occupant agent possesses a smartphone or does not.

Possessing a mobile device does not mean that the occupant will always receive the message. To determine the mobile device check probability, the Global Mobile Consumer Survey was used. The survey includes data about how often people check their smartphone per day by age group (Table 6), and the percentage of people who check their phone while doing different activities during the day (Table 7). Based on these data, we calculate the percentage of checking the smartphone for every age group and day period, which are mapped to the corresponding age groups and periods in the Belgian Time-Use Survey, and assume that the message is received once the phone is checked. The action of smartphone checking ($sc_{t,d}$) depends on the occupants *age*, occupancy state ($os_{t,d}$), day type (workday or weekend), and the time

[1] The Belgian edition of the survey was selected since the probability distributions used in the ABM are calibrated using the Belgian time-use survey.

TABLE 5. Smartphone possession probability by age group.

Age Group	Smartphone Possession Probability (%)
12-17 [2]	86.1
18-24	90.0
25-39	92.0
40-54	83.0
55-64 [3]	83.0
65-75	56.0

TABLE 6. Frequency of checking the smartphone by age group.

Age group (age)	Frequency of checking the smartphone per day
12-17	70
18-24	70
25-39	46
40-54	28
55-64	28
65-75	11

TABLE 7. Percentage of checking the smartphone while doing different activities.

Day Period	Activity	Percentage (%)
Morning (7am-9am)	Within 5 minutes after waking-up	31
	While on road	26
Daytime/ Work Time (9am-5pm)	While working	66
	In a meeting	22
	While Shopping	33
Evening (5pm-11pm)	While on road	26
	While Watching TV	52
	While spending time with friends/family	33
Sleep (11pm-7am)	Within 5 min before sleeping	28
	If sleeping was interrupted	40

of the day as shown in (12).

$$SC : age, os_{t,d}, t, d \rightarrow sc_{t,d} \quad (12)$$

Messages Compliance Simulation: Whenever the occupant agent receives the message, it may comply to it by turning OFF the appliance that is causing the waste. This action happens based on the agent's PER attribute, which embeds different personal and external factors that either allow or prevent the action from happening as outlined in Section IV.

When the message is sent to the occupant agent's mobile device, the agent's smartphone check probability ($sc_{t,d}$) is used along with its occupancy state ($os_{t,d}$), location ($r_{t,d}$) and PER to determine the reaction towards the message as in (13).

$$MC : sc_{t,d}, os_{t,d}, r_{t,d}, PER \rightarrow \{keepOn, turnOff\} \quad (13)$$

Behaviour Change Due to Messaging Intervention: The occupant agents may change their occupant type and consequently their PER assuming that they are becoming more energy aware as a result of the messaging intervention. This is decided by comparing the actual behaviour of the occupant agent and the mean value of the occupant type shown in Table 3. The actual behaviour of the agent is calculated using (14)

$$aB = \frac{nOFF}{supNOFF}, \quad (14)$$

where aB is the ratio of the number of times the occupant agent turned the appliance OFF ($nOFF$) and the number of times it was supposed to turn OFF ($supNOFF$). If the aB exceeds the mean of the more-green occupant type, the agent changes its occupant type to the green side, thus increases its PER attribute. This step is executed every time period T, then the peer pressure behaviour change step (Algorithm 1) is executed such that the occupant agent may affect others' behaviour or the others may affect it. Every step executed by the occupant agent is demonstrated in Fig. 4 with the associated equation/algorithm used in the step. The step is executed until the total time of the simulation is reached (set to one year in the experiments).

VI. EXPERIMENTS AND RESULTS

The aim of these experiments is to show how the proposed simulation model can be used to test energy interventions. The family simulated in these experiments is composed of four occupants: two adults who are 25-39 years old in a full-time job, and two children 12-17 years old who go to school. For this family type, we simulate two scenarios by varying the occupant types and PER values (all follower green families, and all disengaged waster families) to test the effect of energy awareness on the effectiveness of the intervention. In order to test the effectiveness of the proposed message pushing strategy we run two types of scenarios, one where the *proposed strategy* is applied at its entirety as outlined in the previous section, and another where messages are sent whenever the occupants are active at home (hereafter *naive strategy*). With the naive strategy, it is assumed that occupants stop complying to messages when their frequency cap is reached, while the messages continue to be sent by the messaging intervention in response to energy waste incidents. This follows the conclusion reached in [53], where users stop using the application when they receive a high number of notifications. Besides, we vary the savings target of the proposed strategy to get the maximum percentage of saving that can be achieved when applying it.

For every scenario, 100 households were simulated to capture the probabilistic nature of the model. Each household has different income levels, work routines for employed occupants, ages, appliances number and types, and number of rooms in the house, all drawn based on the probability distributions from the real data. Every household is run for one year without any intervention to get the baseline consumption of the house, then for another year while applying the proposed strategy or the naive strategy. The percentage of saving of

[2] The age group 12-17 is not included in the Global Mobile Consumer Survey [76]. Instead, we used a survey by IVox and Wiko who found that 86.1% of children aged 13-16 possess smartphones in 2015. **Reference**: *http://be-nl.wikomobile.com/a4342-Wat-is-de-ideale-leeftijd-om-een-smartphone-te-bezitten* (Accessed 2 May 2018). For the smartphone usage we used the data of the closest age group 18-24 as shown in Table 6

[3] Results for age group 55-64 are not reported in the Global Mobile Consumer Survey report. Therefore, we used the data of the closest age group 40-54 instead. This also applies for smartphone usage percentages in table 6.

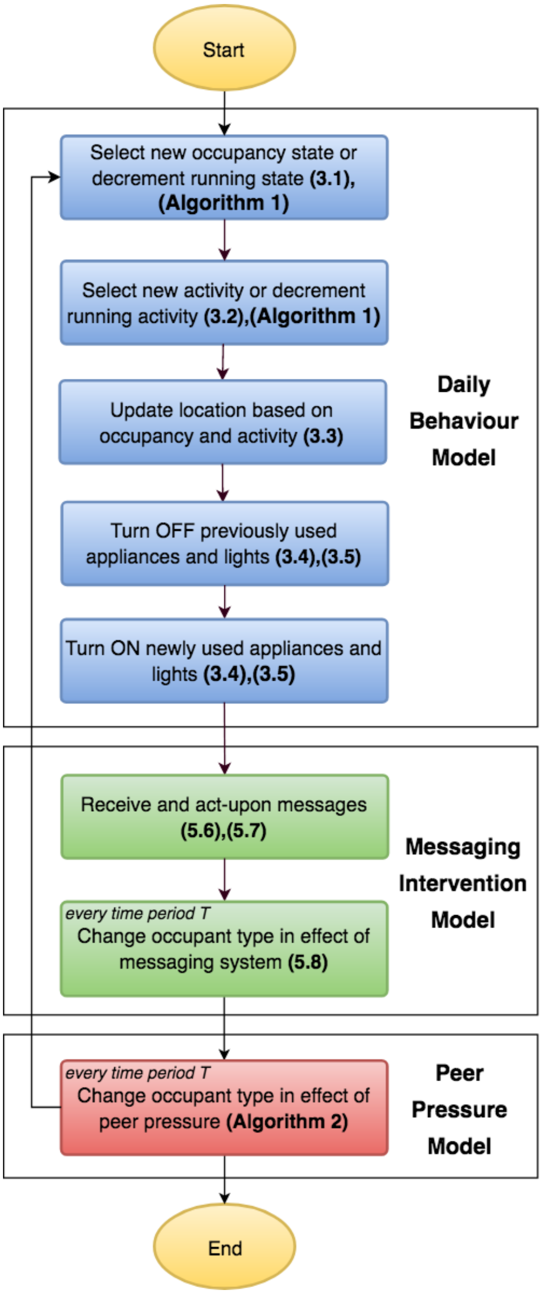


FIGURE 4. Occupant agent execution steps.

every household is calculated using (15)

$$S = \frac{(C_n - C)}{C_n} \times 100, \tag{15}$$

where S is the percentage of saving, C is the yearly consumption when applying the messaging intervention, and C_n is the yearly consumption when no intervention is applied.

In order to measure the level of annoyance that occurs as a result of sending out feedback messages, we calculate the percentage of messages sent in comparison to the frequency cap of the occupants (16)

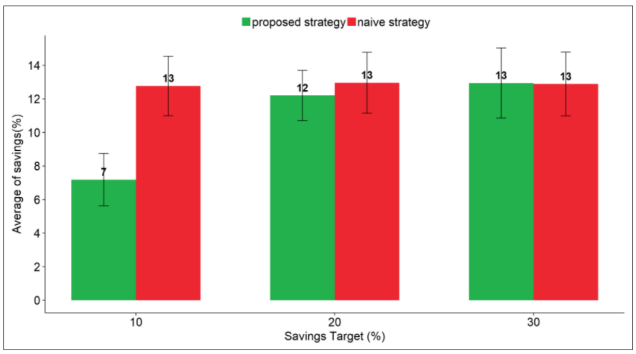
$$A = \frac{NMsg_{total}}{f_{total}} \times 100, \tag{16}$$

where A is the level of annoyance of occupants, $NMsg_{total}$ is the total number of messages sent to the occupants in the whole year, and f_{total} is the total frequency caps of all the occupants in the whole year. A value of annoyance less than 100 means that the occupants were not annoyed by the messages, and a value more than 100 means that they are annoyed by the messages which indicates high probability of switching off the notifications.

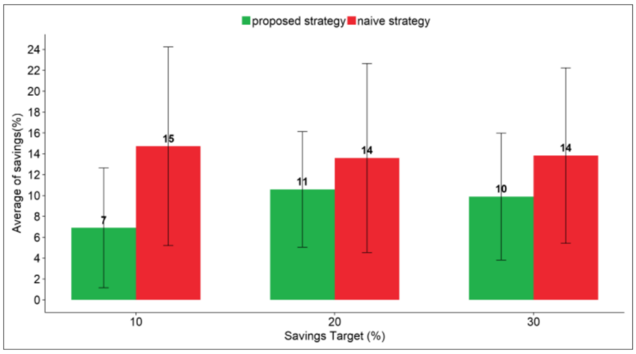
First, we show some general results (average savings and annoyance) of the simulated scenarios, then we present detailed results of the messaging intervention to show how the model can be used to test the performance of the strategy.

A. GENERAL RESULTS

Fig. 5 and Fig. 6 show the average and standard deviation of energy saving and annoyance of the simulated 100 households in each scenario. Scenarios that run with the naive strategy have the same indication when varying the energy saving target since the target does not affect the way the messages are sent. In order to get the maximum saving result of the messaging intervention when applying the proposed strategy, we start by simulating scenarios with low targets (10%) and increase it until we noticed that the average saving is not changing. When the average saving does not increase as the target increases, then this means that the proposed strategy is targeting the maximum number of occupants but the household could not achieve more savings. This is noticed when increasing the target from 20% to 30% where

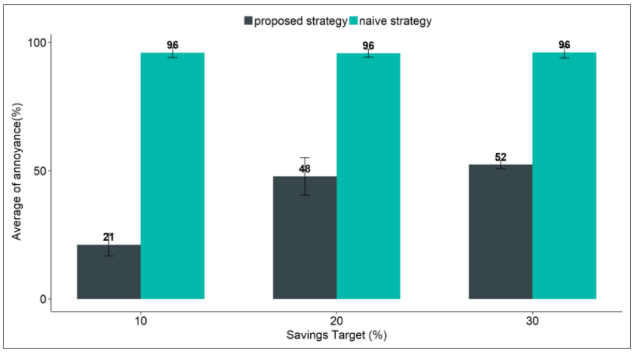


(a)

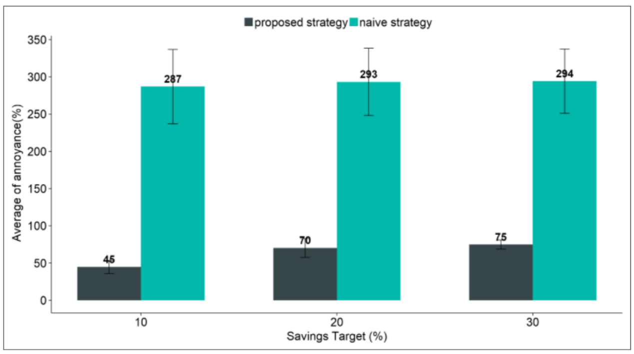


(b)

FIGURE 5. Average of savings when applying the proposed strategy and the naive strategy. (a) All green scenario. (b) All waster scenario.

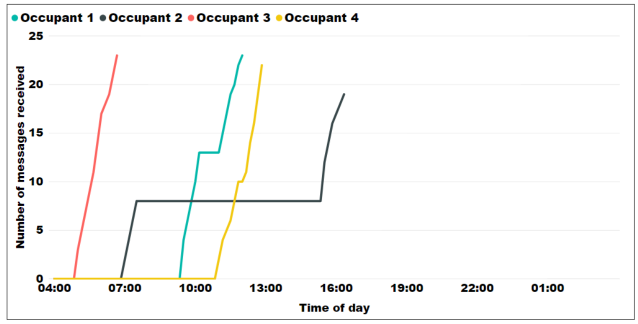


(a)

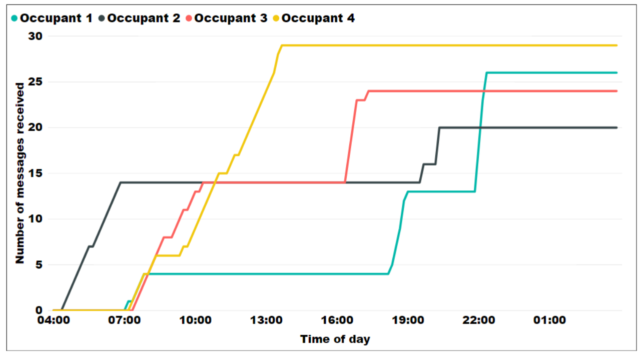


(b)

FIGURE 6. Average of annoyance when applying the proposed strategy and the naive strategy. (a) All green scenario. (b) All waster scenario.



(a)



(b)

FIGURE 7. Messages distribution over the day when using the proposed strategy and the naive strategy. (a) Proposed strategy. (b) Naive strategy.

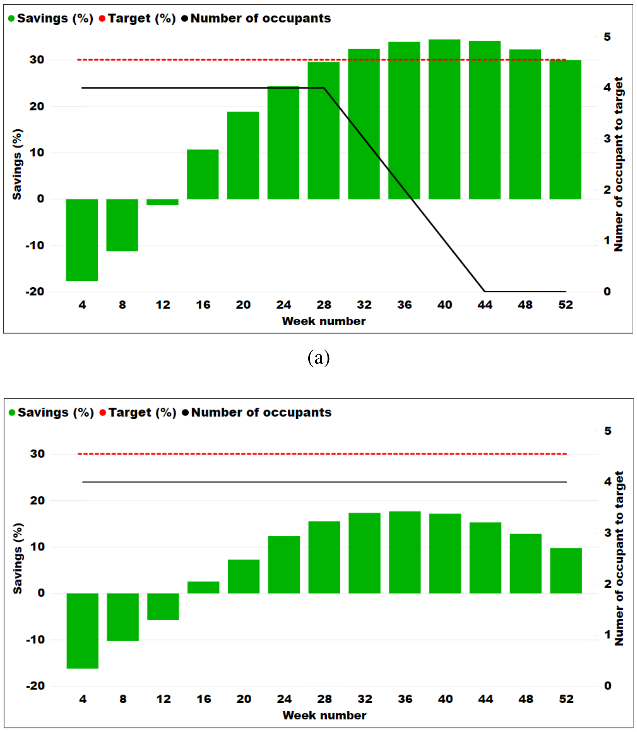
the saving increased only 1% with the green occupants and decreased 1% with waster occupants. Therefore, with the proposed strategy, the maximum average savings for green occupants is 13% and for waster occupants is 11%.

The energy savings of the intervention with the naive strategy ranges between 13-15 % for both green and waster families. While the savings achieved when applying the proposed strategy is between 7-13 %. However, when looking at the annoyance levels, we notice that the proposed strategy is able to achieve these savings with low levels of annoyance (21-52% for green occupants, and 45-75% for waster occupants). While the annoyance level of all waster families with the naive strategy exceeds the frequency cap of the occupants by almost three times (287-294%). This indicates that the saving percentage 14-15% resulting from using the naive strategy could not be achieved in reality because of the high annoyance level. Besides, for green occupants, the proposed strategy achieved the same amount of savings (12-13%) with annoyance level 48-52% compared to 96% annoyance level when the naive strategy is applied. This indicates that the proposed strategy succeeded to keep occupants unannoyed while achieving reasonable savings. This is because it reduces the number of occupants to target when the savings target is reached, and distributes the messages over the day while focusing on high wastage. These results indicate that the proposed intervention strategy is more efficient than the naive one. The details of the proposed strategy will be presented in the next section.

Looking at the standard deviation of the reported results, we notice that results of all waster families is more scattered than green families. This is because waster occupants have the chance to change their occupant type and become more aware, thus achieving different energy savings. An example of two different scenarios will be presented in the next section to show the reason of these scattered results. In terms of achieving the savings target, the proposed strategy did not succeed to achieve the targets in average. The percentage of successful scenarios among the simulated households is 14%, 3%, and 1% for the targets 10%, 20%,and 30% respectively. This reveals that policy makers will need to adjust the messages pushing strategy and/or apply a combined intervention approach such that targets are achieved while minimizing the annoyance levels of the occupants. The proposed model can help evaluate these strategies and interventions before implementing them in reality. Note that these results are specific for the family type tested in this experiment. Different results may be obtained when changing the inputs for the model. City level results can be obtained by feeding the model with the demographic distribution of the city to obtain the effectiveness of the intervention and strategy.

B. DETAILED STRATEGY RESULTS

This section presents detailed examples to show how the proposed strategy works. Fig. 7 compares how the messages are sent over the 24 hours period using the proposed strategy and the naive one. In Fig. 7a where the naive strategy is applied, messages are sent to occupants whenever they are



(a)

(b)

FIGURE 8. Change of energy saving over the year and adjustment of occupants to target. (a) Successful scenario. (b) Unsuccessful scenario.

active at home. It is noticed that most of the messages are sent once the occupants wake up in the morning, and the occupants stop complying to the messages in the middle of the 24 hour period (at 04:00 PM). After this time, the intervention continues sending the messages but it is assumed that the occupants stop complying to them when the number of messages received reaches their frequency cap. Fig. 7b shows how the messages are sent when the proposed strategy is applied. It is clear that the messages continue to be sent until the end of the day (at 10:00 PM), and no messages are sent after the frequency cap of each occupant is reached. This ensures that the messages are distributed over the day while focusing on high waste incidents.

Fig. 8 shows how the energy savings change over the year (tracked every 4 weeks) and how the proposed strategy changes the number of occupants to target accordingly (the left y-axis refers to the savings percentages, and the right y-axis refers to the number of occupants to target). Fig. 8a presents a scenario where the family succeeded to reach the energy saving target (30%) at week 28. As a result the proposed strategy started to decrease the number of occupants to target from 4 until it reaches 0 at week 44. By the end of the year, the family had 30 % of energy saving. This saving percentage was possible because the occupants changed their occupant types from 4 disengaged wasters to 3 regular wasters and one follower green. This is due to both peer pressure and the effect of the messaging intervention. Fig. 8b shows a family that did not succeed to reach the savings target during the whole year. As a result, the number of occupants to target remained equal to the maximum (4 occupants). Talking about the occupant types of this family, all of the occupants remained disengaged wasters by the end of the year. This shows one of the reasons why interventions work in some cases but not in others. In addition, it indicates that in some cases, the messaging intervention is not enough to achieve the savings target, and another type of intervention needs to be combined with it to change occupants awareness and save more energy.

VII. DISCUSSION

This paper introduces an energy messaging intervention. Most existing energy feedback systems display abstract or contextualized energy consumption data [17]–[20]. However, these data need to be further analyzed by occupants to determine energy waste causing activities/actions and minimize their consumption [4], [21]. In this paper, we identify the specifications and enabling technologies & techniques that can support occupants to reduce their energy consumption using sensible feedback; a feedback that tells occupants what appliances are causing high energy waste. Instead of controlling appliances on behalf of occupants, like most existing EMS [5], [24], [27]–[29], we propose to keep occupants in control. Therefore, we suggest that energy wastage messages are forwarded to occupants' mobile devices giving then the choice whether to comply to the feedback message or not.

One challenge that exists when dealing with applications that forward messages to users is the intrusiveness of the messages. Such that the pushed notifications may be sent at the wrong times or in high number/rate. In order to overcome this challenge, we presented a heuristic approach by sending messages only when the occupants transit from one location/activity to another, setting a frequency cap to limit the number of messages, distributing them over the day, and reducing the number of occupants to be targeted when a saving target is reached.

In order to test this messaging intervention, we use a novel layered ABM that simulates the household's energy consumption and the messaging intervention. Opposed to other ABM [47]–[50], the layered ABM is activity-based and generates detailed data, which enhances the accuracy of the simulation. In addition, it simulates occupants peer pressure effect on energy consumption behaviour in comparison to other models that do not simulate peer pressure [35], [45], [46]. The messaging intervention sub-model enables realistic simulation of interventions by using real statistical figures of the possession and usage of smartphones by occupants to simulate the occupants' interaction with the intervention. Therefore, unlike existing models [47], [48], [50], the developed model simulates realistic interaction of occupants with energy interventions, where the result of the intervention can be affected by the occupant daily behaviour and social characteristics.

For the messaging intervention and in order not to annoy occupants with messages, we define a non-intrusive strategy to forward the messages to occupants. The experiments presented in the chapter showed that the proposed intervention strategy was effective as it achieves reasonable saving and keeps the occupants not annoyed when compared to a naive strategy. The presented scenarios also showed the details that can be generated and controlled in the simulation model. This will enable policy makers to evaluate the effectiveness of the intervention, its strategies, and any other energy intervention.

VIII. CONCLUSION AND FUTURE WORK

In this paper, we proposed a non-intrusive messaging intervention that detects and sends waste incidents to occupants to help reduce energy consumption in buildings. It is considered a middle-point between techniques and technologies used for automatic control, and typical feedback displays. The paper has also presented the enabling technologies and techniques that are needed to realize the messaging intervention in reality. In order to avoid occupants annoyance from the notifications (which are suggested to be sent to their mobile devices), we have proposed a strategy that controls the number of occupants to target, the number of messages to send per occupant, and the time of sending the messages.

The intervention is evaluated using a novel layered ABM that combines strengths of existing ABM. It simulates detailed energy consumption and wastage, models the effect of peer pressure, and evaluates energy interventions. The presented experiments showed that the proposed intervention and strategy can result in acceptable energy saving while keeping the occupants comfortable (not annoyed by the messages). It also showed how the model can be used by decision makers to explain how interventions can be effective in some families but not in others and test different approaches of interventions. Although the results in this study are obtained through a realistic simulation model, real world testing is needed because there are many factors that can affect the success of interventions. However, such simulation analysis is needed as a first step towards the evaluation of new approaches that require lots of equipment and time to be installed and tested in real scenarios.

Concerning the proposed messaging intervention, a number of challenges may be observed when applying a human controlled approach. The first challenge is the possibility that the occupants do not comply to the messages. This may be affected by several internal (e.g. personal motivation), and external (e.g. inaccessibility to control the appliances) barriers. Therefore, it is important to identify and overcome these barriers through field testing. Besides, occupants' trust in such a system may be breached if the energy waste incidents are not accurately predicted. This challenge can be addressed by developing and using accurate sensing devices analysis techniques, and taking feedback from the occupants about the provided messages. It is worth to mention that in behaviour change type of problems, there is no ''silver-bullet type of solution'' [8]. Therefore, it cannot be assumed that the proposed intervention will work in any case and type of household where several types of interventions may be needed. Besides, one of the future directions to further develop such interventions is to study it from the social psychological point of view in order to determine the best way of presenting the information – so that occupants are encouraged to take action.

The model presented in this paper is now implemented for lights, televisions and computers which are presence-dependent appliances. The model can be extended to simulate other types of appliances thus testing other types of interventions or actions to control energy consumption. These appliance types include presence-independent and heavy appliances (washing-machine, tumble dryer, dishwasher, HVAC systems etc.) which are not recommended to be switched ON in peak-times. This is called demand response which is applied when the price of electricity unit varies based on the time of the day. In this case, the messaging intervention could suggest to reschedule the heavy appliance to a non-peak time that is convenient for the occupants' schedule and preference, or use an alternative such as line drying instead of using tumble dryer, renewable energy instead of electricity, etc. Demand response benefits both consumers (by reducing their energy bill), and providers (by reducing the generation costs and operating the electricity systems more efficiently) [22]. The other type of energy waste that can be tested is heating/cooling loss. This could happen when heating/cooling devices are ON when occupants are not present and pre-cooling/pre-heating is not scheduled, windows/doors are opened while the devices are ON, or over-heating/cooling is detected. The suggestions in these cases are to turn the device off or adjust the set point of heating/cooling. In order to test these interventions, all the necessary context data will need to be added to the simulation model (specifically the core daily behaviour model) such as occupants schedule, occupants preferences, and internal & external temperature. Then the interventions related to these appliances can be modeled and tested. Besides, various strategies for sending messages out for occupants may be defined, implemented, and tested using the same model. This emphasizes the customizable energy intervention testing feature of the model.

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FATIMA ABDALLAH received the B.S. degree in computer sciences and the M.S. degree in information and decision support systems from Lebanese University, Lebanon, in 2012 and 2014 respectively. She is currently a Ph.D. Researcher with the School of Computing and Digital Technology, Birmingham City University, U.K. Her M.S. project involved developing a context-aware middleware for mobile devices. She has published a number of papers in international conferences in areas, including mobile computing, energy consumption in buildings, and artificial intelligence. Her areas of expertise include agent-based modeling, context-aware computing, and artificial intelligence.

SHADI BASURRA received the B.Sc. degree (Hons.) in computer science from Exeter University, U.K., the M.Sc. degree in distributed systems and networks from Kent University, Canterbury, U.K, and the Ph.D. degree from the University of Bath in collaboration with Bristol University. He is currently a Senior Lecturer in computer science with Birmingham City University, U.K. After his PhD degree, he was with Sony, where he was developing goal decision systems. He has taught postgraduate and undergraduate courses in computer science and networking. He has published a number of peer-reviewed scientific articles in international conferences and journals. His research interests include multi-agent systems, game theory, multi-objective optimization, machine learning in the Internet of Things, energy efficiency in smart buildings, emulation of mobile ad hoc networks, nature-inspired computing, and social networks. He received The Yemen President National Science Prize, in 2010, the Best Presentation at Meeting of Minds Bath, in 2012, the MEX Scholarship, in 2013, the Ph.D. Scholarship from Toshiba Ltd, Great Western Research, and Yemen Government, in 2009, and various academic grants.

MOHAMED MEDHAT GABER received the Ph.D. degree from Monash University, Australia. He held appointments at The University of Sydney, CSIRO, Monash University, the University of Portsmouth, and Robert Gordon University. He is currently a Professor in data analytics with the School of Computing and Digital Technology, Birmingham City University. He has published over 150 papers, co-authored three monograph-style books, and edited/co-edited six books on data mining and knowledge discovery. His work has attracted well over four thousand citations, with an h-index of 32. He is also a member of the International Panel of Expert Advisers for the Australasian Data Mining Conferences. He received the CSIRO Teamwork Award, in 2007. He has served on the program committees of major conferences related to data mining, including ICDM, PAKDD, ECML/PKDD, and ICML. He has also co-chaired numerous scientific events on various data mining topics. He was the Program Committee Co-Chair of the 17th IEEE International Conference on Mobile Data Management 2016.