IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received October 28, 2018, accepted November 24, 2018, date of publication December 11, 2018, date of current version January 7, 2019.

Digital Object Identifier 10.1109/ACCESS.2018.2886146

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)

The work of F. Abdallah was supported by the Faculty of Computing, Engineering and Built Environment, Birmingham City University, through a Full Bursary Ph.D. Scholarship.

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 non-linear (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 sub-model) 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

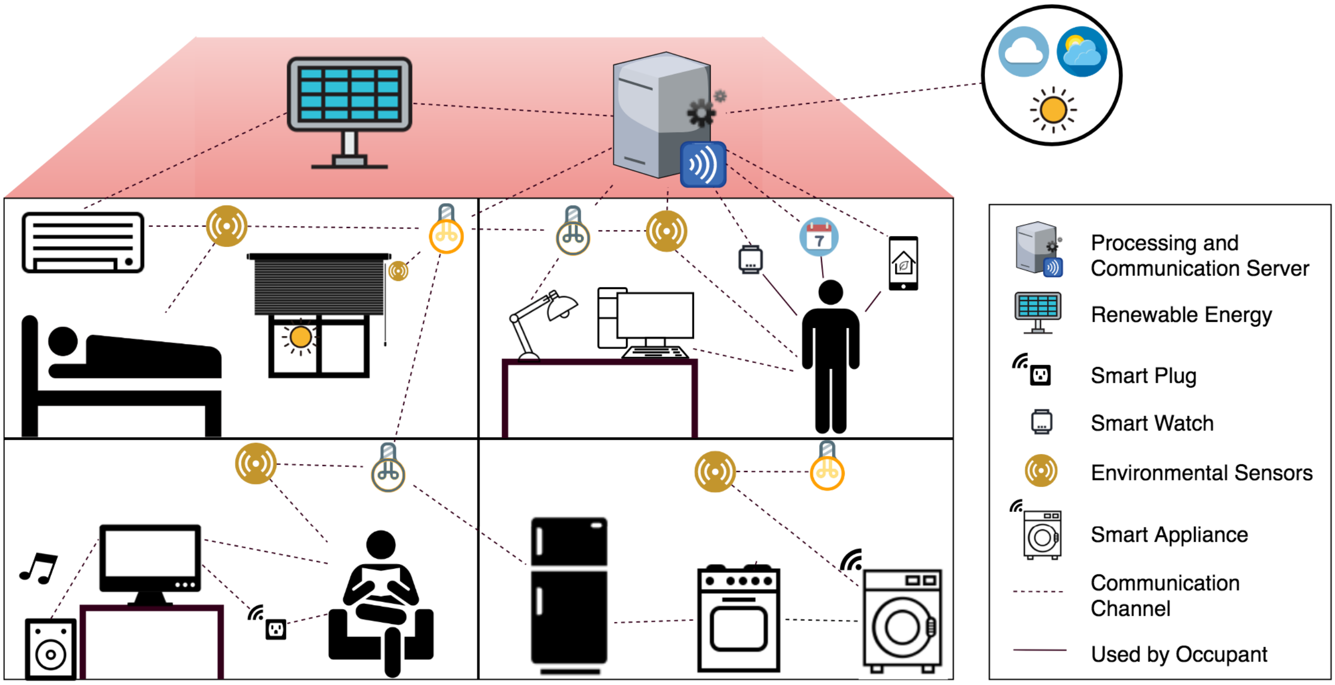


FIGURE 1. Messaging intervention technologies illustration.

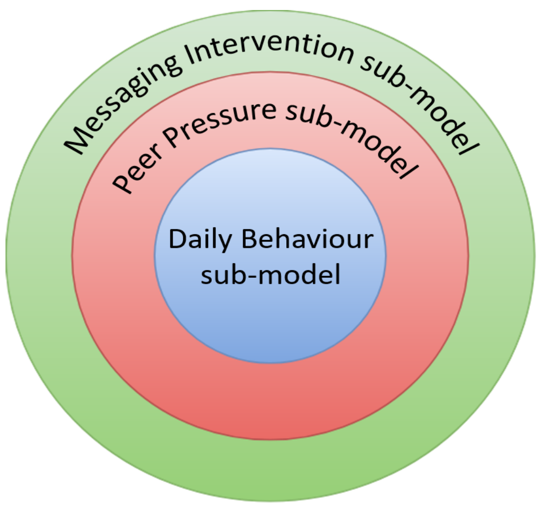


FIGURE 2. The layered agent-based model.

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

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 2nd and 3rd 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

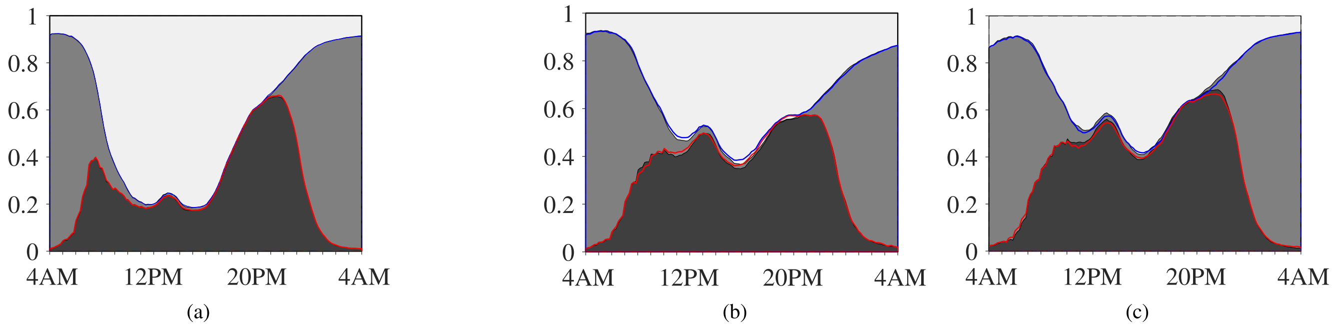


FIGURE 3. Average occupancy data comparison between the developed ABM and the existing PM. (a) Weekdays occupancy. (b) Saturdays occupancy. (c) Sundays occupancy.

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).

$$SC : age, os_{t,d}, t, d \rightarrow sc_{t,d} \tag{12}$$

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).

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

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)

$$aB = \frac{nOFF}{supNOFF}, \tag{14}$$

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.

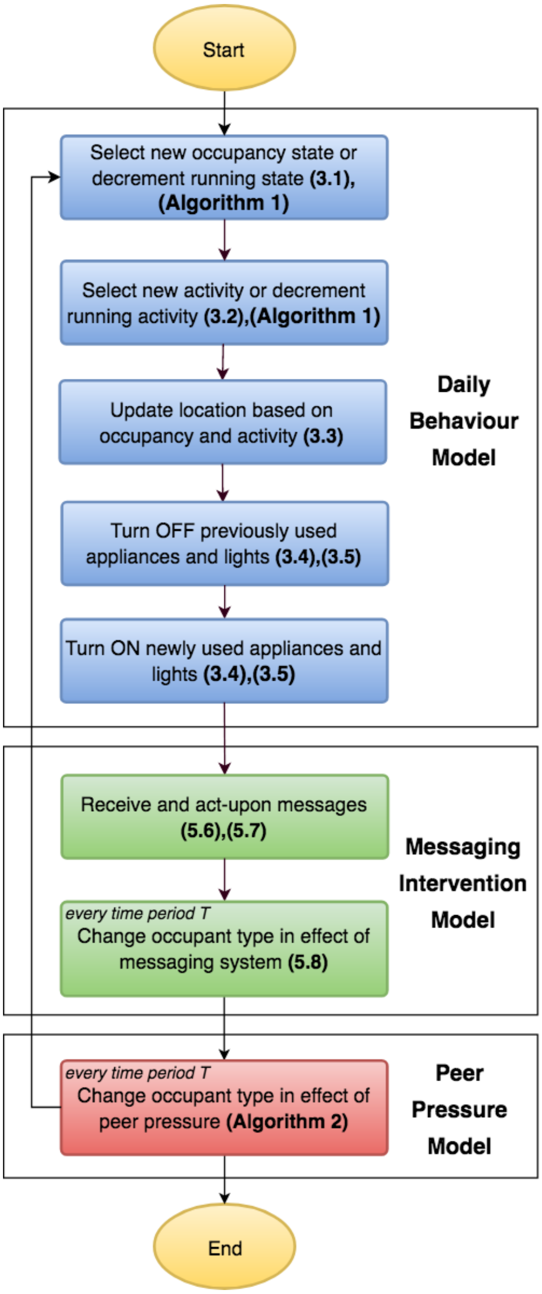


FIGURE 4. Occupant agent execution steps.

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)

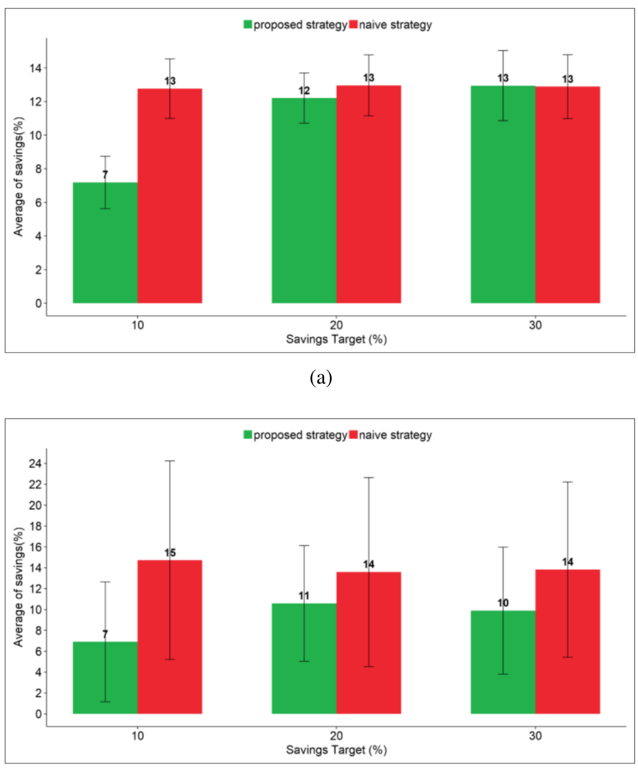
$$A = \frac{NMsg_{total}}{f_{total}} \times 100, \tag{16}$$

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

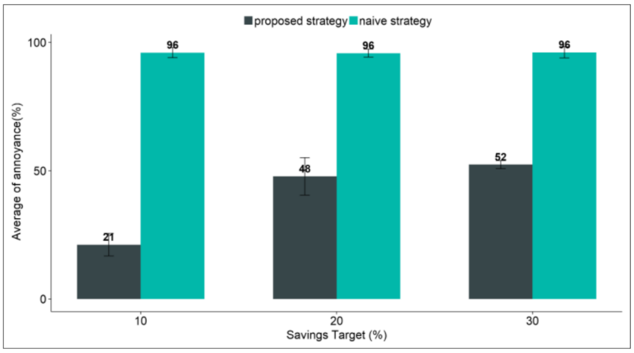
Fig. 5 and Fig. 6 show the average and standard deviation of energy saving and annoyance of the simulated 100 households in each scenario. Scenarios that run with the naive strategy have the same indication when varying the energy saving target since the target does not affect the way the messages are 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



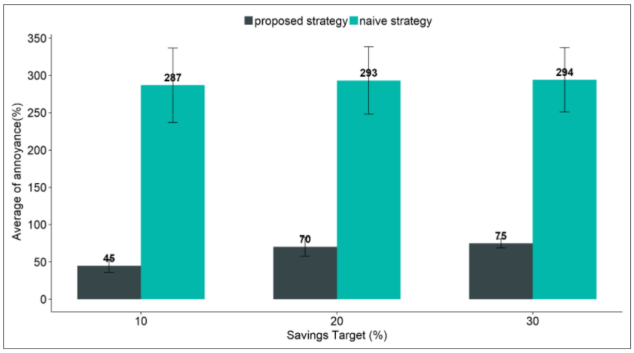
(a)

(b)

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

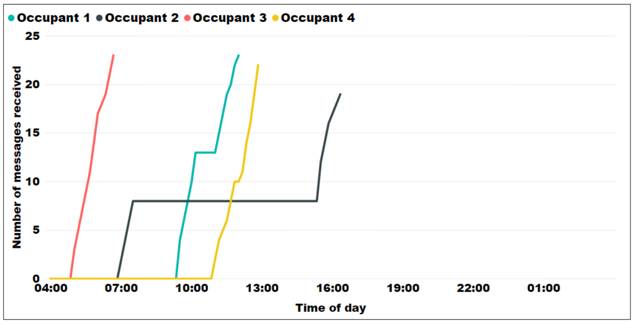


(a)

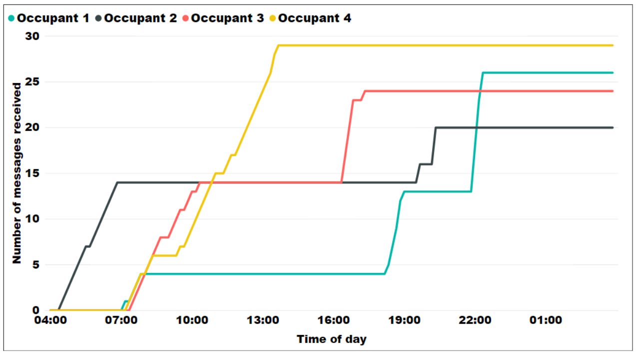


(b)

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.**

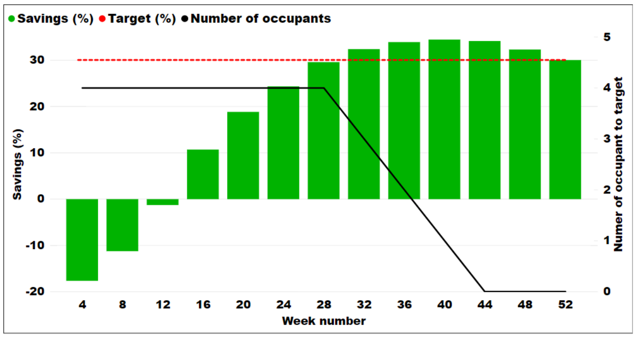
the saving increased only 1% with the green occupants and decreased 1% with waster occupants. Therefore, with the proposed strategy, the maximum average savings for green occupants is 13% and for waster occupants is 11%.

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.

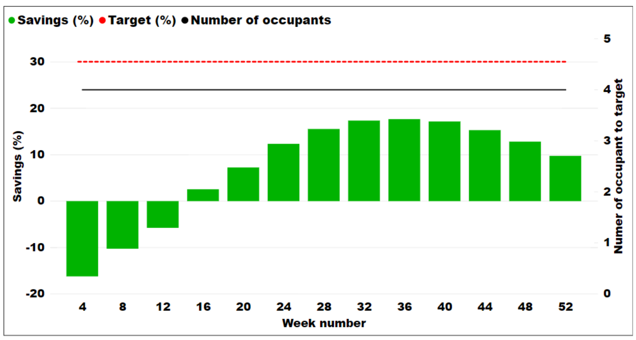
Looking at the standard deviation of the reported results, we notice that results of all waster families is more scattered than green families. This is because waster occupants have the chance to change their occupant type and become more aware, thus achieving different energy savings. An example of 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.

REFERENCES

[1] *Electricity Information Overview 2017*, Int. Energy Agency, Paris, France, 2017.

[2] US Global Cilmate Change Research Program (USGCRP), ''Global climate change,'' in *Global Climate Change Impacts in the United States*. New York, NY, USA: Cambridge Univ. Press, 2009, pp. 13–26.

[3] European Commission. (2011). *Energy Efficiency Plan 2011*. Accessed: Feb. 6, 2018. [Online]. Available: http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52011DC0109&from=EN

[4] Y. A. A. Strengers, ''Designing eco-feedback systems for everyday life,'' in *Proc. ACM SIGCHI Conf. Hum. Factors Comput. Syst.*, Vancouver, BC, Canada, 2011, pp. 2135–2144.

[5] D. Geelen *et al.*, ''An end-user perspective on smart home energy systems The case of PowerMatching City,'' in *Proc. IEEE 4th Innov. Smart Grid Technol. Europe (ISGT) Conf.*, Lyngby, Denmark, 2013, pp. 1–5.

[6] S. Darby, ''The effectiveness of feedback on energy consumption. A review for DEFRA of the literature on metering, billing and direct displays,'' Environ. Change Inst., Univ. Oxford, Oxford, U.K., Tech. Rep., 2006. [Online]. Available: https://www.eci.ox.ac.uk/research/energy/downloads/smart-metering-report.pdf

[7] W. Abrahamse, L. Steg, C. Vlek, and T. Rothengatter, ''A review of intervention studies aimed at household energy conservation,'' *J. Environ. Psychol.*, vol. 25, no. 3, pp. 273–291, 2005.

[8] S. Šćepanović, M. Warnier, and J. K. Nurminen, "The role of context in residential energy interventions: A meta review," *Renew. Sustain. Energy Rev.*, vol. 77, pp. 1146–1168, Sep. 2017.
[9] J. M. Nolan, P. W. Schultz, R. B. Cialdini, N. J. Goldstein, and V. Griskevicius, "Normative social influence is underdetected," *Personality Social Psychol. Bull.*, vol. 34, no. 7, pp. 913–923, 2008.
[10] M. Costanzo, D. Archer, E. Aronson, and T. F. Pettigrew, "Energy conservation behavior. The difficult path from information to action," *Amer. Psychol.*, vol. 41, no. 5, pp. 521–528, 1986.
[11] C. Fischer, "Feedback on household electricity consumption: A tool for saving energy?" *Energy Efficiency*, vol. 1, no. 1, pp. 79–104, 2008.
[12] H. Lovell, M. Pullinger, and J. Webb, "How do meters mediate? Energy meters, boundary objects and household transitions in Australia and the United Kingdom," *Energy Res. Social Sci.*, vol. 34, pp. 252–259, Dec. 2017.
[13] Department for Business Energy & Industrial Strategy. (2017). *Smart Meters Quarterly Report to end September 2017*. [Online]. Available: https://www.gov.uk/government/collections/smart-meters-statistics
[14] T.-J. Yun, "Investigating the impact of a minimalist in-home energy consumption display," in *Proc. ACM Extended Abstr. Hum. Factors Comput. Syst.*. Boston, MA, USA, 2009, pp. 4417–4422.
[15] T. Hargreaves, M. Nye, and J. Burgess, "Making energy visible: A qualitative field study of how householders interact with feedback from smart energy monitors," *Energy Policy*, vol. 38, no. 10, pp. 6111–6119, 2010.
[16] S. Karjalainen, "Consumer preferences for feedback on household electricity consumption," *Energy Buildings*, vol. 43, nos. 2–3, pp. 458–467, 2011.
[17] T. Erickson *et al.*, "The dubuque electricity portal: Evaluation of a city-scale residential electricity consumption feedback system," in *Proc. ACM SIGCHI Conf. Hum. Factors Comput. Syst.*. Paris, France, 2013, pp. 1203–1212.
[18] E. Costanza, S. D. Ramchurn, and N. R. Jennings, "Understanding domestic energy consumption through interactive visualisation: A field study," in *Proc. ACM Conf. Ubiquitous Comput.*. Pittsburgh, PA, USA, 2012, pp. 216–225.
[19] C. Neustaedter, L. Bartram, and A. Mah, "Everyday activities and energy consumption: How families understand the relationship," in *Proc. ACM Annu. Conf. Hum. Factors Comput. Syst.*, Paris, France, 2013, pp. 1183–1192.
[20] N. Castelli, G. Stevens, T. Jakobi, and N. Schönau, "Switch off the light in the living room, please!-Making eco-feedback meaningful through room context information," in *Proc. 28th EnviroInfo Conf.*, Oldenburg, Germany, 2014, pp. 589–596.
[21] M. Pullinger, H. Lovell, and J. Webb, "Influencing household energy practices: A critical review of UK smart metering standards and commercial feedback devices," *Technol. Anal. Strategic Manage.*, vol. 26, no. 10, pp. 1144–1162, 2014.
[22] M. A. Piette, J. Granderson, M. Wetter, and S. Kiliccote, "Intelligent building energy information and control systems for low-energy operations and optimal demand response," *IEEE Des. Test Comput.*, vol. 29, no. 4, pp. 8–16, Aug. 2012.
[23] S. Aman, Y. Simmhan, and V. K. Prasanna, "Energy management systems: State of the art and emerging trends," *IEEE Commun. Mag.*, vol. 51, no. 1, pp. 114–119, Jan. 2013.
[24] H. Kim, S. K. Lee, H. Kim, and H. Kim, "Implementing home energy management system with UPnP and mobile applications," *Comput. Commun.*, vol. 36, no. 1, pp. 51–62, 2012.
[25] M. Jahn, M. Jentsch, C. R. Prause, F. Pramudianto, A. Al-Akkad, and R. Reiners, "The energy aware smart home," in *Proc. IEEE 5th Int. Conf. Future Inf. Technol.*, Busan, South Korea, May 2010, pp. 1–8.
[26] A. De Paola, S. Gaglio, G. Lo Re, and M. Ortolani, "Sensor9k: A testbed for designing and experimenting with WSN-based ambient intelligence applications," *Pervasive Mobile Comput.*, vol. 8, no. 3, pp. 448–466, 2012.
[27] M. Khan, B. N. Silva, and K. Han, "Internet of Things based energy aware smart home control system," *IEEE Access*, vol. 4, pp. 7556–7566, 2016.
[28] B. Dong and B. Andrews, "Sensor-based occupancy behavioral pattern recognition for energy and comfort management in intelligent buildings," in *Proc. 11th Int. IBPSA Conf., Building Simulation*, 2009, pp. 1444–1451.
[29] Y. Agarwal, B. Balaji, R. Gupta, J. Lyles, M. Wei, and T. Weng, "Occupancy-driven energy management for smart building automation," in *Proc. 2nd ACM Workshop Embedded Sens. Syst.*, Zürich, Switzerland, 2010, pp. 1–6.
[30] F. Corucci, G. Anastasi, and F. Marcelloni, "A WSN-based testbed for energy efficiency in buildings," in *Proc. IEEE Symp. Comput. Commun.*, Kerkyra, Greece, Jun./Jul. 2011, pp. 990–993.
[31] G. Anastasi, F. Corucci, and F. Marcelloni, "An intelligent system for electrical energy management in buildings," in *Proc. IEEE 11th Int. Conf. Intell. Syst. Design Appl.*. Cordoba, Spain, Nov. 2011, pp. 702–707.
[32] A. Zipperer *et al.*, "Electric energy management in the smart home: Perspectives on enabling technologies and consumer behavior," *Proc. IEEE*, vol. 101, no. 11, pp. 2397–2408, Nov. 2013.
[33] S. S. Intille, "The goal: Smart people, not smart homes," in *Proc. Int. Conf. Smart Homes Health Telematics*, C. Nugent and J. Augusto, Eds. Amsterdam, The Netherlands: IOS Press, 2006, pp. 3–6.
[34] DNV.GL. (2015). *PowerMatching City, DNV.GL*. Accessed: Jan. 13, 2018. [Online]. Available: https://www.dnvgl.com/cases/powermatching-city-lighthouse-project-79544
[35] T. Zhang, P.-O. Siebers, and U. Aickelin, "Modelling electricity consumption in office buildings: An agent based approach," *Energy Buildings*, vol. 43, pp. 2882–2892, Oct. 2011.
[36] T. Jensen and E. Chappin, "Towards an agent-based model on co-diffusion of technology and behavior: A review," in *Proc. 28th Eur. Conf. Modelling Simulation*. Brescia, Italy: European Council for Modeling and Simulation, 2014, pp. 782–788.
[37] D. Geelen, A. Reinders, and D. Keyson, "Empowering the end-user in smart grids: Recommendations for the design of products and services," *Energy Policy*, vol. 61, pp. 151–161, Oct. 2013.
[38] S. Sorrell, "The rebound effect: An assessment of the evidence for economy-wide energy savings from improved energy efficiency," UK Energy Res. Centre, Res. Councils U.K., Tech. Rep., 2007. [Online]. Available: http://www.ukerc.ac.uk/publications/the-rebound-effect-an-assessment-of-the-evidence-for-economy-wide-energy-savings-from-improved-energy-efficiency.html
[39] D. Leake, A. Maguitman, and T. Reichherzer, "Cases, context, and comfort: Opportunities for case-based reasoning in smart homes," in *Designing Smart Homes* (Lecture Notes in Computer Science), vol. 4008, J. C. Augusto and C. D. Nugent, Eds. Berlin, Germany: Springer, 2006, pp. 109–131.
[40] W. Jager, "Modelling consumer behaviour," Ph.D. dissertation, Centre Environ. Traffic Psychol., Univ. Groningen, Groningen, The Netherlands, 2000.
[41] R. Axtell, "Why agents? On the varied motivations for agent computing in the social sciences," Center Social Econ. Dyn., Brookings Inst., Washington, DC, USA, Tech. Rep., 2000. [Online]. Available: https://www.brookings.edu/research/why-agents-on-the-varied-motivations-for-agent-computing-in-the-social-sciences/
[42] M. Wooldridge and N. R. Jennings, "Intelligent agents: Theory and practice," *Knowl. Eng. Rev.*, vol. 10, no. 2, pp. 115–152, 1995.
[43] E. Bonabeau, "Agent-based modeling: Methods and techniques for simulating human systems," *Proc. Nat. Acad. Sci. USA*, vol. 99, no. 3, pp. 7280–7287, May 2002.
[44] B. Heath, Jr., R. Hill, and F. Ciarallo, "A survey of agent-based modeling practices (January 1998 to July 2008)," *J. Artif. Soc. Social Simul.*, vol. 12, no. 4, p. 9, 2009.
[45] T. Carmenate *et al.*, "Modeling occupant-building-appliance interaction for energy waste analysis," *Procedia Eng.*, vol. 145, pp. 42–49, 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1877705816300169
[46] L. Klein *et al.*, "Coordinating occupant behavior for building energy and comfort management using multi-agent systems," *Autom. Construct.*, vol. 22, pp. 525–536, Mar. 2012.
[47] E. Azar and C. C. Menassa, "Agent-based modeling of occupants and their impact on energy use in commercial buildings," *J. Comput. Civil Eng.*, vol. 26, no. 4, pp. 506–518, 2012.
[48] E. Azar and C. C. Menassa, "A comprehensive framework to quantify energy savings potential from improved operations of commercial building stocks," *Energy Policy*, vol. 67, pp. 459–472, Apr. 2014.
[49] J. Chen, J. E. Taylor, and H. H. Wei, "Modeling building occupant network energy consumption decision-making: The interplay between network structure and conservation," *Energy Buildings*, vol. 47, pp. 515–524, Apr. 2012.
[50] K. Anderson and S. Lee, "An empirically grounded model for simulating normative energy use feedback interventions," *Appl. Energy*, vol. 173, pp. 272–282, Jul. 2016.
[51] F. Abdallah, A. Abdallah, and S. Basurra, "Defining context for home electricity feedback systems," in *Proc. Int. Conf. Zero Carbon Buildings Today Future*, Birmingham, U.K., 2016, pp. 147–152.
[52] E. Cutrell, M. Czerwinski, and E. Horvitz, "Notification, disruption, and memory: Effects of messaging interruptions on memory and performance," in *Proc. Hum.-Comput. Interact. (Interact)*. Amsterdam, The Netherlands: IOS Press, 2001, pp. 263–269.

[53] A. S. Shirazi, N. Henze, T. Dingler, M. Pielot, D. Weber, and A. Schmidt, ''Large-scale assessment of mobile notifications,'' in *Proc. ACM SIGCHI Conf. Hum. Factors Comput. Syst.*. Toronto, ON, Canada, 2014, pp. 3055–3064.
[54] J. Ho and S. S. Intille, ''Using context-aware computing to reduce the perceived burden of interruptions from mobile devices,'' in *Proc. ACM SIGCHI Conf. Hum. Factors Comput. Syst.*, Portland, Oregon, USA, 2005, pp. 909–918.
[55] V. Pejovic and M. Musolesi, ''InterruptMe: Designing intelligent prompting mechanisms for pervasive applications,'' in *Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput.*, Seattle, WA, USA, 2014, pp. 897–908.
[56] M. Pielot, R. de Oliveira, H. Kwak, and N. Oliver, ''Didn't you see my message? Predicting attentiveness to mobile instant messages,'' in *Proc. ACM SIGCHI Conf. Hum. Factors Comput. Syst.*. Toronto, ON, Canada, 2014, pp. 3319–3328.
[57] A. Mehrotra, M. Musolesi, R. Hendley, and V. Pejovic, ''Designing content-driven intelligent notification mechanisms for mobile applications,'' in *Proc. ACM Int. Joint Conf. Pervas. Ubiquitous Comput. (UbiComp)*, Osaka, Japan, 2015, pp. 813–824.
[58] J. E. Fischer, N. Yee, V. Bellotti, N. Good, S. Benford, and C. Greenhalgh, ''Effects of content and time of delivery on receptivity to mobile interruptions,'' in *Proc. ACM 12th Int. Conf. Hum. Comput. Interact. Mobile Devices Services*, Lisbon, Portugal, 2010, pp. 103–112.
[59] D. Li, C. C. Menassa, and A. Karatas, ''Energy use behaviors in buildings: Towards an integrated conceptual framework,'' *Energy Res. Social Sci.*, vol. 23, pp. 97–112, Jan. 2017.
[60] R. Ford, M. Pritoni, A. Sanguinetti, and B. Karlin, ''Categories and functionality of smart home technology for energy management,'' *Building Environ.*, vol. 123, pp. 543–554, Oct. 2017.
[61] C. Nalmpantis and D. Vrakas, ''Machine learning approaches for non-intrusive load monitoring: From qualitative to quantitative comparation,'' *Artif. Intell. Rev.*, pp. 1–27, Jan. 2018. [Online]. Available: https://link.springer.com/article/10.1007/s10462-018-9613-7
[62] A. De Paola, M. Ortolani, G. Lo Re, G. Anastasi, and S. K. Das, ''Intelligent Management Systems for Energy Efficiency in Buildings: A Survey,'' *ACM Comput. Surv.*, vol. 47, no. 1, 2014, Art. no. 13.
[63] C.-H. Lu and L.-C. Fu, ''Robust location-aware activity recognition using wireless sensor network in an attentive home,'' *IEEE Trans. Autom. Sci. Eng.*, vol. 6, no. 4, pp. 598–609, Oct. 2009.
[64] D. Riboni, T. Sztyler, G. Civitarese, and H. Stuckenschmidt, ''Unsupervised recognition of interleaved activities of daily living through ontological and probabilistic reasoning,'' in *Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput.*, Heidelberg, Germany, 2016, pp. 1–12.
[65] G. Bieber, M. Haescher, and M. Vahl, ''Sensor requirements for activity recognition on smart watches,'' in *Proc. ACM 6th Int. Conf. Pervasive Technol. Rel. Assistive Environ.*, Rhodes, Greece, 2013, Art. no. 67.
[66] F. A. Qayyum, M. Naeem, A. S. Khwaja, A. Anpalagan, L. Guan, and B. Venkatesh, ''Appliance scheduling optimization in smart home networks,'' *IEEE Access*, vol. 3, pp. 2176–2190, 2015.
[67] C. Perera, A. Zaslavsky, D. Georgakopoulos, and P. Christen, ''Context aware computing for the Internet of Things: A survey,'' *IEEE Commun. Surveys Tuts.*, vol. 16, no. 1, pp. 414–454, 1st Quart., 2014.
[68] F. Abdallah, S. Basurra, and M. M. Gaber, ''A hybrid agent-based and probabilistic model for fine-grained behavioural energy waste simulation,'' in *Proc. IEEE 29th Int. Conf. Tools Artif. Intell. (ICTAI)*, Nov. 2017, pp. 991–995.
[69] 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*, vol. 10842. Cham, Switzerland: Springer, 2018, pp. 489–503.
[70] D. Aerts, ''Simulations, occupancy and activity modelling for building energy demand, comparative feedback and residential electricity demand characteristics,'' Ph.D. dissertation, Vrije Univ. Brussel, Brussel, Belguim, 2015.
[71] T. Zhang, P.-O. Siebers, and U. Aickelin, ''Simulating user learning in authoritative technology adoption: An agent based model for council-led smart meter deployment planning in the UK,'' *Technol. Forecasting Social Change*, vol. 106, pp. 74–84, May 2016.
[72] K. Frenken, ''Technological innovation and complexity theory,'' *Econ. Innov. New Technol.*, vol. 15, no. 2, pp. 137–155, 2006.
[73] F. Abdallah, S. Basurra, and M. M. Gaber, ''An agent-based collective model to simulate peer pressure effect on energy consumption,'' in *Proc. 10th Int. Conf. Comput. Collective Intell. (ICCCI)*, 2018, pp. 283–296.
[74] M. Granovetter, ''Threshold models of collective behavior,'' *Amer. J. Sociol.*, vol. 83, no. 6, pp. 1420–1443, 1978.
[75] L. Festinger, *A Theory of Cognitive Dissonance*, 2nd ed. Stanford, CA, USA: Stanford Univ. Press, 1962.
[76] M. Gabriel, C. de Schietere De Lophem, and C. Van Bavel, ''State of the smart Consumer: Usage patterns of the smartphone—Global mobile consumer survey (Belgian edition),'' Deliotte, London, U.K., Tech. Rep., 2017. [Online]. Available: https://www2.deloitte.com/content/dam/Deloitte/be/Documents/technology-media-telecommunications/global-mobile-consumer-survey-2017_belgian-edition.pdf

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.