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GreenBe – A System To Capture and Visualize Users' Energy-Related Activities For Facilitating Greener Energy Behavior

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ABSTRACT

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Although technological advancements can help us to live with a lower environmental impact, it is a critical need to embrace sustainability as a lifestyle for humanity to survive in the long term. In this thesis work, we proposed and developed an approach for facilitating greener energy behavior by raising people's awareness of their own behavior and its impact on energy consumption, then motivating and aiding them to change their energy-related practices. Our **Gre**ener **En**ergy **Be**havior (*GreenBe*) system is developed to capture human activities at homes and offices in a non-intrusive manner by utilizing building automation infrastructure, and to find out their suboptimal habits in using energy. Out of the collected data, users' behavioral patterns in relation to energy usage are extracted, and visualized to them. In its demonstration, the system successfully highlighted the potential of energy savings which users could gain by simply changing their behavior. Users who experienced the system found it helpful in aiding them to change their energy-related practices. Better energy savings and sustainability could be achieved even without any automation solutions by directly raising sustainable behavior.

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Rome wasn't built in a day.

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LIST OF SYMBOLS AND ABBREVIATIONS

COP 21	The 21st meeting of the Conference of the Parties (Paris Climate Conference)
GPS	Global Positioning System
GreenBe	Greener Energy Behaviour
ICT	Information and Communication Technology
IEA	International Energy Agency
IoT	Internet of Things
LUT	Lappeenranta University of Technology

Chapter 1

INTRODUCTION

The Paris Agreement reached at COP21 in December 2015 (United Nations 2015) has formalized the target of holding the global temperature rise to well below 2^{o}C above pre-industrial levels and pursuing efforts for 1.5^{o}C. The rapidly increasing world energy consumption has already raised high concerns about exhaustion of natural resources and a tremendous amount of environmental issues such as global warming, and climate change. The fact that energy production and use generate around two-thirds of global greenhouse gas (GHG) emissions (World Energy Council 2016) clearly indicate that actions in the energy sector has a central role in achieving the World's agreed climate goal. In addition to switching from high-carbon to low-carbon energy generation system (e.g. renewables and nuclear), there is a critical need of reducing energy demand and increasing energy efficiency. According to International Energy Agency (IEA)'s analysis (IEA 2015), energy efficiency could contribute the largest share of global emissions reductions toward achieving the ambition of the Paris Agreement to mitigate climate change, surpassing even the role of renewables. Improving energy efficiency and reducing energy consumption require determined actions to tap the considerable potential for higher energy savings of buildings, transport and product and processes (Council of the European Union 2011).

Meanwhile, the operation of buildings remains highly energy intensive with buildings accounting for around 40 percent of EU final consumption and 60 percent of electricity consumption, significantly exceeding the other major sectors: industrial and transportation (Strategy 2015; Lapillonne et al. 2015). High socio-economic development and technological advances result in a continuously increasing building energy demand. Great and attractive opportunities exist to reduce buildings' energy consumption at lower costs and higher results than other sectors (Mulligan 2009). Thus, reducing buildings' energy consumption and CO_2 emission is essential and contributes significantly to sustainable development progress.

Currently, the primary approaches used to achieve the target of reducing energy usage are technological such as sustainable building materials and energy-efficient equipment. Those technologies are effective on increasing energy efficiency, and decreasing overall building's energy consumption and CO_2 emission. For instance, the implementation of smart thermostat could save approximately 28 percent of the overall energy bills (Gao & Whitehouse 2009). The application of home automation could also reduce CO_2 emissions by 13 percent (Louis et al. 2014). However, technology itself can only partly meet the challenge of reducing the over-consumption due to consumers' behaviors (Steg & Vlek 2009; Pothitou et al. 2014). Much development of efficient energy systems designed from a top-down technological perspective fails to address complex processes involved since humans and their actions have a major impacts on the transition to the new systems (Katzeff & Wangel 2015). The energy demand is affected as much by people's choices and behavior, as by technical performance (DOE 2015). Besides, environmental effectiveness of applied eco-technologies strongly depends on the way users interact with them (Midden et al. 2007). Thus, relying solely on technical solutions is insufficient to achieve sustainability since humans play an essential role in sustainable development (Steg & Vlek 2007; Fischer et al. 2012). A radical change in people's habitual behavior of consuming energy is crucial to move towards a sustainable future.

The research challenge addressed in this thesis is to propose an approach to achieve energy efficiency in buildings through facilitating human behavioral changes. To promote energy-efficient behaviors, it is vital to educate people on the consequences of their actions to energy consumption. This requires the ability to (1) capture human activities in a given environment and (2) to find out their careless habits in using energy. By extracting and visualizing users' behavioral patterns in relation to suboptimal energy usage, we can show them the potentials of energy savings that could be gained by simply changing their behaviors. The visualization can also aid them to change their behavior to become more energy-conservative by giving specific behavior change targets and remove ability barriers of adapting more sustainable behaviors.

1.1 Motivation

Individual behavior is the main determinant of total energy use in buildings (Guerra Santin 2013; Pothitou et al. 2014). Occupant behaviors are responsible for one third of energy consumption which clearly indicates that targeting user behavioral changes can be a highly effective means of conserving energy. Households, for example, can save a considerable amount of energy usage by simply being more careful with their energy use at home.

However, most people are unaware of their own behavior and its impact on energy consumption. They usually have careless habits in consuming energy such as leaving lights on when they are not needed, which result in much wasted energy. Besides, many people are already motivated to reduce energy consumption, but lack of knowledge, skills, and resources which aid them to change their energy behavior (Leiserowitz et al. 2014). The potential of energy savings through consumers' behavior changes is usually neglected, in spite of being referred to be as high as those from technological solutions (Lopes et al. 2012).

By knowing and understanding of our habits in sense of excess energy usage we have more motivation and guidelines to change our own behaviors to be more energy-conservative. Besides, people are willing to change their behavioral habits if the infrastructures and technologies make it easy for them to change (Tomlinson 2010). Approaches for influencing human behaviors need to be integrated with existing technological interventions to bring better impacts on behavioral changes. Advanced information and communication technology offers a great ability to reshape the ways people act. In the area of building automation, we are able to find out occupants' careless behaviors and the sub-optimal energy usage. Users' behavioral patterns in relation to energy usage can be extracted from captured user activities by utilizing existing home automation infrastructure. By providing visualization of users' energy-related habitual behaviors and therefore raising awareness about the impacts of their habits on building energy consumption, this thesis work aims at facilitating user behavioral changes to achieve better energy efficiency. Once users change their behaviors, energy-efficient behaviors can be transferred from place to place. For example, behavior changes measured at work can inspire employees to act more conservatively at home. Human behavioral changes and more optimal energy consumption practices lead to a real and persistent energy savings (European Environment Agency 2013).

1.2 Aim and Objectives

This thesis work targets at creating an integrated ICT solution for achieving sustainability through stimulating greener energy behavior. Sustainability is referred as “a development that meets the needs of the present without compromising the ability of future generations to meet their own needs” (Brundtland 1987). The sustainability impacts of an ICT system can be divided into five different perspective including economical, ecological, social, individual, and technical as presented in (Penzenstadler 2014). *Economical* sustainability refers to maintaining capital and adding value. *Ecological* sustainability aims at improving human welfare by protecting the environment and reserving natural resources. *Social* sustainability is the ability of preserving the societal communities in their solidarity and services. *Individual* dimension of sustainability refers to maintaining human capital such as education, knowledge, and access to services. *Technical* perspective of sustainability refers to the long-term existence of the system and its sufficient development considering changing surrounding conditions. This thesis emphasizes at individual, environmental and technical perspectives of sustainability. However, the social and economic aspects are also considered.

The objectives of the thesis is to extract and visualize human behavioral patterns in relation to suboptimal energy usage by utilizing existing home automation infrastructure. The following research questions are identified.

i. How to capture human behavior in home/office environment by using home automation infrastructure?

ii. How to visualize the behavioral patterns in relation to energy usage to the users to facilitate user behavioral changes?

1.3 Research methodology

In this thesis work, design science is applied for (1) development of infrastructure for capturing user activities in home/office, and (2) visualization of user behavioral patterns in relation to suboptimal energy usage to facilitate human behavioral changes. Design science is fundamentally a problem-solving paradigm. A design science research involves the creation of new knowledge through design of innovative artifacts and analysis of the use of the artifacts to sold a real-world problem (Hevner & Chatterjee 2010). Artifacts are, but not limited to concepts, models, methods, and instantiations. In our work, for example, artifacts include user activity capturing infrastructure, activity measurement method, and approaches for visualizing user activities in relation to energy usage.

Adopted from the design science research framework suggested by Hevner and Chatterjee (2010), our research process includes 5 phases as described in *Figure 1*.

Figure 1 – Design Science Research Process

In the first phase of the research process – ***Problem Identification***, the problem is identified. The problem has to be practical relevance. This phase comprises of the following steps: (1) identifying problem, (2) doing literature research and (3) pre-evaluating relevance. As a result of this phase, the research questions are defined.

Requirements Definition phase outlines the solution artifacts and their explicit requirements. The requirements are inferred from the problem definition and knowledge of emerging technologies.

The third phase – ***Solution Design & Development*** creates the solution artifacts. This phase includes determining the functionality, designing the architecture, and implementing of the actual artifacts.

In the next phase, the ***Demonstration*** of how artifacts are used to solve the problem is presented. This involves the use of artifacts in experimentation and simulation.

Finally, the ***Evaluation*** phase, we will compare the artifacts' functionality with the defined objectives and requirements to evaluate if the developed system meets the criteria. In addition, the results of experiments and simulations are analyzed and discussed. Surveys are conducted to measure the effectiveness of our visualization approaches on aiding human behavioral changes.

1.4 Research contributions

This thesis work contributes mainly to the human behavioral field but also to the technical home automation field. The main contributions of the thesis include:

i. The thesis investigated and developed a technical infrastructure for capturing user activities at home and in offices by using building automation infrastructure.

ii. We proposed and developed an integrated system named *GreenBe* to capture and extract user behavioral patterns in relation to energy usage.

iii. Using the developed system, we could identify the potentials for energy savings at office environment that could be achieved by user behavioral changes.

iv. Out of collected data by our *GreenBe* system in an office at Lappeenranta University of Technology, we proposed an approach for visualizing human behavioral patterns in relation to energy usage in order to encourage people to change their energy-related practices in a more efficient way.

1.5 Delimitation

This thesis work is limited to capturing and visualizing human activities in relation to suboptimal energy usage in home/office environment using existing home automation infrastructure. Out of the experiments and the gathered data, users' behavioral patterns are extracted and suitable visualization approach is studied. The impact of the visualization to the final human behavioral change is not included into the research. Similarly, the impact of human change to the sustainability or home automation is left to the future works.

1.6 Thesis structure

The thesis is structured into six chapters. The first chapter introduces the background, problem definition, aim and objectives, contributions, and delimitation of the research. The rest of this thesis is organized as follow.

- **Chapter 2 – Background and Related work**

Chapter two provides the background knowledge of human behavior and principle psychological factors to effectively influence human behavior. In addition, technological advancements in the areas of human activity recognition and home automation which can be used for developing applications to motivate and aid people to change their behavior are presented. Finally, we review the related work of current approaches for achieving energy efficiency through technological interventions and human behavioral changes.

- **Chapter 3 – Greener Energy Behavior System**

In chapter three, we present our Greener Energy Behavior (*GreenBe*) system which is proposed and developed to answer the research questions defined in section 1.2. The system utilizes visualization of users' activities in relation to energy use to the users to achieve more efficient and economical use of energy in buildings.

- **Chapter 4 – Implementation and Deployment**

Chapter four details our proposed system prototype implementation and deployment. The *GreenBe* system prototype was deployed in a real office environment to capture activities data of two occupants in the office. Out of the collected data during user experiment period, we propose an approach for visualizing their energy behavior. Psychological insights and persuasive techniques are also applied in order to effectively stimulate users' greener energy behavior.

- **Chapter 5 – Results and Discussion**

In this chapter, we show the achieved results of the *GreenBe* system regarding the effectiveness of the system in raising people's awareness of their behavior and its impacts on energy consumption, as well as the effectiveness of the system on motivating and aiding people to change their energy behavior in a more efficient way.

- **Chapter 6 – Conclusion and Future work**

Chapter six concludes our work. In addition, future developments and incorporations with other social and technical aspects to improve the effectiveness of the system on facilitating sustainable energy behavior are also discussed.

Chapter 2

BACKGROUND AND RELATED WORK

Facilitating sustainable energy behavior is a complex problem which involves psychological, cultural, social, and technological aspects. Insight from psychology is essential to motivate people to change their behavior. To effectively encode experiences that influence people's behavior, we must understand human behavior and factors that drive human behavior, thus lead to behavioral change. Therefore, in this chapter we discover factors of influencing human behavior and some persuasive techniques. In addition, an overview of emerging technologies in the fields of human activity recognition and home automation, which can be utilized to develop applications for motivating and aiding people to change their behavior, is also provided. Finally, we review the existing approaches for improving energy efficiency and reducing energy consumption, including through technological fixes and human behavioral changes.

2.1 Human behavior change and factors that influence human behavioral change

According to the Transtheoretical Model of Behavior Change (TTM) (Prochaska & DiClemente 1986), a person may progress through five stages of change when trying to modify their behavior. The five stages of behavior change are presented in *Figure 2*.

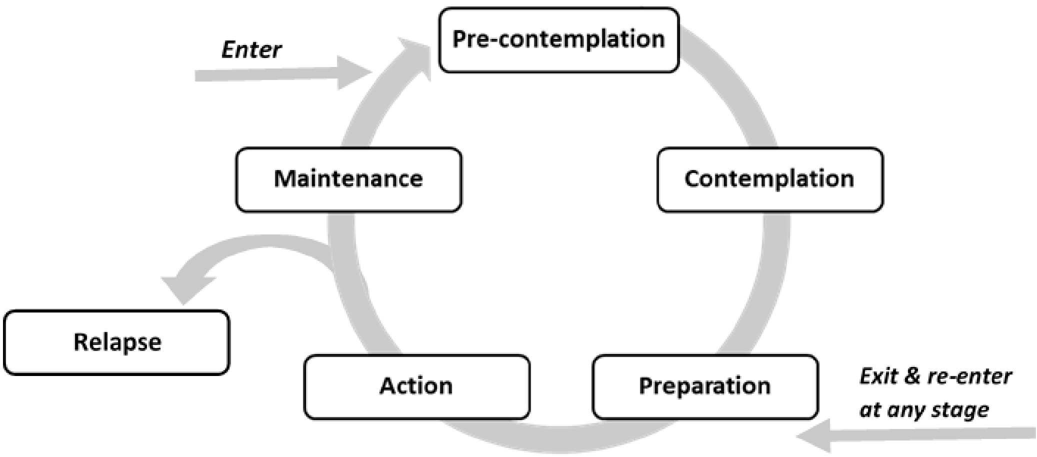


Figure 2 – Stages of Behavior Change by Prochaska & DiClemente

- ***Pre-contemplation*** is the initial stage in which individuals are unaware of problem behavior. Thus, they have no intentions on changing behavior in the foreseeable future.
- At the second stage – ***Contemplation***, the individuals acknowledge their current behavior is a problem and intend to change.
- ***Preparation*** is the stage when the individuals are ready to take action in the immediate future, aim to develop and commit a plan to change their behavior.
- ***Action*** is the third stage when the individuals take action by altering their behavior.
- At the final stage - ***Maintenance, Relapse, Recycling***, the individuals sustain their behavior changes and prevent relapse. If relapse occurs, the individuals need to begin the progress again.

The TTM is useful to design applications for effectively facilitating human behavior change. We need to consider that an intentional behavior change goes through a process in a series of stages rather than a single event. Different techniques and designs should be applied for each stage of behavior change. There are some previous works applied the TTM to motivate people to be more environmentally conscious. For example, He et al. (2010) developed a framework for motivating sustainable energy usage behaviors based on the TTM's stages of change. The motivational framework proposes strategies targeting individual motivations at each stage of behavioral change. The motivational goal(s) followed by recommendation(s), and rationale for how technologies can reach these goals at different stages are presented.

According to the Fogg Behavior Model (Fogg 2009), human behavior is a product of three principle factors comprising motivation, ability, and triggers. *Figure 3* shows the relationship among those three factors.

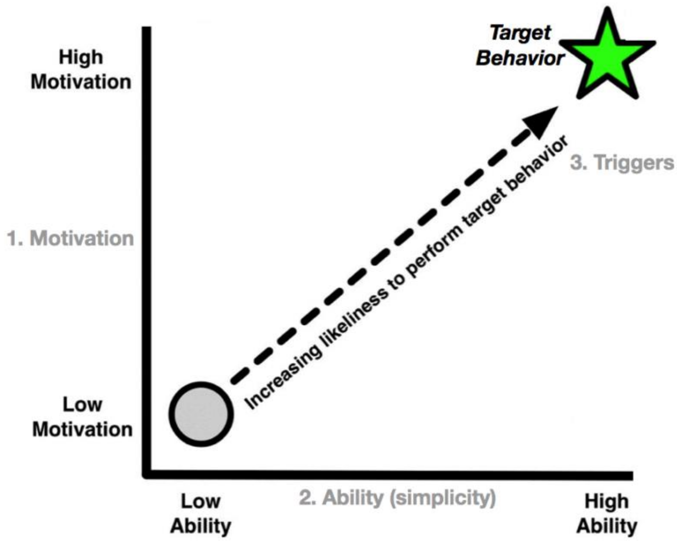


Figure 3 – The Fogg Behavior Model (Fogg 2009)

A person must (1) be sufficiently motivated, (2) have the ability to perform the behavior, and (3) be triggered to perform a specific behavior. In order to effectively persuade people to change their behaviors, all of the three factors must be considered at the same time. The more motivation and ability increase, the more likely the person will perform the target behavior.

In order to effectively motivate people to change their behavior, it is important to distinguish between extrinsic and intrinsic motivations (Hennessey et al. 2005). ***Extrinsic motives*** come from outside the individual. These include economic incentives, rewards, and other external motivators such as being high in social status. In contrast, ***intrinsic motives*** arise from inside the individual. People can be motivated to perform a behavior because it is personally rewarding. People have a variety of motives for conserving resources. However, the study performed by (De Young 1985) shows a strong relationship between intrinsic motivation and everyday conservation behavior. People are more motivated by intrinsic motives and the personal satisfactions derived from conservation activities rather than financial incentives and rewards. In addition, intrinsic motivation leads to more durable behavior change. Durability of behavior change is the ability of "self-sustaining without the need for repeated interventions", which is an important target when motivating sustainable energy behavior (De Young 1993).

Regarding the ability factor, psychologists have repeatedly found three ability barriers to perform behaviors (Swim et al. 2014; Staddon et al. 2016). The first barrier is that people do not know or remember what to do. The second barrier is lack of information whether one is reaching energy-saving target. Finally, the difficulties of behaviors such as insufficient finances, social constrains, lack of time, and complexity of behaviors also make it harder for people to practice pro-environmental behavior. Many people are already motivated to save energy but lack of knowledge about energy actions that they can take. The FBM clearly shows that motivation alone, no matter how strong, may not get people to perform a behavior if the ability barriers remain high. Thus, it is indispensable to find solutions to lower and to eventually remove the barriers in addition to motivating people to overcome these barriers. Programs that remove ability barriers will aid motivated people and encourage less motivated people to change their behaviors (Fogg 2009). Improving behavior-specific abilities by suggesting what to do, making behavioral adoption easier, and showing feedback about progress towards target behavior is a pragmatic approach for facilitating human behavioral change. For instance, Ek and Söderholm (Ek & Söderholm 2010) show that measure of potential savings that is presented in a more concrete and specific way is more likely to influence behavior than general information.

According to the paper "Changing behavior and making it stick – The conceptualization and Management of Conservation Behavior" (De Young 1993), techniques for changing conservation behavior are classified into three categories (1) information techniques; (2) positive motivational techniques; and (3) coercive techniques. Information techniques aim at raising people's awareness of the problem, the necessary behavior needed to resolve the problem or the steps required to carry out this behavior. Positive motivational techniques include the use of different motives to make a behavior more appealing. Coercive techniques use physical or perceptual constrains on people to change their behavior. *Table 1* presents the selected behavior change techniques in each category.

Table 1 – Typology of Behavior Change Techniques adopted from De Young (1993)

SOURCE OF CHANGE	**BEHAVIOR CHANGE TECHNIQUES**		
	Information	**Positive Motivation**	**Coercion**
Environmental/Others *(Tangible)*	• Declarative knowledge • Procedural knowledge • Feedback • Modeling • Prompting	• Material incentives • Social support	• Material disincentives • Social pressure • Legal mandates
Internal *(Intangible)*	• Direct experience • Personal insight • Self-monitoring feedback	• Commitment • Intrinsic satisfactions • Sense of competence • Sense of confidence	• Sense of duty • Feeling of remorse

Pro-environmental behaviors are defined as behaviors that intentionally seek to reduce the negative impacts of an individual’s action on environment such as reducing one’s energy consumption (Unsworth et al. 2013; Staddon et al. 2016). According to V. Blok et al. (Blok et al. 2015) there are several factors that encourage pro-environmental behavior in workplace, including information need, environmental awareness and perceived behavioral control. Satisfying information need is crucial to promote sustainable behaviors. Once individuals are provided information about their energy consumption patterns, there are various actions they can take to reduce their energy usage (Ehrhardt-Martinez 2011). Similarly, environmental awareness has a significant effect on the intention to act sustainably in workplace. Therefore, by raising the environmental awareness and providing sufficient information we can encourage them to change their behavior to become more conservative.

Approaches to influence behavior need to be considered in combination with technological interventions (European Environment Agency 2013). There is a close relationship between behaviors and infrastructure supports. Besides, people are willing to change their behavioral habits if the infrastructures and technologies make it easy for them to change (Tomlinson 2010).

In conclusion, we argue that facilitating sustainable energy behavior change is a complex problem that involves psychological, technological, social and cultural aspects. Approaches for encouraging individuals to change their behavior to become more energy conservative need to consider that human behavior change is a progress involving several stages rather than an event. Different behavior change techniques targeting at different stages should be applied to effectively motivate and support people to modify their behavior. In addition to motivating consumers to reach a behavior target, it is important to build behavior-specific abilities to overcome the ability barriers of performing the behavior. Technological advances offer a great opportunity to shape the way people consume energy. In the next sub-section, we will discover the technical advancement in the fields of human activity recognition and home automation, which can be utilized to develop applications for motivating and aiding people to change their behavior.

2.2 Human activity recognition

Human activities are divided into atomic (simple) and complex (composite) activities. Atomic activity is defined as the most elementary component of human activities. It cannot be divided further given application semantics. Complex activity is defined as two or more atomic activities that emerge within a time interval. Humans in their daily lives performs a large number of complex activities such as “working in an office”, “having a meeting”, or “making dinner”. The complex activity “having a presentation”, for example, involves several atomic activities such as “turning the computer on”, “turning the projector on”, “walking in front of the screen”, and “speaking”. Composite activities might be interleaved and concurrent by their nature. In the following sub-sections, different approaches and techniques for capturing human activities are reviewed. In addition, the importance of context information in activity recognition is also discussed.

2.2.1 Activity recognition approaches

Overall, there are four different approaches for recognizing human behavior, including (1) using questionnaire or user activity diary; (2) observe using audio, visual, voice, sensors; (3) observe using wearable sensors; and (4) observe using simple sensors attached to objects in the environment and interpret the sensor readings.

Although using questionnaires to study human behavior is the simplest method, it requires users to remember their own activities and answer many questions. Hence, the accuracy of behavior recognition depends on the users' memory and honesty, which make it is impractical to find their behavior patterns in real life scenarios. In addition, it is impossible to apply to a large-scale study or applications because the approach is done manually.

Vision-based approach (Xu et al. 2013; Subetha & Chitrakala 2016) uses visual sensing facilities such as video cameras, and computer vision techniques to infer human behavior from the captured videos. It has an important role in many areas such as surveillance and robot learning. Since using cameras for monitoring individuals is perceived as intrusive, the approach raises a considerable concern about user privacy and ethics (Chen et al. 2012). Therefore, it is not widely accepted by users at home and in offices.

The other category is sensor-based activity recognition, which can be later classified into (1) approaches using wearable sensor, and (2) approaches using object-based sensor. Most of the earlier research on sensor-based activity recognition used wearable sensors attached in users' body to record related information, and then infer their activities. Information about the users' body posture, location in open environment and vital signs are obtained through accelerometer, Global Positioning System (GPS) and Bio sensors respectively. Even though the activity recognition based on wearable sensors is effective in capture human behavior, the approach has many limitations such as size, ease of use of the sensors, and general issue of acceptability or willingness to wear them (Chen & Khalil 2011). Users might also change their behaviors due to their awareness of wearable sensors tracking them. In addition, this approach itself is not effective in differentiating activities involving simple physical movements (e.g. making tea and making coffee) as human activities not only involve physical motions, but also interactions with the surrounding environment.

The other approach of sensor-based activity recognition is using object-based sensors. In this approach, sensors are attached to the objects and activities are inferred by detecting user-object interactions. Several sensors such as door sensors, pressure mat sensors are deployed within an environment to capture human activities, thus it is also suitable to create ambient intelligent applications such as smart environments (e.g. smart home). Different activities can be inferred using different sensors. For example, a contact sensor applied on the door can track "opening door" and "closing door" activities. Interactions with objects such as "taking a coffee cup" can be inferred by using RFID sensing technology. A pressure mat sensor on the bed can effectively infer sleeping. The object based activity recognition can address the drawbacks of the other approaches. However, various sensors are needed to effectively infer user activities in a given environment.

To sum up, each of the described approaches has both advantages and disadvantages. They are all suitable to apply in different applications depending on the application requirements. However, the user acceptance of is one of the most important requirements to a system which targets at facilitating sustainable energy behavior. Thus, the chosen approach for capturing user behavior at home and in office must be non-intrusive. Therefore, sensor-based approach of activity recognition is the most appropriate in this thesis work.

2.2.2 Activity recognition techniques

Sensor-based activity recognition techniques can be classified into three major trends, comprising (1) data-driven approaches, (2) knowledge-driven approaches, and (3) hybrid approaches. Data-driven approaches use probabilistic and statistical machine learning techniques for activity modeling. Whereas, knowledge-driven approaches employ knowledge engineering and management techniques to infer human activities.

The use of probabilistic models such as Naive Bayes (Shoaib et al. 2016), decision trees, Hidden Markov Model (Safi et al. 2016) for activity recognition, especially in complex activities recognition has been widely applied. Among these methods, Hidden Markov Model is most commonly used (Chen et al. 2012). The major advantage of probabilistic models based activity recognition algorithm is that they can be able to handle noisy, uncertain and incomplete sensor data (Chen & Khalil 2011). However, this method involves training and learning processes, in which large and different training datasets are required. Thus, the method suffers from many problems including data scarcity, scalability, and reusability.

In contrast, knowledge-driven approaches of activity modeling can handle better reusability and context analysis. The approaches involve knowledge acquisition, formal modelling, and representation. Activity models are built using knowledge engineering and management technologies. The use of ontological reasoning for human behavior recognition (Nguyen et al. 2013; Bae 2014; Meditskos et al. 2016) has been commonly applied. Knowledge driven approaches are semantically clear, logically elegant, and easy to get started. Nevertheless, the approaches have some drawbacks in handling uncertainty and temporal data.

To combine the features of both data-driven and knowledge-based techniques, hybrid activity recognition techniques were introduced. In (Gayathri et al. 2014), for example, the authors proposes activity modeling via Markov Logic Network, a machine learning strategy that combines probabilistic reasoning and logical reasoning within a single framework. Combining ontology-based context reasoning with data driven approaches has shown promising results (Rodríguez et al. 2014).

2.2.3 Context in activity recognition

In the domain of activity recognition, a context attribute is defined as any type of data at time, t that is used to infer an activity or a situation (Saguna et al. 2013). Context is extremely important in activity recognition. Context information can determine current situation of the user. This helps to associate situation with activities and results in faster and more accurate activity recognition.

Context attributes can be inferred from virtual and physical sensors. For instance, GPS collect user's location or temperature is retrieved from a temperature sensor present in user's environment. Similarly, some context attributes such as user's schedule and device activity are retrieved from virtual sensors on the user's devices. Most of occupants' activities in smart home are related to a specific location (Gayathri et al. 2015). Thus, we can use object-based sensors to provide context information directly link to activity, which provides better accuracy in identifying the activity recognition.

Moreover, it is necessary to consider context in analyzing user's behavior and behavior patterns. The purpose of behavior is different if the context when user performs the activity such as time, space, and environment is different. According to Ha et al. (Ha et al. 2006), context components are divided into five factors comprising user, space, time, object, and environment. These components are related to each other as described in *Figure 4*.

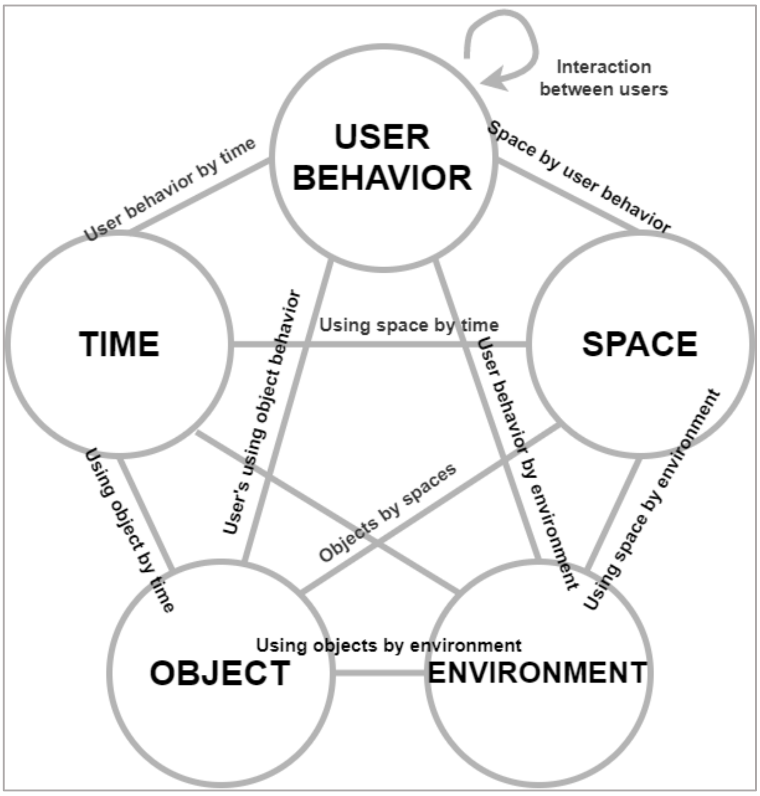


Figure 4 - Relation of context factors adopted from Ha et al. (2006)

2.3 State of the art in home automation

Home automation involves the control and automation of lighting, heating, ventilation, air conditioning, as well as home appliances such as washer, oven or refrigerator. Home automation systems are developed and applied to provide comfort, energy efficiency, security, and several other benefits to the users. They usually include a wide range of connected devices such as motion sensors, door sensors, and switches. The most commonly connected devices in a home automation system is simple binary devices. They include "on and off" devices such as lights and power outlets; as well as sensors which have only two states such as door/window sensors, motion sensors, and switches. All devices can be connected by a network and managed by a control unit.

Various home automation technologies provided by different vendors are currently available in the market. They come with their own way for setting up and configuring devices. In (Withanage et al. 2014), a comparison regarding performance and affordability of popular home automation technologies is presented.

ZigBee (ZigBee Alliance 2017) is an IEEE 802.15 standard used in home automation technology and very closely resembles Bluetooth and Wi-Fi standard. The main advantages of ZigBee is its low power consumption and open specifications which makes the devices ideal for battery operated uses. ZigBee also offers high data security and reliability, and strong data encryption capacities. It is mesh protocol which allows devices talk to one another and act as repeaters. However, it is incompatible with other devices from different vendors, which limits ZigBee from gaining a larger market share.

Z-Wave (Z-Wave Alliance 2017) is a popular wireless standard in home automation and the leading technology in terms of performance. The major strengths of Z-Wave devices are flexibility and security. Z-Wave also offers good network reliability and stability. In addition, open APIs are also provided, which make Z-wave an attractive automation standard for professionals and researchers working on home automation technologies. Even though it is slightly costly than ZigBee systems, it is widely accepted in the current home automation market.

X10 (X10 2017) is a wired home automation protocol, one of the oldest available home automation standard. It comes with low cost but low performance. Although it is the cheapest home automation, it is becoming obsolete.

INSTEON (Insteon 2017) is a dual-band home automation technology that uses both wire and wireless connection. It is designed to integrate power line system with wireless system, allows sensors and switches to be used together using power line and/or radio frequency. It was developed to replace X10 standard, thus is compatible with X10 devices. The main advantages of INSTEON devices include easy installation, high responsibility. However, its drawbacks are limited number of vendors and certified devices available.

EnOcean (EnOcean Alliance Inc 2016) is one of the newest home automation technologies. Its zero energy consumption through energy harvesting feature allows EnOcean devices to work battery-less and wirelessly communicate with other devices. The maintenance of EnOcean devices is minimal as they are self-powered. Radio interference is also minimal since the devices operate in a less crowded 316 MHz band. Nevertheless, EnOcean devices neither work in a mesh network, nor work as repeater. The other disadvantage of EnOcean is it low reliability.

Each of commercially available home automation technologies has its own architecture, communication protocol, and hardware. The intergration of different home automation systems can be done by using a home automation server such as FHEM, openHAB, or Home Assistant.

The implementation of home automation solutions offers a major opportunity of reducing energy costs and cutting down CO_2 emissions (Strategy 2015a). Additionally, Sangogboye et al. (2016) showed that investments in home automation solutions to improve the performance of building could proffer a Return on Investment (ROI) up to 60 percent and less than 2 years of payback time depending on occupants' tendencies and behaviors. However, the investments are usually associated with significant costs. Due to their high cost and design issues, building automation technologies have not been widely adopted even though they have been developed for over four decades (Brush et al. 2011; Gamba et al. 2015).

2.4 Existing approaches for increasing energy efficiency and reducing energy consumption

In this section, we divide current approaches for archiving energy efficiency and reducing total energy consumption into 2 categories comprising (1) by developing and applying means of technology and (2) by raising consumer awareness and targeting behavior changes.

Overall, the current approaches to decrease energy consumption have tended to focus on technological improvements and less on behavioral changes (Ek & Söderholm 2010). However, we have been witnessed the increasing of theoretical and practical studies which target human behavior change to achieve energy conservation in the past few years.

According to the SMARTer2030 report given in (Strategy 2015b), smart building solutions could be applied to large commercial and industrial complexes and smaller homes, helping to drive more efficient use of resource and energy. Smart building solutions consist of automation systems, sensors, integration to Smart Grids via smart meters, energy use analytics and forecasting and the better detection of faults through the use of monitoring technologies. For example, smart meters allow user to monitor their energy use. The installation of automation system can help to control building functions such as lighting, heating, cooling, ventilation based on motion and light sensors. Lights can be automatically turned off when there is enough day-light. Similarly, heating system is off when no one is around. These solutions offer a major opportunity to cut down energy consumption by 5 billion MWh, reduce energy costs by $0.4 trillion and create revenue opportunities of $0.4 trillion.

Other technology-based solutions for the reduction of the usage of energy such as using energy-efficient appliances are commonly applied. However, improving technological energy-efficiency may save less energy than expected due to human behavioral responses evoked by technological improvements. The gains in technological efficiency of energy consumption results in an effective reduction in the per unit price of energy-related services. In some cases, energy efficient innovations may lead to new, unforeseen energy-using applications and products (Sorrell 2015). An increase in technological energy efficiency by 1%, for example, will cause a reduction in resource use that is far below 1% or, in some cases, it can even cause an increase in resource use (Binswanger 2001). This is known as the rebound effect (Berkhout et al. 2000) in which the energy efficiency gain encourage some increase in energy consumption.

Even though technological advancements can help us to live with a lower environmental impact, it is a critical need to embrace sustainability as a lifestyle in order for humanity to survive in the long term (Tomlinson 2010; Gyberg & Palm 2009). At the behavioral level, energy reduction can be achieved by encouraging individual to make home more efficient, selecting energy-efficient appliances, and reducing energy-intensive behaviors (Swim et al. 2014). Energy savings are typically gained as a result of three categories of action: (1) simple changes in daily routines and habitual behaviors; (2) infrequent and low-cost energy stocktaking behaviors (e.g. replacing incandescent bulbs with CFLs); and (3) investments in higher-cost energy-efficient products and appliances (Ehrhardt-Martinez & John 2010). Changing to a more energy-efficient apparatus has become a common advice for energy reduction. However, in this sense energy efficiency is a way of not changing lifestyle but instead changing technical devices and user routines.

A number of theoretical and practical studies have investigated various methods by which to facilitate people to change their energy consumption behavior. These include pricing as an economic instrument, public engagement campaigns, energy labeling, energy advice and eco-feedback. Nevertheless, the results archived are inconclusive (European Environment Agency 2013; Ek & Söderholm 2010).

Economic incentives are commonly applied to alter consumer energy use. In general, energy price changes are effective in controlling energy demand. Higher price results in reduction of overall energy consumption. Several price mechanisms are currently use to decrease or shift energy use during peak time such as dynamic pricing, real-time pricing, and peak-load pricing. However, financial incentives represent only one type of motivator and have their limits (Swim et al. 2014). The limits include (1) the monies distributed have usually exceed the value of energy saved; (2) the effects have often faded over time; and (3) many people are uninterested in material incentives (De Young 1993).

Various *public engagement campaigns* aim at raising awareness and educating the public to reduce their energy consumption. However, such “information deficit” models have been widely criticized on theoretical and pragmatic grounds (Owens & Driffill 2008)(Katzeff & Wangel 2015). Those campaigns fail to take into account the social, cultural and institutional contexts in which human behaviors are formed.

Studies suggest that *energy labeling* can help consumers make energy conscious purchases of household appliances. The Energy Star, for example, is a voluntary energy efficiency-labeling program providing information to promote the purchase of energy-efficient products. Even though the program has showed some positive results (Sanchez et al. 2008), there are no large-scale evaluations are available on the impact of energy efficiency labeling on consumer choices.

Various ICT applications have been developed and used to support users in the imperative global transition towards sustainable consumption. For example, the UCLA Engage project (UCLA 2017) is the one of the largest behavioral experiments in energy conservation in the United States. It investigates the use of real-time, appliance-level energy consumption feedback for promoting energy conservation. Data from appliance level electric metering is used for real-time information display. Insights from behavioral science such as neighborhood comparisons and public status display are also applied to design interventions for changing energy use behavior. The preliminary result shows that consumers adjust their usage in response to comparisons with their neighbors and to messages addressing different impacts of energy use.

In addition, a variety of studies investigates using visualizations of energy consumption in order to raise consumers' energy awareness and induce behavioral changes (Ward et al. 2014; Itoh et al. 2015). There are also several projects which are currently applied in real life. The CS171 final project (Yan et al. 2015), for example, analyzes and displays the energy consumption of 151 buildings at Harvard. Similarly, Sparky D. Dragon (Levy 2015) uses energy dashboards in nice campus buildings to show energy use and give warning if the energy use is high. The QA Graphics' Energy Efficiency Education Dashboard (EEED) (QA Graphics 2017) educates building occupants with real-time energy data and green building features in order to create occupant energy awareness. It is a web application providing display of building performance data, demonstrations of sustainable building features, and tips on how to be efficient. Those visualizations can increase user awareness of energy usage in the building, however, their effectiveness on induce user behavioral changes is vague.

Understanding energy consumption in relation to activity patterns is crucial to achieve energy efficiency. Stimulating consumers to an energy efficient behavior demands control over how different behaviors affect the amount of electricity or heat used (Gyberg & Palm 2009). In the paper "Visualizing energy consumption activities as a tool for making everyday life more sustainable" (Ellegård & Palm 2011), the authors discuss the importance of analyzing and understand energy consumption in relation to households' activity patterns for contributing to an energy efficient life. Their approach uses time-geographic diary together with interviews to analyze when, where, and what energy related activities occur in a household context, and by whom they are performed. Out of the collected data, households' activity patterns and the amount of used energy were visualized as illustrate in *Figure 5*.

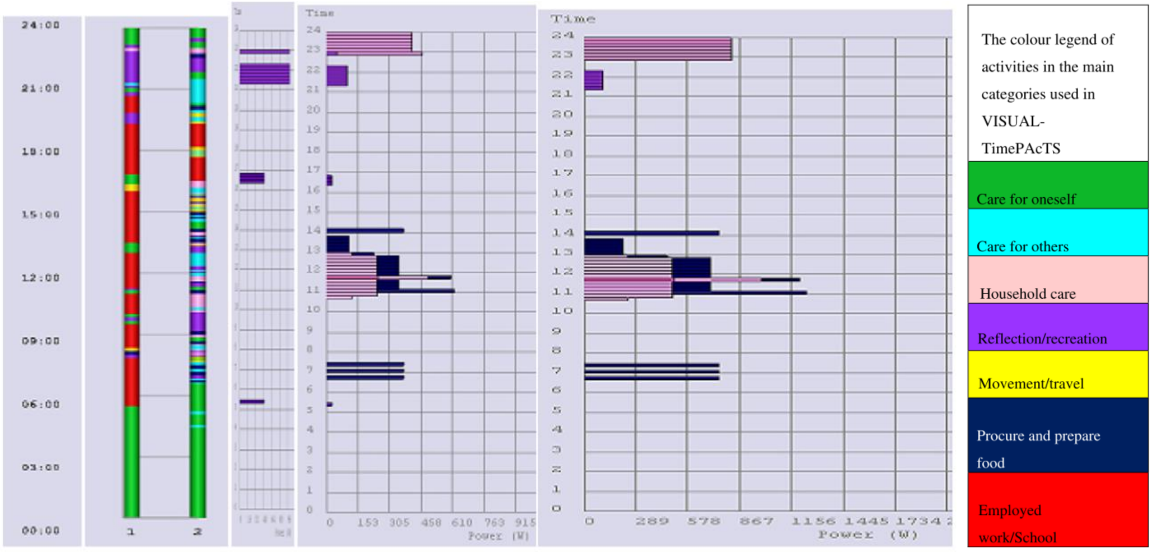


Figure 5 – Visualization of energy consumption activities by Ellegård & Palm (2011)

The visualization shows peoples' activity patterns combined with a curve on how much energy that was needed for various daily activities. The method can give useful feedback with relevant information to households. However, the activity information is manually collected by using activity reports from householders which make it impossible to apply in a large-scale. In addition, the visualization is not easy to understand. Similarly, in the paper "Understanding Domestic Energy Consumption through Interactive Visualization: a Field Study" (Costanza et al. 2012), Costanza at al. introduces *FigureEnergy*, an interactive energy consumption visualization that allows users to engage with and understand their consumption data, relating to concrete activities in their life. The results show that users started to relate their energy consumption to activities rather than just to appliances. Nevertheless, the annotation of users' electricity consumption data and their activities was done manually by the users.

Understanding and shaping behaviors can result in a significant boost in the more efficient use of all energy resources. The behavioral resource might provide about a 25 percent efficiency gain above normal productivity improvements (Ehrhardt-Martinez & John 2010). However, to the best of our knowledge, there are no existing solutions which consider all three primary factors to perform a specific behavior (motivation, ability, and trigger) and different stages of human behavior change to facilitate sustainable energy behavior change. Moreover, the design of ICT solutions targeting human behavioral changes needs to be approached in a more comprehensive way (Hilty & Aebischer 2015). To develop technologies that motivate sustainable energy-related behavior, it is dispensable to focus on people: understanding how and why people use energy. Swim at al. (Swim et al. 2014) suggest that the programs and policies to decrease energy demand should include a behavioral level analysis to help select behaviors that create the most change, design behavioral change strategies that target appropriate motives and abilities, and attend to social and environmental contexts. Making effective approaches for inducing human behavioral changes requires building individual abilities to change behaviors by increasing knowledge about what to do, making behavioral adoption easier, and providing energy feedback about progress toward goals. However, none of the related work aims at easing greener behavior adoption. Thus, this is the first work that investigates and proposes a comprehensive solution considering user activities in relation to energy use for aiding consumers to change their behavioral habits to become more sustainable. The solution embraces the human behavioral insights and technological advancement in the area of home automation and activity recognition.

Chapter 3

GREENER ENERGY BEHAVIOR SYSTEM

This chapters present our **Gre**ener **En**ergy **Be**havior (*GreenBe*) System. As discussed in the previous chapters, occupant behavior has a major impact on how energy is consumed. Targeting human behavior changes can be an effective approach to achieve more energy savings at lower cost than other alternatives. It requires a comprehensive approach which integrates existing technologies and human behavioral insights. To fulfill that requirement, the *GreenBe* system is designed as an integrated system in which the exiting home automation and sensory technologies are used to infer, measure, and extract user behavior at home and in offices. Insights of user behavior and its impact on energy consumption will be delivered to the user in a persuasive manner in order to promote more efficient energy use. Moreover, the collected data can also be used for studying user behavior or improving energy efficiency in smart home.

The chapter is organized as follow. Firstly, the system requirements will be specified. Then, we will present the overall design of the *GreenBe* system which consists several loosely-coupled layers.

3.1 System requirements

In order to successfully integrate user behavior into applications for facilitating more efficient energy use at home and in offices, we defined the following requirements for our proposed solution.

i. The solution can capture user activities in a ***non-intrusive*** manner. This is one of the most important requirements since users might change their behavior if they are always aware of something tracking them, or the installation of devices for activity capturing affect their normal ways of performing activities. In addition, it affects user willingness to use the system.

ii. The system should have ***real-time performance*** in order to give better user experience of using the system which is an important factor to engage users to the *GreenBe* system. In addition, quick feedbacks can help user to adjust their behavior more effectively.

iii. Human activities are concurrent and interleaved by nature. Therefore, the proposed system for capturing user activities must be able to handle ***interleaved and concurrent activities***.

iv. In order to reuse existing equipment, as well as minimize installation costs, it is mandatory for the designed system to be able to ***utilize existing home automation infrastructure***.

v. To apply the solution in a larger scale such as a residential area or the whole office building in the future, we need to ensure the designed system is ***scalable***.

vi. To provide a more comprehensive approach of motivating and aiding people to change their behavior to become more efficient in using energy, more components may be needed to add to the *GreenBe* system in the future. Thus, we must ensure the **extensibility** of the designed solution.

Out of the gathered activity data, suitable solution for delivering the insights of user behavior and its impacts on energy consumption and CO_2 emission will be developed. In order to promote more efficient energy use, the designed solution must fulfill the following three requirements.

i. The solution can effectively raise user's awareness on the impacts of their own behavior on energy consumption.

ii. The solution can effectively motivate people to change their behavior in a more sustainable way.

iii. The solution can effectively aid users to change their behavior to become more energy-conservative.

3.2 System design

Our Greener Energy Behavior (*GreenBe*) system is designed to integrate user behavior into applications for facilitating more efficient energy use at home and office. Since occupant behavior has a major impact on total energy consumption, it is indispensable to incorporate user activity information into approaches for achieving energy efficiency. The proposed *GreenBe* system comprises four layers from infrastructure to application as illustrated in *Figure 6 – The GreenBe System Design*.

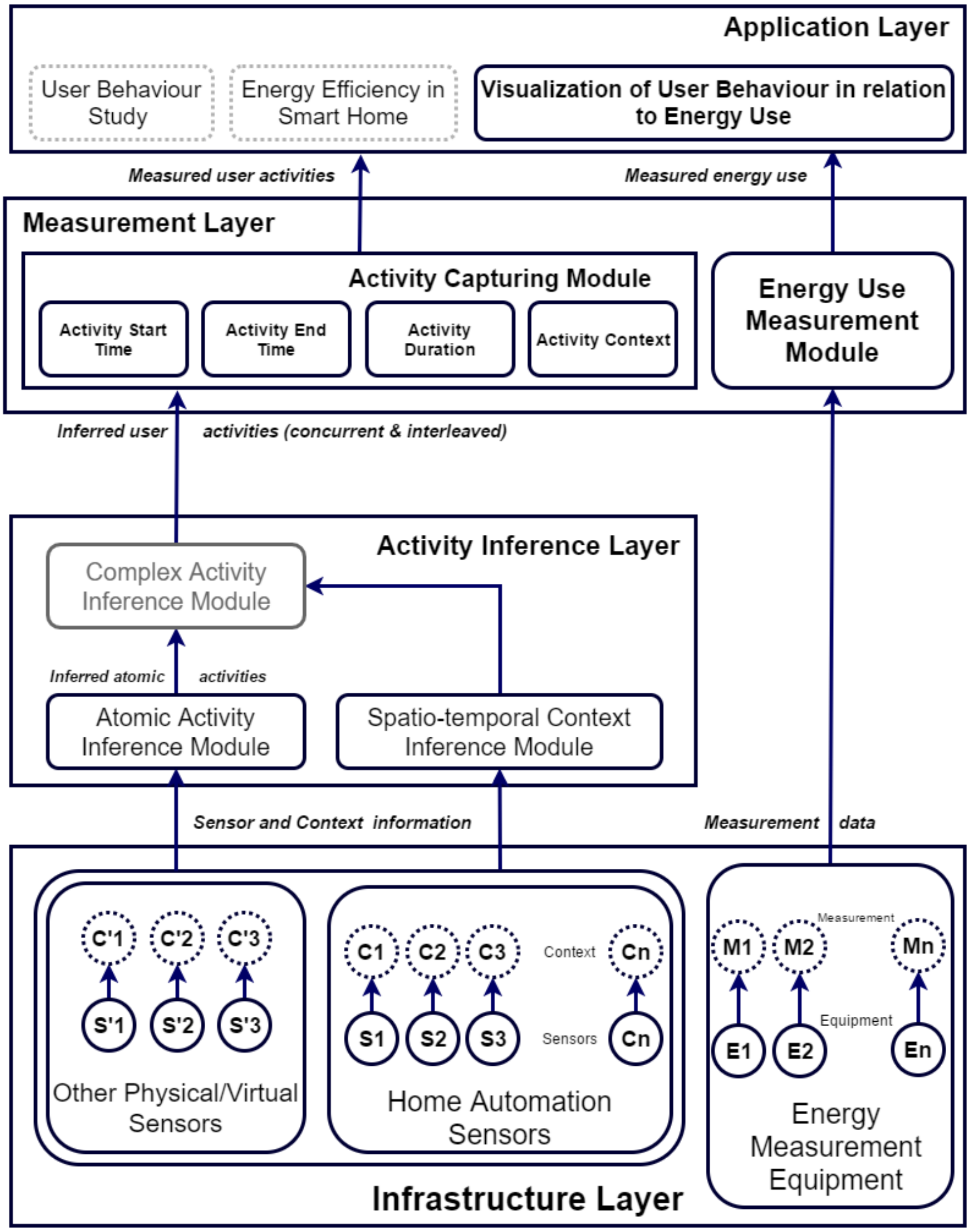


Figure 6 – The GreenBe System Design

3.2.1 Infrastructure layer

The *Infrastructure Layer* includes sensors which are used for capturing user activities and context information, as well as equipment for measuring energy usage. Different types of sensors can be handled in this layer. For instance, presence sensor can be used to infer the situation of a user being in a particular place. RFID tags can be used to capture object-related activities such as “picking up a coffee cup”. Virtual sensors (context data from software applications or services) can also be used to gather information from user’s devices such as schedule of the user from mobile phone. In the proposed system, we especially emphasize the utilization of the existing home automation infrastructure. Various kinds of home automation devices such as door/window sensors, motion sensors, light sensors, and switches can be used to infer human activity, and spatio-temporal context information in an environment.

3.2.2 Activity Inference layer

The Activity Inference Layer is used for recognizing human activities from sensor and context information collected from the infrastructure layer. The layer includes the atomic activity inference module, the spatio-temporal context inference module, and the complex activity inference module. From sensor data, atomic activities are inferred by the Atomic Activity Inference Module. The Spatio-temporal Context Inference Module gathers context information from received sensor data from the infrastructure layer. From the gathered atomic activities, inferred situations and context information, the Complex Activity Inference Module infers complex activities which can be concurrent and interleaved.

Table 2 suggests some example atomic activities and context information which can be inferred from home automation devices.

Table 2 – Suggested activities and context information can be inferred from home automation devices

Home Automation Devices	Context can be inferred	Atomic activities can be inferred
Door/Window sensor	Opened door/window Closed door/window	Opening or closing door/window
Occupancy sensor	Presence of user(s) in a given environment	
Motion sensor	Presence of a user in a given environment	Moving inside a given environment
Switch		Electrical device related activities such as using projector, computer, and coffee-machine.
Light Control Switch and Dimmer	Light on/off	Light related activities such as turn on/off light, adjust brightness level of the light.
Radiator thermostat	Heating on/off	Heating related activities such as turn on/off radiator, adjust heating level.
Temperature and Humidity sensor (indoor and external)	Temperature and Humidity of an indoor or outdoor environment.	
Radio tilt sensor	Object positional deviations	Picking up objects such as trash.

Adopted from Saguna et al. (2013), the *Complex Activity Inference Module* infers complex activities using reasoning about context and atomic activities. A complex activity is inferred from a set of atomic activities, γA, and a set of context, ρC. Each atomic activity A_i and context attribute C_i has a particular weight, $\omega_{CA_k}^{A_i}$ and $\omega_{CA_k}^{C_i}$, respectively. The weights are assigned based on the importance of each A_i and C_i in relation to the occurrence of the corresponding complex activity CA_k. The weight assignment can be expert knowledge-based or computed based on probability analysis. Total weights of all atomic activities $\omega_{CA_k}^{A_i}$ for a complex activity CA_k is 1. Similarly, the sum of all the weights $\omega_{CA_k}^{C_i}$ equals 1. To infer if an activity CA_k is performed successfully, the sum of all the weights ω_{CA_k} for all occurring atomic activities and context is calculated. The activity is inferred as successfully performed when the calculated sum is above a threshold $\omega_{CA_k}^{T}$ and the core set of atomic activities and context occurred. If the sum is less than the threshold, the activity is inferred as being started but abandoned in between. For example, the activity "working in an office" is inferred from a set of atomic activities and context activities as described in *Table 3*. In order to infer that the activity is carried successfully, the following two conditions need to be satisfied. Firstly, the sum of all captured atomic activity and context has to be greater than the defined threshold of the activity which is 0.7. Secondly, the core set of atomic activities and context including A_1, A_4, A_5, and C_1 must happen.

Table 3 –Reasoning about context and atomic ativities for inferring a complex activity

$CA_k(\omega_{CA_k}^{T})$	γA ($\omega_{CA_k}^{A_i}$)	ρC ($\omega_{CA_k}^{C_i}$)	Core γA and ρC	A_S, C_S	A_E , C_E	$T_L$range (minutes)
Working in an office room (0.7)	A_1: enter room (0.2) A_3: walking (0.2) A_4: using laptop/PC (0.2) A_5: leaving room (0.2)	C_1: in office room (0.4) C_2: office lights on (0.2) $\neg C_1$: in office room (0.2) $\neg C_2$: office lights on (0.2)	A_1, A_4, A_5, C_1	A_1, C_1	A_5, $\neg C_1$, $\neg C_2$	5 - 180

3.2.3 Measurement layer

The Measurement Layer consists of the Activity Capturing Module and Energy Use Measurement Module.

- The *Activity Capturing Module* collects activity parameters such as activity start/end time, activity duration, context details such as temperature and humidity. In order to analyze an energy-related activity and infer whether the performed activity is energy-efficient, the context in which the activity is carried must be considered. One specific behavior can be inferred differently in different context. For example, the behavior "leaving window open" can be inferred as the activity that has negative impacts on the energy usage during winter time when the heating system is operating, while, in contrast, it is efficient to leave windows open during summer time to help ventilate the room. Similarly, the activity "using lights in office" can be a sub-optimal energy use activity if the user turns light on when the brightness of natural light is enough for working, while, in the opposite context, it is an efficient use of electricity.

- The *Energy Use Measurement Module* gathers measurement data from the infrastructure layer containing all the equipment, and then calculates and analyses energy usage and how total energy is used during different time and context. There are several available devices with affordable price which can be used in the infrastructure layer. Smart meter, for example, can be used to record electric energy consumption in intervals of an hour or less and communicates that measurement information back to the utility for monitoring. Similarly, the OWL energy monitoring and analysis (Anon n.d.) provides the ability to monitor energy consumption for electrical appliances in real time. Those devices are easing the difficulties with the collection of measurements.

3.2.4 Application layer

The ***Application*** layer consists of all applications which integrate with user activity and energy usage information in order to promote more efficient use of energy. The key focus of this research is the ***Visualization of User Behavior in relation to Energy Use*** application. The application visualizes the insights of user activities in relation to energy use which can be extracted from the Measurement layer. Suitable visualization approaches are studied. Firstly, the details about user activities in relation to energy use can be visualized in order to give user an insight of how their own behavior impacts on energy consumption. In addition, from the collected data of energy use and activity measurements, some analysis can be done to extract information regarding how efficient energy has been used daily, weekly, or monthly. Summarize information will be showed to the user in form of charts. Those visualizations can be delivered to user via web or mobile application. Game elements and persuasive techniques can be applied to make the visualizations more persuasive to people. The details of our visualization approaches will be presented in chapter 4. Furthermore, the extracted information can also be utilized to improve the effectiveness of existing home automation system, or to study about user behavior.

Chapter 4

IMPLEMENTATION AND DEPLOYMENT

To validate the proposed solution, we develop a prototype implementation of the system with the commercially available home automation equipment and deploy the system in a real environment. In this chapter, we present our Greener Energy Behavior (*GreenBe*) system prototype implementation and deployment. The system is developed to extract and visualize human behavior in relation to sub-optimal energy usage by utilizing existing home automation infrastructure. Firstly, the infrastructure for capturing user activities at home and office is designed and implemented. Secondly, we present our system deployment in an office at Lappeenranta University of Technology (LUT) to capture activities of two occupants in the office. Finally, out of the collected data, we suggest an approach for visualizing user activities in relation to sub-optimal energy use which is used in a web application for facilitating greener energy behavior. The suggested application also incorporates some other positive motivational techniques to achieve more positive results in user behavior change.

4.1 Prototype design

Figure 7 describes the design of our *GreenBe* system prototype and data flow. The designed prototype comprises several loosely-coupled components such as User Activity Capturing, Database, Home Automation Infrastructure and Server. A component in the system communicates with other components by sending and receiving message through a central server for message distribution.

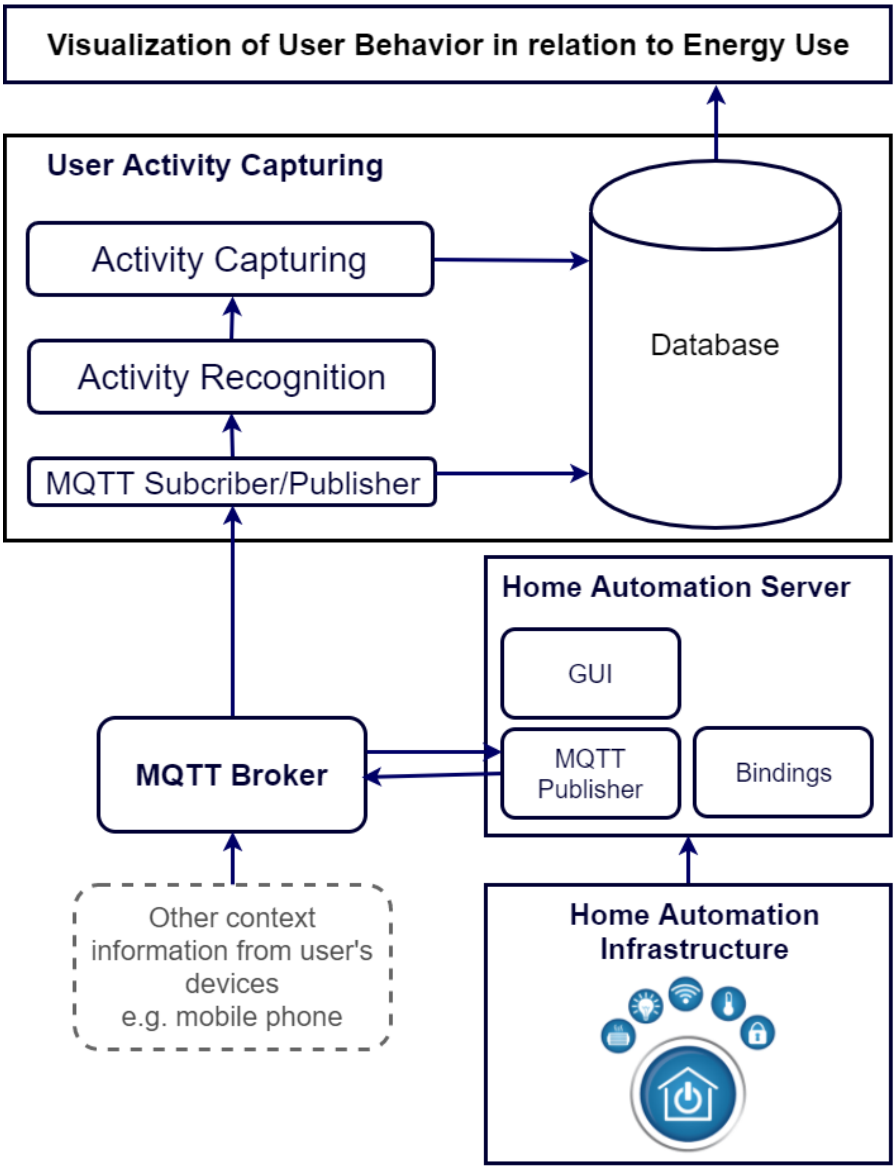


Figure 7 – The GreenBe system's prototype design

MQTT Broker (Server) is the central component for distributing message in the system. MQTT (Banks & Gupta 2014) is a machine-to-machine (M2M)/ "Internet of Things" connectivity protocol. It is a publish/subscribe messaging protocol. In MQTT, there is a broker that contains different topics. Each client can act as a publisher that send information to the broker at a specific topic, and/or a subscriber that receives messages from a broker in the topic that it subscribed. MQTT is lightweight, reliable, and energy-efficient (Karagiannis et al. 2015).

The ***Home Automation Infrastructure*** consists of home automation devices such as motion sensors, door/window sensors, temperature and humidity sensors. Our *GreenBe* system is designed to be able to integrate with different home automation technologies. A wide range of commercially available home automation technologies such as HomeMatic, KXN, Z-Ware, and EnOcean can be easily integrated into the system. In our prototype implementation which will be described later in the section 4.2, we use HomeMatic (eQ-3 2017) devices which are available in our lab at Lappeenranta University of Technology.

The ***Home Automation Server*** is responsible for managing the devices from the home automation infrastructure, providing GUI for developers and end users, as well as sending sensor data to other components. In the designed system, the Home Automation Server also acts as a MQTT publisher, which is responsible for sending sensor data gathered from the Home Automation Infrastructure to the MQTT Broker. There are a variety of commercially available home automation server which can be chosen such as Home Assistant (Home Assistant 2017), OpenHAB (openHAB 2017) , FHEM (FHEM 2017), and HomeGenie (HomeGenie 2017). Among those choices, OpenHAB is one of the best-known home automation tools, with a large user community and a large number of supported devices and integrations. OpenHAB comes with many pluggable add-ons providing integration with different home automation technologies and devices.

The ***User Activity Capturing*** component consists of several modules including MQTT Subscriber, Activity Recognition, and Activity Capturing; as well as a Database for storing data. *MQTT Subscriber* receives sensor data from the MQTT Broker. From the collected sensor data, user activities are inferred by the *Activity Recognition* module. Then, *Activity Capturing* infers the recognized activities' parameters such as start/end time, duration, context when the activities were performed, and saves records of activities into the *Database*. The captured user activities can also be used for real-time feedback for users or stored into the database for later analysis. Raw sensor data is also stored for further study about user behaviour or energy efficiency in smart home.

Out of the recorded user activities, we can visualize and show to users how their own behaviour effects their energy usage in order to help them change their energy-related practices in a more efficient way. In addition, ***other components*** such as context information from user's devices could be added into the system in order to provide more accurate activity capturing feature.

4.2 Implementation details

Our prototype implementation was carried as follow. Firstly, we created a home automation infrastructure using available devices in our lab at LUT. Secondly, the program for capturing user activity using sensor data from the infrastructure was developed.

4.2.1 Home automation system

The home automation system includes the existing home automation infrastructure and a server for integrating different home automation devices into the *GreenBe* system. Our home automation infrastructure consists of HomeMatic devices and sensors which can be used for capturing user activities in an office such as working, opening windows, using lights. HomeMatic (eQ-3 2017) is a proprietary system for home automation system from the company eQ.3. A HomeMatic system can be basically divided into the following classes of devices.

- Central and gateways (e.g. CCU, LAN adapter)
- Transmitters and Controllers (e.g. button and remote)
- Sensors (e.g. thermostats, motion detectors)
- Actuators (e.g. heating controller)

The HomeMatic sensors are connected wirelessly to the central control unit or gateways through BidCos (Bidirectional Communication System) protocol. One of the special feature of this protocol is that it is reliable as the recipient of a message has to acknowledge (ACK). Moreover, it also supports authentication and encryption.

Figure 8 describes the implemented topology of our home automation system. Home automation sensors such as door/window sensors, motion sensors communicate with a HomeMatic Central Control Unit (CCU) by using BidCos protocol. The Home Automation

Server and the CCU are connected to the same switch for getting access to the same network. Thus, home automation server can receive sensor data through the CCU.

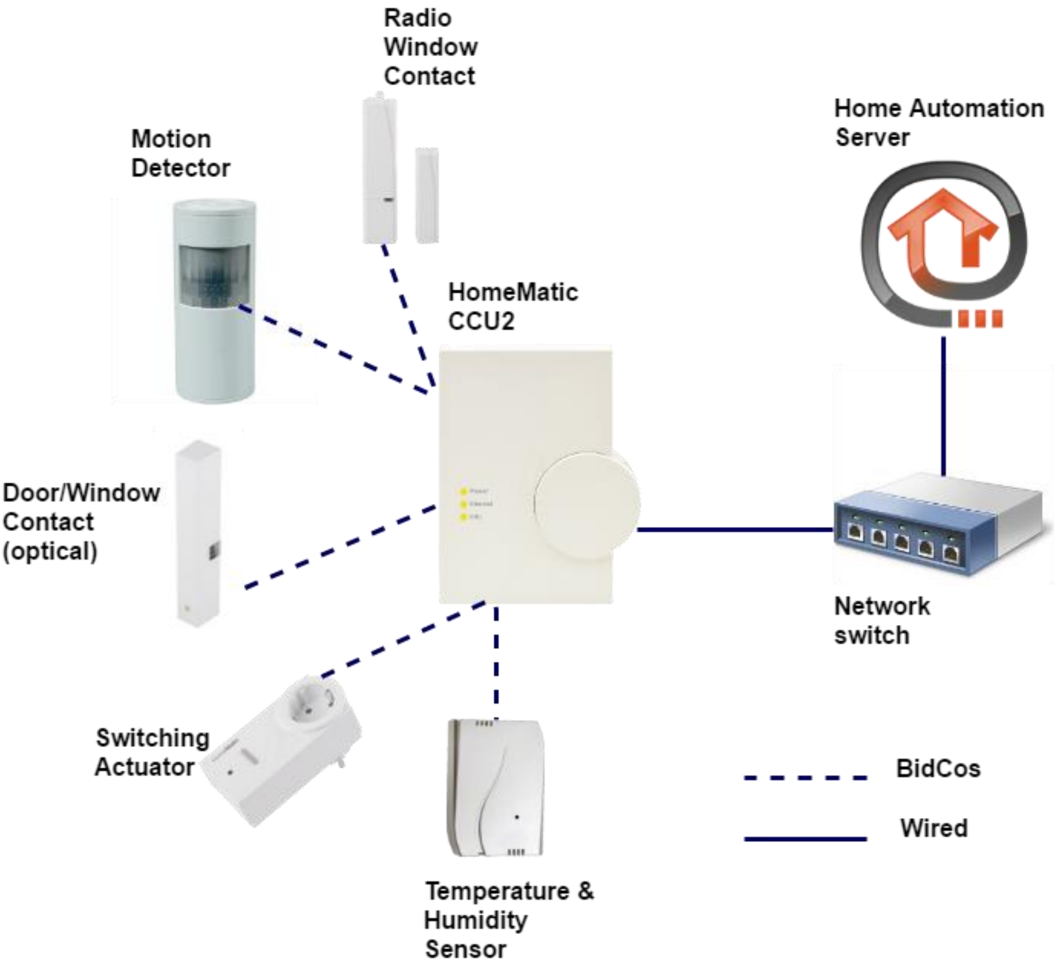


Figure 8 – Topology of the implemented home automation system

Table 4 details set of devices which are used in our system prototype.

Table 4 – Details of devices used in the GreenBe system prototype

Product name	Functionality	User manual
HomeMatic Central Control Unit CCU2	A CCU2 is a central element of a HomeMatic system. It offers ability of controlling, monitoring and configuring	http://www.eq-3.com/Downloads/eq3/downloads_produktkatalog/homematic/bda/HM-Cen-O-TW-

	for all the connected HomeMatic devices in the system.	x-x-2_UM_GE_eQ-3_web.pdf
HomeMatic Wireless Switch Actuator 1 channel	The device enables switching on and off connected consumers (e.g. lights, PC) or other HomeMatic devices, as well as measuring voltage, current consumption, active power, frequency and energy consumption of connected loads.	http://www.eq-3.de/Downloads/eq3/downloads_produktkatalog/homematic/bda/HM-ES-PMSw1-Pl-DN-R1_UM_GEFN_eQ-3_web.pdf
HomeMatic Wireless Motion Detector (inside)	The wireless infrared motion detector picks up movements made by users within detection range. The range is up to 12 meters and the detection range of main lens is 90 degrees.	http://www.eq-3.com/Downloads/eq3/downloads_produktkatalog/homematic/bda/131796_HM-Sec-MDIR-2_UM_GE_eQ-3_150415-web.pdf
HomeMatic Wireless Shutter Contact	The device recognizes open and closed windows and doors, and transmits the current status via radio signal to the central control unit.	http://www.eq-3.com/Downloads/eq3/downloads_produktkatalog/homematic/bda/HM-Sec-SC-2_UM_GE_eQ-3_web.pdf
HomeMatic Wireless Door/Window Sensor (optical)	The device detects open and closed windows and doors with an infrared sensor.	http://www.eq-3.de/produkte/homematic/heizung-und-klima/homematic-funk-tuer-fensterkontakt-optisch.html
HomeMatic Wireless Temperature and Humidity Sensor (indoor)	The device measures indoor temperature and air humidity data, and transmits the current captured status via radio signal to the central control unit.	http://www.eq-3.com/Downloads/eq3/downloads_produktkatalog/homematic/bda/HM-WDS40-TH-I-2_UM_GE_eQ-3_web.pdf

We used openHAB to implement the home automation server. OpenHAB is an open source software for integrating different home automation systems and technologies into one single home automation system. It supports services (bindings) which are developed by the large openHAB community that enable integration with various technologies such as X10, Philips Hue, and KNX. In out implementation, HomeMatic binding was installed to integrate with the eQ-3 HomeMatic solution. Additionally, MQTT binding allows openHAB to act as an MQTT client. Defined openHAB items can send and receive MQTT messages to/from an MQTT broker. OpenHAB is written in Java, thus, can run on any device that is capable of running a Java Virtual Machine including Linux, Mac, and Windows. In our implementation, openHAB server is installed on a Cubieboard running Cubieez OS. The openHAB installation and configuration details are provided in the appendix.

4.2.2 User activity capturing

The User Activity Capturing component was implemented by using Java. The developed Java program consists of 3 main functions (1) MQTT publisher/subscriber; (2) Activity Recognition; and (3) Activity Capturing. The program's source code can be found from the author's GitHub repository[1] .

We developed the activity recognition module to recognize four defined activities in office environment including "working in an office room", "having a presentation", "having a meeting", and "having coffee break". The reasoning about atomic activities and context attributes used to infer the activities are presented in *Table 5*. For our implementation in this thesis work, weights of atomic activities and context attributes are assigned based on our observation of activities perform in offices at Lappeenranta University of Technology, Finland.

[1] https://github.com/tttgiang2510/ActivityCapturing

Table 5 – Recognized activities in office environment

$CA_k(\omega^T_{CA_k})$	γA ($\omega^{A_i}_{CA_k}$)	ρC ($\omega^{C_i}_{CA_k}$)	Core γA and ρC	A_S, C_S	A_E, C_E	$T_L$range (minutes)
Working in an office room (0.7)	A_1: enter room (0.2) A_3: walking (0.2) A_4: using laptop/PC (0.2) A_5: leaving room (0.2)	C_1: in office room (0.4) C_2: office lights on (0.2) $\neg C_1$: in office room (0.2) $\neg C_2$: office lights on (0.2)	A_1, A_4, A_5, C_1	A_1, C_1	A_5, $\neg C_1$, $\neg C_2$	5 - 180
Having a presentation (0.7)	A_1: enter room (0.2) A_3: walking (0.05) A_4: using laptop/PC (0.2) A_6: using projector (0.3) A_7: speaking (0.2) A_5: leaving room (0.05)	C_3: in meeting room (0.4) C_4: meeting room lights on (0.2) $\neg C_3$: in meeting room (0.2) $\neg C_4$: meeting room lights on (0.2)	A_1, A_6, A_7, A_5, C_3	A_1, C_1	A_5, $\neg C_3$, $\neg C_4$	20-180
Having a meeting (0.7)	A_1: enter room (0.2) A_3: walking (0.2) A_4: using laptop/PC (0.2) A_7: speaking (0.2)	C_3: in meeting room (0.4) C_4: meeting room lights on (0.2) $\neg C_3$: in meeting room (0.2) $\neg C_4$: meeting room lights on (0.2)	A_1, A_7, A_5, C_3	A_1, C_1	A_5, $\neg C_3$, $\neg C_4$	10-180

	A_5: leaving room (0.2)					
Having coffee break (0.7)	A_3: walking (0.2) A_7: speaking (0.2) A_8: using coffee machine (0.2) A_9: using electric kettle (0.2) A_{10}: open cupboard (0.2)	C_5: in kitchen (0.4) C_6: kitchen lights on (0.2) $\neg C_5$: in kitchen (0.2) $\neg C_6$: kitchen lights on (0.2)	A3, A8, A10	A3, A8	$\neg C_5$, $\neg C_6$	10-30

The atomic activities and context information are inferred from sensor reading as presented in *Table 6*.

Table 6 – Inferred atomic and context information from sensor reading

Atomic activity/Context	**Sensor**	**Sensor reading**
A_1: enter room	Door sensor Motion detector	OPEN/CLOSED ON
A_5: leaving room	Door sensor Motion detector	CLOSED OFF
A_3: walking	Motion sensor	ON
A_6: using projector	Radio switching actuator which is connected to the projector	ON

C_1: in office room	Motion detector in office room Tracking door sensor state : INACTIVE	ON

The collected data is stored in a database implemented by using MongoDB (MongoDB 2017). MongoDB is a NoSQL database program using JSON-like documents to store data. MongoDB offers great scalability and flexibility which meet the system requirements specified in section 3.1. The stored data includes (1) raw sensor data received from the MQTT publisher/subscriber, and (2) the activities data inferred by the Activity Capturing module.

The MQTT Broker is implemented by using Eclipse Mosquitto (Light 2017). Eclipse Mosquitto is an open source MQTT Broker which supports MQTT protocol version 3.1 and 3.1.1. In our implementation, we defined different topics including *SENSOR*, *ACTIVITY*, and *CONTEXT* for sending and receiving raw sensor data, inferred activities and context data.

4.3 Deployment and Experimental setup

To validate the solution, we deployed the system in a real environment to capture and measure user activities in relation to energy use. The experiment is carried at our own office at the Lappeenranta University of Technology, Finland. *Figure 9* describes how the home automation sensors are mounted in the office. *Figure 10* shows the deployed devices in the office.

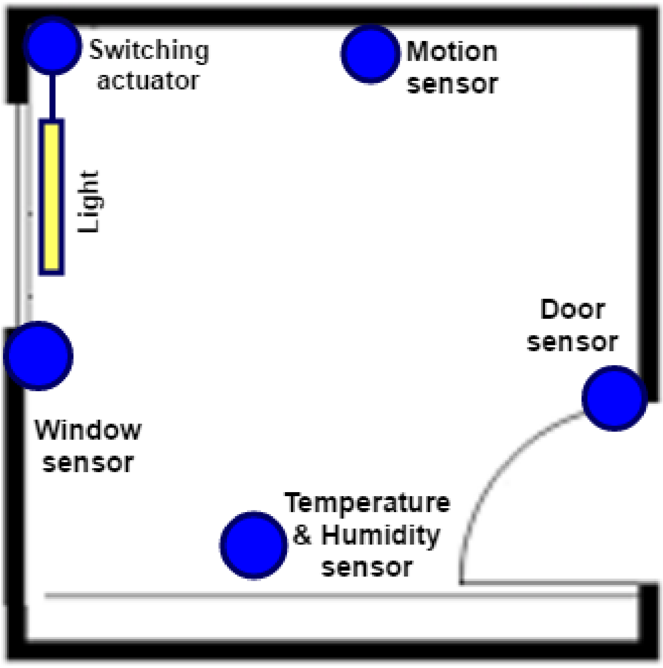


Figure 9 - Sensor deployment at LUT-7615.1

(a)

(b)

(c)

(d)

(e)

(f)

(g)

Figure 10 – Deployed devices (a) Motion detector; (b) Window sensor; (c) Door sensor; (d) CCU2; (e) Switching actuator; (f) Temperature and humidity sensor (g) Home Automation Server

In addition, a user experiment was carried. The office was occupied by two students.

Table 7 details the experiment setup.

Table 7 – Experimental setup

Location	Office room number 7615.1 - Lappeenranta University of Technology, Finland
Number of users	Two
Experiment duration	24 days (from April 10th to May 3rd, 2017)
Evaluation method	Comparison between users' Activity Diary and Measured User Activities

The experiment concern capturing and measuring activities performed by the two students in the office including "working", "using light", "leaving window open", and "absence". Parameters for measuring activities include activity start/end time, activity duration, and activity context such as temperature and humidity. The two students are asked to normally perform their activities in the office, and put records on activity diary. The student activity diary in office is then used as ground truth for evaluation.

4.4 Visualization of user activities in relation to suboptimal energy use

Our assessment argues that current approaches targeting behavior change to improve energy efficiency and reduce energy consumption do not fully consider the three principle factors of human behavior and different stages of behavior change. Firstly, the assumption that raising people's awareness of current environmental issues caused by energy-related activities results in behavior change does not hold for pre-contemplators who have not acknowledged that their behavior is problematic. Secondly, current approaches do not provide consumers with behavior-specific abilities such as suggesting what to do, making behavioral adoption easier. In addition, when the individuals reach the action and maintenance stages of behavior change, it is necessary to give feedback about progress towards target behavior. However, none of the studied related work approaches gives feedback regarding whether one is reaching the behavior target.

To address those short-comings, we propose a more comprehensive approach to raise people's awareness of their behavior and its impacts on energy consumption, as well as motivate and aid people to change their behavior to become more energy-efficient. Our approach involves using visualization of user activities in relation to energy use, and some positive motivation techniques such as goal setting or competition with colleagues for facilitating user behavior change. Information visualization can show people the connection between their behaviors and the effects of those behaviors on energy consumption. We argue that most energy-related behaviors are difficult to track, however, visualizing these behaviors results in more behavioral changes. The proposed approach also takes psychological insights such as the TTM's Stages of Behavior Change, as well as the Fogg Behavior Model into account. In this section, we present the psychological rationale behinds the design of our proposed application, followed by the details of application design.

4.4.1 Psychological rationale

An intentional behavior change goes through a process of a series of stages which includes pre-contemplation, contemplation, preparation, action and maintenance, rather than a single event. Thus, different techniques and designs should be applied for each stage of behavior change to effectively cultivate and maintain more sustainable energy practices. *Table 8* presents the rationale, behavior change target, and our suggested techniques to achieve the target at each stage.

Table 8 – Rationale, target and suggested methods for behavior change

TTM's Stages of Behavior Change	Rationale	Behavior change goal	Suggested method(s)
Pre-contemplation	To make pre-contemplators consider changing their behavior, we need to "plant the seed" for them to acknowledge that their current energy behavior is problematic.	To raise people's awareness of their own behavior and its impacts on the efficiency of energy use and total energy consumption.	Presenting information in a way that can show user the relation between their activities and energy use.
Contemplation	At this stage, consumers are aware that their behavior is problematic and open to change, but not yet ready to take action.	To motivate people to change their energy behavior to become more sustainable.	Some positive motivation techniques such as commitment or sense of competence can be given to encourage consumers to take actions.
Preparation	At this stage, people are already motivated to change their behavior, but not yet know what to do.	To lower ability barriers of adopting new behavior.	Providing individuals with specific energy actions that they can take and possibility

			to make their own plan to change.
Action and Maintenance	At this stages, individuals have already taken actions but do not know whether they are reaching the behavior target or energy-saving target.	To aid people to keep improving their sustainable energy practices.	Providing feedback on the behavior changing progress and recommendation of how they can improve their sustainable practices are needed.

In addition, different methods targeting at different principle factors of human behavior are also suggested as described in the following table.

Table 9 – Behavior change goal and methods for different factors of human behavior

Principle factors of human behavior	**Goal**	**Method(s)**
Motivation	To motivate people to change their behavior to be more energy-efficient.	Positive motivational techniques are applied to encourage people to adopt sustainable energy behavior.
Trigger	To show people the behavior target that they could set for themselves.	Providing individuals with specific energy action they can take and possibility of setting their own plan to reach the target behavior.
Ability	To lower the ability barriers of performing more efficient energy behavior.	Giving people a sense of what to do and giving feedback regarding whether

		ones are reaching energy-saving target.

A target behavior occurs when the three principle factors converge at the same time. It is also important to emphasize that people's motivation comes and goes in waves. When motivation reaches its peaks, people temporarily find it easy to train a greener energy behavior. In contrast, they find it much more difficult to sustain the target behavior when their motivation hit its troughs.

When motivation to use energy more efficiently is high, people have three priorities of things to do to change their behavior.

- **Priority 1**: Do things that structure future behaviour such as commit to a plan, set energy efficiency goal, and invites friends/colleagues to join.
- **Priority 2**: Do things that reduce the obstacles for behavioural change, thus, makes future behaviour easier. For example, users could put notes, set notifications to remind them to save energy.
- **Priority 3**: Do things that increase ability, make adopting and sustaining greener energy behaviour easier.

In order to successfully facilitate users' behaviour change, the designed application need to harness motivation waves, as well as match their current motivation level. People rarely know what to do and how to do to achieve better energy efficiency. Therefore, it is helpful to guide people to structure the target energy behaviour, and lower the ability barriers of performing more efficient energy behavior.

4.4.2 GreenBe web application design

From the activity capturing and measuring phases, we had the data of user activities and their energy use. Out of the collected data, suitable visualization approach will be studied to visualize user activities in relation to energy use. We propose the use of timeline chart to visualize the user activities in relation to how the energy was used. *Figure 11* demonstrates an example of how activities carried at home can be visualized in relation to energy use.

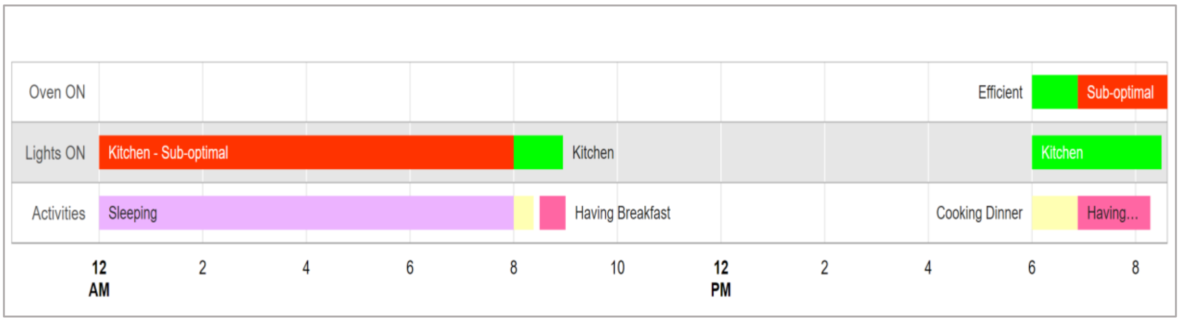


Figure 11 – Visualization of user activities in relation to energy use (example at home)

To highlight the effectiveness of past energy use, different colors are used. If the energy use is efficient, the bar will highlight green. In contrast, the bar will highlight red if the energy use is sub-optimal to show users the potential of energy-savings that they could achieve by simply changing their behavior. In addition, different activities are presented using different colors. The classification of energy-related activities and highlighting sub-optimal energy use give users a hint on what specific behavior they could change to be more energy-efficient.

To implement the proposed application, we use Google chart API (Google Developers 2017) and Java to build the visualization from the collected data of user activity and energy use. The visualization was showed to users through a web application. Google Charts provides different ways from using a simple line chart to complex and combined charts to visualize data. Charts are exposed as JavaScript classes. They provide cross-browser compatibility and cross platform portability to different devices such as Android and iOS. We can provide the visualization feature as single application for facilitating user behavior change or integrated with other building energy management application in different platforms.

In office, sub-optimal energy use is defined as (1) leaving lights on when user is not in the office for more than 5 minutes, and (2) leaving window open when heating is on and the calculated indoor air quality from collected temperature and air humidity data is in comfort level. *Figure 12* presents the visualization of real data that we collected at the office room LUT – 7615.1 on April 18th and 19th, 2017.

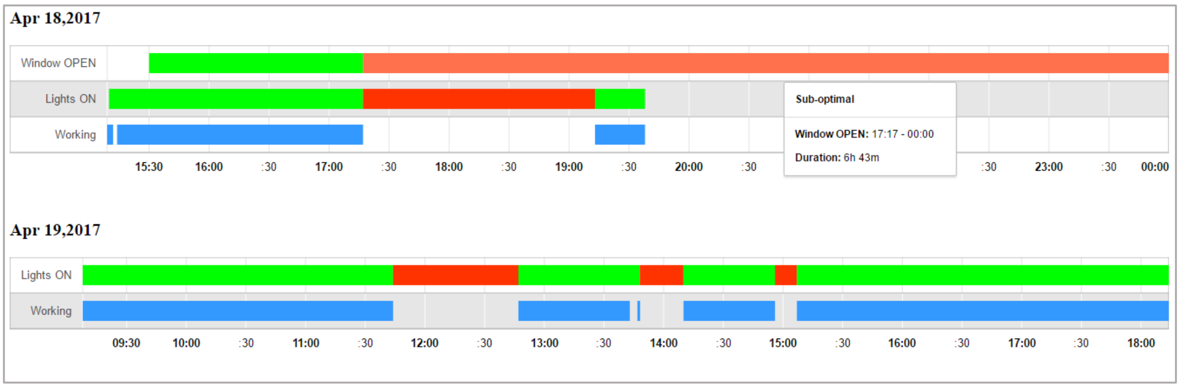


Figure 12 – Visualization of user activities in relation to energy use (real data at office)

In addition, the pie graph are used to present the summary of energy use (*Figure 13*).

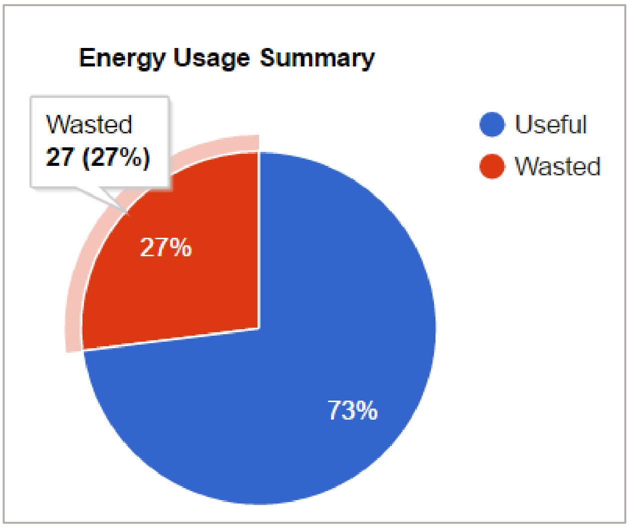


Figure 13 – Energy Usage Summary

From the collected data, the effectiveness of past energy use in the office is also calculated using equation 1.

Equation 1

$$Effectiveness = \frac{Useful\ energy\ use}{Total\ energy\ use}$$

Users can set their own target of changing behavior to achieve more energy efficiency. The energy efficiency target and the pass weekly summary are shown by using the combination chart as demonstrated in *Figure 14*. The chart presents the energy efficiency summary from the collected data from April 16th to 22nd, 2017 at the office room LUT – 7615.1.

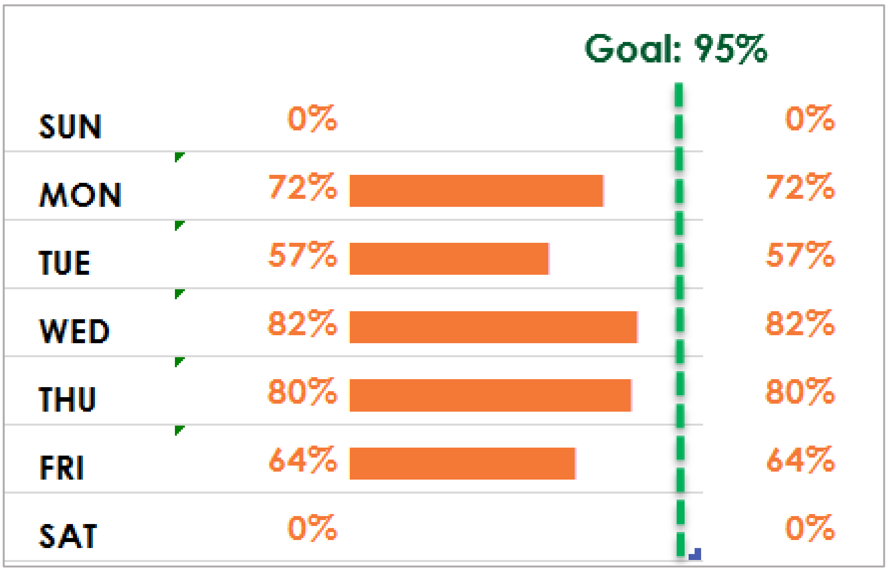


Figure 14 – Weekly energy use summary and Goal setting feature

Some positive motivation techniques are also integrated in the web application to motivate people to improve their energy use practices. Those techniques include (1) social interaction such as competition with neighbor/colleagues and (2) goal setting (commitment). *Figure 14* shows the summary and goal setting feature. The design of the web application's dashboard is presented in *Figure 15*.

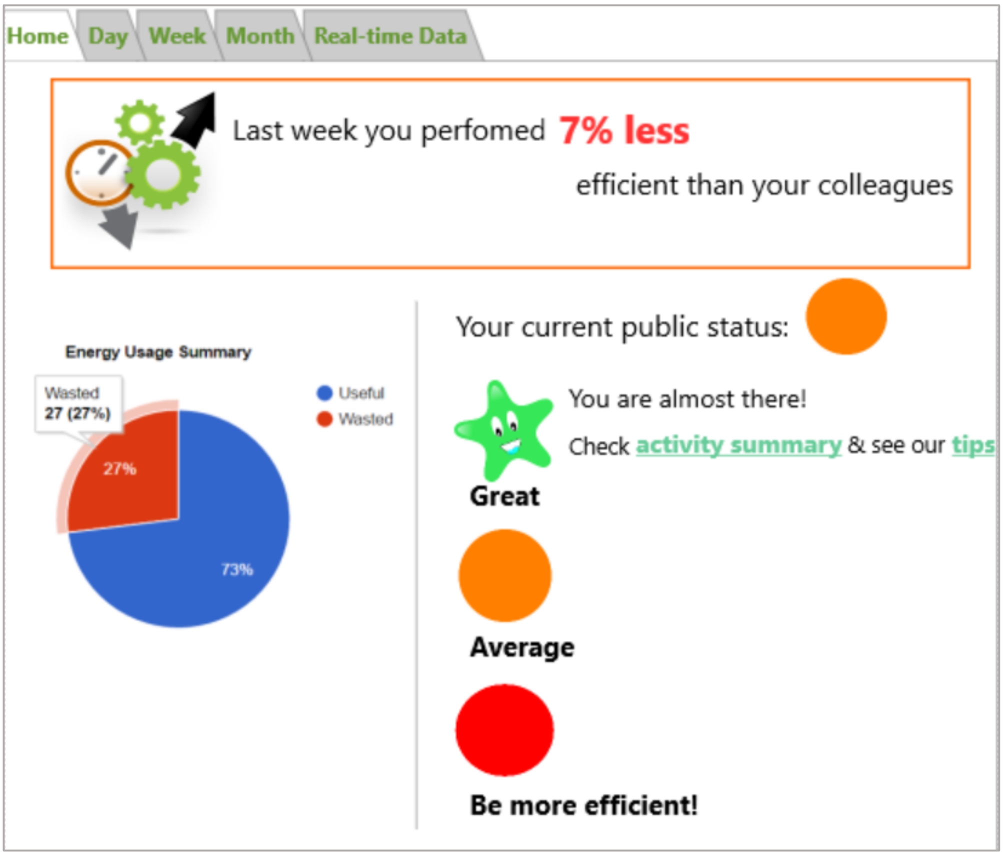


Figure 15 – Dashboard summary integrated with Game elements to persuade users

In addition, the application provides tips to guide users what to do to achieve better energy efficiency. The tips can show up as a popup window when user clicks on the link in the dashboard as illustrated in *Figure 16*.

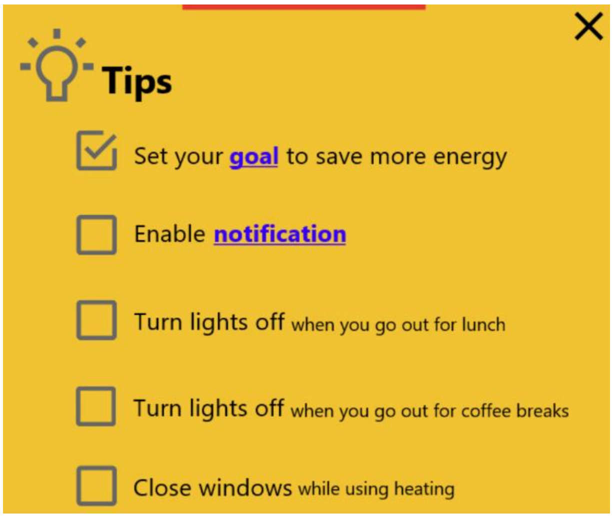


Figure 16 – Examples of things to do to increase ability for behavior change

Chapter 5

RESULTS AND DISCUSSION

In this chapter, we present the results of the thesis including the results from our user experiment and user study. In addition, the sustainable impacts of the *GreenBe* system are analyzed and presented. Finally, we conclude the chapter by giving our reflection and discussion regarding the collected results.

5.1 User experiment result

To evaluate the effectiveness of the system on raising people awareness of their behavior and its impacts on energy consumption, as well as motivating and aiding people to change their behavior to be more efficient in using energy, we conducted a user experiment and a user study. The user experiment was carried at the office 7615.1 (Lappeenranta University of Technology, Finland) during 24 days from April 10th to May 3rd, 2017. The office was occupied by two students. User activity and energy use data was captured for 3 weeks. Out of the collected data, user behavior in relation to energy use was extracted and visualized. Users were showed the visualization of their own activities in relation to energy use in 3 weeks and were asked to complete a survey consisting of 9 questions regarding:

i. The effectiveness of the *GreenBe* system on raising their awareness of their own behavior and its impacts on energy consumption.

ii. The effectiveness of the *GreenBe* system on motivating them to change their own behavior to be more efficient in using energy.

iii. The ability of the *GreenBe* system to aid them to change their behavior in a greener way.

The user responses were positive. The visualization of their own behavior in relation to energy usage raised their awareness of the impacts on their own activities on the effectiveness of energy use, thus motivated them to change their habits of using electricity in the office. The two test users found the system highly effective in aiding them to change their energy behavior by showing them which specific action that they could take to improve energy efficiency.

5.2 GreenBe system user study

Apart from the experiment, a user study was conducted with 59 participants including 54 students, 4 university staffs, and 1 software developer. Their ages varied between 19 and 55 years. The study subjects of the participants varied between computer science, mechanical engineering, economics, strategy and innovation.

The user study was organized in the following form: we presented our *GreenBe* system and the visualization with descriptions. After that, participants were given a survey consisting of 10 questions regarding their willingness to use the system at their home and in their office and how they perceived the system. A five-point rating scale was used for all the questions except the personal background questions.

The user study showed that most participants are willing to use the *GreenBe* system at home (93.22%) and in office (89.83%) (*Figure 17*). According to the survey, there is a slight difference in the number of people would use the system at home compared to office because individuals are not responsible for paying energy bills at office while they have to pay their own bills at home.

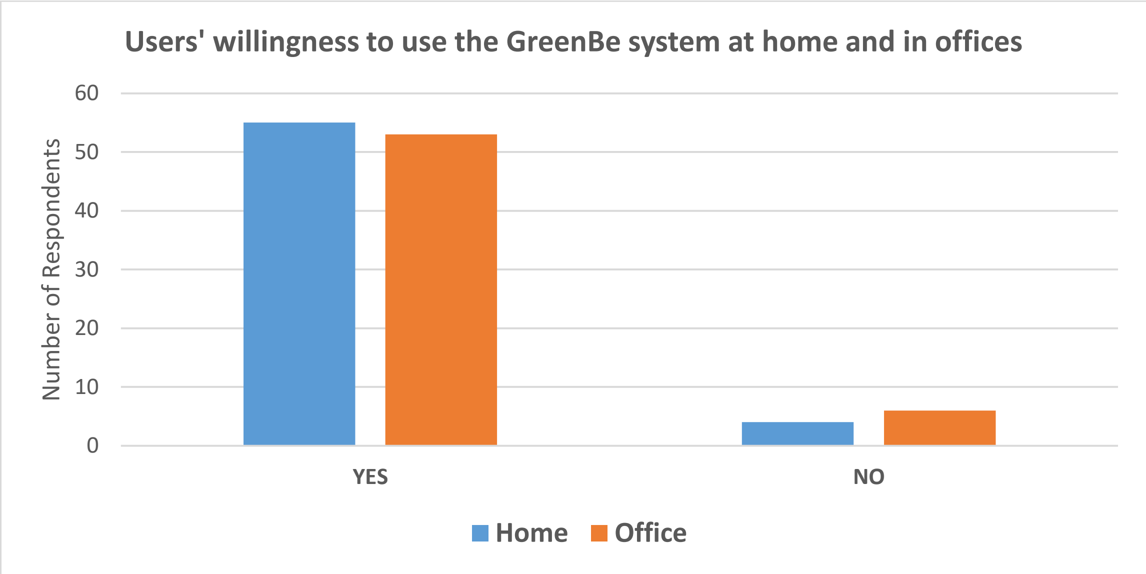


Figure 17 – Users' willingness to use the GreenBe system at home and in offices

Respondents stated that the system could successfully raise their awareness of their own behavior and its impact on energy consumption. Fifty-four out of fifty-nine participants (91.53 percent) found that the visualization helped them to be more aware of the impacts of their own activities on energy consumption.

Regarding the effectiveness of the application on motivating people if it was to be applied, 77.97 percent of participants responded that the application would motive them to change their behavior to be more energy-conservative. The number of people would be motivated is fewer than the number of those whom awareness affected by the application as illustrated in *Figure 18*.

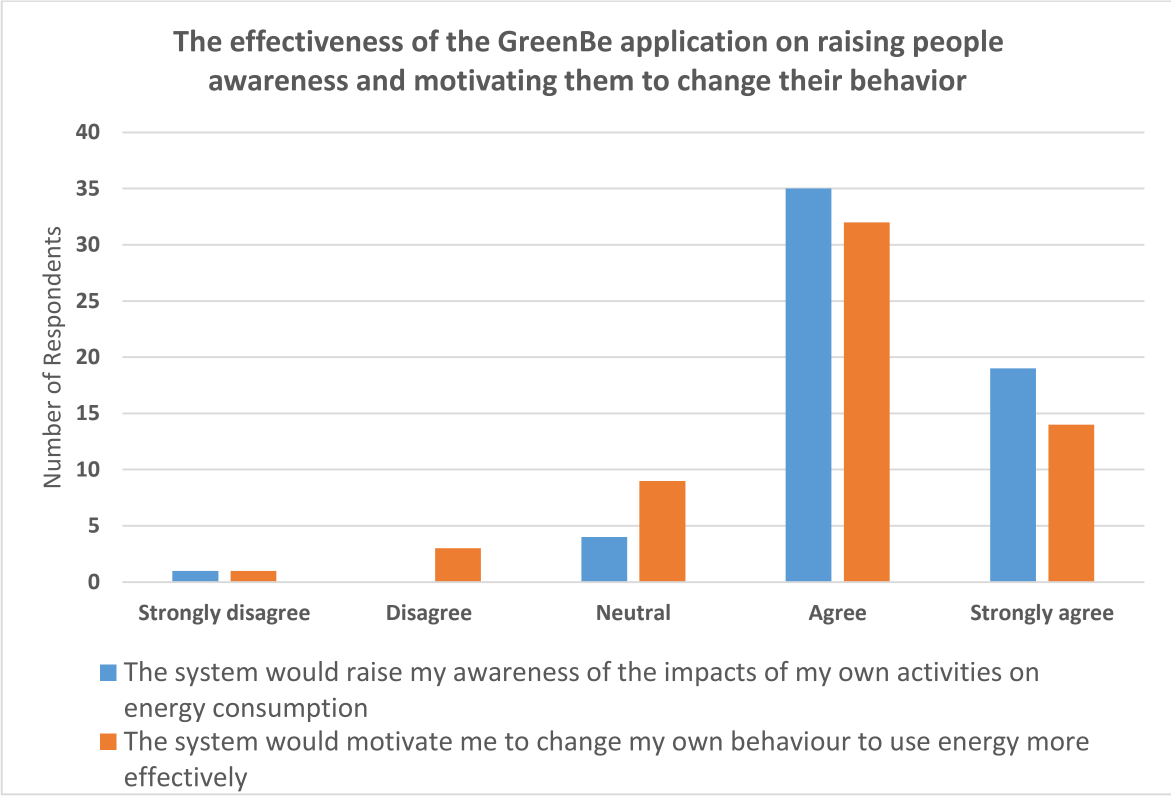
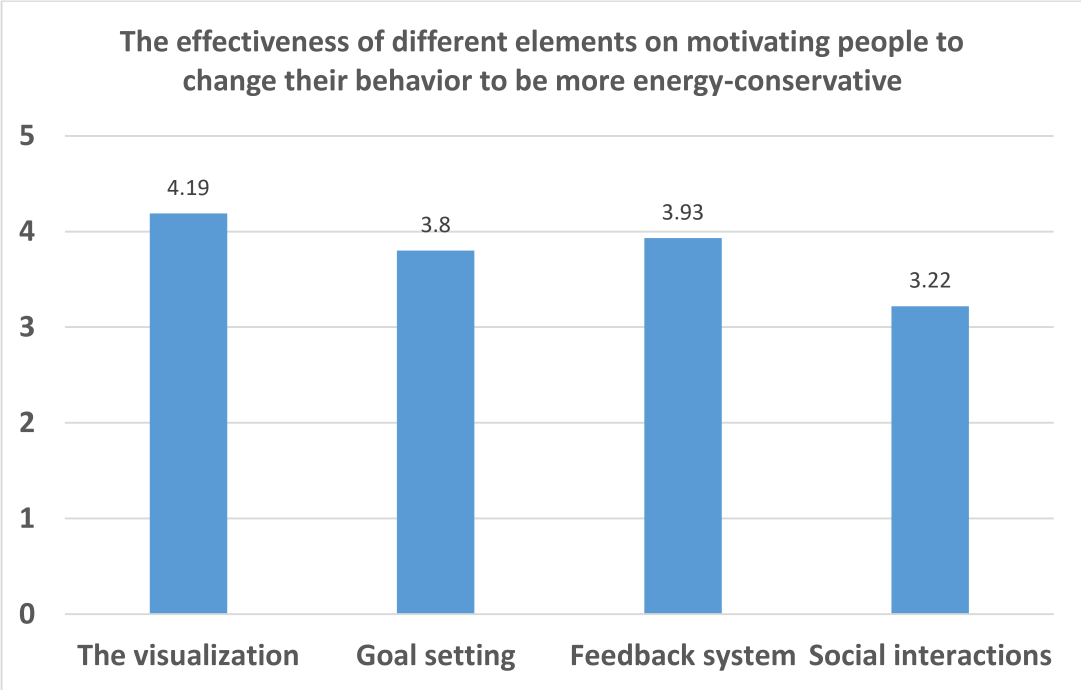
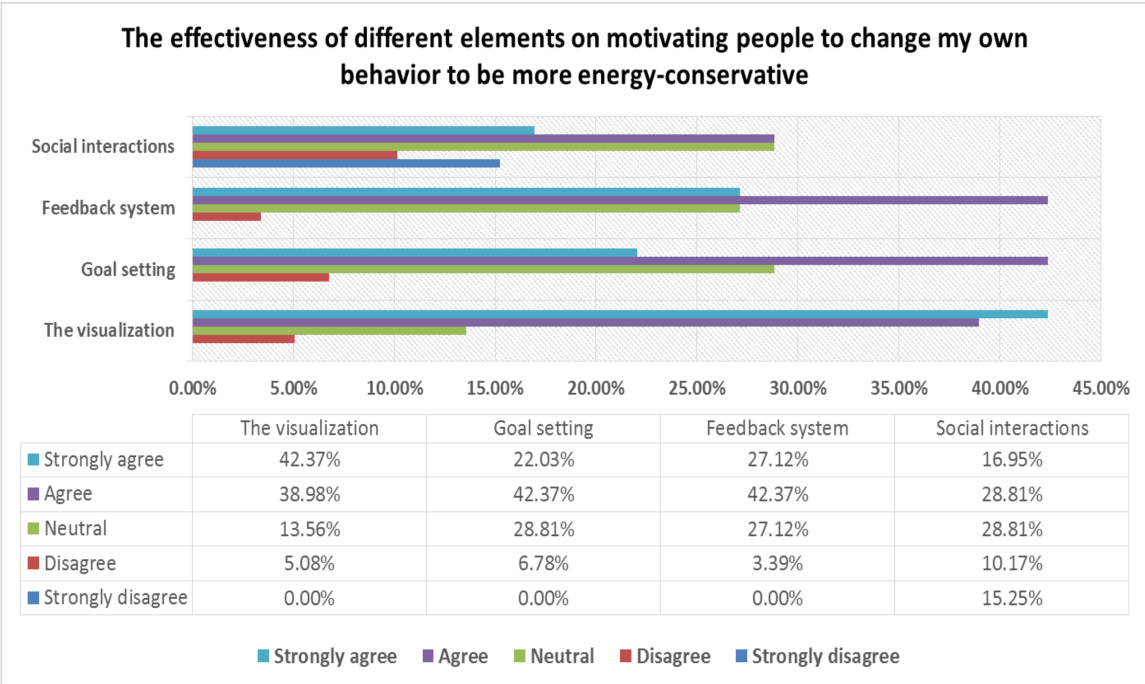


Figure 18 – The effectiveness of the GreenBe application on raising people awareness and motivating them to change their behavior

Figure 19 shows how each elements of the application motivates people to change their behavior to use energy more efficiently. According to the survey, the visualization of user activities in relation to energy use have more positive effect on how people are motivated compared to other elements such as goal setting or social interactions.



(a)



(b)

Figure 19 – The effectiveness of different elements on motivating people to change their behavior (a) average scale of collected responses (b) collected responses' distribution

Regarding the ability of the visualization to aid people to change their behavior to save more energy, 79.66 percent of participants found that the visualization of their own activities in relation to energy use makes it easier for them to change their behavior.

5.3 Sustainability impacts of the GreenBe system

To evaluate the impacts of the *GreenBe* system to sustainability. We carried out the sustainability analysis of the system in five different dimensions and at three levels in each dimension as illustrated in *Figure 20*.

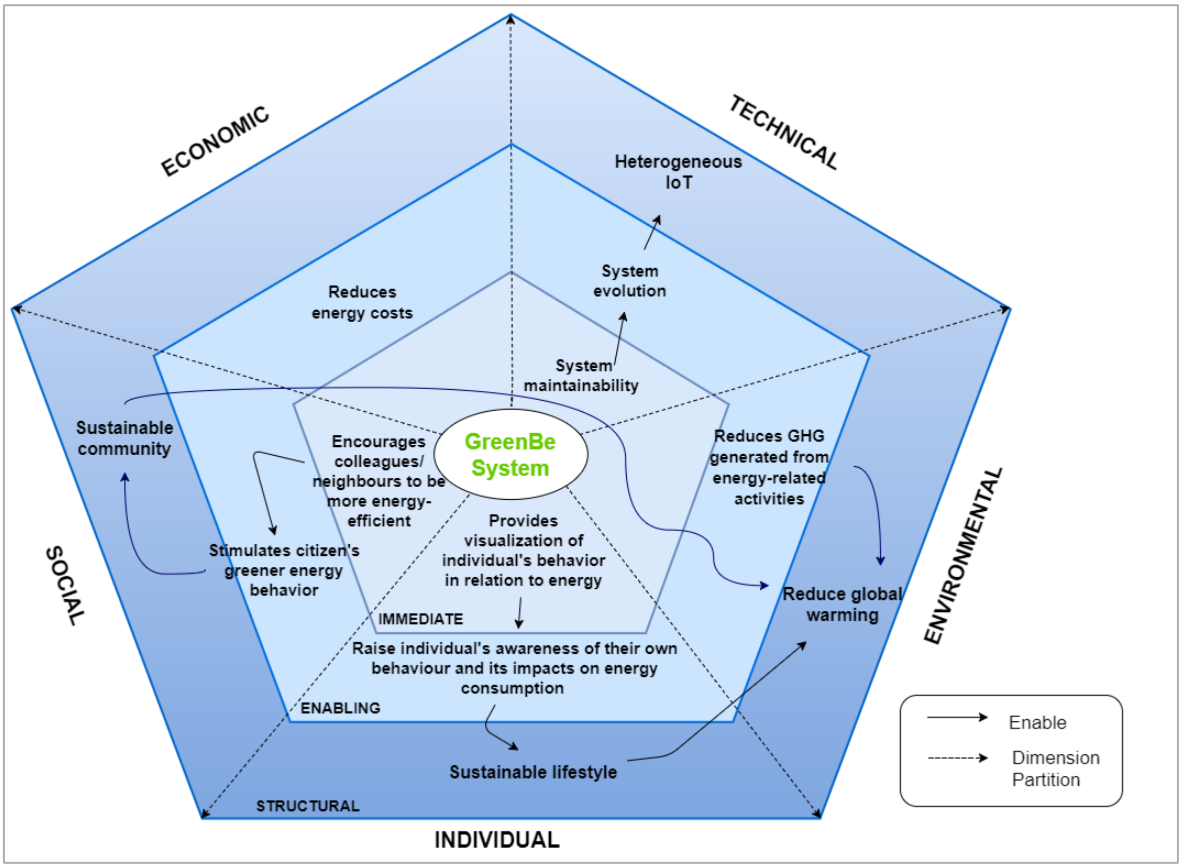


Figure 20 – Sustainability analysis of the GreenBe system

Five key sustainability dimensions of a technical system including individual, social, economic, environmental, and technical were analyzed. In each dimension, the impacts were divided into three different levels. *Immediate* impacts are the directed impacts of the application of the *GreenBe* system. *Enabling* impacts arise from the application of the *GreenBe* system over time. This includes the opportunities offer by the system and other changes induced by the application of the system. *Structural* impacts are observable persistent changes at the macro level. From the individual perspective of sustainability, the system helps people to adopt more efficient energy-related practices, thus leads to a sustainable lifestyle. From the social aspect, the system has potential to enable a sustainable community among neighbors and colleagues by integrating social interactions such as competition with colleagues/neighbors and cooperation with family members/colleagues to achieve an energy-efficient goal. The target of the system is to stimulate consumers' efficient energy behavior, which could result in less energy consumption and GHG emissions generated by energy-related activities. Thus, the system has positive impacts regarding economic and environmental sustainability. In addition, the system is designed in a scalable and extensible manners by integrating loosely-coupled layers and components, thus ensures the technical sustainability of the system.

5.4 Discussion

As reflected from the user study, people are different in attitudes and beliefs and motivated by different elements. Therefore, we suggest that incorporating different persuasive techniques is necessary to achieve better results on human behavior change. The study also shows that number of people motivated is fewer than the number of those whom awareness affected by the application, which suggests that more persuasive techniques need to be integrated to successfully transform individuals from being aware to maintaining greener energy behavior stage. In addition, the slight difference in the number of people who are willing to use the system at home compare to the counterpart in offices implies that different motives could be applied to effectively engage consumers in different environments.

Our test users and participants in the user study also gave some useful suggestions to improve the *GreenBe* system. Firstly, the provided data through the visualization could be more comprehensive such as the amount of CO_2 emission generated or real-time energy consumption compare to their neighbors. Secondly, the feedback could be given in many different forms rather than the energy efficiency indicator such as the amount of money savings gained though behavior changes. Finally, notification feature to remind user what to do could be helpful for users to change their behavior.

Chapter 6

CONCLUSION AND FUTURE WORK

This thesis work is a part of the Erasmus Mundus Master Program in Pervasive Computing and Communications for Sustainable Development (PERCCOM) (Klimova et al. 2016; Porras et al. 2016). The objectives of the thesis is to extract human behavior in relation to suboptimal energy usage by utilizing existing home automation infrastructure, and then to visualize it to users. By showing users the visualization of their own behavior and energy use, then motivating and helping them to change their energy-related practices, this work aims at achieving sustainability by stimulating individuals' behavior change in a more energy-efficient way. Two main research questions were defined and addressed. Firstly, how to capture user activities at home and in offices by using home automation equipment. Secondly, how to visualize the captured activity data to the user in a way that can facilitate sustainable energy behavior change.

To answer the research questions, we proposed and developed the Greener Energy Behavior (*GreenBe*) system. The *GreenBe* system integrates the exiting home automation and sensory technologies, as well as advancement in the activity recognition field to create applications for cultivating sustainable energy behavior. The system has the capacity of capturing user activities and energy use data at home and in offices in a non-intrusive manner, which solves the first research question. Various applications can be implemented on top of the system such as studying user energy behavior or improving the energy effectiveness of home automation solutions. Our key focus in this thesis work is to propose an application using visualization of user activities in relation to energy usage to motivate and aid them to change their behavior in a greener way. Suitable visualization method was studied to effectively motivate and enhance behavioral specific abilities for users to change their behavior. The proposed application takes psychological insights such as the TTM's Stages of Behavior

Change, and the Fogg Behavior Model into account in order to achieve more positive effect on facilitating user behavior change, thus addresses the second research question.

The system prototype was implemented and deployed in a real environment for evaluation. The achieved results are positive. Most people are interested and willing to use the system either at home or in offices. The system successfully showed test users in an office the potential energy savings that could be gained by simply changing their behavior and motivated them to change their current energy-related practices. Users also found it helpful in aiding them to change their behavior to become more efficient in consuming energy. Even though more enhancement and incorporation with other cultural, social, and technological aspects are needed, the system showed promising potential in facilitating consumer energy behavior changes.

Our research aims at creating an integrated ICT solution for achieving sustainability through facilitating more energy-efficient behavior. The impacts of proposed and developed *GreenBe* system to sustainability was analyzed and presented in the previous chapter. The target impacts focus on the individual, environmental and technical aspects of sustainability. However, the system showed that it has also potential impacts in the social and economic dimensions.

To the best if our knowledge, the proposed solution is the first work that embraces the human behavioral insights and technological advancements in the areas of home automation and activity recognition to cultivate more sustainable energy behavior. The prototype implement of the system has received highly positive feedbacks. However, there are several limitations which could be addressed in the future work. Firstly, the system prototype was only deployed in an office environment and the user experiment was performed in a small scale. Larger scale of system deployment and user experiment at home and in offices are required to evaluate fully the effectiveness of the system in capturing user behavior in using energy and facilitating sustainable behavior change. Secondly, the visualization and dashboard designs need to be more attractive to effectively engage users, thus can result in higher effectiveness of the visualization on motivating and aiding users to change their behavior to become more energy-conservative. In addition, many other metrics can be used to visualize to the users and more visualization approaches could be investigated. For example, the energy behavior can also be translated to the amount of carbon dioxide that is produced through the behavior, or the amount of consumed electricity or heat and natural resources were burned out to produce that amount of energy. Finally, providing consumers the visualization of their own activities in relation to energy use is helpful but not sufficient to ensure a durable energy behavior change. People need certain assistance to train sustainable habits. In the future, a decision support system can be integrated into the *GreenBe* system. A feature which provides recommendations or best practices based on recorded user energy-related activity data in order to stimulate more efficient energy behavior can also be implemented on top of the system. At home, for instance, the system can remind users to wash with full machine, or lower heating temperature. Further incorporation of other psychological, cultural, social, and technological aspects to create a more comprehensive approach to cultivate and maintain sustainable energy behavior are also needed.

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APPENDIX 1. Questionnaire details

This is the survey which was given to participants of our user study. The survey consists of some question regarding participants' personal background and 10 questions regarding their willingness to use the system at their home and in their office and how they perceived the system. A five-point rating scale was used for all the questions except the personal background questions.

This survey intends to gather your opinion about the effectiveness of the GreenBe system on motivating and aiding you in changing your own behavior to become more energy-conservative if the system is applied. All data will be anonymized before publication or presentation.

1. Email address:

2. Which option describes you the best?

    - University staff
    - Student
    - Other: ………………………

3. Age Group:

    - 18 or younger
    - 19-25
    - 26-35
    - 36-45
    - 46-55
    - 56-65
    - 66 or older

4. I am willing to use this system if it is applied at my home and office?

   A. At home
   - Yes
   - No

   B. In office
   - Yes
   - No

5. If not, could you please give the reason? (text answer)

If the GreenBe system is applied at my home/office,

6. The system would raise my awareness of the impact of my own activities on energy consumption

   - Strongly disagree
   - Disagree
   - Neutral
   - Agree
   - Strongly agree

7. The system would motivate me to change my own behavior to use energy more effectively

   - Strongly disagree
   - Disagree
   - Neutral
   - Agree
   - Strongly agree

How each element in the system would motivate you to change your own behavior to be more energy-efficient?

8. The visualization of my own activities in relation to my energy use

   - Strongly disagree
   - Disagree
   - Neutral
   - Agree
   - Strongly agree

9. Goal setting

   - Strongly disagree
   - Disagree
   - Neutral
   - Agree
   - Strongly agree

10. Feedback system on how efficient I am in using energy

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

11. Social interaction such as competition with my colleagues/neighbors and cooperation with my family members/colleagues to achieve an energy-efficient goal

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

The effectiveness of the GreenBe system on aiding you to change your own behavior

12. The visualization of my own activities in relation to energy use would make it easier for me to change my energy-related practices

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

13. I would change my behavior to use energy more efficiently (e.g. try to remember to turn lights off when not using them)

- Strongly disagree
- Disagree
- Neutral
- Agree
- Strongly agree

14. If you would not be influenced by the system, why not? What could have been better to aid you to change your habits in using energy? (text answer)

APPENDIX 2. openHAB installation on Cubieez

There are two different approaches to install openHAB (1) Manual installation approach and (2) Installation through a package repository. In our implementation, openHAB was installed through a package repository.

Step 1: The openHAB bintray repository key is added into the system's package manager. HTTPS protocol is allowed

```
wget -qO -
'https://bintray.com/user/downloadSubjectPublicKey?username=openhab' |
sudo apt-key add -

sudo apt-get install apt-transport-https
```

Step 2: The openHAB repository is added to the system's apt sources list. In our implementation, we used stable release which contains the latest official builds.

```
echo 'deb https://dl.bintray.com/openhab/apt-repo2 stable main' | sudo
tee /etc/apt/sources.list.d/openhab2.list
```

Step 3: Resynchronize the package index

```
sudo apt-get update
```

Step 4: Installing openHAB

```
sudo apt-get install openhab2
```

Step 5: Installing openHAB add-ons

```
sudo apt-get install openhab2-addons
```

Step 6: Starting openHAB

```
sudo /etc/init.d/openhab2 start
```

Step 7: Registering openHAB to be automatically executed at system startup

```
sudo update-rc.d openhab2 defaults
```

Step 7.1: openHAB status can be checked by the following command

```
sudo /etc/init.d/openhab2 status
```

Step 8: Starting openHAB for the first time. It can take up to 15 minutes. Access openHAB server through http://<device IP address>:8080

APPENDIX 3. openHAB configuration

Step 1: To configure openHAB to act as a MQTT publisher to the implemented MQTT Broker (Mosquitto), we need to define the broker that we want openHAB to connect to. The configuration file is ***services/mqtt.cfg***

We can also configure quality of service (QoS) level for sending messages to the broker with the following values: 0 (Deliver at most once), 1 (Deliver at least once) or 2 (Deliver exactly once).

```
# URL to the MQTT broker

mosquitto.url=tcp://192.168.1.114:1883


# Client id (max 23 chars) to use when connecting to the broker.

mosquitto.clientId=OpenHAB2


# QoS for sending messages to this broker.

mosquitto.qos=1
```

Step 2: Configuring MQTT publishing on for each sensor in the files ***items/*.items***

The following configurations are door and motion sensors' MQTT publishing configurations

- ***items/DoorSensor.items***

```
Switch Door_MQTT  "Door MQTT" <doorsensor> {channel="homematic:HM-Sec-SC:ccu2:LEQ1086023:1#STATE",mqtt=">[mosquitto:door:state:CLOSED:Door_CLOSED],>[mosquitto:door:state:OPEN:Door_OPEN]"}
```

- ***items/MotionSensor.items***

```
Switch Motion_MQTT  "Motion MQTT" <motionsensor> {channel="homematic:HM-Sec-MDIR-2:ccu2:MEQ0820944:1#MOTION",mqtt=">[mosquitto:motion:state:OFF:Motion_OFF],>[mosquitto:motion:state:ON:Motion_ON]"}
```