DECISION SUPPORT SYSTEMS FOR DOMESTIC RETROFIT PROVISION USING SMART HOME DATA STREAMS

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ABSTRACT

The scope of this paper is a study of the potential of decision support systems for retrofit provision in domestic buildings, using monitoring technologies and performance-based analysis. The key research question is: in the age of proliferation of cheap, mobile and networked sensing equipment, how can measured energy and performance data from multiple in-home sensors be utilised to accelerate building retrofit measures and energy demand reduction? Over the coming decade there will be a significant increase in the amount of measured data available from households, from national Smart Meter rollouts to personal Smart Home systems, which will provide unparalleled insights into how our homes are performing and how households are behaving. The new data streams from Smart Homes will challenge the prevailing research and policy initiatives for understanding and promoting energy-saving building retrofits. This work is part of a £1.5m UK Research Council funded project 'REFIT: Personalised Retrofit Decision Support Tools for UK Homes using Smart Home Technology' (www.refitsmarthomes.org). Three methods are combined to give multiple perspectives of the research challenge: 1) A literature review on Smart Homes with a focus on academic progress to date in this area; 2) Results from actual Smart Home monitored data streams, as measured in an on-going study of UK-based Smart Homes; and 3) a discussion of performance-based analysis leading to insights in decision support system provision for Smart Building owners. The approach outlined in this work will be of significant interest to national governments when promoting Smart Meter roll-outs, to energy companies in promoting new services using Smart Home data and to the academic community in providing a foundation for future studies to meet the domestic building retrofit challenge.

Keywords: Decision Support Systems, Smart Homes, Performance-based analysis, Domestic building retrofit, Household energy monitoring

1. INTRODUCTION

Although the energy used within homes provides essential everyday services and can represent a significant proportion of household budgets, consumers are often lacking a clear understanding of their energy demand and how it could be reduced. Energy use within a home can be complex, with different fuels (such as electricity, gas, coal, oil, solid fuel, wood etc.) providing a range of services including space heating, hot water heating, lighting, cooking, clothes washing, refrigeration, entertainment and communication. For each individual household, energy demand may be influenced by the characteristics of the building (e.g. well or poorly insulated), the efficiency of the energy-consuming devices (e.g. condensing or non-condensing gas boilers, CFL or incandescent light bulbs) and the energy-related practices of the users (e.g. choice of set-point temperature for heating, frequency of appliance use). Energy management in dwellings is further complicated due the differences in preferences of individuals living in the home, such as thermostat settings, which often require negotiation (Hargreaves et al., 2010). Poor understanding of household energy use is compounded by the billing system for the majority of consumers which provides values of total fuel use at infrequent intervals, usually monthly or quarterly, so that results of any actions or changes are difficult to perceive. Often such bills are based on estimated readings (if the meter was not read in person) which further adds to the confusion over the recent actual energy consumption of a household.

However a number of stakeholders require householders to manage, control and reduce their energy use in a much more coherent fashion than is currently seen in practice today. National and local governments view energy demand reduction in homes as a potential major contributor to meeting carbon emission reduction targets and mitigating climate change. For example the UK Government's Low Carbon Transition Plan requires a 29% reduction by 2030 in carbon dioxide emissions from the housing sector (HM Government, 2009), as part of the economy-wide legislative target of 80% reductions by 2050 (HM Government, 2008). Utilities and energy companies are required in many countries to contribute to delivering these energy savings, through legislative schemes such as the UK Energy Company Obligation (ECO) scheme (DECC, 2012). In these cases the utilities are required to design and implement energy efficiency programmes to lower their customers' energy consumption, with the effectiveness of the programmes evaluated and penalties in place for poor performance. Householders themselves also benefit directly from energy demand reduction as it leads to lower energy bills, of particular relevance in countries such as the UK where energy prices doubled in the last ten years over a recent five year period (DECC, 2013).

A clear route to energy demand reduction in housing is through retrofitting existing domestic buildings. Domestic building retrofit options include wall, loft and floor insulation, improved glazing and doors, draft proofing, high efficiency boilers, advanced heating controls, and heating system insulation (on the hot water cylinder and heating system pipes). Additional non-building retrofit options are also available, such as energy efficient household appliances and on-site micro-generation energy supply systems (solar PV, solar thermal, heat pumps, biomass boilers and microchip). Retrofitting can provide long-lasting and significant savings in energy demand, but are often not taken up due to the high initial capital costs. One challenge is provide householders with accurate estimates of the potential savings to be expected if a particular retrofit measures is taken up. The existing energy saving calculations methods employed, such as the UK's SAP method (DECC, 2011), utilise standardised occupancy characteristics, including a standard, fixed heating schedule (e.g. 9 hours at 21°C for weekdays) and a simple occupant number calculation (based on the floor area of the dwelling). However the actual occupancy characteristics of a real-world home will often differ from these assumptions, which can cause any predictions of potential savings to be significantly over or under estimated.

The aim of this work is to explore the potential of decision support systems for retrofit provision in domestic buildings, using Smart Home monitoring technologies and performance-based analysis. The premise is that using the additional data gathered in a Smart Home (such as room temperatures, occupancy sensing and real-time gas consumption) better advice can be given to the householder on the energy savings available from retrofitting. This improved and personalised advice should lead to greater uptake of retrofit options. The paper is structured in four main sections. Section 2 presents a literature review on existing research on the Smart Home concept. Section 3 describes the upgrading of an existing UK home to a Smart Home, including a description of the building characteristics and the technologies used to provide monitoring and automation functionality. Section 4 presents initial results from the Smart Home trial and a discussion on the potential to implement a retrofit decision support system based on the Smart Home data streams. Section 5 presents the conclusions of this initial work in the field of Smart Homes and energy demand reduction.

2. LITERATURE REVIEW

A Smart Home is a home that is equipped with highly advanced automatic systems, such that all lightings, heating, security system, appliances and electronic devices can be controlled remotely via smartphone, computer or other through internet or local network. Figure 1 provides an example of the types of devices that may be present in a Smart Home. In simple terms Smart Homes perform both monitoring and control of the home activities for convenience, better comfort and possibly reduced energy use. Many experts have developed their own vision of what a Smart Home should be. Complete Smart Home systems are currently available in the market, such as the RWE SmartHome product (RWE, 2013). A storyboard for a typical day in a future Smart Home could include: i) the alarm goes off at 7:00, the Smart Home system requests to turn on the bedroom light and the coffee maker in the kitchen; ii) when the occupant steps into the bathroom, the Smart Home system turns on the light, displays the morning news on the bathroom video screen, and turns on the shower; iii) when the occupant finishes, the bathroom light turns off while the kitchen light and menu/schedule display turns on, and the news program moves to the kitchen screen; iv) when the occupant leaves for work, the Smart Home system secures the home, and starts the lawn sprinklers; and v) as the Smart Home system detects that the refrigerator is low on milk and cheese, it automatically places a grocery order to arrive just before the occupant returns home (taken from Das et. al 2002).

Figure 1: One example of the Smart Home concept with 'plug & play' devices (devices shown from RWE, 2013)

A number of previous projects have looked into home control and automation. The Adaptive house project (Mozer, 1998) controlled temperature through heat control and controlled lighting in an attempt to reduce energy use. The techniques involved neural networks as a means to intelligently manage the environment, the system integrated presence and lifestyle data. MavHome (Bhattacharya, 1999 and Das, 2002) created a home which acts as rational agent to maximize comfort and minimize cost. Based on LeZi technique of information theory they have combined usage of databases, multimedia computing, artificial intelligence, mobile computing and robotics to predict the inhabitant's typical path segments, comfort management scheme, and appliance use. Simulated intelligent home project (Lesser, 1999) was aimed at automating some of the tasks being performed by humans in order to improve energy efficiency and quality of service. Their technique was based on Multi-Agent Survivability Simulator (MASS) and Java Agent, their experimental setup included simulation of four rooms, various intelligent agents to control the environment (water-heater, coffeemaker, etc.) and usage of a robot to fetch items and move things from one location to another. The intelligent agent was required to interact and coordinate over shared resources (for example, the Dishwasher agent uses electricity and hot water). The Aware Home Research Initiative (Kidd, 1999) project enabled the elderly to remain in familiar surroundings, improving quality of life. The technique involved hidden Markov models, simple feature-vector averaging, and neural networks. They have built a three story home that functions as a living laboratory for the design, development, and evaluation of future domestic technologies. Objects in house were equipped with radio-frequency transmitters and the occupant interaction interface was LCD touch panels. The philosophy adopted was to develop a system of tracking and sensing technologies to help find frequently lost objects such as wallets, glasses, and remote controls. Microsoft's EasyLiving project (Krumm, 2000 and Brumitt, 2000), based on context aware computing, designed an architecture capable of integrating different devices in a consistent modelling of the environment to ensure automatic control comfort, without human intervention, such as the triggering of lights when the occupant moves at night. The equipment involved tracking video system, walls and floors equipped with motion sensors and active badge for authentication of individuals. The purpose of the study was for the geometric model to provide a sub-meter localisation of occupants in the studied environment. Their research included middleware development, geometric world modelling, computer perception and better service description. Elite CARE (creating an autonomy-risk equilibrium) (Adami, 2003) provided medical support to prolong people’s independence and to help the staff identify health problems early. The purpose was to make use of digital technologies to detect behavioural cues indicating change in an individual’s physical or cognitive condition, and to regulate ambient conditions. Matilda house (Helal, 2003) attempted to optimize comfort by controlling the environment as a function of occupants’ mobility and their habits, the technique used triangulation which relied on high-precision ultrasonic, placed in the four corners of a room and on the shoulders of a person (as laboratory tests) with the aim to perform a precise calculation of the location of the person.

3. METHODOLOGY

3.1 Smart Home data streams

Figure 2 illustrates the range of Smart Home devices readily available to consumers. The devices installed in the home are controlled by a central gateway which allows on-site and remote/mobile access to the Smart Home system through PCs, laptops, tablets and smartphones. Devices can be controlled directly through the user interface (e.g. a light can be instantly switched on by the user) or rules can be defined for automation (e.g. a light switches on when a door opens). The measured data sensed by the Smart Home devices can be logged to provide historic feedback to the householder. These Smart Home data streams can include:

- Room air temperatures (recorded by wall thermostats and radiator thermostats)
- Room humidity (recorded by wall thermostats and radiator thermostats)
- Door and window opening and closing
- Room occupancy
- Appliance electricity consumption (recorded by plug controllers)
- Whole-house electricity consumption (recorded by Smart Meters or AC current clamps)
- Whole-house gas consumption (recorded by Smart Meters)
- Occupant use of wall and radiator thermostats (i.e. when the demand temperatures are adjusted by the occupants)
- Occupant use of plug controllers
- Occupant use of controlling devices such as remotes and switches

Data is collected either at regular intervals (e.g. every 60 seconds) or at the instance when an event occurs (e.g. a timestamp is recorded when a door opens). Often the data arising from Smart Homes will be stored on off-site servers, and is downloaded by the householder as needed.

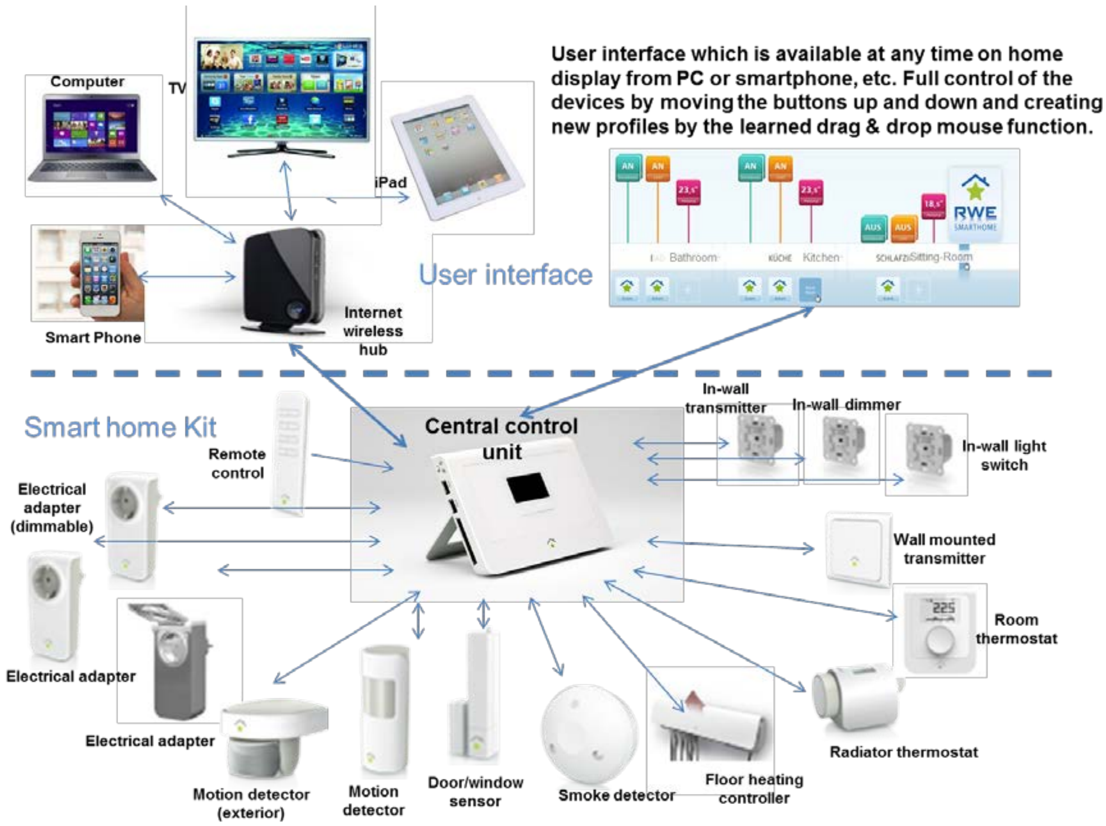

Figure 2: Smart Home devices and network used in the study (devices shown from RWE, 2013)

3.2 Data collection using wireless and standalone sensors

In this work a number of Smart Home data streams were captured from a case-study home using a combination of wireless and standalone monitoring technologies. This is a prior step to a full Smart Home solution being installed, although the data streams recorded are identical. Monitoring equipment was installed in a mid-terraced UK dwelling built circa 1880 using solid wall construction. The main sensors used are shown in Figure 3. Hobo pendant temperature sensors (Tempcon, 2013) measured temperature in the living room and main bedroom at 15 minute intervals. The sensors were placed away from windows and heat sources to ensure that the measurements would be representative of the temperatures in each room. Room occupancy data was captured using stand-alone Hobo occupancy sensors (Tempcon, 2013). Whole house gas and electricity consumption was logged every five minutes by connecting to the pulsed output of the gas monitor and monitoring the flashing LED on the electricity meter.

Individual appliance electricity consumption from major appliances was also monitored at one minute intervals using the Plogg system (Telegesis, 2013). Due to the amount of data collected (i.e. 1440 readings from each appliance per day) a computer was located at the property to store the data which downloaded automatically every 15 minutes. Electricity use was recorded for the fridge-freezer, microwave, washing machine and the audio-visual site which included a combined measurement of television, DVD player and hi-fi. The data collected from these household appliances, coupled with the whole house measurements, enabled other specific energy consumption patterns to be identified (for example the energy used for hot water heating and cooking).

Figure 3: From left to right – gas meter fitted with pulse module, hobo pendant sensor used for temperature monitoring and electricity meter fitted with LED pulse detector.

4. RESULTS AND DISCUSSION

4.1 Initial results from Smart Home monitored data streams

Figure 4 shows the whole-house (metered) gas and electricity consumption, and the living room and bedroom air temperature data, collected from the house for a single day. Electricity consumption occurs continuously throughout the day, with low levels overnight and in the middle of day arising from refrigeration appliances and standby power loads. Peaks of electricity use occur at times of high household activity. Here a morning peak (08:00 – 10:00) and evening peak (18:00 – 22:00) is observed, when other household appliances (such as lighting and cooking appliances) are in use. The gas consumption also occurs at two distinct times, in the morning (07:00 – 09:00) and the evening (18:00 – 21:00). Gas consumption is driven by space heating (providing hot water to the room radiators) and domestic hot water use (for baths, showers etc.). The fact that the morning gas consumption starts an hour before any discernible morning increase in electricity use suggests that the heating system is controlled by a timer (which switches on at 07:00 before the occupants become active in the house at 08:00). The living room and bedroom temperatures range between 16.5°C and 19.0°C throughout the day. Initially the room temperatures decrease in early morning (00:00 – 07:00) as the building loses heat to the outside environment. The morning space heating period (shown by the gas consumption) leads to an increase in room temperatures between 07:00 – 09:00. A similar pattern is observed throughout the day, where room temperatures decrease when the heating is switched off (09:00 – 18:00 and 21:00 – 00:00) and increase when the heating is switched on (18:00 – 21:00). The pattern of occupancy in the house appears to influence the room temperatures. Bedroom temperature decreases less rapidly then living room temperatures in the early morning period (00:00 – 07:00), possibly due to the heat gains from the occupants in the bedroom at this time. During the middle of the day (09:00 – 18:00) the living room and bedroom temperature decrease at a similar rate. In the evening the living room temperature increases to a higher level (19°C) than the bedroom (18.5°C), an effect which could be caused by the heat gains from occupants and household appliances in the living room during the evening period. A higher setting of the thermostatic radiator value in the living room could also cause this higher observed temperature level.

The energy and temperature data streams observed here have the potential to provide information on the characteristics of the house, which could be used to inform retrofit decisions. The rate of decrease of room temperatures when the heating system is switched off is an indication of the heat loss from the building. Several factors will influence the rate of temperature decrease, including fabric thermal conductivity, fabric thermal storage capacity, ventilation and air infiltration rate, external air temperature and internal heat gains in the rooms. Similar factors, along with the amount of gas consumption, will influence the rate and magnitude of room temperature increases during the heating periods. Fabric building retrofits seek to modify the fabric characteristics (e.g. wall insulation to decrease the thermal conductivity) so by better understanding the fabric and ventilation characteristics of a building (derived from the energy and temperature data streams as illustrated above) then improved predictions of the likely effect of a building retrofit measure can be made.

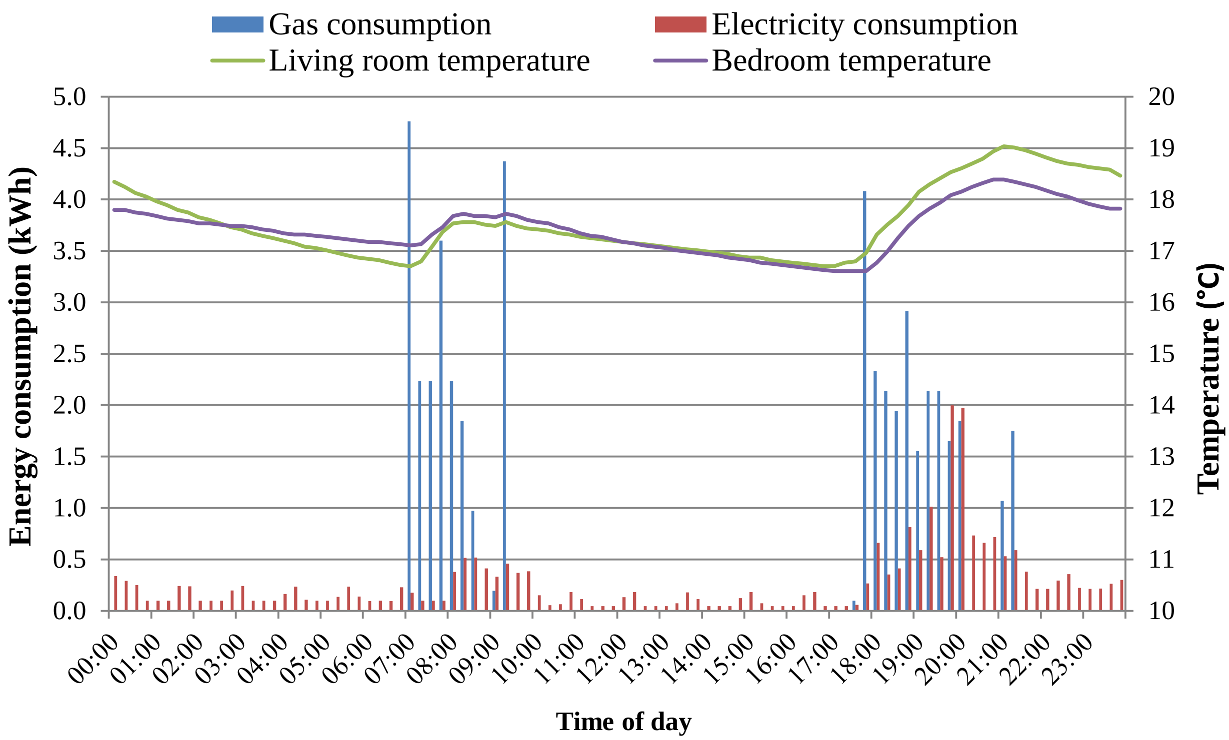

Figure 4: Example of room temperatures and whole-house energy consumption over a single day

Figure 5 shows an example of occupancy data recorded in the living room for the same house over the same day as Figure 4. The occupancy sensor triggers when movement is detected, then deactivates for a defined period of time (e.g. 30 seconds) before 'rearming' itself to sense movement once more. The vertical bars on the figure show the times of day when a movement has been sensed in the living room. Due to the measurement process, it may be possible for an occupant to be present in a room continuously but the occupancy sensor only to detect the presence infrequently (e.g. at 1 to 5 minute intervals) when a movement is detected. The occupancy pattern shown in Figure 5 confirms the inferred occupancy suggested by the electricity consumption in Figure 4. The household occupants are active in the home during a morning period (08:30 – 09:30) and in the evening (18:00 – 21:00). As the occupancy sensor only records movement in a single room, there will be times when the household occupants are active in the home but this is not recorded by this sensor. There are also periods of activity (e.g. 15:30 – 16:30) which were not suggested by the electricity data in Figure 4, representing times when occupants are present in the home but not engaged in an energy-consuming activity.

Occupancy data streams provide two main insights for further analysis. Firstly they can show periods when the occupants are present in a room (and in the house) which is useful for generating internal heat gain estimates, as a part of understanding the rates of heat loss from a home. Secondly the occupancy data can highlight periods when the occupants are present but the heating system is not switched on, and conversely periods when the occupants are not present but the house is still being heated. This information could be used to avoid unnecessary or excessive heating of the house.

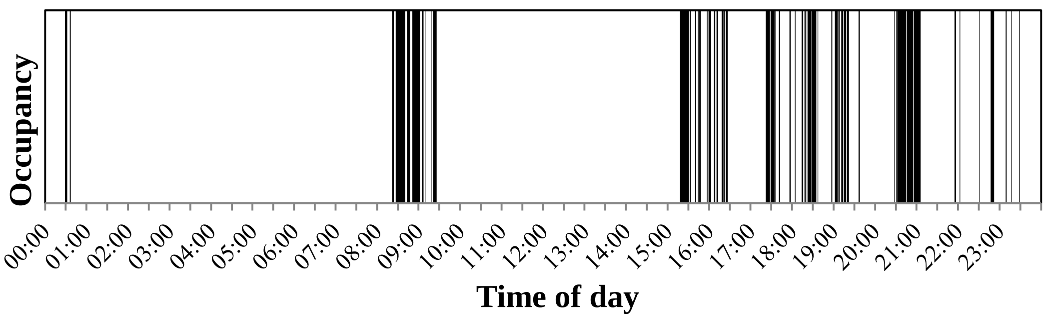

Figure 5: Example of Smart Home occupancy data over a single day

Figure 6 shows electricity consumption measured in the home over a single day. This was recorded on a different day to Figure 4 and 5. The electricity consumption of four household appliances / appliance groups are shown: the microwave, the fridge-freezer, the audio-visual site (this is a combined measurement of a television, set-top box and a DVD player), and the washing machine. The whole-house (metered) electricity consumption was also recorded as is shown in the figure as a cumulative total which increases throughout the day. Individual appliance measurements leads to large data sets and in this simple case a number of observations can be made from the data such as: the fridge-freezer cycles continuously throughout the day, and appears to be in use between 17:00 – 18:00; the audio-visual site has an associated standby power load which is continuous throughout the day; the microwave is used infrequently; and the washing machine cycle has a distinctive pattern with the majority of the electricity consumed at the start of the cycle for heating the washing water. The cumulative whole-house electricity measurement also highlights the use of other appliances, in particular of an electric shower in the morning (around 07:30 and consuming ~0.8 kWh) and an electric cooker in the evening (18:30 – 19:30).

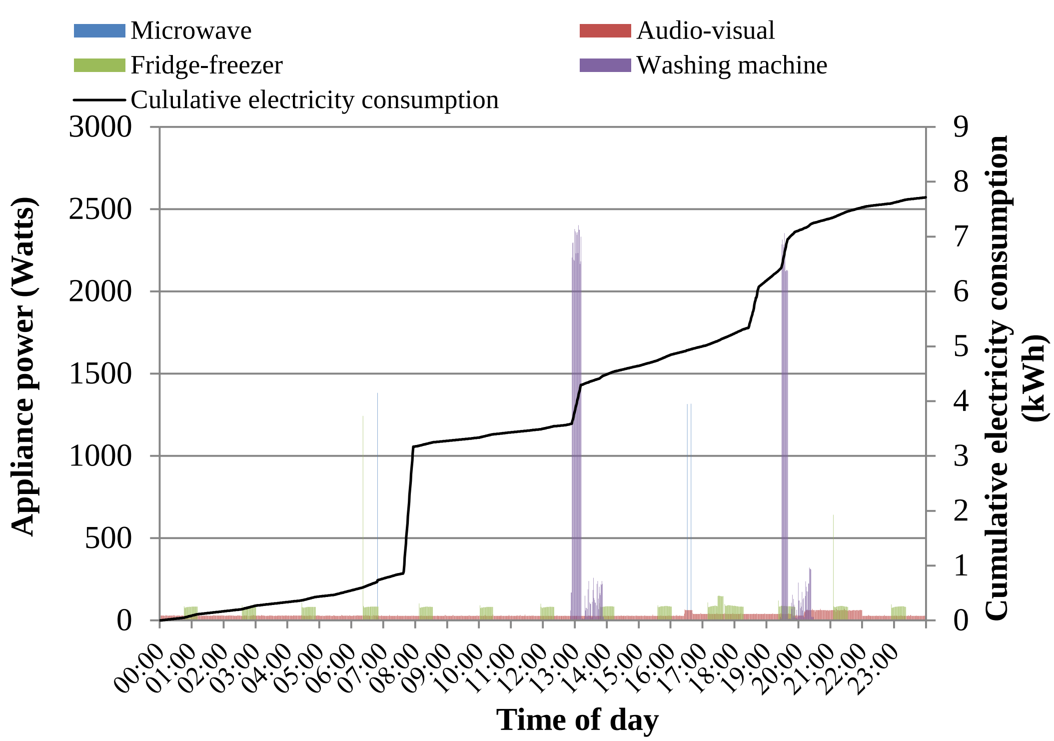

Figure 6: Example of data from monitored appliances

Individual appliance data streams can be used to infer occupancy in a home, and can locate occupant activity to a particular room. For example the use of the microwave in Figure 6 suggests occupant activity in the kitchen. Appliance electricity consumption measurements can also be used to estimate the internal heat gains arising from appliance use. For energy demand reduction, individual appliance data streams can be used to estimate the energy saving potential of replacement appliances with higher energy efficiency. For example replacing a washing machine with a more efficient version. Understanding of the detailed electricity consumption of an existing appliance, and the householders' use of an appliance (such as frequency of use, settings and programmes used etc), will enable better predictions of the potential energy savings available.

4.2 Discussion on Decision Support Systems using performance-based analysis

The uptake of Smart Homes will lead to a significant increase in the amount of measured data available, providing unparalleled insights into how our homes are performing and how households are behaving. Early research and application of these data streams has focussed on feedback of energy (largely electricity-only) consumption statistics to householders, primarily to reduce energy consumption through influencing day-to-day energy-related behaviours. However future research must focus on the wider challenge of accelerating the uptake of thermal retrofit measures in housing stocks, which can lead to significant and sustained energy demand reductions.

The new data streams from Smart Homes, as illustrated in this paper, will challenge the prevailing research and policy initiatives for understanding and promoting energy-saving building retrofits. For example the electricity and gas measurements made by Smart Meters will lead to several innovations in the building retrofit process such as: i) improved identification of the homes throughout the stock which stand to gain the most through retrofit measures, using historic gas consumption data combined with basic building survey information; ii) improved predictions of the energy savings available through retrofit measures, using historic gas consumption data to infer household heating practices which can then be taken into account (a home which is constantly heated is likely to have a greater energy savings potential than one which is rarely heated); and iii) quality assurance checks of retrofit works and the minimisation of rebound, through pre-and post-installation comparisons of energy consumption data. Further innovations also include improved advice for the energy implications of purchasing replacement appliances and better predictions on the impacts of installing on-site micro-generation systems.

Decision support systems using performance-based analysis are one approach to provide the improved and personalised information to householders on their options for retrofitting and making significant energy demand reductions. Decision support systems can utilise a number of methods including cost benefit analysis, lattice method for optimisation, energy rating systems, predicted habitability index, multiple criteria analysis, etc. Here we are concerned with the development and implementation of personalised decision support tool for domestic house retrofitting, which will generate refurbishment solutions for different scenarios and levels of improvement to the building performance. The tool will inform users (householders, designers and evaluators) with detailed building performance assessment leading to improved life cycle cost and user comfort. The tools will be made flexible for adaptation to a range of domestic building types taking into account: building envelope, outdoor and indoor climatic conditions, heating and cooling systems, lighting and controls available, and appliance performance and status. The decisions are expected to be dependant of a mixed range of factors such as the desired indoor conditions, the current performance of heating system, the occupants' practices in terms of energy usage and comfort perception, and the social and economic impacts of retorting the home. The technical element of the decision support tool may include neural networks, databases and expert-based rules.

5. CONCLUSIONS

In conclusion this paper has demonstrated that there exists significant potential to improve our understanding of actual building performance using Smart Home data streams. Through better understanding of the data, decision support systems can be designed to provide improved and personalised advice to householders on the retrofit options available to them. This approach is being explored further in a study of 20 UK homes as part of the wider REFIT project.

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