Occupancy Based Household Energy Disaggregation using Ultra Wideband Radar and Electrical Signature Profiles

Robert Brown, Navid Ghavami, Hafeez-Ur-Rehman Siddiqui, Mounir Adjrad, Mohammad Ghavami and Sandra Dudley*

School of Engineering, London South Bank University, London, SE1 0AA, UK

Abstract

Human behaviour and occupancy accounts for a substantial proportion of variation in the energy efficiency profile of domestic buildings. Yet while people often claim that they would like to reduce their energy bills, rhetoric frequently fails to match action due to the effort involved in understanding and changing deeply engrained energy consumption habits. Here, we present and, through dedicated experiments, test in-house developed software to remotely identify appliance energy usage within buildings, using energy equipment which could be placed at the electricity meter location. Furthermore, we monitor and compare the occupancy of the location under study through Ultra-Wideband (UWB) radar technology and compare the resulting data with those received from the power monitoring software, via time synchronization. These signals when mapped together can potentially provide both occupancy and specific appliances power consumption, which could enable energy usage segregation on a yet impossible scale as well as usage attributable to occupancy behaviour. Such knowledge forms the basis for the implementation of automated energy saving actions based on a households unique energy profile.

Keywords: Appliance power signatures, Ultra wideband radar, UWB Energy saving, Wireless Sensor Networks, Internet of Things, Smart homes, NILM, Occupancy detection.

*Corresponding author

1. Introduction

Currently the effect of human behaviour on domestic building energy consumption is an underestimated factor. Reducing unnecessary energy wastage is becoming a global challenge with responsibility being asked of the individual to make changes, that when summed can have greater national and international significance. Hitherto, human behaviour has not been effectively factored into existing building legislations that have been designed to predict and improve energy consumption. A simple, yet forgettable truth is that "buildings dont use energy, people do" [1], a fact which has been demonstrated in findings that reveal considerable variation in energy demand and consumption between virtually identical apartments [2]. This is further supported by time-use survey data, showing that there are no "average" days or "average" consumer profiles that can reliably predict energy demand and consumption [3].

In recent studies, it has been verified that there is a gap between predicted energy consumption and actual energy consumption [4, 5]. A paper by the Carbon Trust [6] compared the modelling for Part L and the Energy Performance Certificate (EPC) to actual energy through a series of case studies. In one instance, actual energy use was underestimated by five times in the first year alone. Furthermore, even when more detailed modelling and benchmarking were done for other case studies, an average gap of 16% existed between actual use and estimated use. Such findings would indicate that although designers can influence many aspects of the building that determine low carbon outcomes, there are still important areas that can only be influenced by the occupiers. This is further supported by the research findings that have shown even in buildings designed to be energy efficient, an occupants actions account for up to 51% of the variance in heating, and 37% in electricity consumption [2].

Often, occupants form energy habits that are less than optimal in terms of energy usage resulting in over consumption, either intentionally (for comfort reasons) or unintentionally (due to absent mindedness). According to the Energy Saving Trusts report (The Habits of a Lifetime), 71% of consumers left appliances on standby, 67% boiled more water than needed in the kettle, and 63% forgot to turn off the lights in unoccupied rooms.

Of vital importance to the effective design of a successful home energy management system is an understanding of how and why people use energy. Evidently, people do not use energy for the sake of it but rather in the accomplishment of everyday activities such as showering, keeping warm, and cooking [7]. In other words, much of energy consumption is driven by habitual behaviours [8, 9] so deeply embedded into peoples lives that they rarely question the energy use associated with them rendering consumption invisible, both physically and consciously [10]. Energy consumption is also affected by occupants "energy related preferences" which are informed by a myriad of factors including; an individuals subjective experiences of an environment (e.g., some individuals accept larger temperature ranges than others; [11]); social norms (e.g., 55% of people adjust heating to host guests; [12]); and even misconceptions about the most efficient ways of using energy (e.g., qualitative data reveals occupant uncertainty about whether it is more efficient to leave heating on all the time to prevent home cool down and then heat up again).

The Internet of Things (IoT) has changed the way we interact with our environment. Its egress into our daily lives will be expedited if the technology offered is useful, secure and brings benefits without much user effort. Automated and non-intrusive sensing methods to assist users to reduce their energy consumption without them actively having to remember or constantly manually intervene at the expense of other tasks would ultimately help consumers lower energy consumption and with it bring the obvious greener benefits. The current roll out of smart meters although in the right direction for energy awareness does not generally assist citizens to reduce their bills. The information is general and does not normally provide useful feedback on how users can work with their own home to improve consumption reduction efforts. Thus any initial "greener" enthusiasm normally fades after time. Existing energy monitors only report the energy being used, but do not provide information on which appliances within the home are responsible for that energy consumption [13].

This paper reports a system that has been developed to potentially itemize building energy consumption per appliance instance. The development of non-intrusive systems that learns a users "habits" in their own home and automatically initiates energy saving actions: for example reducing the thermostat temperature when the house is unoccupied or changing the thermostat timetable based on the real heating profile of the house and user occupancy is a step-change in energy reduction approaches. Automated actions and feedback approaches without continual user input can engage users more effectively in reducing energy consumption. It can provide the user a true understating of their home's energy profile, how they use energy within their environment and through automation, and help reduce wasteful habits.

Wireless sensor networks (WSNs) are to the fore of IoT egress. They consist of distributed nodes wirelessly connected to different sensors e.g. pollution, temperature, light, and have the capability of duplex communication [14]. WSNs importantly permit the creation of non-intrusive communication system ready for deployment within domestic to large commercial environments. The edge nodes associated with WSNs can be very small in size and accompanied with a mounted microprocessor, memory and transceiver. Within the test bed developed in this work a wireless network based on XBee (using ZigBee protocol) is designed and adapted to UWB set up for transmitting UWB processed data to a remote server to be stored into a database. XBee module based on IEEE 802.15.4 forms a low power, low maintenance and self-organizing WSN [14]. It was essential that any network topology developed was not commercially stinted so that nodes from different commercial suppliers could be integrated depending on the users' need. XBee networks use a single coordinator device, which is responsible for forming the network, handling addresses, and managing the other functions like defining and securing the network. All other XBees in the network connected with the coordinator are known as routers or end devices. Each can join the existing network, send, receive and route information (router only) [15]. A MySQL database was used for data storage, and later retrieval in tabular as well as plotted format.

Ultra-Wideband (UWB) is known as a new and emerging technology, although its first use goes back many decades. In 1973 the first US patent was awarded to Sperry research centre for UWB communications. Following this for many years, most of the applications and development of UWB occurred in the military or work funded by the US government under classified programs and the technology was alternatively referred to as baseband, carrier-free or impulse communication systems. The move to commercialise UWB communication devices and systems arose during the late 1990s, when companies such as Time Domain and Xtreme Spectrum were formed around the idea of consumer communications using UWB [16]. In 2002, the USA based Federal Communication Commission (FCC) [17], allocated a bandwidth of 7.5 GHz for UWB signals [18]. This bandwidth covers a frequency band of 3.1 to 10.6 GHz. In order for any signal to be considered a UWB signal, it must either have a bandwidth of at least 500MHz, or it should have a fractional bandwidth of greater than 20% in the frequency range defined by the FCC.

There are a wide range of advantages associated with UWB signals. The key benefits are high data rates, low equipment cost and low hardware system complexity, multipath immunity, simultaneous ranging and communication, and importantly a very low power non-ionising transmission level, much lower than Wi-Fi or Bluetooth, enabling its use in domestic environments [16]. Having these advantages, ultra-short information pulses along with not requiring sine-wave carriers in modulation, enables UWB signals to be used in a wide range of applications, which include precision navigation, through wall imaging, high resolution ground penetrating radar and short range and high-speed broadband access. Impulse Radio UWB (IR-UWB) communication systems transmit very short duration pulses, resulting in the production of very high bandwidth signals. The short duration of the pulses allows a high level of accuracy with centimetre-level ranging resolution and unmatched performance in multipath environments [16]. Multiple studies can be found in the literature focussing on ranging [18], location and tracking algorithms [19, 20]. Pivotally, UWB sensing when developed appropriately does not require end-users to wear any form of tag to engage with the system. This creates a more natural environment when outputs on movement and occupancy are required, creating more realistic data on user movement.

In this work, the data gathered from UWB detects and identifies the movements of person(s) within an indoor environment. This enables the system to potentially identify the occupancy or non-occupancy rates as well as the exact real time location of person(s) inside the house and to distinguish the number of people in each room.

Augmenting the non-intrusive wireless radar system, algorithms were developed to identify appliance energy usage within an environment, from voltage and current measurement equipment which could be placed at the electricity meter location. This type of system falls under the category of Non-Intrusive Load Monitoring (NILM), so called because the measurement equipment does not intrude onto the consumers property any more than the existing kilowatt hour (kWh) meter [21]. The electrical signature profiling seeks to determine which appliances turn on and off at which times, by processing the aggregate power signals which can be measured at the kWh meter in a pattern recognition scheme. The nearest-neighbour supervised learning technique was used to identify appliances in a typical home, using a training set consisting of laptop, microwave, fan, toaster and kettle power signatures for the experiment in question. Detailed per-appliance energy consumption information was then computed, which could be provided to the consumer.

This paper is organized as follows. In section 2, the theory and methods behind the experiments are explained and section 3 gives a detailed explanation of the lab measurement. The corresponding results and analysis are presented in section 4 while section 5 concludes the paper.

2. Methodology

The overall system developed merges signal profiling and UWB radar into an appliance detection and occupancy scheme. Both systems were designed individually and integrated for physical experimentation as will be described.

Power signals measured at the electrical intake position to a building are the aggregate of each appliance connected to the installation. Figure 1 shows a time series snapshot of a typical household power signature, where appliance usage periods overlap and transients exist in the real and reactive components; the signature shown was generated in the lab by manually switching typical household appliances on and off over an eight minute period, whilst data-logging the aggregate real and reactive power levels. In order to provide energy consumption information for each target appliance category, it is necessary to disaggregate the total energy measured at a single point (the kWh meter position). Several methods for achieving this disaggregation are described in the literature.

Egarter [22] describes a real time unsupervised load disaggregation algorithm which uses only real power values, sampled at 1Hz. The pattern recognition method used is particle filtering, which is computationally expensive. Bijker [23] utilises Real Power and duty cycle as appliance load features. This would predominantly be suited to detect target loads which are switched by an internal thermostat, for example a fridge or cooker. Nguyen [24] describes a system that uses active, reactive and apparent power as appliance features. A decision tree classifier uses step changes in these quantities to identify appliance usage. The decision tree method does not appear to be scalable to large numbers of appliance categories.

Electrical appliances can also be categorized by their steady state real power and reactive power consumption [25], where transients in the signals are ignored in favour of sharp turn-on and turn-off edges. This method was adopted in the NILM software developed, as it does not require a large amount of processing power, and is capable of detecting a wide range of household appliances making it suitable for domestic and business scenario requirements.

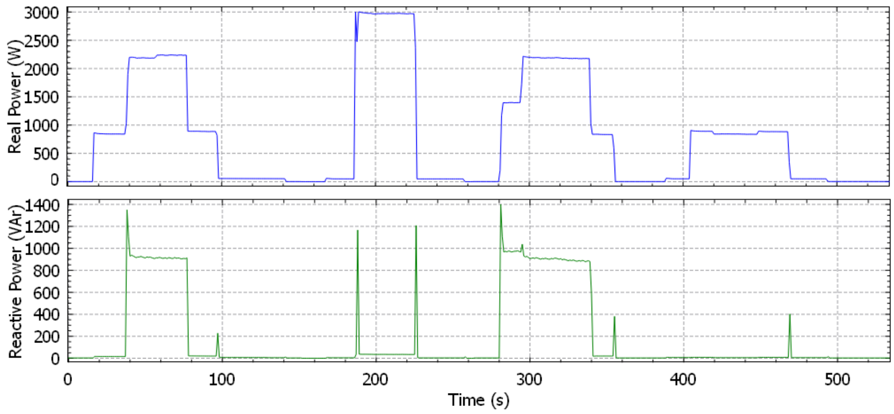

Figure 1: Typical household raw power signature.

The algorithm functions as follows; the acquired power signal is first processed to detect changes in steady state power levels, known as load edges [21], by voltage level normalisation, steady period filtering, and then discrete-time differentiation. Figure 2 shows the real and reactive parts of the processed typical household power signal from figure 1, with load edges now appearing as impulses.

Loads are then detected by pairing on and off edges with similar magnitudes but opposite signs, and classified into appliance categories using the nearest neighbour algorithm in two dimensions. This classifies test appliances according to the training appliance that has the most similar power profile. The training dataset used was formed of experimental data acquired from multiple instances of five test appliance categories, namely microwave, laptop, fan, kettle and toaster.

Python 3.0 code was used for the development of a dedicated program to perform the required signal processing and pattern recognition described above, to recognise each appliance under test and the energy used by each appliance instance, and output an itemised energy usage table. The research team is currently finalising its development alongside energy bills to assist users' understanding of their energy use and will be published once full experiments, currently underway are finished. . The software output included an infographic displaying the total energy consumption for each appliance over a period of time. An algorithm was developed to pre-process the real and reactive power signals by normalising against the voltage signal using the formula [21]:

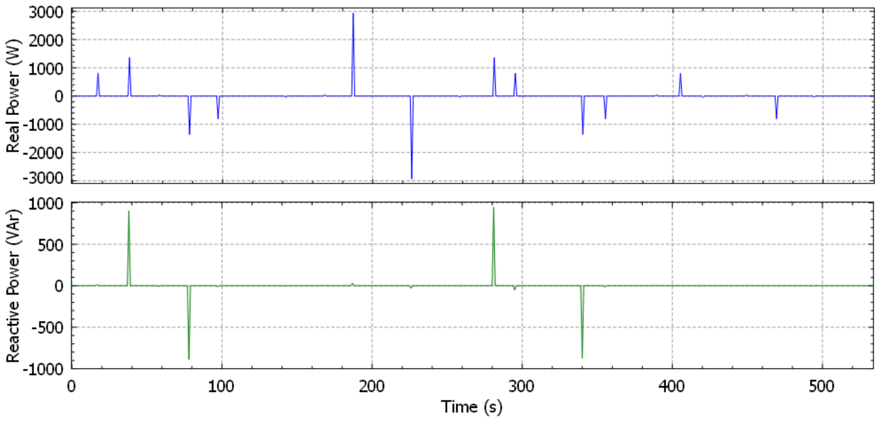

Figure 2: Associated load edges of Figure 1.

$$p_{\text{norm}}(t) = \left(\frac{v_s}{v(t)}\right)^2 p(t) \tag{1}$$

where p_{norm} is the normalized power sample, v_s is the nominal supply voltage (240V AC), and $v(t)$ and $p(t)$ indicate the voltage and power samples, respectively. The output was then filtered using a consecutive steady sample method [21] to remove high frequency transients and sharpen edges. The steady state edges were detected by taking the discrete-time first derivative of the power signals. Load edges, now appearing as impulses (see figure 2), were paired into loops [25] according to testing the real power edges against:

$$\left|\text{Edge}_{on} + \text{Edge}_{off}\right| < \text{Tolerance} \tag{2}$$

A tolerance value of 25W was found to work well for the models undertaken and this tolerance value was used for all subsequent experiments. Each load-edge pair was mapped into an appliance category using the nearest neighbour algorithm, and the training dataset.

Figure 3 is a scatter plot showing the manually labelled experimental training points used for the nearest-neighbour classification. The classification features found to work best were:

- Real power (P)
- Reactive power per real power (Q/P)

Both features were normalized to give equal weighting, and rescaled to percentages for easier human readability. Energy usage was calculated per appliance instance and then re-aggregated by appliance category, in order to produce data for a histogram of each appliances energy usage over a time interval.

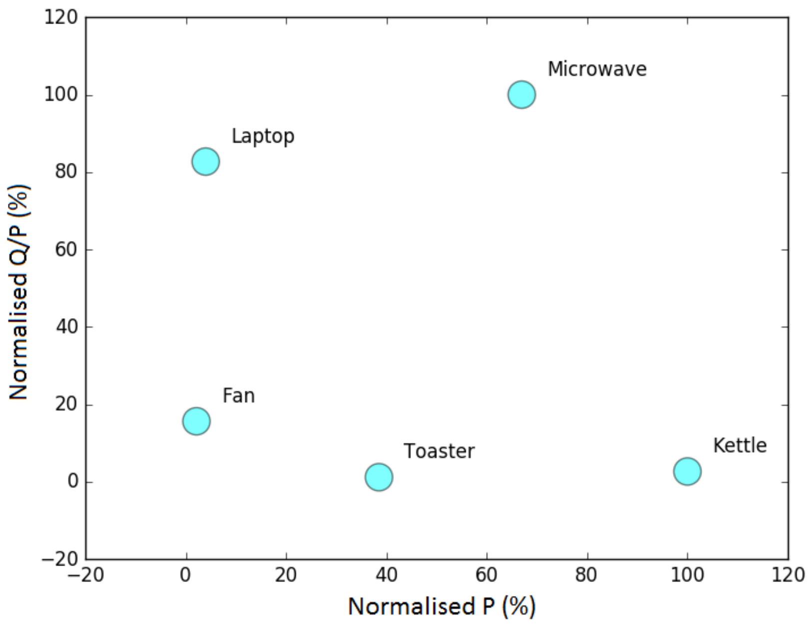

Figure 3: Scatter of training data and kettle test point.

3. Lab experiment

A lab experiment was carried out in a staff kitchen. Real and reactive power signals were sampled at 1Hz, using a standard laboratory power analyser with a BS1363 [26] breakout socket (Voltech PM1000 [27]). The resident toaster, kettle and a microwave were all connected to the breakout socket via a multi-way adaptor, providing an aggregated power signal and the connection is shown below in figure 4.

Figure 5 shows the real time Power Analyser software trend screen, used to confirm that the power signal was being received and logged.

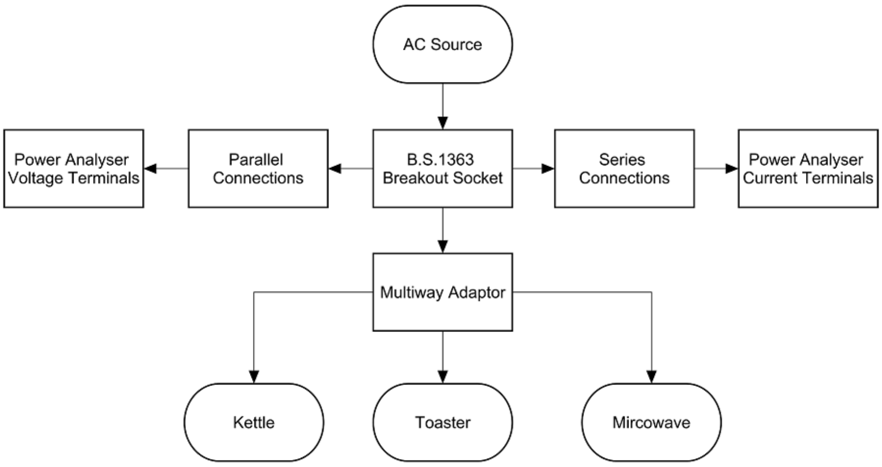

Figure 4: Block diagram of appliance monitoring connections.

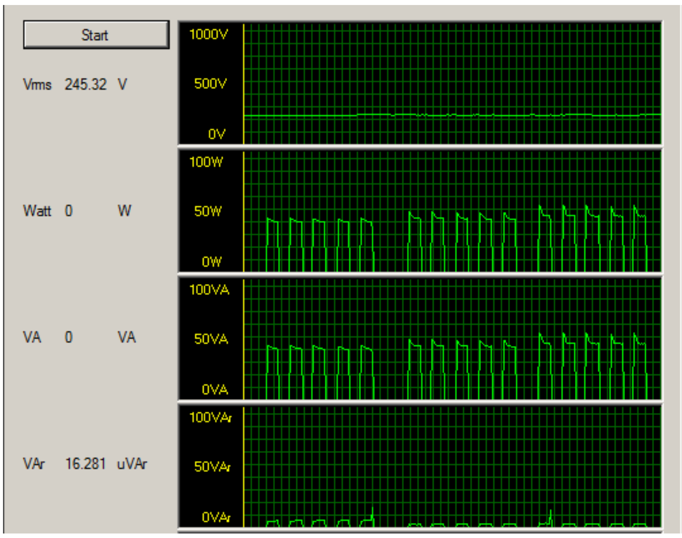

Figure 5: Power signature measurement trend screen.

The monitoring UWB radar set-up employed commercially available hardware and the corresponding in-house developed code was embedded on the radar module to fulfil the required monitoring tasks of the experiment. The UWB radar module, with a bandwidth of 3.1-5.3 GHz, includes one Time-Domain PulsON P410 module board and two Broadspec antennas, one for transmission and one for reception. The UWB board itself is shown in figure

6. For ease of installation and use, the topology of the system must use a single edge sensor type; in this case we use XBee.

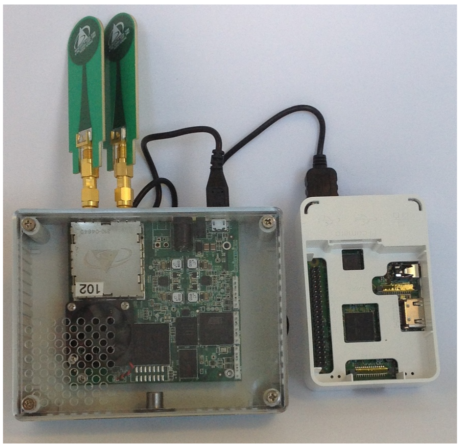

Figure 6: Physical UWB and RPi arrangement.

To receive data back to a single point of the network the UWB data must be converted to XBee format in order for the network coordinator to upload the data to the MYSQL database. To fulfill this requirement the UWB board was integrated with a Raspberry-Pi (R-Pi) interface and an XBee module as shown in Figure 7. Data would be transmitted from the UWB radar system and uploaded to the database via XBee modules, maintaining the pivotal single sensor interface of the scheme.

The UWB transceiver (Figure 7-b) is attached to a Raspberry Pi (RPi) BCM2835 microarchitecture (Figure 7-a) via a USB serial connection. [28, 29]. It is a credit-card sized single board computer running under Debian and Arch Linux ARM distribution [30]. The RPi is subsequently connected to an XBee router. The XBee coordinator (7-d) is connected with the server containing the database (7-e). A computer program, developed in C++, was created to collect the UWB data, perform the signal processing and interpret the occupancy and movements into binary data at the RPi. The binary data was then sent by the XBee router (7-c) to the XBee coordinator once every 500ms (time can be altered depending on application). Subsequently the received data at XBee coordinator was extracted by a Java program running on a remote computer. The Java program stores this received data into MySQL database with a time stamp and displays in a plotted format as shown in upper graph of Figure 11 (Occupancy vs time). The nominal pulse

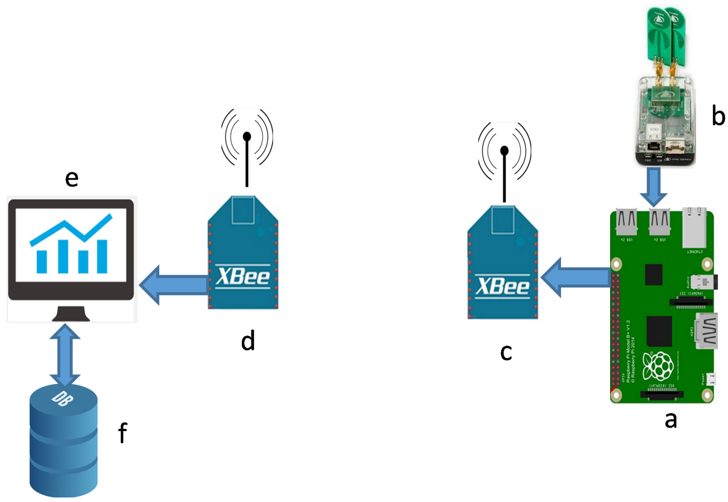

Figure 7: Test set-up sketch of UWB and XBee modules.

Appliance	Actual Time ON
Kettle	13:53
Toaster	13:55
Microwave	13:59

Table 1: Diary of appliance usage.

repetition frequency for the system was 10 MHz and the default gain of the system corresponded to the peak emission power permitted under the FCC rules [16]. The optional parameters of the radar module, such as the required distance range to be covered can be adjusted depending on the size of the building under test. To ensure reliability and accuracy a diary was kept of appliance usage during the kitchen occupation periods (Table 1).

The Comma Separated Value (CSV) file produced by the power analyzer was automatically uploaded to the custom-built Python NILM software. The physical system was deployed in a staff kitchen as mentioned; the kitchen floorplan is shown in Figure 8.

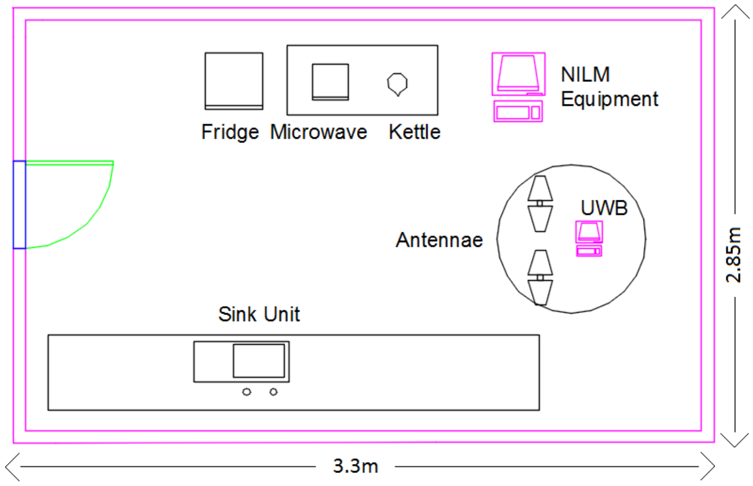

Figure 8: Floor plan of appliances used for power monitoring.

4. Results and analysis

The power signal of appliance usage before processing is shown in the lower graph of Figure 11 (Real power vs Time), clearly displaying the power timelines of the three appliance instances that were available in the kitchen.

The NILM software produced an itemized energy statement shown in Table 2, which details the duration and energy consumption for each appliance instance. The NILM software correctly identified each appliance category by classifying the test points according to load complex steady power, using the nearest neighbour algorithm developed. Figure 9 shows the test points as small red dots. It can be seen that the test points corresponding to the microwave are not in the exact correct location, which is due to the variability in electrical power signatures of the microwave used in training. Appliance instance on-duration, and thus consumed energy, were also calculated by the software, which were then used to generate the aggregated appliance energy usage infographic shown in Figure 10.

The UWB radar system ran for the same timeline and as can be observed in figure 11, excellent correlation between the power consumption data and that of the occupancy (shown in the upper half of figure 11) is shown. In both active instances, the power consumption starts soon after occupancy is noted in the room and ends before those present leave. The waterfall plot from the UWB radar data is shown in figure 12 and displays the processed

	Time ON	Time OFF	Appliance	Duration (s)	Energy (Wh)
0	13:54:14	13:55:08	Kettle	54	31.4118
1	13:55:39	13:56:04	Toaster	25	5.96627
2	13:59:03	13:59:33	Microwave	30	12.5463

Table 2: NILM Software Output of Disaggregated Power.

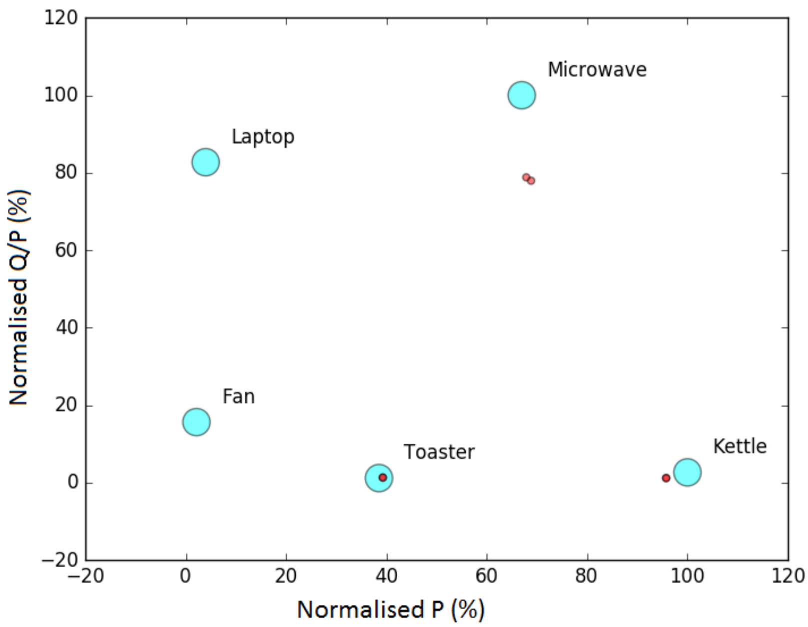

Figure 9: Scatter Plot of Training Set with Test Points.

occupancy data over the period of 15 minutes tested.

Dark regions indicate the time and locations when no movement or occupancy was present while the white patterns represent the real-time movement both within the room. X-axis represents the distance from the radar module while the y-axis is the timestamp ascending from top to bottom. At the top of the figure, persons leaving the room can be detected and further two instances at the bottom half of the figure, where patterns are present at a distance of 2 metres or less (length of radar to kitchen door) match the diary and appliance power signatures.

Further experiments are underway on larger scale settings correlating video, radar and remote appliance algorithm integration to further validate

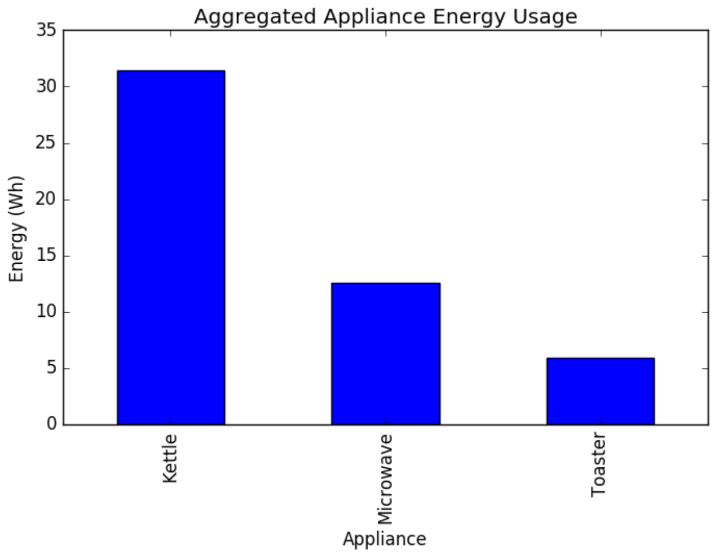

Figure 10: Software-Generated Infographic.

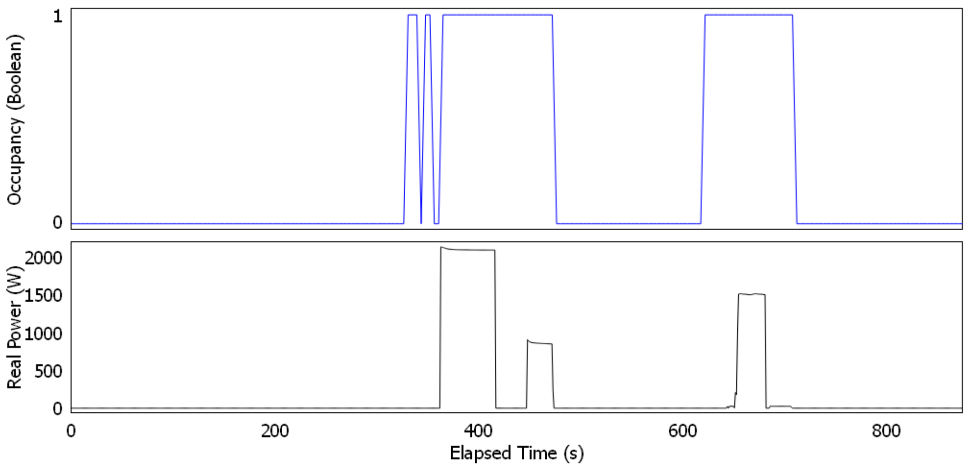

Figure 11: Plot of Occupancy and Real Power vs Time.

the non-intrusive system.

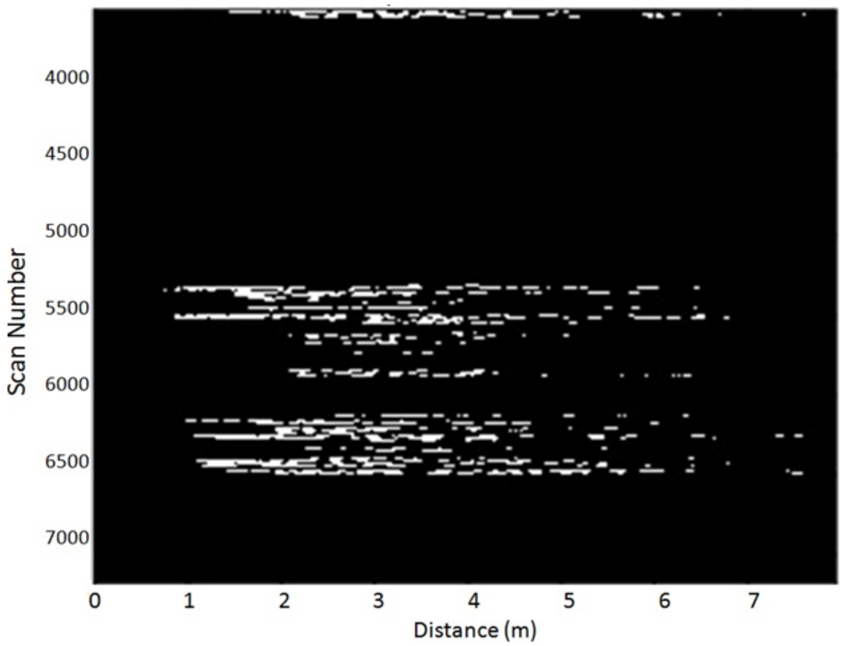

Figure 12: UWB raw data plot during the test period (waterfall plot).

5. Conclusions and future work

In this paper, a lab experiment was performed to analyze if together non-intrusive radar and remote signature profiling could be combined effectively in real-time to understand and pinpoint movement patterns and appliance use.

The results show that non-intrusive wireless monitoring is possible and when augmented by improved signal processing techniques for appliance identification and power consumption, could lead to a step change in understanding how occupants use energy and the buildings they occupy. This approach could be employed to effectively close the energy gap problem between building design and occupancy.

The UWB radar system is part of a larger automated energy saving project in its final stages taking place in flats and houses, where the information gathered from it is combined with information collected from various other sensors and smart plugs, while considering the occupants behavioral patterns to enable the control system to make the best energy saving decisions.

By comparing a recorded diary of activities with results obtained from both the UWB movement tracking and appliance signature monitoring, an effective synchronization was observed. This could enable the further disaggregation of a buildings energy consumption into energy likely to have been used as a result of occupant behaviour, and energy likely to have been used due to background appliance consumption.

Further work will include developing non-intrusive sensor hardware to measure electrical power consumption from the household kilowatt-hour meter position; this would remove the need for the Power Analyser used in the lab experiment, thus making the NILM system capable of retrofitting into dwellings.

The combined UWB and NILM system is designed for remote monitoring of household occupancy and disaggregated energy consumption by uploading relevant gathered data to a remote repository using a gateway installed in the home. This system has obvious implications for smart buildings, understanding how users engage with buildings, and assisted living.

References

[1] K. B. Janda, Buildings dont use energy: people do, Architectural Science Review, 54 (1), 2011, 1522.

[2] J. Morley, & M. Hazas, The significance of difference: Understanding variation in household energy consumption, Proceedings of the eceee 2011 Summer Study (2011).

[3] B. Anderson, The Time and Timing of UK Domestic Energy DEMAND, Keynote paper presented at the 2014 Otago Energy Research Centre Symposium, University of Otago, Dunedin, New Zealand, 28 Nov 2014.

[4] S. Monahan, & A. Gemmell, How Occupants Behave and Interact with Their Homes, NHBC Foundation NF35,2011.

[5] Z. M.Gill, M. J. Tierney, I. M. Pegg, & N. Allan, Low-energy dwellings: the contribution of behaviours to actual performance, Building Research & Information, 38 (5), pp. 491508, 2010.

[6] Carbon Trust, Technology Innovation Needs Assesment, Non Domestic Buildings Summary Report 2012.

[7] E. Shove, & G. Walker, What is energy for? Social practice and energy demand, Theory, Culture & Society, 31(5), 41-58, 2014.

[8] S. Kelly, M. Shipworth, D. Shipworth, M. Gentry, A.Wright, M. Pollitt, & K. Lomas, Predicting the diversity of internal temperatures from the English residential sector using panel methods, Applied Energy, 102, 601-621, 2013.

[9] E. Shove, Converging conventions of comfort, cleanliness and convenience, Journal of Consumer Policy, 26(4), 395-418, 2003.

[10] J. Burgess, & M. Nye, Re-materialising energy use through transparent monitoring systems, Energy Policy, 36(12), pp. 4454-4459, 2008.

[11] C. M. Jacquot, L. Schellen, B. R. Kingma, M. A. van Baak, & W. D. van Marken Lichtenbelt, Influence of thermophysiology on thermal behavior: the essentials of categorization, Physiology & behavior, 128, pp.180-187, 2014.

[12] M. Lipson, Smart Systems and heat Consumer Challenges: An insights report by the Energy Technology Institute, 2015.

[13] Your smart energy monitor, British gas, 2015.

[14] A. F. M. Sultanul Kabir, M. A. Shorif , H. Li and Q. Yu, A study of secured wireless sensor network with XBee and Arduino, 2014. [Online]

[15] F. Robert, Up and Runnin, in Building Wireless Sensor Networks, 1st. ed. California: OREILLY Media Inc, pp. 26, 2010.

[16] M. Ghavami, L. Michael, and R. Kohno, Ultra Wideband Signals and Systems in Communication Engineering. Wiley & Sons, 2007.

[17] A. Leimer, TCB Workshop Ultra-Wideband (UWB), Office of Engineering and Technology/Equipment Authorization Branch FCC Laboratory, May 2004.

[18] L. Yang and G. B. Giannakis, Ultra -wideband communications: An idea whose time has come, IEEE Signal Processing Magazine, vol. 21, no. 6, pp. 2654, Nov. 2004.

[19] S. Gezici, Z. Tian, G. B. Giannakis, H. Kobayashi, A. F. Molisch, H. V. Poor, & Z. Sahinoglu, Localization via ultra-wideband radios: a look at positioning aspects for future sensor networks, IEEE Signal Processing Magazine, 22 (4), pp. 7084, 2005.

[20] F. Seco, A. Jimenez, C. Prieto, J. Roa, & K. Koutsou, A survey of mathematical methods for indoor localization in Intelligent Signal Processing, WISP 2009. IEEE International Symposium on, pp. 914, Aug 2009.

[21] G. W. Hart, Nonintrusive appliance load monitoring, Proceedings of the IEEE, 80 (12), pp. 18701891, 1992.

[22] D. Egarter, et. al., Autonomous Load Disaggregation Approach based on Active Power Measurements, IEEE Workshop on Pervasive Energy Services, pp. 293298, 2015.

[23] A. Bijker, et. al, Active power residential non-intrusive appliance load monitoring system, IEEE Africon, pp. 16, 2009.

[24] M. Nguyen, et. al, A novel feature extraction and classification algorithm based on power components using single-point monitoring for NILM, Proceeding of the IEEE 28th Canadian Conference on Electrical and Computer Engineering, pp. 3740, 2015.

[25] A. I. Cole, et. al, Algorithm for nonintrusive identification of residential appliances, Proceedings of the IEEE International Symposium on Circuits and Systems ISCAS 98., 3, pp. 338341, 1998.

[26] BS 1363 three-pin (rectangular) plugs and sockets. 1947.

[27] Voltech. PM1000+ POWER ANALYZER USER MANUAL. 2011.

[28] A. A. Dharmapurikar, R. B. Waghmare, Design & Implementaion A Secured Wireless Communication System By Using GPRS & Rapsberry Pi in Automatio, March 2015. [Online].

[29] S. G. Nikhade, A. A. Agashe, Wireless sensor network communication terminal based on embedded Linux and Xbee, Circuit, Power and Computing Technologies, 2014, pp. 1468-1473.

[30] S. Jain, A. Vaibhav, L. Goyal, Rabspberry Pi based Interactive Home Automation System through E-mail, Optimization, Reliabilty, and Information Technology, 2014, pp. 277-280.