A TECHNIQUE TO ENABLE THE TRACKING OF PEOPLE FOR DOMESTIC ENERGY MONITORING APPLICATIONS

Tara Louise HUGHES

School of Computing, Science and Engineering
College of Science and Technology
University of Salford, UK

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Abbreviations

BRE	Building Research Establishment
DECC	Department of Energy & Climate Change
EFUS	Energy Follow-Up Survey
EHS	English Housing Survey
GPIO	General Purpose Input/Output
IoT	Internet of Things
M-O	Mass Observation (1937 – 1953)
MOP	Mass Observation Project (1981 – present)
ONS	Office of National Statistics
RFID	Radio Frequency ID
RPi	Raspbery Pi
SSN	Signal Strength Number
TUS	Time Use Survey
WSN	Wireless Sensor Network

Abstract

Domestic energy consumption has increasingly become a cause for concern for governments, energy suppliers, and individual householders. Issues surrounding gas and electricity used in the home relate to the increasing cost of fuel, the rise in the incidence of fuel poverty, carbon dioxide emissions from fossil fuels contributing to climate change, security of supply due to geo-political disagreement and the age and condition of the existing energy infrastructure.

While buildings and appliances have become more energy-efficient, usually driven by legislation, the energy-consuming behaviour of individuals is very difficult to change. Domestic energy monitoring has so far only been carried out at a household level, while the behaviour of individuals within households has remained ambiguous. There is a gap in current knowledge about how people use energy at home, mainly because it is very difficult to capture everyday behaviour without influencing the behaviour being observed. Initiatives and campaigns targeting domestic energy-consuming behaviour have been based on assumptions of how people use energy in their homes, and have been found to be ineffective. There is a need for an unobtrusive method of capturing domestic energy behaviour.

This research presents a technique to deliver this requirement by enabling the tracking of people in their homes with a small number of cost-effective RFID (Radio Frequency ID) devices. Using this technique the location of multiple individuals wearing RFID tags can be determined, thereby creating an unobtrusive RTLS (Real Time Location System). This technique has been extensively evaluated through a series of tests within a typical 1940's semi-detached house in North West England, and has been found to be able to successfully locate individuals to room level. If this RTLS data is matched with appliance level energy data, energy-consumption can be attributed to the individuals responsible, and personalised everyday energy-consuming behaviour can be established. .

Chapter One

1 Introduction

This research is concerned with the gap in current knowledge of how people use energy in the privacy of their homes in the UK. Evidence will be presented to show why this is a problem of great significance, and that concentrated effort to address this gap is justified and timely. In order to fulfil the need to capture domestic energy-consuming behaviour this thesis sets out the development, testing and refining of a technique to enable the tracking of people for domestic energy monitoring applications.

1.1 Context

There are several critical issues surrounding the development of a technique to capture data from human behaviour, in this case domestic energy-consuming behaviour. These key areas are presented below and examined in depth in Chapter Two.

1. **The *everyday***
   This relates to the concept of the ordinariness of daily life. Although it is commonly considered mundane and often overlooked, it contains vital information. In this research it is the everyday domestic energy-consuming behaviour that is desperately needed and is currently not known.

2. **Unobtrusive observation**
   Observing domestic energy-consuming behaviour unobtrusively is required in order to capture the true, typical behaviour of individuals without influencing how people behave. The method of observation must therefore be discreet and acceptable to potential subjects.

3. **UK domestic energy consumption**
   There are many factors contributing to the problems of domestic energy consumption. These include the construction and energy efficiency of the current housing stock, the changes in trends of tenure, and the increasing

costs of energy to homes. Fuel poverty is a growing issue for individuals and organisations, and is a key driver for the successful development of a technique to enable the understanding of how people use energy at home.

4. **Location Determination**
   The use of wireless sensor networks to tag and track objects is common. There are a variety of standards and protocols depending on the application. Additionally, using wireless sensor networks to track people within their own homes helps to reduce the visibility of the system.

5. **Wearable technology**
   Recently the use of wearable technology has grown rapidly and there are many applications, from computer gaming to health and wellbeing monitors. Most of these applications are voluntarily selected by the wearer, although some are imposed in the interests of safety, such as tags worn by vulnerable patients that raise an alarm if they leave a specified area. Wearable technologies tend to be small in size, such as tags or wristbands, and require connection to a device or system for data transmission. These connections can be in the form of constant communication or occasional synchronisation.

1.2 Contribution

The development of a technique that can successfully locate multiple individuals to room level by using a small number of low cost devices that give only coarse-grained data is a major contribution from this research.

Using this method of tagging and tracking people within their homes, and matching their location to appliance-level energy consumption would allow energy use to be attributed to individuals.

An understanding of personalised energy profiles could drastically alter energy supplier operations and future government strategy. The ability to identify how people use energy at home would improve initiatives to help people reduce their energy consumption because these are all currently based on assumptions of how and why people use energy.

This technique would not be limited to concerns about energy efficiency, but could be used in many applications in which tracking a person's location, or movements, within an internal environment would be valuable, such as assisted living.

An additional contribution from this research is the immense amount of real data that could be used by other researchers, specifically data collected describing Radio Frequency Identification (RFID) signal propagation within a typical post-war house and through experiments carried out within the University of Salford's Energy House facility.

Scope

The purpose of this research is to develop and present a technique to enable the tracking of individuals for domestic energy monitoring applications only. The following are aspects that may be related but are beyond the scope of this research and are not included:

- Gas, oil, coal, or other fuels are not included in this research because although there are potential methods to account for these types of fuel, they add significant complexity and cost. In addition, many of these fuels would be used for purposes that are for the good of the entire household (such as heating and cooking) rather than for personal use (such as watching a television or using a computer). The use of fuels other than gas and electricity are non-standard and infrequent.
- Lighting connected to the home electricity consumer unit is not included because this is another use of energy that can be considered for the good of the entire household.
- Smart meters are included in Chapter Two as part of the background to UK domestic energy consumption, but are not an integral aspect of this research.
- Providing energy consumption information to people is not covered in this research as there are no opportunities for feedback. Additionally, giving feedback in the event of the system being used would negate the

unobtrusiveness of any observations made. There are many researchers and organisations examining methods of feedback to energy consumers.

- Behaviour change and theories of how and why people behave the way they do is beyond the remit of this research as the purpose is to enable the capture of energy-consuming behaviour only.
- Although tracking data is collected immediately there is no intention to provide real-time location information. The data is stored, subjected to the algorithm to derive location, and matched up with appliance-level energy consumption at a later time.

1.3 The Garfield Weston Foundation

This research was made possible by a generous grant from the Garfield Weston Foundation [1]. The Garfield Weston Foundation is a philanthropic trust that has supported organisations and charities across the UK for over 50 years. The Foundation's aims include encouraging effective solutions to help those in most need, in this case to further research to alleviate fuel poverty and the problems surrounding UK domestic energy consumption.

1.4 Outline of Thesis

This thesis comprises seven chapters and continues as follows:

Chapter Two presents a detailed evaluation of the five key aspects identified in Section 1.1; the everyday, unobtrusive observation, UK domestic energy consumption, location determination, and wearable technology.

A system design overview of a solution to the research problem is set out in Chapter Three.

Chapter Four describes the experimentation that was employed throughout this research. This chapter sets out how the prototype was developed and goes on to detail how the experiments were conducted, the data was collected and the results were analysed. The testing locations are shown, and the types of tests that were carried out.

Results of the experiments are presented in Chapter Five. These are in the form of signal strength heatmaps, outputs from a Spectrum Analyzer, and charts from the testing locations. There are also comparisons provided with simulations from the Ekahau Professional 7.6.4 site surveying software.

Chapter Six evaluates the resulting data for the ability to provide a location to room-level. This chapter presents signal strength contour maps for the prototype and the development of the algorithm to derive location from signal strength data. Following testing of the algorithm and improvements made, a further set of data was collected and tested the revised algorithm.

Chapter Seven concludes the thesis, with a detailed discussion of the research, contributions, and opportunities for future work.

Chapter Two

2 Literature Review

This chapter sets out the context and current knowledge relevant to this PhD research. This is broken down into five major areas of concern: the everyday, unobtrusive observation, UK domestic energy consumption, location determination, and wearable technology.

2.1 The *everyday*

This section explains the concept of the *everyday*, how it emerged from a socio-philosophical perspective to become a rich seam for researchers to the present day.

As early as 1832 Scottish philosopher, historian and essayist Thomas Carlyle suggested that there was an impending change in the focus of interest from the court, the state and battlefields towards everyday life. He predicted that not only *"the 'House wherein our life was led,' but the Life itself we led there, will be inquired into*"[2, p.84].

Carlyle was correct in that the phenomenon of the quotidian, or everyday life, has been a particular interest of many philosophers and sociologists since and continues to the present day.

French sociologist and philosopher Henri Lefebvre stated that the familiar is not necessarily known and argued that despite its pervasiveness the everyday is widely overlooked and misunderstood [3]. While extraordinary human achievements can be compared to magnificent mountains, Lefebvre suggests that the everyday is the fertile ground we walk over without noticing. It is the earth beneath that "*has a secret life and a richness of its own*" [4, p. 87] and should not be taken for granted or ignored.

Lefebvre explains that the everyday has changed significantly from pre-modern times, when quotidian activity was closely connected to the cycles and rhythms of the natural world and the collective rituals and requirements of community. In a technologically advanced world people are disconnected from community, they have their time clearly defined into productive and leisure time, and they become consumers [5].

The French social theorist Michel De Certeau expanded on Lefebvre's ideas to further develop a theory of the productive and consumptive elements of everyday life [6]. In a consumer society, Certeau argued that there are complex practices that people adopt in their everyday life, and also practices that are imposed on them, that he names *strategies* and *tactics*.

Strategies are described as visible practices that are imposed on people by organisations, institutions or authority, while *tactics* are hidden, improvised, and sometimes anonymous responses to situations. Tactics can also include small acts of resistance, for example; a tactic responding to the strategy of having to pay to use a car park could include giving away a partially used parking ticket to another motorist.

In terms of energy consumption, organisations are often concerned that the energy consumption of their buildings is much greater than anticipated despite specifying energy efficient buildings and equipment, and having highly technical energy management systems and professionals [7]. This disparity between the predicted and actual energy use is referred to as the *Performance Gap* and can be substantial. Post-occupancy evaluations of buildings highlight numerous potential causes for the actual energy use being much greater or even double the prediction, and the behaviour of the people using the buildings is a very important factor. The tactics building users employ can include opening windows and propping doors open while the heating system is on, and using additional heaters and over-riding heating system settings to improve their own immediate thermal comfort.

In addition to strategies and tactics, Certeau stated that in a consumer society it is through consumption that individuals acquire a sense of identity and self-hood, and that those needs are defined by the everyday practices and desires of the consumers themselves [8].

The purpose of this research is to find a way to capture the *typical* electricity use of people in their own homes, to observe the everyday tactics and habits.

Observing the everyday has been a focus for sociologists, psychologists, linguists and philosophers for a long time.

Behavioural research is usually carried out for one of two reasons; (1) to contribute to theories of human behaviour, or (2) to answer specific questions [9]. The first type of research is *basic research*, the second *applied research*. Different behavioural research techniques are used depending on the focus of the research, for instance, to find out how people behave in public the researcher would watch them whereas to investigate how people behave in private, diaries and self-reporting would be used.

One of the longest studies of the everyday is the British Mass Observation Project (M-O) [10]. The original M-O began as a study of everyday life of ordinary British people in 1937. Volunteers were recruited nationally to keep diaries and respond to regular open-ended questions. The first M-O ran until the early 1950's.

In his review of the M-O, Hubble [11] argues that although the initial purpose of the project was merely to provide an anthropology of the British people, the responses actually influenced changes in society. Data from the surveys contributed to the 1941 Budget, informed the introduction of the welfare state, and was used by the Ministry of Information to judge the morale and opinions of the public.

In 1981 the contemporary Mass Observation Project (MOP) was revived and continues to the present day. The MOP still relies on a representative panel of volunteers to submit their candid opinions and experiences in response to questions three times a year. Academics from a wide range of disciplines can apply for particular subjects to be included in the questions and the resulting data are a unique and valuable qualitative resource.

Adams and Raisborough [12] commissioned questions about ethical consumption to be included in the MOP. Specifically, respondents were asked to reflect on how their consumption was influenced by their ethical and personal values. The researchers struggled with the wide range of responses, in terms of quantity and interpretation of the wording of the questions, and felt the inability to probe more deeply was a hindrance. Overall, respondents generally articulated a commitment to ethical consumption but mentioned many barriers and often felt overwhelmed.

Another example of examining contemporary everyday lives in Great Britain are the Time Use Surveys (TUS) carried out by the Office for National Statistics (ONS) [13]. The most recent time use survey was carried out in 2005 and the data comes from 5443 interviews carried out and 4941 diaries returned from a representative sample of households. The interviews and diaries were carried out on four days throughout the year in the months of February, June, September and November. The diaries detail activity of the household for every 10 minutes throughout the selected days.

Women spend more time on domestic and caring activities than men, and this remains true for women in full-time employment. Figure 2.1 shows the time spent in minutes on housework by sex and Figure 2.2 shows the time spent on care-giving activities by sex.

The three main activities carried out by people were sleeping, working, and watching TV and videos/DVDs or listening to music. Together these three activities accounted for 13 hours and 38 minutes out of the 24 hour period.

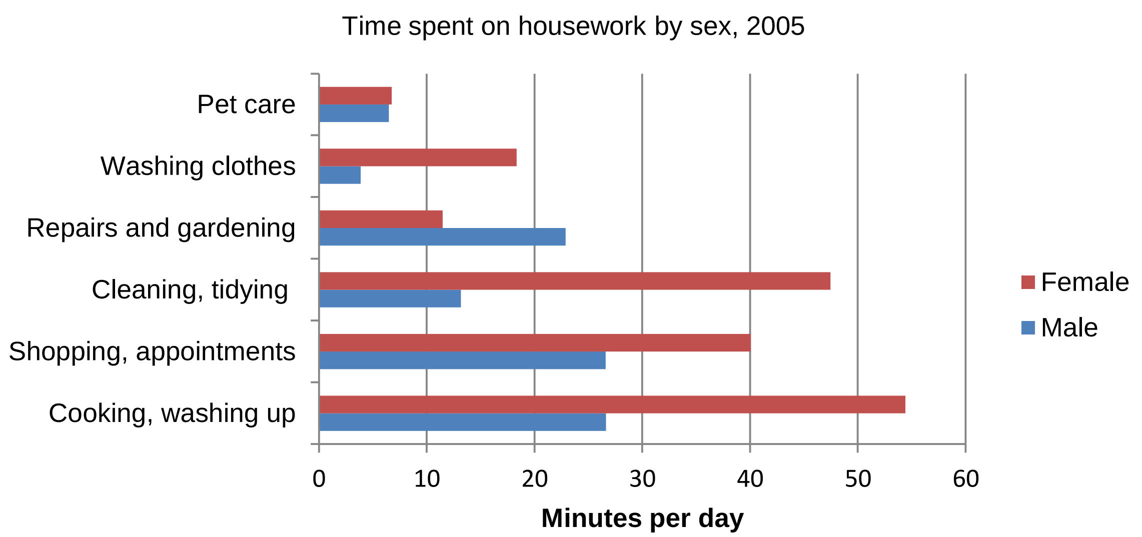


Figure 2.1.Time spent on housework by sex, 2005. Data from Office for National Statistics: July 2006

The use of computers was recorded, and for those that did use computers outside of the workplace (16% of the population) the time spent computing increased from the last Time Use Survey in 2000 from 96 minutes per day to 120 minutes per day in 2005. The coding of the diaries attempted to distinguish between primary and secondary activities, so that using the computer would be designated the secondary activity while also recording the primary purpose of using the computer (shopping, banking, games, or socialising). This was seen to be potentially problematic as during each time slot of 10 minutes several activities could be carried out on a computer. The significant increase of internet enabled devices and mobile technology since TUS2005 and makes the allocation of time spent using a computer even more unclear. The UK communications regulator, Ofcom, reported in 2014 that the average adult in the UK spends more time engaged in digital media or communication activity everyday than sleeping (8 hours 41 minutes and 8 hours 21 minutes respectively [14].

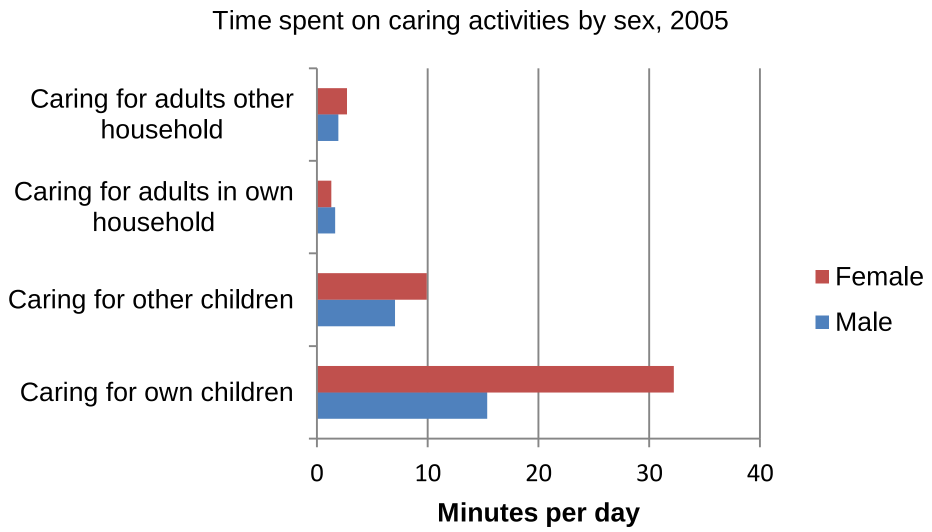


Figure 2.2.Time spent on caring activities by sex, 2005. Data from Office for National Statistics: July 2006

There are other data from surveys and census' available concerned with a wide variety of topics from health, wealth, crime, housing stock, etc., that are not concerned with recording the everyday domestic life.

Some research has been conducted into quotidian domestic energy consumption. Durand-Daubin [15] describes an evaluation of the effectiveness of four methods of data collection as tools to illustrate how and when three household items were used. The four methods were: quantitative questionnaire, qualitative interviews, activity diaries, and energy consumption monitors. The three household items were the TV, the computer, and the washing machine. The participants in the study were 60 self-selecting households in France.

The quantitative questionnaire was made up of over a thousand questions and covered detailed aspects of socio-demographics, building fabric and heating system, appliances, and environmental attitudes. This was followed by an in-depth qualitative interview about the household's energy consumption and motivations. The activity diaries were used for a week and one was dedicated to each room of the dwelling. The participants were required to record all details of all activities within each room including: participants, activity, equipment used, start and end times. During the week of the activity diaries metering equipment was installed to record the time and quantity of electricity consumed.

Comparison of the data showed large discrepancies between reported and actual electricity consumption, especially for the TV and computer. The diaries reported more frequent and shorter duration of use than the measured consumption indicated. The frequency of use of the washing machine was more consistent between diary and metering, although the duration was longer than the participants reported. There were significant difficulties combining the different types of data to produce a clear comprehensive description of energy use by the individuals involved.

Although Durand-Daubin's research attempted to capture the everyday energy consumption of individuals involved, and evaluating the reliability of the methods used, there are several issues that were not resolved. Firstly, the participants were a small sample group of 60 self-selecting households. Information is not available on their motivation for volunteering for the extensive requirements of the study, what their prior experience or knowledge of energy efficiency was, or what incentives they may have received – all of which could affect their behaviour during the period of study.

Another important aspect that can and does change people's behaviour is the knowledge that they are being observed. After answering over one thousand questions, taking part in an in-depth interview, and writing down their activity in every room for a week the participants would be very conscious of being under scrutiny. The importance and practice of unobtrusive observation to capture the everyday is dealt with in the next section.

2.2 Unobtrusive Observation

As described in the previous section, when people know they are being observed their behaviour tends to change. This is a crucial aspect of this research because the gap in knowledge this technique aims to fulfil is to find a way to enable the capture of typical everyday domestic energy-consuming behaviour. This section describes unobtrusive observation, sets out when and why it is needed, and gives examples of how it is carried out.

A frequently mentioned phrase in research into human behaviour is the 'Hawthorne Effect'. Chiesa and Hobbs [16] reviewed the history and facts of the term and found that due to the wide range of contradictory and imprecise definitions, and significant criticism of the original work, use of the term is inappropriate.

'Observation consciousness' is a better description of the concept of people changing their behaviour because they know they are being observed. The changes in behaviour of participants can be conscious or sub-conscious, and is widely accepted as an issue in the field of social research [17, 18].

Observation consciousness is a significant threat to the validity of any research of human behaviour and there have evolved many methods to reduce its impact and achieve more valid results. The flipside of unobtrusive observation are concerns about ethics and privacy.

The British Psychological Society sets out in its Code of Human Research Ethics 2014 [19] that sometimes deception necessary in order to obtain valid data, stating that:

> '*Since there are very many psychological processes that are modifiable by individuals if they are aware that they are being studied, the statement of the research in focus in advance of the collection of data would make much psychological research impossible*.' (p.24)

The code goes on to state that researchers must provide as much information as possible (without compromising their research) in advance to participants, and any deception should be fully disclosed as soon as possible afterwards. The well-being, dignity and privacy of the participants remain the highest ethical concern.

Gaby Judah, a researcher in the Department of Disease Control at the London School of Hygiene and Tropical Medicine, has a special interest in habit formation in relation to health behaviours and uses unobtrusive observation through wireless sensor networks to capture everyday behaviour [20].

Judah [21] describes one project designed to evaluate whether exposure to different messages displayed at the entrance to restrooms affects the rate of handwashing of the travelling public in an English motorway service station. Over the course of the study data was collected on almost 200,000 restroom uses over 32 days. Infra-red sensors recorded the number of people entering and leaving the two restrooms, and sensors inside the soap dispensers recorded each soap use.

The results showed that there was a marked gender difference in the effects of the types of messages on the rate of handwashing, and Judah concludes that:

> '*Unobtrusive monitoring allowed us to avoid the biases inherent in structured observation or self-reporting of behaviour and provided a reliable means of data collection.*' (2009: p.S409)

A follow on project involved installing wireless sensor networks in the bathrooms of participant's homes. For four months, 120 participants in 60 private homes wore a sensor on their wrist and were told they were evaluating a system designed to monitor whether elderly people are capable of taking care of themselves. Two location sensors near the bathroom sink and toilet were installed, along with several object sensors placed on the following items; toothpaste, toothpaste cup, floss box, soap, taps, vitamin C bottle, toilet flush, toilet roll holder, and shower/shower door.

The actual aim of Judah's research was to investigate psychological predictors of habit formation. In order to ensure validity of the research data, this was disclosed to the participants once the project had ended.

Although this research does not include user trials or observations of participants, it is necessary to be mindful of unobtrusive observation in order to develop technology that is unobtrusive. This section is important for driving design decisions only, not for defining a programme of research with participants.

2.3 UK Domestic Energy Consumption

The English Housing Survey (EHS) is an examination of the conditions and energy efficiency of homes in England. Data from the 2012-2013 EHS Households report are based on a sample of 13,652 households [22]. There are an estimated 22.0 million households in England and while the majority are owner occupied (65%, 14.3m), significant numbers are privately rented or socially rented (18%, 4,0m, and 17%, 3.7m respectively).

Private renters tend to be younger people while owner occupiers tend to be older. People with mortgages were typically middle-aged and outright owners were from older age groups. Social renters are spread evenly over the age categories. The average time people have lived at their current address for owner occupiers, social renters and private renters is 17 years, 11 years, and 4 years respectively.

The EHS Energy Efficiency of English Housing report, 2012 is based on physical inspections of 12,763 dwellings [23]. The report finds that 16.6 million dwellings (73% of the housing stock) could benefit from at least one energy improvement measure, such as; installing a condensing boiler, cavity wall insulation, loft insulation. If all the recommended (and cost-effective) energy efficiency measures were installed in all the homes that needed them, this could reduce fuel bills by an average of 14%, and save 21.2 million tonnes/year of CO_2 emissions.

Newer properties tend to be more energy efficient, while over half of the least energy efficient homes were built before 1919 (52%). There are 2.4 million households (11% of the total number of households) that are unable to keep their living room comfortably warm during cold winter weather. Of these inadequately heated households; 20% were couples with children, 15% were lone parents, 36% were households with a person who had a long term illness or disability, and 24% were households in poverty. Half of households unable to heat their homes adequately were aged 16-44 years, and households over 65 years were under-represented.

The economics of energy is an important aspect of domestic energy consumption. As can be seen from Figure 2.3 the cost of fuel to UK households has increased, particularly sharply from 2004. This is a major factor in the growing incidence of fuel poverty. The need to address fuel poverty, and the difficulty of doing this, is a key driver for this research. The lack of knowledge of how people use energy in their own homes is an obstacle to identifying and tackling real-life energy inefficient behaviour.

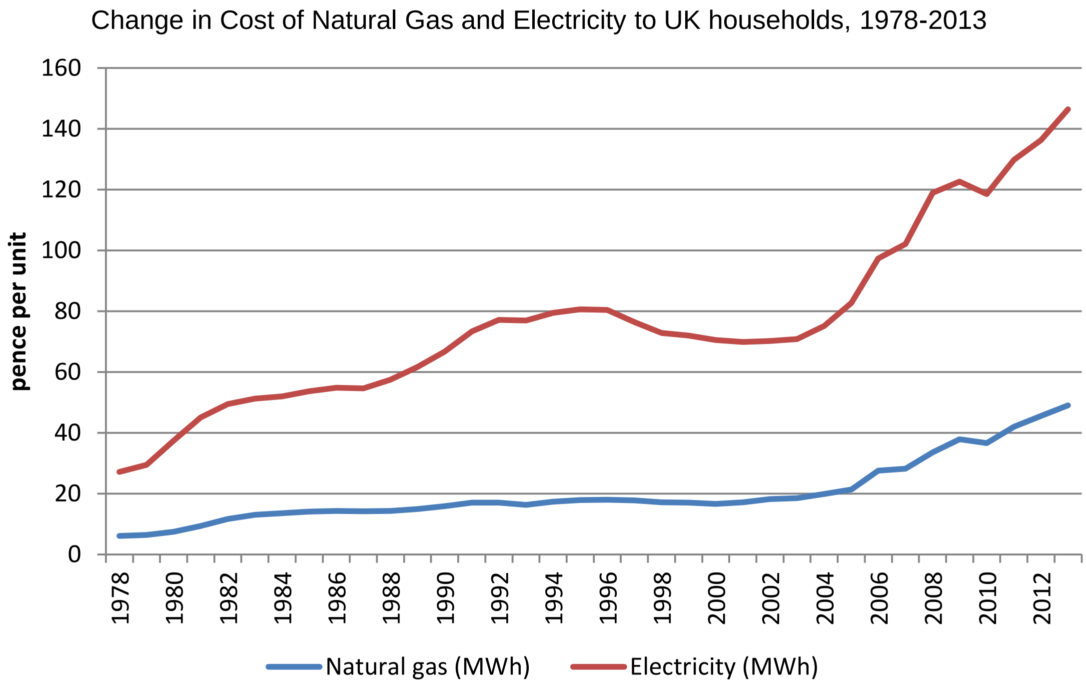


Figure.2.3. The cost of natural gas and electricity to UK households, in pence per unit, from 1978-2013. Dataset from International Energy Agency (2014) [24]

In August 2013 the UK Government changed the definition of fuel poverty from meaning a household that needed to spend more than 10% of its income on fuel to maintain satisfactory conditions to a household that has above average fuel costs and if it were to spend that amount they would have a residual income below the official poverty line [25].

Following the change in definition 1 million households were removed from the category, and the UK Government dropped the commitment to eradicate fuel poverty by 2016. Fuel poverty particularly affects low income households and those who spend a lot of time at home, such as the long term sick, disabled people, young families, and the unemployed.

The Annual Fuel Poverty Statistics Report, 2014 [26] stated that the number of fuel poor households in England was around 2.28 million representing 10.4% of all English households. Due to the calculation of fuel poverty being dependant on income, fuel bills, and consumption, the report struggled to isolate absolute reasons for the drop of 5% from the previous review, but it did suggest that the reduction happened mainly due to increases in income for the higher income fuel poor households. All fuel poor households came from the bottom four income decile groups, with at least 30% of all unemployed households being fuel poor. Private renters were more likely to be fuel poor and owner occupiers were the least likely.

Under the previous 10% indicator, 4.50 million households would be designated as living in fuel poverty, 17% of all households. Increasing energy costs is expected to lead to an increase in fuel poverty in the next review.

In 2011, the Building Research Establishment (BRE) collected further data from a sub-set of households that took part in the 2010/2011 English Housing Survey (EHS). The purpose of this investigation was to update modelling assumptions about how energy is used in the home and resulted in the 2011 Energy Follow-Up Survey (EFUS 2011) published in 2013 [27].

The EFUS consisted of an interview survey of 2,616 homes, a temperature monitoring survey of 823 homes, meter readings data from 1,345 homes, and electricity profiling of 79 homes. The data was scaled and weighted to represent the 21.9 million households in England.

EFUS 2011 shows that gas consumption is closely associated with dwelling type and size whereas electricity consumption is strongly influenced by the number of people in the household. Annual median electricity consumption for single person households and households with at least five people are 2,400 kWh and 6,000 kWh respectively. Analysis of households by tenure showed that owner occupiers tended to consume more gas than any other household type and more electricity than households in the privately rented or local authority sector. There were no significant differences between rates of gas and electricity consumption for renting households, whether private or social.

While 6% of households find it difficult to heat the living room to a comfortable standard during the heating season, 20% of households report having at least one room that cannot be kept comfortably cool during a typical summer. Use of air conditioning systems is rare (less than 3%) but 43% of all households use portable fans and 9% use fixed fans.

Analysis of domestic appliance ownership shows that owner occupiers have more (and newer) appliances than renting households. The survey suggests that there are considerable numbers of appliances over 10 years old (2.1m washing machines, 2.6m tumble dryers, 5m refrigeration appliances, and 4.5m ovens).

Approximately 67% of all households are categorised as ‘underspending’, that is defined as spending less on gas and electricity than is expected by the current fuel poverty methodology predicted necessary to provide adequate energy for heating and other uses in the home. While 35% of all households are underspending by more than 25% of the required fuel bill, 8% of households are underspending by more than 50%.

Underspending households have lower mean internal temperatures and report heating for fewer hours per day than households that are not underspending. Around 80% of fuel poor households (using the new Low Income High Costs definition) underspend compared to 65% of households not in fuel poverty.

A major change in the domestic energy sector is the national roll-out of ‘smart meters’ across the UK which will replace around 53 million gas and electricity meters. Most households will have their traditional gas and electricity meters replaced with ‘smart meters’ between 2015 and 2020. Smart meters communicate directly with energy suppliers so that accurate bills can be generated and so that manual readings and estimated bills will cease. In addition, changing energy suppliers is anticipated to be a more straightforward process for properties with smart meters, enabling householders to more easily switch to cheaper tariffs and save money.

The most recent quarterly statistics released by the UK Government [28] reports that a total of 621,600 domestic smart meters had been installed by 30 September 2014. Of these 543,900 smart meters were operating in 'smart mode' (i.e. communicating with the energy supplier) which represents 1.2% of all domestic meters operated by the larger suppliers.

Energy suppliers are entirely responsible for planning and delivering the installation of smart meters to their customers however suits them as long as they complete the roll-out by the end of 2020.

Smart meter installation programmes have already begun in many countries around the world with varying degrees of success. There has been considerable resistance from householders to smart meters, particularly in the USA [29] and Australia [30]. The backlash has resulted in legal challenges against deployment programmes, residents defending their properties (sometimes while armed), law enforcement involvement, and a change of fortune for many politicians associated with smart meters. Media coverage of lawsuits against energy suppliers, arrests of homeowners, and a distrust of utility companies swelled the ranks of dissenters and had a major impact on the deployment of smart meters. This "Bakersfield Effect", named after the Californian city where the campaign began, has halted installation programmes and taken governments and energy suppliers by surprise.

The objections to smart meters include (but are not limited to); increasing the cost of energy, negative effects on health from electromagnetic fields and wi-fi, concerns that the government or other agencies are spying on residents, the data being sold to third parties, the meters causing fires, hacking resulting in stolen data and/or loss of energy to the household. The Institute of Directors in the UK is an organisation that has been supporting businesses and the people who run them since 1903. They recently reviewed the planned UK rollout of smart meters to all homes and small businesses and called for the scheme to be "*halted, altered, or scrapped*" [31] based on the technology being used, the experience of smart meter projects in other countries and past issues with major IT projects from the UK Government.

In the UK, in addition to smart meters, householders will also be given an In-Home Display (IHD) that shows how much gas and electricity has been used and the cost of that fuel consumption over different time-scales, such as over the last day, month, or year.

The inclusion of IHDs in the UK smart meter rollout is expected to reduce domestic energy consumption because people will be more aware of how much energy they are using and as a direct result reduce their consumption. Darby's [32] comprehensive review of trials of consumer feedback showed that single interventions have limited success in reducing energy consumption unless the recipients are already motivated and knowledgeable in their use of IHD. A 'fit and forget' attitude is prevalent among the majority of consumers unless they are subject to additional motivational interventions, such as advice or community programmes.

This highlights the difficulties of attempting to change the everyday energy-consuming behaviour of people when that behaviour is not understood. If personalised energy-consuming behaviour was known, aspects of that behaviour and the factors that contribute to it could be challenged in a more targeted and potentially effective manner. This research presents a technique that enables the capturing of the unknown behaviour on which better strategies to reduce domestic energy consumption could be based.

2.4 Location Determination

Systems designed to locate individuals or objects can approach the problem by using a smart device or a smart environment. Smart devices determine their location in relation to other known positions, for example a GPS device computes its location from its relative distances from at least four GPS satellites. When smart environments are used the device itself is *dumb* and does not have the complexity to determine its location. In this case the environment is smart and there are a number of sensors or readers that are used to locate the device.

Smart devices are more complex than dumb ones, require more power and host the locating capability and all data. Due to the increased complexity and battery power (and weight) smart devices are not being used for this research. A crucial requirement of the locating system is that it must be unobtrusive, lightweight and robust. If a mobile dumb device is damaged or lost it can be easily replaced with minimal consequences for the system as a whole but if a smart device is damaged or lost the consequences for the system and data collection would be catastrophic.

A system that tracks an aspect of human behaviour needs a method of collecting data. In order to do this without changing the behaviour being observed the system must be unobtrusive as described in the previous section. This requires the minimum of obvious peripherals, such as cables and memory storage devices. Ideal methods of collecting and transmitting data unobtrusively with compact devices are those that use wireless sensor networks. This section explains wireless sensor networks, the benefits of several wireless protocols, and how they have been used in location systems.

The *wireless* in Wireless Sensor Networks (WSN) refers to the transmission of information via modulation of waves in the electromagnetic spectrum [33]. This variation of properties of a waveform with a modulating signal allows information to be transmitted without the use of physical wires. These were previously known as Radio Systems and were used primarily by the military, space agencies, and Citizen's Band (CB) enthusiasts. The development of wireless systems has been significant since the 1970's, when a modem would cost the equivalent of $300,000 and be as big as a microwave oven [34].

The trend in wireless communication has been towards miniaturisation and ubiquity, with wireless access to the internet widely used every day by people at work, at home and through internet enabled smartphones and other devices. This increasing connection of equipment, appliances, and sensors to the internet is termed The Internet of Things (IoT) and describes diverse uses from autonomous vehicles to livestock management [35]. IoT devices are generally small hardware units that can sense one or more aspects of its location and/or perform a task in that environment, such as open or close a window or switch lights or a heating system on or off.

Devices either provide a basic service as a sensor or actuator and need to communicate over a Local Area Network (LAN) to another device, or they can be more advanced and communicate over the web as well as provide the sensing and/or task required. The basic devices are smaller, have a lower energy demand, and need a gateway or base unit locally to communicate with.

Wireless communication between devices, and between devices and base units, is possible using a variety of protocols suited to different applications. Examples of wireless communication protocols, or ‘standards’, include Bluetooth, ZigBee, RFID, and DECT. These are considered below.

2.4.1 Bluetooth

Bluetooth operates in the 2.4 to 2.485GHz frequency band and is a popular method of connecting devices wirelessly over a short range, such as wireless headsets to mobile phones. Until recently Bluetooth had a slow connection speed and high energy demand, although there is now Bluetooth Low Energy (BLE) which consumes 10 to 20 times less energy than the original technology [34].

2.4.2 ZigBee

ZigBee can operate at frequencies of 868MHz and 2.4GHz and is an example of a Wireless Local Area Network (WLAN). ZigBee forms a mesh network using a number of nodes with no one central transmitter/receiver. ZigBee is widely used in control and monitoring applications, including domestic automation systems. An advantage of ZigBee is low power consumption and longer battery life, but object tracking is problematic as the accuracy is poor [35].

2.4.3 RFID

Radio Frequency Identification (RFID) is currently used for many tracking applications. Examples include tagging marathon runners, shopping trolleys, livestock, luggage, and merchandise. RFID tags can be active and have their own power supply so that they can transmit a signal, or they can be passive without a power supply and need to be in close proximity to a transceiver to be read. Oktem and Aydin [36] designed a system to guide visually impaired people through an environment with obstacles using RFID tags placed in a grid.

2.4.4 DECT

Digital Enhanced Cordless Telecommunications (DECT) is primarily used in cordless telephones, although it has been used in wireless microphones and home care pendants. Advantages of DECT include the range and compatibility of existing products available, but the power consumption is heavily influenced by the frequency of wake-up events and is not suitable for applications with a high incidence of trigger events [37].

When using WSNs to determine location there are several methods to consider. These include proximity, trilateration, hyperbolic lateration, triangulation, fingerprinting, and dead reckoning [38]. These approaches are set out below.

2.4.5 Proximity

Proximity, or presence detection, can indicate when a device is close to a known reference point. This is a simple method and detects the presence of the device but not necessarily the identity or any other details. In the case of a communication system with a very small range, it can be used to assume that the device is at the same location as the reference point. In systems with greater ranges and multiple reference points, the device location can be estimated from the locations of all the reference points it is within range of.

2.4.6 Trilateration

With this method, the location of the device is derived from measuring the distance of the device from several reference points at known locations. One way of measuring the distance from the device to the reference points requires the ability to very accurately measure the time for a signal to travel between the device and the reference points. From the differences between the times taken it is possible to compute the location of the device. This method requires numerous reference points and very precise synchronisation.

2.4.7 Hyperbolic Lateration

This technique uses the Time Difference of Arrival (TDOA) of a signal from the device to three or more reference points. This requires reference point nodes with a very accurate timer and a mechanism to detect an emitted pulse from the device. A very high level of synchronisation is required.

2.4.8 Triangulation

Triangulation uses the Angle of Arrival (AOA) of a signal emitted by the device to reference points to estimate the device location. When the angle of the signal to the reference points is known, the lines along each AOA intersect where the device is located. Triangulation can be attempted in 2D with two reference points but is more accurate with more reference points. Directional antennae or an antenna array is required, usually at the reference points and not the mobile device.

2.4.9 Fingerprinting

Fingerprinting relies on specific properties of radio waves, for RF these are temporal stability and spatial variability. Temporal stability is the stability of the radio signal at one point over time, and spatial variability is the change in signal strength at different locations. Fingerprinting requires prior knowledge of the signal profiles at different locations, and the accuracy is heavily dependent on the spatial variability because signal strengths should be similar on different days and weeks. This method does not model radio propagation so numerous measurements must be taken in advance so that the location of the device can be determined from comparison with previous signal strengths recorded.

2.4.10 Dead Reckoning

Computing the location of a device based on its previously known location, direction, speed of movement, or other data is called Dead Reckoning. It is a way of filling in gaps and inferring location from what is already known and sensible possibilities. The accuracy of this method can be improved by using accurate data, such as accelerometers on the device, or extrapolating data from two or more previous known locations.

Holler et al [39] draw attention to the fact that the experience of real-world deployment of IoT devices is often very different from the expectations resulting from laboratory tests. Devices in real-world situations are subject to a multitude of external factors that are not present in laboratories, such as electromagnetic influences and environmental elements (temperature, humidity, behaviour and presence of people, etc.). Potential sources of errors arising in location systems include inadequate clock synchronisation and multipath issues when a signal can take numerous paths to the destination due to interaction with obstacles.

Faragher [40] argues that the best solution to indoor positioning is by using smartphones and has presented a technique based on opportunistic sensing and machine learning techniques, such as Simultaneous Localization and Mapping (SLAM) used in the robotics industry. The technique for smartphones, named SmartSLAM, uses the patterns of radio signal strength measurements (WiFi, cellular signals, etc.) at any location to determine its location without the need for extensive mapping beforehand. A further smartphone technique has been developed using BLE beacons as opposed to relying on existing WiFi infrastructure [41].

Although these new techniques are providing positive results during tests, the use of smartphones as part of a RTLS for this research is not feasible due to the costs and uncertainty related to compatibility with changes to operating systems. As smart devices are not being pursued in this research, a smart environment with dumb devices is required. To capture the location of individuals it is necessary to have dumb devices that people can wear.

2.5 Wearable Technology

There are many examples of systems that track an aspect of human behaviour using wearable technologies. When connected to an appropriate wireless sensor network these systems can monitor and collect a great deal of data. This is a key requirement of this research.

Tagging systems are currently used for a wide variety of purposes, from monitoring compliance with Home Detention Curfews to health traceability of livestock and improved stock control and logistics [42]. Competitive runners can purchase commercial RFID wristbands that not only accurately log their timings, but also store their bib number, name, gender, age, medical information and emergency contacts. Wearable tags can be used in medical settings to both give a quick and accurate identification of patients, their medical history and allergies, etc. but also to give warnings when they are leaving the environment. This has been successfully used to reduce instances of potentially life-threatening cases of confused patients leaving hospital grounds [43].

There have also been several systems developed to locate and track people and objects within closed environments [44, 45]. These systems frequently use triangulation and multi-lateration methods using light, ultrasound or radio signals. The purpose of indoor positioning systems is to locate people and/or objects in large buildings, such as offices and hospitals.

The *Active Badge* system was the first indoor location sensing system developed by AT&T [46]. This is an infrared positioning system as every person wears a small infrared beacon that emits a unique code identifier every 15 seconds. The network of IR sensors within the building detects these transmissions and sends the information to a central data bank. In contrast the *Active Bat* system is an ultrasonic system and the users are tagged with ultrasonic tags that emit signals that are picked up by receivers. Active Bats performed better than Active Badges but required a large number of sensors mounted in the ceiling.

Wearable RFID is increasingly being developed to improve interactivity with computer gaming. Two wearable RFID systems developed by Intel Research Seattle include the iGlove and the iBracelet [47]. While the iGlove has the components mounted on the hand of the glove and the antennae wire sewn into the palm, the iBracelet has everything encased in a hard plastic shell around the wrist of the wearer. The technology is being developed to reduce the size and there are several games already being developed specifically for RFID interaction.

In addition to the world of computer gaming, wearable technology has become popular with people wanting to tag themselves voluntarily. There are several models available from several manufacturers and the functions range from basic pedometers to wristbands that log different intensity activities, distance and steps, quality and quantity of sleep, heart rate, GPS location, and idle alerts. These devices communicate with apps on smart phones to provide numerous ways of presenting the data collected, set goals and include the ability to add further data manually, such as food and water intake. The smartphones also act as a gateway to social media and other users of the devices.

The medical community also see opportunities for wearable technology, to not only observe and manage conditions, but also to aid diagnosis. Mackinnon [48] argues that wearable sensors could assist the diagnosis of movement disorders. Conditions, such as Parkinson's Disease, have symptoms that are highly episodic and so may not be reliably captured by clinicians. If sensors monitor symptoms over a period of time this would greatly help physicians both diagnose and assess the efficacy of a treatment plan.

Sahakian [49] suggests that wearable technology could, and should, be exploited in the interests of brain health and wellbeing. There are many existing health apps [50] including those that use sensors and Sahakian argues that it is imperative that these technologies are applied to brain health. An example is a wearable sensor that can recognise when a person's behaviour alters, which could indicate the onset of an episode of poor mental health. In this instance, a professional would be alerted to intervene at a much earlier stage than currently happens, and then be able to prevent an escalation to crisis point. This would save considerable resources and the involvement of numerous agencies, and minimise mental distress of the person being helped.

One common cause for concern of wearable technologies is that of privacy of the wearer's data. There is an interesting paradox revealed by experiments that shows that the more control people have over publishing their private data the more likely they are to share it [51]. In contrast, when people have less control over their personal information the more concerns they have about privacy, and the less willing they are to have their information published. People consistently tend to share very personal information, in this case on social media, even when they are aware that strangers could access that information.

2.6 Summary

This chapter presented detailed information on the five key issues of this research. Section 2.1 set out how the *everyday* is ubiquitous and yet often elusive. Common methods of recording daily life, including the Mass Observation Project and Time Use Survey, require the co-operation of fully-informed participants. A challenge in capturing truly typical quotidian behaviour is that people under scrutiny behave differently when they are aware of being observed.

Section 2.2 introduced the technique of unobtrusive observation. Although this research did not include working with participants, the requirement to discreetly monitor human behaviour was a critical design objective.

There are many sources of data concerning UK domestic energy consumption, including extensive data on housing stock and households. The increasing cost of energy to domestic consumers is a major contributory factor in the rise in the incidence of fuel poverty, which is a key motivation for this research. The gap in knowledge of how people use energy at home means that initiatives aimed at reducing consumption are based on assumptions and are found to be ineffective over the long-term. If personalised energy consuming profiles were known, advice and initiatives could be better focused to understand and change energy inefficient behaviours.

Most people in the UK come into contact with wireless networks every day, at work, home, while travelling, and in many other locations. Ofcom reported that in 2014 the average adult spends more time each day on digital media and communications than sleeping. Most, if not all of this is through wireless networks. Wireless protocols that enable devices to communicate with each other were presented in Section 2.4 Location Determination, followed by methods and examples of deriving location.

As shown in Section 2.5, wearable technologies are increasingly being used by individuals to monitor their own health and activity levels. When a wearable technology is combined with an appropriate wireless sensor network, the ability to capture a great deal of data is possible.

This literature review has shown that there is an imperative to find new ways to address the growing problem of domestic energy consumption in the UK. While capturing everyday human behaviour is difficult, by using wearable technology connected to a wireless network it is possible to develop a system that unobtrusively observes people as they use energy at home if they wear dumb devices in a smart environment.

Chapter Three

3 System Design Overview

As has been described in Chapter One, this research is proposed to address the development of a technique to enable the capture of personalised, domestic electricity consuming behaviour. Chapter Two has set out the key issues, and this chapter explains the requirements of this technology in order to fulfil the need for information on how people use energy at home.

The fundamental requirements of this technique must include:

1. The ability to locate individuals to room-level
2. Accurate recording of the location, an individual's identity, and the time
3. Appliance level electricity consumption data, also recorded with time and location

Matching an individual's location data with the energy consumption data from appliances will allow the energy used at that location at that time to be attributed to the person or persons present. Rules of attribution are included at the end of this chapter to ensure household members with care-giving responsibilities are not unfairly held responsible for energy use that is for the good of the household.

Chapter Two clearly showed the need for discretion when observing human behaviour. Although it could be possible to use cameras to record whoever is in the location when energy is being used, this is problematic for several reasons. Using cameras in private homes without the householder's fully informed consent would be at the very least unethical, and with consent would make the system obtrusive and therefore unreliable as a method of observing typical behaviour. Additionally, the camera recordings would have to be monitored and the individuals matched to the energy consumption manually.

Chapter Two highlighted the use of wireless sensor networks and wearable technology to monitor human behaviour. By using small unobtrusive devices worn by people in their home that transmit data wirelessly a system can be developed to provide location data. The system must be effective and reliable, acceptable to people, and able to capture the everyday energy consuming behaviour without influencing it. It has been shown in the previous chapter that this kind of system does not currently exist.

Previous research of indoor tracking systems show that they have significant differences from the one needed for this research. These include a mobile home-care system that uses RFID to enable health workers to access real-time physiological data (blood pressure and heart rate) of a patient remotely [52]. In this case the patient is static and connected to a health monitor in one location and the health worker receives the data via RFID.

Further examples of wireless sensor network location tracking systems used in non-open spaces have used numerous RFID readers in a grid pattern or near doorways [53, 54]. The use of multiple readers helps to increase confidence in location inference due to the many readings of close proximity to the large number of readers, but having a large number of readers in a person's home would render the system highly visible.

In the interests of keeping the system as unobtrusive as possible, a limited number of fixed readers are needed to determine the location of householders wearing mobile tags. The entire system must also be cost-effective, and easy to retrofit to properties. Additional essential characteristics of the wearable tags, fixed readers and the controlling base system are set out in Table 3.1.

System Element	Essential Characteristics	Rationale
wearable tags	lightweight	To record the *everyday* energy consuming behaviour the tags must be as unobtrusive as possible. This is unlikely if the wearable tags are heavy, uncomfortable, or cause irritation to the person wearing one.
	comfortable to wear	
	low allergen	
	water resistant	The tags do not record energy consumption in wet rooms but it is possible that they could come into contact with moisture through normal domestic activities.
	child and animal-safe	Although children are not tagged, reasonable efforts must be made to ensure the tags do not present a danger to children or animals in the household.
	low energy demand	If tags require very regular battery changes by the wearer this increases the attention to the tags and therefore reduces the unobtrusiveness and effectiveness as a method of capturing the everyday. Tags that stop working due to battery failure poses a risk of loss of data.
fixed sensors and base station	no sound, light or vibration emitted	Any sound, light or vibration from the base station increases awareness of the system and reduces the unobtrusiveness.
	low energy demand	People should not have to use an excessive amount of energy in order to have their energy consumption monitored.
	quick to install	A complex installation potentially increases annoyance with, and awareness of the system.
	flexibility	Flexibility is required so that the reader antenna can be positioned in the optimum location and orientation to avoid obstruction by furniture and building elements.

Table 3.1 The essential characteristics of tags and base station

3.1 Energy Consumption

The majority of previous research into domestic energy consumption monitored household energy use only. This is adequate as a measure of whole house characteristics but inadequate for personalised energy monitoring. Appliance level electricity monitoring is required so that when an appliance is used, and the location of the appliance and individuals are known, it is possible to directly link the electricity use with the individuals at that location.

Plugwise Energy Management and Control System

Plugwise is an energy management and control system for monitoring individual appliances in buildings. The Plugwise system is based on a wireless mesh network (Zigbee 2.4 Hz).

The Plugwise system has been used in previous energy monitoring research by the University of Salford, and the Plugwise company donated an advanced licence for the purposes of this investigation. The system is straightforward to set up and several test networks were evaluated over a period of six months in which the units performed well and reliably recorded energy consumption of the appliances they were monitoring.

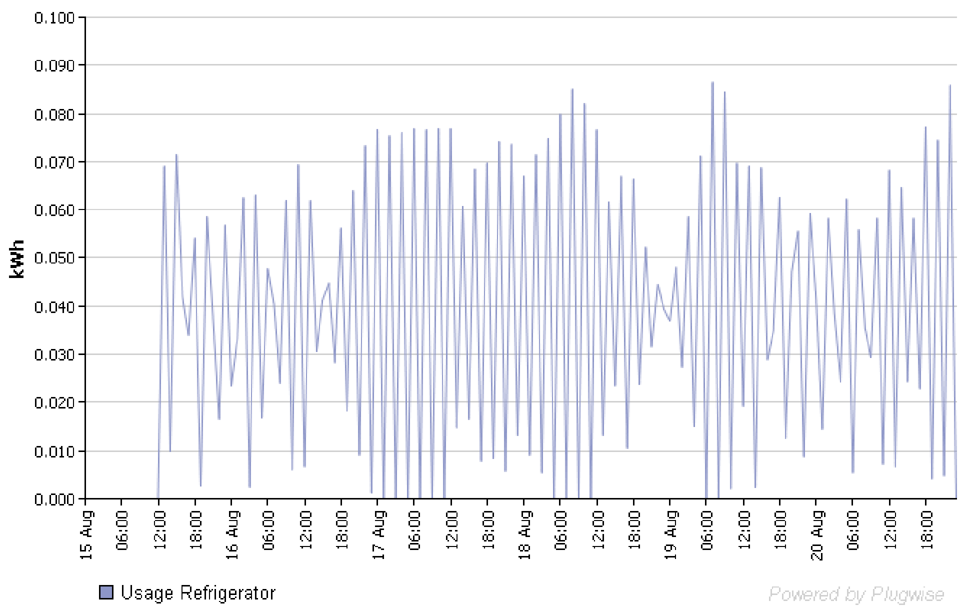


Figure 3.1 Hourly Energy Consumption pattern over several days for a refrigerator

An example of the graphical output from the system is presented in Figure 3.1, this shows the hourly energy consumption of a refrigerator over several days.

In addition to the graphical outputs from Plugwise, with the enhanced donated licences the raw data can be exported in csv format. The maximum number of Plugwise devices, and therefore appliances being monitored, in any single network is 65. Further details of the energy monitoring system can be found in Appendix A. Energy Monitoring System.

3.2 Real Time Location System

A Real Time Location System (RTLS) is a group of devices that when used together can capture data from which the location of the object or person being tracked can be derived. As previously discussed in Chapter Two there are different communication protocols and location derivation methods currently in use. Two potential locating devices are described in this section. These are the Texas Instruments eZ340-Chronos Development Tool and the Loc8tor device.

In addition to units that obtain data for computing location, a RTLS requires a gateway, or base station. Communication between the base station and location sensors is an essential element as this is how the sensors are controlled, data is received and accurate timings achieved. Although some RTLS systems can feed back near-instantaneous location data to individuals or organisations, such as GPS or high specification security applications, this is not always required. For the purposes of this research, it is only necessary to record time-stamped location data so that this can later be matched with time-stamped energy consumption data to obtain the identity of the person or persons present when that energy was being consumed.

3.2.1 Locating Systems

Texas Instruments eZ430-Chronos Development Tool

The eZ430-Chronos software development tool is a wearable system that is based on the CC430F6137 microcontroller with sub 1 GHz wireless transceiver. The design is based on a sports watch and includes a three-axis accelerometer, pressure sensor, temperature sensor and battery voltage sensor.

The watch can act as a central hub for nearby wireless sensors, such as pedometers or heart rate monitors. Included is also an eZ430-RF USB emulator that connects the eZ430-Chronos to a PC for programming and debugging. The watch has to be disassembled to be reprogrammed with custom applications. There is an active online community of enthusiasts investigating the capability of the watch and documenting their successes and failures.

Figure 3.2 The Texas Instruments eZ430-Chronos Development Tool (image from Texas Instruments)

The watch could be programmed as an RFID transceiver emitting an RF signal periodically to a network of RF receivers in fixed locations within a building to potentially form part of a RTLS. From RSSI or TDOA calculations this could give the location of the individual in the property.

The Chronos watch was considered as a potential element of the location system. The watch has many functions including the one that is required, but a major concern was that the watch was large. Whether someone was an existing watch-wearer or not, wearing the Chronos watch would be a constant reminder that your behaviour was being observed.

Figure 3.3 Chronos watch (left), UK 5 pence (centre), and Loc8tor tag (right)

The software that controls the Chronos watch is proprietary and is incompatible with many devices which restricted communication with anything other than a standard computer or laptop. For these reasons the Chronos was discounted as a component in the locating system.

Loc8tor

The Loc8tor is a UK made RFID homing device. It is relatively inexpensive and marketed as a method of helping people find mislaid possessions, pets, and other people. The system comprises of a handheld unit and up to four tags. The Loc8tor works on the 2.45GHz frequency band, and the handheld unit and tags both transmit and receive signals.

Figure 3.4 The Loc8tor Lite handheld unit with two tags (image from Loc8tor.com)

Each active tag has a unique identifying signal and must be registered with the handheld unit and allocated to one of the four numbered buttons. The process for finding tags is shown in Figure 3.5.

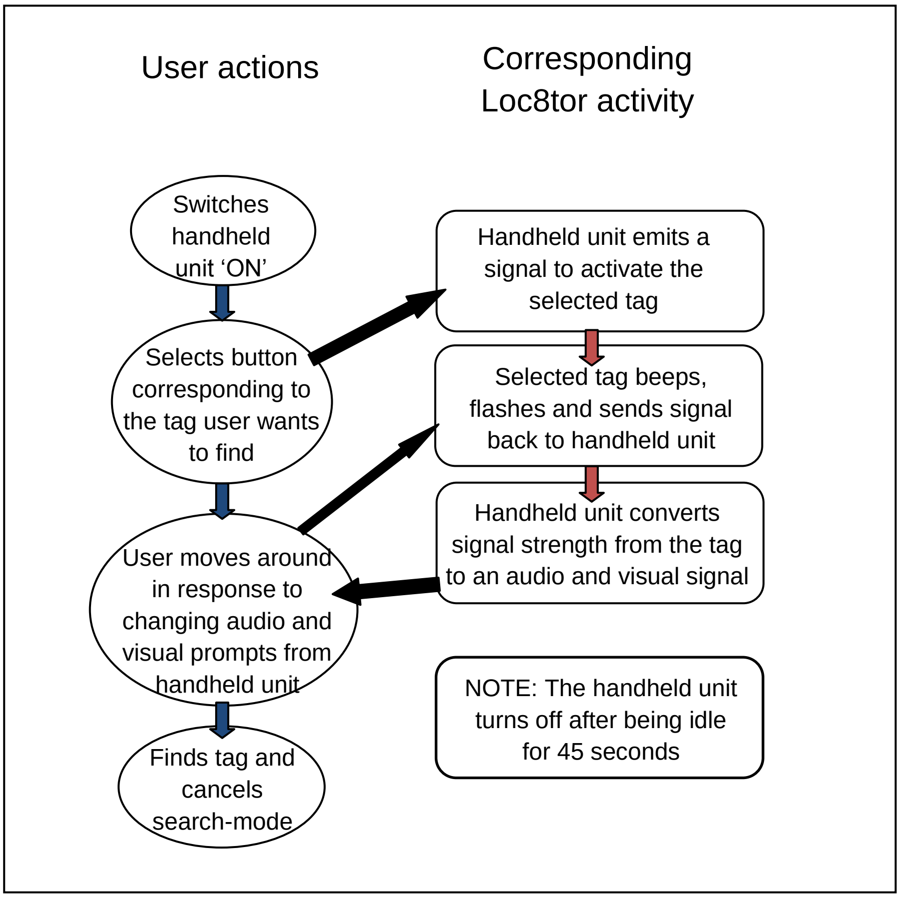


Figure 3.5 User actions and corresponding Loc8tor activity during search-mode

The handheld unit has eight LEDs that indicate the signal strength. There are two red, three amber and three green lights. Up to three lights are active at a time in general search-mode giving a series of nine patterns to indicate signal strength. These are shown in Figure 3.6 along with the Signal Strength Number (SSN) these patterns have been assigned for this research.

In addition to the nine identified Signal Strength Numbers and corresponding pattern of LED activity, the Loc8tor system does have an additional 'zooming-in' mode. In this mode all the lights are active when the searched-for tag is very close to the handheld unit. This only happens when the tag is closer than 30cms and is not relevant for the purpose of tracking people's location around their homes.

Although the handheld unit and the tags come with integral speakers to give an audio signal when searching for tags, these can be easily disabled.

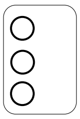
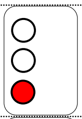
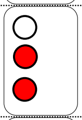
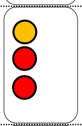
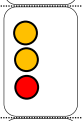
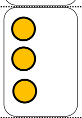
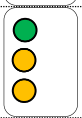
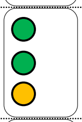
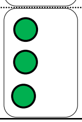
Visual signal from Loc8tor Lite handheld unit	Signal Strength Number (SSN)	LED# lit up at that signal strength
	**1**	**-**
	**2**	**1**
	**3**	**1,2**
	**4**	**1,2,3**
	**5**	**2,3,4**
	**6**	**3,4,5**
	**7**	**4,5,6**
	**8**	**5,6,7**
	**9**	**6,7,8**

Figure 3.6 The patterns of signal strength and allocated Signal Strength Number (SSN)

The tags are not waterproof but there are water-resistant wristbands available and plastic covers for attaching tags to pet collars. The handheld unit can register a maximum of four tags, and each tag can only be registered to one handheld unit. Discussions with the company that manufactured the Loc8tor revealed that the PCB's could be cloned which would enable the tags to be registered to more than one unit.

3.2.2 Base Station

The base station of the RTLS controls the sensors in the network, receives data from the sensor network, and manages the storage of data, either locally or by transmission to a server. Judah recommends, from experience, that remote access to the sensor networks is vital so that any errors or malfunctions can be quickly identified and rectified.

Tablet computers and mobile phones could potentially act as a base station, although there are several disadvantages to this, including; the risk of theft, the expense of purchasing the equipment and ongoing costs, and compatibility issues between the different operating systems of the devices. In addition, tablet computers and mobile phones are over-engineered for the application as a base station as only a small proportion of their capabilities would be used.

A cost-effective solution is the Raspberry Pi (RPi) computer. This is a credit-card sized computer that has been designed and made cheaply to encourage more people, especially children, to learn programming. The Model B Raspberry Pi has 256Mb RAM, 2 USB ports and an Ethernet port. The RPi boots up from an SD card pre-loaded with the choice of several operating systems and communicates with a wide variety of devices and sensors via a choice of coding packages, such as Python.

The RPi is very economical because it consists of the bare PCB with very little additional components. It is necessary to have additional components to work with the RPi. These include: a powered USB hub, keyboard, mouse, HDMI monitor or HDMI connector to use a non-HDMI monitor. There is no wireless or Bluetooth connectivity on board the RPi but dongles can be used if required.

An additional benefit of the RPi as a base station is the small size, enabling a compact RTLS to be developed. Figure 3.10 shows the RPi with a UK five pence coin for scale.

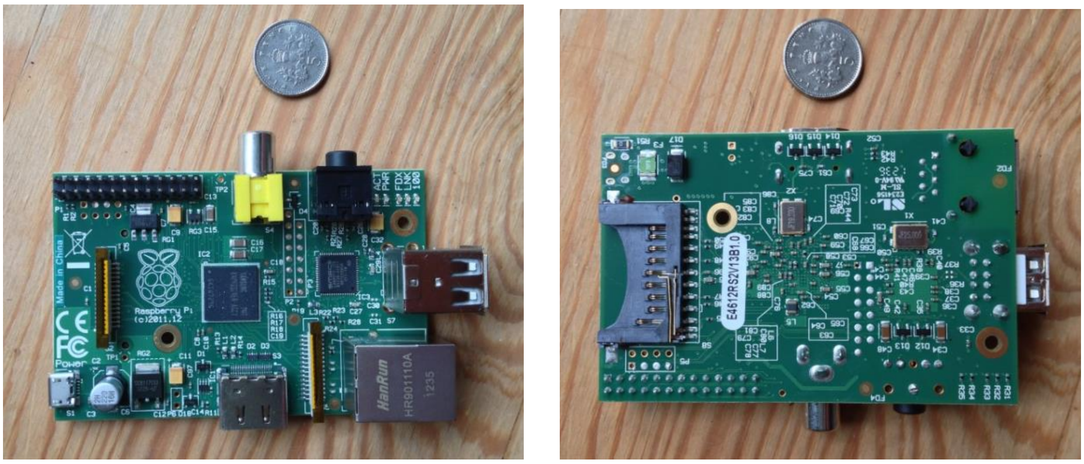


Figure 3.7 Top (left) and underside (right) of the Raspberry Pi (RPi) computer, with a UK 5 pence coin for scale

3.3 Rules of Attribution

Rules of attribution must be applied to appropriately attribute energy consumption to the correct individuals. For example:

1. Individuals in the same location at the same time share responsibility for the energy being consumed in that location at that time.
2. If an individual is present and alone when energy consumption increases in one location and then moves to another location without the energy consumption decreasing, it will be assumed that the person turned on an appliance and left it on when they left the location. In this case they will be responsible for the energy consumed in their absence until another person comes into the location. The new person will become responsible for the energy consumption of the appliance.

In the interests of gender equality and to avoid unfairly attributing excess energy consumption to the individuals within households that have care-giving responsibilities, all the energy that is consumed within the kitchen is assumed to be for the good of the entire household and is not monitored and attributed to individuals. Due to the lack of appliances present and the damp environment, bathrooms and wet rooms are not monitored. The energy consuming behaviour of children is not monitored. In this case this refers to the UK age of majority, which is 18 years of age.

3.4 Summary

The appliance-level electricity monitoring system from Plugwise was considered to be a well-established and reliable method of recording the energy use of household appliances. The generous donation of the professional licences for this research by the Plugwise company ensured that the consumption data could be exported in csv format. This enhances the task of matching location data of individuals to electricity consumed at the same time and location.

This chapter has explained why previous attempts to tag and track objects are not suitable for this project due to the large number of readers required and the fact this would significantly increase the visibility of the system.

The Chronos watch was over-engineered for the purposes of this research and could only communicate with a limited number of devices due to software incompatibilities. In addition the size and conspicuous form of the watch was seen not to be an ideal candidate for inclusion of this research.

The Loc8tor tags however are small and lightweight and could be worn on a lanyard, attached to a belt or item of clothing, or worn on a wristband to suit the preferences of household members in the event of the system being used in trials. This would be similar to the forms of id employees wear and are often visible when people forget to take them off outside of their employment.

The Loc8tor system is less complex than the Chronos watch and designed for the only purpose that is required by this project. The ability to clone the units is an additional potential benefit when more than one reader is required in a home. For these reasons the Loc8tor system was selected for use in this research.

The Rapsberry Pi computer was selected as the base station due to its size, simplicity, and cost-effectiveness. The RPi is inherently flexible with a great deal of choice of software to run on the computer and GPIO pins to make physical connections. RPis can connect and synchronise to a Local Area Network via a wi-fi dongle, and can read and write to USB memory drives.

By using the Plugwise system, Loc8tor RFID tags and reader, and the RPi as a base station the fundamental requirements of accurate recording of an individual's location and appliance level electricity consumption are met. The remaining requirement for the ability to locate individuals by room-level was to be determined through thorough experimentation. Chapter Four and Appendix A set out how the prototype was developed, and once proof of concept was obtained, how the experiments with the system were carried out and the data analysed to investigate whether room-level location identification was possible.

Chapter Four

4 Experimentation

This chapter explains how the experimental phase of this research was carried out and the data was collected and analysed. Details of the RTLS prototype development are included, the equipment used and testing procedure for all the tests set out. Information about the testing locations and their form and construction are included, and methods of data collection and analysis. The design and purpose of specific types of tests are also presented.

4.1 Prototype Development

This section briefly summarises the development of the prototype until proof of concept was achieved. More details of the manufacture of the prototype are included in Appendix A. Prototype Manufacture.

The Printed Circuit Board (PCB) of the Loc8tor handheld unit was released from its protective casing and each of the circuits related to the eight LEDs were identified and connected to the GPIO header of the RPi. A computer programme, written in the Python coding language, was written that controlled the tags, interpreted which LED circuits were active, time-stamped and stored the data to a USB memory stick. The Python programme is included in Appendix B. Python Programme.

The resulting prototype and code enabled the capture and storage of data from the tags recording the specific tag, time, and signal strength.

4.2 Experimental Set-up

The following equipment was used in all the experiments conducted in this research:

- **Prototype:** four complete prototypes were built from four Loc8tor handheld units, with additional elements to connect to a RPi.
- **RPi:** Each prototype was connected to and controlled by a dedicated RPi.
- **Loc8tor tags:** Up to four tags were linked to each prototype.

- **Powered USB Hub:** RPis have two USB ports only. The powered USB hub was necessary to enable each RPi to be connected to a monitor, keyboard, mouse, and USB memory stick.
- **Monitor, keyboard, and mouse:** In order to load, amend, and view the Python code and data being collected.
- **USB memory stick:** For local storage of the resulting data from the prototype.
- **USB wi-fi dongl**e: Connection to a wi-fi network enabled accurate time-stamping of data.
- **1 metre stand:** In order to ensure all signal strength readings were taken at a consistent height above floor level, and at a height similar to that which would result from the tag being worn on a person's wrist, a 1 metre stand was used on which the tags were placed.

As well as all tag readings being taken at a height of 1 metre above floor level, each testing location was marked out in advance with a grid of 1 metre squares and each sampling point was individually named. Some experiments were also carried out with a Rohde & Schwarz FSH3 Handheld Spectrum Analyzer in order to investigate the signals between the prototype and tags. Figure 4.1 shows an experimental set-up with the spectrum analyzer.

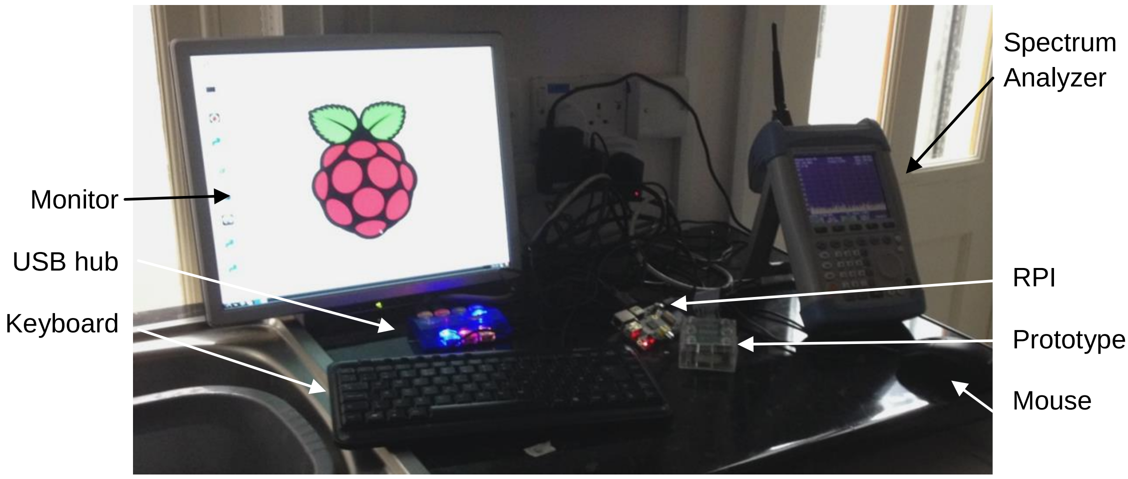


Figure 4.1 Experimental Set-up with Spectrum Analyzer (from l-r monitor, keyboard, powered USB hub, RPi, prototype, spectrum analyzer, mouse)

4.3 Test Procedure

For each test, the prototype and RPi were placed in the required location in the testing location. With the Python programme running and the prototype activated, the tags were moved to the sampling points, placed on the 1 metre stand, and the signal strength readings were recorded. Tests were carried out in the Salford Energy House and a house in Stockport, Greater Manchester.

4.3.1 Testing Locations

<u>The Salford Energy House</u>

The Energy House at the University of Salford is a full scale house built inside an environmental chamber. The house is a fully furnished two-bedroomed solid wall end terrace from 1919. It was rebuilt inside a laboratory in 2011 using traditional methods and materials, and represents 21% of UK housing stock [55].

Figure 4.2 The front (left) and rear (right) elevations of the Salford Energy House with the full-height 1/3 width house next door visible

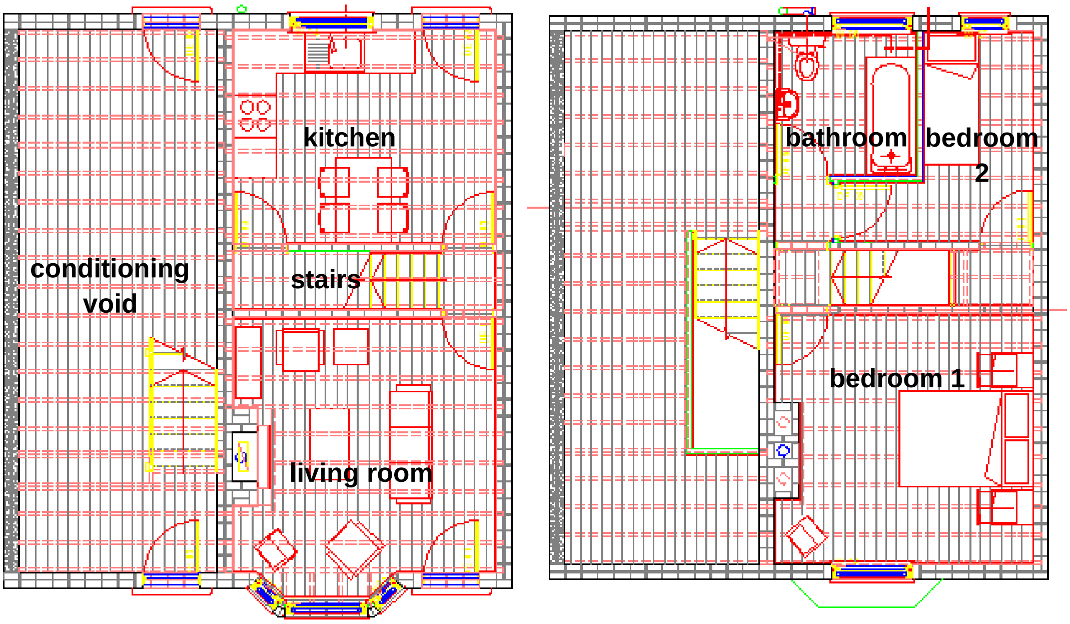


Figure 4.3 Layout of the Salford Energy House ground floor (left) and first floor (right)

As can be seen from the floorplans in Figure 4.3 the house is of a traditional two-up two-down design. There is an additional full-height and 1/3-width house built adjacent to the property (the conditioning void) to correspond to the energy house being an end terraced dwelling.

Prior to testing, a 1 metre grid was marked out and each sampling point given a unique identifier. The location of these sampling points is shown in Figure 4.4.

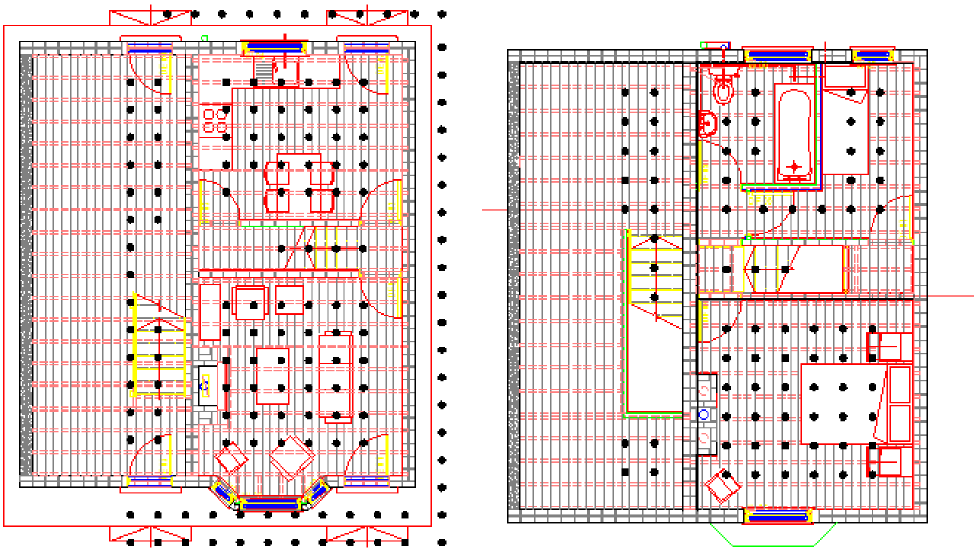


Figure 4.4 The 222 sampling points at the Salford Energy House ground floor (left) and first floor (right)

In total there were 222 unique sampling points used, comprised of the following:

- 146 on the ground floor:
  - Living room – 36
  - Stairs – 4
  - Kitchen – 29
  - External – 52
  - Conditioning void - 25
- 76 on the first floor:
  - Bedroom 1 – 36
  - Stairs – 3
  - Bathroom – 6
  - Bedroom 2 – 14
  - Conditioning void – 17

Images from the Salford Energy House tests can be found in Appendix D. Salford Energy House tests.

<u>Home1</u>

Home1 is a three-bedroomed semi detached house in Stockport, Greater Manchester, and is typical of the houses built in the early post-war (1945-1964) social housing building boom [56]. At this time there was a great demand for homes to replace those destroyed and damaged during the war. There was a shortage of construction materials and skilled workers so houses from this era have less ornamentation than previous periods, such as bay windows, resulting in a more basic 'boxy' design. Common features include solid concrete floors, cavity walls and chimneys. Homes built in this period account for over 22% of the existing English housing stock [57].

Figure 4.5 Front elevation of Home1, a typically constructed early post-war three bedroomed semi-detached house in Stockport, Greater Manchester

The layout of Home1 is shown in Figure 4.6 below. The property is fully furnished and occupied by a family. The ground floor comprises a large living room, a kitchen and entrance hall and on the first floor are three bedrooms. There is a full height chimney breast located centrally in the house.

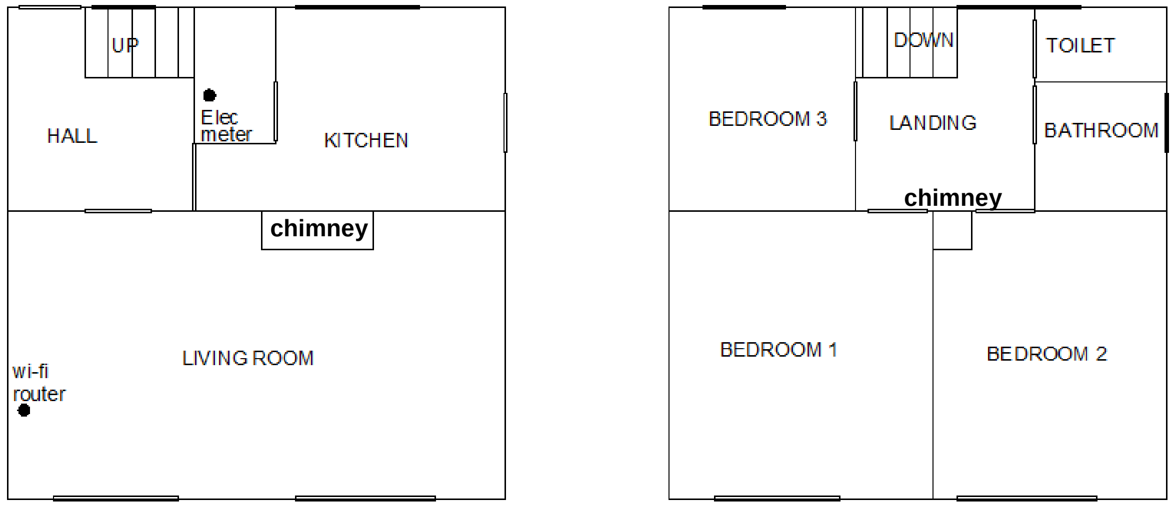


Figure 4.6. The layout of Home 1 ground floor (left) and first floor (right)

Due to Home1 being filled with a lot more furniture than the unoccupied Energy House, there were some restrictions on the selection of sampling points. A total of 171 unique sampling points were used. These are shown in Figure 4.7.

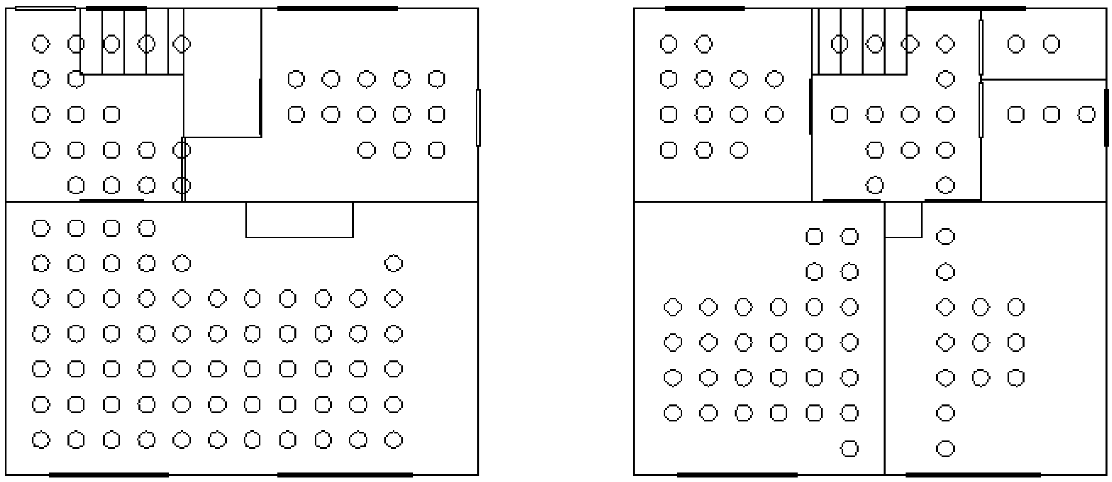


Figure 4.7. The 171 unique sampling points in Home1, ground floor (left) and first floor (right)

The 171 sampling points in Home1 comprises:

- 97 sampling points on the ground floor:
  - Living room - 65
  - Kitchen - 13
  - Hall - 16
  - Stairs - 3
- 74 sampling point on the first floor:
  - Bedroom 1 - 29
  - Bedroom 2 - 13
  - Bedroom 3 – 13
  - Landing - 11
  - Toilet - 2
  - Bathroom - 3
  - Stairs - 3

Naming Convention of the Sampling Points

In order to aid the accurate recording and analysis of data, a consistent naming convention was applied to all the sampling points. Each sampling point was numbered and had a prefix that indicated the location of the room it was in. An initial prefix of G indicated that the location was on the ground floor, and F indicated first floor. Additional letters were also used to indicate the specific room, such as K for kitchen, L for living room, etc. Table 4.1 shows the prefixes used and Figure 4.8 shows the locations these codes applied to.

Testing Location	**Prefix**	**Specific Location (floor, room)**
Energy House	GL	Ground, Living Room
	GK	Ground, Kitchen
	GS	Ground, Stairs
	GE	Ground, External
	GCV	Ground, Conditioning Void
	FB1	First, Bedroom 1
	FB2	First, Bedroom 2
	FBA	First, Bathroom
	FS	First, Stairs
	FCV	First, Conditioning Void
Home1	GL	Ground, Living Room
	GK	Ground, Kitchen
	GH	Ground, Hall
	GS	Ground, Stairs

	FB1	First, Bedroom 1
	FB2	First, Bedroom 2
	FB3	First, Bedroom 3
	FL	First, Landing
	FS	First, Stairs
	FT	First, Toilet
	FBA	First, Bathroom

Table 4.1 Summary of the naming conventions used to identify each sampling point

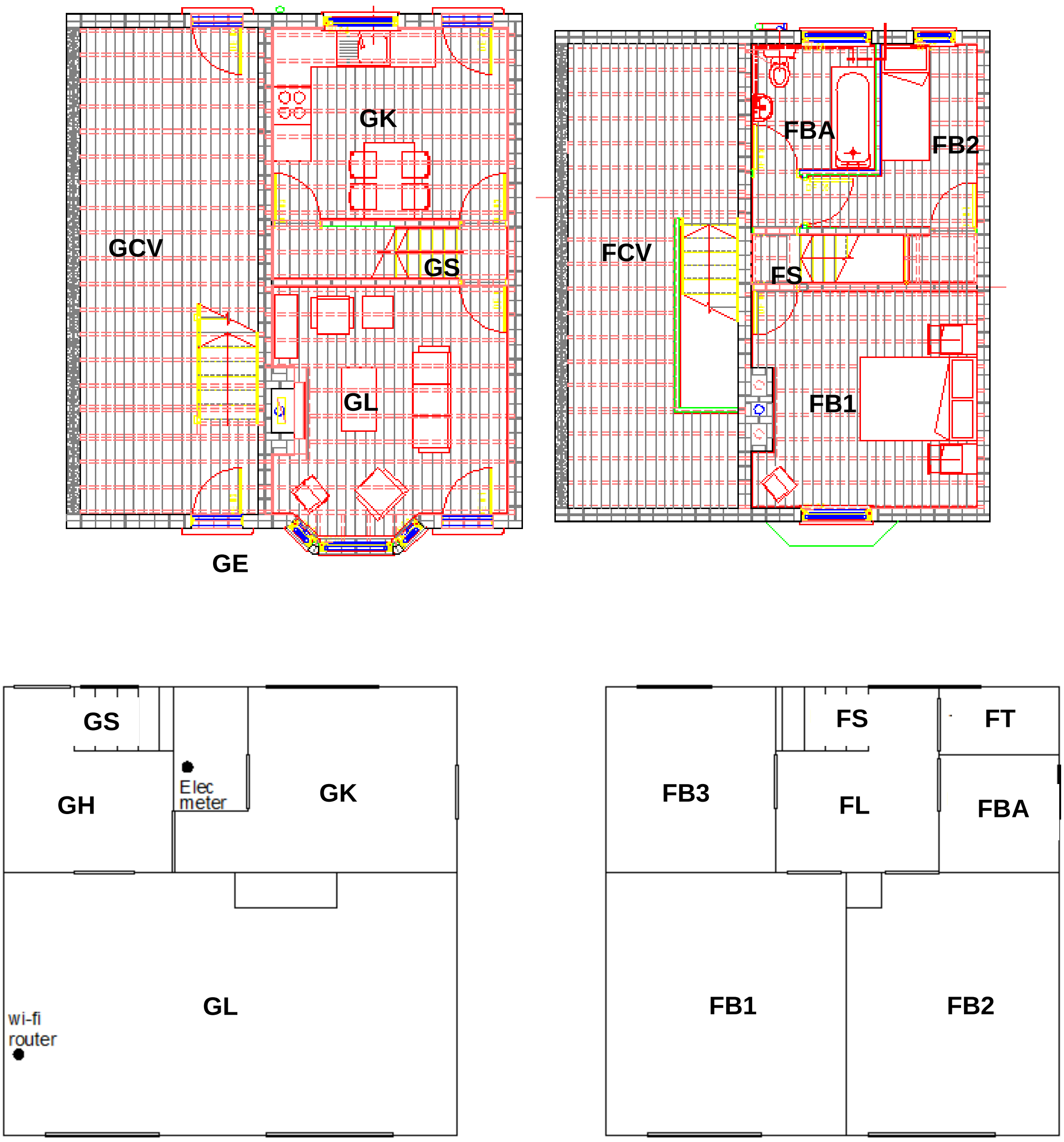


Figure 4.8 the locations that the naming convention refers to at the Salford Energy House (top) and Home1 (above)

4.3.2 Types of Tests

The purposes of the tests varied over the testing period and location. The specific aims and details of these tests are described below.

Signal Strength

Although signal strength was recorded throughout all the tests, some initial tests were specifically designed to map the signal strength behaviour of the prototypes at the testing locations. This was to derive a baseline understanding of how the prototypes behaved and to determine the effects of fixed and common building elements present, such as the centrally located chimney in Home1.

Orientation

The orientation tests were carried out to investigate the effect on signal strength of tilting the reader antenna in different orientations. This was in order to ensure the optimum orientation for the reader when deriving location from signal strength readings.

Examples of orientation tests include taking entire sets of readings with the RPi in the same location but at different orientations, such as at 45^{o} towards the floor, horizontal, and at 45^{o} towards the ceiling.

Environmental effects

Previous research [58] has suggested that environmental factors, such as temperature and humidity, have a significant impact on the performance of RFID systems. Tests were carried out in Home1 to investigate the effect of expected variations in temperature and humidity on the prototype in a domestic setting.

During these tests, the tags were placed in specified locations over a period of many hours and the signal strength was time-stamped and recorded to USB memory stick. During analysis the data was examined for changes in signal strength and compared to changes in local temperature, humidity, and weather conditions.

Home1 is not in a climate-controlled condition, unlike the Energy House, and does not include unusual or non-domestic activities that are expected to significantly affect the internal temperature and humidity levels. There is adequate natural ventilation and no damp or mould present.

The testing period was not taking place in the domestic heating season and some windows were usually open during the tests. Local meteorological conditions were most likely to influence the temperature and humidity within Home1.

The Met Office is the UK's national weather and climate service. As well as generating forecasts for the Public Weather Service and National Severe Weather Warning Service the organisation carries out a significant amount of research and records over 10 million weather observations every day.

The Met Office provides a wide range of data for researchers through their DataPoint scheme. For the purposes of these tests the UK hourly observations for the nearest observation station was obtained. The data provides hourly recorded information on nine parameters and 30 weather types available in xml format. The data variables recorded are shown in Table 4.2.

Parameter	**units**	**Weather Type**	
Wind Gust	mph	NA Not available	15 Heavy rain
Temperature	C	0 Clear night	16 Sleet shower (night)
Visibility	m	1 Sunny day	17 Sleet shower (day)
Wind Direction		2 Partly cloudy (night)	18 Sleet
Wind Speed	mph	3 Partly cloudy (day)	19 Hail shower (night)
Pressure	hpa	4 Not used	20 Hail shower (day)
Pressure Tendency	Pa/s	5 Mist	21 Hail
Dew Point	C	6 Fog	22 Light snow shower (night)
Screen Relative Humidity	%	7 Cloudy	23 Light snow shower (day)
		8 Overcast	24 Light snow
		9 Light rain shower (night)	25 Heavy snow shower (night)
		10 Light rain shower (day)	26 Heavy snow shower (day)
		11 Drizzle	27 Heavy snow
		12 Light rain	28 Thunder shower (night)
		13 Heavy rain shower (night)	29 Thunder shower (day)
		14 Heavy rain shower (day)	30 Thunder

Table 4.2. The nine parameters and 30 weather types available from the Met Office DataPoint hourly observations

The nearest Met Office observation station to Home1 was Rostherne No 2. The differences between the locations of Home1 and Rostherne No 2 are shown in Table 4.3. The differences between the two locations were considered to be minor and Rostherne No 2 was selected as the observation station to use observation data from.

	Home1	Rostherne No.2
location	53.4065, -2.1574	53.3598, -2.38053
altitude above mean sea level	67m	35m
distance between locations	10 miles	

Table 4.3 location differences between Home1 and Met Office observation station Rostherne No.2

The Met Office DataPoint observation data uses Greenwich Mean Time (GMT).

<u>Triple Point Positioning of Prototypes</u>

An essential element of the tests was to determine the optimum location and orientation of prototypes in order to locate the tag to an accuracy of room-level. In a cube the best locations for three sensors to be placed in order to determine the location of a tag within the cube is shown in Figure 4.9. Each of the three antennae is directed towards the opposite diagonal corner of the cube.

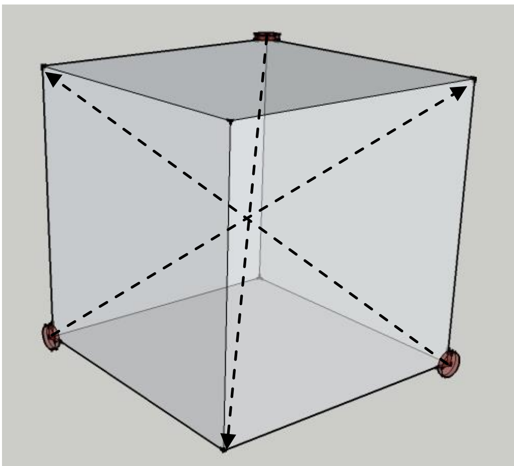


Figure 4.9 The ideal locations for readers when using triple points to locate tags within the cube.

Home1 can be considered to be a cube with a square footprint of 6.5 metres by 6.5 metres. Taking into account the practical limitations of the layout of Home1 the actual locations of the triple point positions for the RPi's are shown in Figure 4.10.

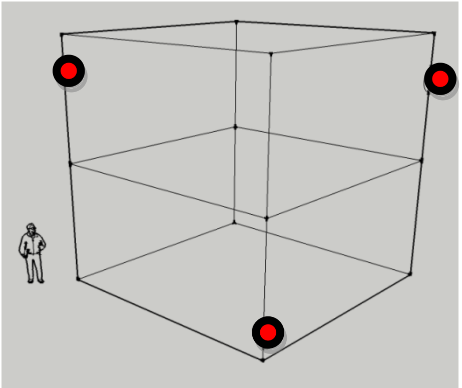


Figure 4.10.The nearest to ideal locations for the Rpi's for the triple point tests in Home1

Figure 4.11 shows the layout of Home 1 with the uses of those rooms.

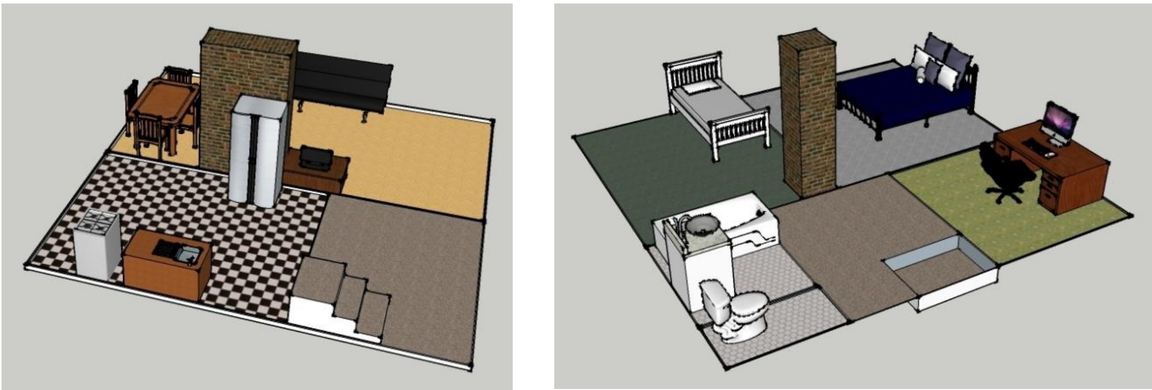


Figure 4.11.The layout of Home1 showing room usage on the ground floor (left) and first floor (right)

The actual locations of the three RPis during the triple tests in Home1 are shown in Figure 4.12. RPi1 was placed in bedroom 2, RPi2 in bedroom 3 (currently in use as an office), and RPi3 was located on the ground floor in the living room.

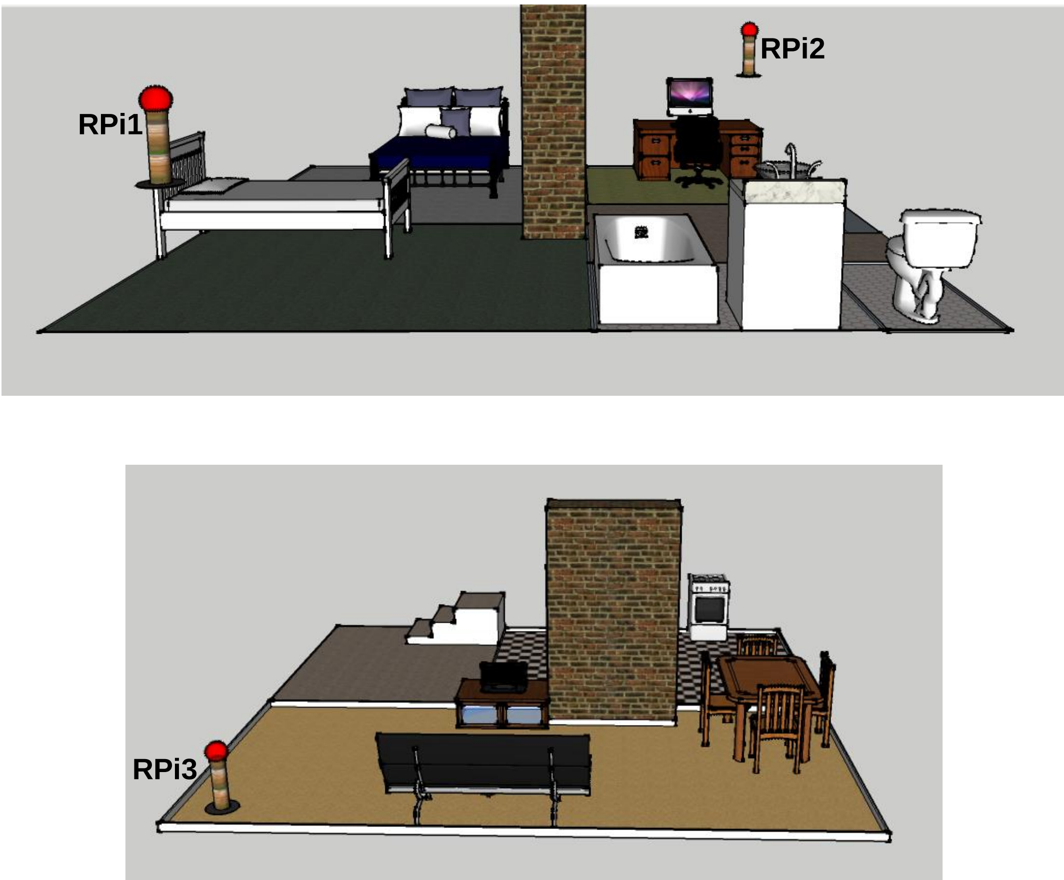


Figure 4.12 The actual locations of the RPi's within Home1 for the triple tests

During the triple tests, a RPi and prototype was placed in one of the specified triangulation points and communicated with one tag. The tag was moved between a reduced selection of sampling points that were chosen to cover the extents and space within the rooms. The 40 sampling points used in the triangulation tests is shown in Figure 4.13.

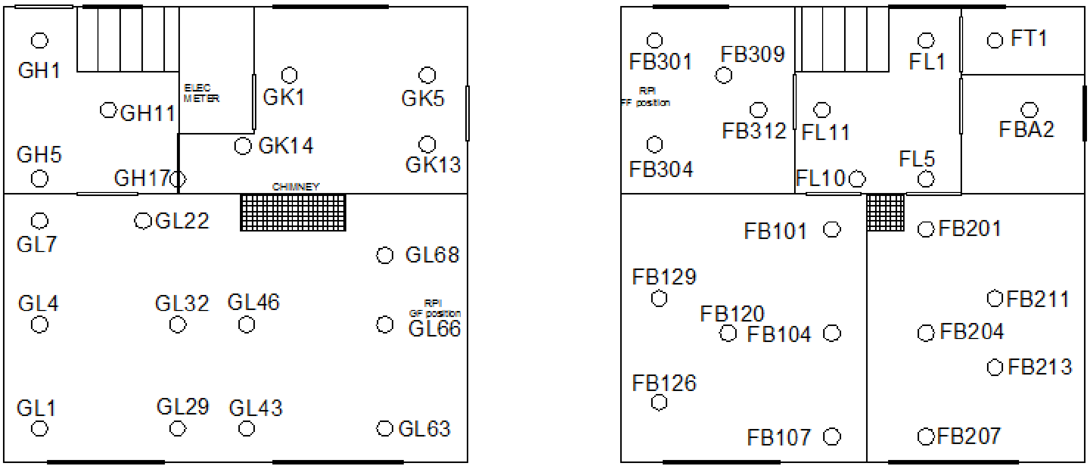


Figure 4.13.Map of sampling points used for triple tests

The test was repeated in each of the three RPi positions with the same RPi, prototype and tag. This was to reduce variances of performance between the tags and the readers. The resulting data from these tests provide three signal strength readings for each RPi triple point position for the 40 sampling points.

Mobile walk-through

In addition to tests with the tags at specific sampling points, a mobile walk-through was carried out in which the tag was worn by a person walking a specific route around Home1 while the signal strength was being continuously collected by the prototypes. The walk-through took 17 minutes to complete and included several pause points. The route and pause points are shown in Figure 4.14.

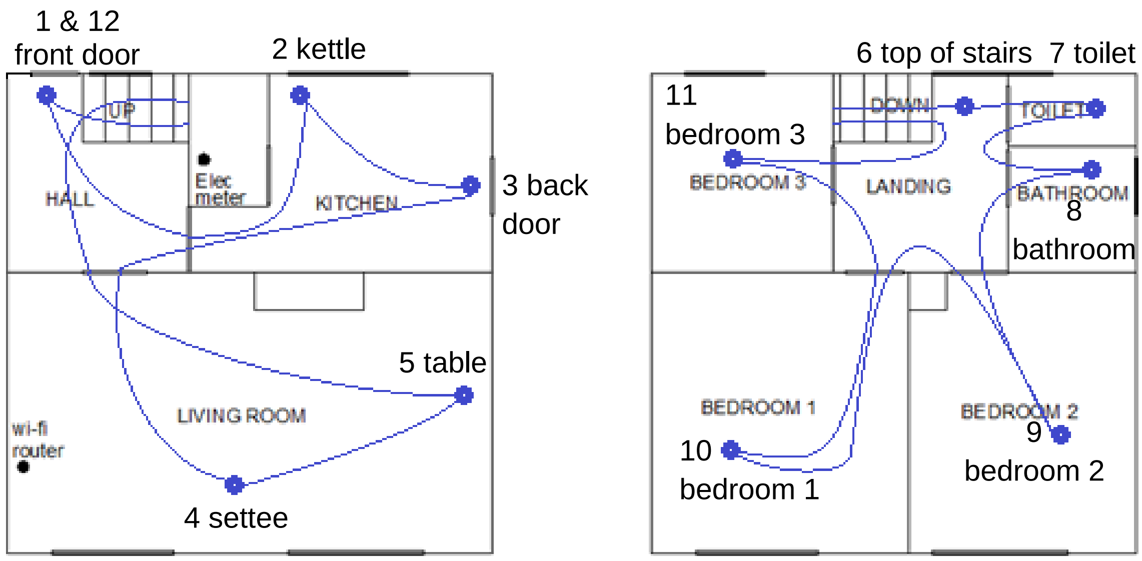


Figure 4.14 The walk-through route and 12 pause points at Home1, ground floor (left) and first floor (right)

The walk-through route was used in conjunction with the RPi triple point positions. The resulting data provides three signal strength readings (related to each RPi position) for the 12 known pause points and several more for the gaps between the pause points.

4.4 Data Collection

Signal strength data from the prototypes during experiments was recorded either manually with the sampling point location, or was saved in csv format locally to a

USB memory stick connected to the RPi and time-stamped. Data from the spectrum analyzer was recorded manually, and examples of the signal behaviour captured and saved on the device.

When the signal strength readings were saved to USB memory stick, the output from the RPi presents ten readings and ten timestamps for each tag on each line before moving on to the next tag. The form and timings of this output data is described in Table 4.4.

	18 seconds from Tag1 timestamp1 to Tag1 timestamp10																				
Tag1	r1	t1	r2	t2	r3	t3	r4	t4	r5	t5	r6	t6	r7	t7	r8	t8	r9	t9	r10	t10	--
8 seconds between Tag1 timestamp10 and Tag2 timestamp1																					
Tag2	r1	t1	r2	t2	r3	t3	r4	t4	r5	t5	r6	t6	r7	t7	r8	t8	r9	t9	r10	t10	
Tag3	r1	t1	r2	t2	r3	t3	r4	t4	r5	t5	r6	t6	r7	t7	r8	t8	r9	t9	r10	t10	
Tag4	r1	t1	r2	t2	r3	t3	r4	t4	r5	t5	r6	t6	r7	t7	r8	t8	r9	t9	r10	t10	
	87 seconds between Tag1 timestamp10 to the next Tag1 timestamp1																				
Tag1	r1	t1	r2	t2	r3	t3	r4	t4	r5	t5	r6	t6	r7	t7	r8	t8	r9	t9	r10	t10	

where:

r = signal strength reading

t = time-stamp

Table 4.4. the form of the lines of the output file with timings indicated

Reading the tags over an extended period of time results in multiple lines. The output from 24 hours results in 833 lines of results and returns 8330 signal strength readings for each tag.

When the Rohde & Schwarz FSH3 Handheld Spectrum Analyzer was used during tests, the signal was observed and recorded manually. An example of the signal transmitted from a tag is shown in Figure 4.15. The signal can be seen to be symmetrical with a central frequency of 2.445GHz and a span of approximately 2.4MHz. The peak signal strength occurred at the central frequency and this was recorded at each sampling point.

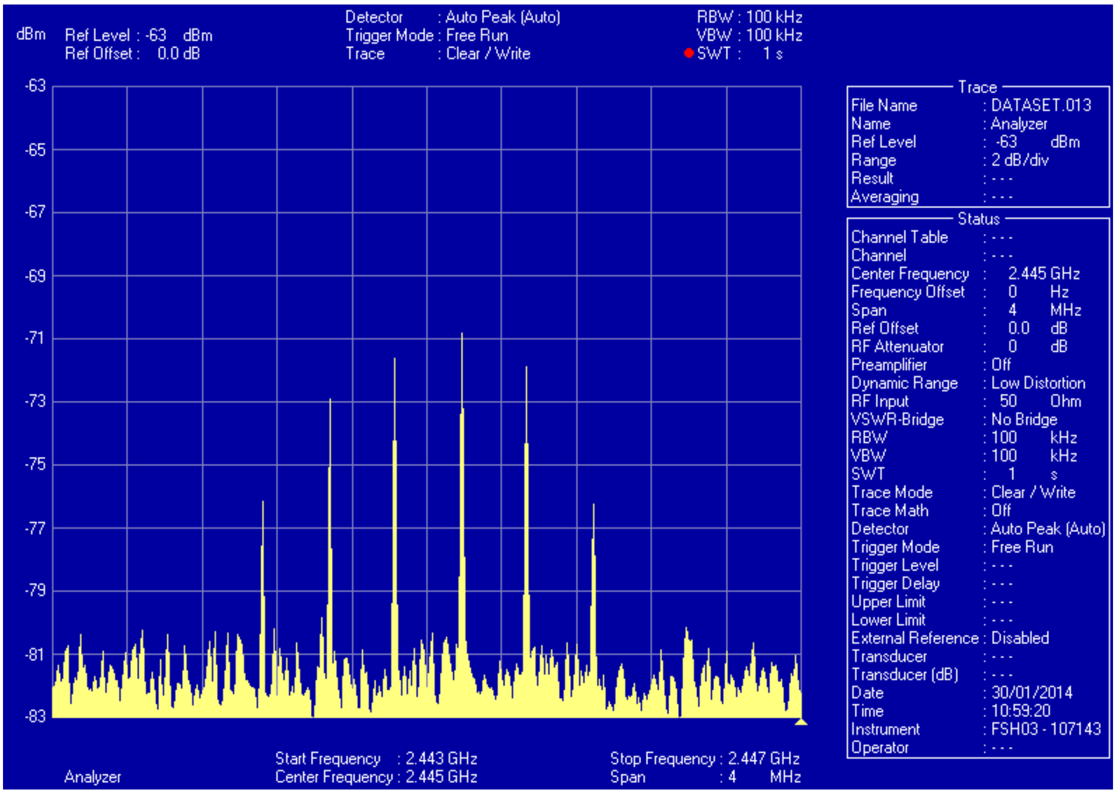


Figure 4.15 Output from the spectrum analyzer showing a peak tag signal at -71dBm during tests at the Salford Energy House

4.5 Data Analysis

From the recorded signal strength data, heatmaps were constructed as CAD drawings using different colours to indicate the signal strength at each sampling point. Figure 4.16 shows a heatmap from one of the tests at the Salford Energy House. This shows that the majority of the sampling points inside the house gave a signal strength reading of SSN5 to SSN8, with the remaining three interior locations closest to the RPi giving a SSN9. It can also be seen that the signal remains very strong on the first floor.

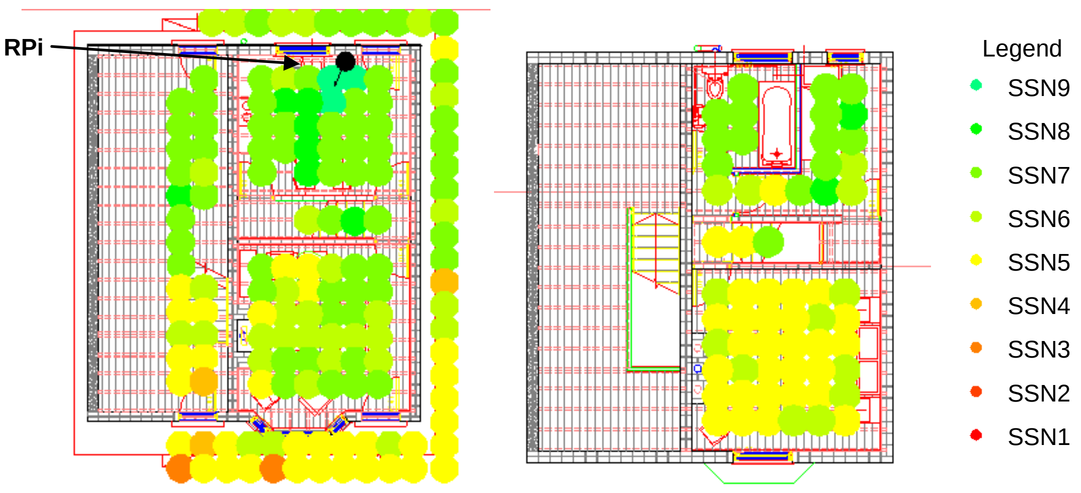


Figure 4.16. Example of a heatmap from a test at the Salford Energy House (ground floor (left) and first floor (right)). The RPi position and reader direction indicated as in the kitchen and towards the opposite corner of the house.

The heatmaps show the effect on signal strength of distance from the RPi, and obstructions between the reader and the tag. Heatmaps constructed from experimental data was also compared with anticipated signal strength heatmaps from signal modelling software. Figure 4.17 shows a model of the same test at the Salford Energy House.

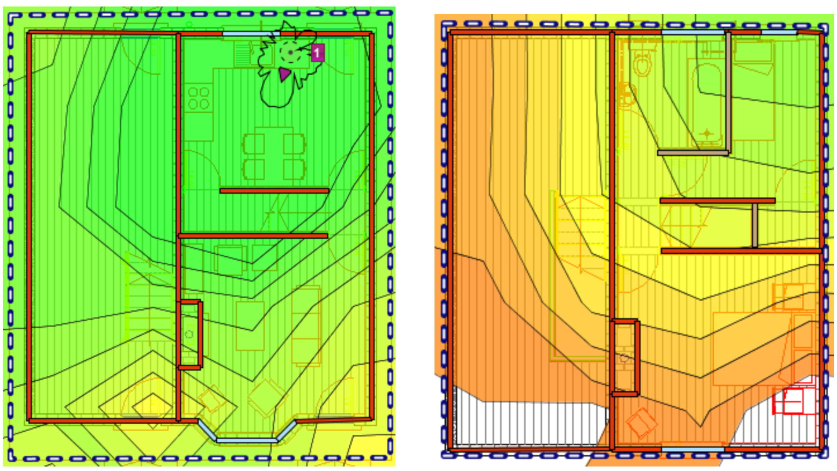


Figure 4.17. Heatmap of the Salford Energy House ground floor (left) and first floor (right) using Ekahau ESS Pro 7.6.4 software.

The software used to model heatmaps at the testing locations was the Ekahau ESS Pro 7.6.4 site surveying software from Ekahau, Inc.[59]. This licensed software, which was generously donated for the purposes of this research, allows the user to upload floorplans and add specific details, such as wall, ceiling and floor construction. There is a great deal of flexibility in choice and placement of

Access Point, and in multifloor buildings the signal is predicted throughout all floors wherever the Access Point is placed.

There are 976 Access Point antennae to choose from in the software. The one used in the modelling for this project was the Motorola ML-2499-BYGA2-01R 2.4GHz 15 dBi 35 Degree Yagi because this has the most similar attenuation profile to the prototype. Azimuth and elevation patterns of the selected antenna can be found in Appendix E.

In addition to the location of the Access Point, the height above floor level and orientation were specified. The modelled signal strength indicated on the heatmaps is what signal would be expected at a height of 1 metre above floor level.

As well as the data being used to produce signal strength heatmaps, the resulting data was also manipulated in csv format, subject to smoothing algorithms, and used to create relevant charts and graphs for analyses.

4.6 Summary

This chapter has set out how the prototype was developed and how the equipment was used. Detailed information of the testing locations and their construction has been presented. It has been shown that the testing protocol was consistent across locations and different types of tests. All stationary sampling points were placed on a 1 metre grid and at a height of 1 metre above floor level. The resulting signal strength data was recorded either manually or automatically saved to USB memory stick depending on the type of test being carried out.

Information has been presented to validate the choice of environmental data from the nearest Met Office observation station, and the methods of data analysis discussed. Manipulation of the data and production of signal strength heatmaps and simulations were executed in a consistent manner throughout the tests in order to absent the researcher as much as possible to avoid potential influence and increase comparability between datasets.

Chapter Five

5 Test Results Analysis

This chapter presents the results of the testing carried with the prototype. Section 5.1 details the results of the spectrum analyzer and Sections 5.2 and 5.3 show the results from the Salford Energy House and Home1 respectively.

Section 5.4 sets out the results of the tests investigating potential environmental factors that could influence the signal strength, including temperature, humidity, occupation, and the effects of having more than one prototype active at the same time.

Results from placing the prototypes in the previously defined triple point positions (Chapter Four) are presented in Sections 5.5 and 5.6. Data collected from stationary sampling points are presented in addition to data from a mobile walk-through test. This chapter closes with a summary of the findings from the investigations in Section 5.7.

5.1 Spectrum Analyzer

Signal strength heatmaps from three tests using the spectrum analyzer at the Salford Energy House are presented in Figures 5.1, 5.2, and 5.3. In the heatmaps the location of the RPi and prototype are indicated and the signal strength is colour coded. The sampling points that are the brightest green indicates the strongest signal and dark red indicates the weakest or no discernible signal present, as shown in Table 5.1.

Sampling Point Colour	Signal Strength (dBm)
	-50 to -54
	-55 to -59
	-60 to -64
	-65 to -69
	-70 to -74
	-75 to -79
	-80

	No discernible signal

Table 5.1. Legend to the Spectrum Analyzer signal strength heatmaps

During Test 1 the prototype was located in the living room and directed downwards. The resulting spectrum analyzer heatmap shows that the signal strength in the living room is very strong, and reduces considerably further away. The signal strength in the kitchen, bedroom 2 and bathroom was very weak.

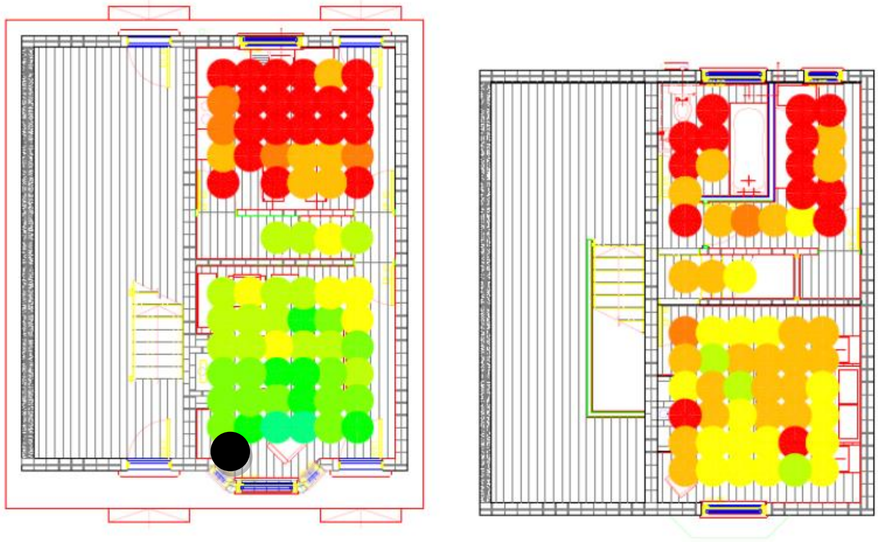


Figure 5.1. Spectrum analyzer results from Test 1 at the Salford Energy House, ground floor (left) and first floor (right)

The prototype was located in the same position in the living room and directed diagonally across the house towards the back door in Test 2. Figure 5.2 shows that the resulting signal strength continues to be strongest in the same room and that the signal strength in the kitchen, bedroom 2 and bathroom is improved.

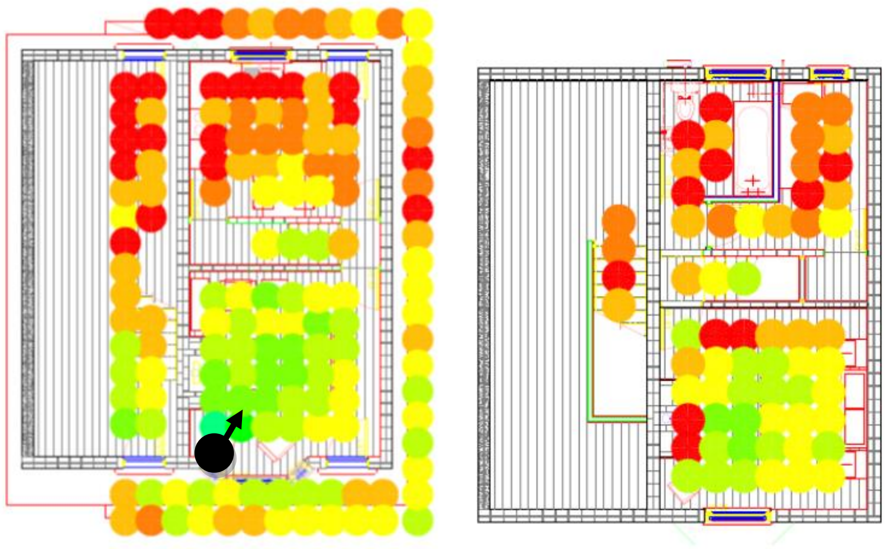


Figure 5.2. Spectrum analyzer results from Test 2 at the Salford Energy House, ground floor (left) and first floor (right)

Placing the prototype in the kitchen and directing the antenna towards the opposite diagonal corner of the house gave the results shown in Figure 5.3. In this case the signal strength is strongest in the same room, and in the rooms directly above, as the prototype. The results in the living room suggest a disruption of the signal strength, in the form of a shadow cast by the storage space under the stairs.

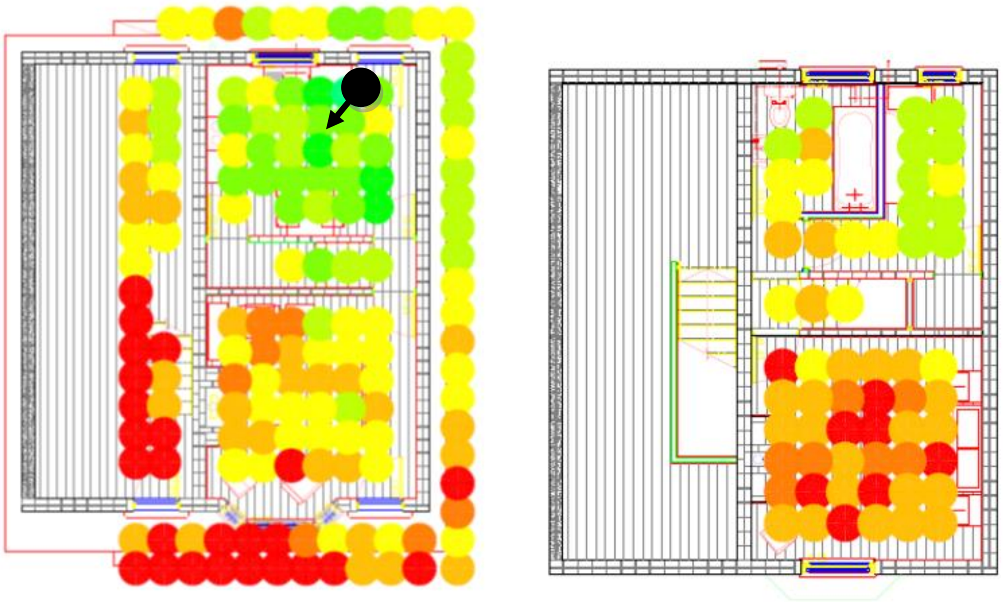


Figure 5.3. Spectrum analyzer results from Test 3 at the Salford Energy House, ground floor (left) and first floor (right)

Figure 5.4 shows a comparison of the simulated signal strength by the Ekahau software and the actual results from the spectrum analyzer. This shows that the observed actual signal strength behaviour is very different from the heatmap predicted by the modelling software. Possible causes of the difference between the modelled and actual signal strength patterns include the inability to model the fact that the Energy House is built within another building. The surrounding construction and metallic elements around the Energy House appear to cause a great deal of disturbance on signal propagation within the house, resulting in the high incidence of no discernible signal received by the spectrum analyzer (indicated by red signal strength testing points).

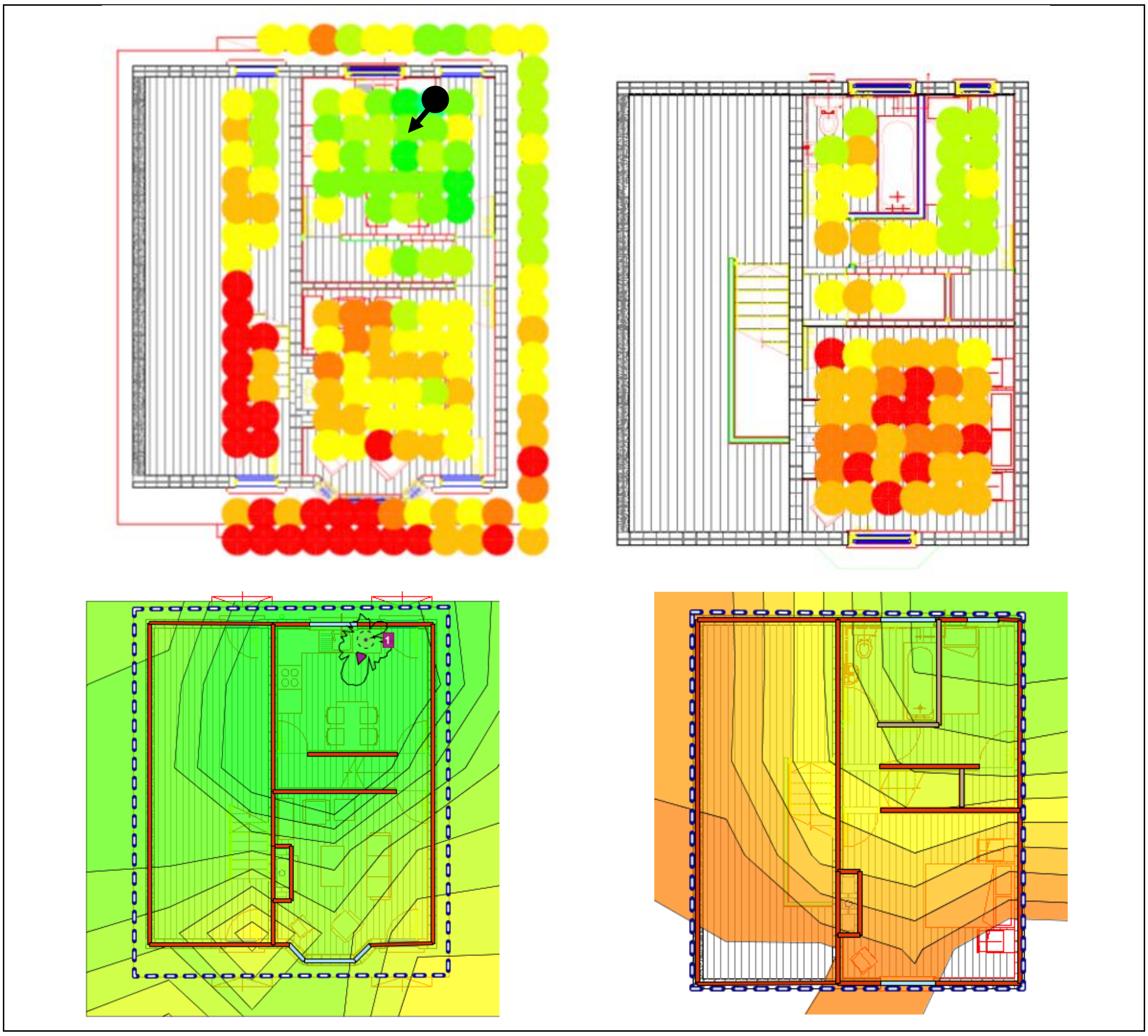


Figure 5.4 Comparison of the spectrum analyzer results (top) and Ekahau modelling of the Energy House, ground floor (left) and first floor (right)

While using the spectrum analyzer the broad spectrum signal transmitted by the Loc8tor PCB to the tags was captured and is shown in Figure 5.5. This signal was how the Loc8tor receiver activated the tags in order to commence reading the signal strength from the tags. The wake-up signal peaked at almost -40dBm at a centre frequency of 2.445GHz.

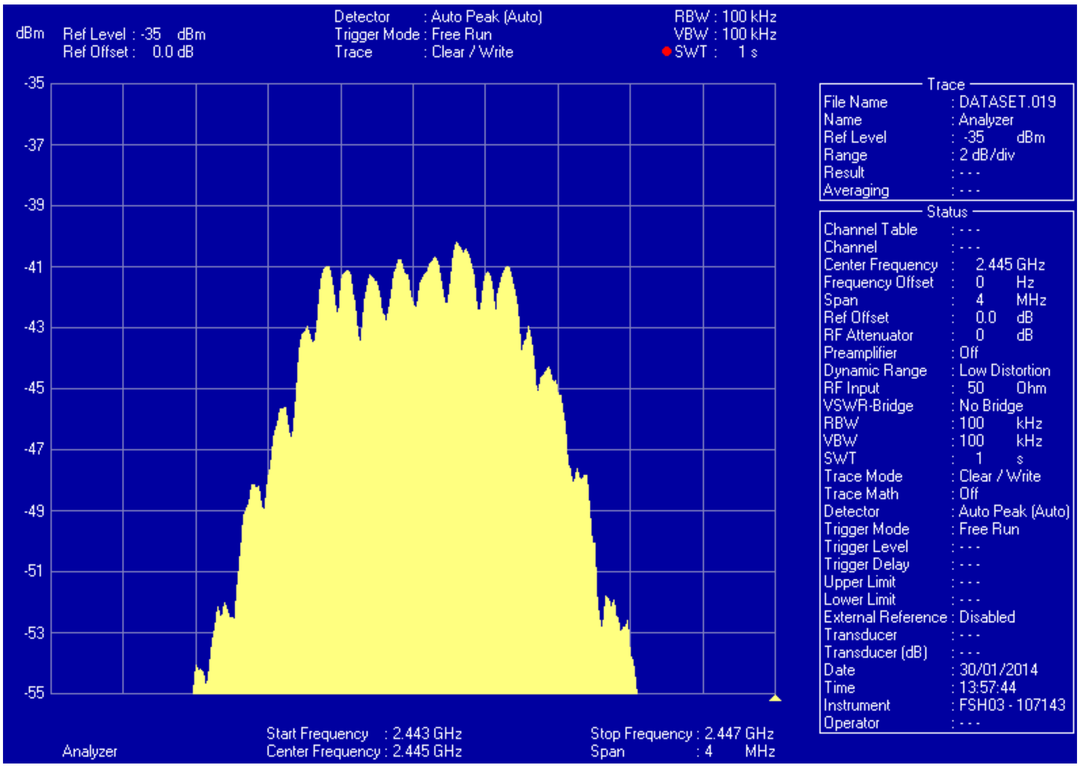


Figure 5.5 Example of the broad spectrum signal from the Loc8tor handheld unit to activate a tag

During testing there were several occasions when the signal strength from the tag was not distinguishable from the background. A typical example of this is shown in Figure 5.6.

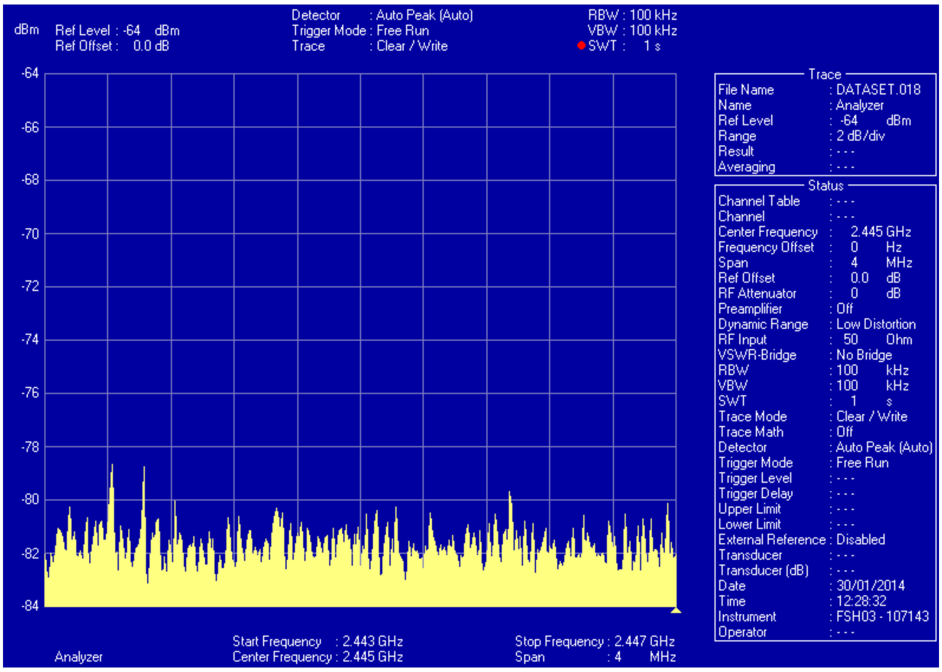


Figure 5.6 Example of Spectrum Analyzer with no distinguishable signal strength visible above the background

5.2 Salford Energy House

The purpose of the Energy House tests was to gain knowledge of the performance and characteristics of the prototype, and to investigate the potential to locate the tag by room level with one or more prototypes.

This section presents the resulting signal strength heatmaps from three tests at the Salford Energy House, and analysis of two of the tests with regards to using the combined signal strength readings to determine tag location. The legend for the SSN heatmaps is shown in Table 5.2.

Sampling Point Colour	RPi signal strength (SSN)
	9
	8
	7
	6
	5
	4
	3
	2
	1

Table 5.2 Legend for the SSN heatmaps

During the first test at the Energy House the prototype was placed in the living room as indicated in the heatmap (Figure 5.7) and was aimed towards the floor. The signal strength results show that while the strongest signal strengths, SSN7 and SSN8, were found in the living room close to the RPi these were also found in the conditioning void and external areas through a brick wall.

Strong signal strengths of SSN7 and SSN6 were also found on the first floor in the bedroom directly above the living room, and on the first floor of the conditioning void. The weakest signal strength during this test was SSN1 in the kitchen despite being on the same floor level as the RPi.

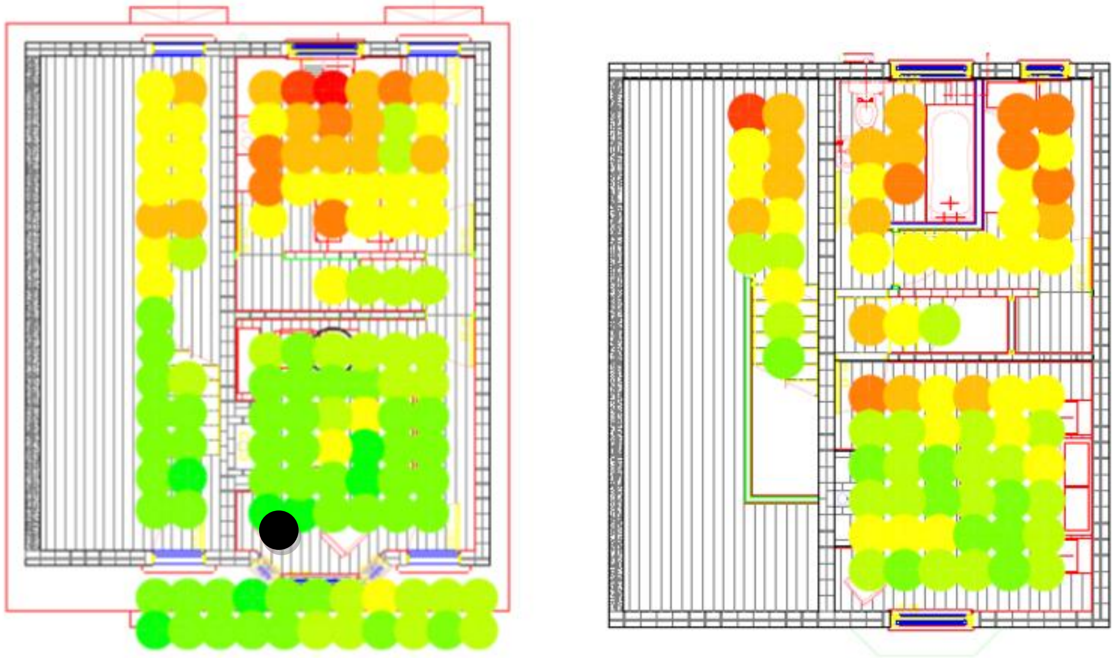


Figure 5.7. RPi results from Test 1 at the Salford Energy House, ground floor (left) and first floor (right)

During Test 2 the prototype was in the same location as Test 1, in the living room, and was pointed horizontally diagonally across the house towards the back door, as shown in Figure 5.8.

The resulting heatmap indicates stronger signals than Test 1 in the whole of the living room, with all the sampling points being SSN9, SSN8, or SSN7 compared to most points being SSN5, SSN6, and SSN7 in Test 1. The signal strength in bedroom 1 is also stronger and mostly SSN7 with some SSN8 and SSN6 compared to signal strengths of SSN3, SSN4, SSN5, SSN6, and SSN7 during Test 1.

The same area of the kitchen remains a weak signal strength zone, although the lowest signal is SSN3 rather than SSN1 observed in the previous test. It is however more apparent that the obstruction under the stairs casts a shadow that significantly reduces signal strength in the kitchen during Test 2. The cause of the signal disturbance was a bank of 14 meters and submeters located in the storage space under the stairs.

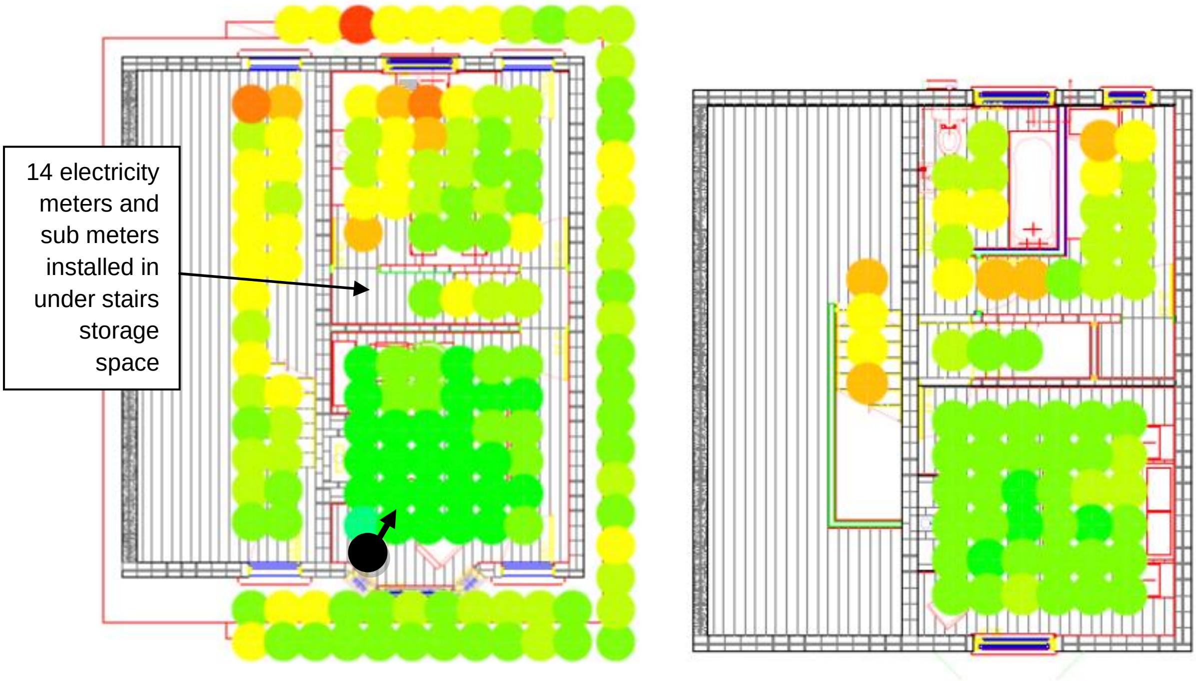


Figure 5.8. RPi results from Test 2 at the Salford Energy House, ground floor (left) and first floor (right)

During Test 3 the prototype was located in the kitchen, with the antenna horizontal and directed diagonally across the house towards the corner of the living room that was the location of the previous test.

The resulting heatmap (Figure 5.9) shows that the meters and sub-meters under the stairs obstruct the signal strength in the living room. Signal strength in the kitchen, in the same room as the prototype, is the only location that SSN9 is observed. The second strongest signal strength, SSN8, is also observed in the kitchen and other locations (ground floor conditioning void, stairs, and bedroom 2).

The dominant signal strengths throughout the house are SSN7 (kitchen, stairs, living room, bedroom 2, bathroom) and SSN6 (stairs, living room, bedroom 1, bedroom 2, bathroom). SSN5 occurs mostly in bedroom 1.

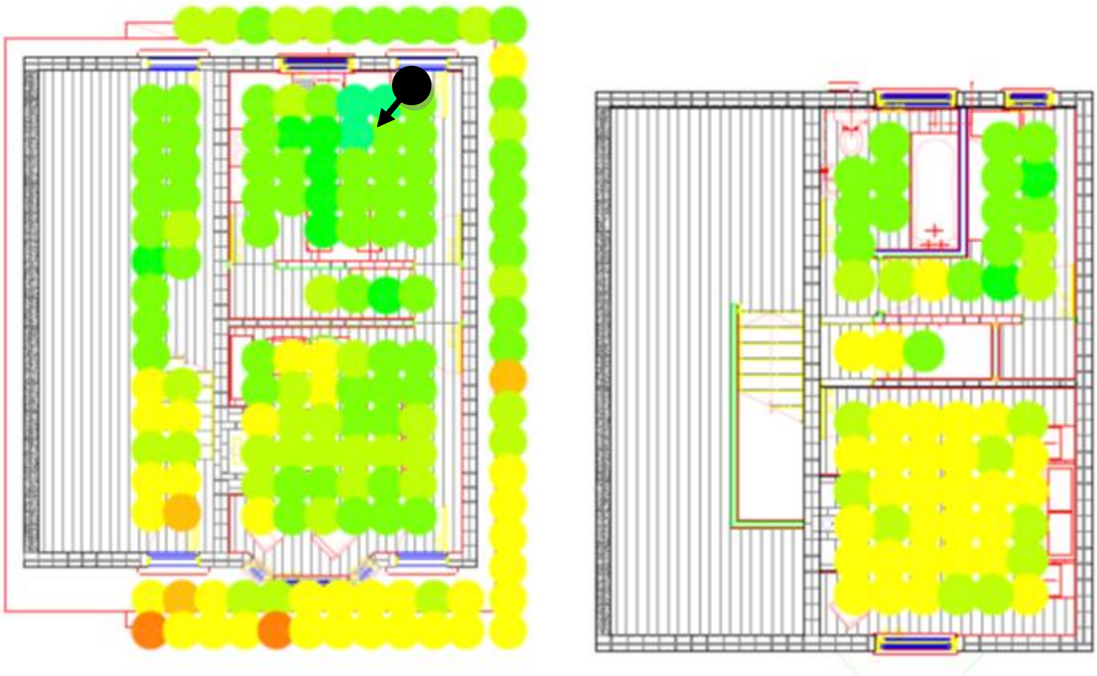


Figure 5.9. RPi results from Test 3 at the Salford Energy House, ground floor (left) and first floor (right)

In order to evaluate the viability of using data from two tests to determine the tag location to room level, the results of Test 2 and Test 3 were analysed further. Combining the signal strengths so that each sampling point had two signal strengths in the following format: (*a, b*) where *a* was the signal strength from Test 2, and *b* was the signal strength from Test 3. This allowed identification of locations with the same combinations.

Figure 5.10 shows the locations of the most commonly occurring combinations from Test 2 and Test 3. Unlike previous heatmaps, these colours are not an indication of signal strength but rather each colour denotes locations with the same signal strength combinations.

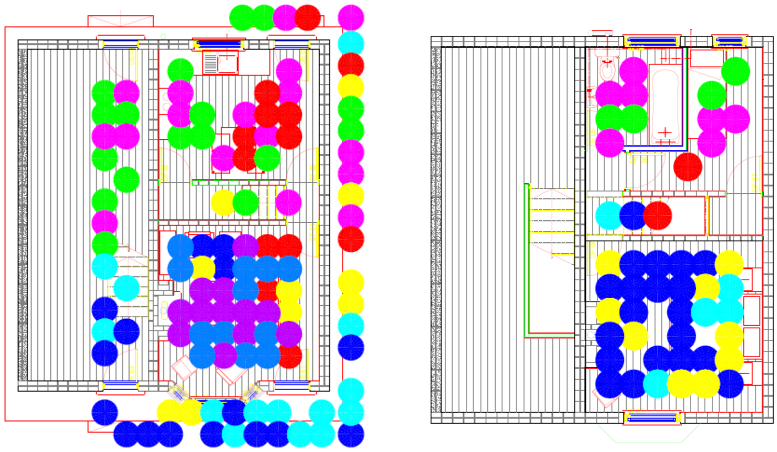


Figure 5.10 all the locations of the most commonly occurring signal strength combinations from the Energy House tests 2 and 3.

As can be seen from the mapping of the eight most common combinations, 143 of the sampling points (equivalent to 70% of the total number of sampling points) are represented.

The most frequent combination was (7, 5) and resulted from a signal strength of SSN7 in Test 2 and SSN5 in Test 3. These account for 36 sampling points, which is 18% of the total number of sampling points. The locations that this combination occurred are shown in Figure 5.11.

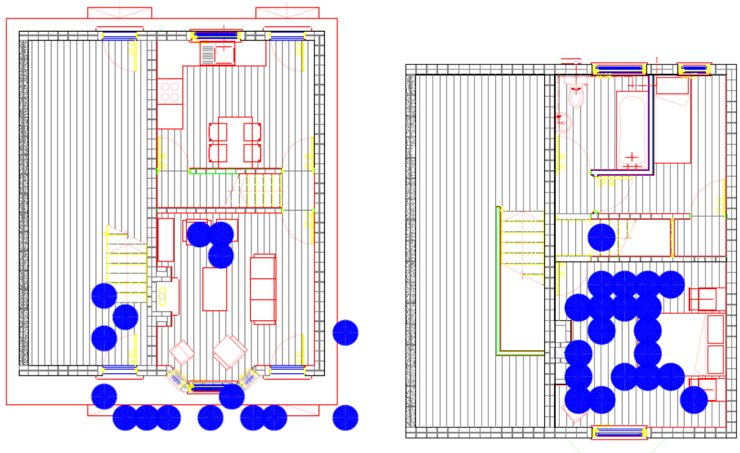


Figure 5.11 the most common combination (7, 5) occurred at 36 sampling points

Signal strength combination (7, 5) occurred most often in bedroom 1, but was also found in the living room and first floor stairs. The second most common combination was (6, 7) and occurred at 24 sampling points (12% of the total sampling points). The locations of these points is shown in Figure 5.12.

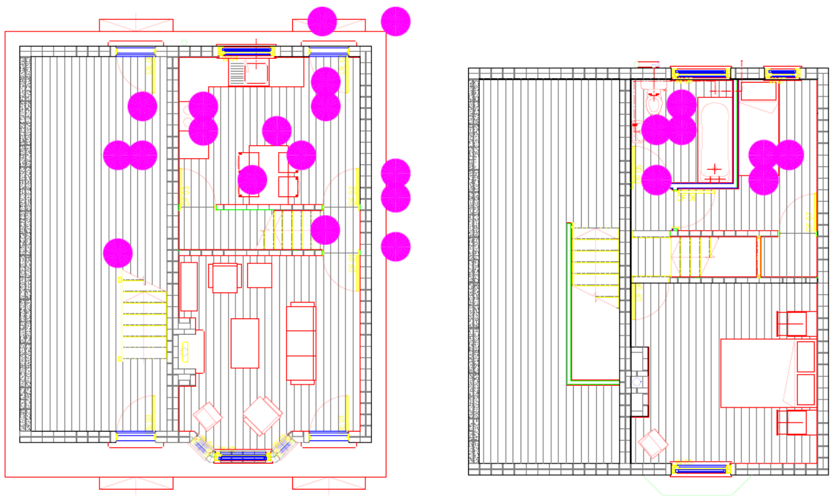


Figure 5.12 the locations of signal strengths (6, 7)

(6, 7) is most likely to occur in the kitchen, but it also found in the bathroom, bedroom 2 and ground floor stairs. The location of 21 sampling points (10% of total) with a combination of (5, 7) is shown in Figure 5.13..

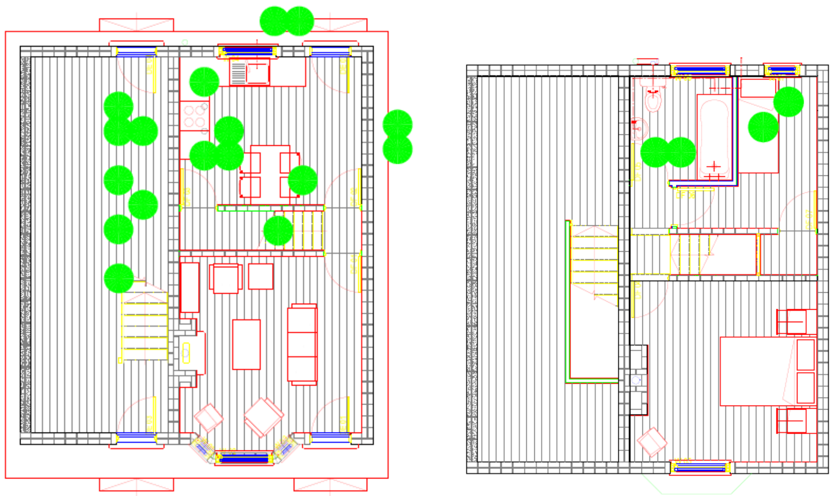


Figure 5.13 The 21 locations with a combination of (5, 7)

(5, 7) could indicate tag location of kitchen, bathroom, bedroom 2, or ground floor stairs. Figure 5.14 shoes the nineteen sampling points that shared a combination of (7, 6). This could indicate a tag location of living room, bedroom 1 or first floor stairs.

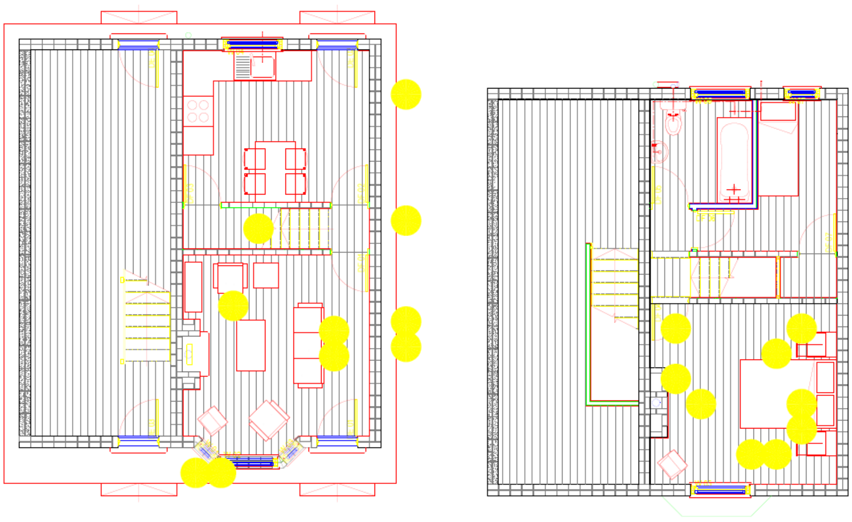


Figure 5.14 Nineteen sampling points share a combination of (7,6)

Another nineteen sampling points shared a combination of (6, 5), as shown in Figure 5.15. This combination could locate a tag in bedroom 1 or the first floor stairs.

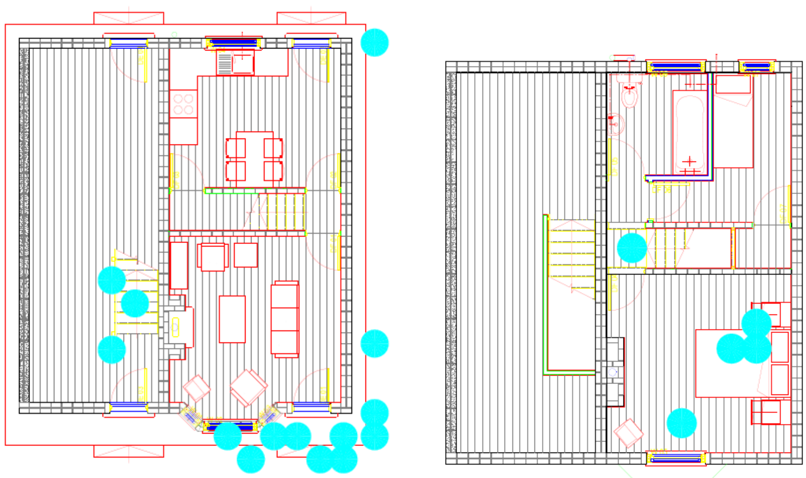


Figure 5.15 Nineteen sampling points with a combination of (6,5)

The only combinations that only occurred in one location were (8, 6) and (8, 7). There were twelve each of these combinations and they all occurred in the living room. This is shown in Figure 5.16.

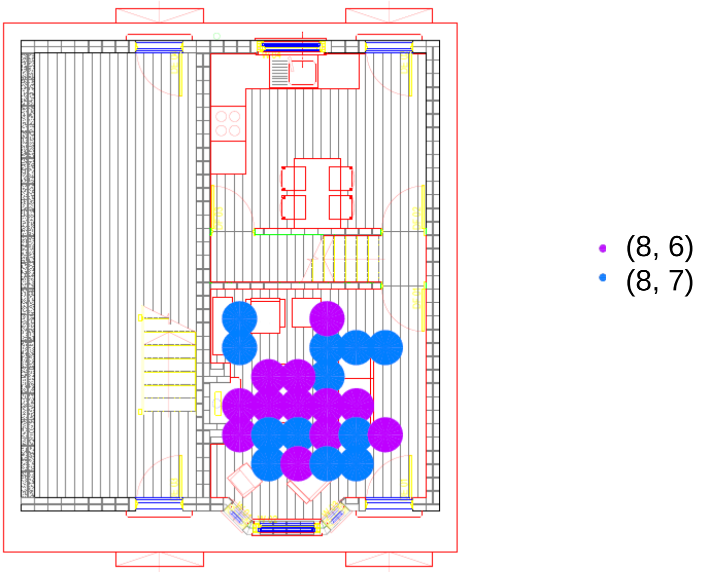


Figure 5.16 (8, 6) and (8, 7) only occurred in the living room

Further analysis of the combinations showed that there were 22 sampling points that resulted in the same signal strength reading from both tests. These are shown in Figure 5.17. The 22 sampling points that had the same signal strength were spread across the kitchen, living room, bedroom 2 and first floor stairs.

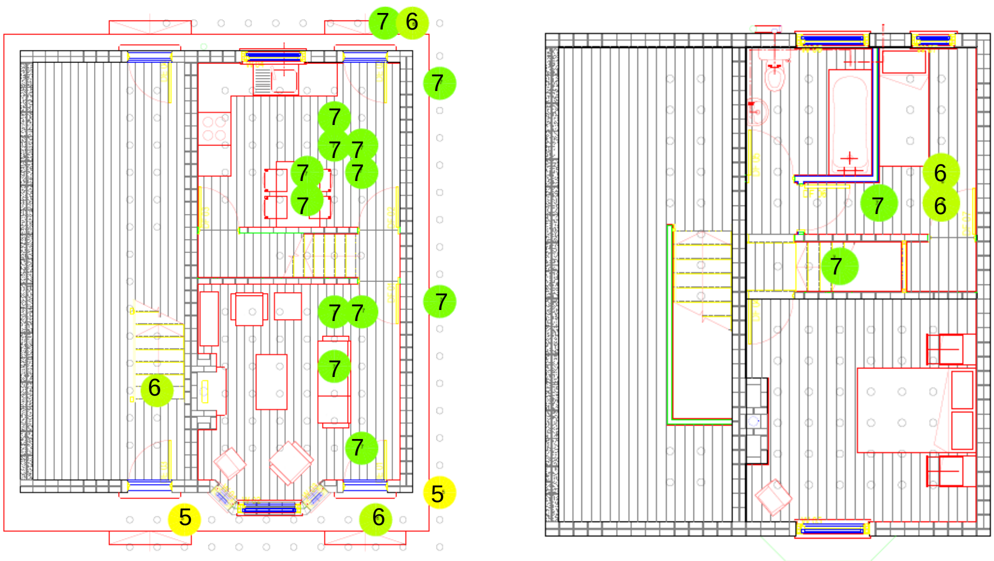


Figure 5.17. Twenty two sampling points that had the same signal strength in both tests

Comparison of the results obtained in Energy House Test 2 and the model generated by the Ekahau software (Figure 5.18) shows that the shadow cast by the meters and sub-meters located in the Energy House is not replicated in the simulated signal strength heatmap.

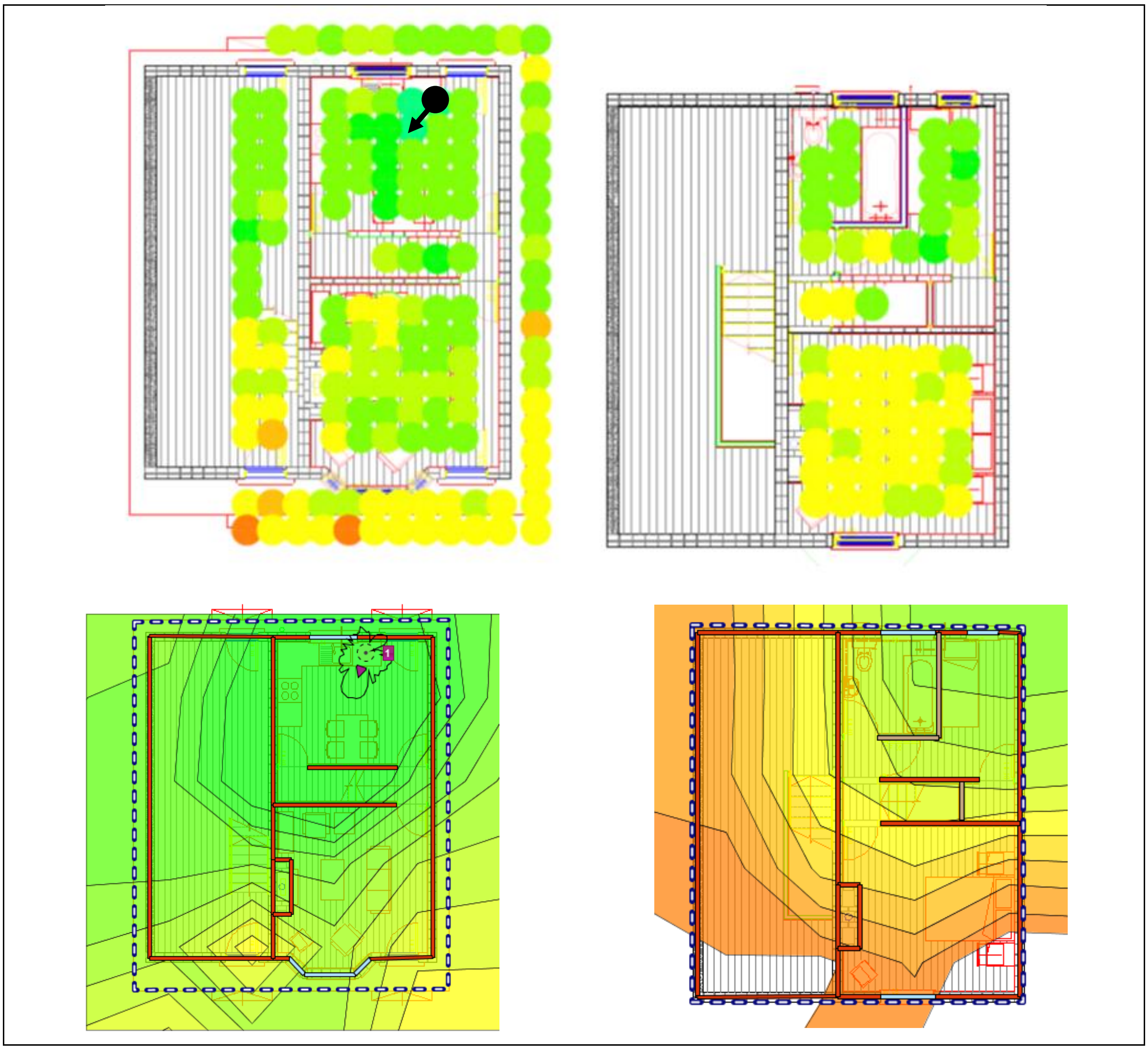


Figure 5.18 Comparison of modelled signal strength (bottom) and actual signal strength (above) at the Salford Energy House, ground floor (left) and first floor (right)

Analysis of the signal strengths obtained with the spectrum analyzer and from the prototype was carried out to discover the relationship between dBm and SSN. As can be seen from Figure 5.19 the comparison shows a great deal of overlap and does not allow identification of the actual signal strength ranges indicated by the SSNs. The only SSN that correlates with a dBm range that does not occur with other SSNs is SSN9 that is present when the spectrum analyzer signal strength results are between -50 to -54dBm.

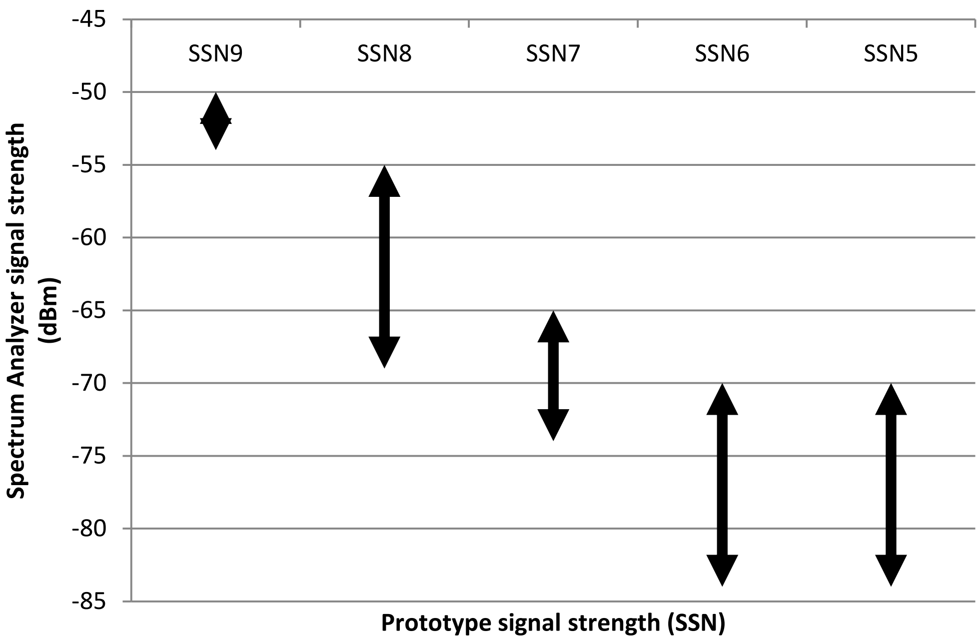


Figure 5.19. Comparison of spectrum analyzer and prototype signal strength

5.3 Home1

The Home1 tests were carried out to investigate how the prototype behaved in a typical residential location as opposed to the laboratory conditions of the Salford Energy House. The heatmaps were produced using the existing protocol.

Sampling Point Colour	RPi signal strength
●	9
●	8
●	7
●	6
●	5
●	4
●	3
●	2
●	1

Figure 5.3 Legend for the Home1 signal strength heatmaps

The results for the tests in Home1 are presented here in the order they were carried out. In Test 4 the prototype was placed in the living room, horizontal and directed diagonally towards the front door, as shown in Figure 5.20.

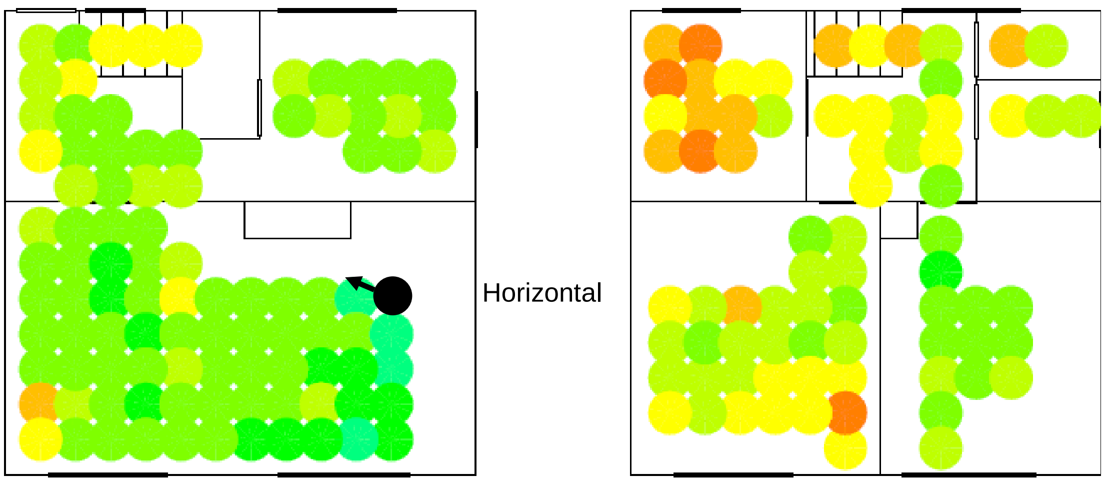


Figure 5.20 Home1 Test 4 with the RPi placed in the living room, horizontal and directed towards the front door. Ground floor (left) and first floor (right)

With the prototype horizontal in the living room the strongest signal strengths (SSN9 and SSN8) are only found in the same room. SSN7 is commonly found throughout the ground floor and in locations directly above the RPi on the first floor. The weakest signal (SSN3) was only found on the first floor, and generally clustered in the furthest sampling points from the RPi position. During Home1 Test 5 the RPi was placed in the same position and at the same direction as the previous test and inclined 45^{o} upwards towards the ceiling.

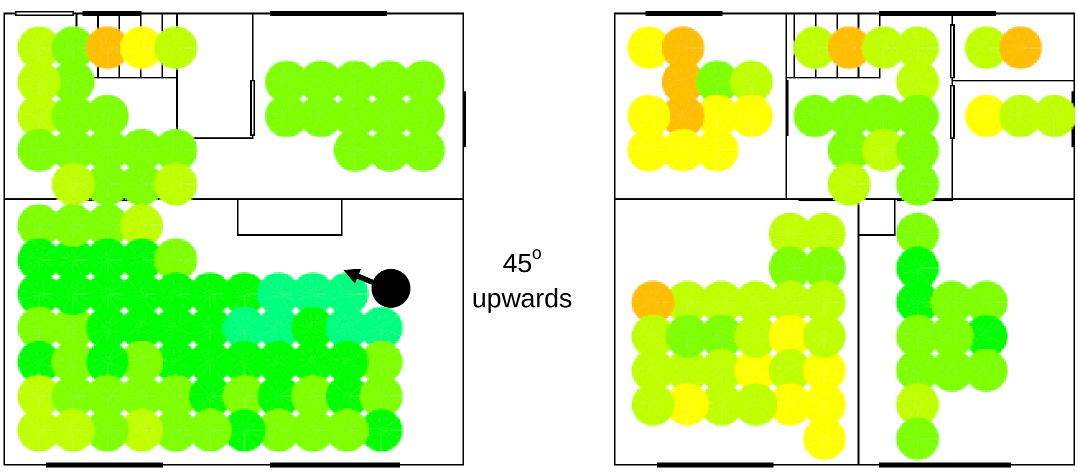


Figure 5.21 The results of Home1 Test 5, ground floor (left) and first floor (right)

Figure 5.21 shows that the effect of inclining the reader 45^{o} towards the ceiling greatly increases the number of the highest signal strength readings in the living room, and has a general influence to increase the signal strengths on the first floor. The weakest signal observed is SSN4, and seen in fewer locations that in the previous test. The effect of the full height brick built chimney breast in the centre of the house is seen to affect the signal strengths found in bedroom 3 and the ground floor stairs in both Test 4 and 5.

Test 6 was the first test with the prototype placed on the first floor, as indicated in Figure 5.22. The RPi was horizontal and directed towards the opposite diagonal corner of the house.

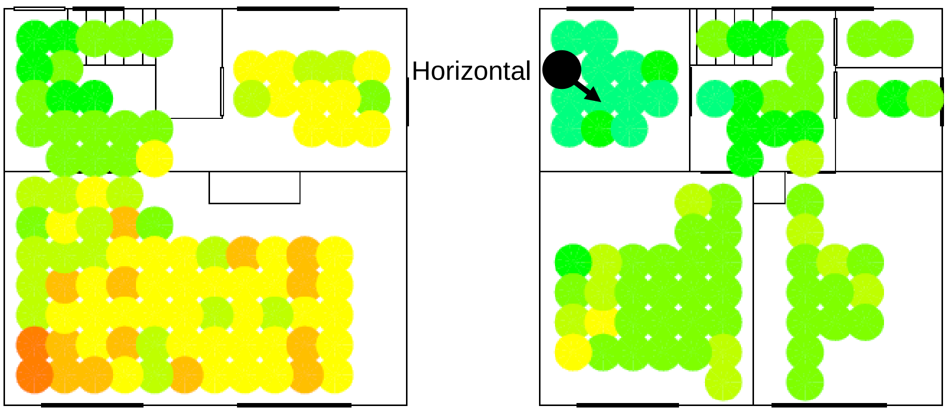


Figure 5.22. Heatmap of Home1 Test 6, ground floor (left), first floor (right)

With the prototype horizontal and on the first floor, the signal strengths are lowest (SSN3) at the bottom left hand corner of the house, in the living room. Figure 5.23 shows the resulting heatmap from Home1 Test 7, in which the RPi was placed on the first floor and inclined at 45^o upwards.

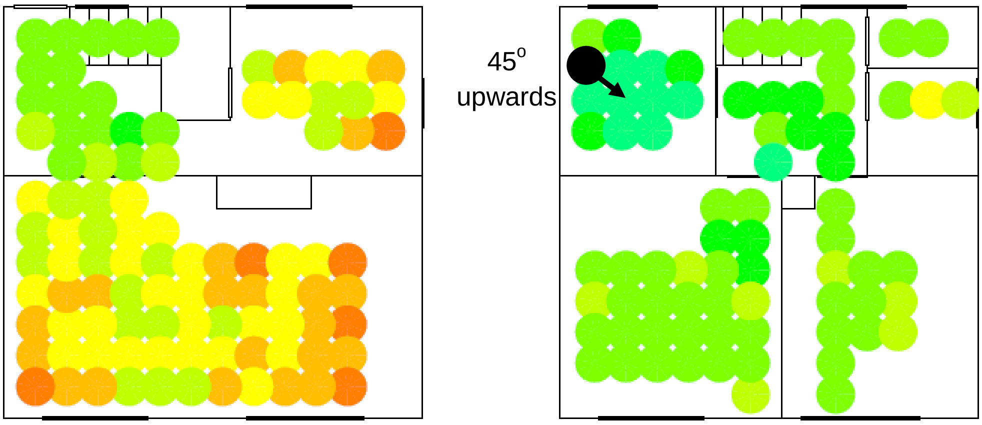


Figure 5.23 Home1 Test 7 ground floor (left), first floor (right)

Inclining the RPi 45^o upwards has the effect of increasing the number of low signal strength readings on the ground floor.

For Test 8 and Test 9, the prototype was located in the previous positions, ground floor and first floor respectively, and inclined 45° towards the floor. The resulting heatmaps for Test 8 and Test 9 are shown in Figures 5.24 and 5.25.

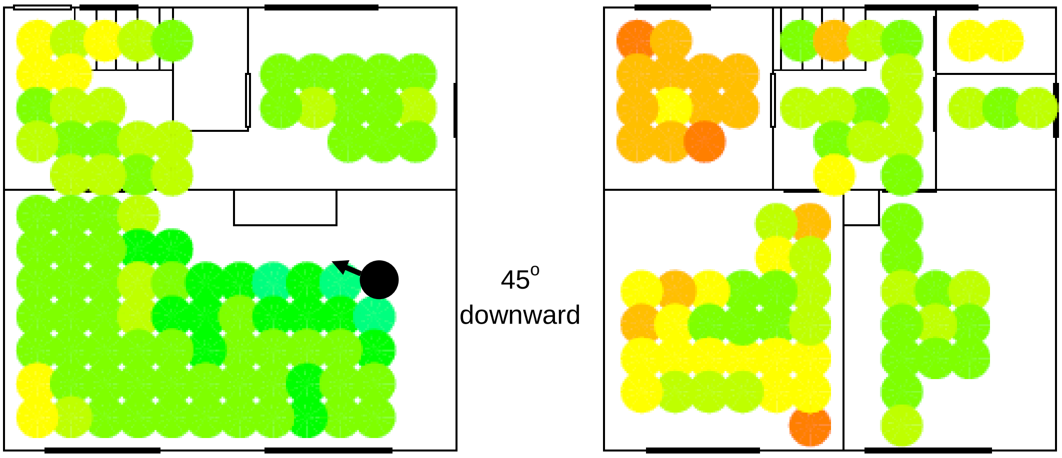


Figure 5.24. Heatmap from Test 8.

Inclining the RPi 45° downwards on the ground floor tends to reduce the signal strengths obtained on the first floor. Despite this, there are many SSN7 and SSN6 results upstairs in bedroom 1, bedroom 2, first floor landing, bathroom, stairs and throughout the ground floor.

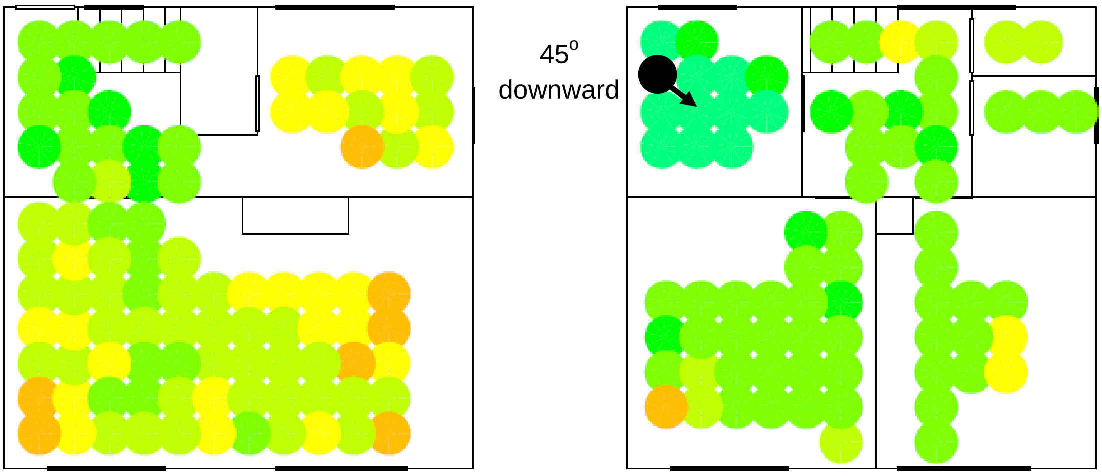


Figure 5.25. Heatmap from Test 9.

Inclining the RPi on the first floor downwards reduces the number of low signal strengths on the ground floor, with the lowest readings being SSN4. The effect of the chimney can be identified in both Test 8 and 9.

A further two signal strength tests were carried out to examine if the use of an attenuation tube connected to the prototype antenna helped to focus the signal to better enable location detection. The resulting heatmaps from these tests are shown in Figures 5.26 and 5.27.

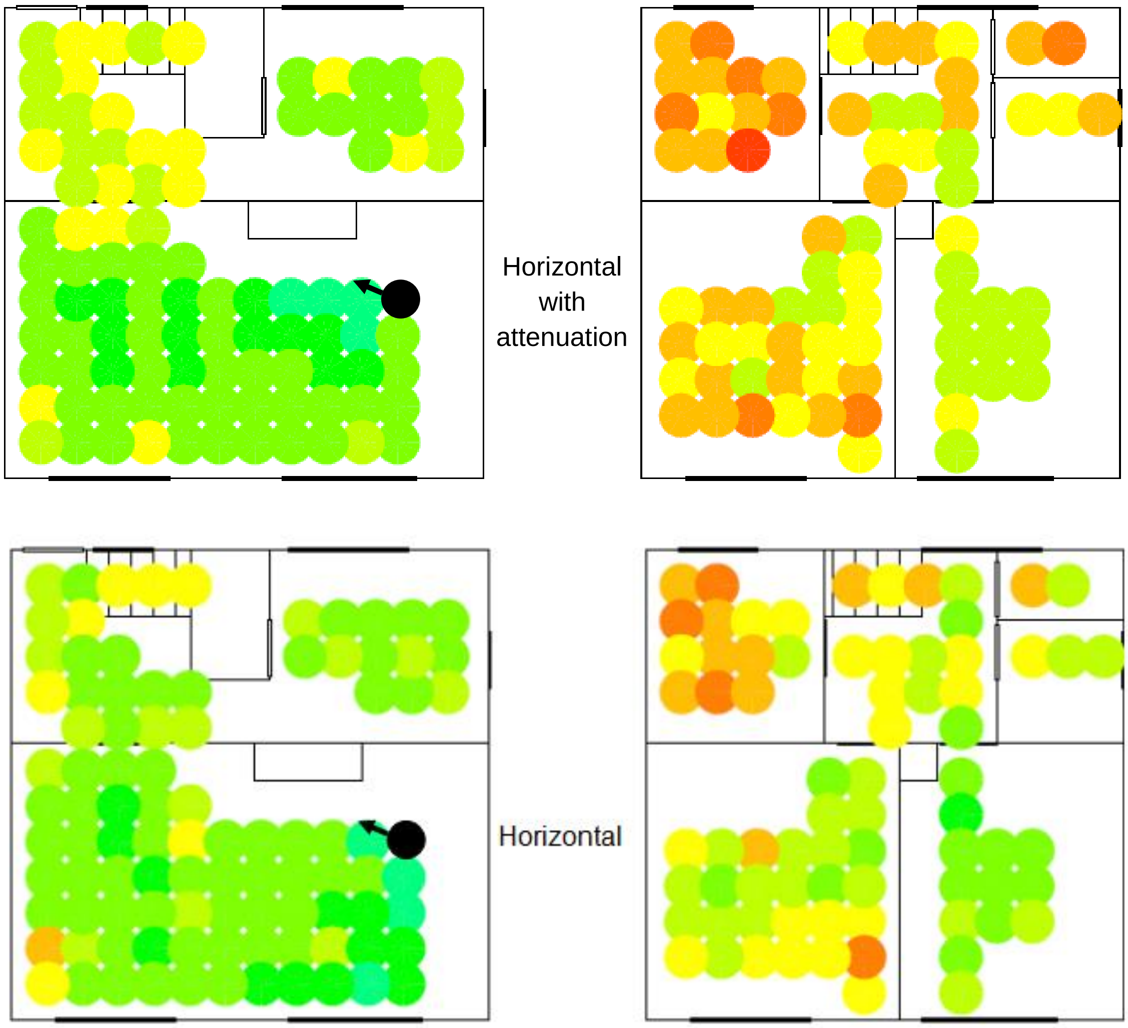


Figure 5.26 Resulting heatmaps from Test 10 with attenuation (top) and Test 4 without attenuation (bottom)

Comparison of the resulting heatmaps from Test 10 (with attenuation) and Test 4 (without attenuation) shows that the attenuation tube reduces the incidence of higher signal strengths on the first floor. Without attenuation signal strengths of SSN8 and SSN7 are present on the first floor whereas with attenuation the highest signal strength upstairs is SSN6.

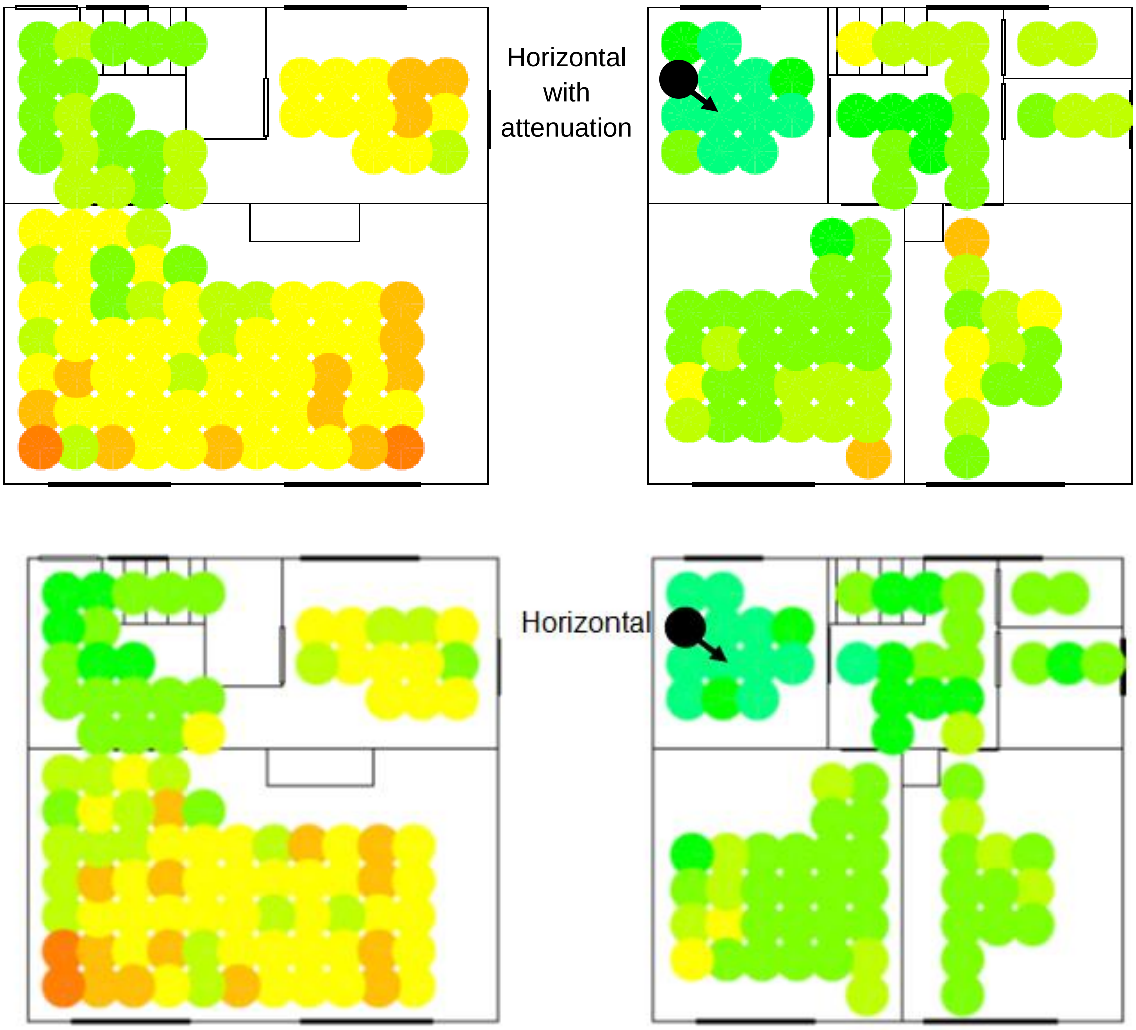


Figure 5.27. Resulting heatmaps from Test 11 with attenuation (top) and Test 6 without attenuation (bottom)

When attenuation was used in Test 11 on the first floor, this also reduced the incidence of higher signal strengths on the ground floor. Without attenuation (Test 6) five occurrences of SSN8 were found on the ground floor, with attenuation this reduced to zero. The use of an attenuation tube was seen to be beneficial to differentiate the signal strength between floors, and was used in all the following tests.

5.4 Environmental Effects Tests

In addition to the previous tests, further tests and analyses were carried out in Home1 to determine the effects of changes in the local environment, specifically in temperature and humidity. Three tests were run in Home1 in which the tags remained stationary for long periods of time and any variation in received signal strength analysed and compared with environmental changes.

Environmental Effects Test 1

The first environmental effects test used one RPi communicating with four tags over a period of 24 hours. The RPi was located on the ground floor as shown in Figure 5.28. Two tags were fixed in place at ground floor locations, and two in fixed locations on the first floor.

Figure 5.28. Plan of Home1 ground floor (left) and first floor (right) showing the location of the RPi and four tags.

The approximate distances from the tags to the RPi and intervening fixed obstructions were as follows:

Tag	location	approximate distance from RPi (m)	Fixed obstructions between tag and RPi
1	ground floor, Living Room GL67	5	none
2	ground floor, Hall GH14	3	10cm internal wall
3	first floor, Bedroom1 FB106	5	internal floor
4	first floor, Bedroom2 FB213	7	internal floor and wall

Table 5.4 Approximate distances from tags to RPi and details of obstructions

Tag1 was in the same room as the RPi with no fixed obstructions between it and the RPi. The three other tags have at least one internal wall or floor between them and the RPi. The weather conditions over this 24 hour period were obtained and the temperature and humidity are shown in Figure 5.29.

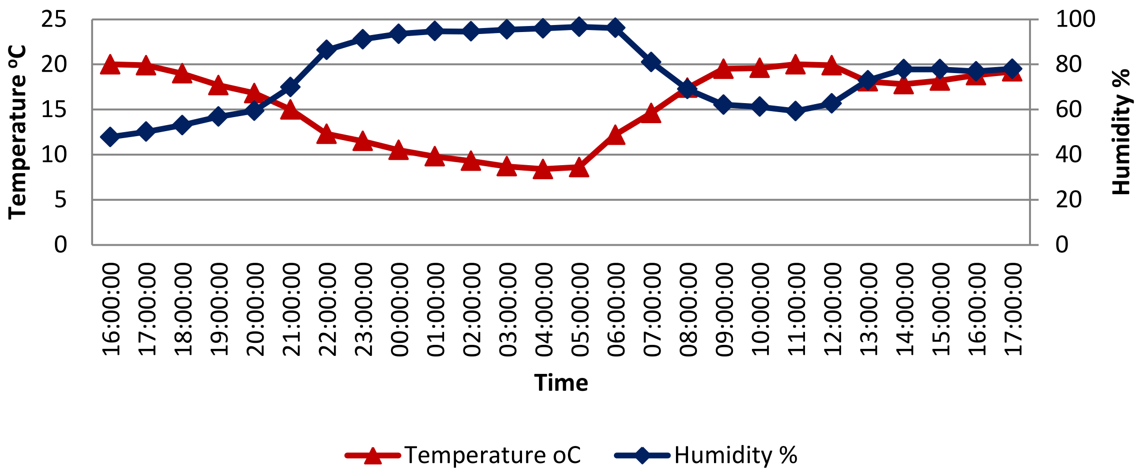


Figure 5.29 The humidity and temperature observations during the period of Environmental Effects Test 1

During this period of testing the temperature ranged from 8.4 to 20°C and the humidity varied between 47.8 and 96.6%. There was little change in the weather and it was mainly cloudy, partly cloudy, or overcast.

Time	Humidity %	Temp °C	Weather	Time	Humidity %	Temp °C	Weather
16:00	47.8	20	Cloudy	05:00	96.6	8.6	Sunny day
17:00	50.1	19.9	Cloudy	06:00	96.1	12.2	Cloudy
18:00	53	19	Partly cloudy (day)	07:00	81	14.6	Partly cloudy (day)
19:00	56.8	17.7	Cloudy	08:00	69	17.4	Cloudy
20:00	59.4	16.8	Overcast	09:00	62.1	19.5	Partly cloudy (day)
21:00	69.9	15	Cloudy	10:00	61.2	19.6	Cloudy
22:00	86.3	12.3	Clear night	11:00	59.3	20	Cloudy
23:00	91.1	11.5	Cloudy	12:00	62.6	19.9	Overcast
00:00	93.5	10.5	Clear night	13:00	72.9	18.1	Overcast
01:00	94.7	9.8	Partly cloudy (night)	14:00	77.8	17.8	Cloudy
02:00	94.6	9.3	Partly cloudy (night)	15:00	77.8	18.2	Cloudy
03:00	95.4	8.7	Clear night	16:00	76.9	18.8	Cloudy
04:00	95.9	8.4	Partly cloudy (night)	17:00	78	19.2	Cloudy

Table 5.5. Observed weather type and data over the 24 hours of testing

Collecting signal strength data for 24 hours resulted in a considerable number of readings, over 8,300 for each tag. The raw data for Tag 1 was cleaned to remove errors and gaps, and presented as a 10 period moving average trendline.

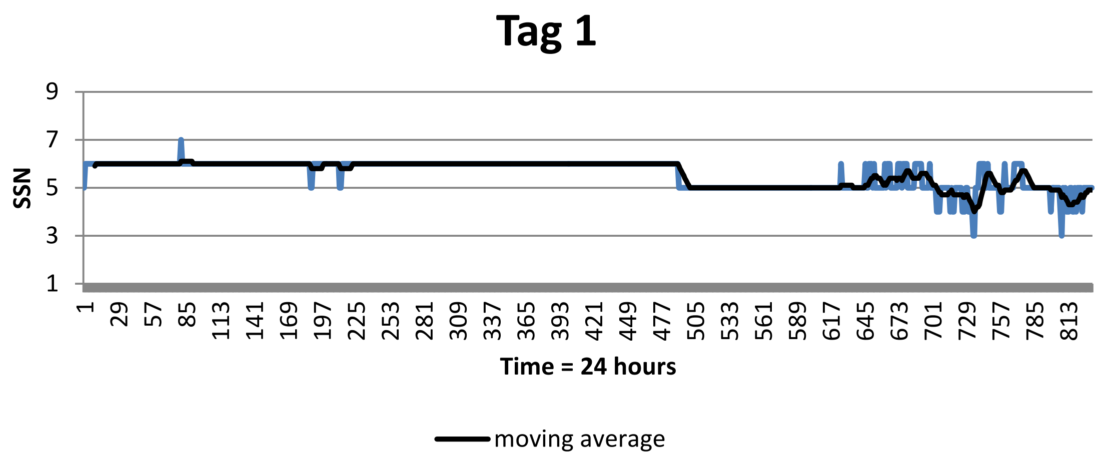


Figure 5.30 Tag 1 over 24 hours with a 10 period moving average

The signal strength from Tag 1 displayed a steady value of SSN6 as shown in Figure 5.30 over the first half of the test before dropping to SSN5 and becoming very disruptive over the last 6 hours.

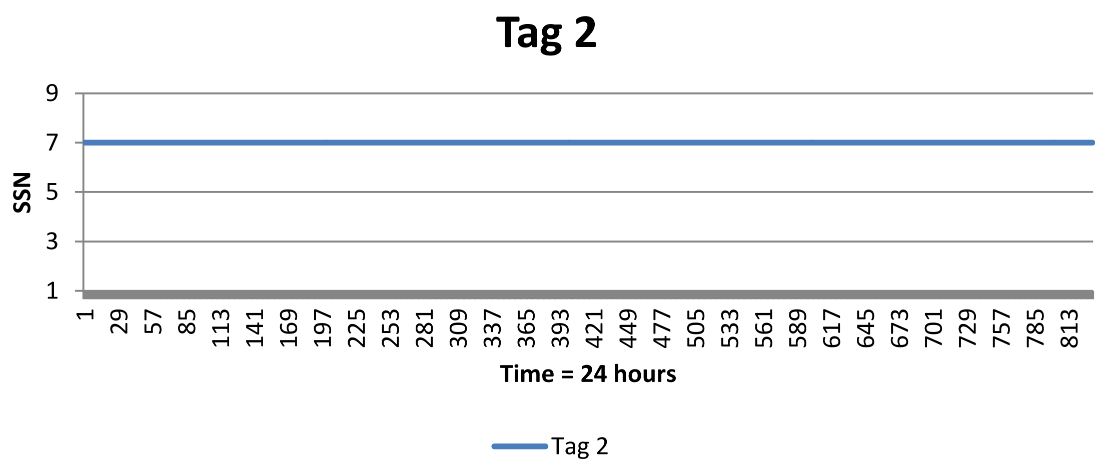


Figure 5.31.Tag 2 over 24 hours

As shown in Figure 5.31 Tag 2 gave a consistent signal strength of SSN7 throughout the 24 hours of the test.

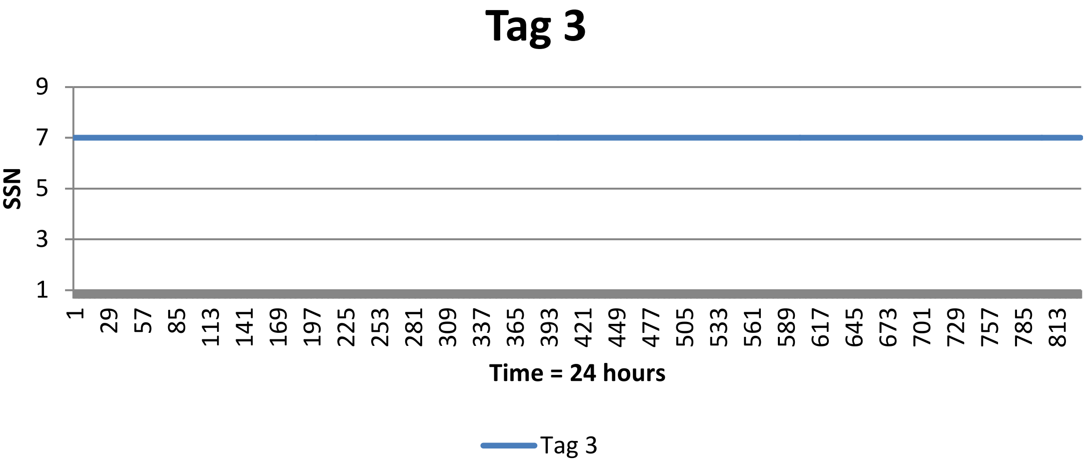


Figure 5.32 Tag 3 over 24 hours

Similarly to Tag 2, the signal strength of Tag 3 as shown in Figure 5.32 remained constant at SSN7 throughout the test with no observed disruption.

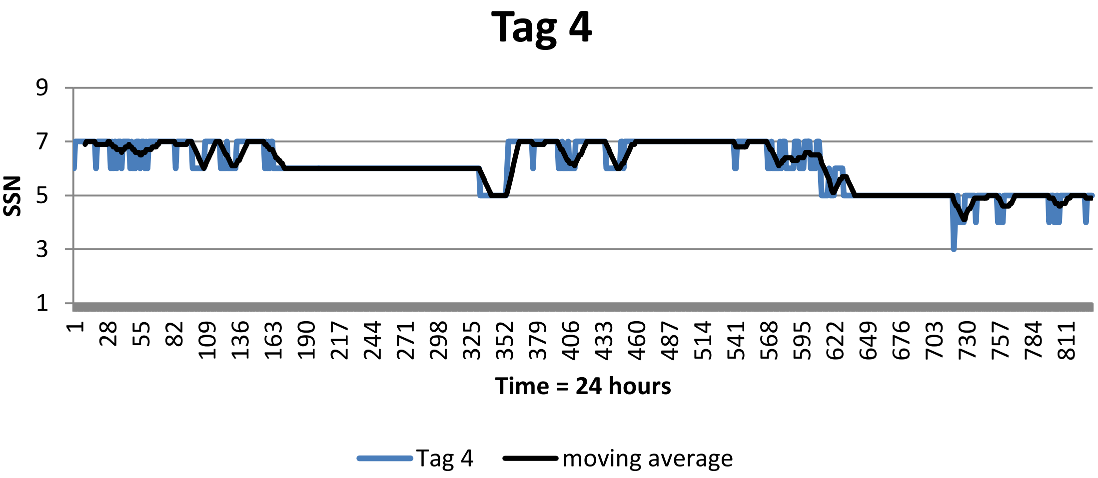


Figure 5.33 Tag 4 with 10 period moving average over 24 hours

Similar to Tag 1, Tag 4 as shown in Figure 5.33 displayed several disruptive events in signal strength during the test. These periods of disruption do not correlate with each other, or with periods of high or low temperature or humidity. The signal from Tag 4 was the most disturbed of any of the tags during the test. Possible reasons for this include this tag being the furthest distance from the RPi and having the most construction element obstructions between the tag and reader (an internal floor and wall).

Environmental Effects Test 2

This test used two RPi's, one located on the ground floor and the other on the first floor. The ground floor RPi communicated with tags 1, 2, 3 and 4. The RPi located on the first floor communicated with tags 5, 6, 7 and 8. The eight tags were stationary throughout the test and placed in one of four locations. Each tag location had one tag from the ground floor RPi and one tag from the first floor RPi as shown in Figure 5.33.

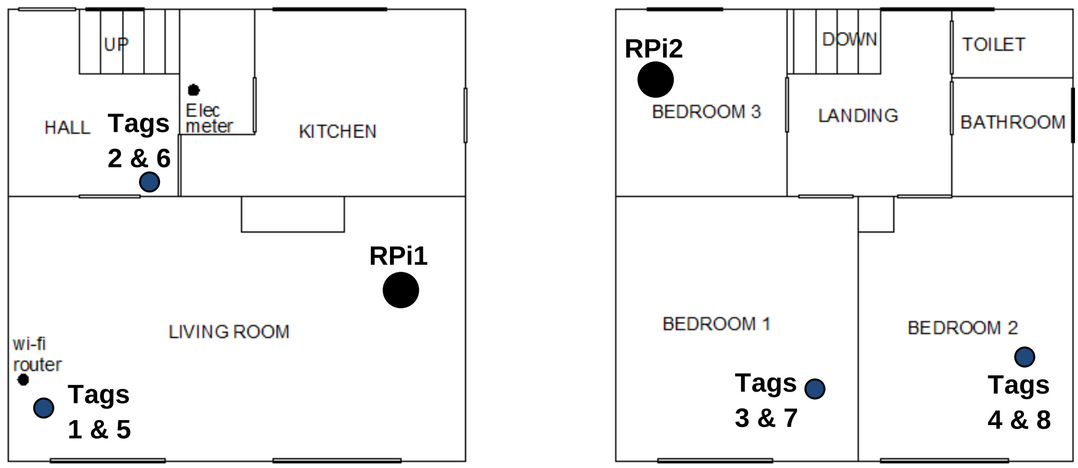


Figure 5.33. The RPi and tag locations during the Environmental Effects Test 2

Further details of the tags and the fixed obstructions between them and their corresponding RPi are shown in Table 5.6.

Tag	RPi	Tag location	approximate distance to RPi (m)	Fixed obstructions between tag and RPi
1	1 – ground floor	ground floor, Living Room GL1	5	none
2	1 – ground floor	ground floor, Hall GH14	3	internal wall
3	1 – ground floor	first floor, Bedroom1 FB106	5	internal floor
4	1 – ground floor	first floor, Bedroom2 FB213	3	internal floor and wall
5	2 – first floor	ground floor, Living Room GL1	5	internal floor and wall
6	2 – first floor	ground floor, Hall GH14	3	internal floor
7	2 – first floor	first floor, Bedroom1 FB106	5	internal wall
8	2 – first floor	first floor, Bedroom2 FB213	7	two internal walls

Table 5.6. The tag distances from and obstructions between them and their corresponding RPi during Environmental Effects Test 2

The test ran for six hours and during the time there was very little variation in humidity, temperature and local weather conditions as can be seen from Figures 5.34 and Table 5.7. The weather conditions over the testing period was light rain or overcast, the temperature ranged between 11.9 and 13.2^{o}C and humidity varied between 78.3 and 93.6%.

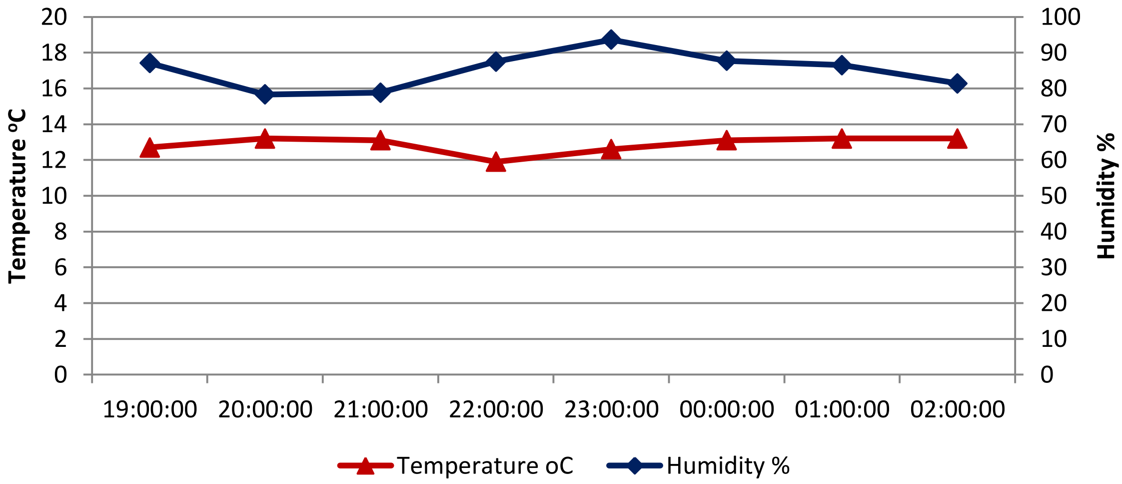
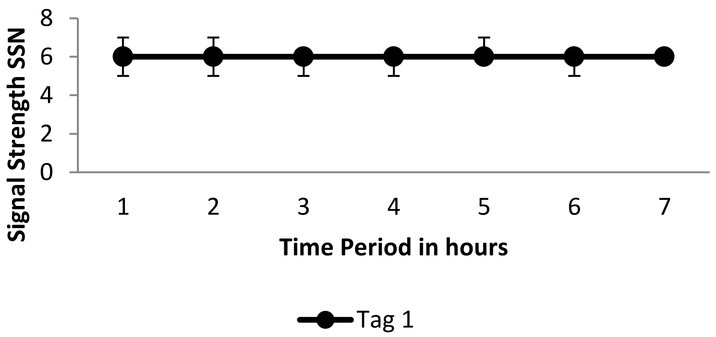


Figure 5.34. The temperature and humidity conditions during Environmental Effects Test 2

Time	Humidity %	Temperature ^oC	Weather Type
19:00	87.1	12.7	overcast
20:00	78.3	13.2	overcast
21:00	78.8	13.1	light rain shower (night)
22:00	87.5	11.9	light rain
23:00	93.6	12.6	light rain
00:00	87.7	13.1	overcast
01:00	86.5	13.2	light rain shower (night)
02:00	81.4	13.2	overcast

Table 5.7. The temperature, humidity and weather condition observations from Met Office DataPoint

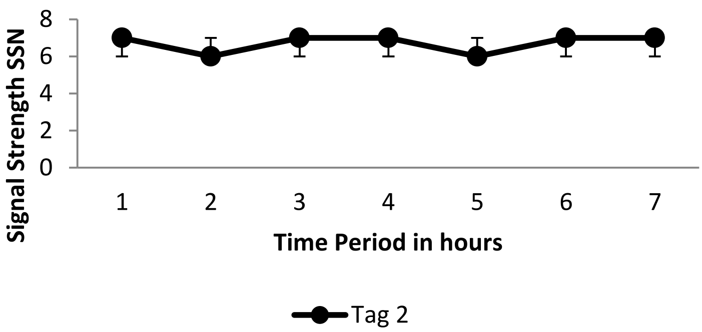
In addition to recording weather, temperature and humidity data during the test, periods of occupation of the rooms the tags were located in was also recorded. This is indicated by shading in the tables, and a summary of this data for each of the tags is shown in the following figures.



		Signal Strength		
hour	time	most	max	min
1	19:11 - 19:59	6	7	5
2	20:00 - 20:59	6	7	5
3	21:00 - 21:59	6		5
4	22:00 - 22:59	6		5
5	23:00 - 23:59	6	7	
6	00:00 - 00:59	6		5
7	01:00 - 01:20	6		

Figure 5.35. Resulting signal strength of Tag 1 during Environmental Effects Test 2 and periods of occupation

Figure 5.35 shows that the signal strength of Tag1 does not appear to be influenced by the periods of occupation within the same room during hours 1 to 4. During periods of occupation the most common, maximum and minimum signal strength readings remain the same as the period when the room is not occupied, hours 5 to 7. The most common signal strength remains as SSN6 throughout the test.

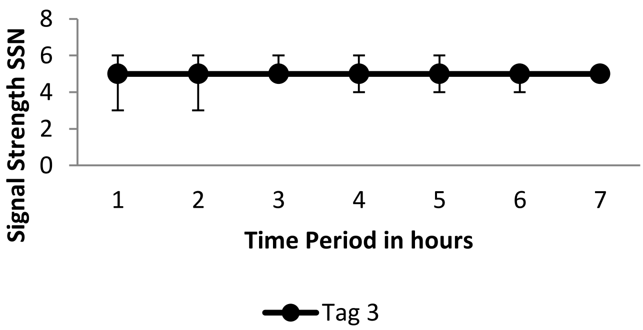


		Signal Strength		
hour	time	most	max	min
1	19:11 - 19:59	7		6
2	20:00 - 20:59	6	7	
3	21:00 - 21:59	7		6
4	22:00 - 22:59	7		6
5	23:00 - 23:59	6	7	
6	00:00 - 00:59	7		6
7	01:00 - 01:20	7		6

Figure 5.36. Resulting signal strength of Tag 2 during Environmental Effects Test 2

Figure 5.36 shows that Tag 2 does not have indicated periods of occupancy as this tag was located in a hallway and not in a room. Tag 2 was fluctuating between SSN6 and SSN7 throughout the testing period.

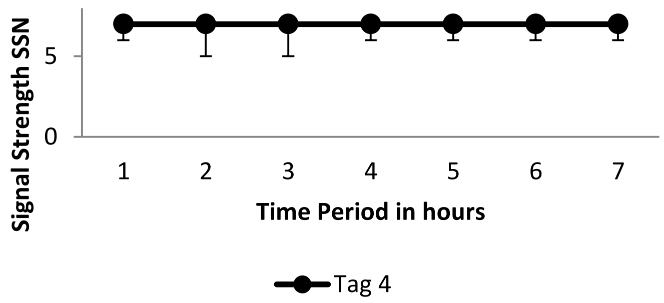
Figure 5.37 show that Tag 3 shows a wider variation in signal strength, ranging from a maximum of SSN6 to a minimum of SSN 3 in hours 1 and 2. The range changes slightly to between a maximum of SSN6 and minimum of SSN4 during hours 4, 5, and 6.



		Signal Strength		
hour	time	most	max	min
1	19:11 - 19:59	5	6	3
2	20:00 - 20:59	5	6	3
3	21:00 - 21:59	5	6	
4	22:00 - 22:59	5	6	4
5	23:00 - 23:59	5	6	4
6	00:00 - 00:59	5		4
7	01:00 - 01:20	5		

Figure 5.37. Resulting signal strength of Tag3 during Environmental Effects Test 2 and periods of occupation

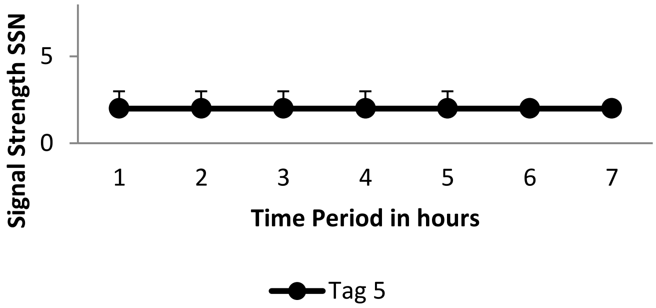
Figure 5.38 shows that Tag 4 fluctuated between SSN6 and SSN7, with occasional SSN5 results occurring during hours 2 and 3. The signal strength does not appear to be influenced by periods of occupation.



		Signal Strength		
hour	time	most	max	min
1	19:11 - 19:59	7		6
2	20:00 - 20:59	7		5
3	21:00 - 21:59	7		5
4	22:00 - 22:59	7		6
5	23:00 - 23:59	7		6
6	00:00 - 00:59	7		6
7	01:00 - 01:20	7		6

Figure 5.38. Resulting signal strength of Tag4 during Environmental Effects Test 2 and periods of occupation

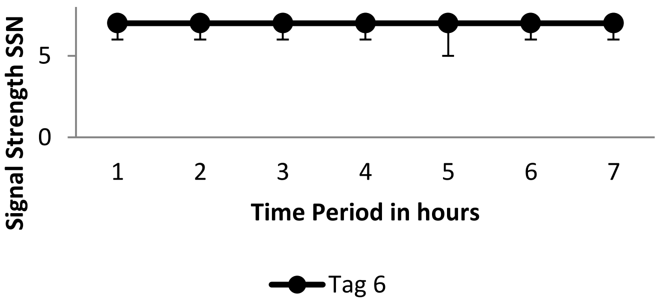
Figure 5.39 shows that Tag 5 fluctuated between SSN2 and SSN3. The periods of occupation, during hours 1 to 4, does not appear to have influenced the signal strength.



		Signal Strength		
hour	time	most	max	min
1	19:11 - 19:59	2	3	
2	20:00 - 20:59	2	3	
3	21:00 - 21:59	2	3	
4	22:00 - 22:59	2	3	
5	23:00 - 23:59	2	3	
6	00:00 - 00:59	2		
7	01:00 - 01:20	2		

Figure 5.39. Resulting signal strength of Tag 5 during Environmental Effects Test 2, and periods of occupation

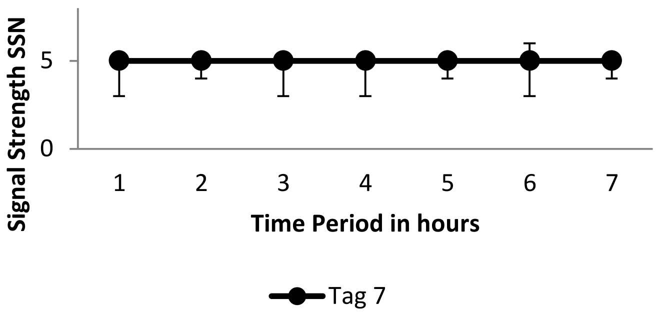
Figure 5.40 shows that Tag 6 showed very little variation from fluctuating between SSN6 and SSN7 except for one dip to SSN5 during hour 5. There is no indication of occupancy for Tag 6 as this was located in the hallway and not a room.



		Signal Strength		
hour	time	most	max	min
1	19:11 - 19:59	7		6
2	20:00 - 20:59	7		6
3	21:00 - 21:59	7		6
4	22:00 - 22:59	7		6
5	23:00 - 23:59	7		5
6	00:00 - 00:59	7		6
7	01:00 - 01:20	7		6

Figure 5.40. Resulting signal strength of Tag 6 during Environmental Effects Test 2

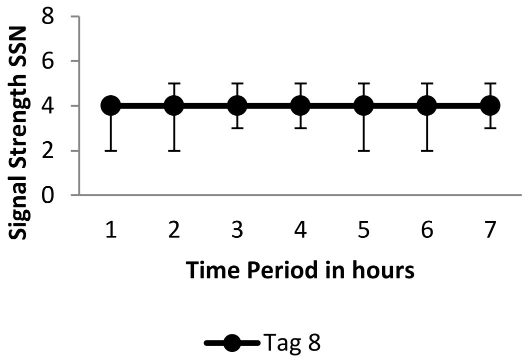
Figure 5.41 shows that Tag 7 had a wider variation of signal strengths, down to as low as SSN3 occasionally. These dips in signal strength occur equally in occupied and unoccupied periods. Although there is one spike of signal strength to SSN6 at 00:58, there does not appear to be a relationship between occupancy and signal strength. Tag 7 was located in an adjacent room to the RPi with one internal wall between the tag and its reader. There is no evidence to suggest what the cause of the anomalous SSN6 result was.



		Signal Strength		
hour	time	most	max	min
1	19:11 - 19:59	5		3
2	20:00 - 20:59	5		4
3	21:00 - 21:59	5		3
4	22:00 - 22:59	5		3
5	23:00 - 23:59	5		4
6	00:00 - 00:59	5	6	3
7	01:00 - 01:20	5		4

Figure 5.41. Resulting signal strength of Tag 7 during Environmental Effects Test 2 and periods of occupation

Figure 5.42 shows that theTag 8 signal strength varied greatly during this test. The variation was not indicative of a period of transition from one dominant signal strength to another, or of a signal strength bordering two signal strengths, but was due to the signal strength spanning three SSNs. During the first hour and a half the signal strength spanned SSN2, SSN3, and SSN4. Over the remaining period of testing the signal strength generally spanned SSN3, SSN4, and SSN5 with occasional SSN2 events. During most of the testing period the room was occupied, during hours 2 – 7, so it was not possible to infer an influence of occupancy on signal strength.



		Signal Strength		
hour	time	most	max	min
1	19:11 - 19:59	4		2
2	20:00 - 20:59	4	5	2
3	21:00 - 21:59	4	5	3
4	22:00 - 22:59	4	5	3
5	23:00 - 23:59	4	5	2
6	00:00 - 00:59	4	5	2
7	01:00 - 01:20	4	5	3

Figure 5.42. Resulting signal strength of Tag 8 during Environmental Effects Test 2 and periods of occupation

The tags were stationary and placed in pairs in one of the four tag locations. Comparison of the signal strength behaviour of tags in the same location are shown in Figures 5.43-5.46. Tag 1 and Tag 5 were both located on the ground floor in the living room at testing point GL1. Tag1 communicated with the RPi located in the same room, and Tag 5 was controlled by the RPi located on the first floor.

Both Tag 1 and Tag 5 gave steady results for the most commonly occurring signal strength, Tag 1 being SSN6 and Tag 5 being SSN2. While Tag1 ranged from a maximum of SSN6 to a minimum of SSN5, Tag 5 only ranged +1 SSN to SSN3.

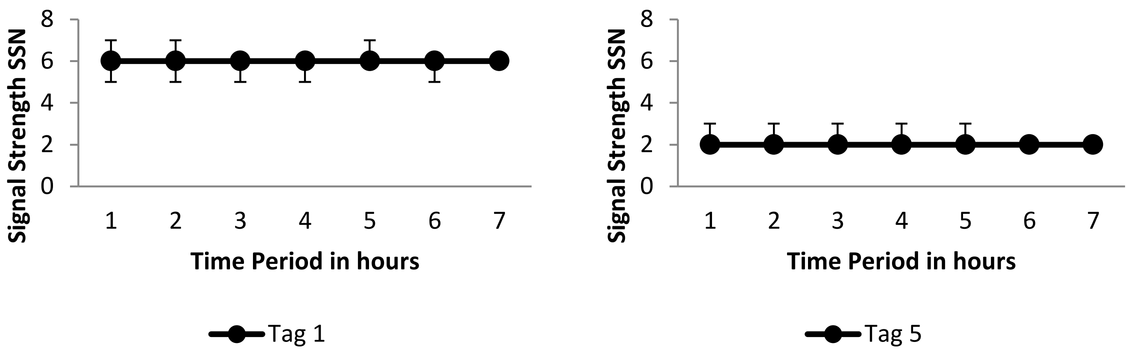


Figure 5.43. Tag 1 and Tag 5 signal strength behaviour at the same location during Environmental Effects Test 2

Tag 2 and Tag 6 were co-located in the ground floor hallway, at testing point GH14. Tag 2 communicated with the ground floor RPi and Tag 6 with the RPi on the first floor. As can be seen from Figure 5.44 Tag 2 fluctuated between SSN6 and SSN7. Tag 6 was generally steady throughout the testing period, remaining at SSN7 with a minimum of SSN6, although there was one hour in which the minimum signal strength reduced to SSN5.

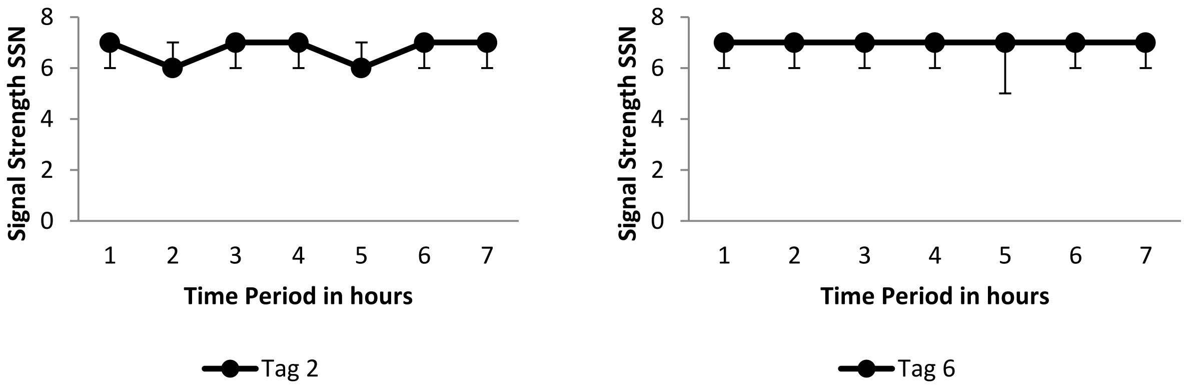


Figure 5.44. Tag 2 and Tag 6 signal strength behaviour at the same location during Environmental Effects Test 2

Tag 3 and Tag 7 were located on the first floor in Bedroom1 at testing point FB106. Tag 3 communicated with the ground floor RPi and Tag 7 with the first floor RPi. Results from both tags gave a steady SSN5 for the most common signal strength throughout the period of testing. Both tags had minimum values of signal strength of SSN3 and maximum values of SSN6, although at different times during the test.

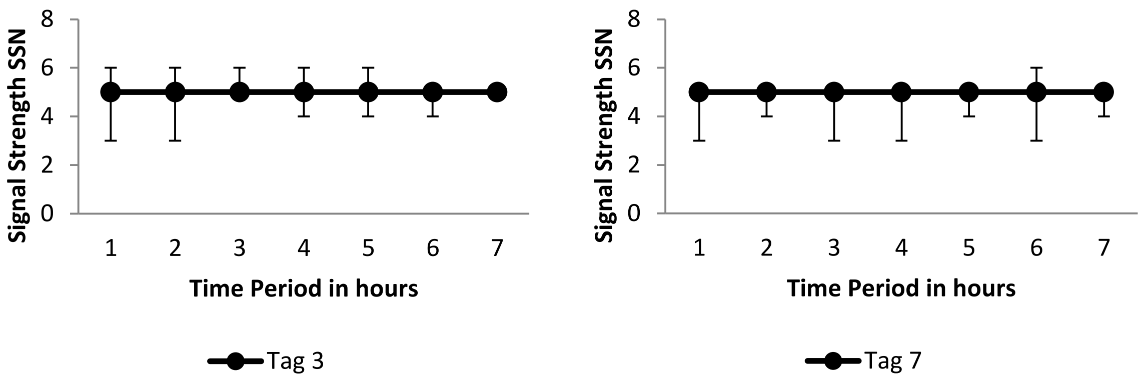


Figure 5.45. Tag 3 and Tag 7 signal strength behaviour at the same location during Environmental Effects Test 2

Tag 4 and Tag 8 were placed on the first floor in Bedroom 2 at testing position FB213. Tag 4 was controlled by the ground floor RPi and Tag 8 communicated with the first floor RPi. Results from both tags show a steady most common signal strength, SSN7 for Tag 4 and SSN4 for Tag 8. Both tags also dipped to a minimum signal strength by 2SSN, to SSN5 for Tag 4 and to SSN2 for Tag 8. These events happened at different times for the tags.

While the signal strength from Tag 4 did not increase above the most common, SSN7, Tag 8 did report a +1SSN maximum. This would indicate that what was influencing the changes in range in signal strength in the two tags was different and more likely related to the relationship between the tag and its corresponding RPi rather than a direct result of an event or factor at the tag location.

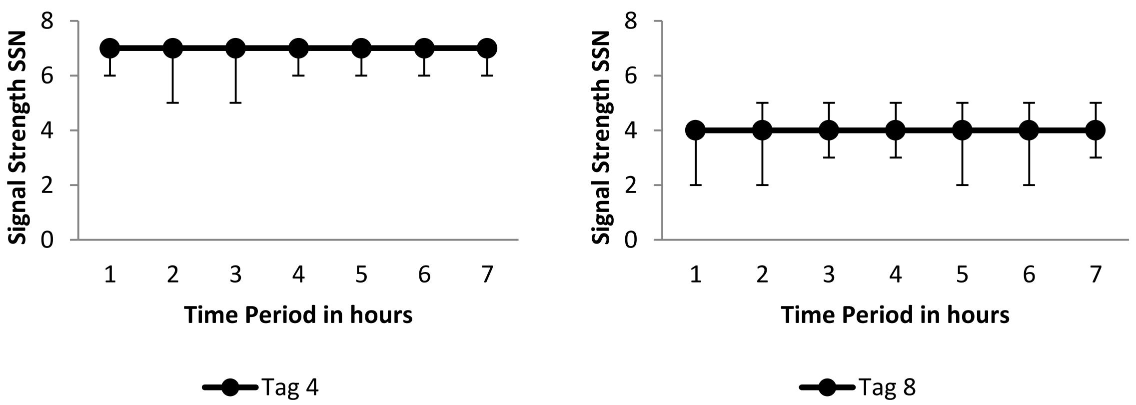


Figure 5.46. Tag4 and Tag8 signal strength behaviour at the same location during Environmental Effects Test 2

All the tags reported a steady most common signal strength over the period of testing. The ranges from minimum to maximum did alter over time but these events were not replicated by co-located tags at the same location as they happened at different times. There does not appear to be a correlation between the signal strengths reported by partner tags. Occupancy does not appear to influence the signal strength.

Environmental Effects Test 3

Following the previous 6 hour test, this investigation ran for an extended period of time to enable a more comprehensive analysis of the signal strength over three days. The eight tags and two RPi's were placed in the same locations as in Environmental Effects Test 2 and signal strength data was collected for over 72 hours.

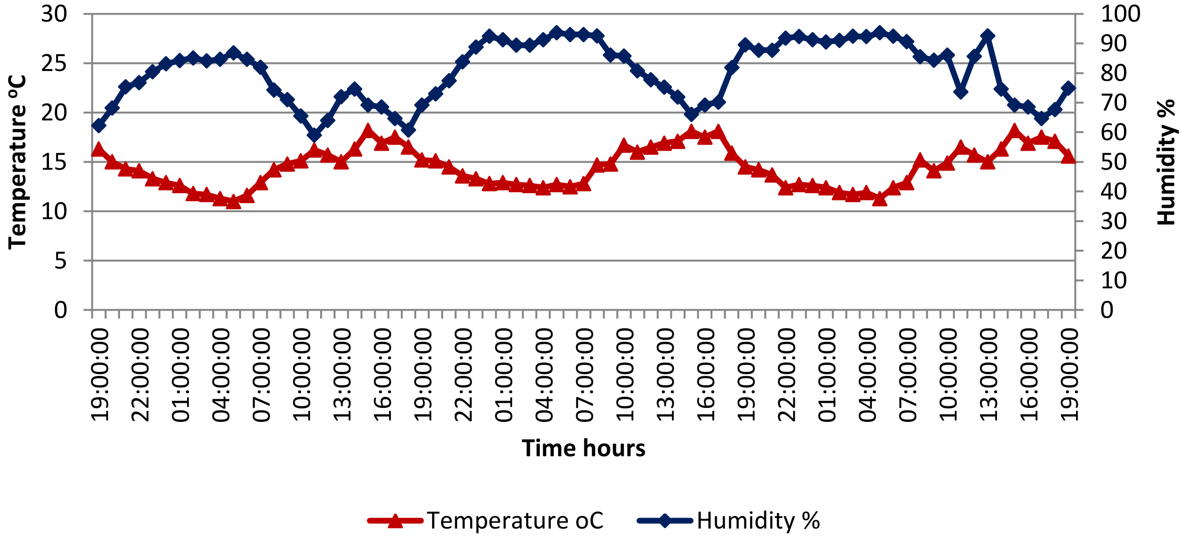


Figure 5.47. Hourly temperature and humidity observation data for the 72 hour testing period

Figure 5.47 shows that the three day testing period enabled observation of signal strength through a wider range of temperature, humidity and weather types. Over the 3 days humidity ranged between 59% and 93.6%, the temperature between 11^{o}C and 18.1^{o}C, and several weather types were observed that had not been observed in previous tests, such as periods of heavy rain.

The extended period of testing also increased the opportunity to observe the effect on signal strength of the tag batteries failing and to learn how long the batteries would last when being used in this unexpected way.

Time	Humidity %	Temp °C	Weather Type	Time	Humidity %	Temp °C	Weather Type
19:00	62.3	16.3	sunny day	08:00	92.5	14.7	overcast
20:00	68.2	15	clear night	09:00	86.1	14.8	overcast
21:00	75.3	14.3	partly cloudy (night)	10:00	85.7	16.7	cloudy
22:00	76.8	14.1	partly cloudy (night)	11:00	80.8	16	overcast
23:00	80.4	13.3	clear night	12:00	77.7	16.5	overcast
00:00	83.1	12.9	clear night	13:00	75.2	16.9	overcast
01:00	84.2	12.6	clear night	14:00	71.9	17.1	overcast
02:00	85.1	11.8	clear night	15:00	66.1	18.1	overcast
03:00	84.1	11.7	clear night	16:00	69.2	17.5	overcast
04:00	84.6	11.3	clear night	17:00	70.2	18.1	overcast
05:00	86.8	11	sunny day	18:00	81.8	15.9	heavy rain shower (day)
06:00	84.6	11.6	sunny day	19:00	89.5	14.5	heavy rain shower (day)
07:00	82	12.9	cloudy	20:00	87.7	14.2	cloudy
08:00	74.3	14.2	cloudy	21:00	87.7	13.7	cloudy
09:00	71	14.8	cloudy	22:00	91.8	12.4	clear night
10:00	65.5	15.1	cloudy	23:00	92.3	12.7	clear night
11:00	59	16.2	overcast	00:00	91.2	12.6	cloudy
12:00	64	15.7	cloudy	01:00	90.5	12.4	overcast
13:00	72	15	light rain shower (day)	02:00	91	11.9	overcast
14:00	74.6	16.3	overcast	03:00	92.4	11.7	cloudy
15:00	69.2	18.2	overcast	04:00	92.3	11.9	cloudy
16:00	68.5	16.9	cloudy	05:00	93.6	11.3	cloudy
17:00	64.7	17.5	cloudy	06:00	92.4	12.4	cloudy
18:00	60.8	16.5	cloudy	07:00	90.6	12.9	cloudy
19:00	69.2	15.2	light rain shower (day)	08:00	85.5	15.2	sunny day
20:00	73	15.1	overcast	09:00	84.3	14.1	heavy rain shower (day)
21:00	77.4	14.5	overcast	10:00	86.1	14.9	cloudy
22:00	83.8	13.6	overcast	11:00	73.6	16.5	cloudy
23:00	88.8	13.3	heavy rain shower (night)	12:00	85.6	15.7	cloudy
00:00	92.4	12.8	overcast	13:00	92.5	15	light rain shower (day)
01:00	91.2	12.9	overcast	14:00	74.6	16.3	overcast
02:00	89.4	12.7	overcast	15:00	69.2	18.2	overcast
03:00	89.4	12.6	cloudy	16:00	68.5	16.9	cloudy
04:00	91.2	12.4	light rain shower (night)	17:00	64.7	17.5	cloudy
05:00	93.6	12.7	overcast	18:00	67.7	17.1	cloudy
06:00	93	12.5	overcast	19:00	74.9	15.6	cloudy
07:00	93	12.8	overcast				

Table 5.8. Humidity, temperature and weather type observation data for the three day testing period of Environmental Effects Test 3

Collecting data from the tags continuously for 72 hours results in 24,830 signal strength readings per tag. The first stage of cleaning the data was to combine and average each ten readings. This reduced dataset of 2,483 readings was further manipulated to remove instances of no signal received, and is presented in the following figures. A 10 period moving average is also included to further smooth the data.

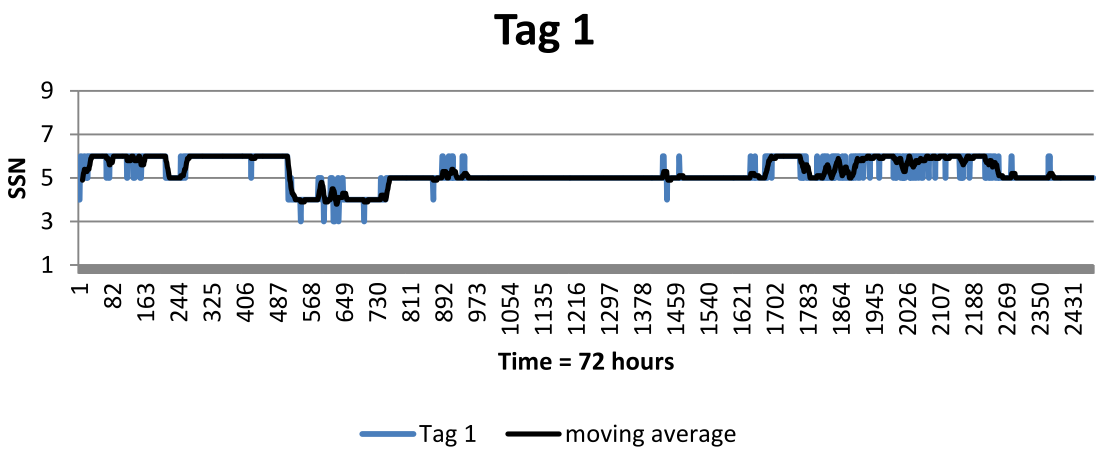


Figure 5.48 Tag 1 signal strength over 72 hours in the Environmental Effects Test 3

Figure 5.48 shows the signal strength performance of Tag 1 in a stationary position over 72 hours. There are periods of disruption during day 1 and day 3 while day 2 remains mostly steady with a signal strength of SSN5.

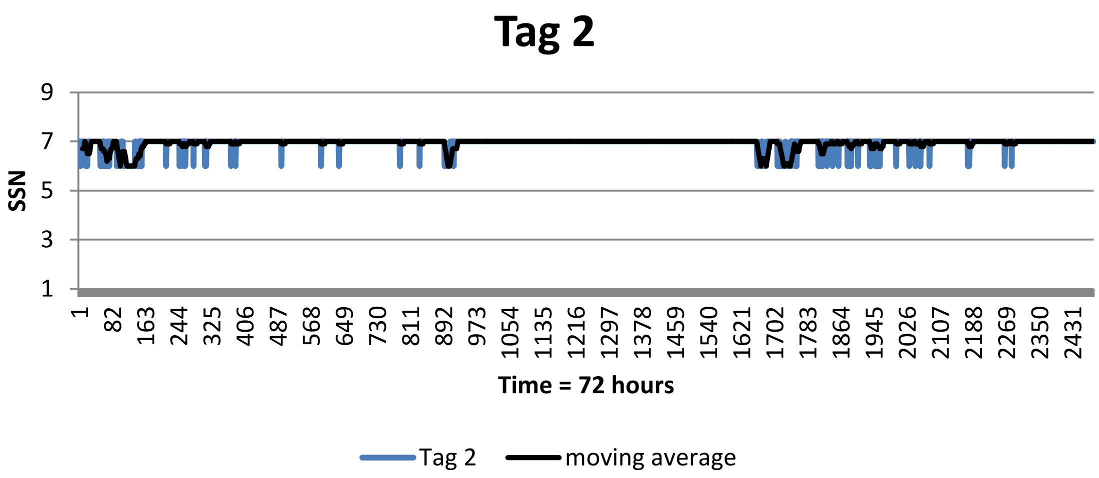


Figure 5.49 Tag 2 signal strength over 72 hours in the Environmental Effects Test 3

Figure 5.49 presents the resulting signal strength from Tag 2.The signal from Tag 2 was less disrupted than Tag 1 and tends to remain at SSN7 throughout the three days of the test. .

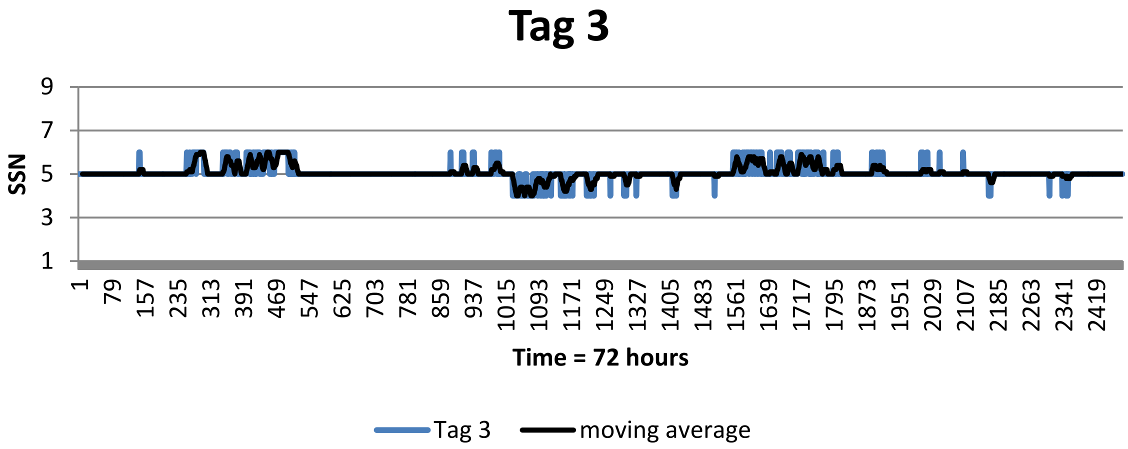


Figure 5.50.Tag 3 over 72 hours in Environmental Effects Test 3

Figure 5.50 shows the results from Tag 3. The Tag 3 signal strength shows some variation on all three days of the observation. The predominant signal strength is SSN5.

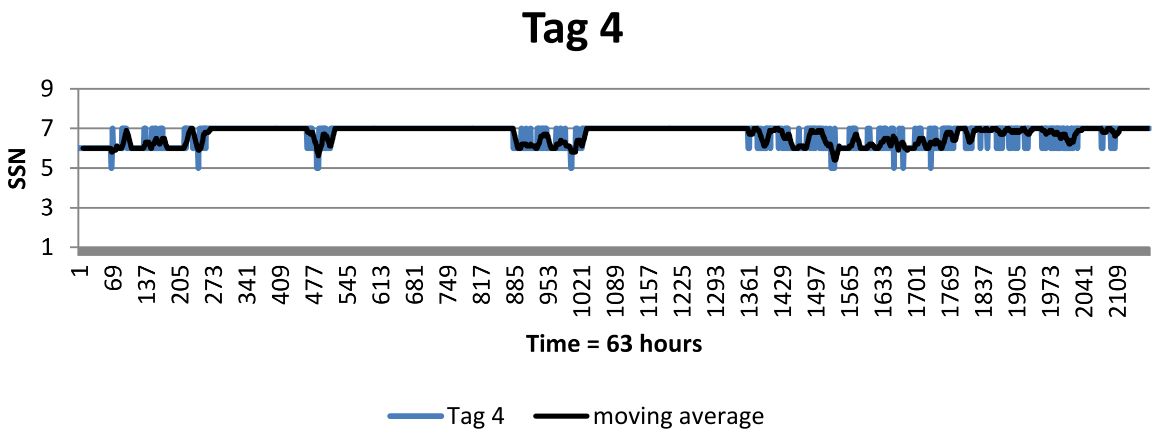


Figure 5.51.Tag 4 over 63 hours in Environmental Effects Test 3

Figure 5.51 shows the results from Tag 4.Tag 4 ceased responding after 63 hours. The signal strength results show some variability on all three days of the test, with a dominant signal strength of SSN7.

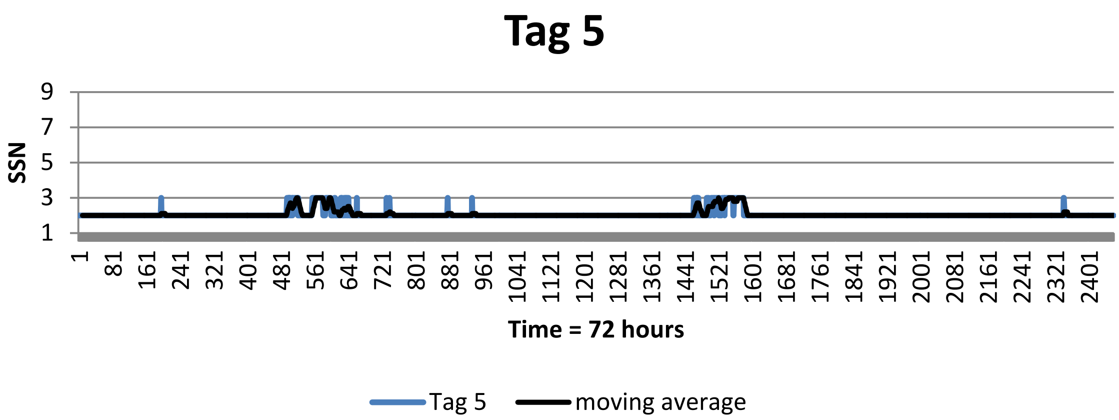


Figure 5.52.Tag 5 over 72 hours in Environmental Effects Test 3

Figure 5.52 shows that the signal from Tag 5 had few events of signal disruption and gave a general reading of SSN2 throughout the test.

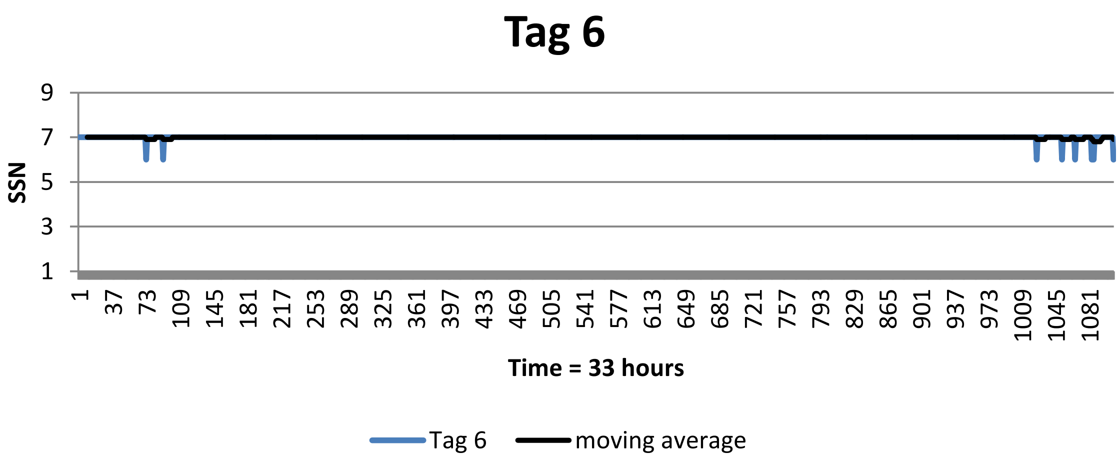


Figure 5.53 Tag 6 over 33 hours in Environmental Effects Test 3

Tag 6 failed after 33 hours and the results are shown in Figure 5.53. Tag 6 showed little disruption throughout the 33 hours it was active and gave a steady signal strength of SSN7 throughout.

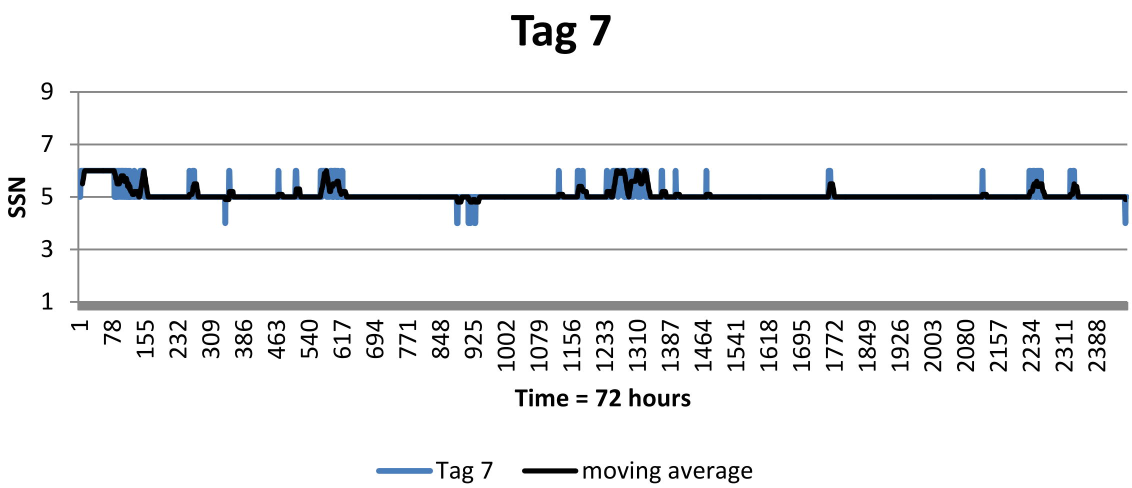


Figure 5.54 Tag 7 over 72 hours in Environmental Effects Test 3

Figure 5.54 shows that the signal strength from Tag 7 was a dominant SSN5 with several fluctuation events on all three days of the test.

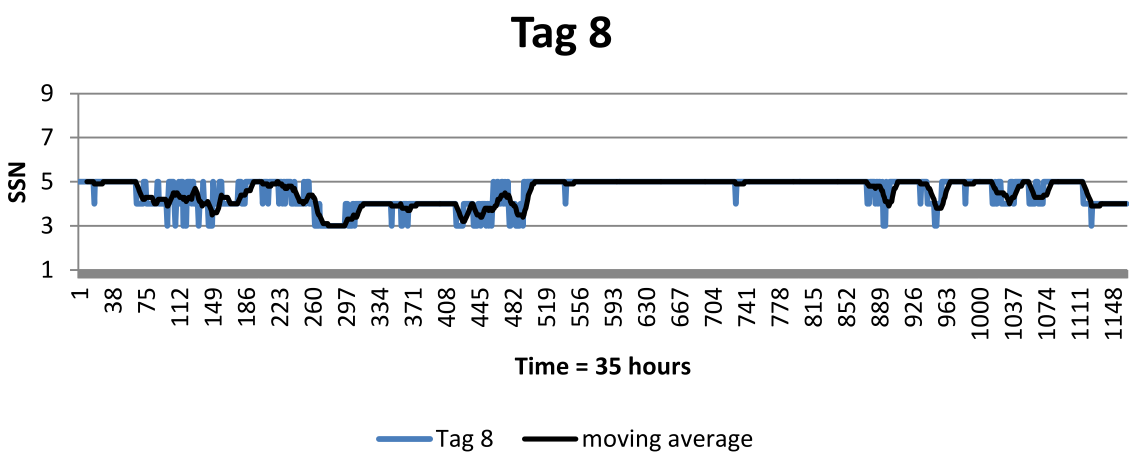
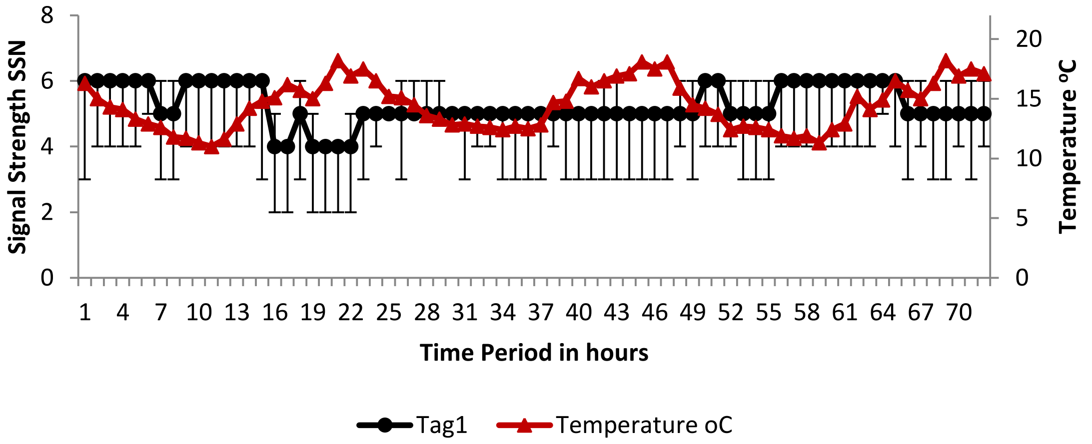


Figure 5.55 Tag 8 over 35 hours in Environmental Effects Test 3

Figure 5.55 shows that Tag 8 resulted in a greater variability of signal strength during the first 15 hours of the test. Following this the signal strength remained fairly steady at SSN5 before becoming disrupted again before ceasing to respond after 35 hours.

In order to investigate whether the variation in temperature and humidity matched the signal strength variation over the period of the test, a series of charts were produced for each Tag. Figure 5.56 shows the dominant signal strength from Tag 1 over each hour of the testing period with error bars indicating the maximum and minimum signal strength readings over that hour. Comparison with the temperature and humidity over the same period is provided for each of the eight tags although only Tag 1 is shown here. The complete set of graphs for all 8 tags is in Appendix F. Environmental Effects Test 3 Results Detail.

Tag 1



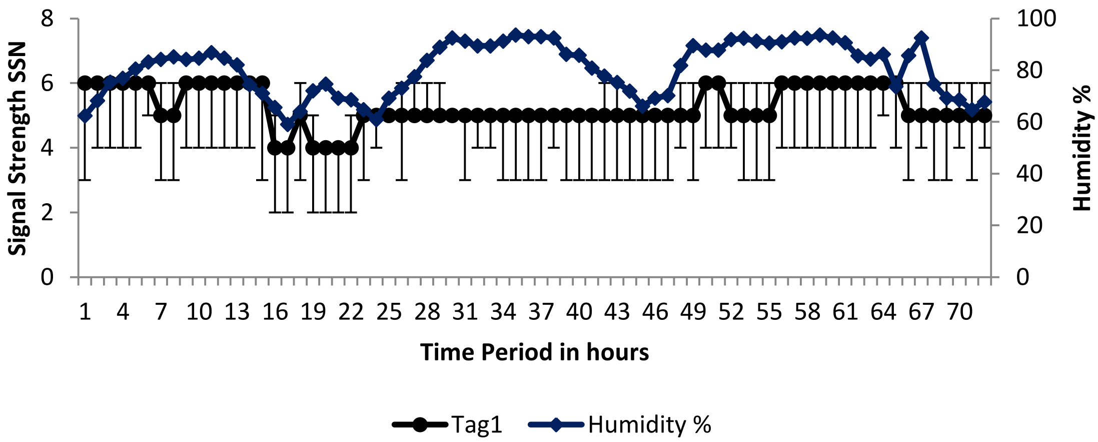


Figure 5.56 Comparison of Tag 1 with the environmental conditions

Figure 5.56 shows that on one occasion at hour 22 when the temperature is at one of the highest values, the most common signal strength dips to SSN4. This does not occur at other high temperature peaks, at hours 46 and 70. Therefore the signal strength of Tag 1 cannot be said to be directly related to the local temperature during this test. Likewise, the peaks and troughs of relative humidity does not correlate with increases or decreases in signal strength. Comparison of the temperature and humidity data with signal strength from all 8 tags showed no apparent relationship between the signal strength and variability in temperature and humidity.

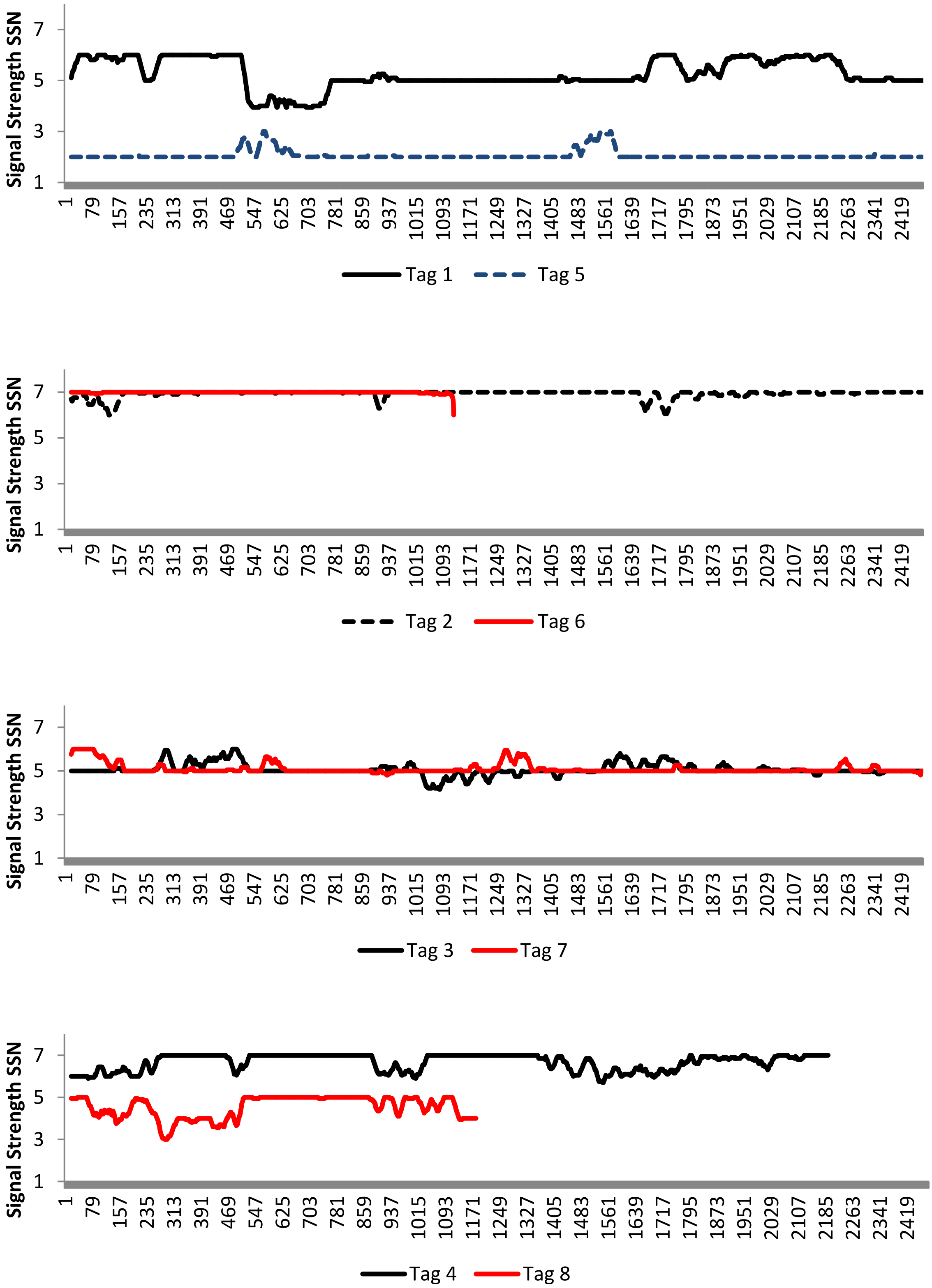


Figure 5.57 Comparison of resulting signal strengths from co-located tags

A final analysis of the resulting data from this test was carried out to compare the signal strength behaviour of the paired tags at the same location. Each pair of tags was comprised of one that communicated with the ground floor prototype and one that communicated with the prototype on the first floor. Figure 5.57 shows the resulting signal strengths of the co-located tags.

There is no indication of a relationship between the signal strengths of the tags that were located in the same position during the test. From observing the time the batteries failed in Tags 4, 6, and 8, and the length of time of previous tests it was found that the tag life of the batteries was between 111 and 120 hours of continuous use.

Environmental Effects Test 4

This test was designed to investigate the effect of having two detection systems active at the same time. The total time of this test was 6 hours and each prototype was active for four hours. As can be seen from Figure 5.58 there was a two hour overlap when both prototypes and eight tags were active. The eight tags that were used during this test were stationary throughout.

<table>
<tr><th>Hour</th><th>Tag1</th><th>Tag2</th><th>Tag3</th><th>Tag4</th><th>Tag5</th><th>Tag6</th><th>Tag7</th><th>Tag8</th></tr>
<tr><td>1</td><td colspan="4" rowspan="2">ground floor RPi and 4 tags only on</td><td colspan="4" rowspan="2"></td></tr>
<tr><td>2</td></tr>
<tr><td>3</td><td colspan="8" rowspan="2">both RPi’s and all tags on</td></tr>
<tr><td>4</td></tr>
<tr><td>5</td><td colspan="4" rowspan="2"></td><td colspan="4" rowspan="2">first floor RPi and 4 tags only on</td></tr>
<tr><td>6</td></tr>
</table>

Figure 5.58 The process of Environmental Effects Test 4

The resulting signal strengths of the tags communicating with the ground floor prototype are shown in Figure 5.59, and those connected to the first floor prototype are presented in Figure 5.60.

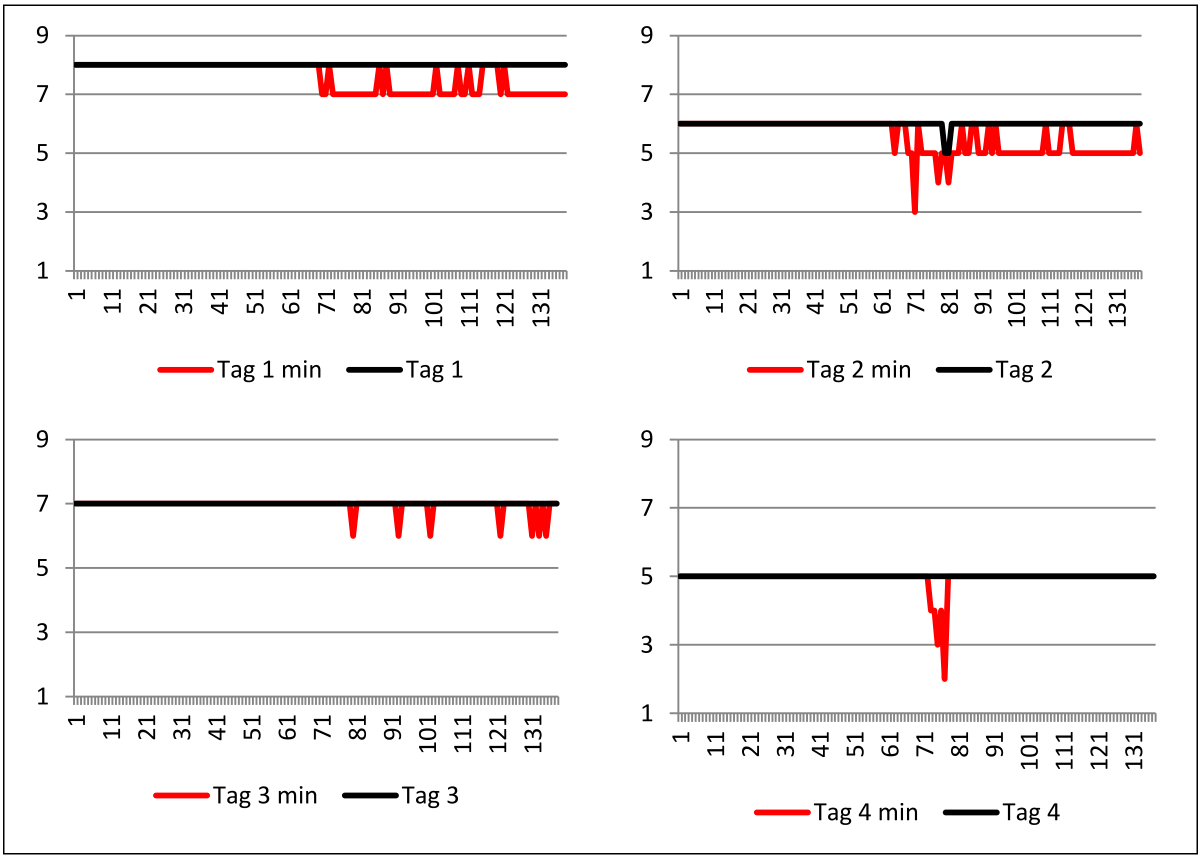


Figure 5.59 The signal strengths of Tags 1, 2, 3, and 4 during hours 1 – 4

The data showed that there was positive disruption of the signal strength of the four tags during the second half of their active period compared to the first half. Whilst the disruption observed from Tag 4 is not conclusive evidence of a continuous disruption and could be considered a single event, the change in stability of the signals from Tags 1, 2, and 3 are a strong indicator that the activity of the second prototype is responsible for the disruption.

The results for Tags 5, 6, 7, and 8 are presented in Figure 5.60. These tags were controlled by the second prototype and were active from hours 2 to 6 of the test.

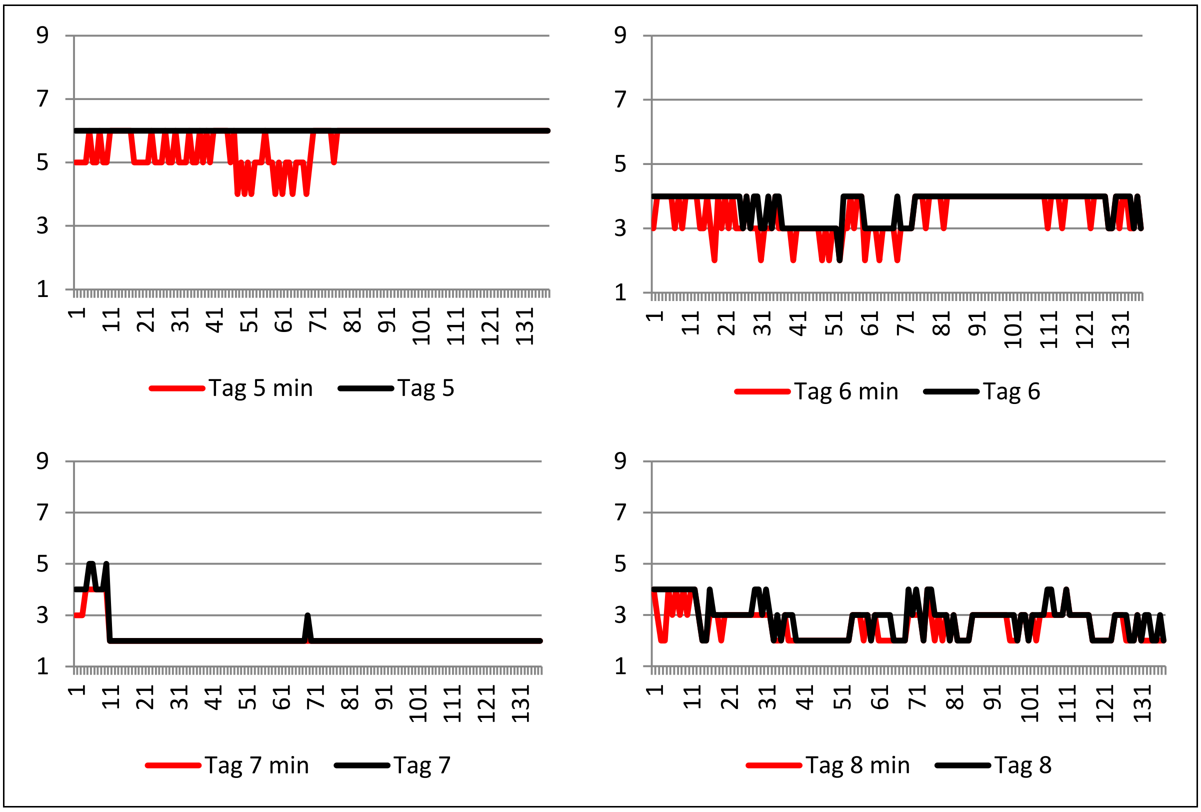


Figure 5.60 The signal strengths of Tags 5, 6, 7, and 8 during hours 2 - 6

The results from Tags 5, 6, and 7 showed a greater level of disruption during the first half of the test when the other prototype was also active. Tag 6 was variable throughout the test but is seen to be more disturbed in the first two hours. Tag 7 is not conclusively affected by a persistent disruption and Tag 8 is very disruptive throughout.

5.5 Triple Points

Three sets of readings were taken with the prototype placed in the triple points described in Chapter Four. Following investigation into the effect of having more than one prototype active at the same time and causing disturbance only one prototype was used at a time. The same prototype and tags were used for all the triple point tests to reduce potential variation between individual units.

The resulting signal strength readings were recorded and used to create the heatmaps in Figure 5.61. From this it can be seen that the lowest signal strengths obtained are SSN3 and occurred with RPi2 and RPi3. The lowest signal strength from RPi1 was SSN4. The maximum signal strength, SSN9, was clustered in close proximity to each RPi position.

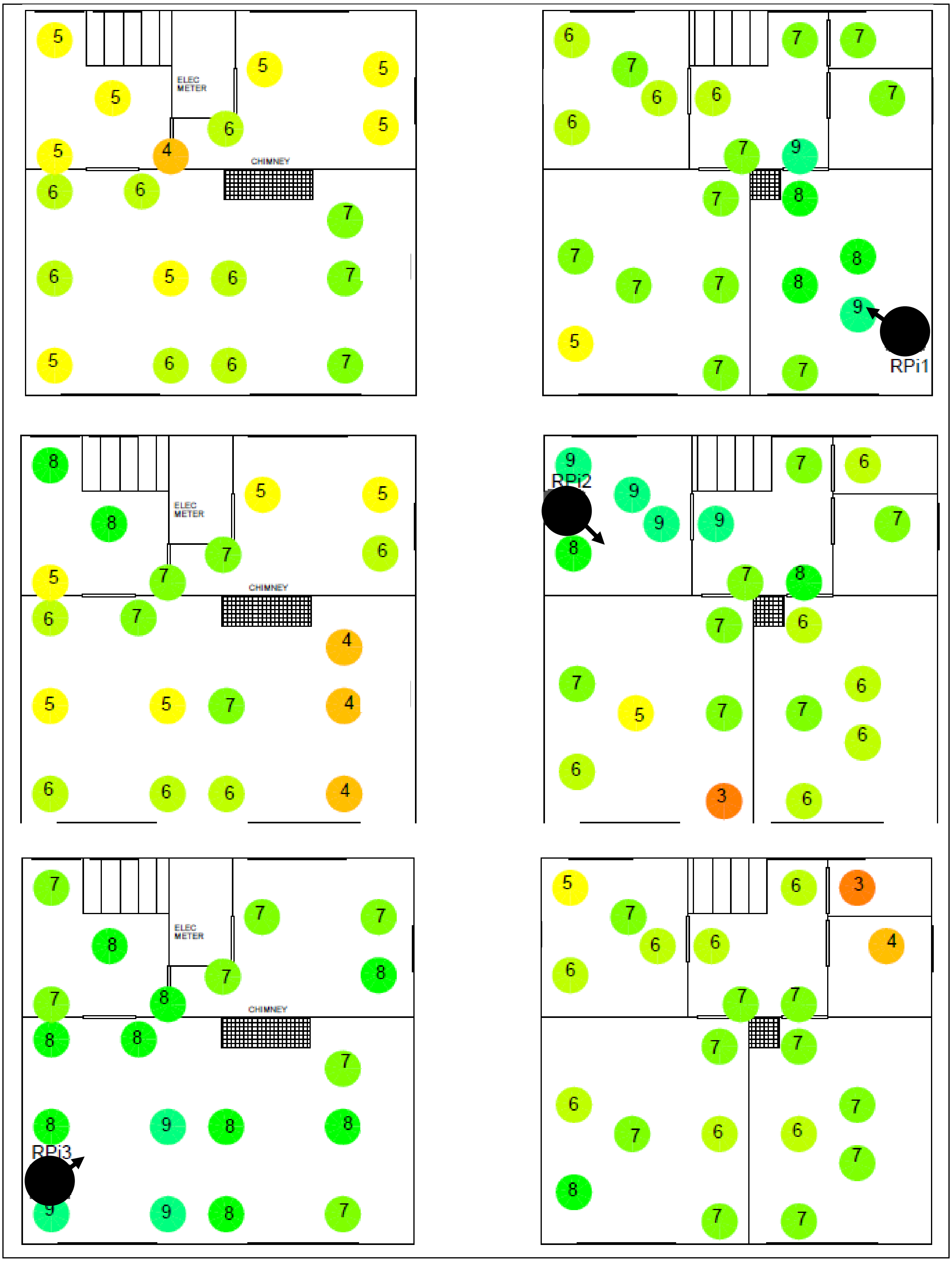


Figure 5.61 The three triple point resulting heatmaps at Home 1, ground floor (left) and first floor (right)

The signal strengths from the three tests are shown with the locations in Figure 5.62. Twenty six of the 40 sampling points had a unique combination of signal strengths and seven signal strength combinations occur twice. These 14 sampling points are indicated on the location map.

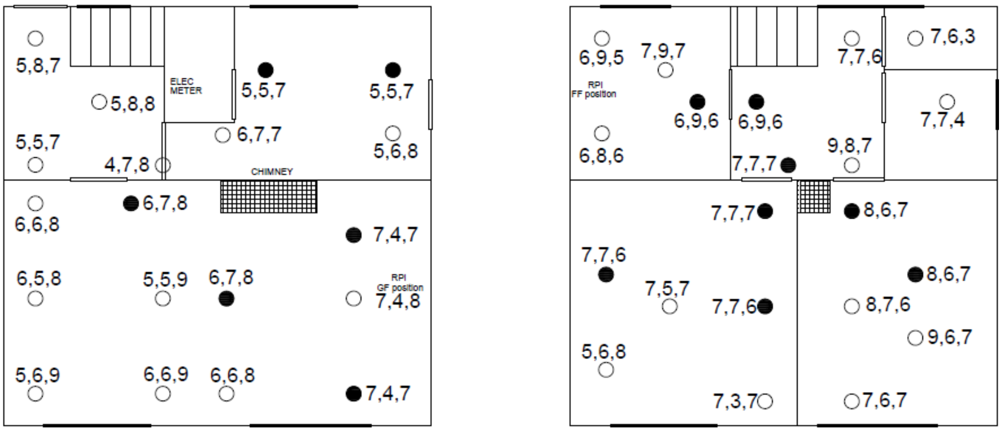


Figure 5.62 The triple point signal strength combinations

The maximum distance between two sampling points that share the same signal strength combination is 1.5 metres.

Figure 5.63 shows the 3D scatter plot of the triple point results and indicates that the signal strength combinations in different rooms are dissimilar. This increases the confidence of being able to use the results from three prototypes in the triangulation positions to locate the tag to room-level. The results from the toilet (FT) and bathroom (FBA) can be seen to be outliers, separate from the majority of the other results. The plots from the same rooms tend to cluster with other points from the same room, and differ from results from other rooms.

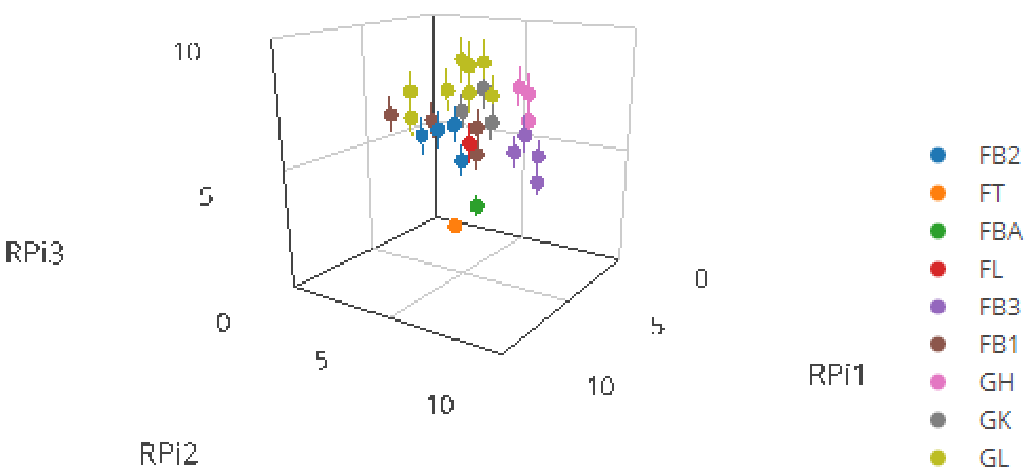


Figure 5.63. 3D scatter plot of the triple point results

5.6 Mobile Walk-through

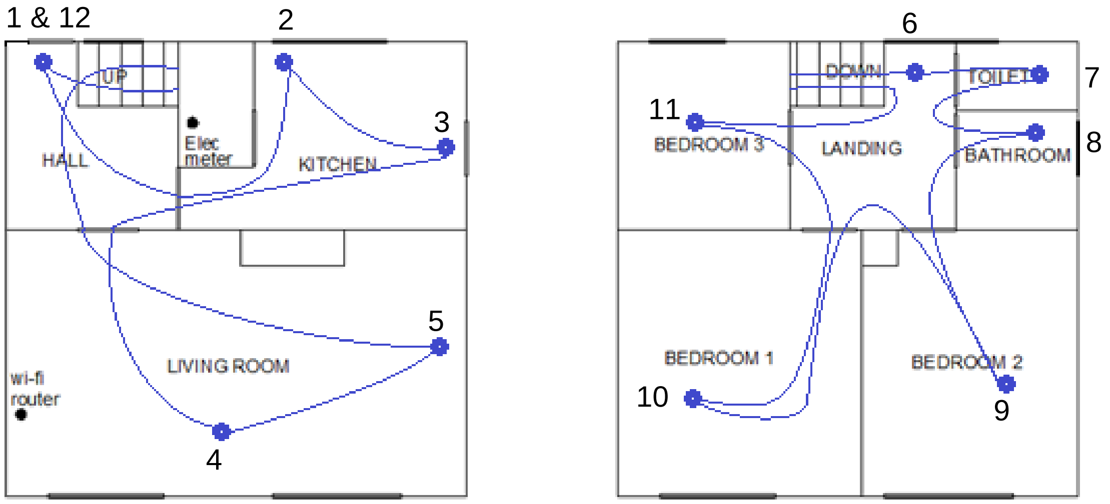


Figure 5.64 The walk-through route in Home1 with pause points

Figure 5.64 shows the path and pause points that were used in a walk-through test. Using the same prototype and tag, three sets of readings were collected by the prototype at each of the three triple points. The use of pause points allowed the data from the three tests to be coordinated. This resulted in 12 signal strength combinations for the 12 known pause point locations, and an additional 22 combinations relating to the intermediate unknown locations.

The 34 signal strength combinations that were obtained during the test are shown in Figure 5.65. Analysis of the data was carried out into the changes in signal strength throughout the mobile walk-through. The majority of consecutive signal strength readings varied by 1SSN or zero. Changes in consecutive signal strength readings of greater than 1 SSN were highlighted and investigated further.

RPi1	change in SSN	RPi2	change in SSN	RPi3	change in SSN	pause point
5	-		-		-	1
4	-1		0	7	0	
	+2	7	0	8	+1	
	0		0		-1	
6	0	5	**-2**	7	0	2
	0		0		0	
	0	6	+1	6	-1	3
	0	7	+1		+1	
	+1		-1	7	0	4
	0	6	0	8	+1	
7	0		0	7	-1	
	0	5	-1	8	+1	5
	0	6	+1	7	-1	
5	**-2**		+1		+1	
8	**+3**		0	8	0	6
7	-1	7	0	6	**-2**	
5	**-2**		0	5	-1	7
	+1	8	+1	3	**-2**	
6	0		0	4	+1	8
8	**+2**	5	**-3**	5	+1	
9	+1	6	+1	7	**+2**	9
	0		+1		+1	
	-2	7	0	8	0	
	0		0		-1	10
7	0		-1		0	
	0	6	0	7	0	
8	+1	7	+1		0	
	-1		**+2**	6	-1	11
	0	9	0	7	+1	
7	0		0	6	-1	
	0	7	**-2**		+1	
6	-1	6	-1	7	0	
	-1	5	-1	6	-1	
5	0	7	**+2**	7	+1	12

Figure 5.65 The signal strength combinations obtained during the mobile walk-through test

Figure 5.65 shows that from each set of results the signal tends to rise and fall in a smooth manner with no jumps from a high signal strength to a low one from one reading to the next. There was however fourteen instances when the signal increased or decreased greater than +/-1SSN between readings, and these were explored to determine possible causes of these events.

Analysis of events giving rise to a signal strength variation greater than 1SSN:

<u>From RPi1:</u>

- moving from position 5 to 6 meant moving from directly under the RPi to the furthest distance from the RPi and then going upstairs towards the RPi. This resulted in changes of signal strength of -2SSN and then a +3SSN.
- moving from position 6 to position 7 involved moving to a location with two internal walls between the tag and the RPi and resulted in a decrease of -2SSN.
- moving from position 8 to position 9 meant moving from the bathroom with one internal wall obstruction towards the RPi with no internal walls between the tag and RPi. This resulted in an increase of +2SSN.

<u>From RPi2:</u>

- moving from position 1 to position 2 involved moving from directly below the RPi in the hall to the kitchen with significant building element obstructions between the tag and RPi. The obstructions included a brick wall and electricity meter, and resulted in a loss of signal of -2SSN.
- Between position 8 and position 9 the tag moved from a mostly unobstructed position in the bathroom to the furthest corner in bedroom 2 with several obstructions including two internal walls and the chimney breast. This resulted in a weakening of signal strength of -3SSN.
- Moving from position 10 to position 11 the tag moved from a room adjacent to the room with the RPi directly towards the RPi, resulting in a signal gain of +2SSN.
- position 11 to position 12 involved moving away from close proximity to the RPi to the top of the stairs and ending in the hall directly under the RPi. This is responsible for a signal loss of -2SSN followed by a gain of +2SSN.

<u>From RPi3:</u>

- the route from position 6 to position 9 required the tag to move from a position unobstructed by the chimney breast to one that was (toilet) and then towards another obstructed position (bathroom) and ending in bedroom 2. These moves resulted in signal loss of -2SSN, followed by a further loss of -2SSN and ending with a gain of +2SSN.

The mobile walk-through tests gave 102 signal strength readings and the majority of consecutive signal strength readings varied within +/-1SSN. Of the 14 signal strengths that differed more than 1SSN from the previous reading, all can be accounted by the change in obstructions between the tag and the RPi position.

5.7 Summary

<u>Spectrum Analyzer</u>

The experiments with the spectrum analyzer in the Salford Energy House showed that there was considerable background signal in the 2.45GHz frequency range. This resulted in many occurrences when no discernible signal from the prototype was obtained. When signal strength was detected, communication between the Loc8tor handheld unit and tags was observed. These tests gave the first indication of disruption to signal from elements within the Energy House and potential causes of the disparity between the modelled signal behaviour and the actual results.

<u>Salford Energy House</u>

The signal strength results from testing the prototype in the Energy House clearly demonstrated the effect of the substantial metering equipment located in the space under the stairs. The monitoring equipment reduced the signal strength markedly when it was between the tag and the prototype, in the form of a shadow that was identifiable in the resulting signal strength heatmaps.

Combining the signal strength results of two tests in order to determine tag location showed that the eight most frequent combinations accounted for 70% of the total number of sampling points. These combinations could not be used to locate the tag reliably as most occurred in several different rooms.

Comparison of the simulated and actual signal strength behaviour varied noticeably. The Energy House was designed and built to replicate thermal behaviour of domestic properties and is located inside a laboratory with extensive metallic and building elements surrounding it. It is not analogous to the way signals travel through ordinary homes.

Home 1

The signal behaviour at Home 1 was observed to be less disturbed than at the Energy House. The disruption from internal elements, such as the central full height brick chimney, was more apparent and the orientation tests showed that changes in direction of the antenna could be used to improve the signal strength, and hence the differentiation to within rooms to assist location detection. The use of an attenuation tube to focus the signal improved the differentiation of signal strength between floor levels.

Environmental Effects Tests

Investigations into potential environmental effects on signal propagation through the house showed that the humidity and temperature changes experienced did not correlate with variation in signal strength. Environmental Effects Test 2 also showed that occupation of the rooms in which the tag was placed also did not affect the resulting signal strength. Environmental Effect Test 4 however did show a clear disruption to signal when two prototypes were active at the same time. The battery life of the tags was found to be between 111 and 120 hours of continuous use.

Triple Point Positions

The use of the triple point positions to collect signal strength data provided 40 combinations with the clearest ability to identify tag location to room level. These results are further evaluated in Chapter Six in order to develop an algorithm to detect location from signal strength data.

Mobile Walk-Through

Walking through the house while collecting signal strength data from the triple point positions resulted in a set of 34 signal strength combinations. While twelve of these combinations occurred in known positions (the pause points) the remaining 22 combination locations was not known, and could relate to any location between pause points. In Chapter Six, this dataset is used to test the algorithm developed from the stationary tests to ensure reliability with real-life mobile results.

A detailed analysis of the results presented in this chapter is given in Chapter 6.

Chapter Six

6 Test Results Evaluation

This chapter expands on the results presented in the previous chapter. The triple point method, using three prototypes at three corners of the house (two on the first floor and one on the ground floor) gave the best differentiation of results between rooms. These results are used to produce signal strength contour maps for the prototypes and to develop an algorithm to determine room location by signal strength. Data from the mobile walk-through was then used to test and refine the algorithm. The mobile test was then repeated and the new data subjected to the algorithm to evaluate the success of deriving tag location by room.

6.1 Contour Maps

In order to produce contour maps for the prototypes, the results from the triple point tests were compared with the Ekahau simulations. This was to ensure the placement of contours reflects how signals are expected to behave with respect to the actual obstructive influences present in the house, such as the chimney.

The limitations of the Ekahau software is apparent when it comes to modelling the effect the chimney structure has on signal propagation through the house. Although the chimney is represented as a combination of brick walls this does not adequately reflect the impact observed in tests. Additionally, there are other factors present in Home 1, such as items of furniture, which influences the strength of signal received by the prototype. Examples of these incidences are highlighted in the following comparisons.

<u>RPi1</u>

Figure 6.1 shows the simulated and actual signal strength results with the prototype at position 1, on the first floor. The experimental results vary from the modelled prediction when the chimney structure is between the tag and reader, for instance the SSN4 observed in the ground floor hall. There are also a number of SSN5 results present in the living room and bedroom 1 that do not correspond to the model. The remaining results broadly correlate with the simulation.

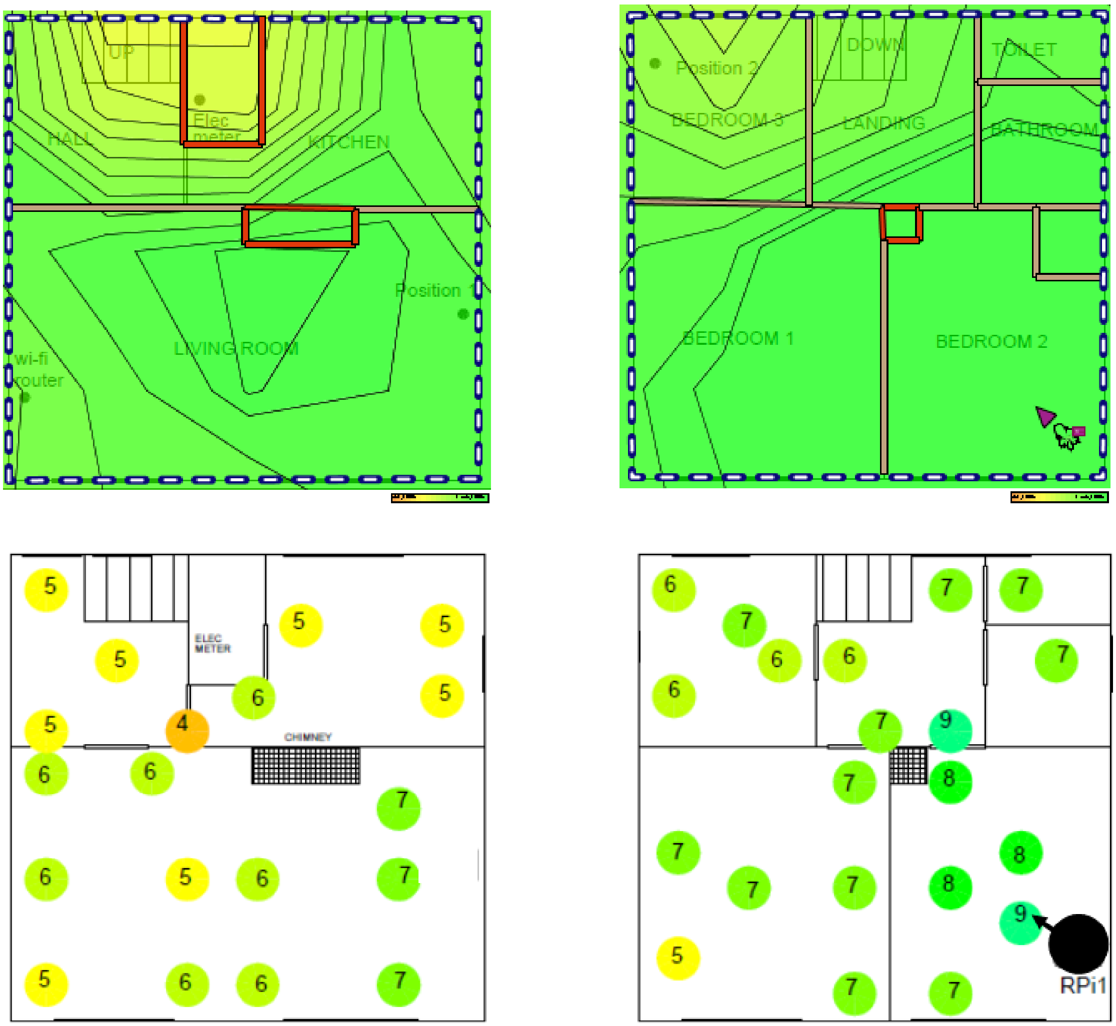


Figure 6.1 The simulated signal contour map (above) and actual signal strength results (bottom) from triple point position 1 at Home1, ground floor (left) first floor (right)

<u>RPi2</u>

The comparison of the triple point position 2 is shown in Figure 6.2. This shows that the lowest signal strength result of SSN3 occurred in bedroom 1. This is an atypical result because the prototype is on the same floor, in the next room and directed towards the sampling point. This signal strength is not obstructed by the chimney and must be affected by other obstructions, most likely a metal filing cabinet in bedroom 3.

Apart from one incidence of SSN3, the other low strengths were found in the living room, SSN4, and the furthest away from the prototype position on the other side of the chimney structure. Similarly to the results from RPi1, there are three outliers of SSN5, in this case in the living room and hall, where higher signal strength could reasonably be expected.

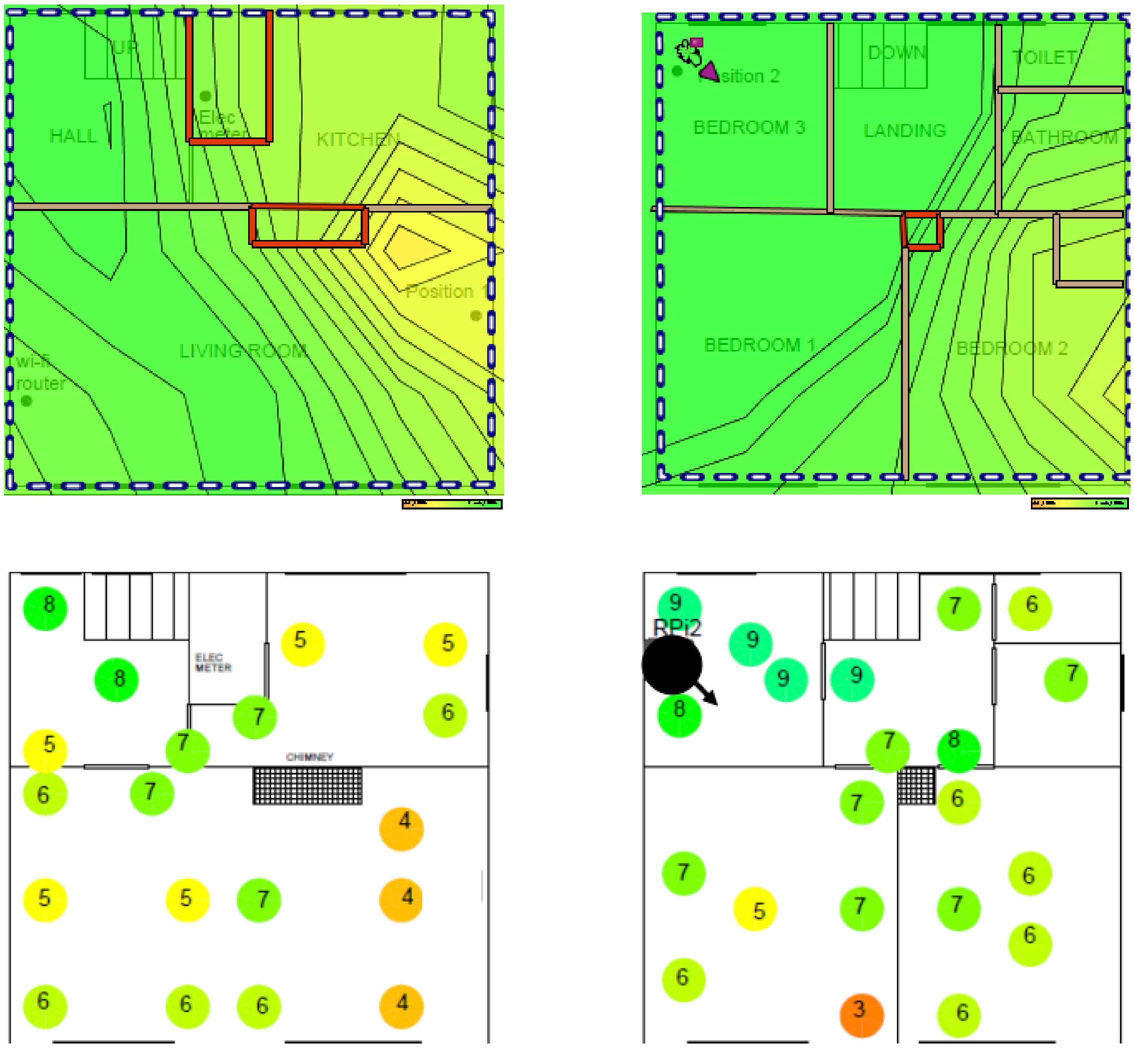


Figure 6.2 The simulated signal contour map (above) and actual signal strength results (bottom) from triple point position 2 at Home1, ground floor (left) first floor (right)

RPi3

Figure 6.3 shows the results from RPi position 3 have the lowest signal strengths in the first floor toilet and bathroom, SSN3 and SSN4 respectively. These points are the furthest away from the RPi position and have internal walls, floor and chimney obstructions between them and the receiver. These low signal areas correlate with expected low signals in the simulation.

Disturbance in the model from the brick pantry and electricity meter in the kitchen had less effect on the actual results, and the kitchen points remained high at

SSN7 and SSN8. Signal strength results on the first floor were found to be more diverse than expected, with several strengths more affected by the furniture than if the signal was travelling through only the wall structures that could be modelled.

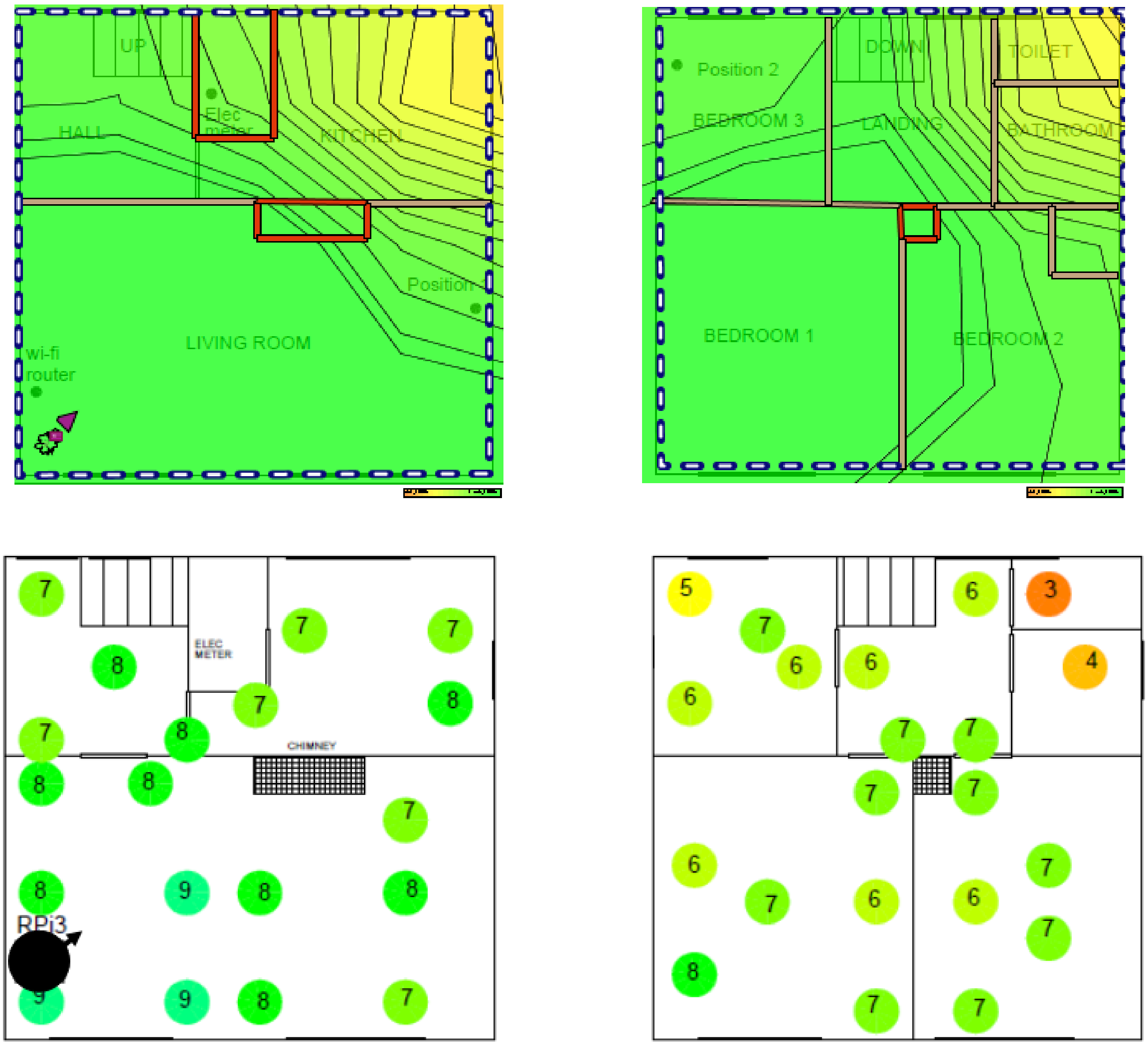


Figure 6.3 The simulated signal contour map (above) and actual signal strength results (bottom) from triple point position 3 at Home1, ground floor (left) first floor (right)

From evaluating how the actual and predicted signal strengths differed, and the factors that influenced this divergence, a set of contour maps for the prototype at the three triple point positions was developed. These signal strength contour maps show the general areas of signal strength without the atypical readings due to the fixtures and fittings present in the house. These contour maps are shown in Figure 6.4.

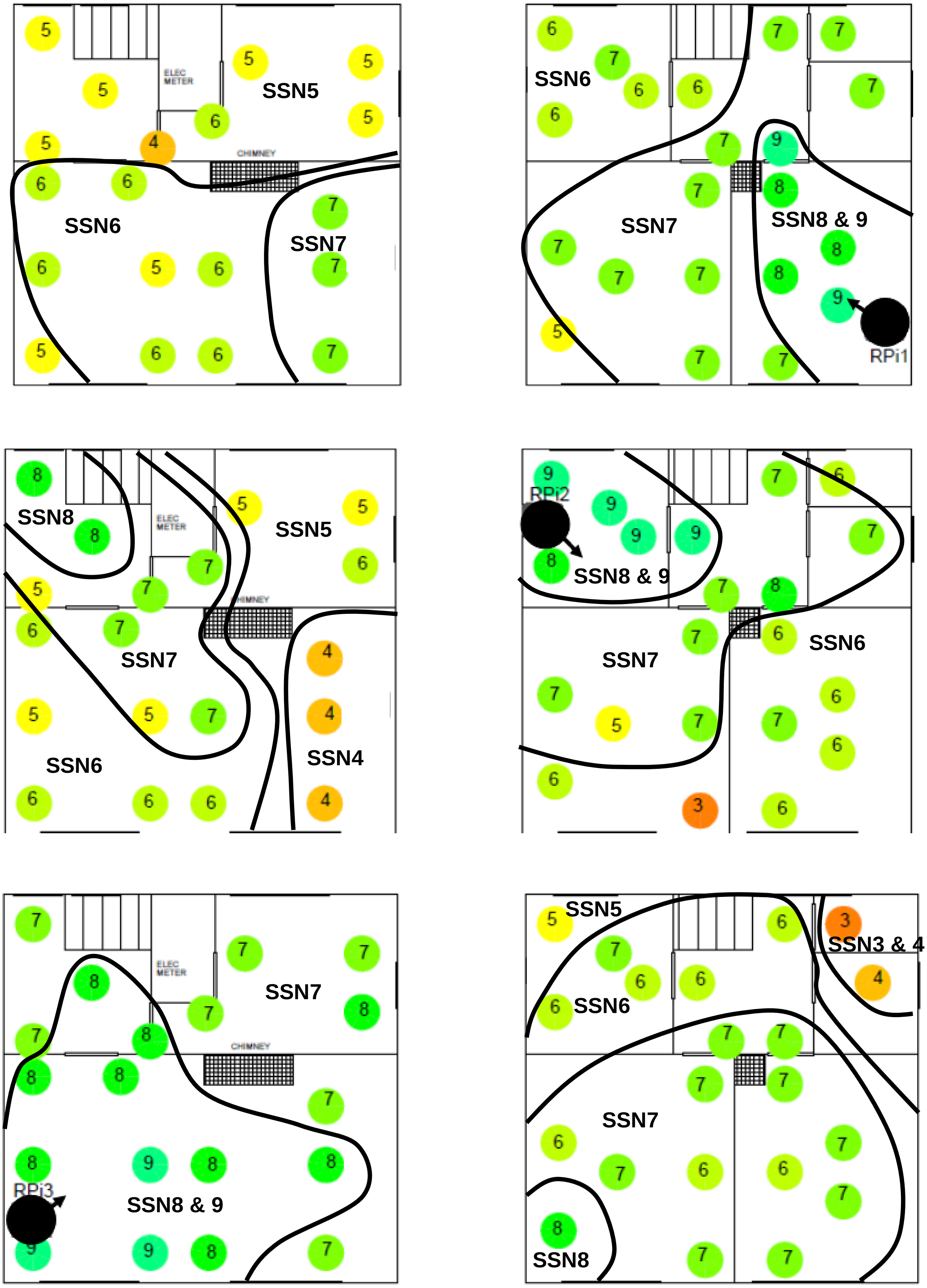


Figure 6.4 The signal strength contour maps of the prototype

The contour maps are useful to show how the signal between the tag and receiver generally behaves, but is not appropriate to base an algorithm on because the atypical signal strengths that do not fit neatly into the contours must be taken into account. The following section describes how the algorithm was developed from all the actual signal strength results.

6.2 Algorithm Development

To develop an algorithm that can derive tag location to room-level from a combination of three signal strength readings with the receivers in the triple point positions, it was necessary to clarify the room locations in which each SSN was observed. This is shown in Table 6.1. The signal strength readings are denoted as *a*, *b*, or *c* from RPi positions 1, 2, and 3 respectively.

signal strength	locations present
a = SSN4	GH
a = SSN5	GH, GK, GL, FB1
a = SSN6	GK, GL, FB3, FL
a = SSN7	GL, FB3, FB1, FL, FT, FBA, FB2
a = SSN8	FB2, FL
a = SSN9	FB2
b = SSN3	FB1
b = SSN4	GL
b = SSN5	GH, GL, GK, FB1
b = SSN6	GL, GK, FB1, FB2, FT
b = SSN7	GL, GH, GK, FL, FBA, FB1, FB2
b = SSN8	GH, FL, FB3
b = SSN9	FB3, FL
c = SSN3	FT
c = SSN4	FBA
c = SSN5	FB3
c = SSN6	FB3, FL, FB1, FB2
c = SSN7	GH, GK, GL, FB3, Fl, FB1, FB2
c = SSN8	GH, GL, GK, FB1
c = SSN9	GL

Table 6.1 the rooms signal strengths a, b, or c were present

There were eight signal strengths that only occurred in one room; these were when the signal strength was the strongest (SSN9) and the weakest (SSN3 and SSN4) for each RPi position. SSN7 was present in seven rooms from all three RPi positions. To derive location from the values of a, b, and c, a decision tree was developed from all of the values combined and their associated possible locations. Figure 6.5 presents the process when the signal strength from RPi1 is SSN4.

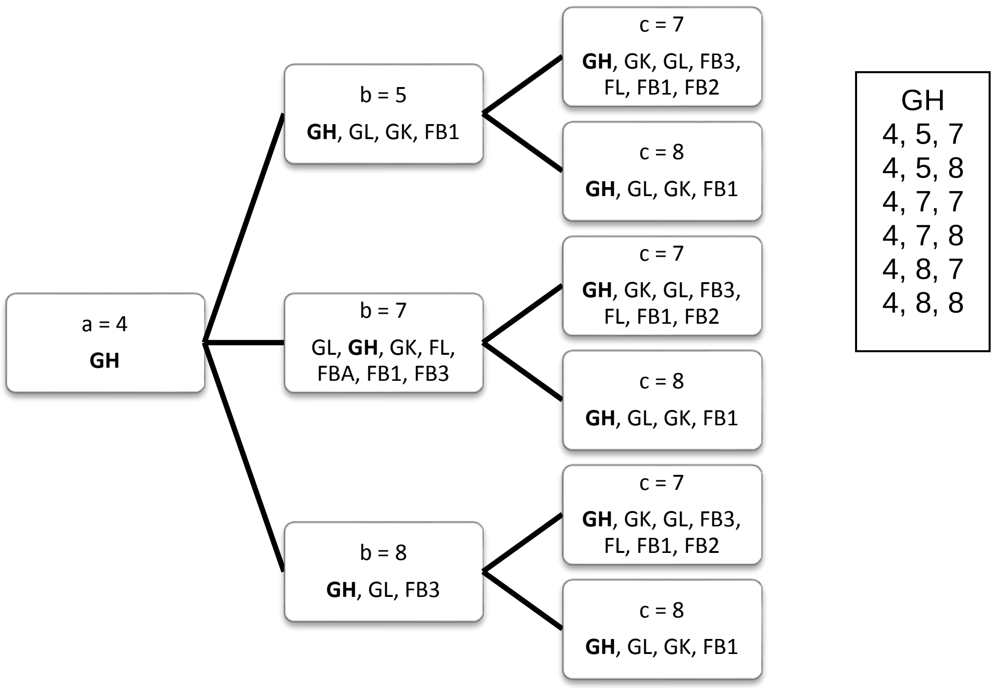


Figure 6.5 Decision tree for *a = SSN4*

In the figures of the decision trees, the box with the value for a, b, or c, also shows all the locations that value was observed in, i.e. one room for a = 4, seven rooms for b = 7, etc. Also included are the resulting signal strength combinations that can indicate location in one room.

Although *a = SSN4* only occurs at location GH, the process of the deriving the combinations of signal strength to determine room location is shown in full. The method started with the value for *a,* and then continues to the only possible values from *b* and *c*. This is repeated for all the other values of signal strength.

Combinations can only confirm a room location if a, b, and c all occur in that location. As can be seen from the decision tree when *a = SSN5*, Figure 6.6, in additions to signal combinations that specify one room, there are also combinations that can be attributed to two or more rooms. Details of the room combinations that suggest more than one room are valuable data and can be used to determine probable and possible locations in circumstances where there is doubt.

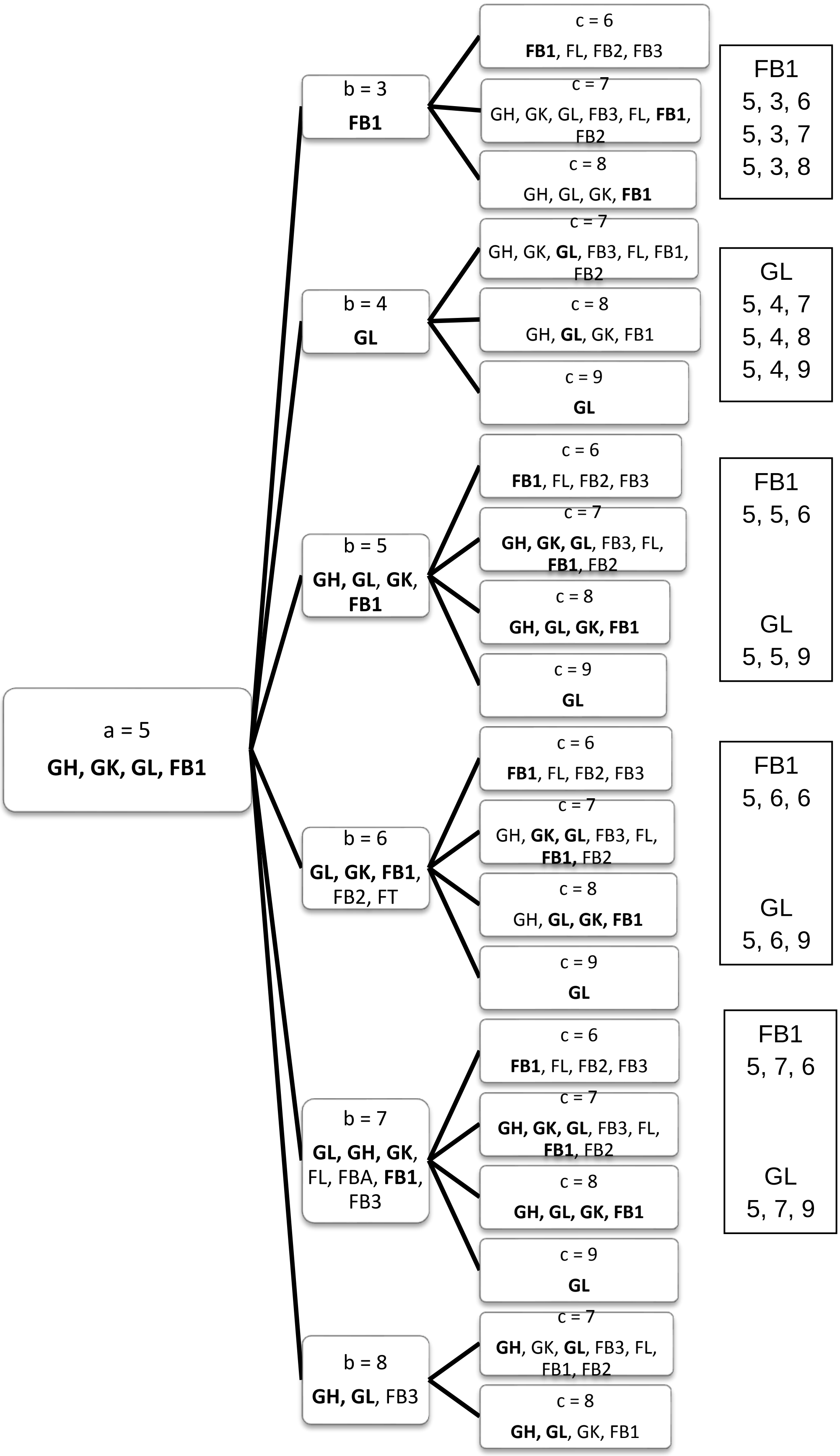


Figure 6.6. Decision tree for *a = SSN5*

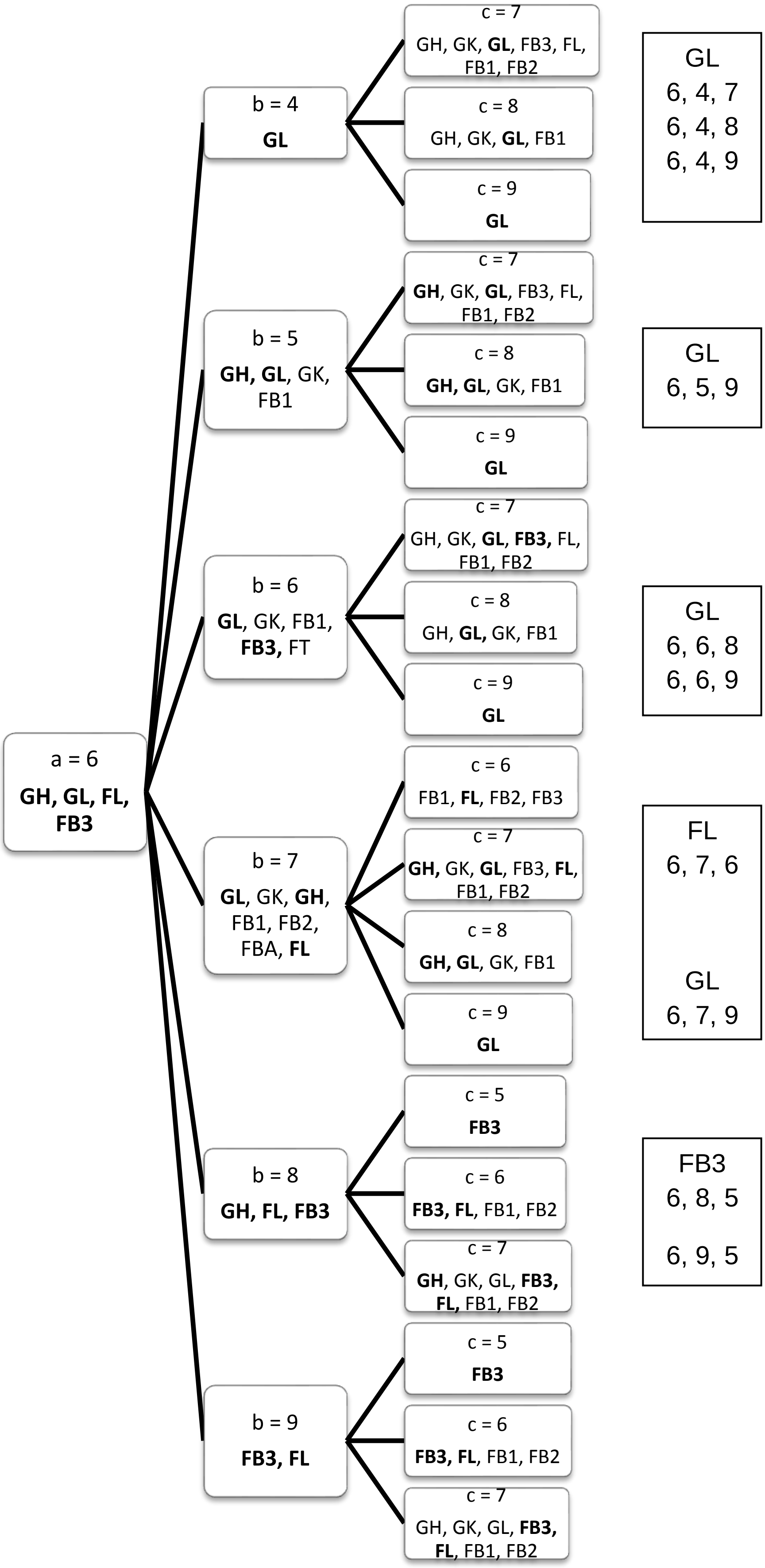


Figure 6.7 Decision tree for *a = SSN6*

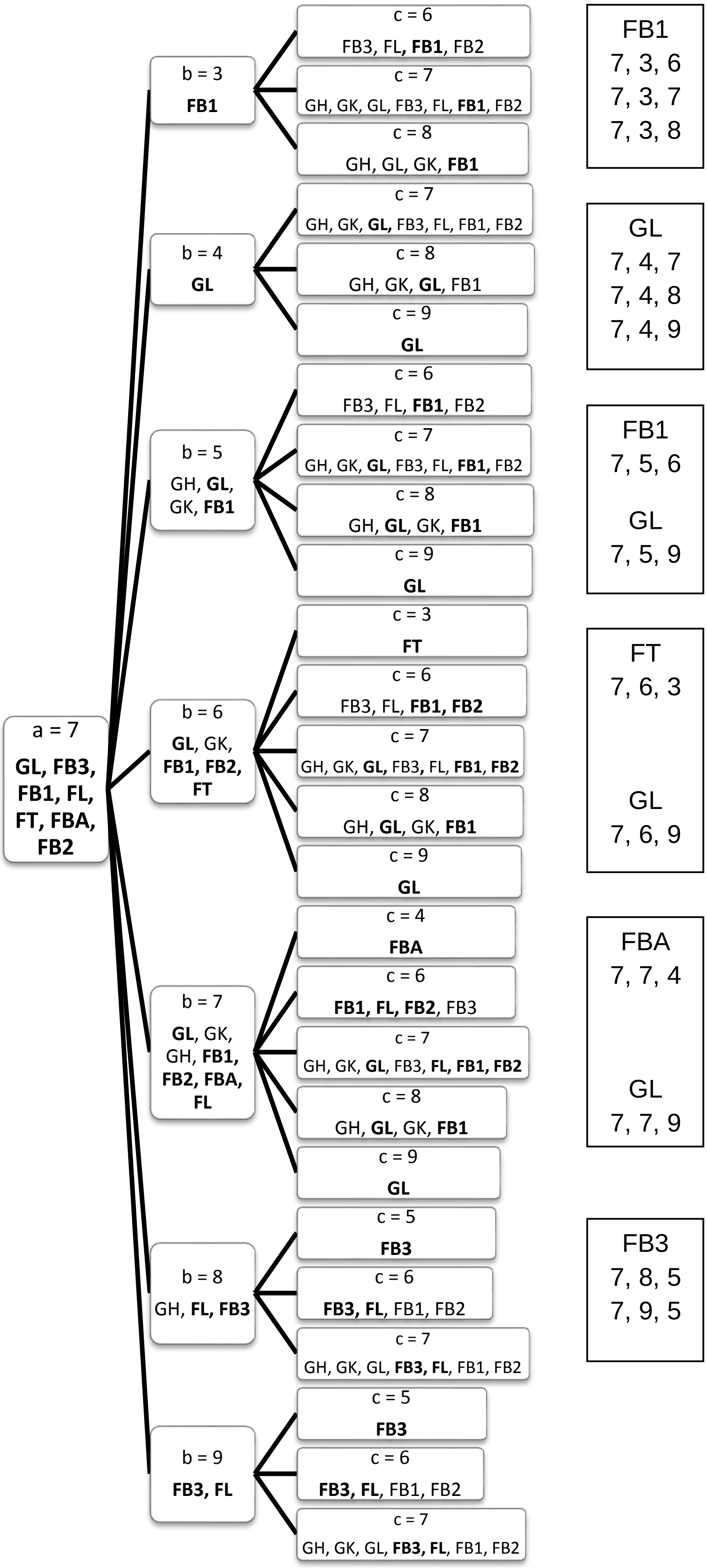


Figure 6.8 Decision tree for *a = SSN7*

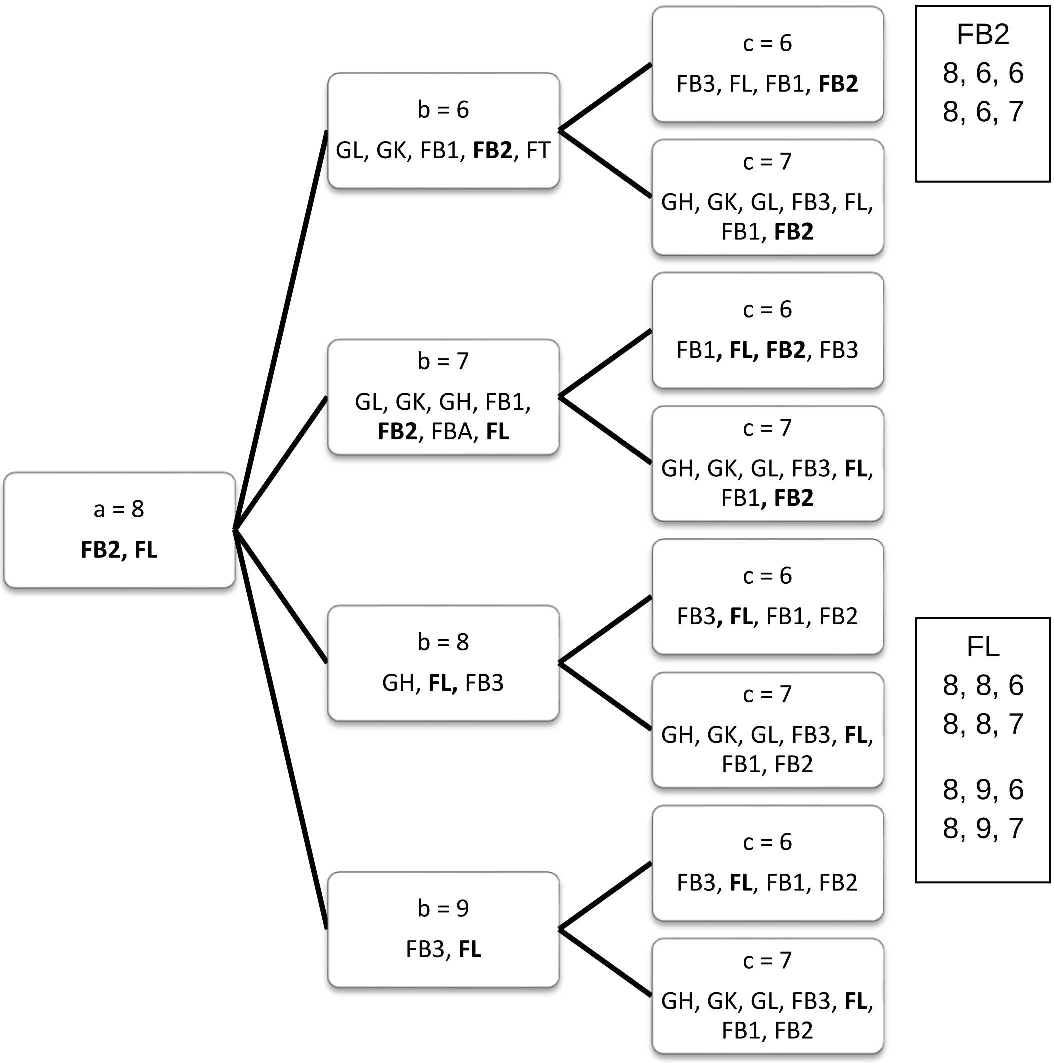


Figure 6.9 Decision tree for *a = SSN8*

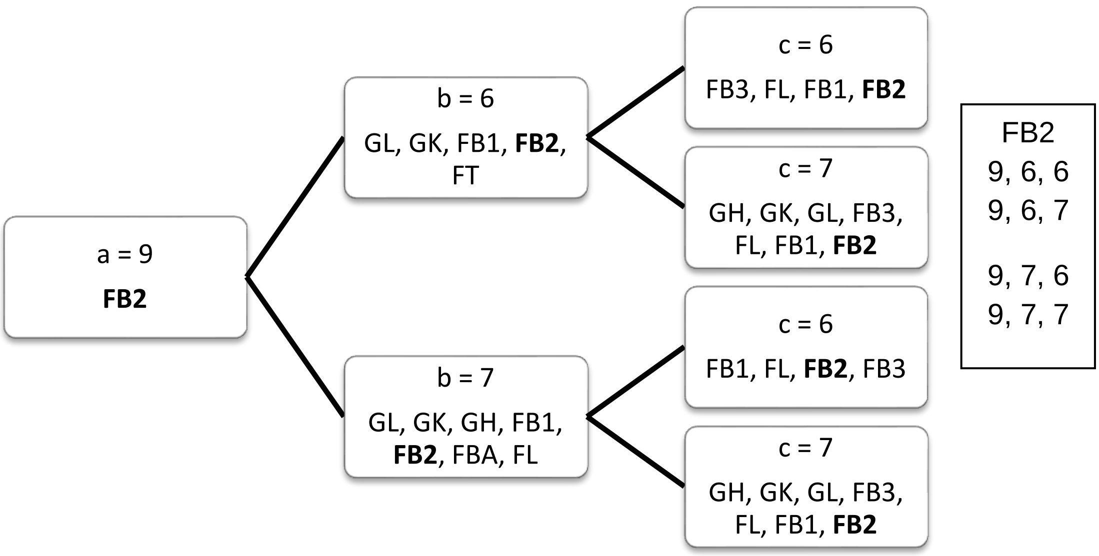


Figure 6.10 Decision tree for *a = SSN9*

It is apparent that there are a greater number of combinations from mid-range signal strength (SSN5 to SSN7) than at the high and low signal strengths. As can be seen from the decision trees, there are combinations that denote one room, and others that indicate one or more rooms. These combination types can be arranged into the hierarchy as shown in Table 6.2.

combination type	indicates location in	number of combinations
Group 1	one room	50
Group 2	two rooms	19
Group 3	three rooms	6
Group 4	four rooms	4

Table 6.2 The groups of signal combinations

Group 1 combinations give the greatest confidence of the tag being present in the room indicated as they indicate one room only. These signal strength combinations are the most abundant, at 2 ½ times the number of Group 2 combinations. The locations relating to Group 1 combinations are shown in Table 6.3.

rooms	Group 1 combinations		
GH	4, 5, 7	4, 5, 8	
	4, 7, 7	4, 7, 8	
	4, 8, 7	4, 8, 8	
FB1	5, 3, 6	5, 3, 7	5, 3, 8
	5, 5, 6	5, 6, 6	
	7, 3, 6	7, 3, 7	7, 3, 8
	7, 5, 6		
GL	5, 4, 7	5, 4, 8	5, 4, 9
	5, 5, 9	5, 7, 9	
	6, 4, 7	6, 4, 8	6, 4, 9
	6, 5, 9		
	6, 6, 8	6, 6, 9	
	6, 7, 9		
	7, 4, 7	7, 4, 8	7, 4, 9
	7, 5, 9	7, 6, 9	7, 7, 9
FL	6, 7, 6		
	8, 8, 6	8, 8, 7	
	8, 9, 6	8, 9, 7	
FB3	6, 8, 5	6, 9, 5	
	7, 8, 5	7, 9, 5	
FT	7, 6, 3		
FBA	7, 7, 4		
FB2	8, 6, 6	8, 6, 7	
	9, 6, 6	9, 6, 7	
	9, 7, 6	9, 7, 7	

Table 6.3 Group 1 combinations

The only room in Home 1 that does not have any Group 1 signal combinations is GK (Ground floor, Kitchen). As shown in Table 6.4, GL (Ground floor, Living room) has the highest number of Group 1 combinations at 18, twice as many as the second highest in Bedroom 1 at 9.

room location			number of Group 1 combinations
code	floor	room	
GL	Ground	living room	18
FB1	First	bedroom 1	9
FB2	First	bedroom 2	6
GH	Ground	hall	6
FL	First	landing	5
FB3	First	bedroom 3	4
FT	First	toilet	1
FBA	First	bathroom	1
GK	Ground	kitchen	0
		Total	50

Table 6.4 Number of Group 1 combinations by room

The locations and signal strengths of the Group 2, 3, and 4 combinations shown in Table 6.5 shows that of the combinations that occur in more than one room, 19 indicate two rooms, 6 three rooms, and 4 in four rooms. GK is associated with two Group 3 and four Group 4 combinations.

	rooms indicated				combinations present		
Group 2	GH	GL			5, 8, 7	5, 8, 8	
					6, 5, 7	6, 5, 8	
					6, 7, 8		
	GL	FB3			6, 6, 7		
	FL	FB3			6, 8, 6	6, 9, 6	6, 9, 7
					7, 8, 6	7, 8, 7	
					7, 9, 6	7, 9, 7	
	GL	FB1			7, 5, 7	7, 5, 8	7, 7, 8
	FB1	FB2			7, 6, 6		
	FL	FB2			8, 7, 6	8, 7, 7	
Group 3	GK	GL	FB1		5, 6, 7	5, 6, 8	
	GL	GH	FL		6, 7, 7		
	GH	FB3	FL		6, 8, 7		
	FB1	FB2	FL		7, 7, 6	7, 7, 7	
Group 4	GH	GK	GL	FB1	5, 5, 7	5, 5, 8	
					5, 7, 7	5, 7, 8	

Table 6.5. Group 2, 3, and 4 combinations by type and room

Using the signal strength from each set of readings that only occur in one room, it was possible to develop the first stage of an algorithm, as shown in Figure 6.11.

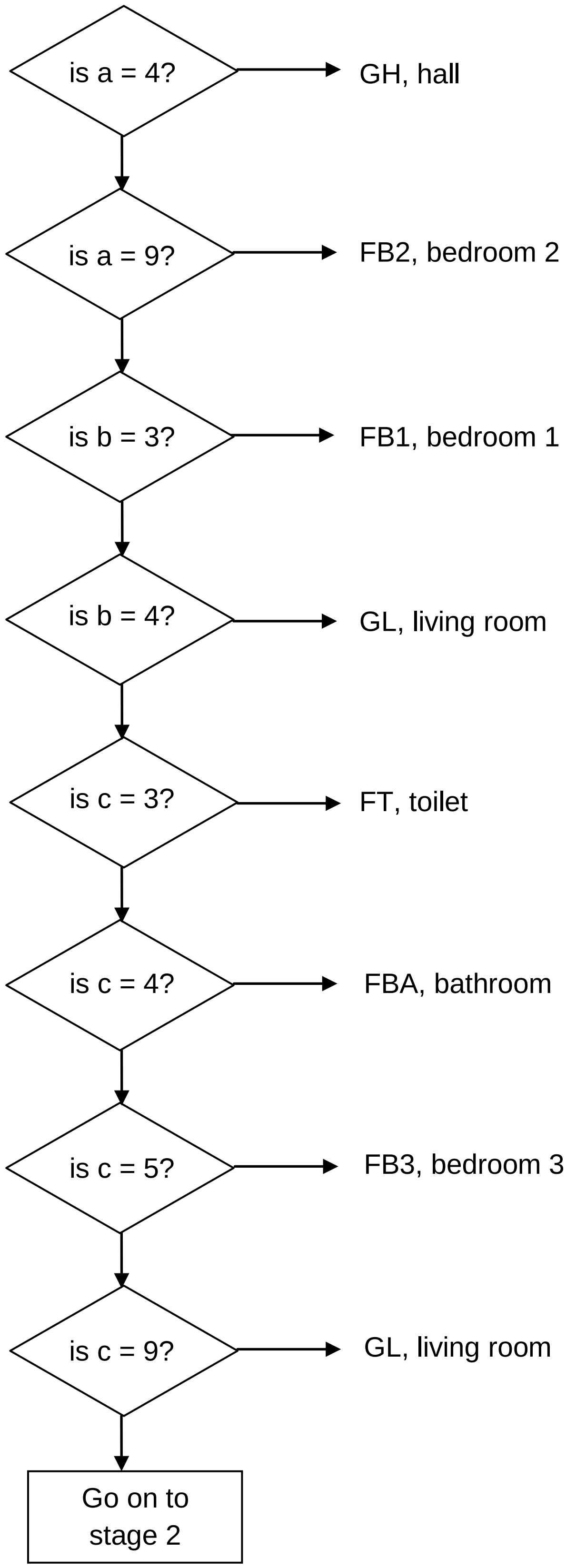


Figure 6.11. Stage 1 of the algorithm

Removing the signal strength combinations that overlap with those in Stage 1 and contain the eight single signal strengths that indicate one room only significantly reduces the number of combinations in Group 1. The remaining 11 Group 1 combinations were used to construct the second stage of the algorithm. This is shown in Figure 6.12.

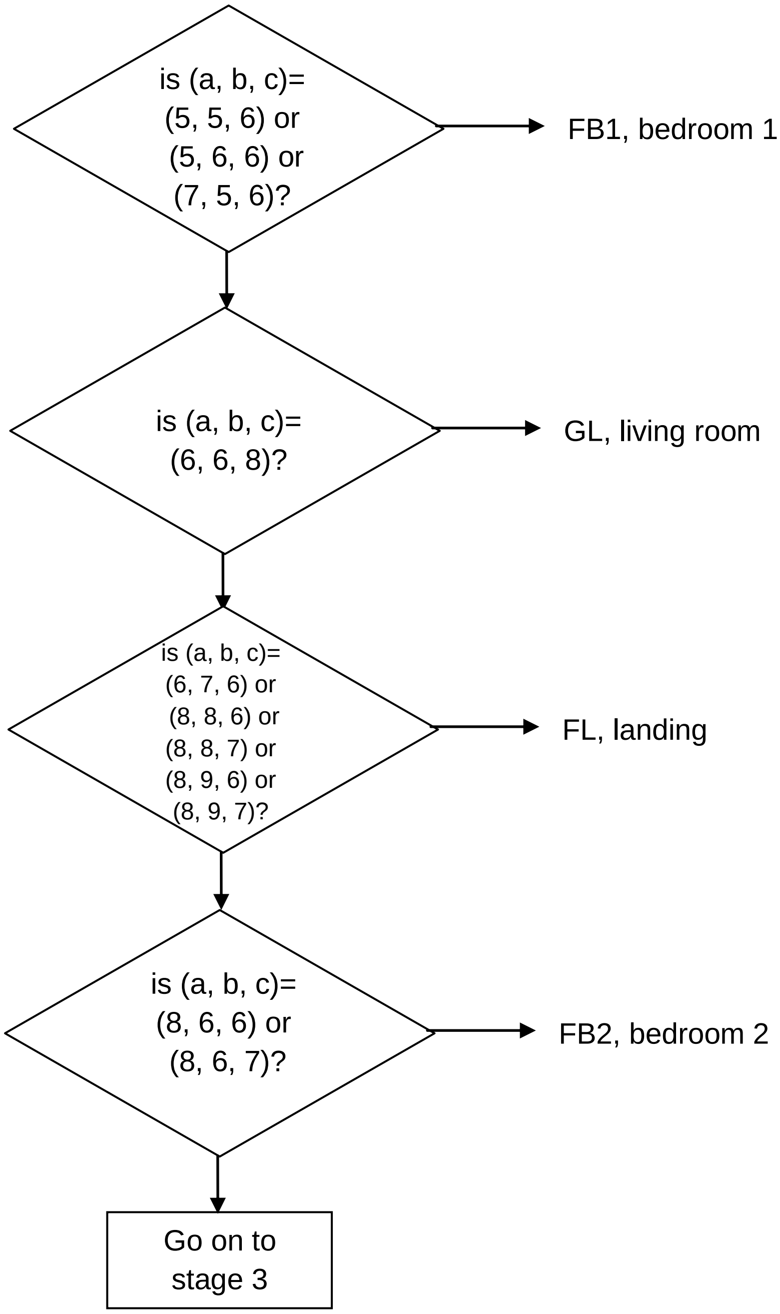


Figure 6.12. Stage 2 of the algorithm

Stage 3 of the algorithm entails comparison of the signal strengths with those from Groups 2, 3, and 4. These groups contain the signal strength combinations that cannot indicate one single room, but occur in two, three, or four rooms. The following section explains how the algorithm was tested with the results from the mobile walk-through.

6.3 Algorithm Testing

Analysis of the algorithm applied to the mobile walk-through test is shown in Table 6.6. Of the 34 readings, five are correctly identified to a room when Stage 1 of the algorithm is used. A further two readings (17 & 20) are incorrectly allocated to bedroom 3 when this is not possible because the route of the walk-through is known. This erroneous allocation indicates that the assumption c = 5 occurs only in bedroom 3 is incorrect.

There is one location derived by applying Stage 2 of the algorithm, at reading 33, suggesting the tag was located in bedroom 1. Again this is known to be incorrect because the reading took place between pause points 11 and 12, and could only be in bedroom 3, the landing, or the hall. This shows that in this case (5, 5, 6) did not occur in bedroom 1.

Eighteen of the readings were compared with the Group 2, 3, and 4 combinations during Stage 3 of applying the algorithm. Fifteen of these indicate the correct room in one of the locations the tag could be present in. Three of these readings (5, 6, & 32) did not have their room location as one of the ones suggested.

The remaining eight readings (7, 9, 10, 11, 13, 15, 25 & 26) did not generate any location suggestions. On five of these occasions the signal strength combination was the same (7, 6, 7) and was present when the tag was known to be in the living room and between bedroom 1 and bedroom 3. Additionally, the kitchen was not indicated at all.

These results are indicated in the table by; highlighting the correct predicted room location in bold, striking through incorrect room predictions, and differentiating the results that correlate with Stage 1 in green, Stage 3 in amber, and previously unseen combinations in red.

reading number	RPi1 SSN	RPi2 SSN	RPi3 SSN	pause point	Stage 1	Stage 2	Stage 3	actual room
1	**5**	**7**	**7**	1			**GH**, GK, GL, FB1	GH
2	**4**	**7**	**7**		**GH**			
3	**6**	**7**	**8**				**GH**, GL	
4	**6**	**7**	**7**				GL, **GH**, FL	
5	**6**	**5**	**7**	2			~~GH, GL~~	GK
6	**6**	**5**	**7**				~~GH, GL~~	
7	**6**	**6**	**6**	3				GK
8	**6**	**7**	**7**				**GL**, GH, FL	
9	**7**	**6**	**7**	4				GL
10	**7**	**6**	**8**					
11	**7**	**6**	**7**					
12	**7**	**5**	**8**	5			**GL**, FB1	GL
13	**7**	**6**	**7**					
14	**5**	**7**	**8**				**GH**, GK, GL, FB1	
15	**8**	**7**	**8**	6				FL
16	**7**	**7**	**6**				FB1, FB2, **FL**	
17	**5**	**7**	**5**	7	~~FB3~~			FT
18	**6**	**8**	**3**		**FT**			
19	**6**	**8**	**4**	8	**FBA**			FBA
20	**8**	**5**	**5**		~~FB3~~			
21	**9**	**6**	**7**	9	**FB2**			FB2
22	**9**	**7**	**8**		**FB2**			
23	**7**	**7**	**8**				GL, **FB1**	
24	**7**	**7**	**7**	10			**FB1**, FB2, FL	FB1
25	**7**	**6**	**7**					
26	**7**	**6**	**7**					
27	**8**	**7**	**7**				**FL**, FB2	
28	**7**	**9**	**6**	11			FL, **FB3**	FB3
29	**7**	**9**	**7**				FL, **FB3**	
30	**7**	**9**	**6**				**FL**, FB3	
31	**7**	**7**	**7**				FB1, FB2, **FL**	
32	**6**	**6**	**7**				~~GL, FB3~~	
33	**5**	**5**	**6**			~~FB1~~		
34	**5**	**7**	**7**	12			**GH**, GK, GL, FB1	GH

Table 6.6 First test of the algorithm with the mobile walk-through results

These results clearly indicated that the algorithm derived from stationary data needed refining to properly identify tag location to room-level. In order to improve the algorithm it was necessary to identify where the predictions correlated with the results and where they diverged. This analysis of Stage 1 of the algorithm is shown in Table 6.7. Of the eight conditions in Stage 1, four were confirmed, one was denied, and three were not tested as they were not present in the data from the mobile walk-through.

Stage 1 conditions	confirmed		
a = 4 -> GH		Yes	
a = 9 -> FB2		Yes	
b = 3 -> FB1	not tested		
b = 4 -> GL	not tested		
c = 3 -> FT		Yes	
c = 4 -> FBA		Yes	
c = 5 -> FB3			No
c = 9 -> GL	not tested		

Table 6.7 Result of testing the Stage 1 conditions

Only the Stage 1 conditions that were confirmed would go on to be included in the improved algorithm. Stage 2 conditions that were not met consist of eight signal strength combinations that were either incorrectly allocated to a room or were not recognised by the algorithm. These are shown in Table 6.8.

combination	predicted location	actual location
(5, 5, 6)	FB1	FL or GH
(6, 5, 7)	GH or GL	GK
(6, 6, 6)	-	GK
(7, 6, 7)	-	GL
(7, 6, 8)	-	GL
(8, 7, 8)	-	FL
(5, 7, 5)	FB3	FT
(6, 6, 7)	GL or FB3	FL or GH

Table 6.8 Stage 2 conditions that were not met

Creation of decision trees from the known locations the signal strengths occurred in the mobile walk-through tests were developed and are shown in Figures 6.13 – 6.16. Decision trees for a = 4 and a = 9 were not created because these conditions were confirmed during the algorithm test to correctly identify tag location in the hall and bedroom 2 respectively.

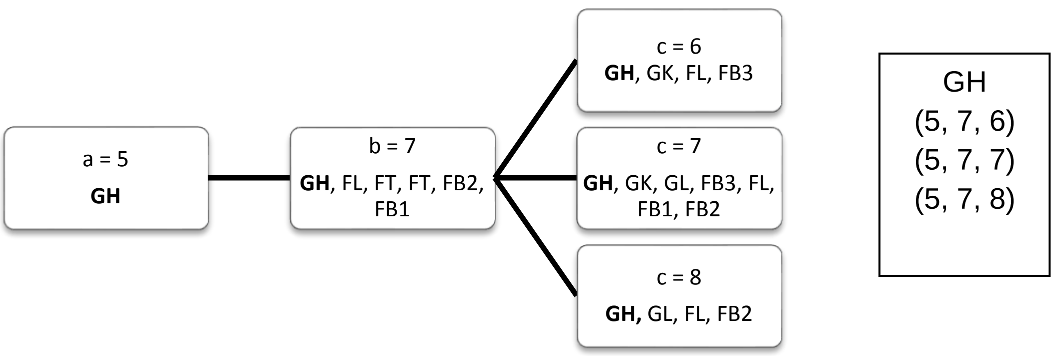


Figure 6.13 Decision tree of a = 5 from mobile data

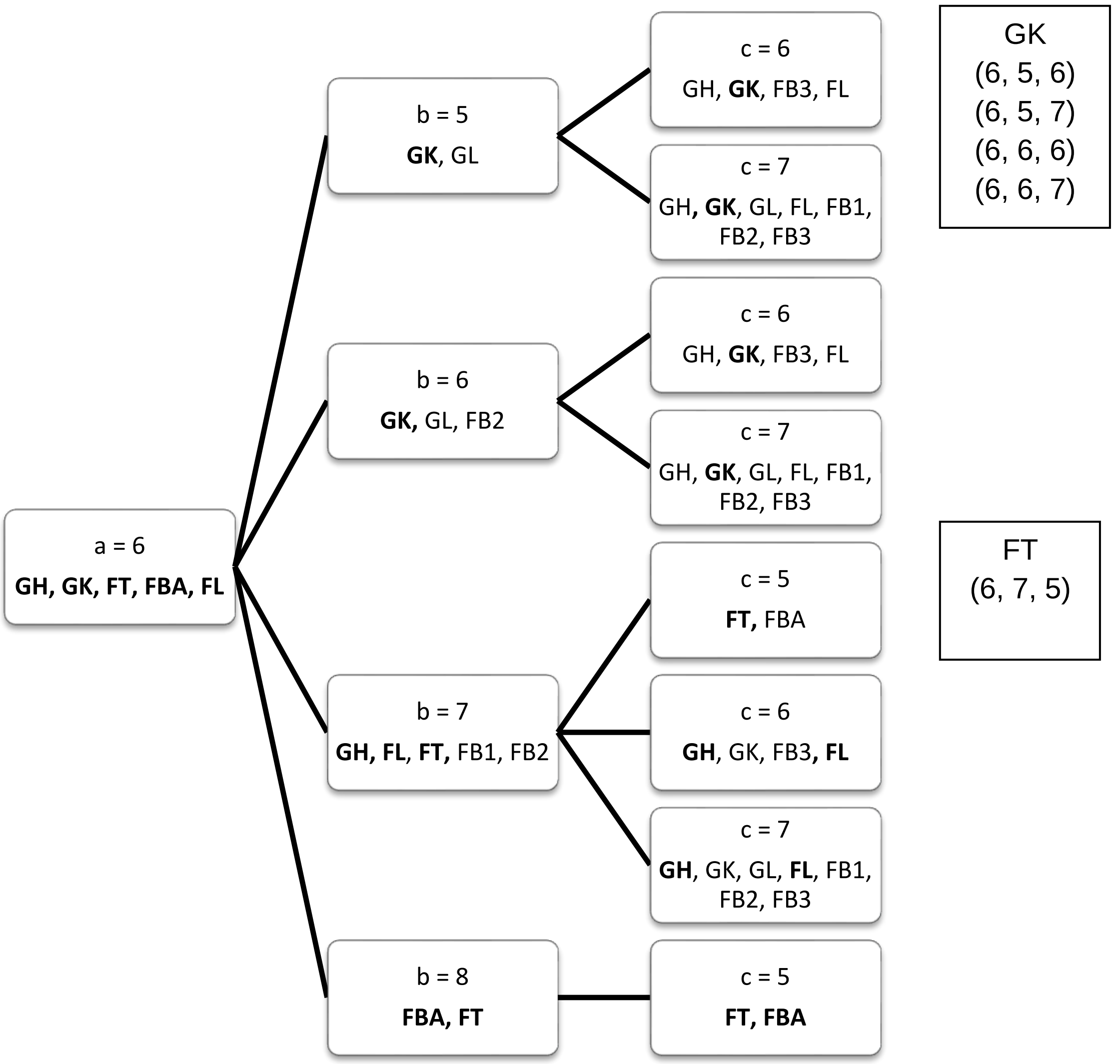


Figure 6.14 Decision tree for a = 6 from mobile data

The decision trees from the mobile data are smaller than those for the stationary data as the signal strength readings are fewer in number. Any combinations resulting from the analysis from the mobile data would be in addition to, not replacing analyses from the stationary data. The purpose of including this data is to fill in the gaps, such as the previous lack of combinations relating to the kitchen.

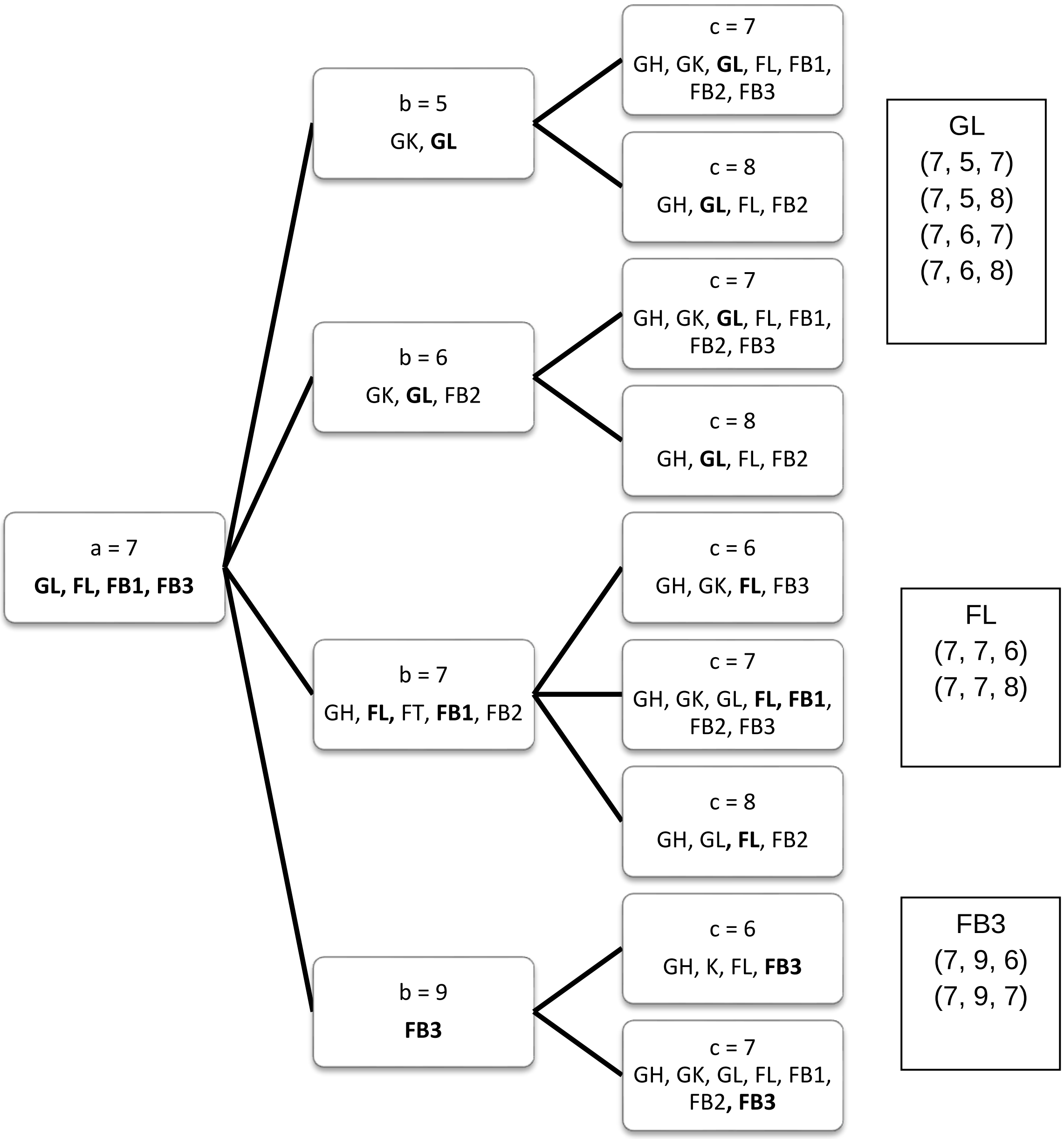


Figure 6.15 Decision tree for a = 7 from the mobile data.

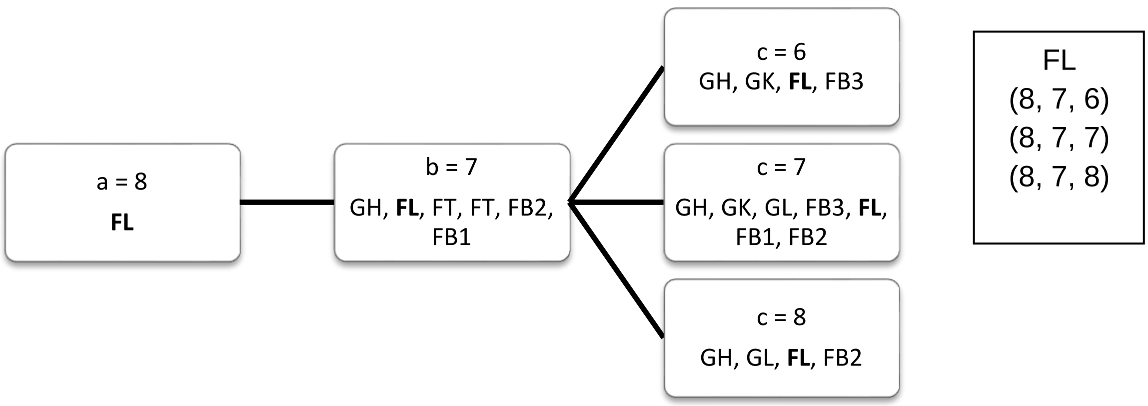


Figure 6.16 Decision tree for a = 8 from the mobile data

Tables 6.9 and 6.10 show that analysis of the mobile walk-through data resulted in an additional 19 Group 1 combinations that could be used to locate the tag to one room, and 4 Group 2 combinations that indicate two possible rooms. These were added to the existing Group 1 and 2 combinations.

rooms	Group 1 combinations		
GH	5, 7, 6	5, 7, 7	5,7, 8
FB1	5, 3, 6	5, 3, 7	5, 3, 8
	5, 5, 6	5, 6, 6	
	7, 3, 6	7, 3, 7	7, 3, 8
	7, 5, 6		
GL	5, 4, 7	5, 4, 8	5, 4, 9
	5, 5, 9	5, 7, 9	
	6, 4, 7	6, 4, 8	6, 4, 9
	6, 5, 9		
	6, 6, 8	6, 6, 9	
	6, 7, 9		
	7, 4, 7	7, 4, 8	7, 4, 9
	7, 5, 9	7, 6, 9	7, 7, 9
	7, 5, 7	7, 5, 8	
	7, 6, 7	7, 6, 8	
FL	6, 7, 6		
	7, 7, 6	7, 7, 8	
	8, 7, 6	8, 7, 7	8, 7, 8
	8, 8, 6	8, 8, 7	
	8, 9, 6	8, 9, 7	
FB3	6, 8, 5	6, 9, 5	
	7, 8, 5	7, 9, 5	
	7, 9, 6	7, 9, 7	
FT	7, 6, 3	6, 7, 5	
FB2	8, 6, 6	8, 6, 7	
GK	6, 5, 6	6, 5, 7	
	6, 6, 6	6, 6, 7	

Table 6.9 Group 1 combinations by room

The kitchen is now indicated by four Group 1 combinations.

	rooms indicated				combinations present		
Group 2	GH	GL			5, 8, 7 6, 5, 8	5, 8, 8 6, 7, 8	
	FL	FB3			6, 8, 6 7, 8, 6	6, 9, 6 7, 8, 7	6, 9, 7
	FB1	FB2			7, 6, 6		
	FL	FB1			7, 7, 7		
	GH	FL			6, 7, 6	6, 7, 7	
	FT	FBA			6, 8, 5		
Group 3	GK	GL	FB1		5, 6, 7	5, 6, 8	
	GH	FB3	FL		6, 8, 7		
Group 4	GH	GK	GL	FB1	5, 5, 7	5, 5, 8	

Table 6.10 Group 2, 3, and 4 combinations

Removing the conditions that were not confirmed by the test of the algorithm reduces Stage 1 of the algorithm from 8 conditions to 4, as shown in Figure 6.17.

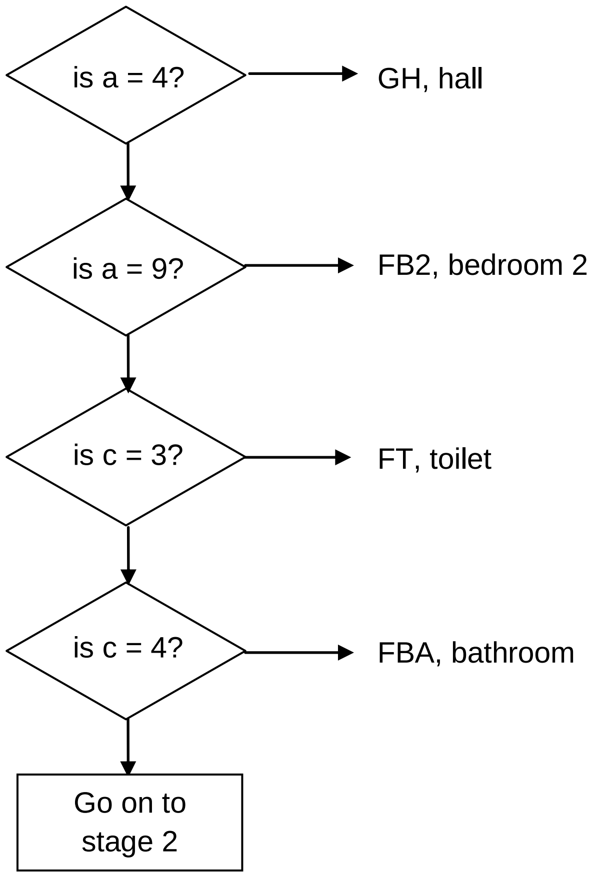


Figure 6.17. Updated Stage 1 of the algorithm

Stage 2 of the algorithm was expanded to include the results of analysing the mobile data, and those combinations had previously been covered by the four conditions that were removed, i.e, all the combinations that include b= 3 or c = 5. The improved Stage 2 of the algorithm is shown in Table 6.11.

if (*a, b, c*) equals:				tag location is: code	room
5, 7, 6	**5, 7, 7**	**5, 7, 8**		**GH**	hall
5, 3, 6 **5, 5, 6** **7, 3, 6**	**5, 3, 7** **5, 6, 6** **7, 3, 7**	**5, 3, 8** **7, 3, 8**	 **7, 5, 6**	**FB1**	bedroom 1
5, 4, 7 **5, 5, 9** **6, 4, 7** **6, 6, 8** **7, 4, 7** **7, 6, 9** **7, 5, 7**	**5, 4, 8** **5, 7, 9** **6, 4, 8** **6, 6, 9** **7, 4, 8** **7, 7, 9** **7, 5, 8**	**5, 4, 9** **6, 4, 9** **6, 7, 9** **7, 4, 9** **7, 6, 7**	 **6, 5, 9** **7, 5, 9** **7, 6, 8**	**GL**	living room
6, 7, 6 **8, 7, 6** **8, 8, 6**	**7, 7, 6** **8, 7, 7** **8, 8, 7**	**7, 7, 8** **8, 7, 8** **8, 9, 6**	 **8, 9, 7**	**FL**	landing
6, 8, 5 **7, 9, 6**	**6, 9, 5** **7, 9, 7**	**7, 8, 5**	**7, 9, 5**	**FB3**	bedroom 3
7, 6, 3				**FT**	toilet
8, 6, 6	**8, 6, 7**			**FB2**	bedroom 2
6, 5, 6	**6, 5, 7**	**6, 6, 6**	**6, 6, 7**	**GK**	kitchen

Table 6.11 Improved Stage 2 of the algorithm

Applying the updated algorithm to the mobile walk-through data gave the following results in Table 6.12. The resulting room indication was improved. Twenty three of the thirty four readings were correctly located by Stage 1 and Stage 2 of the algorithm to a single room and a further five readings (3, 4, 8, 24 & 31) gave the correct location in one of two rooms. Two readings (25 & 26) gave a false reading of the living room when they were in the room above in bedroom 1 and four readings (17, 20, 32 & 33) did not return any locations.

Unlike the previous algorithm that failed to identify the kitchen at any reading, the kitchen was correctly identified in three instances (readings 5, 6, and 7) by the improved algorithm.

reading number	RPi1 SSN	RPi2 SSN	RPi3 SSN	pause point	Stage 1	Stage 2	Stage 3	actual room
1	5	7	7	1		**GH**		GH
2	4	7	7		**GH**			
3	6	7	8				**GH**, GL	
4	6	7	7				**GH**, FL	
5	6	5	7	2		**GK**		GK
6	6	5	7			**GK**		
7	6	6	6	3		**GK**		GK
8	6	7	7				**GH,** FL	
9	7	6	7	4		**GL**		GL
10	7	6	8			**GL**		
11	7	6	7			**GL**		
12	7	5	8	5		**GL**		GL
13	7	6	7			**GL**		
14	5	7	8			**GH**		
15	8	7	8	6		**FL**		FL
16	7	7	6			**FL**		
17	5	7	5	7				FT
18	6	8	3		**FT**			
19	6	8	4	8	**FBA**			FBA
20	8	5	5					
21	9	6	7	9	**FB2**			FB2
22	9	7	8		**FB2**			
23	7	7	8			**FL**		
24	7	7	7	10			**FB1**, FL	FB1
25	7	6	7			~~GL~~		
26	7	6	7			~~GL~~		
27	8	7	7			**FL**		
28	7	9	6	11		**FB3**		FB3
29	7	9	7			**FB3**		
30	7	9	6			**FB3**		
31	7	7	7				FB1, **FL**	
32	6	6	7					
33	5	5	6					
34	5	7	7	12		**GH**		GH

Table 6.12. Application of improved algorithm on the original walk-through test results

To further test the improved algorithm a repeat of the walk-through test was carried out and new data was collected. The resulting data comprises 35 readings and is shown in Table 6.13. The improved algorithm was applied to the new data and the resulting indication of tag location was greatly improved. Twenty nine of the thirty five readings were correctly allocated to one room and four were predicted to be in either the correct room or one other location. The location of these four readings (4, 18, 26, & 29) could be derived by dead reckoning, i.e. reviewing the previous and following locations to determine which of the two rooms would be right. For instance reading 4 could be in GH or GL while readings 1, 2, and 3 are in GH and readings 5, 6, and 7 were in GK, therefore reading 4 can be attributed to GH rather than GL.

reading number	RPi1 SSN	RPi2 SSN	RPi3 SSN	pause point	Stage 1	Stage 2	Stage 3	actual room
1	**5**	**7**	**7**	1		**GH**		GH
2	**4**	**6**	**7**		**GH**			
3	**4**	**6**	**7**		**GH**			
4	**6**	**7**	**8**				**GH**, GL	
5	**6**	**5**	**7**	2		**GK**		GK
6	**6**	**5**	**7**			**GK**		
7	**6**	**6**	**6**	3		**GK**		GK
8	**6**	**7**	**6**			**FL**		
9	**7**	**6**	**7**	4		**GL**		GL
10	**7**	**6**	**8**			**GL**		
11	**7**	**6**	**7**			**GL**		
12	**7**	**5**	**8**	5		**GL**		GL
13	**7**	**5**	**8**			**GL**		
14	**5**	**7**	**6**			**GH**		
15	**5**	**6**	**8**	6				FL
16	**8**	**7**	**7**			**FL**		
17	**8**	**7**	**6**			**FL**		
18	**6**	**8**	**5**	7			**FT**, FBA	FT
19	**6**	**7**	**3**		**FT**			
20	**6**	**7**	**4**		**FBA**			
21	**6**	**8**	**4**	8	**FBA**			FBA
22	**6**	**8**	**4**		**FBA**			
23	**9**	**7**	**5**		**FB2**			
24	**8**	**6**	**6**	9		**FB2**		FB2
25	**9**	**6**	**6**		**FB2**			
26	**7**	**7**	**7**				**FL**, FB1	
27	**7**	**5**	**6**	10		**FB1**		FB1
28	**7**	**5**	**6**			**FB1**		
29	**7**	**7**	**7**				**FL**, FB1	
30	**7**	**9**	**6**	11		**FB3**		FB3
31	**8**	**9**	**6**			**FL**		
32	**6**	**8**	**7**				**FL**, FB3, **GH**	
33	**5**	**7**	**6**			**GH**		
34	**5**	**7**	**7**			**GH**		
35	**5**	**7**	**7**	12		**GH**		GH

Table 6.13 Improved algorithm applied to the new mobile walk-through data

The least straightforward readings were readings 15 and 32. These either gave no indication of a room or the choice of three rooms. It is significant that both these readings occurred between the ground floor and the first floor. This indicates that the stairs are a problematic area and the signal strengths are not as easily identifiable as when the tag is in a room.

6.4 Summary

Contour maps

The Ekahau modelling software is a very useful tool to visualise how signal behaves generally. The limitations of the software include the narrow range of wall and floor structures available to represent the location being modelled. The biggest restriction however is that Ekahau models signal loss through building elements and cannot replicate how signals reflect off surfaces.

The contour maps were developed with reference to the Ekahau modelling of Home 1 and show the effects of the chimney structure in the centre of the house. The contour maps also show that while most of the signal strength readings fit within the contour lines, there are many examples of signal strength outliers. These signal strengths are the result of reflection off and disruption caused by elements and obstructions, such as furniture, present in the house.

Algorithm development and testing

The development of the algorithm took into account all the signal strengths observed in the triple point tests, not just those that fit into contour lines, because it was essential to base the algorithm on the signal's actual behaviour rather than its best behaviour.

Initially the algorithm was based on the stationary signal strengths and was found to have many flaws. Among these was the lack of ability to locate the tag within the kitchen. The kitchen represented the only corner of Home 1 without an RPi position as the three RPi positions were located in the other three corners of the house, one at ground level and two on the first floor.

Application of the algorithm to the data from the mobile walk-through test showed a high level of failure to identify the correct tag location. This first test of the algorithm only identified the correct room on 5 occasions. This required a significant evaluation of signal strength results from the mobile walk-through and resulted in major changes to the tag location procedure.

Using the mobile data, a large number of additional signal strength combinations and their locations were developed and added to the algorithm. When the improved algorithm was tested against the original mobile walk-through data the resulting identification of tag location by room was improved and the kitchen was included in rooms that were identified, unlike in the previous test of the original algorithm.

To more fully evaluate the accuracy of the improved algorithm a repeat of the mobile walk-through test was carried out and new data was collected. When this data was subjected to the improved algorithm the results were greatly improved and twenty-nine of the thirty-five readings were located to the correct rooms immediately. Four of the six remaining readings were identified as being in one of two rooms, and in all these cases the correct room could be determined by dead reckoning. This meant that in 33 of the 35 readings the tag location could be correctly identified by room.

The weakest two readings corresponded with either going upstairs or coming downstairs and neither could be identified to one particular room. The stairs therefore form a zone of uncertainty within Home 1. Due to the fact that people do not use energy or spend time on the stairs, having this zone of uncertainty does not detract from the acceptability of the use of the system with the improved algorithm to monitor personal energy-consuming behaviour.

Chapter Seven

7 Conclusions

This chapter reviews the research carried out, identifies the contributions made to current knowledge and opportunities for future work.

The Salford Energy House

The energy house is an excellent resource for modelling the thermal performance of homes and testing the effectiveness of methods for improving elements within homes. Unfortunately it was not an ideal location for observing RFID signal strength behaviour due to the multiple causes of signal disturbance. In addition to the numerous meters and sub-meters in the house that had a visible impact on signal strength, there are multiple sensors in every room. The energy house is also built inside a laboratory and surrounded by metallic and building elements that disrupt signal propagation.

Despite the drawbacks of testing the RFID system in the energy house, important lessons were learned about identifying the effects of disruptive elements. Observations of communication signals between the tags and reader were captured by the spectrum analyzer.

Home 1

Having access to a family home was essential to test the location system in a typical residential environment. The construction of Home 1, a three-bedroomed semi-detached house, is representative of 22% of current English housing stock as an example of an early post-war cavity wall building.

It was apparent from tests that there were disruptive elements present in Home 1. Some were easily identifiable, such as the large brick chimney in the centre of the house, which cast a shadow of reduced signal strength readings when it was in between the tag and the reader. Other disruptions were indicated by atypical signal readings but were not easy to attribute to any one specific object or element. Multipath errors in RFID systems are caused by reflection of the radio signal off surfaces and objects, in the case of Home 1 the fixtures and furniture within the home.

These multipath errors account for some of the differences between the actual results and the simulated model as Ekahau can only predict loss of signal through elements. Other differences are related to the narrow range of walls and floors that can be specified in the modelling programme. Although the software includes almost 1,000 antennae to choose from and the one used was selected because it was the most similar to the Loc8tor antenna, the simulations could be improved if the actual antenna used was included in the modelling software. Despite the limitations of the Ekahau software, the simulations broadly correlated with the signal contours of the system. This implies reliability of the data collected due to the systematic, consistent approach of the experimental methodology.

Factors affecting signal strength

Many tests were carried out to investigate the influence of environmental factors on the signal strength of the system. It was found that local humidity between 47.8% and 96.6%, and temperatures between 11^{o}C and 20^{o}C did not affect the signal strength readings. Likewise, occupation of the same room as the tag did not change the signal strengths received.

Tests of co-located tags communicating with different RPis did not exhibit the same signal strength behaviour. This indicated that the local environment of the tag was not a factor in its performance, rather what is between the tag and its paired RPi is crucial.

A definite cause of disruption found in the tests occurred when two RPis were active at the same time. The tags clearly exhibited significant disruption compared to when the RPis were active in isolation. This can be eliminated by synchronising the base stations to ensure RFID communication is staggered and does not occur simultaneously.

Location Detection

Results from the tests clearly showed that using one or two RPis did not provide adequate differentiation to enable location identification. Because the Loc8tor system converts the received signal strength into a limited number of signal strengths indicated by activity of the LEDs, this results in a series of nine Signal Strength Numbers (SSNs) from SSN1 (no signal) to SSN9 (the strongest signal).

During the experiments it was found that the majority of readings in Home 1 were SSN7. The strongest signal (SSN9) occurred in close proximity to the RPi and very low signal strengths of SSN2 never occurred. SSN1 (no signal) did occur in occasional instances due to a lack of communication between the tag and reader. Other low signal strengths of SSN3 and SSN4 were observed rarely during the tests. Chapter Five showed that the nine SSN's from the nine patterns of LED activity could not be clearly placed in specific ranges of signal strength dBm.

When three RPis are placed in three corners of the building and directed towards their opposite diagonal corner, the differentiation of the signal strength readings was found to be sufficient to enable derivation of tag location to room-level with the algorithm. The final test of the algorithm successfully determined the tag location to one room in 83% of readings. A further 11% of readings were allocated to one of two rooms comprising the correct room and one other room. In these cases it was clear from the preceding and following locations which of the two options were the correct room. For example during the final walk-through test a reading indicated the tag was located in either GH or GL, was preceded by GH, GH, GH and followed by GK, GK, GK therefore it was apparent that the tag could not be present in GL and had to be in GH. Including comparison of previous and subsequent locations to rule out non-sensible location options in the algorithm resulted in a prediction system accuracy of 94%.

Development of the algorithm had to include all the results from the triple point position tests, including the outliers, and not be based on the contour maps only. This is because the algorithm had to take into account the impacts of all disrupting influences present in the house. Following testing and refinement of the algorithm it was found to be successful when used on a new set of results from a second mobile walk-through test. The only exception to successful location of the tags to room-level is when the tag is between floors. As there are no appliances on the stairs and people do not spend a lot of time there this is an acceptable omission.

The ultimate location method used to achieve 94% success rate of locating the tag within the correct room was a combination of proximity and inference from preceding and following positions. When united with energy consumption data, the time and location of appliance energy use will provide further data to corroborate location.

In conclusion, the location system and the appliance level monitors together form the technique that fulfils the fundamental requirements of this research as set out in Chapter Three. These are:

1. The ability to locate individuals to room-level
2. Accurate recording of the location, individual, and time
3. Appliance level electricity consumption data, also recorded with time and location

The algorithm works by using data from the triple point positions that give the best differentiation of signal strength combinations between rooms. Following this, if necessary, interpolation is used to derive location from analysis of preceding and following signal strengths to eliminate non-sensible locations. As a final back up, the appliance-level electricity consumption when matched to location data would provide an additional location confirmation.

7.1 Contribution

The primary contribution from this research is the demonstration that this technique can successfully locate multiple people to room level by using a small number of low-cost devices. With this technique it has been shown that the real-time location system can locate an RFID Loc8tor tag to the room it is in with an accuracy of 94% from only the coarse-grained data from the devices. This has been proven in a real family home of standard construction, with all the fixtures and furniture present.

The system is capable of locating up to four people at a time, the maximum number of RFID tags that can be registered to each handheld reader, and results from tests showed that signal strength was not impaired by the presence of people or observed variations in temperature or humidity.

The location data, when combined with Plugwise appliance-level energy consumption data, makes possible the capture of personalised domestic energy consuming behaviour of individuals. The lack of understanding of how people use energy at home is a significant gap in current knowledge.

The ability to determine domestic energy profiles could considerably alter (and improve) the approach of energy suppliers and the government to help reduce domestic energy consumption, and therefore fuel poverty, in the UK.

Although the technique was developed with the intention of capturing domestic energy consuming behaviour, the location system would be suitable for many other applications, such as assisted living.

An additional contribution is the very large quantity of data from the testing of the system that could be used by other researchers. This data comprises signal strength readings from numerous experiments and describes the signal propagation through the Salford Energy House and a fully furnished family home in Greater Manchester.

7.2 Future Work

There are inherent difficulties using RFID in non-open spaces due to multipath issues. Predicting signal propagation indoors requires detailed knowledge of the location. The 94% accuracy of location detection obtained followed a period of intense experimentation and data collection. It would be unrealistic to suggest this system is ready for immediate deployment in any location.

Proof of concept and location accuracy has been achieved in one location and in order to use this system in other locations it would be necessary to condense the information gathering stage of the homes it would be installed in, such as floor plans and construction details. This would enable simulation of the properties using software such as Ekahau to predict how the system would behave in those homes.

Therefore an opportunity for future implementation of this technique would be in the form of long term testing across several households with a range of family occupancies in a new housing development. In this case the homes could be modelled from the architectural drawings in advance of installation of the personalised energy monitoring system. Deploying the system in a housing scheme has the advantages that detailed plans would be readily available, there tends to be a repetition of house styles in new developments, and once tenants moved in a quick survey could identify the location of potential disruptive influences.

Other opportunities for the real-time location system include additional functions to record more data, such as an accelerometer, thermistor, or light-dependent resistor. These functions would make the system a potential solution to health and well-being monitors, such as remote home-care systems. The data could be collected and available in real-time and have alerts if specified conditions are met, such as periods of inactivity, low temperature or darkness.

Appendix A. Energy Monitoring System

Plugwise Energy Management and Control System

Plugwise is a Dutch company that supplies wireless energy management and control systems for appliances in buildings. The Plugwise system is based on a wireless mesh network (Zigbee 2.4 Hz) and has the following features:

- Energy efficient components;
- 128-bit AES encryption to ensure security of energy consumption data;
- Mesh network support – the mesh re-organizes itself, new appliances are recognised and incorporated automatically;
- Open international standard – meaning the system is easily extendable with other modules;
- Individually coded and identifiable components.

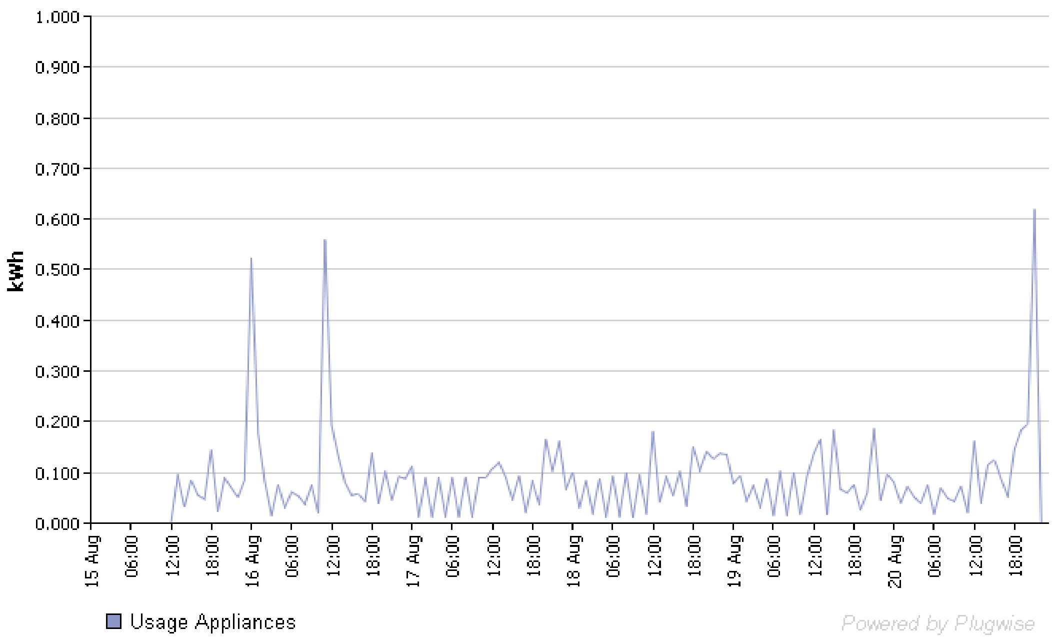
As well as providing details of energy consumption at appliance level, switching schemes can be set up so that appliances can be switched on and off at specified times. Appliances can be grouped together by location or type, and can be switched on and off as a group. Each complete Plugwise system consists of a Circle+, one or more Circles, a Stick and the Source software. These elements are shown below.

Circle +	The Circle+ is the co-ordinator of the network. This module contains the clock that the other modules use to synchronise their time stamps.	
Circle	This is the basic unit of the network. It measures energy consumption through it and can switch the connected appliance on and off.	

Stick	This is the USB dongle that enables communication between the Source software and the units. The stick receives data from and transmits tasks to the modules.	
Source	This is the software that the system is controlled by. Energy consumption data is displayed on diagrams and switching schemes can be created.	

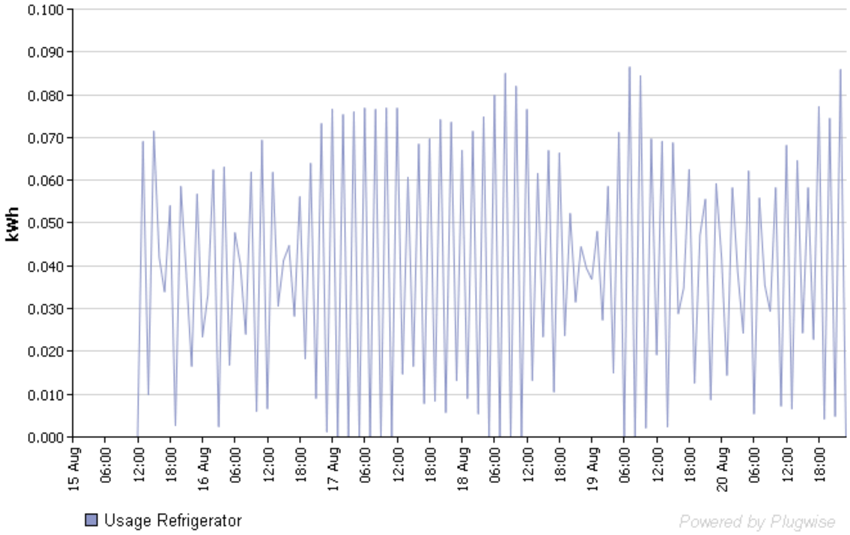
The Elements that make up the Plugwise Energy Management and Control System. (images from www.plugwise.com)

The Plugwise system has been used in previous energy monitoring research by the University of Salford, and the Plugwise company donated an advanced licence for the purposes of this investigation. The system is straightforward to set up and several test networks were evaluated over a period of six months. Apart from the added bulk of the units, which added 4cm to the depth of existing plugs and made installation in confined spaces difficult, the units performed well and reliably recorded energy consumption of the appliances they were dedicated to.

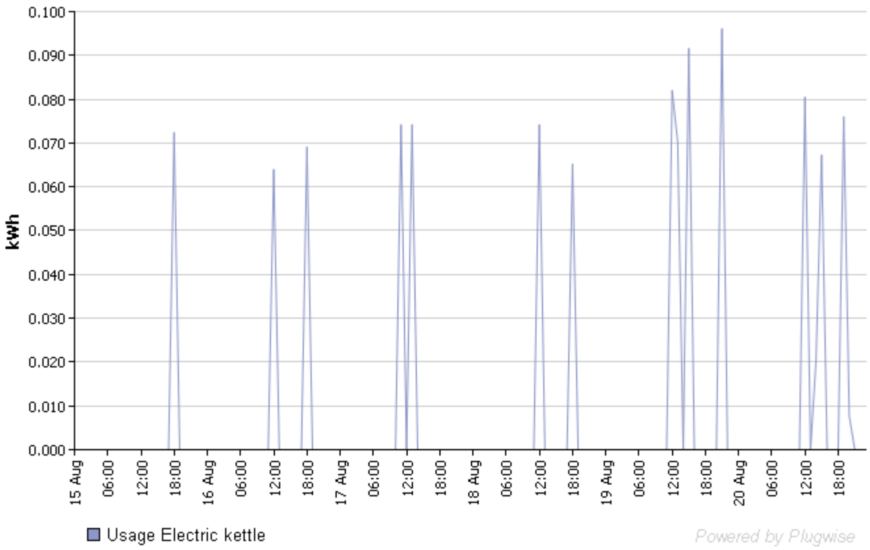


Example of a graph showing total energy consumption for the network

Graphical outputs from the Plugwise system are shown for the total energy consumption of a network, and hourly consumption over several days of a refrigerator and electric kettle.



Hourly Energy Consumption pattern over several days for a refrigerator



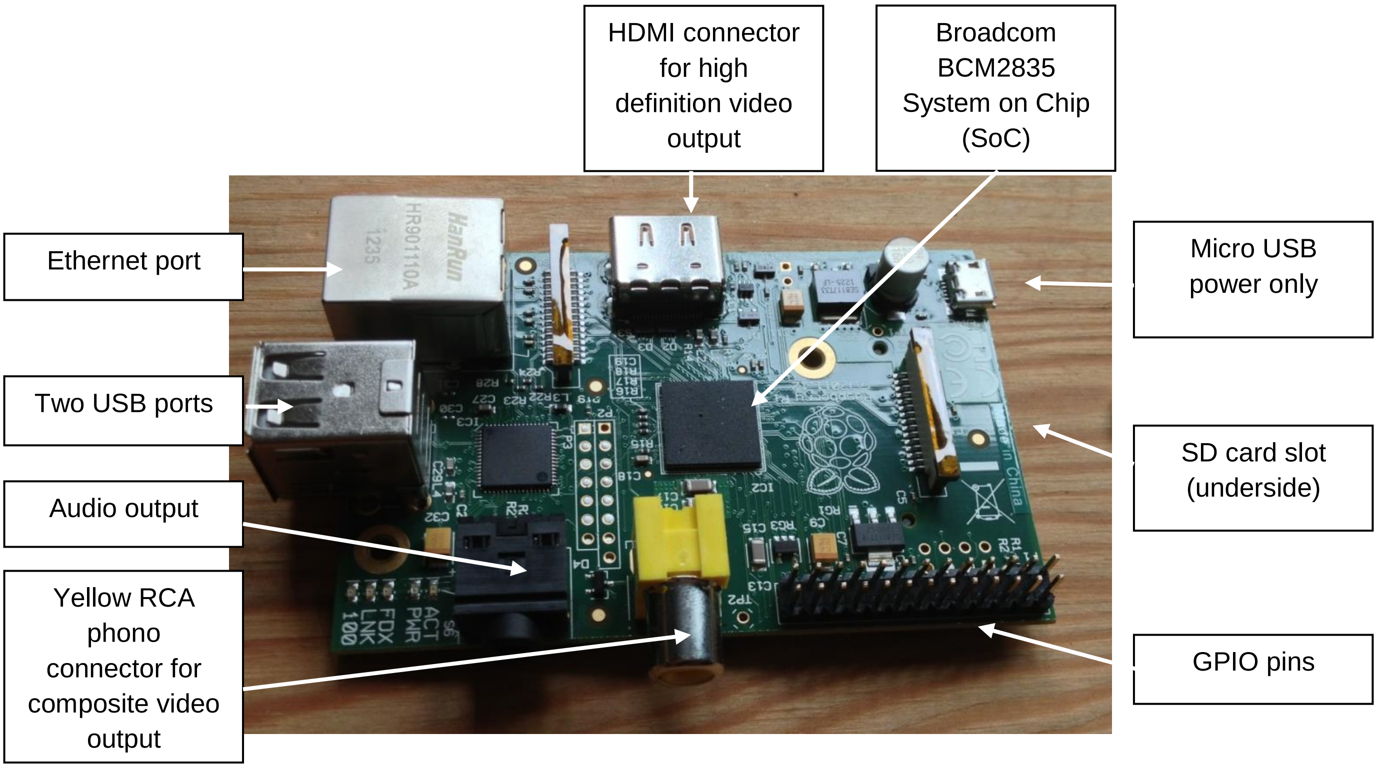
Hourly Energy Consumption pattern over several days for a kettle

In addition to the graphical outputs from Plugwise, with the enhanced donated licences the raw data can be exported in csv format. The maximum number of Plugwise devices, and therefore appliances being monitored, in any single network is 65.

Appendix B. Prototype Manufacture

This Appendix explains how the prototype was developed. It covers the physical connection between the Raspberry Pi computer and the Loc8tor circuit board, and the development of the Python programme.

The elements of the Raspberry Pi (RPi) computer are shown below.



Elements of the Raspberry Pi (RPi) computer

The benefits of the RPi include:

- Very low power consumption – the RPi operates on 5V 1A power supplied by the micro-USB port,
- The operating system is open source – unlike Microsoft Windows or Apple OS X the RPi is designed to run GNU/Linux,
- Several distributions of the operating system are available to choose from, to suit the needs and level of experience of the user,
- Many common software packages offer a Linux version – this is a crucial difference between the RPi and other options for the base station, such as mobile phones and tablet computers,
- There is a very active global community of RPi enthusiasts and developers, dedicated to expanding the functionality of the computer, and committed to

the aims of the Raspberry Pi Foundation by making all their solutions and software openly available.

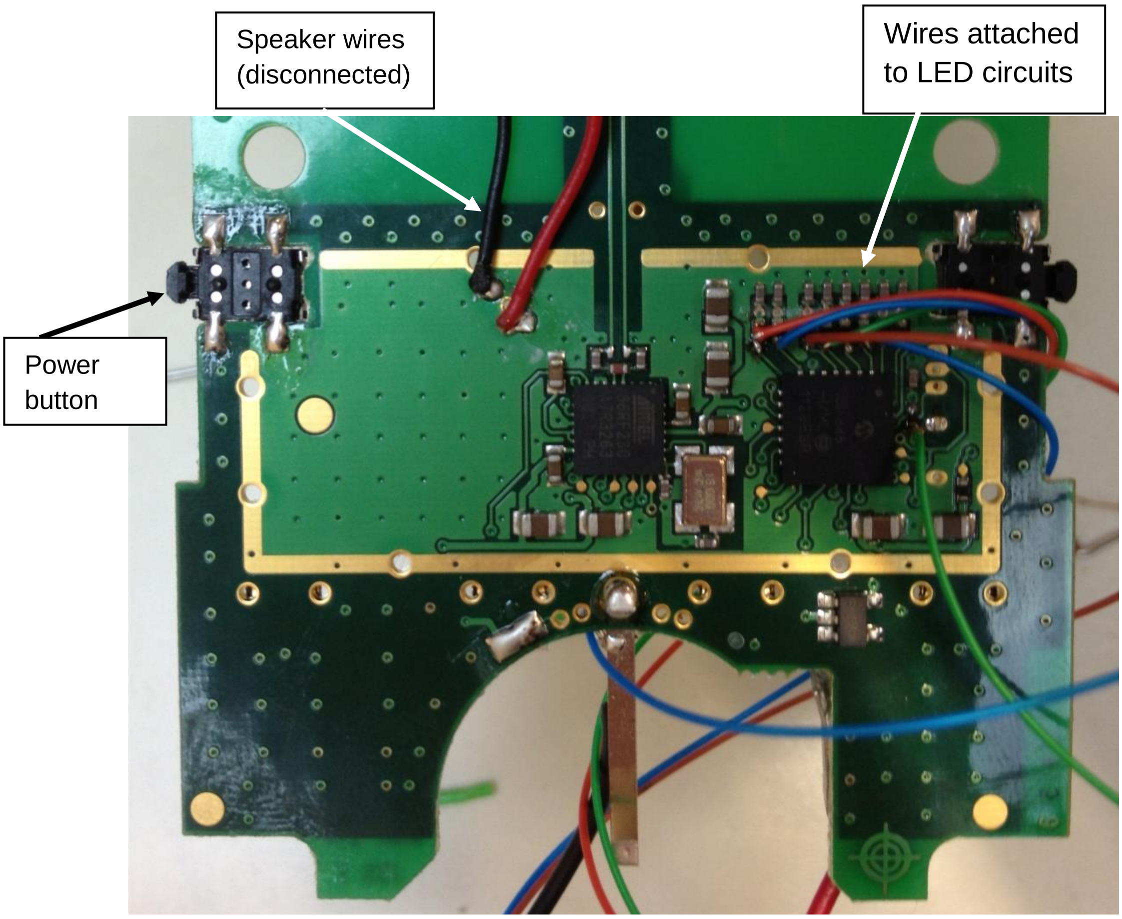
	Pin #	RPi GPIO header		Pin #	
3.3V	**1**	**O**	**O**	**2**	**5V**
I^2C SDA	**3**	**O**	**O**	**4**	**5V**
I^2C SCL	**5**	**O**	**O**	**6**	**Ground**
General Purpose Clock	**7**	**O**	**O**	**8**	UART Transmit
Ground	**9**	**O**	**O**	**10**	UART Receive
	11	**O**	**O**	**12**	
	13	**O**	**O**	**14**	**Ground**
	15	**O**	**O**	**16**	
3.3V	**17**	**O**	**O**	**18**	
SPI MOSI	**19**	**O**	**O**	**20**	**Ground**
SPI MISO	**21**	**O**	**O**	**22**	
SPI SCLK	**23**	**O**	**O**	**24**	SPI Chip Select 0
Ground	**25**	**O**	**O**	**26**	SPI Chip Select 1

The layout and alternative functions of the GPIO header

The RPi has 26 ports in two rows of 13 male 2.54mm pins on the GPIO header. There are four powered pins, two at 3.3V and two at 5V, and five grounded pins. Seven pins are designated as general purpose only, while an additional ten have additional functions when used in combination to form particular circuits. These additional functions are as follows:

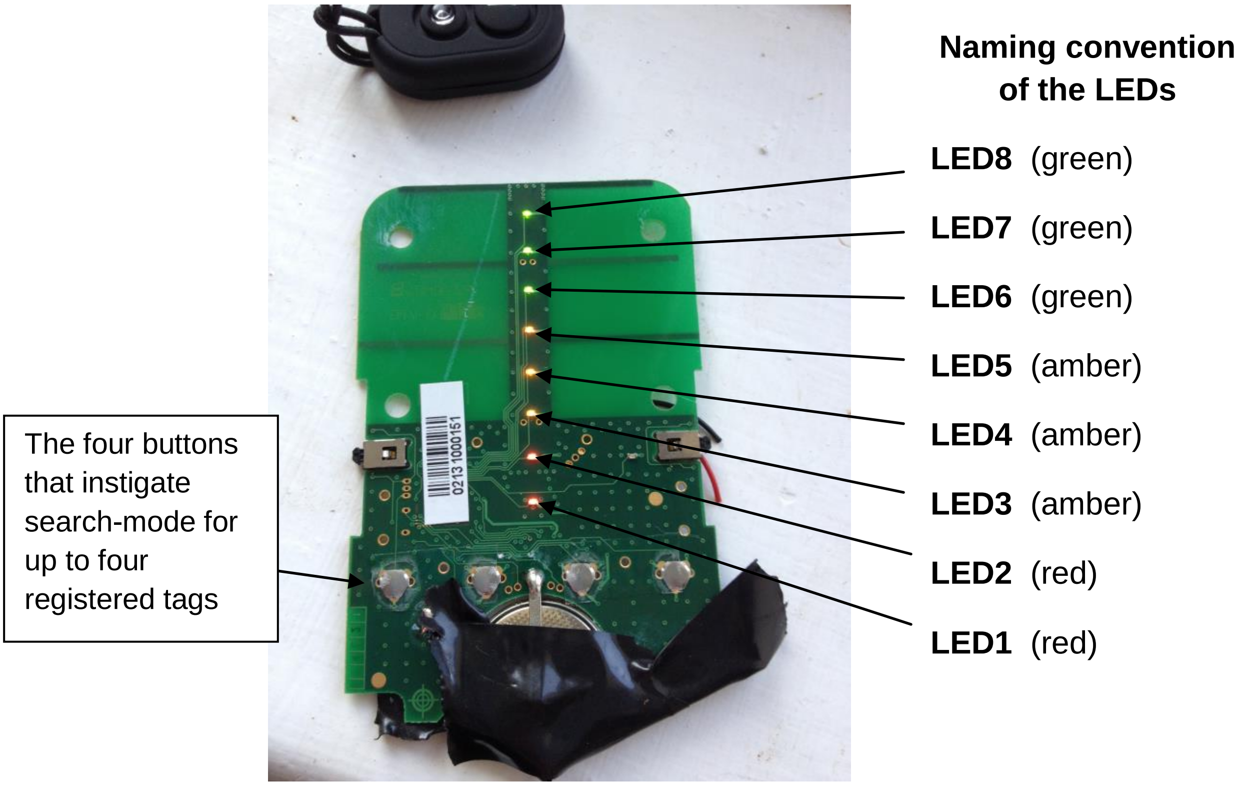
- UART Serial Bus – The *Universal Asynchronous Receiver/Transmitter* (UART) serial bus provides a two wire serial interface at pin 8 (transmit) and pin 10 (receive).
- I^2C bus – The *Inter-Integrated Circuit* (I^2C) bus is designed to provide communications between multiple integrated circuits. Pin 3 is the Serial Data Line (SDA) and pin 5 is the Serial Clock (SCL) signal.
- SPI bus – *The Serial Peripheral Interface* (SPI) bus is a synchronous is a four wire bus with chip select lines to allow communication with more than one target device. Pin 19 is the SPI Master Output, Slave Input (MOSI) signal, pin 21 is the SPI Master Input, Slave Output (MISO) signal, pin 23 is the Serial Clock (SLCK) used to synchronise communication and pins 24 and 25 provide the Chip Select signals for up to two independent slave devices.

The first step in manufacturing the prototype required the Printed Circuit Board (PCB) of the Loc8tor handheld unit to be released from its protective casing. Wires were manually soldered to the 8 circuits related to the 8 LEDs that light up to indicate signal strength. Elements of this stage of the manufacture are shown below.



Photograph of the reverse of the Loc8tor handheld unit showing the wires connected to LED circuits on the Loc8tor handheld unit.

Mapping the eight LED circuits required extensive laboratory testing with a multimeter or oscilloscope. The next stage of construction involved connecting the wires from the LED circuits to the General Purpose Input Output (GPIO) pins from the Raspberry Pi (RPi). A naming convention for the LEDs was used as follows.



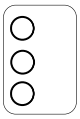
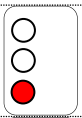
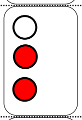
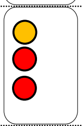
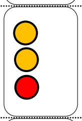
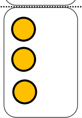
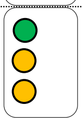
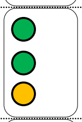
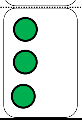
The naming convention of the LEDs on the handheld unit PCB.

Wires were connected to the battery holder of the handheld unit to enable the unit to be powered directly from the RPi's 3.3V GPIO pin. The speaker of the handheld unit was disconnected.

A Python programme was written to take the output from the LED circuits and display which LEDs were active. This programme ran on the RPi and when the RPi pins were connected to the LED circuits the programme checked each LED in turn and returned a message on screen to indicate which LEDs were lit.

The Python programme read the inputs from the LEDs as either of two states: *high* (True or 1) if the voltage detected is above 1.7V or *low* (False or 0) if less than 1.7V. The RPi is based on 3.3V logic and the GPIO pins can deliver an output of 3.3V. The outputs were used to activate the switches to initiate search-mode.

In order to have a better representation of the signal strength returned by the Python programme, a method of deriving the Signal Strength Number (SSN) by manipulating the inputs, rather than merely displaying which LEDs were on, was necessary. The patterns of LED activity is shown as follows.

Visual signal from Loc8tor Lite handheld unit	Signal Strength Number (SSN)	LED# lit up at that signal strength
	**1**	**-**
	**2**	**1**
	**3**	**1,2**
	**4**	**1,2,3**
	**5**	**2,3,4**
	**6**	**3,4,5**
	**7**	**4,5,6**
	**8**	**5,6,7**
	**9**	**6,7,8**

The patterns of LED activity, corresponding SSN and active LEDs in that state

There are only nine patterns of LED activity during search-mode, although there are an additional five LED patterns when the tag being searched for is in very close (and increasing) proximity to the handheld unit. This happens when the tag is between 2 and 30 cms away from the handheld unit. Knowing the additional five states when the tag is less than 30cms to 2cms from the unit was not considered valuable enough to warrant allocating additional SSNs, so all zooming-in modes were treated as being SSN9, as that is the strongest signal strength.

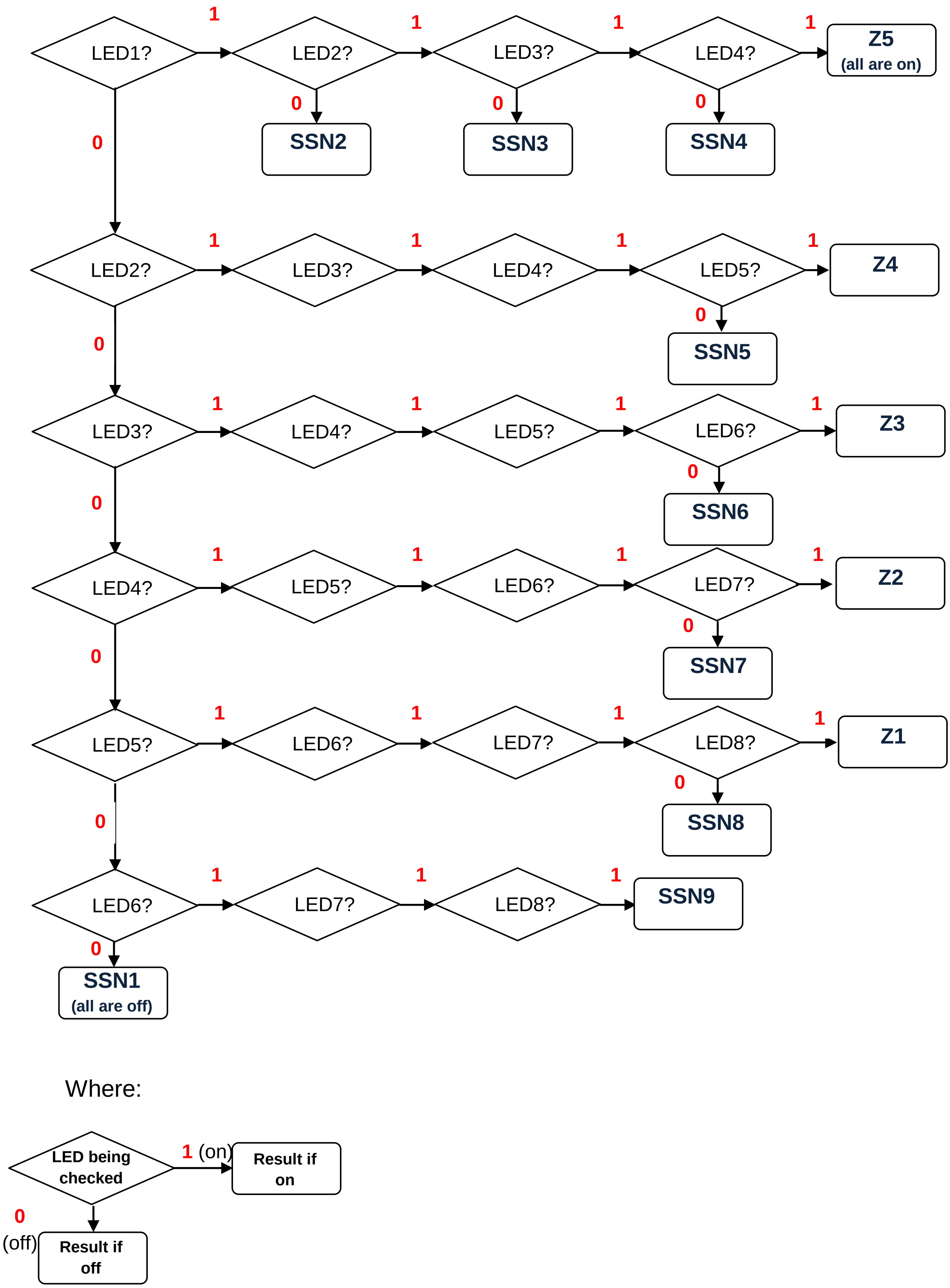
The following table shows the only possible patterns of LED activity available with the Loc8tor system. Nine of these are the search mode patterns and five are the additional zooming in mode.

SSN	LED8	LED7	LED6	LED5	LED4	LED3	LED2	LED1	
1	0	0	0	0	0	0	0	0	Search-mode
2	0	0	0	0	0	0	0	**1**	
3	0	0	0	0	0	0	**1**	**1**	
4	0	0	0	0	0	**1**	**1**	**1**	
5	0	0	0	0	**1**	**1**	**1**	0	
6	0	0	0	**1**	**1**	**1**	0	0	
7	0	0	**1**	**1**	**1**	0	0	0	
8	0	**1**	**1**	**1**	0	0	0	0	
9	**1**	**1**	**1**	0	0	0	0	0	
Z1	**1**	**1**	**1**	**1**	0	0	0	0	Zoom in mode
Z2	**1**	**1**	**1**	**1**	**1**	0	0	0	
Z3	**1**	**1**	**1**	**1**	**1**	**1**	0	0	
Z4	**1**	**1**	**1**	**1**	**1**	**1**	**1**	0	
Z5	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	

The only possible patterns of active LEDs in the two modes, search mode and zooming in, where a '1' indicates that LED is active

Because there were so few patterns of LED activity it was possible to write a Python programme that doesn't constantly 'poll' all the LEDs at once, but to check the LEDs in a particular order. The purpose of doing this was to reduce the number of checks needed and to make the programme more efficient.

The decision flow-chart for the least number of checks on the RPi GPIO pin inputs needed in order to determine the Signal Strength Number is shown below. This shows that the number of checks needed ranges from two (to determine SSN of 2) to eight (when the SSN is 9). As stated previously, determination of zoom-in modes will return a SSN of 9.



The decision flowchart of the Python programme designed to carry out the least number of checks of the LEDs in order to correctly determine the Signal Strength Number (SSN)

Further wired connections were made to the PCB so that the reader was powered by the RPi, and the four manual switches that activate search mode were controlled by the RPi. The final 14 connections to the RPi GPIO are shown below.

	Pin#	RPi GPIO pins		Pin#	
3.3V	**1**	**O**	**O**	**2**	
SWITCH1	**3**	**O**	**O**	**4**	
SWITCH2	**5**	**O**	**O**	**6**	
LED 8	**7**	**O**	**O**	**8**	
	9	**O**	**O**	**10**	
LED 7	**11**	**O**	**O**	**12**	LED 4
LED 6	**13**	**O**	**O**	**14**	
LED 5	**15**	**O**	**O**	**16**	LED 3
	17	**O**	**O**	**18**	LED 2
SWITCH3	**19**	**O**	**O**	**20**	
SWITCH4	**21**	**O**	**O**	**22**	LED 1
	23	**O**	**O**	**24**	
Ground	**25**	**O**	**O**	**26**	

Schematic of the 14 wired connections to the RPi GPIO header

As can be seen from the schematic above, pins 1 and 25 were the power connections (3.3V and ground respectively). Pins 3, 5, 19, and 21 were connected to the four switches and set as outputs. This means that they were set up as having an initial value of 1, equating to 3.3V. When these pin values were changed to zero search-mode for the switch was initiated.

Pins 7, 11, 12, 13, 15, 16, 18, and 22 were connected to each of the eight LEDs and were set up as inputs. When the Python programme polled these pins and read either a *high* (True or 1) or *low* (False or 0) value this indicated whether the LED was on or off. High readings relate to a voltage of 1.7V and above, and low values are less than 1.7V.

Thorough laboratory testing was carried out to ensure the GPIO pins accurately reflected the signal strengths by comparison with an additional entire Loc8tor system. Extensive testing informed the placement and length of pauses required in the Python programme to ensure enough time was allowed for communication between the Loc8tor handheld unit and the tags.

Once proof of concept and reliability was achieved for the prototype, the system was installed in different locations for the data collection phase.

Appendix C. Python Programme

```
# programme to search for all four tags in turn then read the signal strength#
#timestamp and write to usb#

#setting up the RPi GPIO pins and importing time and datetime#
import RPi.GPIO as GPIO
GPIO.setmode(GPIO.BOARD)
GPIO.setwarnings(False)
from time import sleep
import datetime
GPIO.setup(3, GPIO.OUT, initial=1)
GPIO.setup(5, GPIO.OUT, initial=1)
GPIO.setup(19, GPIO.OUT, initial=1)
GPIO.setup(21, GPIO.OUT, initial=1)
GPIO.setup(7, GPIO.IN)
GPIO.setup(11, GPIO.IN)
GPIO.setup(13, GPIO.IN)
GPIO.setup(15, GPIO.IN)
GPIO.setup(12, GPIO.IN)
GPIO.setup(16, GPIO.IN)
GPIO.setup(18, GPIO.IN)
GPIO.setup(22, GPIO.IN)

#function to search for Tag1#
def searchTag1():
    saveFile = open('/media/USB STICK_/out2.txt', 'a')
    GPIO.output(21, 0)
    sleep(2)
    GPIO.output(21, 1)
    sleep(4)
    saveFile.write("\n$Tag1,")
```

```
    saveFile.close() #do I need close here#

#function to search for Tag2#
def searchTag2():
    saveFile = open('/media/USB STICK_/out2.txt', 'a')
    GPIO.output(19, 0)
    sleep(2)
    GPIO.output(19, 1)
    sleep(4)
    saveFile.write("\n$Tag2,")

#function to search for Tag3#
def searchTag3():
    saveFile = open('/media/USB STICK_.out2.txt', 'a')
    GPIO.output(5, 0)
    sleep(2)
    GPIO.output(5, 1)
    sleep(4)
    saveFile.write("\n$Tag3,")

#function to search for Tag4#
def searchTag4():
    saveFile = open('/media/USB STICK_/out2.txt', 'a')
    GPIO.output(3, 0)
    sleep(2)
    GPIO.output(3, 1)
    sleep(4)
    saveFile.write("\n$Tag4,")

#function to read signal strength, timestamp and write to usb#
def readingSSN():
```

```
for i in range(10):
    sleep(2)
    n=datetime.datetime.now()
    n=str(n)
    saveFile = open('/media/USB STICK_/out2.txt', 'a')


    input_value_8 = GPIO.input(7)
    input_value_7 = GPIO.input(11)
    input_value_6 = GPIO.input(13)
    input_value_5 = GPIO.input(15)
    input_value_4 = GPIO.input(12)
    input_value_3 = GPIO.input(16)
    input_value_2 = GPIO.input(18)
    input_value_1 = GPIO.input(22)


    if input_value_1 ==True and input_value_2 ==True and input_value_3 ==True and
input_value_4 ==True:
        saveFile.write("SSN9 - Z5 all on,")
        saveFile.write(n)
        saveFile.write(",")
        saveFile.close()
    elif input_value_1 ==True and input_value_2 ==False:
        saveFile.write("SSN2,")
        saveFile.write(n)
        saveFile.write(",")
        saveFile.close()
    elif input_value_1 ==True and input_value_2 ==True and input_value_3 ==False:
        saveFile.write("SSN3,")
        saveFile.write(n)
        saveFile.write(",")
        saveFile.close()
```

```
elif input_value_1 ==True and input_value_2 ==True and input_value_3 ==True and input_value_4 ==False:

    saveFile.write("SSN4,")

    saveFile.write(n)

    saveFile.write(",")

    saveFile.close()

elif input_value_1 ==False and input_value_2 ==True and input_value_3 ==True and input_value_4 ==True and input_value_5 ==True:

    saveFile.write("SSN9 - Z4,")

    saveFile.write(n)

    saveFile.write(",")

    saveFile.close()

elif input_value_1 ==False and input_value_2 ==True and input_value_3 ==True and input_value_4 ==True and input_value_5 ==False:

    saveFile.write("SSN5,")

    saveFile.write(n)

    saveFile.write(",")

    saveFile.close()

elif input_value_1 ==False and input_value_2 ==False and input_value_3 ==True and input_value_4 ==True and input_value_5 ==True and input_value_6 ==False:

    saveFile.write("SSN6,")

    saveFile.write(n)

    saveFile.write(",")

    saveFile.close()

elif input_value_1 ==False and input_value_2 ==False and input_value_3 ==True and input_value_4 ==True and input_value_5 ==True and input_value_6 ==True:

    saveFile.write("SSN9 - Z3,")

    saveFile.write(n)

    saveFile.write(",")

    saveFile.close()

elif input_value_1 ==False and input_value_2 ==False and input_value_3 ==False and input_value_4 ==True and input_value_5 ==True and input_value_6 ==True and input_value_7 ==True:

    saveFile.write("SSN9 - Z2,")
```

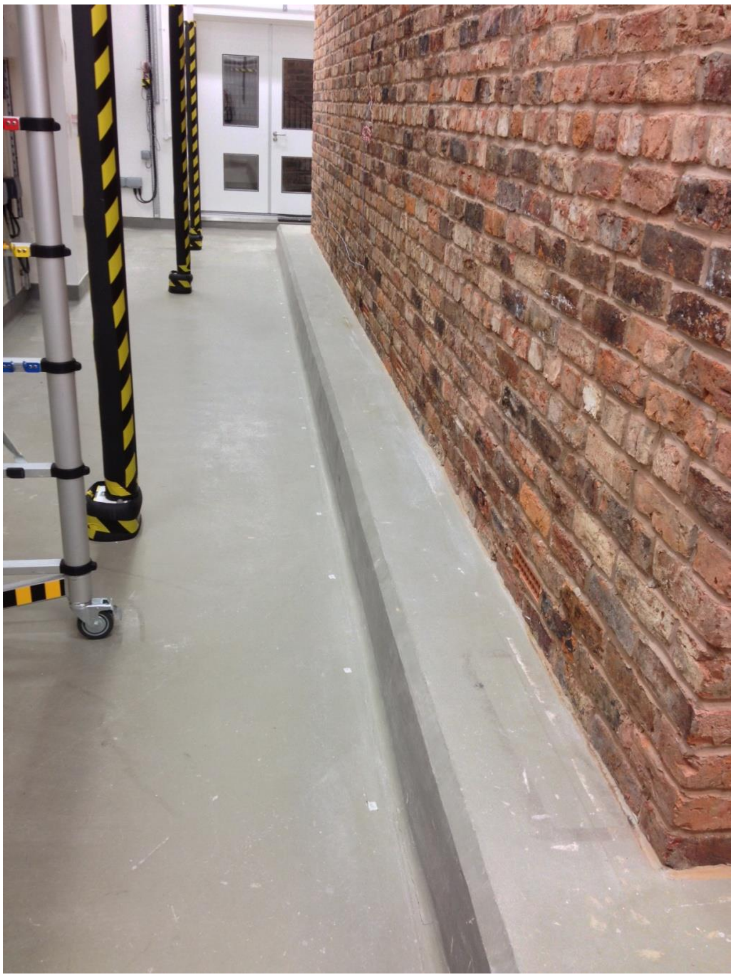
```
        saveFile.write(n)

        saveFile.write(",")

        saveFile.close()

    elif input_value_1 ==False and input_value_2 ==False and input_value_3 ==False
and input_value_4 ==True and input_value_5 ==True and input_value_6 ==True and
input_value_7 ==False:

        saveFile.write("SSN7,")

        saveFile.write(n)

        saveFile.write(",")

        saveFile.close()

    elif input_value_1 ==False and input_value_2 ==False and input_value_3 ==False
and input_value_4 ==False and input_value_5 ==True and input_value_6 ==True and
input_value_7 ==True and input_value_8 ==False:

        saveFile.write("SSN8,")

        saveFile.write(n)

        saveFile.write(",")

        saveFile.close()

    elif input_value_1 ==False and input_value_2 ==False and input_value_3 ==False
and input_value_4 ==False and input_value_5 ==True and input_value_6 ==True and
input_value_7 ==True and input_value_8 ==True:

        saveFile.write("SSN9 - Z1,")

        saveFile.write(n)

        saveFile.write(",")

        saveFile.close()

    elif input_value_1 ==False and input_value_2 ==False and input_value_3 ==False
and input_value_4 ==False and input_value_5 ==False and input_value_6 ==False:

        saveFile.write("SSN1 - all off,")

        saveFile.write(n)

        saveFile.write(",")

        saveFile.close()

    elif input_value_1 ==False and input_value_2 ==False and input_value_3 ==False
and input_value_4 ==False and input_value_5 ==False and input_value_6 ==True and
input_value_7 ==True and input_value_8 ==True:

        saveFile.write("SSN9,")

        saveFile.write(n)
```

```
            saveFile.write(",")
            saveFile.close()
        else:
            saveFile.write("error?,")
            saveFile.write(n)
            saveFile.write(",")
            saveFile.close()

#function main program calling the other already defined functions#
def main():
    searchTag1()
    readingSSN()
    searchTag2()
    readingSSN()
    searchTag3()
    readingSSN()
    searchTag4()
    readingSSN()

#infinite loop#
while 1==1:
    main()
```

Appendix D. Salford Energy House tests

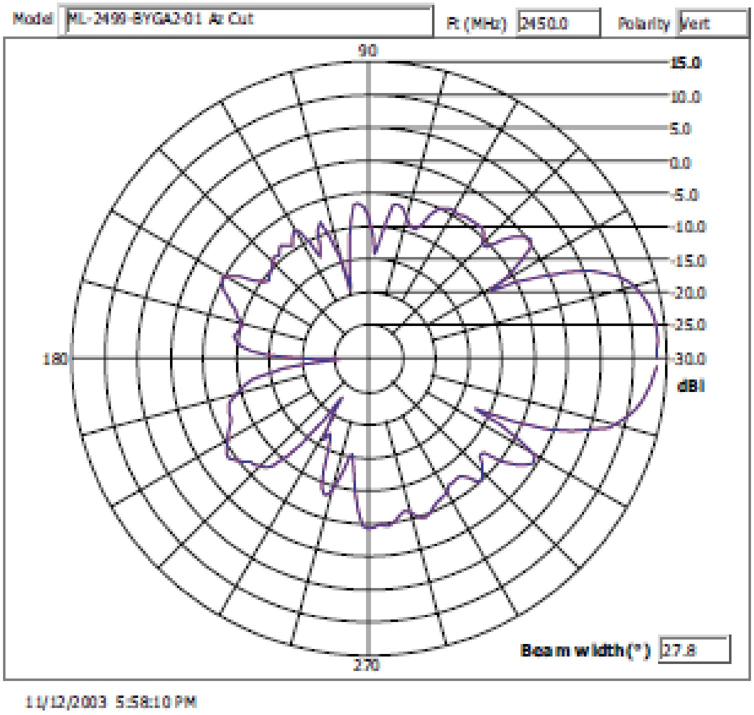
The Salford Energy House living room (above) and main bedroom (left) with 1 metre grid marked out.

The interior of the conditioning void (left) and Salford Energy House kitchen (below)

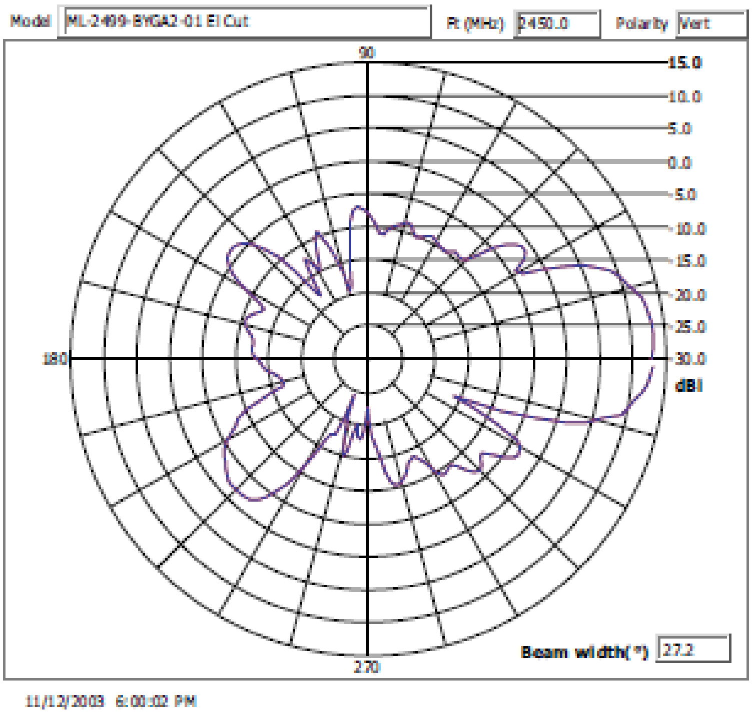


The gable end of the end terraced Salford Energy House

Appendix E. Azimuth and Elevation Patterns of the Motorola ML-2499-BYGA2-01R 2.4GHz 15 dBi 35 Degree Yagi



Azimuth Pattern



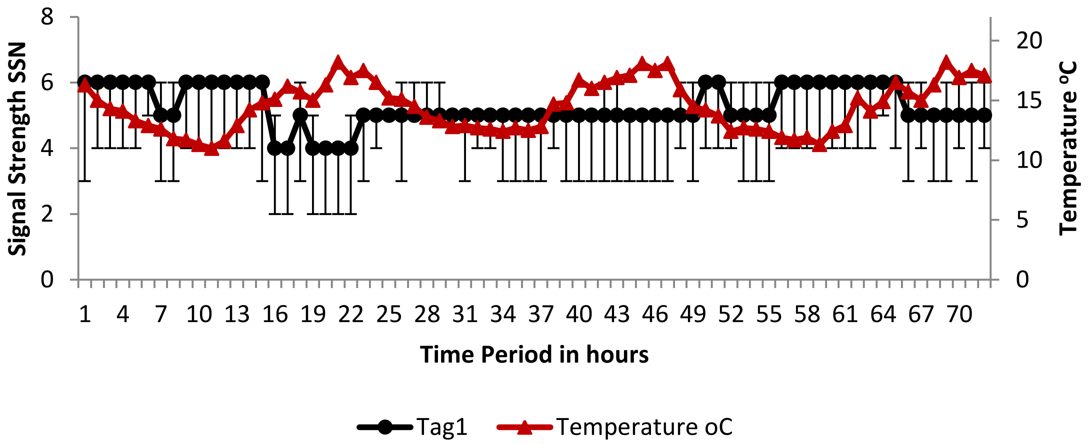
Elevation Pattern

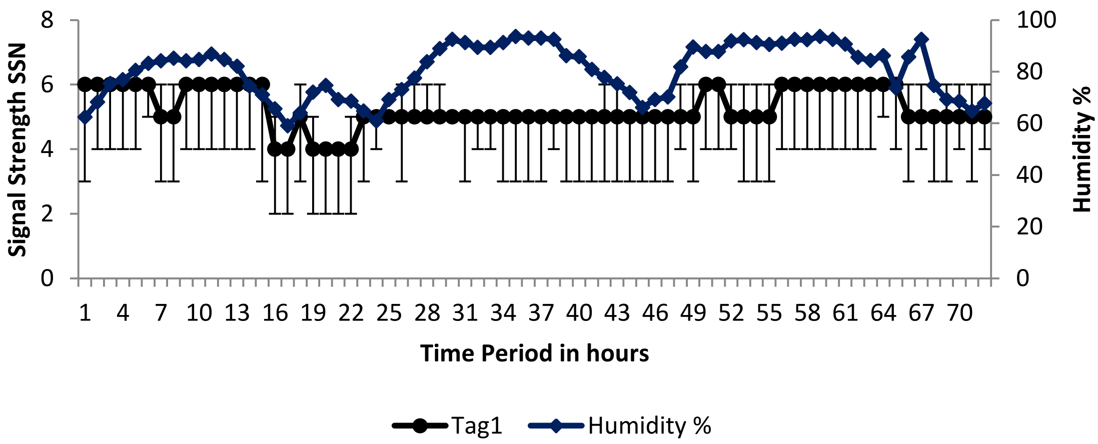
Azimuth and Elevation Pattern of the antenna used in the modelling software, from Motorola [58]

Appendix F. Environmental Effects Test 3 Results Detail

In order to investigate whether the variation in temperature and humidity matched the signal strength variation over the period of the test, a series of charts were produced for each Tag. In the following figures over each hour of the testing period the dominant signal strength is plotted and the error bars indicate the maximum and minimum signal strength readings over that hour. Comparison with the temperature and humidity over the same period is provided for each of the eight tags.

<u>Tag 1</u>

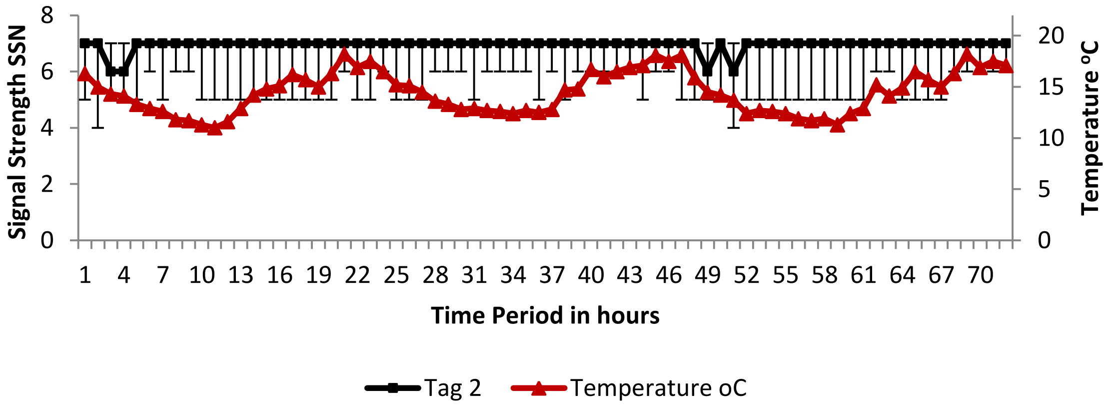


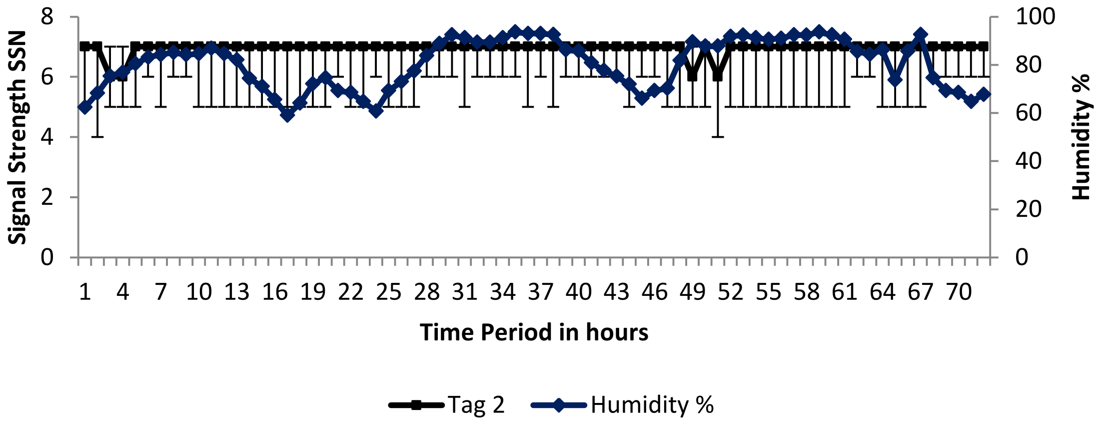


Comparison of Tag 1 with the environmental conditions

This shows that on one occasion at hour 22 when the temperature is at one of the highest values, the most common signal strength dips to SSN4. This does not occur at other high temperature peaks, at hours 46 and 70. Therefore the signal strength of Tag 1 cannot be said to be directly related to the local temperature during this test. Likewise, the peaks and troughs of relative humidity does not correlate with increases or decreases in signal strength.

<u>Tag 2</u>

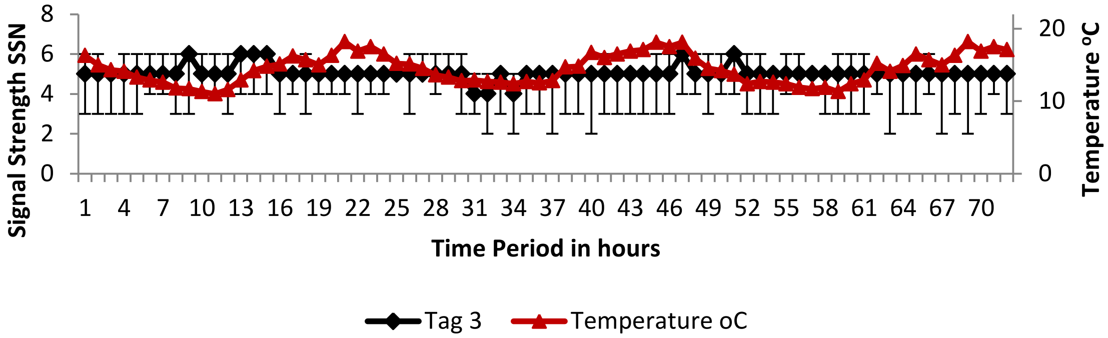


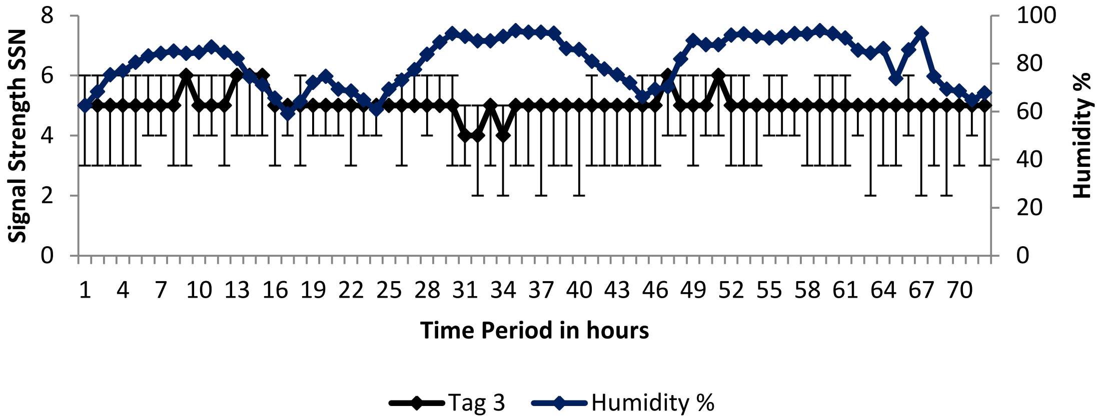


Comparison of Tag 2 with the environmental conditions.

The figure above shows very little variation in the signal strength for Tag 2 over the three days. When differences do occur (at hours 4 and 49) this does not correspond to high or low values of temperature or humidity.

Tag 3

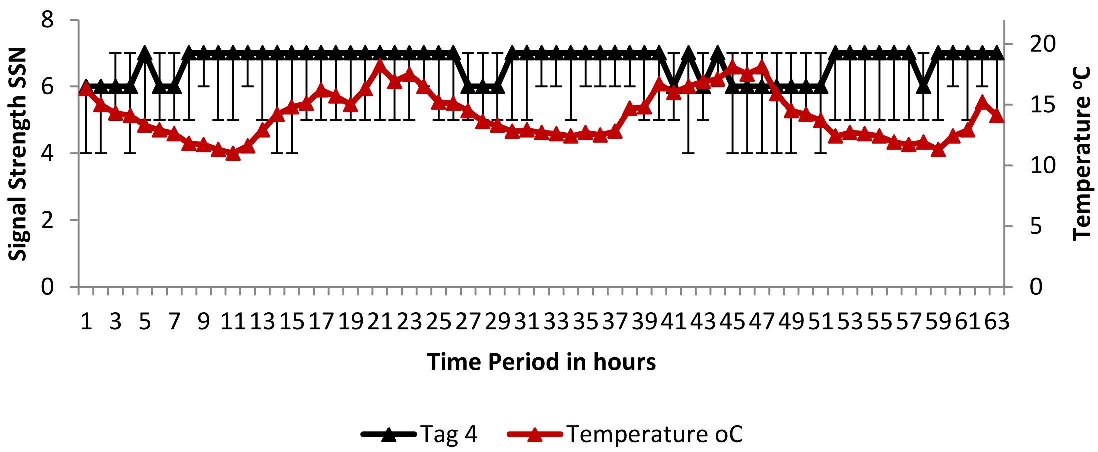




Comparison of Tag 3 with environmental conditions

This comparison shows that the variations in signal strength from Tag 3 do not correspond consistently with the temperature or humidity.

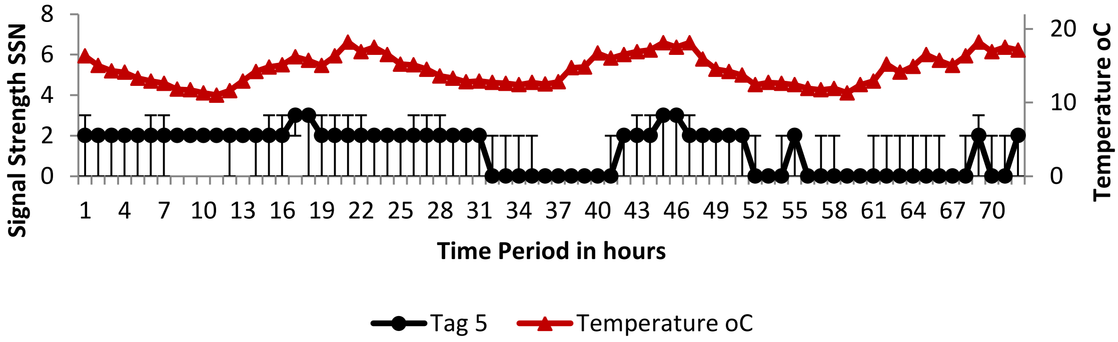
Tag 4

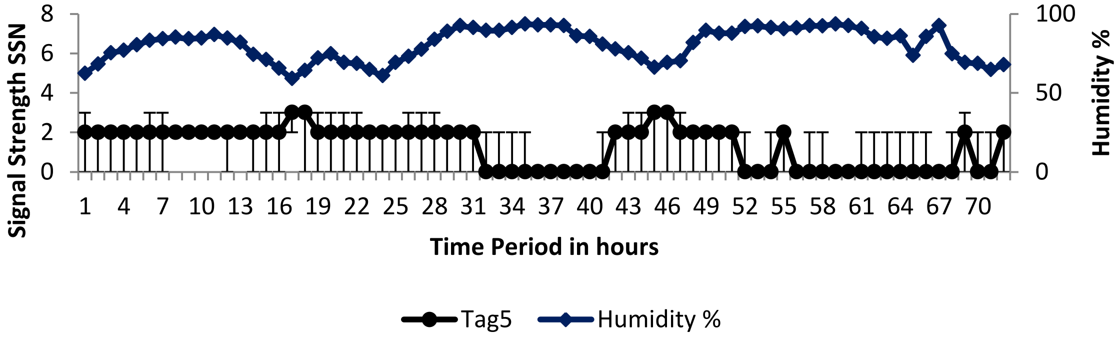


Comparison of Tag 4 with environmental conditions

It can be seen that the signal strength of Tag 4 does not correspond consistently with temperature or humidity.

<u>Tag 5</u>

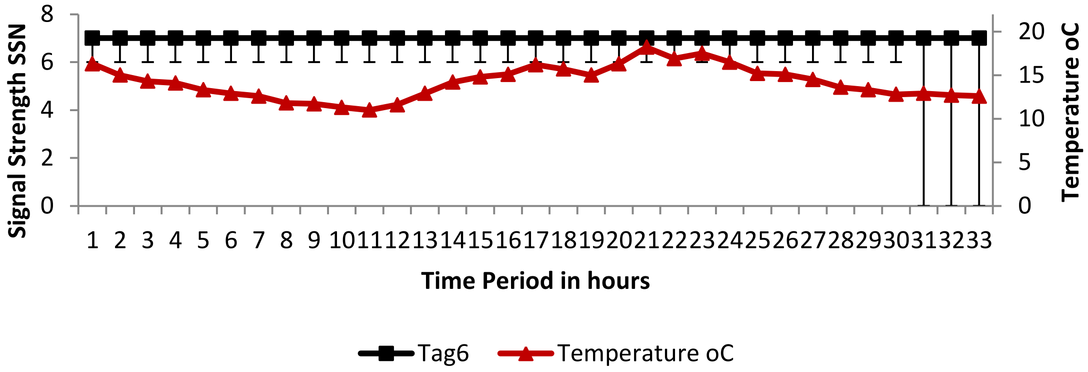


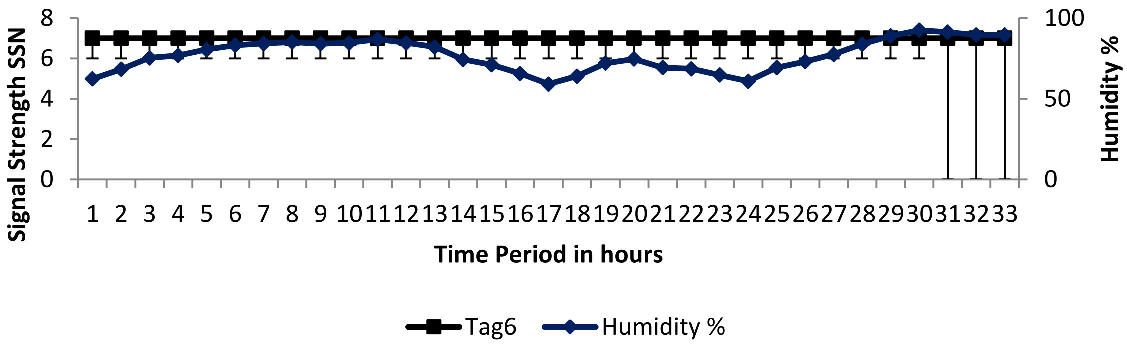


Comparison of Tag 5 with environmental conditions

Although there are occasions when low signal strength of Tag 5 appears at the same time as a peak in humidity, this is not replicated for all peaks of high humidity or low signal strength. There is no apparent co-incidence of signal strength and temperature.

Tag 6

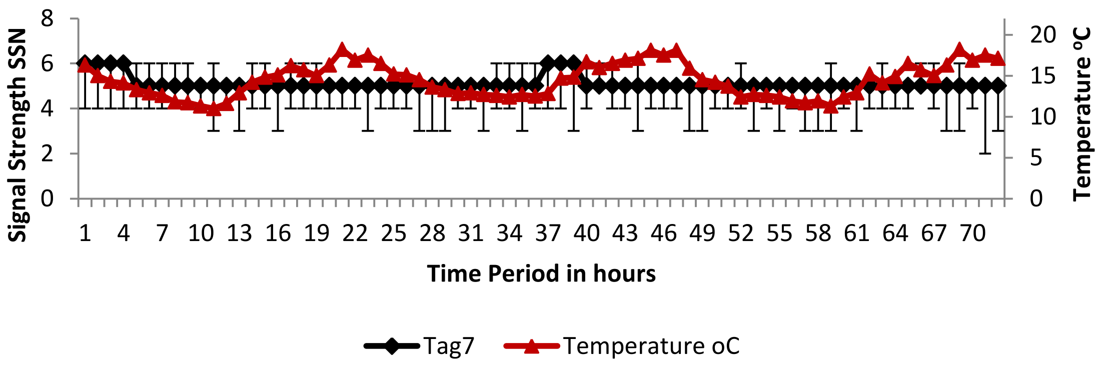


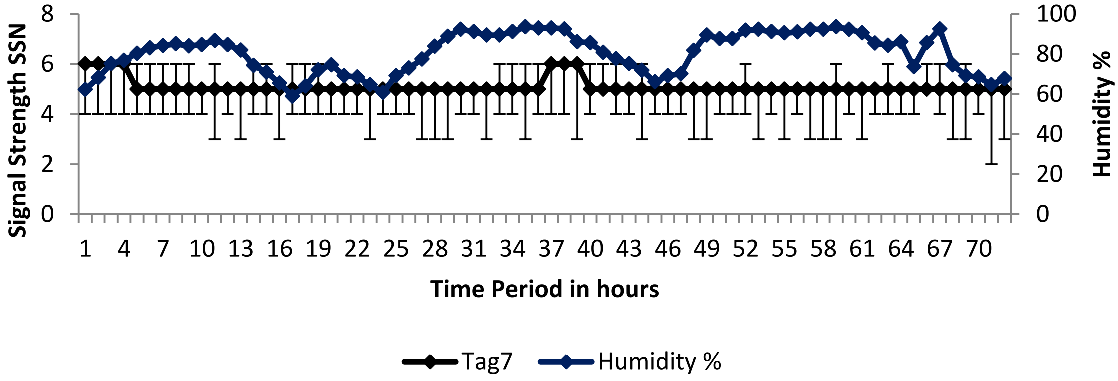


Comparison of Tag 6 with environmental conditions

Tag 6 gave a steady signal strength of SSN7 over the 33 hours it was responding. There is no apparent relationship between the tag's signal strength and the temperature or humidity changes during the test.

Tag 7

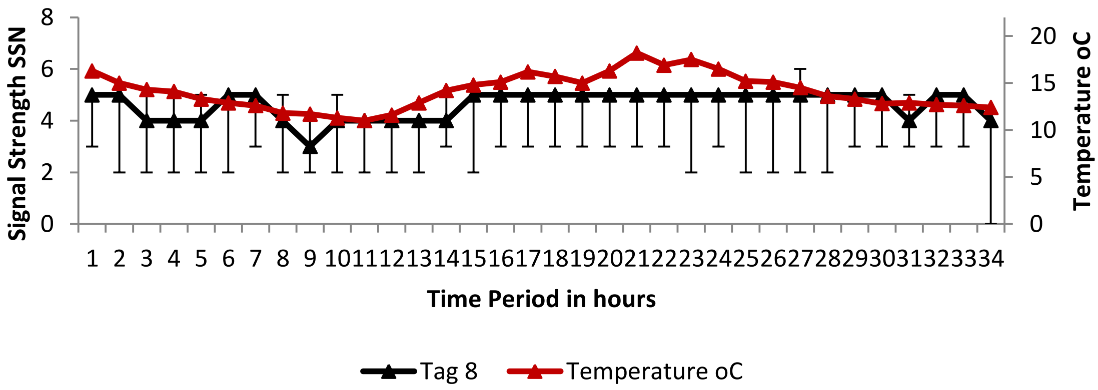


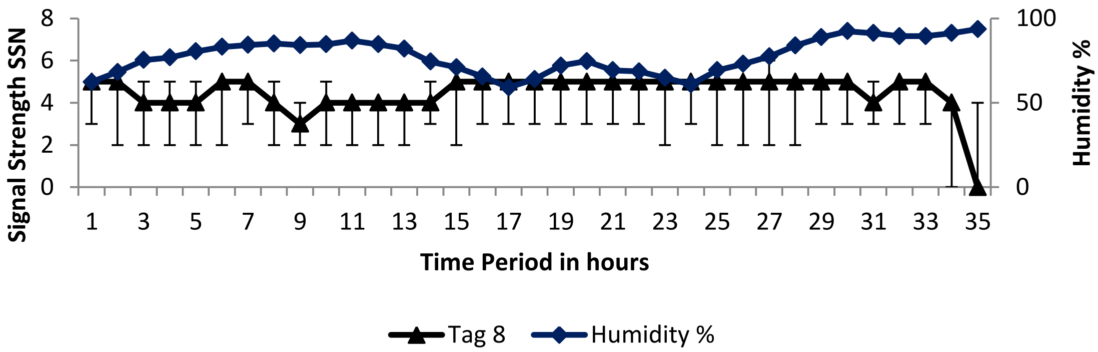


Comparison of Tag 7 with environmental conditions

The signal strength of Tag 7 does not appear to be related to the temperature and humidity conditions during the test.

<u>Tag 8</u>





Comparison of Tag 8 with environmental conditions

Tag 8 was responsive for 35 hours, and during this time there was no apparent relationship between the signal strength and variability in temperature and humidity.

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