USE OF WI-FI SENSOR NETWORK
IN MEASURING
OCCUPANCY AND PEOPLE CIRCULATION IN BUILDINGS

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Abstract

This research project investigated the potential in using a Wi-Fi sensor network composed of Open Mesh sensor nodes to measure both localized and non-localized occupants in the Architecture Building at Ryerson University with two different sensor node configurations. It also experimented with the use of Raspberry Pi, a low-cost infrared motion sensor, as a people counter. The results show that the proposed sensor network is not capable of measuring non-localized (transient) occupants due to their short duration of stay in the measurement area. The number of non-localized occupants and their duration of stay can be more accurately measured by the people counter. As for localized (in one location for longer periods) occupants, the results find that while the proposed system cannot provide an accurate occupant count, it can produce a fairly accurate overall occupancy pattern under both perimeter node and single node configurations.

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1. Introduction

Occupancy is an important factor that affects building performance. This research project looks at how to best measure occupancy levels and patterns in a building. The project is carried out as the first part of a two-part project. Part one examines the use of a Wi-Fi sensor network to measure both localized and non-localized occupancy. A proven Wi-Fi sensor system has the potential to be integrated with an existing Wi-Fi infrastructure in order to economize its use in Wi-Fi-ready buildings. Part two will examine the possibility in using Wi-Fi sensor systems to improve the building performance of Ryerson University's future Daphne Cockwell Health Sciences Complex.

The following sections, namely indoor environmental quality (IEQ), building energy use, and building usage, explain how building performance is affected by occupancy and why measuring occupancy is crucial to improving building performance.

1.1 Indoor environmental quality

According to a survey conducted by the National Human Activity Pattern Survey (NHAPS), survey respondents from the 48 states in the U.S. spend an average of 87% of their time in enclosed buildings (Hern et al., 2001). People who are spending prolonged hours in an indoor environment are also exposed to potential indoor air pollutant and thermal discomfort inside a building for longer periods of time. Therefore, indoor environmental quality (IEQ) is important to the well-being of building occupants.

One major component in assessing IEQ is indoor air quality (IAQ). The US Environmental Protection Agency (EPA) has repeatedly named indoor air pollution as one of the top five environmental public health risks (EPA, 2003). Poor air quality can cause various health problems including short-term illnesses such as fatigue and nausea, and long-term diseases such as chronic respiratory diseases, heart disease and lung cancer (EPA, 2003 & Spengler et al., 2001).

The other key component in assessing IEQ is thermal comfort (Huizenga et al., 2006). A study carried out in 215 buildings across the Unites States, Canada and Finland shows that thermal comfort has the second lowest satisfaction score among all the categories scored, with air quality having the third lowest score. Thermal discomfort not only reduces work productivity, but it also increases potential health risks. Studies show that increased air temperatures are associated with increases in SBS (Sick Building Syndrome) symptoms (Mendell, 1993).

Without changing the architecture of a building, one key and practical improvement to IEQ can be achieved by appropriately adjusting the supply of HVAC (heating, ventilation and air-conditioning) systems according to need. For example, studies suggest that an increase in ventilation rate can potentially decrease inhalation exposure to infectious aerosols by more than a factor of two, and lower indexes of respiratory illness by 15% in schools and 76% in nursing homes (Mendell, 1993). In order to provide a HVAC system responding to occupant's need, real-time occupancy information is required and it can only be provided by an active occupancy measuring system. Therefore, occupancy is a crucial factor in improving IEQ. Another study carried out in school classrooms by Wargocki & Wyon (2007) also shows that an improvement in room temperature from slightly too warm to neutral and an increase of outdoor air supply rate from 11.0 to 20.3 cfm per person help improve students' academic performance on numeric exercises and language-based tests. This proves that the well-being of building occupants is affected by IEQ.

1.2 Building energy use

In developed countries, buildings are the primary source of non-renewable energy consumption, contributing to over 40% in the U.S.A. and over 37% in the E.U. in final energy consumption (Pérez-Lombard et al., 2008). With the continuously diminishing fossil fuel reserve worldwide, a reduction in energy consumption by the built environment is crucial to resolving the global energy demand on these natural resources.

Amongst all the sources of energy consumption in buildings, space heating and cooling alone accounted for more than 60% of energy end-use in both residential and commercial buildings in Canada in 2005 (Natural Resources Canada, 2016). According to a study by Aiello and Nguyen (2013), HVAC demand and energy usage is heavily impacted by occupant presence and behavior in buildings. Compared to occupant behavior which is difficult to regulate, occupant presence can be more easily monitored as a means to control HVAC supply in a smart building system. By implementing building control approaches more closely related to actual building occupancy patterns and numbers, energy savings of up to one-third of building’s energy usage may be achieved (Aiello and Nguyen, 2013). Therefore, occupancy information is essential in improving building energy use.

1.3 Building usage

A building has a higher performance when it is actively used. According to the case studies carried out by Sensible Building Science (2014), measuring actual building occupancy can reveal frequency and intensity of usage in each space. This data is useful in quantifying the extent and cost of space underutilization. Room schedules of the underutilized space can thus be re-configured to maximize their usage. In addition, occupancy data is also used as a major component in post occupancy evaluation (POE) (Barlex, 2006). It can serve as the basis for evaluating how a building works for its intended use. The information generated from POE can be used to fine-tune new buildings and improve building operations.

1.4 Building occupancy data

As pointed out by Aiello and Nguyen (2013), energy savings of up to one-third of the building's HVAC energy use may be possible when energy-conscious decisions are being made in operating buildings. One of these decisions is a HVAC control system driven by accurate occupancy information, which is also a possible and practical means to improve IEQ and building water use. In order to provide such a system, a collection of fine-grained information on building occupancy data is required.

Unlike coarse-grained occupancy information in which occupancy profiles and schedules are assumed and they remain static throughout the day, fine-grained occupancy information is constantly changing over 24 hours (Zhao et al., 2015). In addition to its dynamic nature, fine-grained occupancy information is capable of providing a real-time accurate occupant count and activity, which is important for delivering effective control of the HVAC systems to improve building performance.

Studies conducted by Sensible Building Science (2014) regarding the use of real-time occupancy data on energy-and-cost savings for facilities at the University of British Columbia shows that occupancy data can be effectively used as a tool to correlate HVAC supply with the occupancy profile to reduce total energy use. These studies further support that building occupancy data and measurements are valuable tools with tremendous potential in improving various building performance-related issues.

1.5 Fine-grained occupancy information

According to Teixeira et al. (n.d.), there are multiple spatial-temporal properties that can be used to assess fine-grained occupancy information provided by various kinds of sensing systems. This research project will focus particularly on three spatial-temporal properties: presence, count and activity (see Fig. 1), which are all crucial to the effective control of an HVAC system.

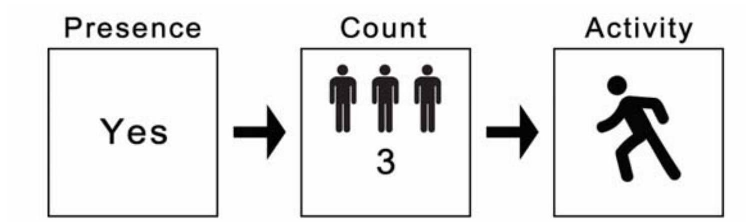


Fig. 1. *Fine-grained occupancy information.*

1) Presence - This property indicates if an occupant is present in the measurement location. A positive measurement will signal "where" HVAC supply is required. It is important to note that heating and cooling to a comfort level is needed whether there is only one individual or more occupants, but only the setback temperature is needed when the space is empty. In regards to this property, this research project will examine if a sensor system has to be terminal-based (Lee et al., 2006), which means that a device has to be carried by an occupant for the detection.

2) Count - This property indicates how many occupants are in the measurement location. The number measured will signal "how much" HVAC supply is required. This is important because ventilation rate is dependent on the number of people present. In regards to this property, this research project will examine if a sensor system can produce a count that can effectively reflect number of occupants present.

3) Activity - This property indicates what kind of activities the occupants are doing in the measurement location. The activity level measured will signal "how much" and "to what extent the conditioned supply" from the HVAC system is required. In regards to this property, this research project will examine if a sensor system can accurately describe the metabolic activity (Dougan and Damiano, 2004) of occupants.

Other distinct properties that do not directly affect the effective control of a HVAC control system will also be examined. This includes privacy issues and cost.

1.6 Research objective

This research aims to determine whether Wi-Fi sensor technology can be employed to measure both localized and non-localized occupants in a building. Localized occupants are people who stay in the same location for a longer period of time, for example 5 - 30 minutes. Non-localized occupants are people who only stay in the same location for a very short period of time, for example 5 - 10 seconds, usually these are people moving through a space. In particular, the aim is to first find out whether it is possible to use Wi-Fi network connections to measure the number of occupants inside a room, for example a lecture room, and its accuracy. Secondly, this research aims to test if the system is also able to measure how many people pass through a particular point at a circulation space, such as a stairway or an elevator.

These two questions are important because a high accuracy in measuring people circulation and occupancy in buildings would allow the Wi-Fi sensor technology to potentially replace the current conventional detection systems. The integration of Wi-Fi sensor technology to an existing Wi-Fi network not only reduces the cost needed for the installation of additional equipment and infrastructure, it can also improve building performance as mentioned earlier.

1.7 Wi-Fi sensor technology

MAC address format

In order to identify each measured Wi-Fi enabled device, a MAC address is used. MAC address stands for Media Access Control address. It is frequently referred to as the physical address of a computer or a network technology device. MAC addresses are used as a network address for most IEEE 802 network technologies, including Ethernet and Wi-Fi. All MAC addresses are unique, which mean that no two network technology devices have the same MAC address. Therefore, MAC addresses are used by Wi-Fi sensor networks as a way to measure the presence of unique network devices.

Each MAC address number consists of 12 digits. The first 6 digits identify the manufacturer of the device and are referred as the Organizationally Unique Identifier (OUI). The last 6 digits are referred as the Network Interface Controller (NIC) and they designate the serial number for that device. It is important to note that even two smartphones of the same model from the same factory can have a different OUI because each manufacturer can register more than one OUI under their name. The resulting MAC address is a random mix and match of OUI and NIC numbers. Their manufacturer can be found by looking up the OUI in the OUI listing provided by The *IEEE* Registration Authority (IEEE Standards Association, n.d.).

Received signal strength (RSS)

At the same time as when a MAC address is detected by the sensor network, the received signal strength (RSS) associated with the detection of the Wi-Fi device is also recorded. RSS, sometimes referred to as RSSI (Received signal strength indicator), measures the power present in a radio signal received by a sensor. The RSS values are measured in dBm and have typical negative values ranging between 0 dBm (excellent signal) and -110 dBm (extremely poor signal) (Accuware, 2015). The unit dBm is an abbreviation for the power ratio in decibels (dB) of the measured power referenced to one milliwatt (mW). It is used in radio, microwave and fiber optic networks to define signal strength. According to the Institute of Electrical and Electronics Engineers (IEEE), the difference between RSS and RSSI is that RSS is an absolute number representing power levels in mW (milliwatts) while RSSI is an a relative index only. The scale of RSSI depends on the maximum RSSI value set by the manufacturer of each chipset. Since the RSS value decreases when the device is further away from the sensor, a distance can be derived from the RSS value using mathematical equations (Osa et al., 2012). This derived distance can then be used to estimate the distance between the sensor and the device. With one RSS value measured by one sensor for one Wi-Fi device, it is possible to estimate how far this device is from the sensor. With three or more RSS values measured by three or more sensors for one Wi-Fi device, it is possible to estimate the location of the device using the triangulation of these RSS values. Using either way, the location of the device can be approximated to reveal if the device is inside a specific measurement area. A positive detection is counted as one occupant. With the use of MAC address and RSS value, a Wi-Fi sensor network can detect the presence and the approximate location of a Wi-Fi device.

2. Literature review

The literature review is divided into two sections. First, it will examine alternative occupancy detection systems on their capabilities in providing fine-grained occupancy information regarding presence, count and activity. Second, it will review how other researchers have used Wi-Fi networks to measure occupancy and the use of Wi-Fi technology on location detection.

2.1 Occupancy measurement approaches

Occupancy measurement systems can be classified into two different approaches, namely occupancy detection and occupancy counting. In general, occupancy detection works more passively than occupancy counting. It works as a response system that measures the presence of occupants only after the occupants are already present in a space. On the other hand, occupant counting devices actively measure at the moment people are egressing in and out of a space. A summary of the major occupancy sensor detection systems is shown in Tab. 1 and are discussed below.

Sensor Systems	Presence	Terminal Based	Count	Activity	Privacy Issue	Cost	Other
CO_2	✓	X	✓	✓	X	Low	CO_2 concentration can be influenced by environmental factors
PIR	✓	X	X	X	X	Low	PIR is susceptible to false-OFFs
Ultrasonic	✓	X	X	X	X	Low	PIR is susceptible to false-ONs
Vision	✓	X	✓	✓	✓	High	Have major privacy concern
Audio	✓	X	✓	X	X	Low	Can count only when sound is being made by all occupants
Energy	✓	X	✓	✓	✓	Low	Can only estimate activity related to metered equipment
RFID tag	✓	✓	✓	X	✓	High	Can only estimate presence & count of occupants with RFID tags
IPS App	✓	✓	✓	X	✓	Low	Can only estimate presence & count of occupants with app

							actively on
PIR Counter	✓	X	✓	X	X	High	Can only estimate presence & count by counting occupants going in and out
Wi-Fi	✓	✓	✓	X	✓	Low	Can only estimate presence & count of devices with Wi-Fi ON

Tab. 1. *Summary of major occupancy sensor detection systems.*

2.1.1 CO_2 based detection systems

The two basic types of CO_2 sensors for occupancy detection, namely photometric and photoacoustic sensors, indirectly measure the concentration of CO_2 in a space in parts-per-million (ppm) (Emmerich and Persily, 2001). Since the amount of CO_2 tends to vary with the number of people present in a space. Therefore, it is possible to estimate the number of occupants by measuring the concentration of CO_2.

1) Presence - The strength of this system is that it can detect occupant presence without being terminal based, which means there is no need for occupants to carry any devices in order to be tracked.

2) Count & 3) Activity - The system alone cannot provide accurate information regarding occupant count or activity, since an increase in CO_2 concentration can be a result of an increase in occupancy and/or an increase in occupants' activity level. However, it is able to respond to a rise in CO_2 levels by increasing the ventilation supply. This is why CO_2 systems have been a commonly used tool to control HVAC systems and has been in use for over 20 years (Nassif, 2012).

The drawback of this system is that the CO_2 level and thus the sensor accuracy can be easily affected in a dynamic environment by external factors such as interference from other gases (e.g. water vapor), drift, wind speed, and location of sensors (Emmerich and Persily, 2001).

Current research shows that the CO_2 sensors can be used to measure occupancy quite accurately in residential and office buildings. CO_2 sensor systems can also be used to reduce energy use in buildings. To experiment with the use of the CO_2 sensor for detecting occupant presence and count, Mumma (2004) carried out an experiment to estimate real-time occupancy by measuring the CO_2 concentration in a space, the supply air CO_2 concentration, and the supply airflow rate. Occupancy was then computed using either a steady state or a transient equation. They found that, for a total occupant size of around 45 people inside a classroom facility, the estimated occupancy only varies from the actual occupancy by two people. The estimated occupancy pattern also follows the actual pattern. It is important to note that the occupants in this case had a similar activity rate since it is a classroom. This helps establish a more direct and stable relationship between the CO_2 concentration (ppm) and the number of occupants for an easier calibration.

To further investigate the energy savings and comfort in an office building by the application of CO_2 concentration sensor, Nassif (2012) carried out an experiment by comparing air supply based on 1) occupancy measured by CO_2 sensors and 2) assumption of full occupancy in a multi-zone VAV system. To estimate occupancy in case one, a CO_2 concentration sensor was installed at the air return duct and air supply was modified based on the occupancy estimated by the sensor. And in case two, the sensor was installed at the air supply duct to maintain the CO_2 concentration at a (fixed) set-point value based on full occupancy at the building.

The results show that energy savings of up to 23% can be achieved depending on the location of the rooms and the actual occupancy profile in case one. However, the author pointed out that in practice there is difficulty in obtaining the actual occupancy in each individual zone in a multi-zone system without installing a CO_2 sensor in each zone at a "high and unjustified" cost. Without such accurate occupancy data, both over- or under-ventilation could result, thus wasting energy or causing occupant discomfort.

Cali et al. (2015) further demonstrated that high accuracy in estimating occupancy could be achieved under both mechanical and natural ventilation. In the experiment, an algorithm for the detection of occupants in the indoor environment was employed in both residential and office buildings under both types of ventilation. The results show that an accuracy of up to 95.8% was recorded for detecting occupant presence and up to 80.6% for determining the exact number of occupants. The author pointed out that knowledge on the status of windows and doors, and the air-exchange rate were crucial in achieving high measurement accuracy, since these parameters influence the concentration of CO_2 inside the room directly.

2.1.2 *Passive infrared (PIR) detection systems*

Passive infrared occupancy sensors are composed of a pyroelectric detector and a Fresnel lens. They essentially detect a change in heat energy given off by objects including humans in its view (Guo et al., 2010). The sensors are passive and they send out a signal whenever there is a change in the temperature pattern in the sensed environment (Guo et al., 2010).

1) Presence - The strength of this system is that it can detect occupant presence without being terminal based, as long as the occupants are within its line of sight and are in motion (Guo et al., 2010).

2) Count & 3) Activity - Since PIR sensors cannot distinguish between different amount of disturbance triggered by different number of occupants, it cannot provide any accurate information on occupant count or activity level. Therefore, its main drawback is that practically it can only be used to turn on and off appliances. As a result, PIR sensors are mainly limited to occupant driven control of lighting systems (Goyal et al., 2015).

Apart from false triggers due to non-human movement in the surroundings of the sensors, research by Verein Deutscher Ingenieure (2003) shows that PIR sensors are also susceptible to false-ONs due to heat related events such as heat current given off by the HVAC system.

Current research shows that the use of PIR sensors to provide energy savings for HVAC systems is feasible when they are applied in small occupancy areas with a proper time delay setting. Experiments show that PIR sensors can be feasible in larger areas where advanced filter processing is applied to the data collected by the sensors.

Despite the limitation of PIR sensors to only be able to detect occupant presence, Maniccia et al. (1999) carried out an experiment to utilize PIR sensors to control lighting and HVAC system inside the smaller offices within an office building. The experiment took place in 60 perimeter offices and 21 interior personal offices in a building. Photosensors that were infrared-based were used to control both lighting and HVAC through a building automation system. A time delay setting of 30 minutes was used. The results show that energy savings of up to 43% could be achieved. It also found that throughout a typical 10-hour workday, the offices were occupied for only around 30% of the time. This research has supported the use of PIR sensors to effectively control HVAC system in small occupancy areas. The author pointed out that the level of energy savings could be furthered increased by reducing the length of time delay. However, a shorter time delay may result in more complaints from occupants whose work is interrupted by the automatic turn off of systems such as lighting.

A recent experiment by Goyal et al. (2015) also achieved a similar result. The experiment took place in a small office of 4.4 m x 3.8 m in a university building. An occupant number of three people was assigned to each positive detection of occupant presence by the PIR sensor. The room was designed to have an occupancy of two people. The number three was chosen in order to build in a safety factor in the case the more than two people were present, but it was assumed that no more than two people would be present most of the time. The HVAC system was then adjusted to provide a flow rate for three people when presence was detected. Compared to the same room without PIR sensor, the results show that an energy reduction of up to 40% can be achieved even with a more conservative safety factor of three. This supports the potential use of PIR sensor alone to control the HVAC system. However, as the author pointed out, this system may only be applicable to building zones with small occupancy, for example, an office composed of many small rooms.

It is important to note that the above experiments mentioned were carried out in small areas. According to Guo et al. (2010) and the National Lighting Product Information Program (1998), PIR sensors have difficulty detecting small movement when the object is far away from the sensor. Most importantly, PIR sensors require a clear line of sight in order to detect any movement. Even an open office with many partition walls could prevent an occupant from being detected. These properties have made it difficult to deploy PIR sensors to monitor a large space. Yokoishi et al. (2012) further pointed out that using PIR sensors to cover a large room such as a university classroom is difficult because they are insensitive to occupants who are motionless. Also, it is not easy to obtain full coverage even with the use of multiple PIR sensors.

To solve this issue, Yokoishi et al. (2012) proposed the use of particle filtering that involves multiple networked PIR sensor data to improve the accuracy of occupancy measurement. The experiment took place in a room of around 6.4 m x 15.3 m using 4 PIR sensors. The results show that, with the use of a particle filter, the occupancy measurement accuracy increases from 29.6% to 98.3% in the case involving only one occupant with small movement in the room. In the case with an occupant going in and out the room, the accuracy increases from 55.0% to 65.0%. In terms of energy savings, it was found that around 3.5 hours of lighting power per day could be saved by the application of the particle filter over a period of 3 months.

2.1.3 Ultrasonic detection systems

Ultrasonic motion detectors used in commercial buildings are composed of an ultrasonic wave emitter and a receiver. They actively emit ultrasonic sound waves and receive reflected sound energy to detect the motion of occupants through the use of Doppler Effect (Guo et al., 2010).

1) Presence - Like PIR sensors, this system can detect occupant presence without being terminal based, as long as motion is being made in the environment. The strength of this system over PIR sensors is that a line of sight is not required as the reflection of ultrasonic sound waves can effectively cover all parts of a room regardless of the shape of the space (Guo et al., 2010).

2) Count & 3) Activity - This system also shares the same drawbacks as the PIR sensors, as they cannot provide occupant information regarding count and activity.

Additionally, ultrasonic motion detectors detect motion more effectively than PIR sensors which makes it more vulnerable to false trigger by non-occupant related movements in the environment (Guo et al., 2010).

Previous research shows that the use of ultrasonic detection systems in buildings for energy savings is feasible when they are carefully planned and commissioned with a proper time delay setting. However, ultrasonic detection systems are rarely used for detection of occupant presence due to their vulnerability to false-ONs.

Because of their inability to measure occupant count, ultrasonic motion sensors are mostly used for lighting control that only requires occupant information on presence. Earlier research on the effectiveness of ultrasonic sensors also focused on energy savings from their application on lighting. Richman et al. (1996) conducted an experiment on energy savings through the use of ultrasonic occupancy sensors in 154 sample data periods with a total of 54,700 test hours. The experiment was carried out in various spaces in both offices and laboratory buildings. Lighting loggers were used to measure how long the light was on and each logger was connected to an ultrasonic occupancy sensor. The author pointed out that the sensor was not 100% accurate in detecting motion, especially when the movement was very slow and the object was very small. Therefore, a time delay was applied prior to turning off the light. The results shows that potential savings increase with a decrease in the time delay in all types of space tested in the experiment. For a time delay setting of 10-minutes, energy savings of up to 79% and 59% were achieved in a restroom and a manager office, respectively. When the time delay was changed from 2 minutes to 20 minutes in the manager offices, the potential savings dropped by half from 84% to only 41%. This indicates that time delay is the key component in managing energy savings by motion sensors such as ultrasonic sensors in lighting energy use.

Floyd et al. (1996) experimented with lighting energy savings by retrofitting occupancy sensors in one office and two school buildings. Occupancy sensors which used either ultrasonic or PIR sensors, or a combination of both were first installed on these buildings and monitored for 6 months. Afterwards, the sensors were optimized by fine-tuning the time delay at different times of the day and of the week, and by correcting false triggers. In one particular school building, negative energy savings were observed both after sensor installation and after sensor optimization. It was found that false-ONs and occupant behaviors were the reasons. False-ONs due to paper printing and people momentarily stepping into a room caused the lights to turn on and energy was further wasted due to the time delay setting. On the other hand, occupants no longer turned off the lights when they left rooms which contributed to more energy wastage than before. This example not only shows the drawbacks suffered by a typical motion sensor system, but it also points out that potential energy savings through the use of motion sensors are dependent on the room usage. As also pointed out by Richman et al. (1996), spaces such as classrooms and storage spaces that are only temporarily used by the occupants usually have the lights turned off when the occupants leave the room. However, in rooms such as a lunchroom or restroom which are frequently used by every occupant, the occupants tend to leave the lights on even when no one is using it. Energy savings potential is higher for rooms that are owned by everyone.

There is a lack of current literature that focuses on using ultrasonic technology in occupant detection. As pointed out by Guo et al. (2010), ultrasonic detection systems inherit the drawbacks suffered from PIR detection systems which make the use not viable in measuring occupancy. In addition to that, because ultrasonic systems are more effective in detecting small movement without requiring a line of sight, the resulting false-ONs wasted energy especially during off-business hours. Therefore, the use of ultrasonic devices as occupancy sensors has to be carefully planned and set up to provide energy savings.

2.1.4 Vision-based detection system

This system makes use of image recording devices to capture occupant information based on the changes in each image frame in a period of time.

1) Presence -This system is non-terminal based since no devices need to be carried by occupants. The system can detect occupant presence as long as they are moving.

2) Count & 3) Activity - This system can provide occupant count by identifying the human shapes on the image. It can also estimate the level of activity by measuring how fast the images are changing.

The biggest drawback of this system is privacy. Since it is image based, the faces and actions of occupants are being recorded. Therefore, this system has been widely used for security purposes. Also, it requires comprehensive signal processing that involves costly equipment to produce an accurate occupant count.

Previous research shows that the use of vision-based detection systems in measuring occupancy is feasible with an advanced image processing system and a clear line of sight. To investigate the effectiveness of the system in measuring occupancy, Benezeth et al. (2011) proposed an image recording system using a static camera which was based on video analysis. The detection process first identified the changes in the static images as foreground pixels. Then it tracked the movement of the pixels and finally classified the isolated foreground into either human or non-human shapes. According to Benezeth et al. (2011), the strength of this system is that it can provide both a fairly accurate measurement of occupant count and level of activity in two distinctly different scenarios: meeting rooms and hallways. By measuring the level of changes between images against a set number of time frames, the level of activity can be deduced. The results show that it can achieve an occupant detection rate of up to 97% in most scenarios. However, this image analysis based system has difficulty in detecting static occupants. Occupants who have been inactive for a prolonged period of time could be falsely recognized as part of the background which would subsequently affect later measurements when the occupants move again.

In another similar experiment carried out by Liu et al. (2012), the author used video cameras to detect occupants by identifying only their heads, instead of the whole body, as a way to further improve the accuracy of measurements. The shape of heads was used because their elliptical shapes tended to be fairly constant when viewed from different angles by the surveillance cameras. Body shapes tended to change dramatically such as between standing and sitting positions, and when viewed from above or afar. Another improvement to solve the difficulty in detecting static occupants as found by Benezeth et al. (2011) was the use of motion analysis. Liu et al. (2012) demonstrated the use of a motion analysis program to detect the slow movements of heads as a way to distinguish the head from other static head-like objects such as handbags on a desk. The use of motion analysis was also shown to successfully eliminate false detection when there was a change in lighting or contrast level, a concern in the experiment by Benezeth et al. (2011). With less false detections, the vision-based detection system can measure the movement of occupants more accurately. As a result, it can estimate the occupants' activity level more correctly.

However, as pointed out by Liu et al. (2012) in his experiment which used video detectors to detect occupants by identifying their heads, the requirement for a clear line of sight is still a main drawback in an image-based detection system and it can be difficult to achieve using only one camera in a room. Therefore, this technology has not been widely used for the sole purpose of occupant detection (Aiello and Nguyen, 2013).

2.1.5 Audible sound / passive acoustic detection systems

This system makes use of microphones or audio sensors to detect noises. Like PIR sensors, this system is passive as it only receives signals and does not emit any (Guo et al., 2010).

1) Presence - The strength of this system is that it can detect occupant presence easily as the majority of human activities involve making noise (Uziel et al., 2013). It can also be applied conveniently as it is not terminal based.

2) Count & 3) Activity - This system can indirectly estimate the count or activity of occupants by the

different level of noise detected. However, the numbers are not accurate due to the difficulty in finding suitable audio signal descriptors to calibrate each interval in relationship to the number or activity of occupants (Uziel et al., 2013).

Another drawback is that this system is highly susceptible to false ONs because of the variety of noise made by non-human activities in the environment such as noise from vehicles on the street (Uziel et al., 2013). Therefore, a sound detection system is usually used in combination with other sensors in occupant detection applications (Guo et al., 2010).

Current research shows that the use of audio sound detection system alone in measuring occupancy is limited due to the fact that it requires occupants to be actively making sound in order to produce an accurate count. Research on audio sound detection systems mainly focus on improving estimations of occupant count based on the sound waves received by the microphones. Uziel et al. (2013) and (Kattanek, 2014) both experimented with a sound detection system that used an occupancy detection algorithm to calculate the number of occupants present. Two approaches, namely acoustic localization algorithm (ALG) and machine learning algorithms (MLG) were tested, using an array of microphones. The ALG approach estimated an occupant number by localizing the sound source in a pre-defined, grid-like map. The second approach (MLG) made use of a library of audio samples to estimate occupancy. It was shown to have improved accuracy because it was able to distinguish between human and non-human noise sources.

To provide an alternative to the systems proposed by Uziel et al. (2013) and Kattanek (2014), Huang et al. (2016) proposed an occupancy estimation system that used speaker recognition and background audio energy estimation to estimate the occupancy in a room. Their research focused on the human speech produced from inside a room and only an insignificant amount of sound was transmitted from other rooms. This experiment used an advanced audio signal processing program and an extensive calibration of the experiment area that involved the geometry of the office, the location of the microphone, and the relative locations of occupants with respect to the microphones. In the experiment, speakers were used instead of real people. The results show varying degrees of accuracy depending on the number of speakers. It was found that, for a speech measurement time of 5 seconds, an accuracy of 85-98% was achieved for 5, 40 and 80 speakers. The accuracy dropped to 60-75% when there were only 10 and 20 speakers. But overall, accuracy increased to over 90% when the speech measurement time was increased to 15 seconds.

However, these studies are based on the assumption that occupants are actively making sound simultaneously which is not realistic in a real life scenario. This renders the use of audio sensors alone for occupancy measurement impractical. But their ability to measure sound shows great potential to be used in combination with other types of sensors to improve the detection of occupant presence. In an effort to solve the so-called "silent" presence, occupancy sensors were developed by Fernández et al. (2012), combining audio and ultrasonic sensors. With the use of an audio sensor, "still" presence could also be detected. The experiment took place in an office room with a ceiling-mounted configuration. Results showed that it was able to achieve zero false alarms with the use of the fusion sensors and a careful calibration of the system. The research also showed that the probability of occupant detection increased from within 35 - 70% to 88 - 96% when audio sensors were fused to ultrasonic sensors and the probability of false alarms remained lower than 1%. However, a person who is silent and still would not be detected by the fusion sensors.

2.1.6 Energy-related activities based detection systems

This system makes use of metered equipment in detecting occupancy. By measuring the number of equipment being used, an occupant count can be produced.

1) Presence - This system can detect occupant presence without being terminal based as the occupant does not have to carry a device.

2) Count & 3) Activity - In an environment where most activities involve the use of equipment that can be metered, this system can produce a fairly accurate occupant count. Since each piece of equipment is associated with a certain use, occupant activity can also be identified.

This system still presents issues of privacy. For example, each computer and work desk is usually associated with a particular occupant in an office setting.

Current research shows that the use of energy-related activities based detection systems are limited to office-use environment where most activities involve equipment that can be metered. Also, the system requires dual technologies that are crucial for achieving the recorded high accuracy rates. With metered devices alone, any office occupants who are not actively using any equipment may not be detected

Research on energy-related activities based detection systems started as a response to the deficiency experienced by PIR, ultrasonic, and CO_2 sensors. Also, these commonly used sensors are required in large numbers and involve installation costs. Patel et al. (2007) first proposed the use of a single plug-in sensor at any electrical outlet in a home to detect occupant presence by measuring a variety of electrical events throughout the home. It was based on the fact that an electrical load was produced every time a switch is turned on or off, and when the electrical equipment was operating. By carefully calibrating the duration and magnitude of the transient noise produced by these actions, the presence of an occupant was assumed. The results showed that up to 85 - 90% of occupant actions were detected.

However, this experiment presents some major defects for measuring occupancy. First, an operating electrical device, such as a fan, is not necessarily associated with an occupant presence. Secondly, as mentioned by the author, the heavy usage of mobile electronic devices such as smartphones could not be detected at all by this system. In addition, there are many other activities that take place in a home that do not involve any electrical equipment, such as reading a book during the daytime or sleeping. Therefore, this technology may not even be applicable to a "home-like" environment.

To further improve the accuracy and applicability of the above system, Milenkovic and Amft (2013) proposed a system mainly composed of per-desk passive infrared (PIR) sensors and power plug meters for various equipment and appliances specifically used in office buildings. By measuring the change in energy consumption levels of these devices, particularly a change in the device status from idle to active, occupant detection was produced. PIR sensors were added to detect office work that did not involve any metered equipment. An office setting was chosen for the research because most office work involves electrical equipment that can be metered. This more refined experiment is also able to produce an occupant count in an office as each person at work is usually assigned an office station. By detecting how many stations are being actively used, the number of occupants can be obtained.

This research shows that the system is capable of producing a highly accurate measurement of occupant count and the level of desk activities in office building types. It also found that the sensors achieve an occupant count accuracy of 87% in single-person office rooms and 78% in multi-person office rooms. It can also distinguish between computer work and desk work at an accuracy of 99%. Although the level of accuracy is influenced by the amount of training data available, only 30 - 50 training hours are required for robust recognition.

There is other research on detection systems based on building activities and the use of appliances that are also partly associated with energy-related activities. This further shows the possibility of how this system can be applied in combination with other sensor systems. Froehlich et al. (2009) proposed a detection system which monitored the use of water that involved appliances such as dishwashers. Patel et al (2008) proposed another detection system which measured differential pressure in HVAC systems that involved appliances such as fans and air conditioning units. With the inclusion of a wider variety of activities and other sensor systems, energy-related detection systems can be more applicable to other building types rather than solely in offices.

2.1.7 RFID tags detection systems

This system makes use of active radio frequency identification (RFID) tags carried by occupants and a network of physical RFID sensors (readers) installed on site. The RSS (received signal strength) given out by the tags are received by the surrounding sensors. By mapping out the relationship between the RSS and the distance of the tag from each sensor, the location of the tag can be determined

1) Presence & 2) Count - The strength of the system is that it can provide occupant information on presence and count at an average of room-level accuracy when a sufficient density of sensors is employed (Weekly et al., 2014).

3) Activity - This system cannot provide any information on activity as the tag does not transmit any other information.

Its strength over other terminal-based system is that, unlike mobile devices, the occupant does not need to interact with or "turn on" the tags in order to be detected. All an occupant needs to do is carry a tag that can easily fit into their pockets. The main drawback is that this system is terminal based which means only occupants actively carrying a tag can be detected. The assignment of tags to each particular user also raises concerns about privacy. In addition, this system cannot provide information on occupant activity.

Current research shows that the use of RFID tag detection systems can provide very high accuracy on occupant presence and count. This technology has been widely used in building types such as hospitals, offices and warehouses that need to keep track of the occupants and/or goods. However, the infrastructural cost is high due to the need for expensive readers and a high-density employment to achieve such high accuracy. Also, the requirement of a tag restricts detection to only "closed" environments such as offices with known occupants (Zhao et al., 2015). Khoury and Kamat (2009) carried out an experiment with the use of ultra-wideband (UWB) RFID tags. In this experiment, 4 receivers were positioned around the perimeter of a maze-like partition wall setting inside a room. A UWB RFID tag was carried by a robot that was moving around the maze. The results show that a real-time position accuracy of up to 50 cm was achieved. However, such high accuracy came with a high cost. The 4 receivers and 1 processing hub with the associated accessories cost approximately USD $15,000.

A similarly high level of accuracy was also achieved in an experiment carried out by Weekly et al. (2014) in an office area of 16.5 m × 13.2 m using a grid of 24 sensors embedded inside the false ceiling. The sensors were arranged in a 6 x 4 configuration with spacing of 3.3 m and 4.4 m. RFID tags placed at different locations were then detected by the sensors. The results show that an average of room-level accuracy of 2 - 3 m was achieved. The author pointed out that a higher accuracy could be further achieved if the 4.4 m spacing was decreased to 3 m.

The high level of real-time location accuracy makes it possible to track occupant locations in addition to an accurate count. Rahman et al. (2012) carried out an experiment using RFID tags to track occupant movements in a high-rise building for evacuation planning. In the experiment, seven occupants were each given a long-range RFID tag. Their locations in a 3-storey building were tracked by the readers strategically positioned to cover the entire floor area. The results show that the movement of all occupants was correctly shown on the dashboard using the BEMS software. This further supports the use of RFID technology in applications that require close-to 100% location accuracy.

2.1.8 Indoor positioning system (IPS) based mobile application (app) systems

Currently there is no scholarly literature on the review of applications of mobile apps for occupancy detection. This review is mainly based on the product literature by IndoorAtlas, which is one of the leading providers of IPS based mobile application (app) systems for commercial and retail use. This system makes use of the IPS-based application installed on mobile devices. When an occupant turns on their app on their mobile device inside a location, such as a store that is pre-calibrated by the app, the occupant's location can then be detected by the system.

1) Presence & 2) Count -This system can detect occupant presence whenever the apps are turned on from a mobile device (IndoorAtlas, n.d.). However, occupants who do not have the apps installed on their mobile devices or do not have them running continuously will not be detected. Also if they leave their device in one space and go to another space, they will not be measured either. Therefore, an accurate count is not possible.

3) Activity - No occupant activity is measured as the system only detects the active status of the app.

This system is entirely terminal based. Each occupant is usually required to input personal information when they sign up for the app. Therefore, privacy is a major issue as the device (terminal) is being tracked constantly by the application when the app is on (Zhao, 2015).

While there is no current research on the actual performance of these app based detection systems, their benefits and drawbacks are revealed in different product literature. According to IndoorAtlas (n.d.) and Accuware Indoor Navigation, the location accuracy of the system is largely dependent on the density of available Wi-Fi or Beacon signals. They mention that a high location accuracy of 1 - 2 m can be achieved. The room-level accuracy helps determine which room an occupant is present.

Compared with other detection systems where sensors are physically installed in each location, the particular strength of the app system is that it requires less physical infrastructural devices. The major platforms in this system make use of Wi-Fi, beacons or a cloud-based control network which are relatively less costly and easier to install (IndoorAtlas, n.d.).

However, this system has some major drawbacks. First, occupancy detection is passive because it depends on whether the occupants choose to turn on the app. In addition, the mobile app has to be continuously connected to the internet even after being activated (turned on) by the occupant in order to be continuously detected (IndoorAtlas, n.d.). It is unlikely that occupants will have the app on during their entire duration of stay in a retail location. Also, tracking of these devices is only possible when the app is kept on the foreground for iOS devices. As for Android devices, the app can be shut off by the OS when resources are needed for other applications (IndoorAtlas, n.d.). This further makes it difficult to keep track of occupant presence and count during their stay. Because of its passive and occupant-driven nature, this system currently is being used primarily for way-finding and searching for point-of-interest, as promoted on the IndoorAtlas website.

2.1.9 (Overhead) PIR people counter

Unlike abovementioned occupancy detection systems, the PIR people counter is an occupancy counting system. It makes use of pyroelectric infrared (PIR) sensors that can detect the movement of people and their direction of travel when they interact with the sensor. They are usually installed at the overhead position of each door or egress location of the measured space to actively detect infrared energy bouncing off from the heads of the occupants walking underneath them (Infodev, 2014 & Irisys, 2015). By counting how many people pass through an entrance in each direction, the system can count how many people are inside a building.

1) Presence & 2) Count - This system can detect the occupant presence and count the occupant traffic going in and out of each room. The level of accuracy is usually influenced by the number of sensors and the extent of area coverage. An extremely accurate occupant number can be obtained when the sensors are closely deployed. However, they tend to measure people passing by a particular location which makes them less useful in counting the number of people in a room.

3) Activity - No occupant activity is measured as the system only counts.

The strength of this system is that it is non-terminal based and it can very accurately measure occupant presence and count

Substantial research have been carried out on the use of PIR sensors with both digital and analog outputs in detecting the movement and direction of people and the associated count in each direction. This includes research by Hashimoto et al. (1997), Wahl et al. (2012) and Zappi et al. (2007). The results show consistently high accuracy in both outputs.

For PIR digital outputs, Hashimoto et al. (1997) experimented with an overhead sensor module of this sensing system consisting of a 1-dimensional 8-element detector array and an IR-transparent lens to measure occupancy at a 200 cm width x 270 cm height door. A pattern recognition algorithm was employed to analyze the number of people walking by and their directions of travel. The results show an accuracy of 99% in detecting movement and 95% in detecting number of people walking by. Wahl et al. (2012) experimented with a people counting system on several real-life, single-and multiple-occupancy offices using pairs of PIR sensors and algorithms to analyze sensor data. The results show an error rate of less than 1% in detecting people count using the hardware prototype sensor they developed.

For PIR analog outputs, Zappi et al. (2007) experimented with an array of low-cost pyroelectric sensors with a wireless network based platform to measure the movement and directions of a group of 2 - 3 people walking in different configurations. These configurations included people walking in line and side by side in both frontward and backward directions. The results show a 100% accuracy in measuring movement direction. In measuring the number of people walking by, the accuracy dropped from 89% for people walking in line to 75% for people walking side by side. Other similar experiments carried out by Zappi et al. (2008, 2010) also showed 100% accuracy in detecting movement direction and 83% – 95% accuracy in detecting distance intervals. A more recent study by Yun and Song (2014) using two orthogonally aligned PIR sensors with modified lenses to measure the movement and directions of people also showed a high accuracy of 98% correct detection. In addition to their high accuracy, these sensors also come pre-calibrated and thus on-site adjustment is not required (Infodev, 2014 & Irisys, 2015). They are proven technologies that have been heavily used by occupancy-sensitive industries such as shopping malls and casinos.

The major drawback of this system is its high infrastructure and maintenance cost. At the time of this writing, each overhead PIR sensor costs around $500 - $1000, with the less expensive ones requiring a higher density of deployment. This cost does not include installation, central server (gateway), cost for wiring power and data cables to each sensor and a subscription for system support. Because of the complexity of this system, it requires substantial planning and design before its implementation. In addition, this system cannot provide occupant information regarding activity.

2.2 Wi-Fi sensor network detection systems

This system makes use of Wi-Fi sensor nodes or a wireless network to detect the presence of Wi-Fi enabled devices, such as a smartphone or a laptop, in a space by measuring the wireless activeness carried out on these devices. The number of occupants can then be estimated by counting how many Wi-Fi devices are present.

1) Presence & 2) Count - The system is able to detect presence and thus count each Wi-Fi device when the device is actively transmitting wireless signals. However, occupant count may only be obtained if each occupant only has one Wi-Fi device.

3) Activity - Since the system only detects Wi-Fi enabled devices, no occupant activity can be revealed by system.

Privacy issue is a big concern in this system as each Wi-Fi device is usually associated with one particular occupant. By monitoring the device, the location of the occupant can be tracked.

While there is considerable research on the use of Wi-Fi sensor networks to measure occupancy-related parameters inside a building, very few actually use Wi-Fi network to measure occupancy directly. One particular study by Khoury and Kamat (2008) investigated the tracking and localization of indoor occupants using a wireless local area network (WLAN), an indoor global position system (IGPS) and a UWB RFID system. For the wireless network system, a Wi-Fi enabled device was carried around the two testing areas, namely a rectangular room and a maze-like partition wall arrangement in the other room. By matching the received signal strengths (RSS) collected by the Wi-Fi access points to a calibrated RSS fingerprint of the location, the results show that a location accuracy of 1.5 - 2 m was achieved. Although the wireless system has a lower accuracy than IGPS (1 - 2m) and RFID (0 - 0.5 m), its advantage is that it does not require a clear line of sight and the cost is much lower than the other two systems. The wireless network uses radio waves that can propagate through walls and obstructions, unlike infrared, ultrasonic, and sound detection systems that are constrained by the enclosure of a room. Another major strength is the overlapping coverage by the Wi-Fi networks that allow continuous tracking of the device when it moves from one area to another. It would not be possible with the use of a PIR sensor. Therefore, this technology is suitable for measurements such as occupancy detection that does not require precise location accuracy as long as it can achieve room-level accuracy.

Recent research by Ali et al. (2016), Abraham and Li (2014), Ferdoush and Li (2014) all made use of a mesh Wi-Fi network that further improved the connectivity between the sensors and reduced the number of Ethernet cable connections. Instead of communicating to one base station, the sensor nodes could transmit signals with neighboring nodes (Jang et al. 2008). This added flexibility allowed ease of deployment for the sensors in terms of installation locations and expansion of the sensor area.

As mentioned by Khoury and Kamat (2008), the major disadvantage of such a system is the need for a site-specific calibration that is not needed for a RFID tag detection system. For a floor plan that has many different rooms and configurations, this can be a labor- and- time consuming process. There are also other difficulties in applying the Wi-Fi sensor network to a specific occupancy. Vebree et al. (2013) experimented with a commercial grade product (Libelium Meshlium Xtreme monitor) to measure the number of Wi-Fi enabled devices in its range as a way to track how many visitors are in a specific room inside a museum. The Xtreme monitor acted as a Wi-Fi sensor and measured the RSS associated with each Wi-Fi device. Since RSS is inversely proportional to distance, by measuring the RSS of a device it is possible to find out how far away the device is from the sensor.

This experiment revealed several drawbacks of the Wi-Fi detection system. First it is found that a device that is asleep is harder to be scanned as they send out a Wi-Fi signals (probe requests) at a much larger time interval. Second, for non-localized visitors, the long interval between two successful scans was found to be incapable of measuring their devices before these visitors moved to another room. Third, the results show that the Xtreme monitor had to be constantly updated in order to be able to scan newer devices.

In an effort to further reduce installation costs from adding a sensor system, Christensen et al. (2014) experimented with the use of existing Wi-Fi infrastructure to estimate building occupancy. The research used the monitoring of IP and MAC addresses in existing Wi-Fi access points and routers to estimate occupancy. The results show that the estimated occupancy pattern is close to the actual occupancy pattern observed. However, there is difficulty in obtaining an accurate occupant count. It was shown that there is inconsistency in relating the number of the occupants to the number of measured Wi-Fi devices. The authors pointed out that some occupants could have several devices at one time, but this number is not constant every day. The experiment also confirmed the drawbacks experienced by the Xtreme scanner. To name a few, the unstable Wi-Fi connectivity of smartphones to the network made them fail to be detected. Also, a device on one floor could have connected to the access point on another floor with a stronger signal, causing a false presence on that floor. These variables made it difficult to simply extract data from the existing Wi-Fi network for occupancy estimation.

In terms of strength, Khoury and Kamat (2008), Christensen et al. (2014) and Vebree et al. (2013) show that the main advantage of a Wi-Fi sensor network is that occupants do not need to install or carry any applications in order to be detected by the Wi-Fi monitors, assuming each occupant has a mobile device like a smartphone and has the Wi-Fi button on. There will actually be no additional infrastructural cost if the existing Wi-Fi network can be doubled as the sensor system. Also, because of the Wi-Fi nature of the detection system, any data collected can be accessed instantly online so real-time occupancy information can be obtained.

2.3 Wi-Fi technology for location detection

The key in measuring building occupancy using a Wi-Fi sensor network is to locate the Wi-Fi devices being used by the occupants. According to Osa et al. (2012) and Verbree et al. (2013), there are two different ways in locating a user (Wi-Fi device). The first one is to locate a user by estimating the distance between the user and the sensor station. This is achieved by using a RSS-derived distance estimate. It is the distance calculated using the signal strength received from the device by the sensor (El Amine et al., 2014). The second way is to estimate the exact location of the user. This is achieved by using triangulation and database correlation (fingerprinting) (Osa et al., 2012). In both methods, received signal strength (RSS) is used as a tool to measure the location of the user.

Triangulation

The device location is calculated using estimation of distances or angles from three or more sensor locations. These estimated distances are converted from the received signal strength and/or propagation time measured from the sensor locations (Osa et al., 2012). Propagation time refers to the time of arrival of the signal received in different sensors or the difference of this time of arrival between different sensors. Due to the influence of noise level in the RSS measured, the propagation time is used to improve the precision of location estimation (Kaaranen et al., 2005). The limitation caused by high noise level is explained later in this section.

Database correlation (Fingerprinting)

As for database correlation, the RSS values from a device collected by the sensor points are analyzed against a database of calibrated values for that specific area to provide the two-dimensional coordinates of the device. It is different than an active triangulation process as the RSS analysis used in the database correlation was more about matching the existing fingerprint of a location (Khoury and Kamat, 2008). That is why this method is also referred to as fingerprinting. The set of calibrated values for a specific area is referred to as a radio map and it is prepared during the offline phase using conventional drive testing equipment or accurate prediction tools (Osa et al., 2012). During the online phase, the RSS values measured from a device is then compared to the radio map and a location with the highest probability is selected (Vebree et al., 2013).

RSS noise

The abovementioned location estimation methods primarily depend on RSS values. Although RSS can be easily provided by sensor stations in a cost-effective way, there is inherent deficiency in the measurement RSS values. First, there is a lack of precision in RSS values. The RSS measured from two devices at the same position could fluctuate up to 10 dBm (Osa et al., 2012). Second, RSS is affected by environmental factors such as scattering and reflection of electromagnetic waves (Hashemi, 1993). Obstacles can also affect RSS measured. These obstacles include the number of walls and other obstructions, and the presence of water in proximity of the sensor (Accuware, 2015). In addition to obstacles, the number of people also affects the RSS. According to Bahl et al. (2000), RSS can be reduced by 3 - 5 dBm by the body of a person. Ground effects and echoes also affect the RSS (El Amine, 2014). These interferences from the environment has consequently created a high level of noise in the RSS measured (Mardini et al., 2014). The noise and interference could cause a high degree of uncertainty that impacts localization mechanisms that are based on fingerprinting (Osa et al., 2012).

RSS noise reduction

Lotcher et al. (2005) pointed out that, even with the influence from the noise in the surrounding environment, there is still a strong correlation between the distance of a sensor station and RSS measured. As a result, considerable research has been carried out on filtering the noise in improving the accuracy of the RSS-derived distance for the positioning system. El Amine et al. (2014) developed three algorithms based on the RSSI fingerprinting as a way to reduce the noise associated with the RSSI values. These algorithms work similarly to the Kalman filter, which is a statistical tool that can reduce noise collected in data to produce more precise estimates. The algorithms were applied on an indoor wireless localization application using XBee wireless sensors. The results show that the resulting localization application is able to locate a person inside a building with a location accuracy of 80 cm and an efficiency of 90%. Another research by Mardini et al. (2014) experimented to improve accuracy of RSSI-based localization techniques in ZigBee Networks using a two-State Markov model with moving average to detect unpredictable RSSI values that negatively affect the location estimation. The results show that the location inaccuracy was significantly reduced from 11.7 m to 3 m using the proposed model.

Unlike other research that focused on filtering out the RSS noise to calculate a device's current coordinates, Locher et al. (2015) experimented with an approach that specifically operated with the high fluctuation in the RSS to obtain the logical position of the device. Logical location refers to the general location of the device, for example a room, a floor or area. During the experiment, measurements were carried out at each logical location and the measured RSS patterns were recorded. A data map was created using this information and was then used to infer the most probable logical location of the device. The experiment shows that RSS values follow a normal distribution in a longer time period. Therefore, the accuracy of the data map created can be increased to a confidence level when measurements are collected for a long period of time. Overall, the experiment results show that a high logical location accuracy can be achieved in the proposed methodology.

To conclude, previous research suggests that Wi-Fi technology for location detection can provide a high level of logical location accuracy. This level of accuracy can be further increased to obtain coordinates of the device when RSS filter is applied to reduce the noise and interference from the environment.

2.4 Summary of major occupancy sensor detection systems

Overall, for single-technology applications, RFID tags and PIR counter detection systems have the highest accuracy in producing occupant presence and count. They are proven technologies which are widely used in commercial and industrial applications. However, they are the most expensive in terms of infrastructure costs. For dual-technology applications, PIR sensors work particularly well when coupled with other detection systems that can detect "still" presence which PIR sensors cannot detect. These systems include energy-related activities detection systems that can also provide occupant count, and audio sensor systems that can detect "still" occupants and occupants not in the clear line of sight. However, the two technologies have to be used at the same time.

As for ultrasonic detection systems, their high sensitivity makes them unsuitable to be used as a stand-alone system. They are mainly used as substitutes for PIR sensors in areas where a clear line of sight cannot be provided for the PIR sensors. For direct indoor environmental quality monitoring that can affect occupant comfort, CO_2 detection systems are the most effective as it measures the CO_2 concentration inside the sensed area, which other systems cannot do. However, CO_2 concentration can be affected by indoor environment such as windows or doors that are opened to the exterior or another space. Also, detection systems using measurement of indoor environmental data such as temperature and relative humidity do not directly indicate the presence of occupants. An increasing temperature may not be due to an increase in occupancy.

While vision-based detection systems can provide high accuracy in terms of presence and count, they pose a major concern in privacy as both location and activities are being recorded. As a result, their use is usually limited to security systems in places such as airports and casinos. Passive terminal-based detection systems such as mobile app-based systems that rely on the occupants' interaction with their devices for successful detection tend to produce a lower accuracy in terms of occupant count. They also require an application to be installed and turned on in order for an occupant to be detected.

Compared to major occupancy detection systems, Wi-Fi sensor networks have the advantage of being low-cost and they require minimal infrastructural changes to support their installation. In most cases, only power and Internet connections are required for the Wi-Fi sensor networks. Also, Wi-Fi sensor networks do not require a clear line of sight. They are not affected by movement and noise in the surroundings. They are also not susceptible to changes in indoor environment such as temperature or relative humidity. Regarding privacy, unlike vision-based detection systems that record activities and images of an occupant, Wi-Fi sensor networks only record the MAC addresses of the devices detected. Also, they do not require the installation of a specific mobile application for a device to be detected. As long as the Wi-Fi radio button is turned on, a device using Wi-Fi activity can potentially be detected. These advantages of Wi-Fi sensor networks over other detection systems support their use to measure occupancy in buildings.

3. Wi-Fi sensor network experiment methodology

Since Wi-Fi sensor networks record the instances when each Wi-Fi device is transmitting wireless signals to the Wi-Fi access points, this research proposes to measure how accurately such a network can measure building occupant presence and count. The original intention of this project was to obtain the data recorded by tapping into the Wi-Fi network of a building at Ryerson University and using this data to establish occupancy. However, due to technical difficulties and different constraints in obtaining such data from the university, an independent Wi-Fi sensor network was instead installed for this research project.

There are commercial technologies available that can detect the presence of building occupants. However, not many of them are capable of providing fine-grained occupancy information, especially occupant count as required to control HVAC systems (Zhao et al., 2015). This is because many of these technologies, such as sound detection sensors, are not terminal-based and they tend to measure occupancy by detecting the actions of the occupants instead of the occupants themselves. In a terminal-based detection system, carrying a device is needed in order to be detected, and this helps establish a direct relationship between the number of devices present and the number of people present.

A Wi-Fi sensor network detection system that is entirely terminal-based is proposed for this research project because of its potential ability in overcoming the difficulty to provide a real-time occupancy count. There are not many specific studies detailing the experimental use of how a Wi-Fi sensor network can be set up for such a purpose. According to the case study carried out on a mixed-use building at the University of British Columbia by Sensible Building Science, it is estimated that a 7% reduction in annual energy usage can be achieved by extracting occupancy counts from the data on the existing Wi-Fi infrastructure and feeding it to the building automation system (BAS) to control ventilation. This shows that energy reduction through the use of a Wi-Fi network is possible. Also, Wi-Fi sensor networks have been increasingly used in combination with different types of sensors in collecting indoor environmental data, such as temperature and CO_2 concentration, because of its low cost and high scalability (Li and Ferdoush, 2014). These features also support the proposed use of a Wi-Fi network in measuring occupancy.

3.1 Selection of Wi-Fi sensors

Three different Wi-Fi sensor detection systems were considered at the beginning of this research. The first one is a low-cost build-it-yourself Wi-Fi sensor, using a Raspberry Pi (R-Pi) computer and two Wi-Fi dongles. A program named Kismet would be installed in the R-Pi computer. The device, as a result, could use one Wi-Fi dongle to detect nearby Wi-Fi enabled devices and use the second Wi-Fi dongle to transmit the collected data to the server to be downloaded later. However, the device constructed was not able to function due to potential compatibility issues between the operating system on the R-Pi computer, the Kismet software, and the Wi-Fi dongles. Therefore, due to time limitations it was not possible to experiment with the R-Pi Wi-Fi sensor.

Another Wi-Fi detection sensor system considered was the Meshlium Scanner AP. This is a commercial-grade sensor that can detect any device that works with Wi-Fi or Bluetooth interfaces within 15 - 30 m depending on the line of sight (Libelium, n.d.). According to the manufacturer's literature, this scanner is weather-proof and can be even placed outdoors. Its most recent version has an extremely short scanning rate of 1 second, which means that more devices with less Wi-Fi activity can be detected under this setting. The biggest drawback of this scanner is its high cost. One Meshlium Scanner AP costs around CAN $1,450 (€1,000). In order to measure two rooms at the same time, at least two scanners would be required depending on the sizes of the rooms. Therefore, it is an expensive piece of equipment to deploy on a large scale to simply measure occupancy. Furthermore, since it has to be imported from Europe, there is no technical support in North America should anything happen to this equipment. As promoted, it is used more for measuring the traffic flow of people and vehicles on streets. Therefore, it is not used in this research.

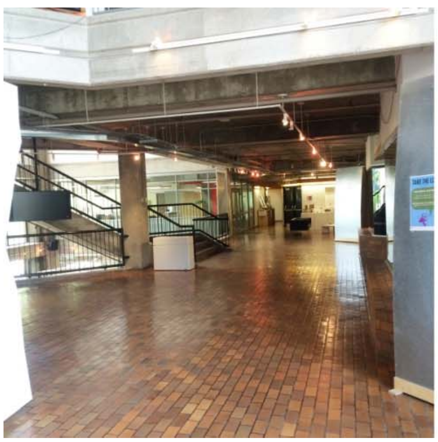
The third system considered and selected is a Wi-Fi sensor network making use of Open Mesh sensor nodes (Accuware, 2015). Unlike Meshlium scanners, each node costs only CAN $100 (US $75), which makes it more financially economical to be deployed at a large scale to measure occupancy in different rooms simultaneously. Like Meshlium scanners, they can form a mesh network that allows for flexible configuration of the nodes (see Chapter 3.3 Data acquisition) and they are also capable of becoming Wi-Fi access points. Open Mesh nodes are also simpler pieces of equipment that can be fixed easier by amateurs. However, unlike the Meshlium scanner, Open Mesh nodes cannot directly provide the collected data in a sorted and ready-to-be-read format. Therefore, a subscription was made to a San

Diego based company called Accuware for its cloud-based server and application program interface (see Appendix A) in order to monitor the nodes system online and to receive the processed data collected by the nodes. The subscription fee is also around CAN $100 (US $75) per node per month. With the subscription, Accuware provides an analytics dashboard service (see Appendix B) that can show real-time and historical occupants (referred as "visitors" in Accuware dashboards) data. In addition, the Accuware Indoor Triangulation System (I.T.S.) Density Maps dashboard, though still under development, can provide some insight regarding the density of occupants for an entire day in 1-hour increments (see Fig. 2). These analytic tools may help provide useful information regarding the performance of the Wi-Fi sensor system.

Fig. 2. *Accuware Indoor Triangulation System (I.T.S.) Density Maps dashboard.*

3.2 Experiment description

A Wi-Fi sensor network was set up using Open Mesh nodes in order to measure the number of unique Wi-Fi devices for two different types of occupants, namely localized and non-localized occupants, on the second floor (main floor) in the Architecture Building at Ryerson University (See Fig. 3 & 4). Two different node configurations, namely perimeter node configuration (configuration A) and central node configuration (configuration B), were tested. For the measurement of localized occupants, the experiment aimed to find out how the sensor network would perform in detecting devices that would be more actively used and connected to Wi-Fi in the same location for a longer time period. This measurement involved a variety of mobile devices including laptops, smartphones and tablet computers. For the measurement of non-localized occupants in circulation space, the experiment aimed to examine if the sensor system detected devices that were mostly in sleeping mode and were only in the measurement range for a short time. Unlike the measurement of localized occupants, this primarily involved detecting smartphone devices which most likely were carried around the building by occupants. The results produced were compared with a physical count to check the accuracy of the system.



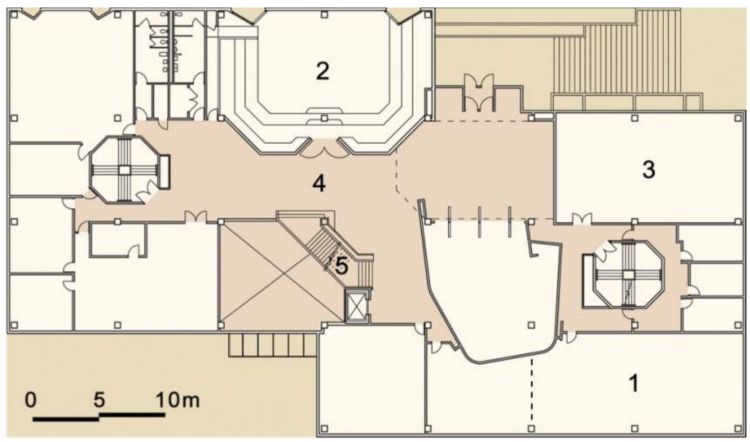


Fig. 3 (left). *Ryerson University Architecture Building's second floor.*

Fig. 4 (right). *Second floor plan of the Architecture Building. (1) Room ARC 200B-D: Master of Building Science (MBSc) Studio. (2) Room ARC 202: Lecture room (Pit). (3) Room ARC 200 G-F: Master of Architecture (MArch) Studio. (4) Circulation area. (5) Second floor stairway.*

Experiment Layout

The experiment was carried out in two phases. In phase 1, configurations A & B were tested on localized occupants in two studios (MBSc Studio and MArch Studio) and a lecture room. In phase 2, configuration B was tested on non-localized occupants in the circulation area and the stairway between second and third floor. Lastly, a low-cost people counter was constructed using a Raspberry Pi computer and a passive infrared motion sensor to compare its occupant measurement accuracy with the Wi-Fi network. The intention was to primarily use the people counter to measure occupancy at locations such as stairways and hallways that involve constantly-moving occupants.

Physical count

For the measurement of localized occupants, a physical count was carried out for time periods of several hours in location-based experiments to measure how many unique persons are present in each one-hour time period. For the measurement of non-localized occupants, time periods of 10 minutes and 30 minutes were used for stairway and circulation space respectively. Only unique occupants at each time period were counted as the sensor network only registers the unique MAC address from each device. For example, if an occupant walks by the stairway three times in a measurement period of ten minutes, this occupant would only be counted as one unique occupant. The physical count was carried out using visual observation.

Mean multiplier (Mean detection ratio)

Since each occupant may have more than one Wi-Fi device, such as a laptop as well as a smartphone, connected to the Wi-Fi system at any time, it would be incorrect to assume that the number of detected MAC addresses is exactly equal to the number of occupants. Therefore, a mean multiplier using the division of the number of MAC detections divided by the number of unique occupants counted was used to estimate proportionally how many devices the Wi-Fi sensor system detected when compared to actual number of unique occupants present within each time period.

A multiplier (M) at each 1-hour time period was used to estimate how many Wi-Fi devices were carried by each unique occupant in each time period. The mean of the multipliers on each day (M_{mean}) was used to estimate the extent of variation in the number of Wi-Fi devices per person throughout the day. The average of the mean multipliers (Average M_{mean}) measured at each experiment was used to compare the variation in the number of Wi-Fi devices per person on different measurement days. By analyzing these multipliers, it is possible to evaluate the consistency and accuracy of the experimental Wi-Fi sensor network. The multiplier equations are shown below:

M = number of MAC detections / number of unique people at each 1-hour time period (1)

M_{mean} = sum of all multipliers at each 1-hour time period on each day / number of multipliers (2)

Average M_{mean} = sum of all mean multipliers on each day / number of mean multipliers (3)

Accuware Analytics Dashboard

In addition to the CSV files provided by the Accuware server, the Accuware Analytics Dashboard provides both real-time and historical data on the number of "unique visitors" and "in-place visitors" detected by each node in a selected time period (number of days). This detection system is based on the detection radius set by inputting a specific RSS cut-off value under the Settings toolbar. The dashboard shows how many devices are inside the detection radius. This measuring mechanism theoretically works the same way as a central node configuration. One major drawback of this analytical tool is that only one RSS cut-off value can be set prior to the actual detection. Therefore, it is not possible to test the data with different RSS cut-off values after the data is collected. In this research project, the performance of this analytic tool was analyzed using a central node configuration in Phase 1.

3.3 Data acquisition

Wi-Fi sensor nodes are the main hardware of the proposed wireless sensor network. A sensor node is a device that is capable of processing and gathering sensory information, and communicating with other connected nodes in a sensor network. Nodes of "Model# OM2P - External Antenna, Long range" from Open Mesh OM Series were used. Fig. 5 & 6 show images of the node. The node consists of a processor, a radio and a long-range external antenna. For power options, each node has one low-voltage power supply injector and one Ethernet port for Power over Ethernet (PoE) injector. For internet connection, each node is equipped with one dedicated Ethernet port.


Fig. 5 (left). *Front view of Open Mesh sensor node.*

Fig. 6 (right). *Back view of Open Mesh sensor node. The black wire is power cable and the blue wire is Ethernet cable.*

The Open Mesh nodes (OM2P) are small radio transmitters that function in the same way as a wireless router. The processor processes the analog signal received by the antenna and converts the raw data into digital form and then transmits it to the gateway node through the radio transmitter. The nodes are programmed to communicate with each other through hopping wirelessly from one node to another in the shortest route. This process is known as *dynamic routing*.

In a Wi-Fi sensor (mesh) network, only one node in a group of six to ten nodes needs to be physically wired to a network connection like a DSL Internet modem. The number of wired nodes required depends on the desired location accuracy of the Wi-Fi detection. The wired node (gateway) shares its Internet connection wirelessly with all other nodes (repeater) in its surroundings, which share the connection wirelessly with the nodes closest to them. The nodes then form a sensor network that detects Wi-Fi-enabled devices in the vicinity (Jang et al., 2008). The main advantage of a mesh network is that it is self-healing, i.e. the network can still operate when some nodes are down because the operating nodes can still communicate with the next closest node.

In the wireless sensor network, all nodes constantly detect the MAC addresses and the associated received signal strengths (RSS) of Wi-Fi devices at a scanning rate of every 5 seconds. This scanning rate is fixed by Accuware. The data collected by both the repeater and the gateway node is then transmitted to the gateway nodes through the mesh network. The gateway nodes periodically upload a list of MAC addresses and the associated received signal strengths (RSS) to the cloud server provided by Cloudtrax through internet connection. Data transmitted to Cloudtrax is also fed into the cloud-based server provided by Accuware. With the monthly subscription to the Accuware Indoor Triangulation System (I.T.S.), data on the various dashboards provided by Accuware can be accessed remotely through the Internet. The data acquisition process is shown in Fig. 7. Accuware dashboards provide a different website interface where data is shown in a graphical visualization (see Appendixes A & B). Collected data in CSV (comma separated values) file format can be downloaded daily from the Accuware server for data analysis. For the purpose of this research project, CSV files were used to investigate the effectiveness of the wireless sensor network in measuring Wi-Fi devices.

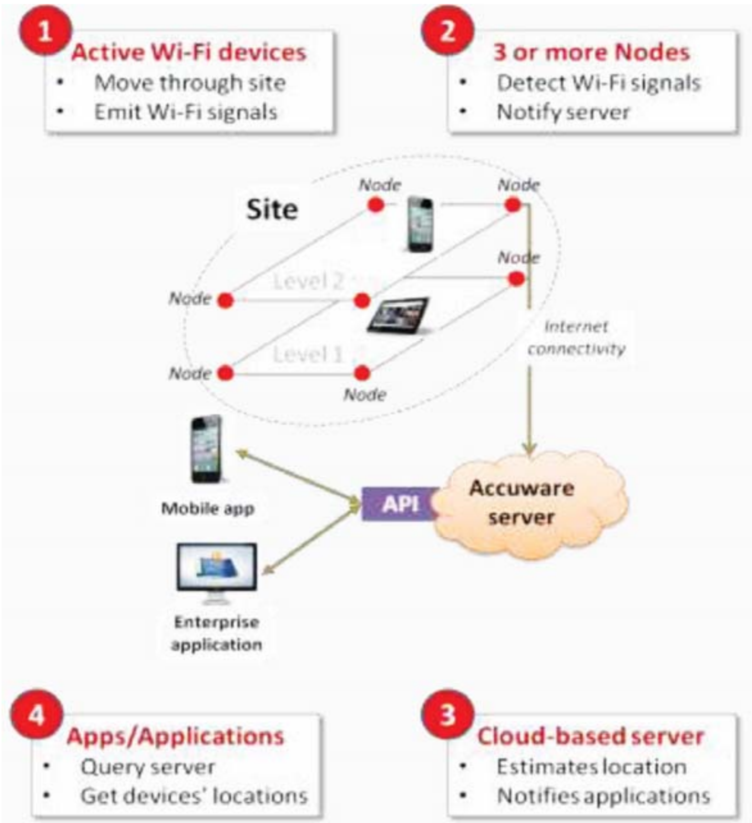


Fig. 7. *Flow diagram of Accuware indoor Triangulation System (I.T.S.) (Accuware, 2015).*

3.4 Data structure of the downloaded files

CSV file format

Data inside the CSV (Comma-Separated Values) files are grouped by the MAC address of each Wi-Fi device, and the records for each MAC address are ordered by the Unix epoch timestamp. Each downloaded CSV file contains the MAC addresses and the associated RSS values of the 10 nodes that detected the 10 highest RSS values (see Tab. 2).

1. Unix Epoch time-stamp Time	2. MAC address	3. Level ID	4. Latitude	5. Longitude	6. MAC address	7. (Highest) RSS	8. MAC address	9. (2nd Highest) RSS
1465841045	XXXXXXE69BD0	0	43.659417	-79.378336	AC86744E5090	-75	AC86744E5150	-76
1465841080	XXXXXXE69BD0	0	43.659364	-79.378585	AC86744E5090	-78		
1465841225	XXXXXXE69BD0	0	43.659439	-79.378504	AC86744E5150	-80	AC86744E5088	-81
1465841235	XXXXXXE69BD0	0	43.659529	-79.378446	AC86744E5150	-80	AC86744E5088	-81
1465841430	XXXXXXE69BD0	0	43.659111	-79.378599	AC86744E5150	-82		
1465841535	XXXXXXE69BD0	0	43.659111	-79.378599	AC86744E5150	-82		

Tab. 2. *CSV file format.*

Where the fields are (columns from left to right):

1. **Unix Epoch time-stamp**
2. **MAC address** of a Wi-Fi device detected by the node(s)
3. **Level ID** of the MAC addresses detected. Since all the nodes are installed on level 0 (second floor), all Mac detections are shown to be on level 0, regardless of where the devices are.
4. **Latitude** of the MAC address detection coordinates
5. **Longitude** of the MAC address detection coordinates
6. **MAC address** of the node that detects the highest RSS from the Wi-Fi device in column (2)
7. **(Highest) RSS** detected by the node in column (6)
8. **MAC address** of the node that detects the 2nd highest RSS from the Wi-Fi device in column (2)
9. **(2nd Highest) RSS** detected by the node in column (8)
10. **MAC address** of the node that detects the 3nd highest RSS from the Wi-Fi device in column (2)
11. **(3rd Highest) RSS** detected by the node in column (10)
12. ...

24. ...
25. **(10th Highest) RSS** detected by the node in column (24)

Excel file format

For the research project, each CSV file was saved in Excel (Macro-enabled) Workbook format as shown in Tab. 3. Titles were added to each column and a few fields were added for data processing and filtering. In addition, the MAC address of each node was replaced by the name of each node for easier review.

Unix Time	Toronto Time	MAC	Lvl	Lat	Lng	X-axis	Y-axis	Coordinates Filter or RSS Filter	Node	RSS (Highest) / dBm	Node	RSS (2nd Highest) / dBm
1465841045	6/13/16 2:04 PM	XXXXXXE69BD0	0	43.659417	-79.378336	79.378336	43.659417	0	Node 7	-75	Node 5	-76
1465841080	6/13/16 2:04 PM	XXXXXXE69BD0	0	43.659364	-79.378585	79.378585	43.659364	0	Node 7	-78		
1465841225	6/13/16 2:07 PM	XXXXXXE69BD0	0	43.659439	-79.378504	79.378504	43.659439	1	Node 5	-80	Node 3	-81
1465841235	6/13/16 2:07 PM	XXXXXXE69BD0	0	43.659529	-79.378446	79.378446	43.659529	0	Node 5	-80	Node 3	-81
1465841430	6/13/16 2:10 PM	XXXXXXE69BD0	0	43.659111	-79.378599	79.378599	43.659111	1	Node 5	-82		
1465841535	6/13/16 2:12 PM	XXXXXXE69BD0	0	43.659111	-79.378599	79.378599	43.659111	1	Node 5	-82		

Tab. 3. *CSV file converted to Excel file format.*

The following fields are added:

1. **Toronto Time** - An Excel formula was employed to convert the Unix Epoch time-stamp into the Eastern Time Zone in which Toronto is located. Since the experiment took place when daylight savings were in effect, n = - 4, i.e. four hours behind Greenwich Mean Time, was applied to the formula.

    The formula: (A1/86400) + 25569 + (n/24), where A1 = Unix Epoch time-stamp, n = -5 for Eastern Time or n = - 4 for Eastern Time under daylight savings.

2. **Coordinates Filter** - When the nodes were applied in nodes-on-perimeter (configuration A) application, the coordinates (X-axis & Y-axis values) were then used in the coordinates filter to verify if the detection was within the nodes perimeter. A positive detection was indicated by "1" and a false detection was indicated by "0".

3. **RSS** cut-off value - This cut-off value was used in central node (configuration B) application to indicate if a MAC address detected was within the measurement area. The filter first used the node numbers of the nodes employed in the measurement area to select MAC detections by those nodes. Then it used a RSS value based on the RSS calibration carried out in the room to eliminate the MAC addresses detected to be outside the room. A positive detection was indicated by "1" and a false detection was indicated by "0".

3.5 Experiment setup

A maximum of 10 nodes were deployed simultaneously (see Fig. 8). Since Accuware's installation literature (Accuware, 2015) recommends that 1 in every group of 6 - 7 nodes should be connected to the Internet as the gateway node using a wired connection, 2 nodes, namely Nodes 5 & 6, were wired to the Internet using Ethernet cables for the entire experiment. These two nodes were used as gateway nodes because these two locations had the most direct access to an open Ethernet cable outlet. The rest of the nodes not wired to the Internet were repeaters.

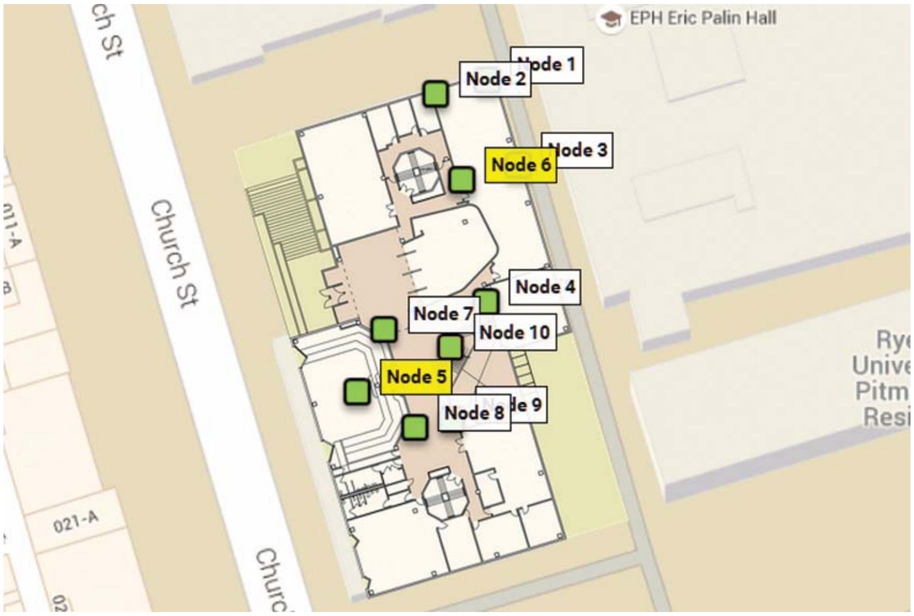


Fig. 8. *Nodes 5 & 6 as node gateways (Highlighted in yellow).*


Fig. 9 (left). *Typical node installation height.*

Fig. 10 (middle). *Enlarged photo of node installation on a lighting fixture at MBSc Studio.*

Fig. 11 (right). *Enlarged photo of node installation on a water pipe at MBSc Studio. Node 6 shown is a gateway.*

Accuware's installation literature (Accuware, 2015) recommends that nodes should be installed on the ground for the best performance of measurement. It also states that mixed configurations of physical installation locations should be avoided since the performance of the nodes will be negatively affected due to a different propagation of the Wi-Fi signal. For this experiment, it was desired for the Wi-Fi sensor network to be integrated with the Wi-Fi access points installed on the ceiling of each room in the future. Therefore, in order to create a scenario to imitate how nodes will perform when integrated with Wi-Fi access points, the nodes were installed close to the ceiling. For easy installation, the nodes were fixed under the utility pipes and lighting fixtures as shown in Fig. 9 - 11. As recommended by Accuware, all nodes were installed at a similar height, approximately 2.75 m above floor level and 500 mm underneath the exposed concrete ceiling.

3.6 Experiment with node configurations A & B

According to Accuware's installation literature, there are two types of node configurations (Accuware, 2015). Configuration A has the nodes installed along the perimeter of the measurement area with additional nodes in the middle area to provide the spacing required. Configuration B has nodes installed at the center of each room. Accuware suggests that configuration A should be used for measuring occupancy in an area as it can provide a better localization accuracy of occupants. On the other hand, configuration B is not recommended for such a purpose, but can be used to simply measure occupancy in a more squared-shaped room. Both configurations were examined during the experiment.

3.7 Configuration A: Nodes on perimeter of a defined area

According to the Accuware's Installation Literature (Accuware, 2015), with a node spacing of approximately 12 - 15 m, the triangulation of the nodes will allow the Wi-Fi devices within the nodes' perimeter (see Fig. 12) to have a detected location accuracy of 2-3 m. This implies that a Wi-Fi device that is physically present within this perimeter will be very likely to have a detected location that is also within this perimeter. By applying a coordinates filter, the devices suspected to be detected outside the nodes' perimeter should be eliminated.

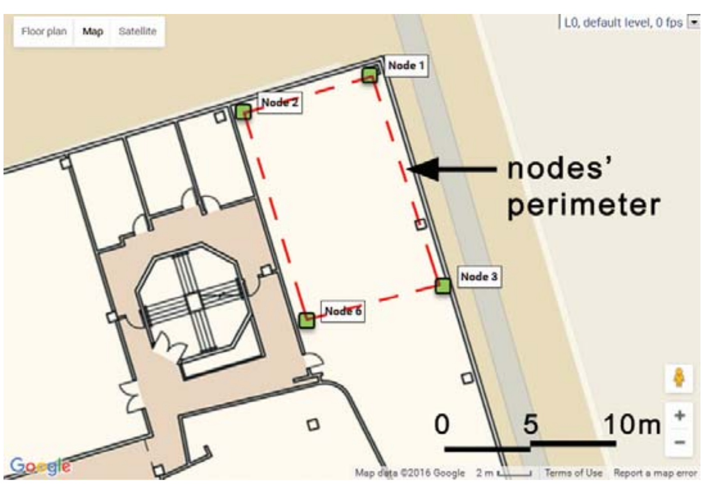


***Fig. 12**. Triangulation by sensor nodes at MBSc Studio.*

For this configuration, the following filters were applied in order to filter the MAC addresses of interest from all those detected by the system. Filters are used by Accuware as a method to select the MAC detections of interest. The details of the filters used are described below:

1. Coordinates (location) filter
2. Received signal strength (RSS) cut-off value
3. Time filter
4. Detection frequency filter

Coordinates (location) filter was used to eliminate any MAC address detections outside the measurement area. Each node is a Wi-Fi device and is thus detected by other nodes in the vicinity. The coordinates of each node were provided by the triangulation of other nodes. The latitude and longitude of the Architecture Building were inputted on the Accuware dashboard. The approximate locations of each node were also positioned within the floor plan on the dashboard. Cloudtrax then used the relative locations of the nodes with respect to the coordinates of the Architecture Building to calculate the coordinates of each node. These coordinates were shown on both Cloudtrax's and Accuware's dashboards (see Tab. 4).

Name	MAC	Description	Level ID	Latitude	Longitude	Action
Node 1	AC86744E50B0		0	43.659649	-79.377816	
Node 10	AC86744E51C8		0	43.659326	-79.377877	
Node 2	AC86744E51A8		0	43.659631	-79.377902	
Node 3	AC86744E5088		0	43.659545	-79.377766	

Tab. 4. *Latitude and longitude of Nodes on Accuware dashboard.*

With the coordinates of the nodes, the points outlining each measurement area on the x-y plane were defined. A Macro program was created in Excel spreadsheets to eliminate any points outside the defined polygon. This program is based on the concept of "points within a polygon" and the exact Macro script is detailed in Appendix F. With the Macro command enabled on Excel, any points within the polygon would register as "1" in the column and these coordinates were then selected.

Received signal strength (RSS) cut-off value was then used to eliminate the MAC address detection with weaker RSS values on the floors above and below the measurement area. To determine the value to be employed for the RSS cut-off value in each measurement area, a calibration was carried out to measure the RSS values of a Wi-Fi device detected by the concerned node. In the calibration process, the Apple iPhone 5s & 6s smartphones were used. The Wi-Fi and cellular networks on the smartphone were first disconnected. The smartphone was then placed at each specific location at an approximate height of 80 cm. With the automatic lock-screen of the smartphone disabled, the Wi-Fi connection was then turned on to ensure that the smartphone was actively transmitting Wi-Fi traffic to the Ryerson Wi-Fi network during the whole duration of the test. The RSS values were then obtained on the Accuware website by entering the appropriate URL command in a web browser. The RSS values and the associated nodes for the detection were returned on the browser as shown below:

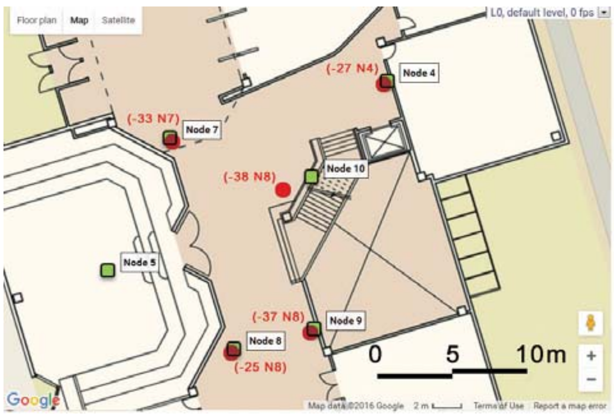
{"mac":"XXXX96DE052E","loc":{"lat":43.659591,"lng":79.377932,"levelId":0,"prec":4.29}, "lrrt":17,"rss":{"AC86744E5178":-55,"AC86744E5088":-67,"AC86744E51A8":-66,"AC86744E5128":-64,"AC86744E51C8":-73,"AC86744E50B0":-52}}

The field "mac" indicates the MAC address of the Wi-Fi device detected by the nodes. In this example, the MAC is "XXXX96DE052E". "AC86744E5178" is the MAC address of the node that detected the highest RSS value of "-55" dBm. Similarly, " AC86744E5088" is the MAC address of the node that detected the second RSS value of "-67" dBm.

This process was repeated at least ten times until a stable RSS value was obtained. This is because RSS values fluctuate in a range of approximately plus-or-minus (±) 10 dBm. The RSS cut-off value that will eliminate most of the devices detected vertically above and below the floor being studied, and devices outside the measurement area should be selected. According to Accuware, the selection of a RSS cut-off value is a trial-and-error process. Different cut-off values have to be tested to see which one is better related to the number of unique occupants present.

In general, the calibration results show that the RSS detected on the floor above and below have a much lower value (more negative) than on the nodes installation floor. The difference is around 10 - 20 dBm. This is because the Wi-Fi device tested was physically further away from the sensor node. The reinforced concrete floor slab also further reduced the signal strength measured by the node. However, this difference was reduced to 5 - 10 dBm when the detection was carried out at locations directly above or below the node. It is because the Wi-Fi device was closer to the node in terms of distance.

In Fig. 13 & 14, the red dot denotes the detection location at approximately 80 cm above floor level. The number denotes the RSS value detected. All the values are negative which indicates that the signal strength is decreasing from the node's physical location on the ceiling. The node responsible for the largest RSS detections is indicated by **N**<u>**x**</u> where x is the node number. For example, N2 indicates Node 2. A maximum of 2 largest RSS values are shown on the calibration diagram.



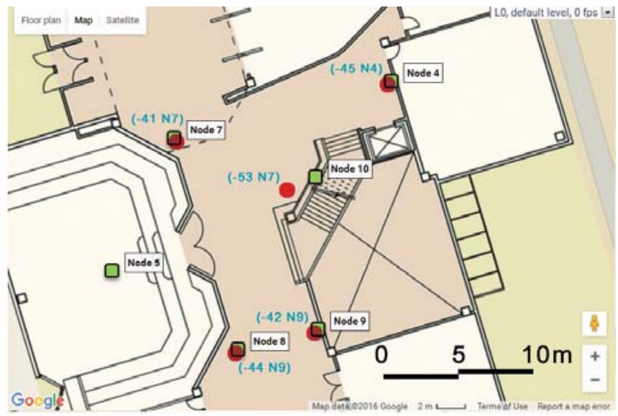


Fig. 13 (left). *RSS calibration at circulation area.*

Fig. 14 (right). *RSS calibration above circulation area.*

Time filter was used to eliminate any MAC address detections outside the measurement time period. A time filter was required in order to show the number of unique MAC addresses within each selected time period for comparison. Tab. 5 illustrates a time filter of "6/13/16 2:00 - 2:59 PM" was applied to the Excel file. The highlighted rows (in red) show all the instances that Device A was detected between 2:00 to 2:59 PM.

Unix Time	Toronto Time	MAC	Lvl	Lat	Lng	X-axis	Y-axis	Coordinates or RSS Filter	Node	RSS (Highest) / dBm	Node	RSS (2nd Highest) / dBm
1465841045	6/13/16 2:04 PM	Device A	0	43.659417	-79.378336	79.378336	43.659417	0	Node 7	-75	Node 5	-76
1465841080	6/13/16 2:04 PM	Device A	0	43.659364	-79.378585	79.378585	43.659364	0	Node 7	-78		
1465841225	6/13/16 2:07 PM	Device A	0	43.659439	-79.378504	79.378504	43.659439	0	Node 5	-80	Node 3	-81
1465841235	6/13/16 2:07 PM	Device A	0	43.659529	-79.378446	79.378446	43.659529	0	Node 5	-80	Node 3	-81
1465841430	6/13/16 2:10 PM	Device A	0	43.659111	-79.378599	79.378599	43.659111	0	Node 5	-82		
1465841535	6/13/16 2:12 PM	Device A	0	43.659111	-79.378599	79.378599	43.659111	0	Node 5	-82		
1465841560	6/13/16 2:12 PM	Device A	0	43.658985	-79.377583	79.377583	43.658985	0	Node 5	-80	Node 4	-81
1465841580	6/13/16 2:13 PM	Device A	0	43.658985	-79.377583	79.377583	43.658985	0	Node 5	-80	Node 4	-81
1465841700	6/13/16 2:15 PM	Device A	0	43.659744	-79.378226	79.378226	43.659744	0	Node 1	-77	Node 5	-80
1465841740	6/13/16 2:15 PM	Device A	0	43.659217	-79.378278	79.378278	43.659217	0	Node 5	-75	Node 7	-76
1465841755	6/13/16 2:15 PM	Device A	0	43.659217	-79.378278	79.378278	43.659217	0	Node 5	-75	Node 7	-76
1465841405	6/13/16 2:10 PM	Device B	0	43.659154	-79.378342	79.378342	43.659154	0	Node 5	-68		
1465841200	6/13/16 2:06 PM	Device C	0	43.659634	-79.377372	79.377372	43.659634	0	Node 3	-70		

Tab. 5. *Application of time filter "6/13/16 2:00 - 3:00 PM to the Excel file.*

Detection frequency filter was used to eliminate any MAC addresses associated with permanently installed Wi-Fi devices inside the measurement area. A detection frequency filter was applied to the data only when an 1-hour time period was used For the measurement. Based on the experiment results, MAC addresses of permanently installed Wi-Fi devices such as Wi-Fi access points tended to have a constantly high detection frequency of more than 100 times/hour. The number of these permanent devices becomes relatively significant when there is only a few occupants present in the measured area. Therefore, a detection frequency filter of 100 times/hour was used to eliminate these permanent devices. This filter was not used when the measurement time period was less than 1 hour as the detection frequency of these devices became less significant. Two of these permanent devices, namely 083E8E18001B and 083E8E18003B, are shown in Tab. 6. By searching their OUI or the first 6 digits of their MAC in the OUI Organization Company ID registry, it is revealed that their manufacturer is "Hon Hai Precision Ind. Co., Ltd.", which is one of the manufacturers of the Wi-Fi access points installed in the Architecture Building.

June 13 18:00 - 19:00 PM			
Unique Wi-Fi devices detected	Detection freq	No. of devices w/ detection freq > 100	No. of devices w/ detection freq < 100
		2	6
Device I (Macbook)	1	0	1
Device A	1	0	1
083E8E18001B	217	1	0
083E8E18003B	164	1	0
Device J (Macbook)	4	0	1
Device B	2	0	1
Device E	2	0	1
Device C	41	0	1

Tab. 6. *Unique MAC addresses identified by detection frequency filter of 100 times/hour.*

Example results after application of the filters for configuration A are shown in Appendix C.

3.8 Configuration B: Central nodes at center of a defined area

Since the RSS value for a Wi-Fi device is inversely proportional to the distance between the device and the node, by choosing a RSS cut-off value that corresponds to a certain detection radius (see Fig. 15), it is possible to approximate how many devices are within the measurement area.

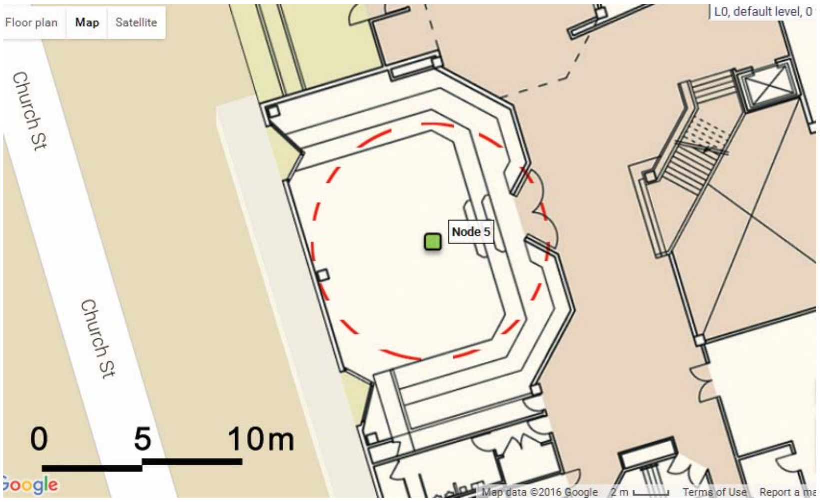


Fig. 15. *Central node application at lecture room (Pit).*

For this configuration, the following filters were applied in order to filter the MAC addresses of interest from all those detected by the system. The details are described below:

1. Received signal strength (RSS) & Node numbers filter
2. Time filter
3. Detection frequency filter

Received signal strength (RSS) & Node numbers filter was used to eliminate any MAC address detections not measured by the specific nodes installed inside the measurement area, and to eliminate any MAC address detections outside the measurement area. The RSS values and the associated node numbers were listed in the CSV file in the descending order of RSS values. In the experiment, there were measurement areas adjacent to each other with nodes that were deployed in close proximity. As a result, not all Wi-Fi devices inside a particular measurement area, for example the lecture room (Pit), had their largest RSS values detected by the designated node inside the lecture room. Therefore, it was not possible to simply select the RSS values detected by that particular node inside the lecture room. To solve that, an Excel formula was developed to select all the MAC addresses with RSS values that were both greater than the selected RSS cut-off value and were detected by that particular node.

For example, if a Wi-Fi device inside the lecture room has its largest or second largest RSS value detected by Node 5 inside the room as Node 5 is the node closest to these devices, and a RSS cut-off value of greater than or equal to - 39 dBm is selected for Node 5, the formula shown below will be applied to the Excel file to select these RSS values:

=IF(OR(AND(H2=" Node 5",I2>-40), AND(J2=" Node 5",K2>-40)),1,0)

H2 is the name of the node that detects the highest RSS from the Wi-Fi device; I2 is the highest RSS detected by H2; J2 is the name of the node that detects the 2nd highest RSS from the Wi-Fi device; K2 is the second highest RSS detected by the J2. Any MAC addresses with RSS values measured by Node 5 that is greater than -40 dBm will register "1" in the Excel column and they can then be selected.

Time filter and detection frequency filters as per perimeter node configuration.

4. Evaluation of Wi-Fi sensor network system performance

The evaluation was divided into two phases. Phase 1 examined the performance of node configurations A & B in measuring localized occupants in two studios and a lecture room. Phase 2 examined the performance of node configurations A & B in measuring non-localized occupants in a circulation space and a stairway.

4.1 Experiment phase 1: Comparison of configurations A & B on localized occupants

Experiment phase 1 aimed to investigate which node configuration was more capable in producing useful occupancy data on presence, count and activity for localized occupants.

4.1.1 Configuration A at MBSc Studio

This configuration aimed to examine a perimeter node arrangement with localized occupants using the space for a longer period of time.

Location diagram

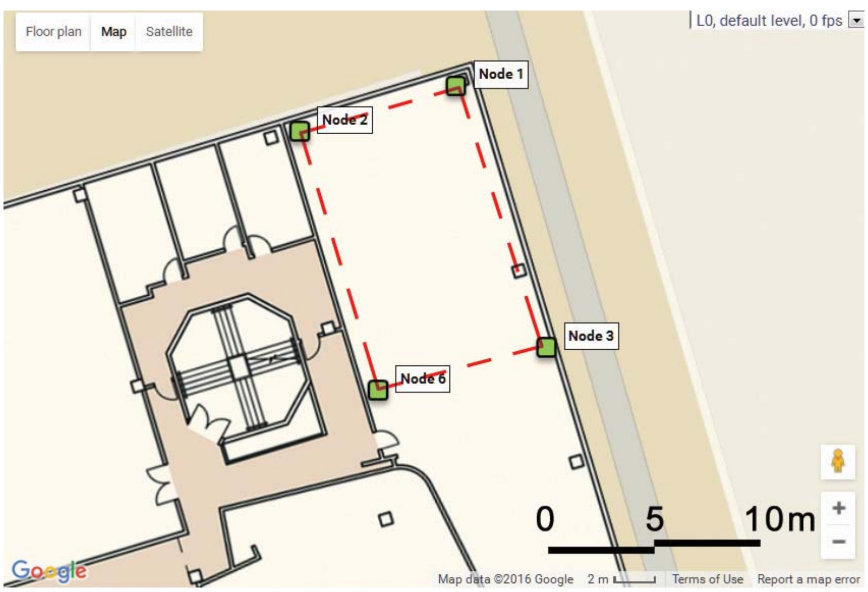


Fig. 16. *Perimeter node application at MBSc Studio.*

Setup

Nodes 1, 2, 6 & 3 were installed underneath the utility pipes about 500 mm away from the ceiling at the perimeter of the MBSc studio from May 30 to June 15 (see Fig. 16). Node 6 was a gateway while Nodes 1, 2 & 3 were repeaters. The nodes were spaced between 8 - 12 m from each other.

RSS calibration

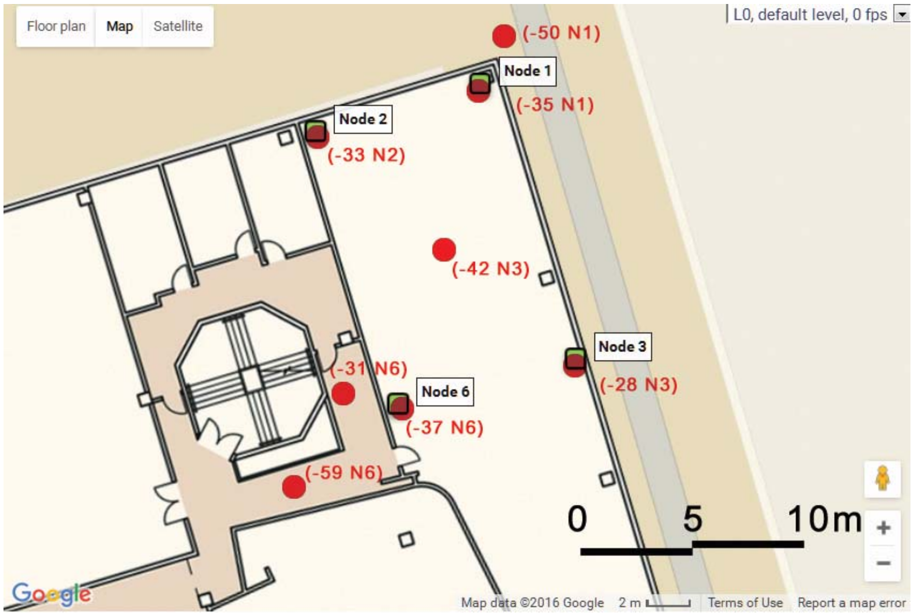


Fig. 17. *RSS calibration at MBSc Studio.*

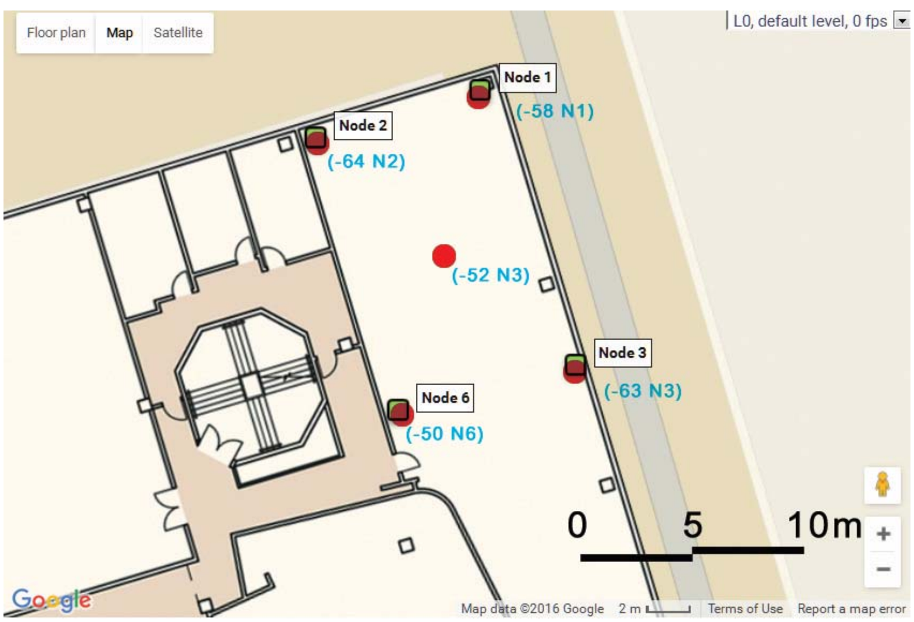


Fig. 18. *RSS calibration on floor above MBSc Studio.*

Fig. 17 & 18 show that the RSS values detected at the center of the measurement area was - 42 dBm, which was the smallest within the measurement area. The RSS value detected immediately outside the MBSc Studio in the hallway was - 31dBm. The RSS values detected in the hallway (to the atrium), outside the building and on the floor above, were all smaller than or equal to - 50 dBm. Therefore, a RSS cut-off value of greater than or equal to - 42 dBm would eliminate any MAC detections from the floor above and it would keep all the MAC detections inside the measurement area on the floor being studied. Although the RSS measured right outside the studio was larger than -42dBm, this MAC detection would possibly be eliminated by the coordinates filter since its latitude and longitude were outside the measurement area.

Using a RSS cut-off value of greater than or equal to - 42 dBm, the results show that the number of MAC detections were at several instances double or even triple the number of unique occupants observed. Therefore, a larger RSS cut-off value is required to produce a more accurate estimation. After several tests, a RSS cut-off value of greater than or equal to - 39 dBm was selected because the results show that this did not eliminate any MAC detections of known devices (see Tab. 7). Although an even larger (less negative) value would bring the number of MAC detections closer to the number of unique people counted, it may risk eliminating devices that were present. Therefore, a number larger than - 39 dBm was not used.

Results

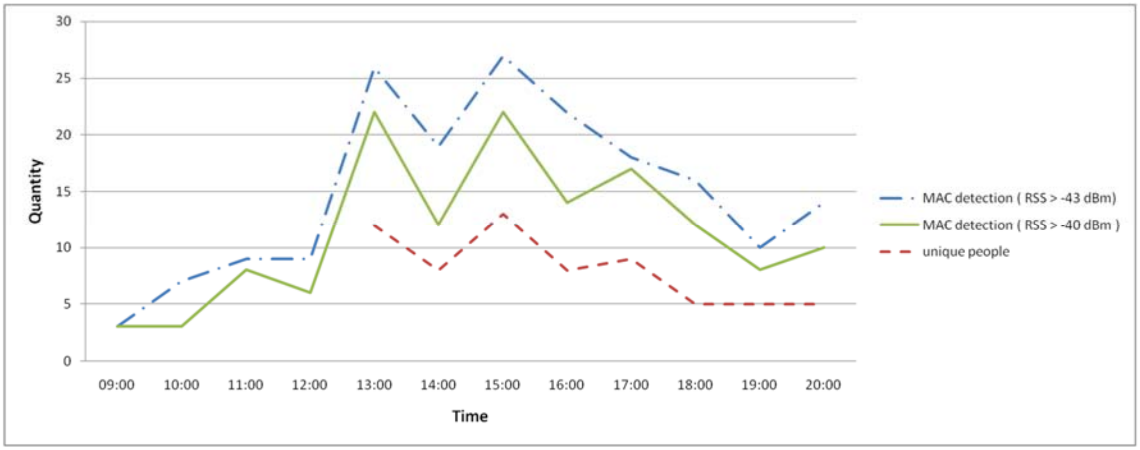


Fig. 19. *MAC detections vs. unique people in each 1-hour time period (June 9).*

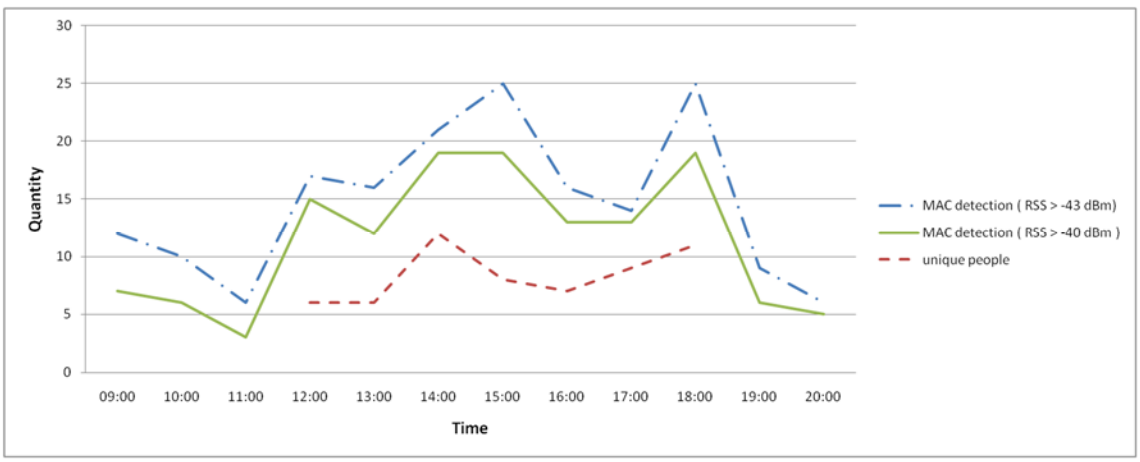


Fig. 20. *MAC detections vs. unique people in each 1-hour time period (June 13).*

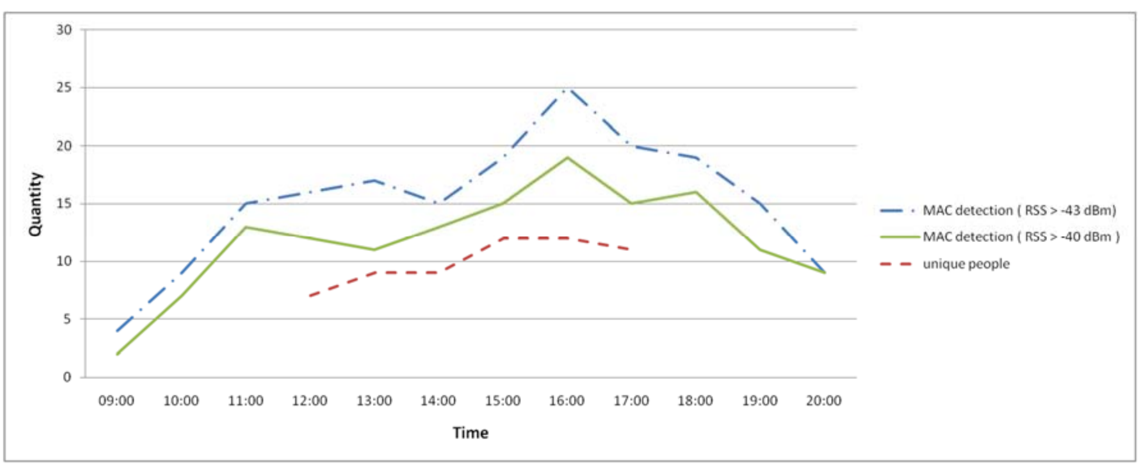


Fig. 21. *MAC detections vs. unique people in each 1-hour time period (June 14).*

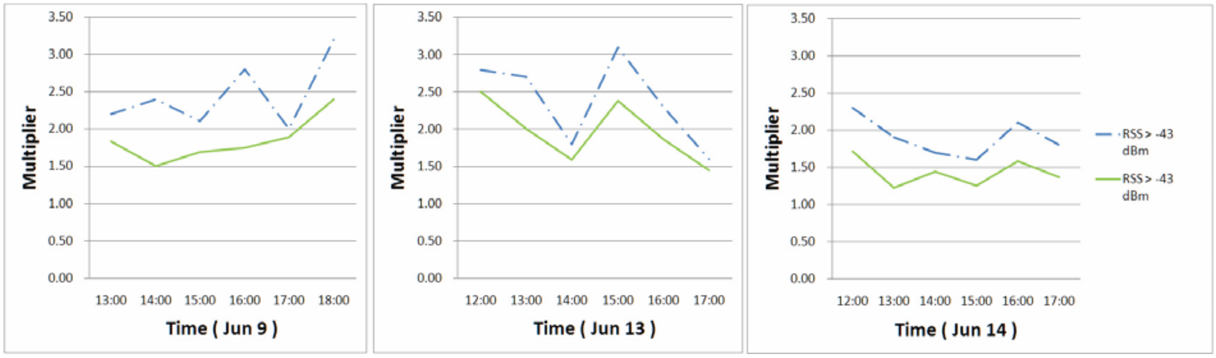


Fig. 22. *Multiplier vs. time on June 9, 13 & 14.*

	June 9		June 13		June 14	
	RSS > - 43 dBm	**RSS > - 40 dBm**	**RSS > - 43 dBm**	**RSS > - 40 dBm**	**RSS > - 40 dBm**	**RSS > - 40 dBm**
Mean multiplier	2.4	1.8	2.4	1.9	1.9	1.4
Range of multipliers	2.0 - 3.2	1.5 - 2.4	1.6 - 3.1	1.4 - 2.5	1.7 - 2.3	1.2 - 1.7

Tab. 7. *Mean multiplier & range of multipliers on June 9, 13 & 14.*

	Overall result (June 9, 13 & 14)	
	RSS > - 43 dBm	**RSS > - 40 dBm**
Average mean multiplier	2.2	1.7

Tab. 8. *Average mean multiplier on June 9, 13 & 14.*

In order to validate the results regarding: (1) Whether the Wi-Fi sensor network was actually measuring unique devices inside the studio, and (2) whether the use of a larger RSS value had only eliminated the MAC addresses not associated with the unique devices (i.e. devices outside the node perimeter), it was necessary to verify if the detected MAC addresses belonged to the devices inside the studio. Therefore, the MAC addresses of some of the devices deployed inside the studio were checked. From the list of unique devices detected by the Wi-Fi sensor network, the number of known devices detected were counted. This number was shown in columns labeled "Number of known devices detected" in Tab. 9.

Time	June 13			
	RSS > - 43 dBm		RSS > - 40 dBm	
	Number of unique devices detected	Number of known devices detected	Number of unique devices detected	Number of known devices detected
12:00 PM	17	13	15	13
13:00 PM	16	8	12	8
14:00 PM	21	15	19	15
15:00 PM	25	12	19	12
16:00 PM	16	10	13	10
17:00 PM	14	9	13	9

Tab. 9. *Number of known devices detected by the Wi-Fi sensor network.*

Tab. 9 shows that the number of known devices detected are the same under both RSS cut-off values. This suggests that the use of a higher (less negative) RSS value (RSS > - 40 dBm) in this case is capable of eliminating MAC detections most likely not associated with the unique devices inside the measurement area, while still keeping the MAC detections associated with the devices present.

According to Fig. 19 - 21, the general occupancy patterns exhibited by the number of MAC detections tends to follow the same trend exhibited by the number of unique occupants present in all three cases, meaning that the number of MAC detections tends to increase when the number of unique occupants increases, and vice versa. This proximity of occupancy patterns was higher on June 9 & 13.

At a RSS cut-off value that is greater than or equal to - 40 dBm, the mean multipliers range from 1.4 to 1.9 (see Fig. 22 & Tab. 7) and the average mean multiplier is 1.7 (see Tab. 8). This suggests that on average, each occupant had between 1.4 and 1.9 devices. An ANOVA analysis was carried out to conclusively determine whether there was significant variance between the multipliers measured on the three different days. The multipliers from the three sets of data collected on the three days were used to create an ANOVA table as shown in Tab. 11. The data input table for ANOVA is shown in Tab. 10.

	Day 1	Day 2	Day 3
Configuration A (perimeter node) RSS > -40 dBm	Multipliers on June 9 (n = 6)	Multipliers on June 13 (n = 6)	Multipliers on June 14 (n = 6)

Tab. 10. *Data input table for ANOVA.*

Anova: Single Factor						
Alpha = 0.05						
SUMMARY						
Groups	Count	Sum	Average	Variance		
Day 1 (Jun 9)	6	11.10	1.85	0.09		
Day 2 (Jun 13)	6	11.80	1.97	0.19		
Day 3 (Jun 14)	6	8.60	1.43	0.03		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.94333	2	0.47	4.53	0.029	3.68
Within Groups	1.56167	15	0.10			
Total	2.505	17				

Tab. 11. *ANOVA table for configuration A comparison at MBSc Studio on June 9, 13 & 14.*

June 9, 13, and 14 have multiplier averages of 1.85, 1.97 and 1.43 respectively. The null hypothesis in this case states that these three multiplier averages are statistically equal. Since the p-value calculated (0.029) is less than the significance level of 0.05, the differences between the three multiplier averages are statistically significant. Based on ANOVA results, configuration A has statistically unequal multiplier averages within the three days. This finding is possibly due to sampling error, small sample size, or less stable performance in detecting MAC addresses in this configuration.

To conclude, the perimeter node arrangement can detect presence and give some indication of count with limited accuracy for localized occupants, however, it cannot provide any information on activity. This arrangement also appears to be capable of estimating the overall occupancy pattern (general trend) of these localized occupants, but not the absolute number of occupants.

4.1.2 Configuration B at MBSc Studio

This configuration aimed to examine a central node arrangement with localized occupants using the space for a longer period of time.

Location diagram

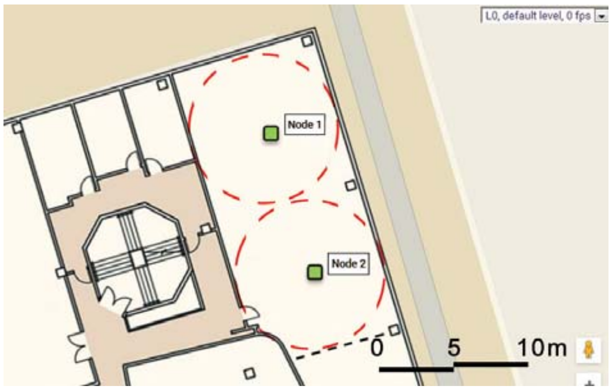


Fig. 23. Central nodes application at MBSc Studio.

Setup

Nodes 1 & 2 were installed underneath the lighting fixtures about 500 mm away from the ceiling at the center of the 2 bays which contain the MBSc studio from June 16 to June 30 (see Fig. 23). Both nodes were repeaters.

RSS Calibration

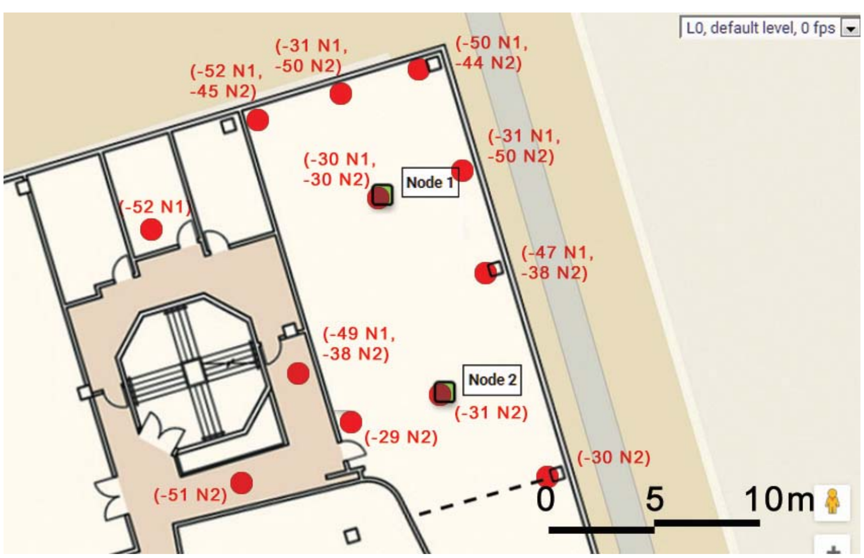


Fig. 24. RSS calibration at MBSc Studio.

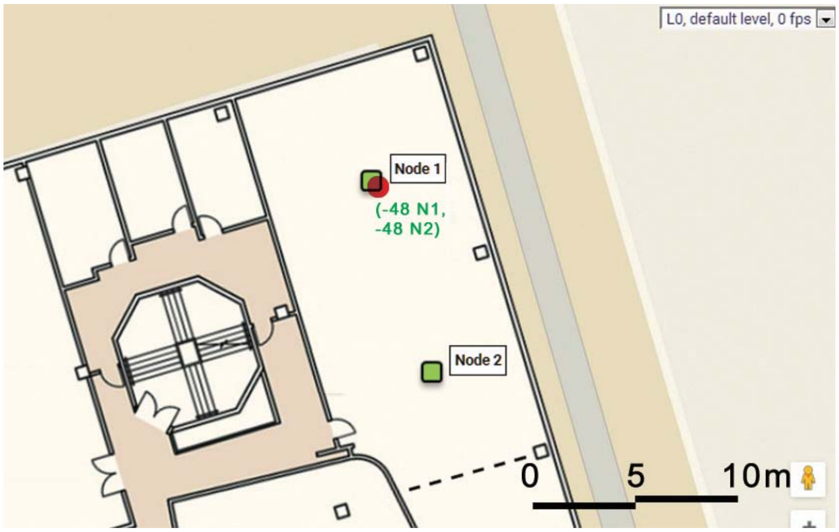


Fig. 25. *RSS calibration on floor above MBSc Studio.*

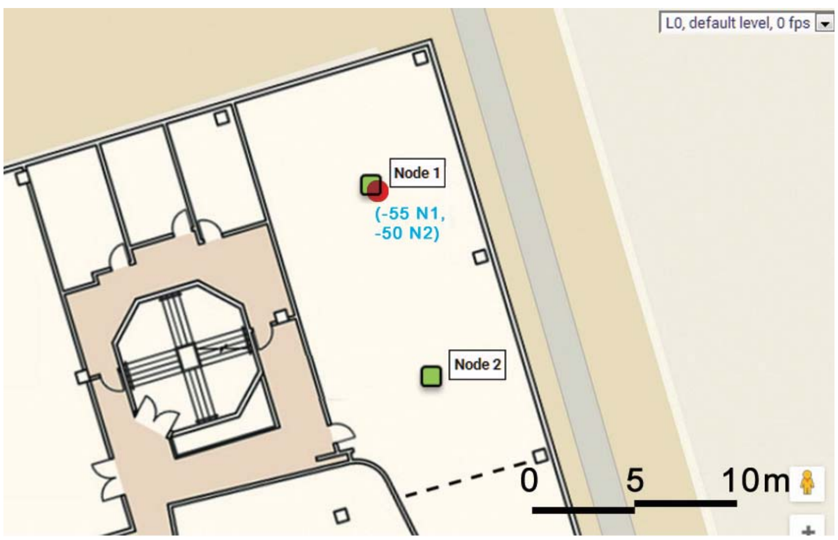


Fig. 26. *RSS calibration on floor below MBSc Studio.*

Fig. 24 - 26 show that the RSS values detected within the measurement area varied between - 29 dBm to - 45 dBm. The RSS values detected on the floors directly above and below Node 1 were smaller than or equal to - 48 dBm. The RSS value detected immediately outside the MBSc Studio in the hallway was - 38 dBm. A RSS cut-off value of greater than or equal to - 39 dBm was selected. Although this number was greater than the RSS values detected at the top left and top right corners of the studio, the decision was a compromise made to reduce the chance of MAC detections in the hallway. Since the results show that the RSS values detected from a device fluctuated within plus-or-minus (±) 10 dBm within 1 hour, a RSS cut-off value of greater than or equal to -39 dBm can capture the MAC addresses within the measurement area, but also eliminate the detections that were only in the hallway briefly.

Results

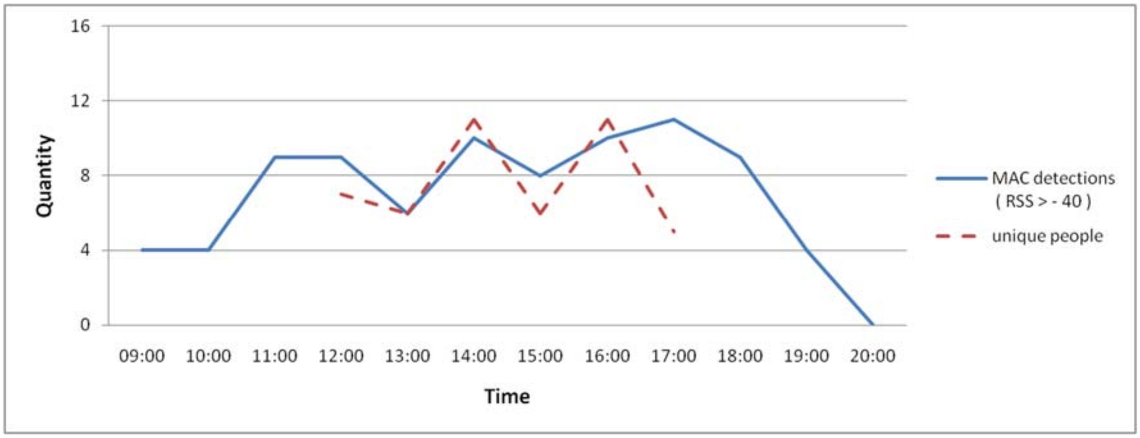


Fig. 27. MAC detections vs. unique people in each 1-hour time period (June 17).

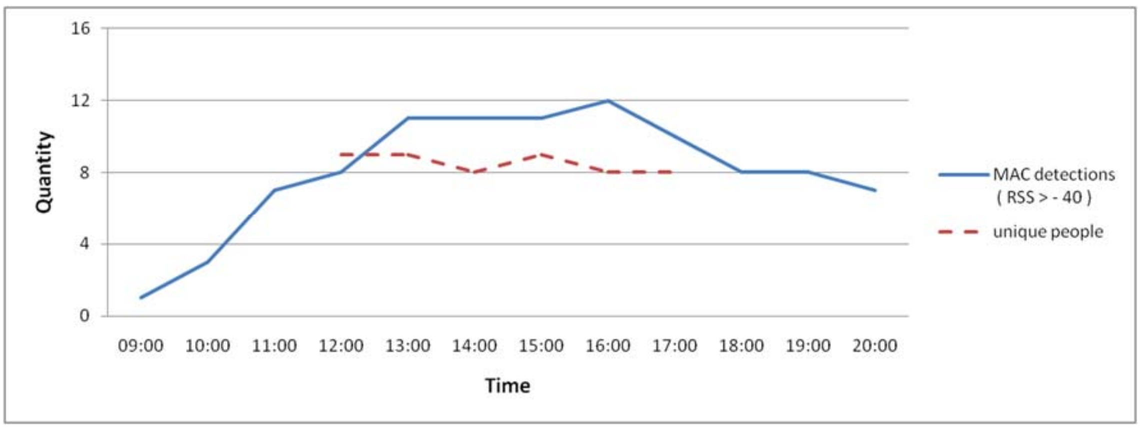


Fig. 28. MAC detections vs. unique people in each 1-hour time period (June 20).

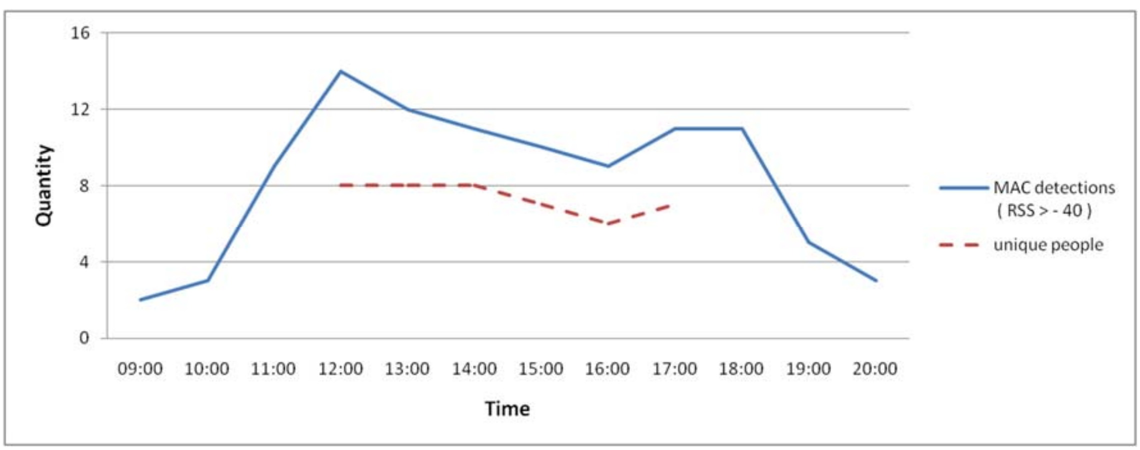


Fig. 29. MAC detections vs. unique people in each 1-hour time period (June 21).

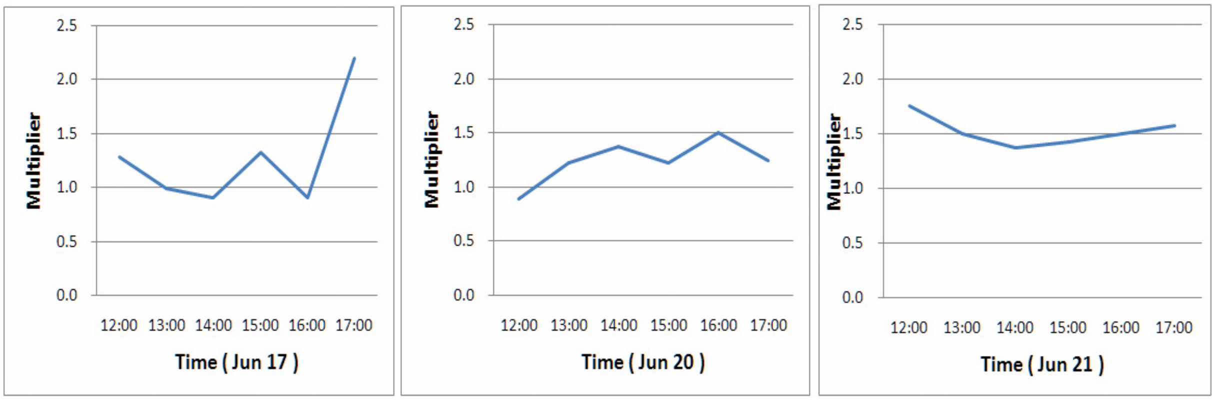


Fig. 30. *Multiplier vs. time on June 17, 20 & 21.*

	June 17	June 20	June 21
	RSS > - 40 dBm		
Mean multiplier	1.3	1.2	1.5
Range of multipliers	0.9 - 2.2	0.9 - 1.5	1.4 - 1.8
Average mean multiplier	1.3		

Tab. 12. *Mean multiplier, range of multipliers & average mean multiplier on June 17, 20 & 21.*

To verify if the MAC addresses detected were mostly within the measurement area, the MAC addresses of some of the devices deployed inside the studio were checked. From the list of unique devices detected by the Wi-Fi sensor network, the number of detected known devices were counted. This number is shown in the columns labeled "Number of known devices detected" in Tab. 13, which shows that the majority of the "unique devices detected" are "known devices" on both days of the measurement period. This implies that the Wi-Fi network was able to detect the MAC addresses inside the measurement area.

Time	June 20		June 21	
	RSS > - 40 dBm			
	Number of unique devices detected	Number of known devices detected	Number of unique devices detected	Number of known devices detected
12:00 PM	8	6	14	11
13:00 PM	11	9	12	10
14:00 PM	11	8	11	9
15:00 PM	11	8	10	7
16:00 PM	12	10	9	8
17:00 PM	10	8	11	10

Note: 12:00 PM = Time period of 11:00 - 12:00 PM

Tab. 13. *Number of known devices detected on June 20 & 21.*

According to Fig. 27 & 29, the general occupancy patterns exhibited by the number of MAC detections tends to follow the same trend exhibited by the number of unique occupants present. However, this similarity is not indicated in Fig. 28. The mean multipliers range from 1.2 to 1.5 (see Fig. 30 & Tab. 12). This suggests that on average,, each occupant had between 1.2 and 1.5 devices.

An ANOVA analysis was carried out to conclusively determine whether there was significant variance between the multipliers measured on the three different days. The multipliers from the three sets of data collected on the three days were used to create an ANOVA table as shown in Tab. 15. The data input table for ANOVA is shown in Tab. 14.

	Day 1	**Day 2**	**Day 3**
Configuration B (perimeter node)	Multipliers on June 17 (n = 6)	Multipliers on June 20 (n = 6)	Multipliers on June 21 (n = 6)

Tab. 14. *Data input table for ANOVA.*

Anova: Single Factor
Alpha = 0.05
SUMMARY

Groups	Count	Sum	Average	Variance
Day 1 (Jun 17)	6	7.6	1.27	0.24
Day 2 (Jun 20)	6	7.5	1.25	0.04
Day 3 (Jun 21)	6	9.2	1.53	0.02

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.30333	2	0.15	1.48	0.26	3.68
Within Groups	1.54167	15	0.10			
Total	1.845	17				

Tab. 15. *ANOVA table for configuration B comparison at MBSc Studio on June 17, 20 & 21.*

June 17, 20 and 21 have multiplier averages of 1.27, 1.25 and 1.53 respectively. The null hypothesis in this case states that these three multiplier averages are statistically equal. Since the p-value calculated (0.26) is greater than the significance level of 0.05, the differences between the three multiplier averages are statistically insignificant. Based on ANOVA results, configuration B has a statistically equal multiplier averages within the three days.

To conclude, similar to the perimeter node configuration experiment carried out in the MBSc studio, the central node arrangement can detect presence and give some indication of count with limited accuracy for localized occupants, however, it cannot provide any information on activity. This arrangement also appears to be capable of estimating the overall occupancy pattern (general trend) of these localized occupants, but not the absolute number of occupants.

4.1.3 Configuration B at extended MBSc Studio with an additional node

This configuration aimed to improve on the previous central node arrangement experiment with an additional node for the full coverage of the studio room to measure localized occupants using the space for a longer period of time.

Location diagram

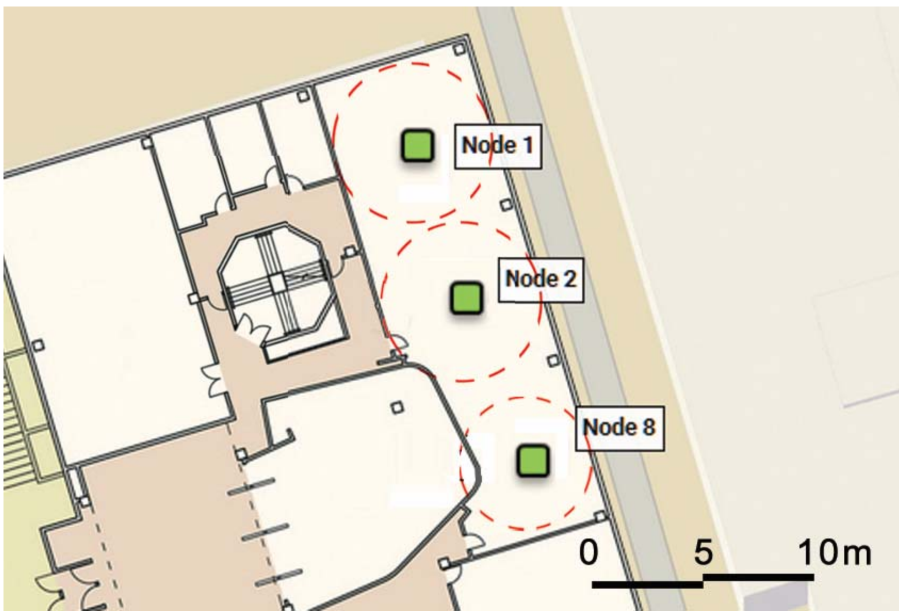


Fig. 31. *Central node application with an additional node at MBSc Studio.*

Setup

In addition to Nodes 1 & 2 that were installed inside the first two bays of the MBSc studio in the previous experiment, another node (Node 8), was installed underneath the lighting fixtures about 500 mm away from the ceiling at the center of the third smaller bay to cover the remaining part of the MBSc studio from June 27 to June 30 (see Fig. 31). All three nodes were repeaters. It was hoped that by including the occupants on the other end of the MBSc studio with an additional sensor node, the accuracy of the network could be increased.

RSS calibration for Node 8

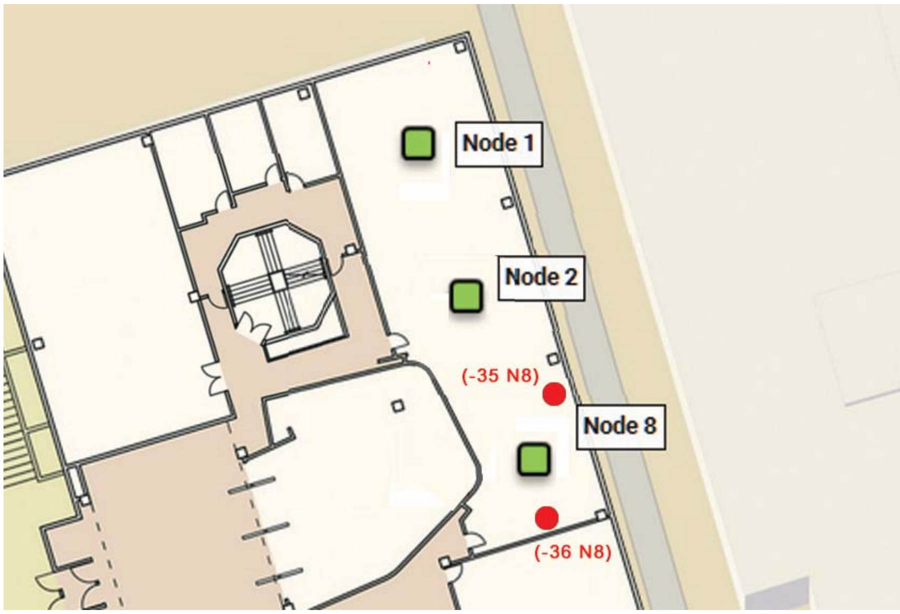


Fig. 32. *RSS calibration for additional Node 8 at MBSc Studio.*

Fig. 32 shows that the RSS values detected at the works desk were greater than or equal to - 36 dBm. Therefore, a RSS cut-off value of greater than or equal to - 36 dBm was used for Node 8 to detect devices in the area around this node. For the areas covered by Nodes 1 & 2, since the calibration shows that the previous RSS values measured were still the same. The same RSS cut-off value of greater than or equal to - 39 dBm was used for Node 1 & 2.

Results

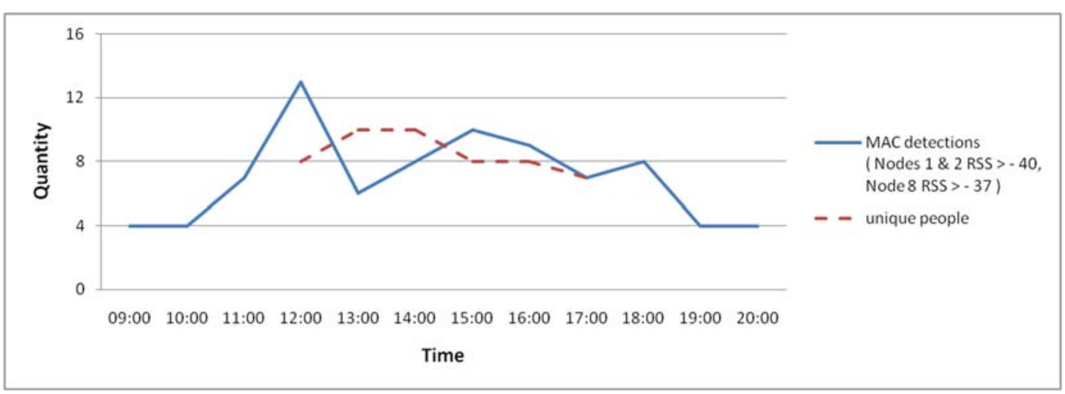


Fig. 33. *MAC detections vs. unique people in each 1-hour time period (June 27).*

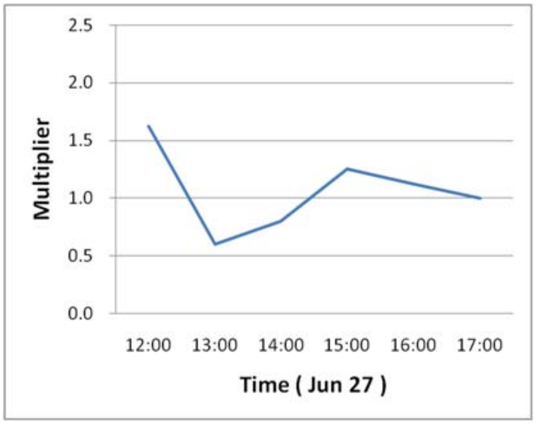


Fig. 34. *Multiplier vs. time on June 27.*

June 27	
Nodes 1 & 2 RSS > - 40 dBm, Node 8 RSS > - 37 dBm	
Mean multiplier	1.1
Range of multipliers	0.6 - 1.6

Tab. 16. *Mean multiplier & range of multipliers on June 27.*

According to Fig. 33 & 34, the results show no similarity between the occupancy patterns (trend) exhibited by the number of MAC detections and that exhibited by the number of unique occupants present. The mean multiplier is 1.1 (see Tab. 16), which is lower than the average mean multiplier from the previous experiment without the additional node. This suggests that on average, each occupant had about 1.1 devices. The range of multipliers varies largely between 0.6 and 1.6 from hour to hour. However, it was observed that most occupants have between 1 to 2 Wi-Fi devices.

An ANOVA analysis was carried out to conclusively determine whether there was significant variance between the multipliers measured in this configuration and the one without the additional node. The multipliers from the two sets of data collected on the two experiments were used to create an ANOVA table as shown in Tab. 18. The data input table for ANOVA is shown in Tab. 17.

	With additional node	**Without additional node**
Configuration B (perimeter node)	Multipliers on June 27 (n = 6)	Multipliers on June 17, 20 & 21 (n = 18)

Tab. 17. *Data input table for ANOVA.*

Anova: Single Factor						
Alpha = 0.05						
SUMMARY						
Groups	Count	Sum	Average	Variance		
With additional node	6	6.4	1.07	0.13		
Without additional node	18	24.3	1.35	0.11		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.36125	1	0.36	3.21	0.087	4.30
Within Groups	2.47833	22	0.11			
Total	2.83958	23				

Tab. 18. *ANOVA table for configuration B comparison (with and without an additional node) at MBSc Studio.*

The two experiments, with an additional node and without an additional node, have multiplier averages of 1.07 and 1.35 respectively. The null hypothesis in this case states that these two multiplier averages are statistically equal. Since the p-value calculated (0.087) is greater than the significance level of 0.05, the differences between the three multiplier averages are statistically insignificant. Based on ANOVA results, both configuration B, with and without an additional node, have a statistically equal multiplier averages in the measurement periods.

To conclude, the central node arrangement with the additional node does not show any noticeable difference from the previous experiment without the additional node. This arrangement can detect presence and give some indication of count with limited accuracy. However, this arrangement cannot provide any information on activity.

4.1.4 *Configuration B at MArch Studio*

This configuration aimed to examine a central node arrangement with a larger group of localized occupants (10 - 20) occupying the space for a longer period of time.

Location diagram

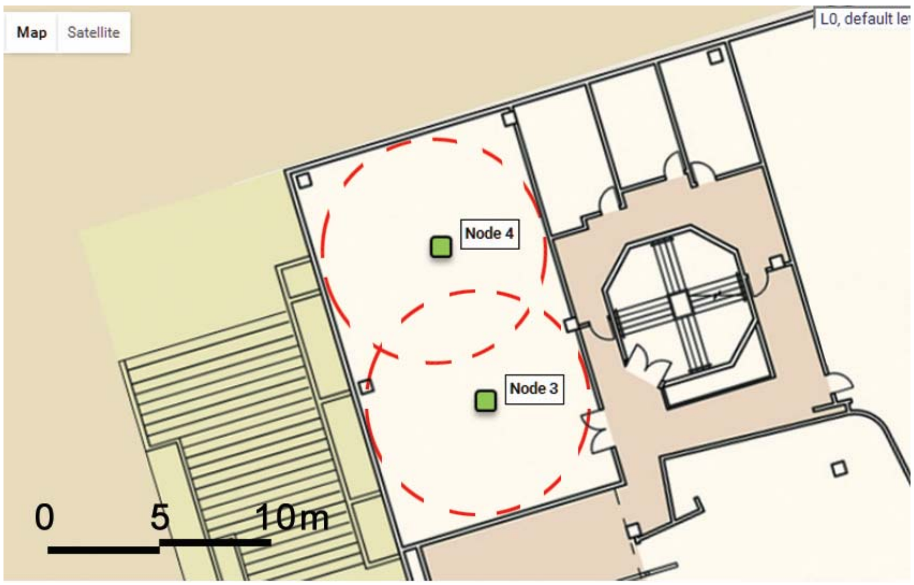


Fig. 35. *Central node application at MArch Studio.*

Setup

Nodes 3 & 4 were installed underneath the lighting fixtures about 500 mm away from the ceiling at the center of the 2 bays which contain the MArch studio from June 16 to June 30 (see Fig. 35). Both nodes were repeaters.

RSS calibration

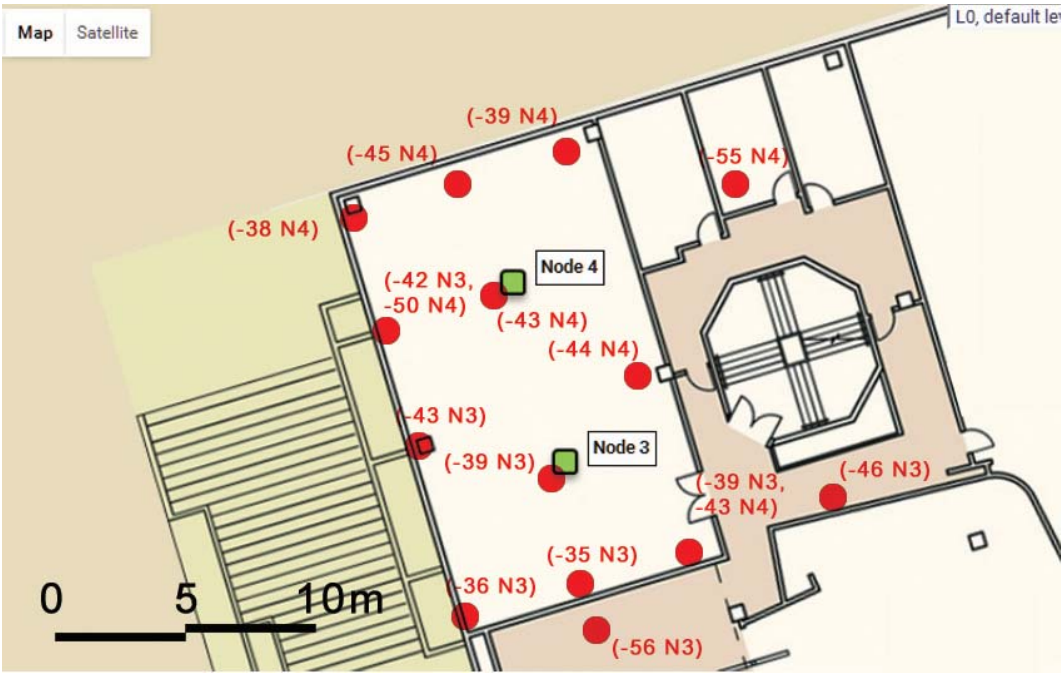


__Fig. 36.__ RSS calibration at MArch Studio.

The design and the construction of the MArch Studio is basically the same the MBSc Studio. As shown previously in the RSS calibration at MBSc Studio, the RSS values detected directly on the floor above and below the nodes were around 10 dBm smaller than the ones detected within the measurement area. The RSS calibration for the MArch Studio was only carried out at MArch Studio. Fig. 36 shows that the RSS values detected within the measurement area varied between - 35 dBm and - 45 dBm. However, the value of - 45 dBm was very close to the value of - 46dBm taken in the middle of the hallway between the two studios.

On the other hand, the RSS values measured at the four corners of the studio, which were the furthest points measured from the nodes, varied only between - 36 dBm and - 39 dBm. In order to reduce the chance of the MAC address detected in the hallway, a RSS cut-off value of greater than or equal to - 40 dBm was used.

Results

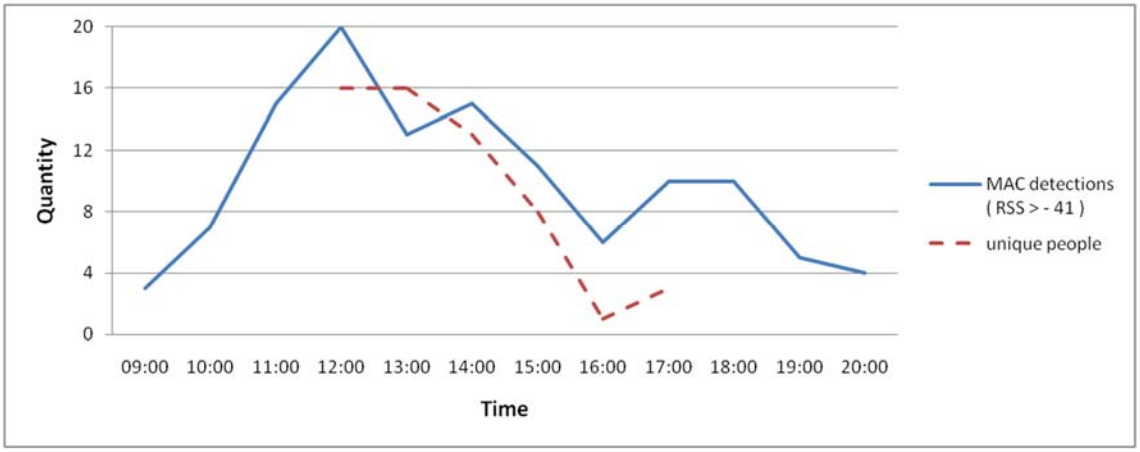


Fig. 37. *MAC detections vs. unique people in each 1-hour time period (June 17).*

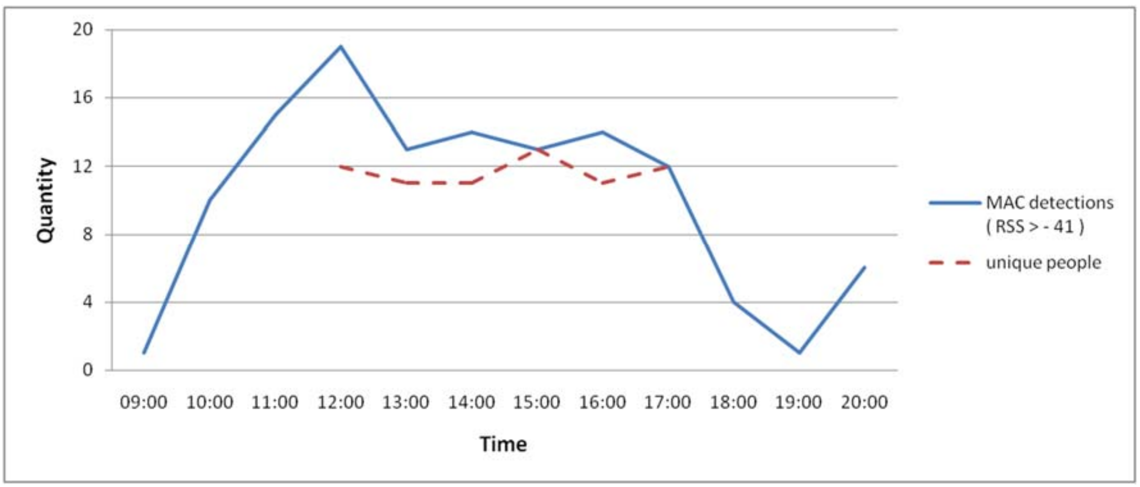


Fig. 38. *MAC detections vs. unique people in each 1-hour time period (June 20).*

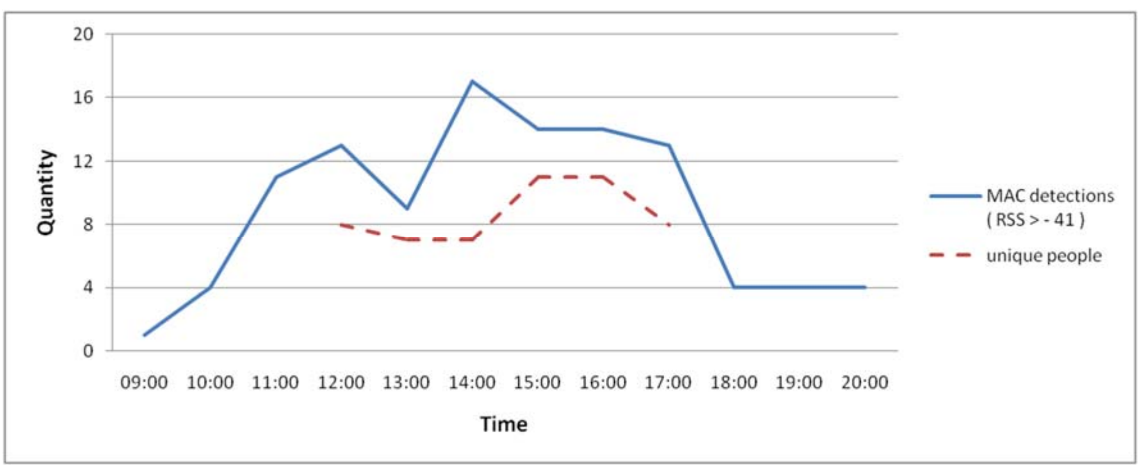


Fig. 39. *MAC detections vs. unique people in each 1-hour time period (June 21).*

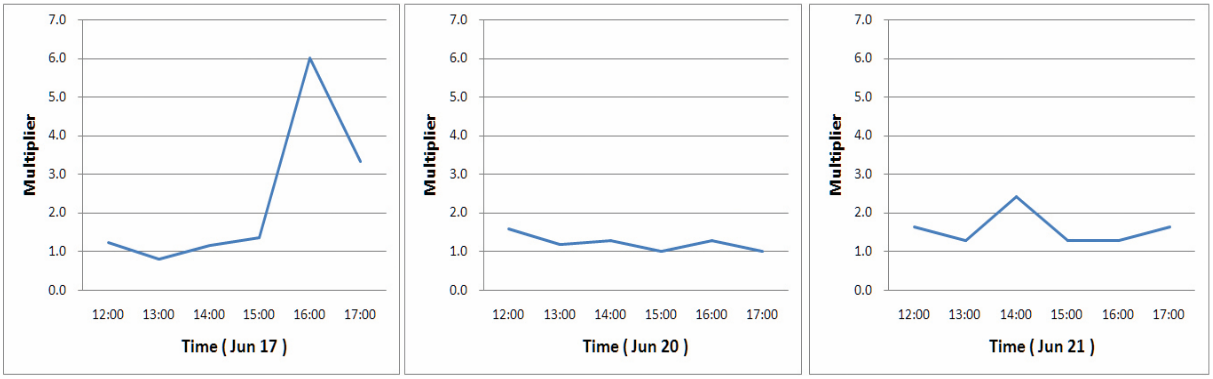


Fig. 40. *Multiplier vs. time on June 17, 20 & 21.*

	June 17	June 20	June 21
	RSS > - 41 dBm		
Mean multiplier	1.6	1.2	1.6
Range of multipliers	0.8 - 3.3	1.0 - 1.6	1.3 - 2.4
Average mean multiplier	1.5		

Tab. 19. *Mean multiplier, range of multipliers & average mean multiplier on June 17, 20 & 21.*

Since not all the MAC addresses of the Wi-Fi devices used in the experiment at the MArch studio were available, the validity of the MAC detections was verified by comparing them against how many 1-hour time periods were they present throughout the 12-hour measurement period. Tab. 20 shows that more than half of the total MAC addresses detected were present in more than one 1-hour time period. And almost half of the MAC addresses detected were present for more than two 1-hour time periods. The results are consistent with the physical count as the number of unique occupants were only present all at the same time in one 1-hour time period in the studio. Therefore, it is possible that the Wi-Fi sensor network was mostly detecting MAC addresses within the measurement area.

June 21			
RSS > - 40 dBm			
MArch Studio			
Total number of unique MAC detection from 8:00 AM - 20:00 PM	**Number of 1-hr time period presence within 12 1-hr time period from 8:00 AM - 20:00 PM**	**Number of MAC addresses**	**% of MAC addresses within total number of unique MAC detection**
40	> 1	22	55%
	> 2	19	48%
	> 3	15	38%
	> 4	13	33%
	> 5	13	33%

Tab. 20. *Number of MAC addresses present in number of 1-hr time period within twelve 1-hr time period from 8:00 AM - 20:00 PM*

The experiment results are very similar to the central node arrangement measured at the MBSc Studio. According to Fig. 37 & 39, the general occupancy patterns exhibited by the number of MAC detections tends to follow the same trend exhibited by the number of unique occupants present. The results from Fig. 38, however, show no similarity in occupancy patterns between the two sets of data. The mean multipliers range from 1.2 to 1.6 (see Fig. 40 & Tab. 19). This suggests that on average, each occupant had between 1.2 and 1.6 devices.

An ANOVA analysis was carried out to conclusively determine whether there was significant variance between the multipliers measured over the three different days. The multipliers from the three sets of data collected on the three days were used to create an ANOVA table as shown in Tab. 22. The data input table for ANOVA is shown in Tab. 21.

	Day 1	**Day 2**	**Day 3**
Configuration B (perimeter node)	Multipliers on June 17 (n = 5)	Multipliers on June 20 (n = 6)	Multipliers on June 21 (n = 6)

Tab. 21. *Data input table for ANOVA.*

Anova: Single Factor
Alpha = 0.05
SUMMARY

Groups	Count	Sum	Average	Variance
Day 1 (Jun 17)	5	8	1.60	0.96
Day 2 (Jun 20)	6	7.4	1.23	0.05
Day 3 (Jun 21)	6	9.5	1.58	0.18

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.49716	2	0.25	0.70	0.51	3.74
Within Groups	4.98167	14	0.36			
Total	5.47882	16				

Tab. 22. *ANOVA table for configuration B comparison at MArch Studio on June 17, 20 & 21.*

June 17, 20 & 21 have multiplier averages of 1.60, 1.23 and 1.58 respectively. The null hypothesis in this case states that these two multiplier averages are statistically equal. Since the p-value calculated (0.51) is greater than the significance level of 0.05, the differences between the three multiplier averages are statistically insignificant. Based on ANOVA results, configuration B has a statistically equal multiplier averages within the three days.

To conclude, similar to the central node arrangement measured at the MBSc Studio, the central node arrangement can detect presence and give some indication of count with limited accuracy. However, this arrangement cannot provide any information on activity.

4.1.5 Configuration B at lecture room (Pit)

This configuration aimed to examine a central node arrangement with localized occupants using the space for a longer period of time.

Fig. 41. *Lecture room (Pit).*

Location diagram

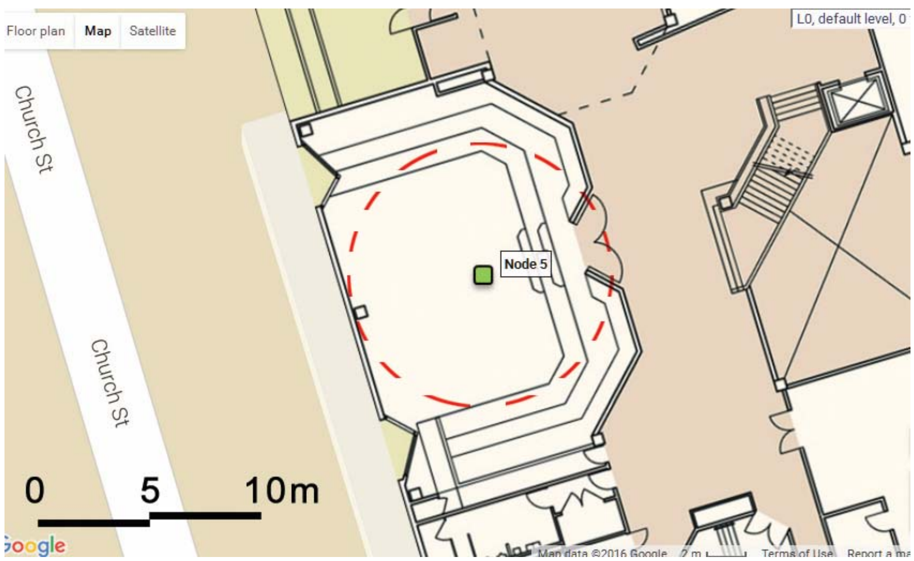


Fig. 42. *Central node application at lecture room (Pit).*

Setup

Node 5 was installed underneath the lighting power supply about 700 mm away from the ceiling inside the lecture room from May 30 to August 31 (see Fig. 41 & 42). Node 5 was a gateway.

RSS calibration

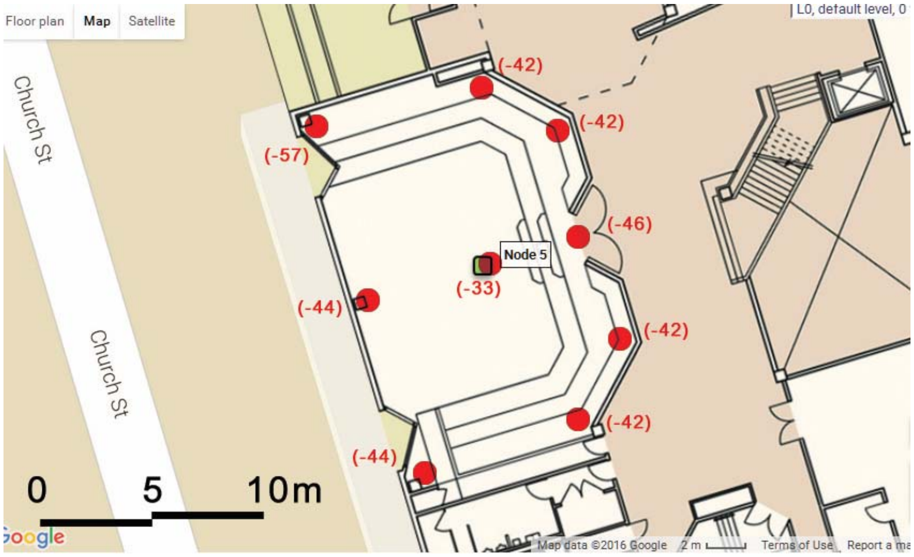


Fig. 43. *RSS calibration at lecture room.*

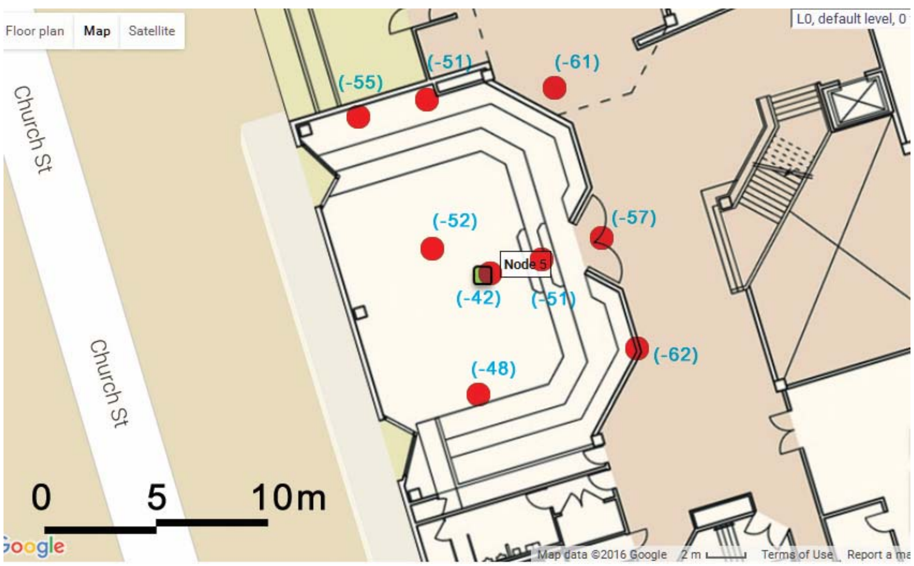


Fig. 44. *RSS calibration on floor above lecture room.*

Fig. 43 & 44 show that the RSS values detected at the center of the lecture room were - 33 dBm, which was the largest (least negative) within the measurement area. The RSS values detected within the lecture room were greater than or equal to - 46 dBm, except for the RSS value of -57 dBm measured at the top left corner. The RSS values detected on the floor above were greater than or equal to - 48 dBm, except for the RSS value of- 42 dBm measured directly above Node 5. Therefore, a RSS cut-off value of greater than or equal to - 46 dBm was selected.

Results

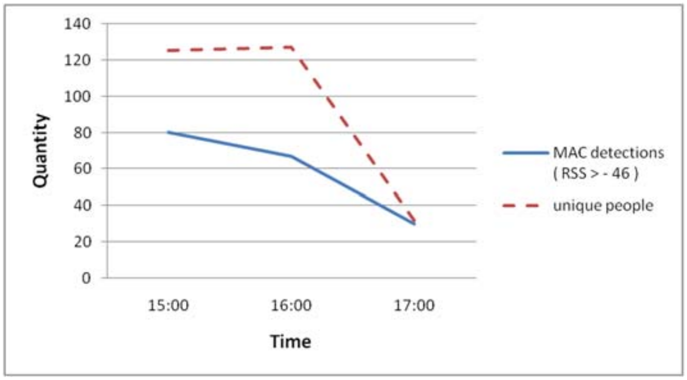


Fig. 45. MAC detections vs. unique people in each 1-hour time period (June 2).

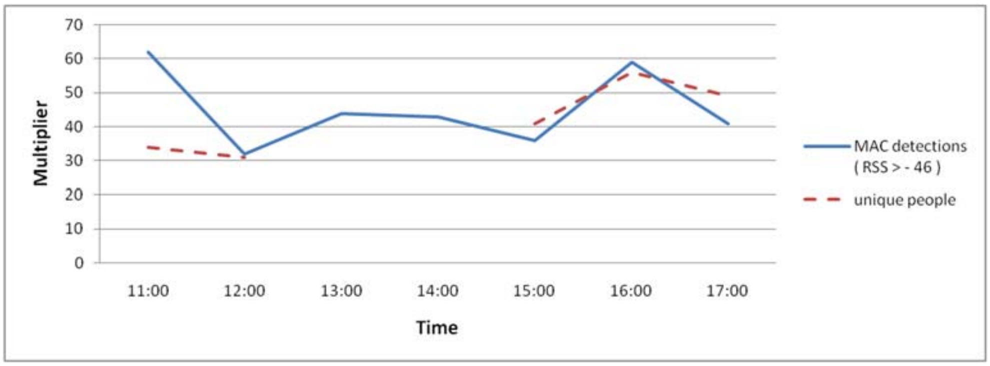


Fig. 46. MAC detections vs. unique people in each 1-hour time period (June 3).

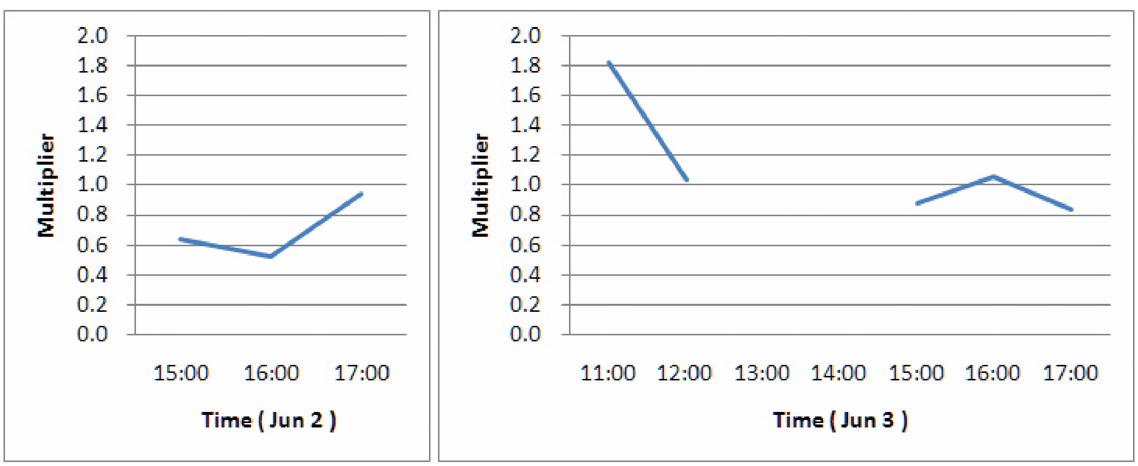


Fig. 47. Multiplier vs. time on June 2 & 3.

	June 2	June 3
	RSS > - 46 dBm	
Mean multiplier	0.7	1.1
Range of multipliers	0.5 - 0.9	0.8 - 1.8

Tab. 23. Mean multiplier and range of multipliers on June 2 & 3.

The measurements were taken during a convention attended by visitors outside the university. It was observed that most visitors did not have a laptop during their duration of stay in the lecture room. Fig. 45 & 46 shows that the number of MAC detections appears to increase when occupant numbers increase, and vice versa. However, a direct relationship cannot be established. The mean multipliers vary from 0.7 to 1.1 (see Fig. 47 & Tab. 23), which suggests that on average each occupant had between 0.7 and 1.1 devices. This number seems to correlate with the observation. However, the measurements taken on the 2 different days show very different results. The number of MAC detections on June 3 appears to be much closer to the number of unique people than the results from June 2.

An ANOVA analysis was carried out to conclusively determine whether there was significant variance between the multipliers measured in the lecture room on two different days using configuration B. The multipliers from the two sets of data collected on the two days were used to create an ANOVA table as shown in Tab. 25. The data input table for ANOVA is shown in Tab. 24.

	lecture room, June 2	**lecture room, June 3**
Configuration B (central node)	Multipliers on June 2 (n = 3)	Multipliers on June 3 (n = 5)

Tab. 24. *Data input table for ANOVA.*

Anova: Single Factor
Alpha = 0.05

SUMMARY

Groups	Count	Sum	Average	Variance
Lecture room on Jun 2 (configuration B)	3	2.11	0.70	0.04
Lecture room on Jun 3 (configuration B)	5	5.64	1.13	0.17

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.34	1	0.34	2.69	0.15	5.99
Within Groups	0.76	6	0.13			
Total	1.10	7				

Tab. 25. *ANOV table for configuration B comparison at lecture room on June 2 & 3.*

June 2 and June 3 have multiplier averages of 0.70 and 1.33 respectively. The null hypothesis in this case states that these two multiplier averages are statistically equal. Since the *p*-value calculated from ANOVA (0.15) is greater than the significance level (alpha) of 0.05, there is not enough evidence to reject this null hypothesis. This indicates that the differences between the two multiplier averages are statistically insignificant. Based on ANOVA results, configuration B has a statistically equal multiplier averages on both days.

To conclude, the central node arrangement can detect presence of localized occupants, however, it cannot provide useful information on count. This arrangement also cannot provide any information on activity.

4.1.6 Configurations A & B analysis using ANOVA

Configurations A & B at MBSc Studio

ANOVA (analysis of variance) was used to conclusively determine whether there was significant variance between the multipliers (detection ratio) measured in configurations A and B. The multipliers from the two sets of data collected at MBSc Studio using node configurations A & B were used to create an ANOVA table as shown in Tab. 27. The data input table for ANOVA is shown in Tab. 26.

	Configuration A (perimeter node), RSS > - 40 dBm	**Configuration B (central node), RSS > - 40 dBm**
MBSc Studio	Multipliers from each of the repeated measurements on June 9, 13 & 14 (n = 18)	Multipliers from each of the repeated measurements on June 17, 20 & 21(n = 18)

Tab. 26. *Data input table for ANOVA.*

Anova: Single Factor
Alpha = 0.05
SUMMARY

Groups	Count	Sum	Average	Variance
Configuration A (perimeter node)	18	31.5	1.75	0.15
Configuration B (central node)	18	24.3	1.35	0.11

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1.44	1	1.44	11.26	0.0020	4.13
Within Groups	4.35	34	0.13			
Total	5.79	35				

Tab. 27. *ANOV table for configurations A & B comparison at MBSc Studio.*

Configuration A and B have multiplier averages of 1.75 and 1.35 respectively. The null hypothesis in this case states that these two multiplier averages are statistically equal. Since the p-value calculated (0.0020) is less than the significance level of 0.05, the differences between the two multiplier averages are statistically significant. Based on ANOVA results, configurations A and B have statistically different multiplier averages with configuration A having a higher one. The results reflect the characteristics of the multipliers rather than just a sampling error. However, ANOVA does not determine which configuration has a higher accuracy in detecting occupant count or presence. Configuration A has a higher detection ratio probably because it has a larger total detection area. The nodes were arranged along the perimeter of the studio in configuration A, while the nodes in configuration B were arranged along the centerline of the space. Since the RSS cut-off values used were the same in the two studios, theoretically configuration A has double the detection area as configuration B. With occasional incorrect triangulation (see Chapter 6. Discussion), more devices outside the perimeter were detected by the sensor and therefore, the average multiplier is higher.

Configuration B at MBSc Studio & MArch Studio

ANOVA was used also to conclusively determine whether there was significant variance between the multipliers measured in MBSc & MArch studios using configuration B. The multipliers from the two sets of data collected at the two studios were used to create an ANOVA table as shown in Tab. 29. The data input table for ANOVA is shown in Tab. 28.

	Location A (MBSc Studio)	**Location B (MArch Studio)**
Configuration B (central node)	Multipliers from each of the repeated measurements on June 17, 20 & 21(n = 18)	Multipliers from each of the repeated measurements on June 17, 20 & 21(n = 18)

Tab. 28. *Data input table for ANOVA.*

Anova: Single Factor						
Alpha = 0.05						
SUMMARY						
Groups	Count	Sum	Average	Variance		
Location A (MBSc Studio)	18	24.3	1.35	0.11		
Location B (MArch Studio)	18	30.9	1.72	1.47		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1.21	1	1.21	1.54	0.22	4.13
Within Groups	26.75	34	0.79			
Total	27.96	35				

Tab. 29. *ANOV table for configuration B comparison at MBSc & MArch studios.*

Locations A and B have multiplier averages of 1.35 and 1.72 respectively. The null hypothesis in this case states that these two multiplier averages are statistically equal. Since the p-value calculated from ANOVA (0.22) is greater than the significance level (alpha) of 0.05, there is not enough evidence to reject this null hypothesis. This means that the differences between the two multiplier averages are statistically insignificant. Based on ANOVA results, configuration B has a statistically equal multiplier averages at both studios. This finding is reasonable because both studios are very similar in terms of occupant types and functions.

To conclude, configurations A & B have different multiplier averages. However, the results do not determine which one has a higher performance in providing useful occupant information on count and presence.

4.1.7 *Evaluation of Accuware Analytics Dashboard with configuration B at MArch Studio*

In addition, the performance of Accuware Analytics Dashboard in a central node arrangement with localized occupants was analyzed. The Analytics Dashboard used the same CSV files, but presented the number of MAC detections in a format different from what was demonstrated in the previous experiments. This evaluation examined whether the Analytics Dashboard could provide more useful occupancy data in its format. The node arrangement (location and setup) was the same as configuration B at MArch Studio (see Fig. 48).

Location diagram

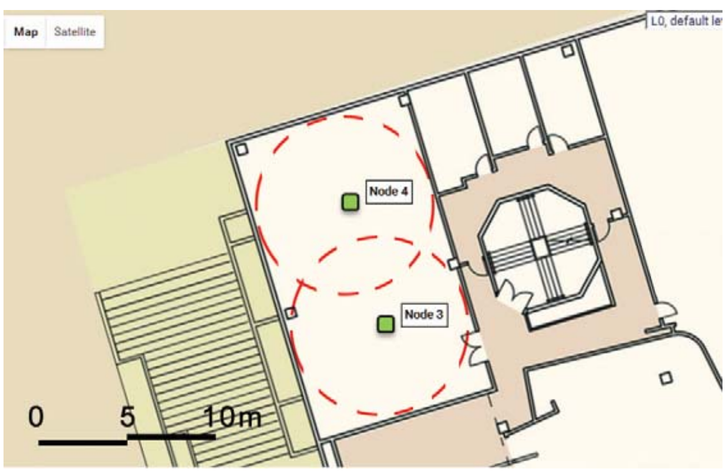


Fig. 48. *Central nodes application at MArch Studio.*

According to Accuware, "unmc" refers to "unique visitors" and counts the number of unique MAC addresses. If an occupant walks by any time between 10:00 AM and 10:59 AM, he or she is counted one time, and if the same occupant walks by at 11:00 AM, he or she is counted again. On the other hand, "idh3" refers to "In-place visitors" and it represents for each hour, the number of unique occupants detected in the previous three hours, and is used to measure “stationary visitors”. This means that if a visitor is in proximity of the node between 7:00 AM and 7:59 AM, 8:00 AM and 8:59 AM, 9:00 AM and 9:59 AM, then at 10.00 AM, the visitor will be counted as 1 “in-place visitor”.

Results

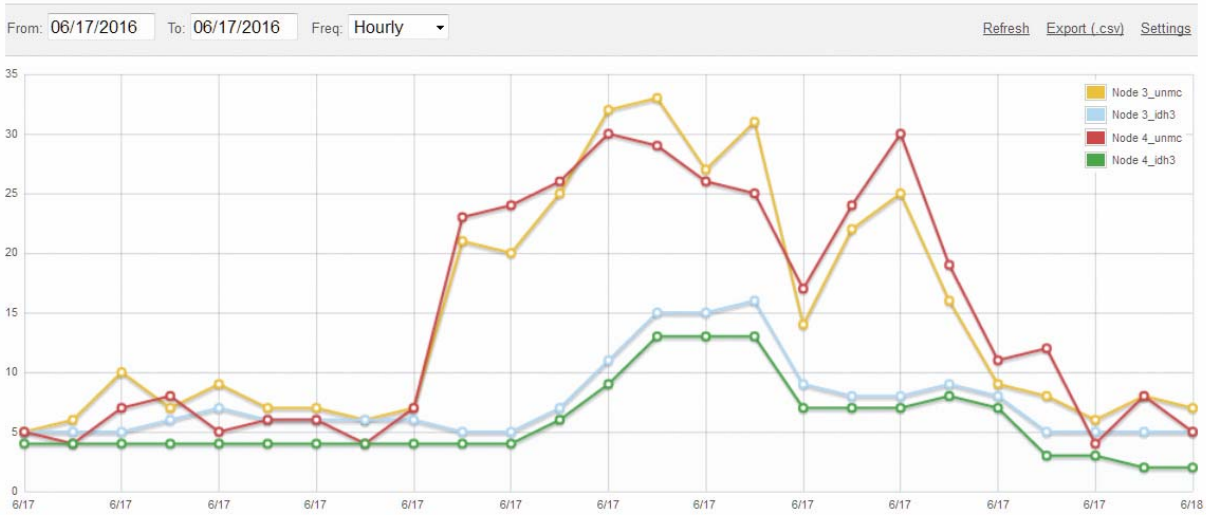


Fig. 49. *MAC detections in a period of 1 day with RSS cut-off value > - 41 dBm (June 17).*

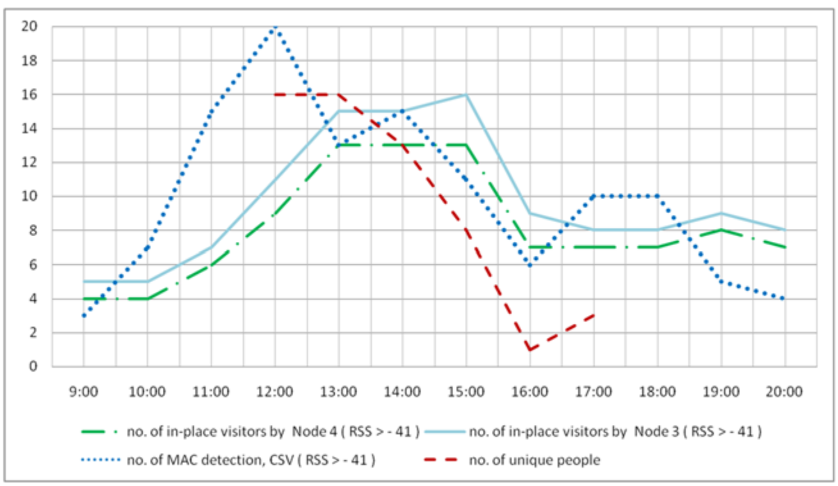


Fig. 50. *Analytics Dashboard result (in-place visitors) compared with result from CSV file analysis (June 17).*

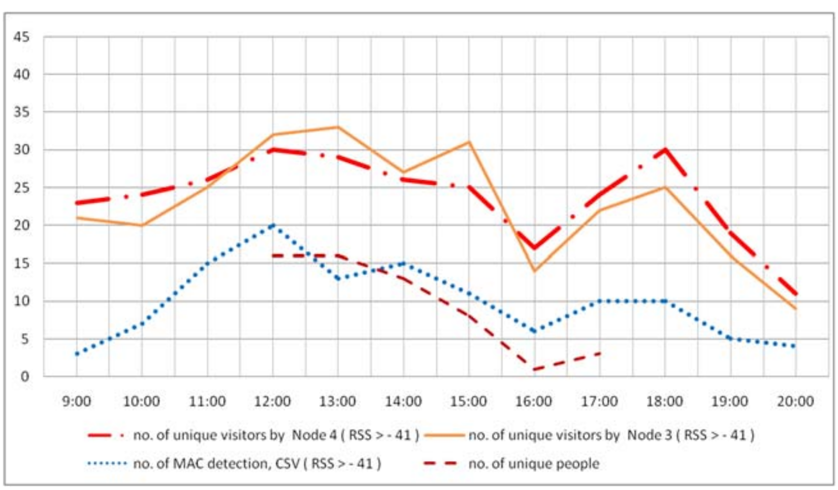


Fig. 51. *Analytics Dashboard result (unique visitors) compared with result from CSV file analysis (June 17).*

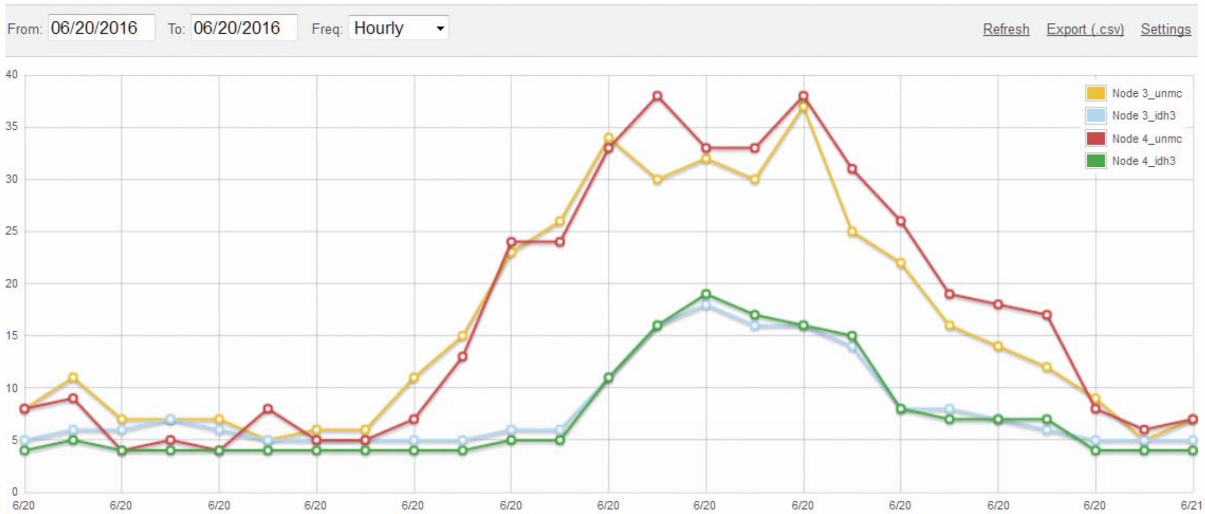


Fig. 52. *MAC detections in a period of 1 day with RSS cut-off value > - 41 dBm (June 20).*

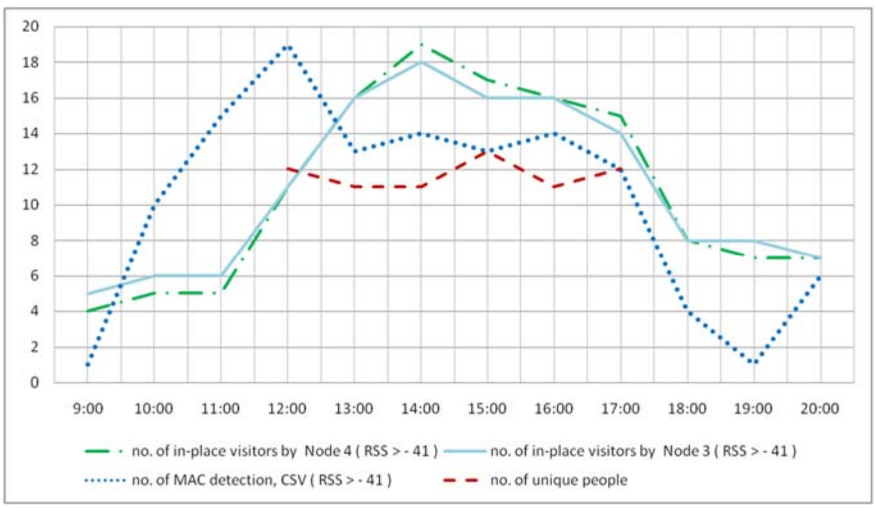


Fig. 53. *Analytics Dashboard result (in-place visitors) compared with result from CSV file analysis (June 20).*

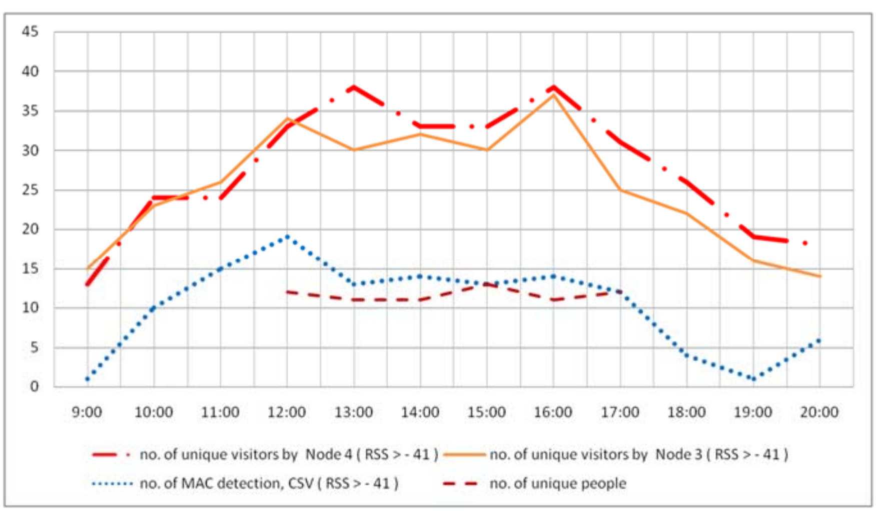


Fig. 54. *Analytics Dashboard result (unique visitors) compared with result from CSV file analysis (June 20).*

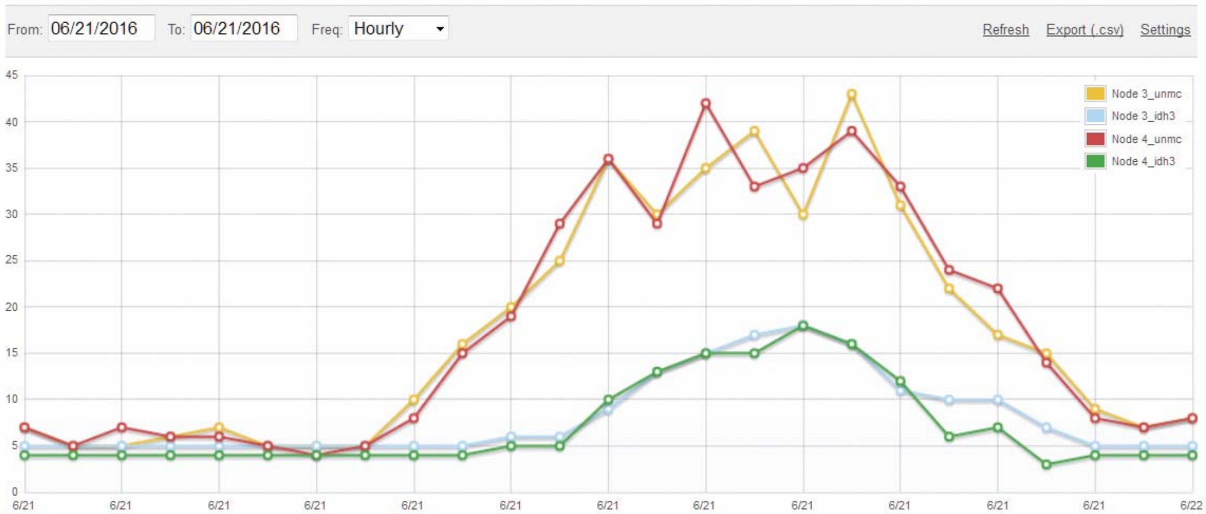


Fig. 55. *MAC detections in a period of 1 day with RSS cut-off value > - 41 dBm (June 21).*

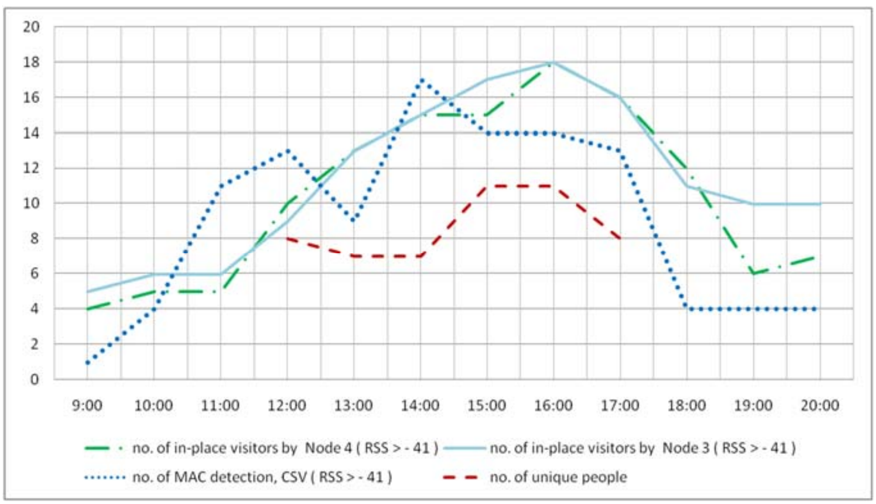


Fig. 56. *Analytics Dashboard result (in-place visitors) compared with result from CSV file analysis (June 21).*

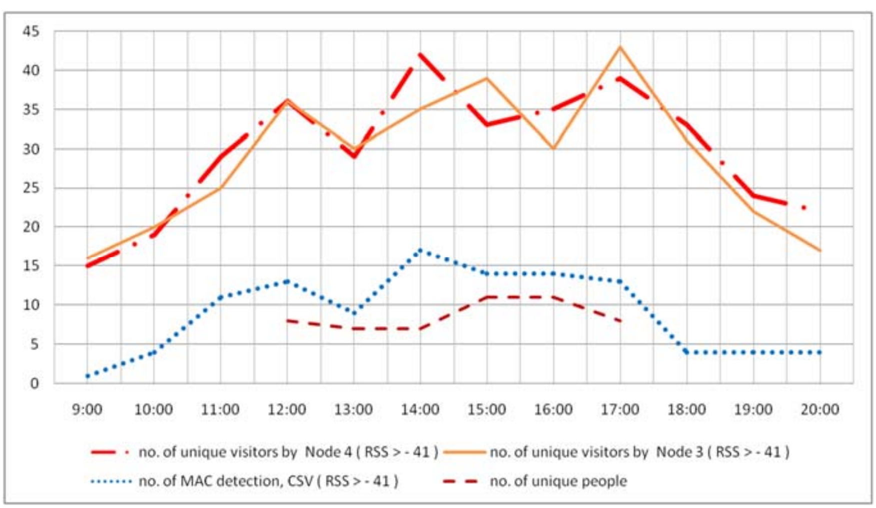


Fig. 57. *Analytics Dashboard result (unique visitors) compared with result from CSV file analysis (June 21).*

In terms of the number of MAC detections, Fig. 49, 52 & 55 show that the number of "in-place visitors" detected by each node is much more relevant (closer) to the number of occupants counted than the number of "unique visitors" detected by each node. The number of "unique visitors" detected is much larger because each occupant only needs to be detected once in a 1-hour time period in order to be counted, while an occupant needs to be detected in 3 consecutive 1-hour time periods in order to be counted as 1 "in-place visitor".

Also, the numbers of "in-place visitors" measured by Node 3 and Node 4 were almost the same on all three days. It appears that the occupants inside the MArch Studio were detected by both nodes at the same time. Therefore, it is possible that the number of "in-place visitors" can be represented by either of the two nodes. The number of "in-place visitors" detected was then superimposed with the number of MAC detections generated previously from the CSV files, along with the number of unique occupants counted in Fig. 50, 53 & 56. The results show that the general occupancy patterns exhibited by the number of "in-place visitors" tends to follow the same trend exhibited by the number of MAC detections. However, there is a difference of two hours when the curve is going up, i.e. the number of MAC detections leads the number of "in-place visitors".

For example, the initial rise in the number of "in-place visitors" lags about 2 hours behind the rise in the number of MAC detections in all 3 days. The number of MAC detections and the number of "in-place visitors" started to increase at 9 AM and 11 AM respectively. This also applies to the peaks of the 2 occupant patterns on all 3 days. However, when the number of overall MAC detections decreases, the number of "in-place visitors" decreases at a similar time. This is probably due to the fact that an occupant needs to be detected in 3 consecutive 1-hour time periods in order to be counted as 1 "in-place visitor" in the third 1-hour time period. This mechanism only has a time-delay effect on the general occupancy pattern when the overall number of occupants is increasing. This is because the system will detect one less occupant when the occupant is not present in that 1-hour time period. Therefore, there is no time delay for decreasing occupancy. As a result, as shown in Fig. 51, 54 & 57, the number of "unique visitors" starts to rise about 2 hours before the number of "in-place visitors", but both numbers start to drop at about the same time. In addition, there is no constant relationship between the number of "in-place visitors" and the number of unique occupants counted.
In terms of occupancy pattern, the figures exhibited by the number of "unique visitors" detected by each node aligns more in time with the number of MAC detections measured in real-time from the CSV

files. This is because both systems measure "unique visitors" in each 1-hour time period. It could not be determined why the number of "unique visitors" measured by each node is consistently many more than the number of MAC detections obtained from filtering the CSV files. This could be due to Accuware's settings. The unreasonably high number of "unique visitors" makes the Analytics Dashboard not useful in distinguishing between the occupants who spend a longer period of time in the studio from the ones who are only there briefly.

To conclude, the "in-place visitors" figures can show the number of MAC detections that is closer to the number of unique occupants present with a two-hour time delay when the number is rising. The "unique visitors" figures can show a real-time occupancy trend, but with the number of MAC detections much higher than the number of unique occupants present. However, analysis using CSV files can provide the number of MAC detections that is closer to the number of unique occupants present in real time. Therefore, the Analytics Dashboard does not provide more useful information in its format.

4.1.8 Evaluation of Accuware Analytics Dashboard over a period of 9 days

The Accuware Analytics Dashboard can also display historical data for any time period longer than 1 day. Therefore, it was possible to analyze the data from June 18 to June 26.

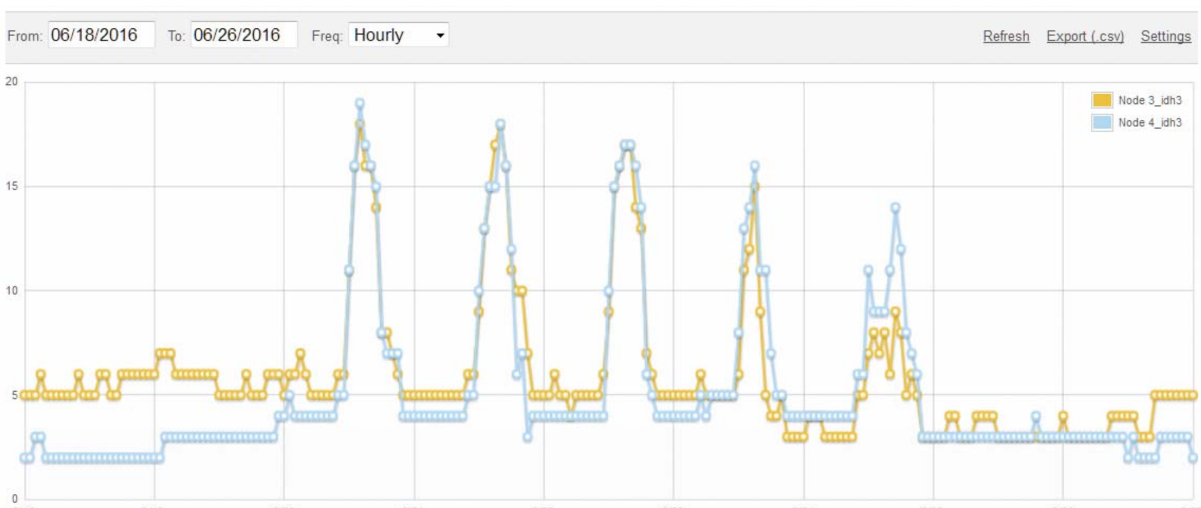


Fig. 58. *MAC detections (in-place visitors) with RSS cut-off value > - 41 dBm (June 18 - 26).*

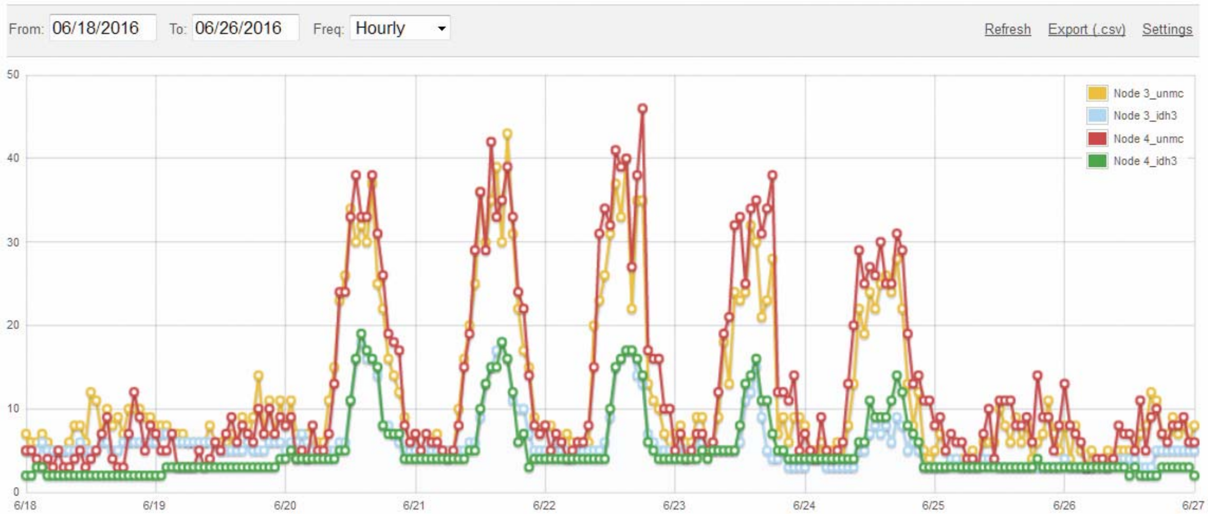


Fig. 59. *MAC detections (in-place visitors & unique visitors) with RSS cut-off value > - 41 dBm (June 18 - 26).*

Fig. 58 above shows the number of "in-place visitors" detected over the course of 9 days. For Node 3, the number of "in-place visitors" detected reached its peak around 2 - 5 PM from Monday to Friday (June 20 to 24). With the adjustment of the 2 hours time delay, the number of "in-place visitors" detected actually reached its peak around 12 - 3 PM, which was close to the observation at the studio. The number of "in-place visitors" reached its minimum of 4 - 5 detections around 6 - 8 PM (with time adjustment), which was also close to the observation as classes ended around 4 PM. This minimum of 4 - 5 detections was constant throughout the night until 8 AM (with time adjustment) from Monday to Friday, and throughout Saturday and Sunday. Since there was no occupant inside the studio at those hours, these detections were actually due to the permanent Wi-Fi devices such as Wi-Fi access points installed around the studio. As the number of these permanent devices was constant, their detections by Node 3 was also constant.

Comparing the data in Fig. 59 (showing number of "unique visitors") with the data in Fig. 58 (showing number of "in-place visitors"), Fig. 58 shows a more stabilized curve throughout each day with a clear indication of peak and minimum occupants. While the Accuware Analytics Dashboard may not be able to correctly estimate the small changes between each 1-hour time period as shown earlier, the figures above indicate that it can be used to estimate the overall occupancy pattern over a longer time period. The "unique visitors" setting is more capable in predicting when the overall occupancy pattern starts to rise. The "in-place visitors" setting is more capable in predicting the peak (with 2-hour time delay) and the moment with no or minimal occupants. It also has a closer proximity to the actual number of MAC detections.

To conclude, the Accuware Analytics Dashboard is capable of providing some indications of the overall pattern of space use for localized occupants over a longer period of time, for example a day or a week. The major advantage of using the Dashboard over analysis of the downloaded CSV files to estimate occupancy is its ease of use.

4.2 Experiment phase 2: Comparison of configurations A & B on non-localized occupants

Experiment phase 2 aimed to investigate which node configuration was more capable in producing useful occupancy data on presence, count and activity for non-localized occupants.

4.2.1 Configuration A at circulation area

This configuration aimed to examine a perimeter node arrangement with non-localized occupants using the space for a shorter period of time.

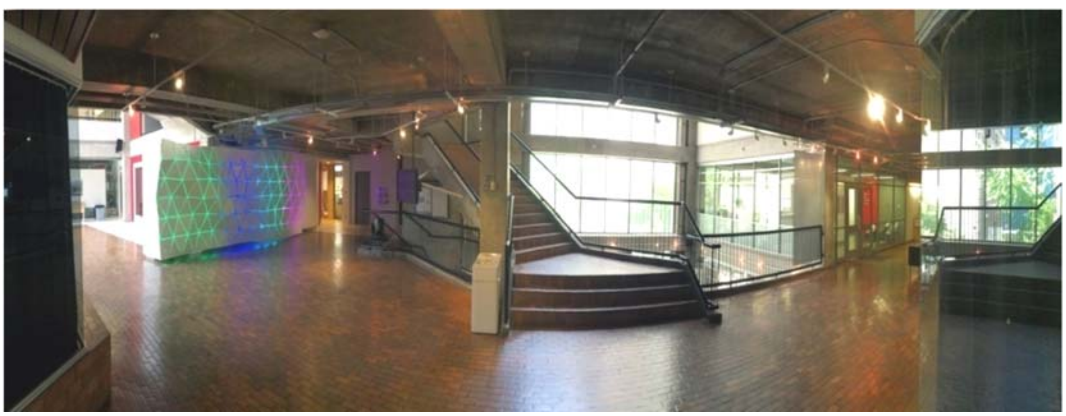


Fig. 60. *Circulation area*

Location diagram

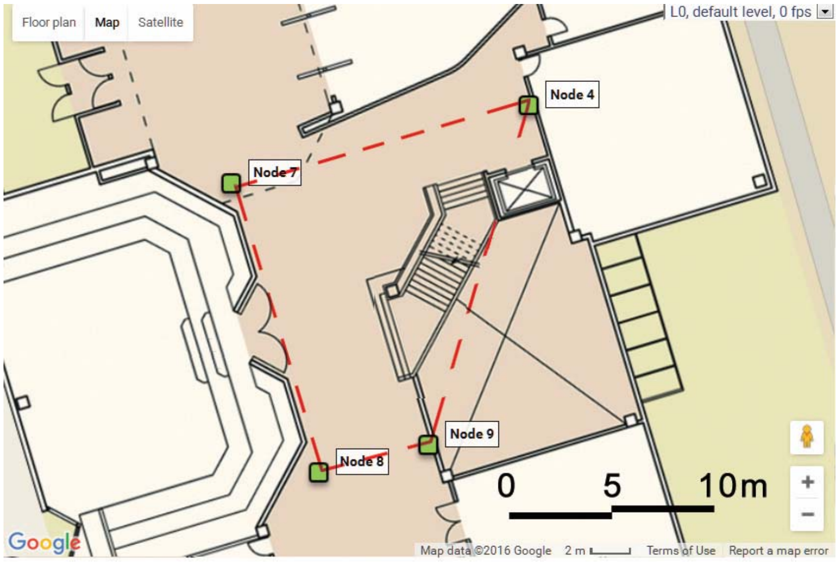


Fig. 61. *Perimeter node application at circulation area.*

Setup

Nodes 4, 7, 8 & 9 were installed underneath the utility pipes about 500 mm away from the ceiling at 4 points inside the circulation space from May 30 to June 15 (see Fig. 60 & 61). The nodes were spaced between 6 - 14 m apart.

RSS calibration

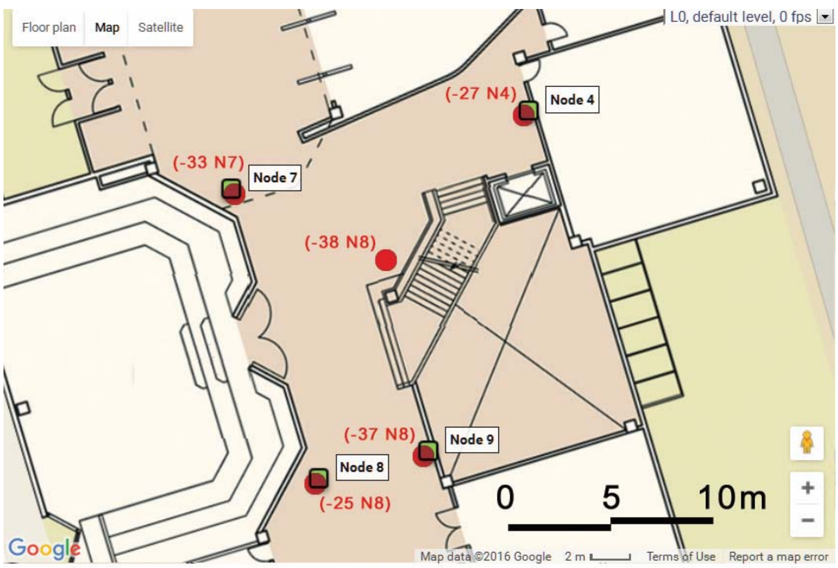


Fig. 62. *RSS calibration at circulation area.*

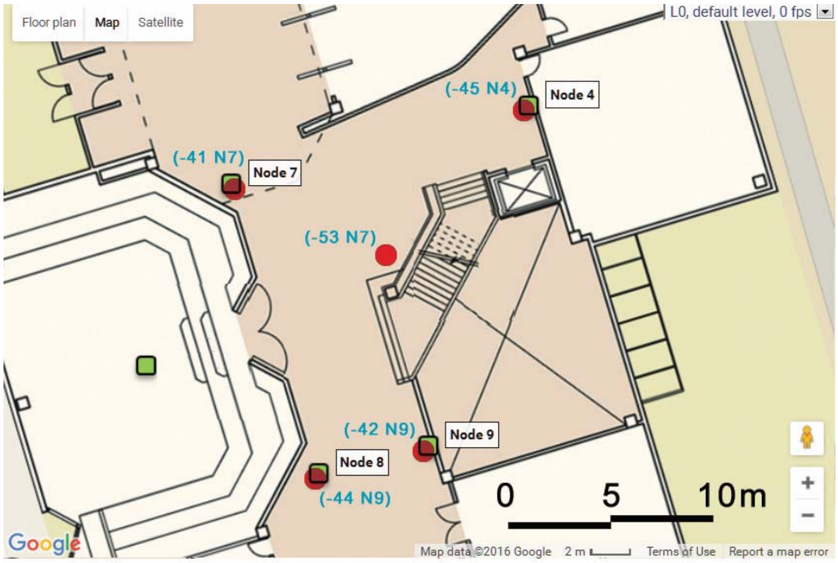
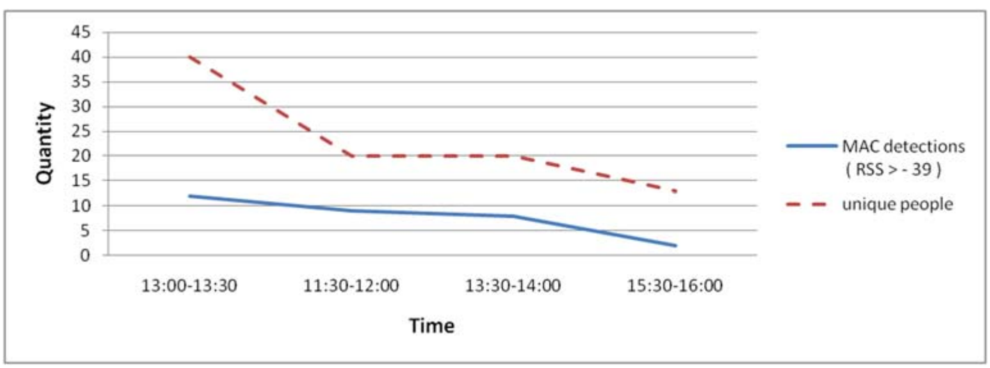


Fig. 63. *RSS calibration on floor above circulation area.*

Fig. 62 & 63 show that the RSS values detected at the center of the measurement area was - 38dBm, which was the smallest within the measurement area. The RSS values detected on the floor above were all smaller than or equal to - 40dBm. Therefore, a RSS cut-off value that was greater than or equal to - 38dBm was selected.

Results



Data 1: 13:00 - 13:30 PM, June 9 Data 2: 11:30 - 12:00 PM, June 13
Data 3: 13:30 - 14:00 PM, June 13 Data 4: 15:30 - 16:00 PM, June 13

Fig. 64. *MAC detections vs. unique people in each 30-minute time period (June 9 & 13).*

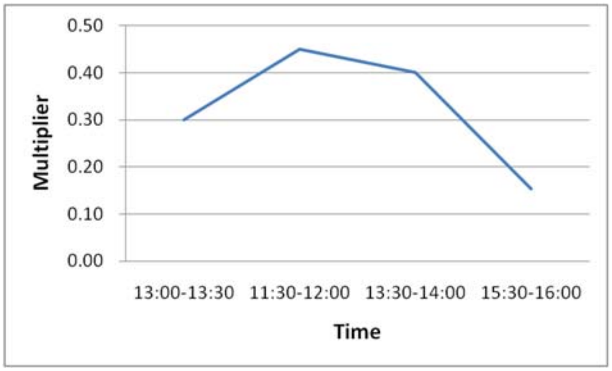


Fig. 65. *Multiplier vs. time on June 9 & 13.*

	June 9	June 13	June 13	June 13
	RSS > - 39 dBm			
	13:00 - 13:30 PM	11:30 - 12:00 PM	13:30 - 14:00 PM	15:30 - 16:00 PM
Multiplier	0.30	0.45	0.40	0.15
Range of multipliers	0.15 - 0.45			
Mean multiplier	0.33			

Tab. 30. *Multiplier, range of multipliers & mean multiplier on June 9 & 13.*

Even with a higher RSS cut-off value of greater than or equal to - 38dBm, a device that was close to the location on the floor directly above Node 8 was still detected by the sensor nodes in the circulation area. This was demonstrated by the detection of Device A (smartphone) with a frequency of 11 times, as shown in Tab. 31. The detection of a device from the floor above suggests that there were potentially more MAC detections included in the circulation area than were present.

June 9	
RSS > - 39 dBm 13:00 - 13:30 PM	
Unique MAC addresses	Detection freq
Device E	3
Device F	2
Device B	2
Device C (smartphone)	2
Device G	2
Device H	2
Device I	2
Device J	1
Device D (smartphone)	1
Device K	1
Device L	1
Device A (smartphone)	11
Device M	6

Tab. 31. *Device A detected on floor above with a high detection frequency.*

Fig. 64 shows that in all four different time periods, the number of MAC addresses detected was less than half of the number of unique occupants counted. It suggests that the sensor network was not capable of measuring half of the unique devices. More importantly, there was little consistency in the results. The multipliers vary between 0.15 and 0.45 see (Fig. 65 & Tab. 30). This suggests that on average, each occupant who passed through the circulation was carrying less than 1 device. This was unlikely since site observations indicated that almost all of the occupants were carrying a smartphone.

To conclude, the perimeter node arrangement does not provide reliable data for measuring non-localized occupants on presence or count. This arrangement also cannot provide any information on activity.

4.2.2 Configuration B at second floor stairway

This configuration aimed to examine a central node arrangement with non-localized occupants using the space for a very short period of time.

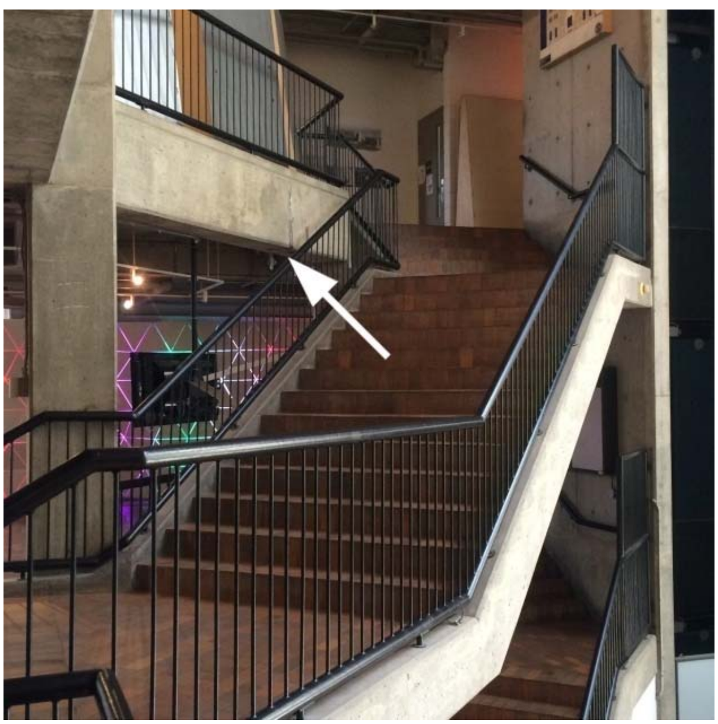


Fig. 66. *Second floor stairway. Arrow indicates Node 10 installation location.*

Location diagram

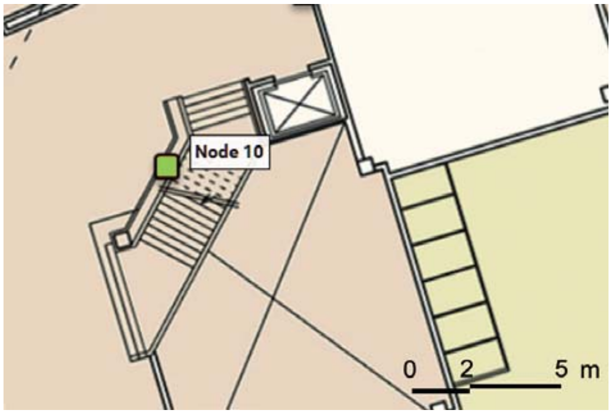


Fig. 67. Central node application at stairway.

Setup

Node 10 was installed underneath the concrete slab adjacent to the handrail at the midpoint of the flight of open stairway from May 30 to June 8 (see Fig. 66 & 67). Node 10 was a repeater.

RSS calibration

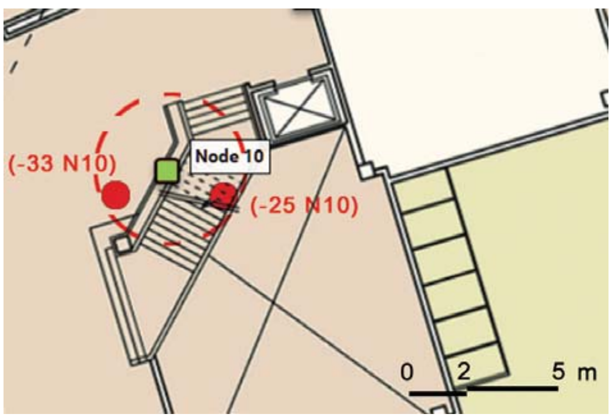


Fig. 68. RSS calibration at Stairway.

Fig. 68 shows that the RSS values detected at one end of the stairway was - 25 dBm. A smaller RSS cut-off value would create a larger detection radius measured from the node and that may result in falsely detecting MAC addresses on the floor above and below the stairway. Therefore, a RSS cut-off value of -25 dBm was used.

Results

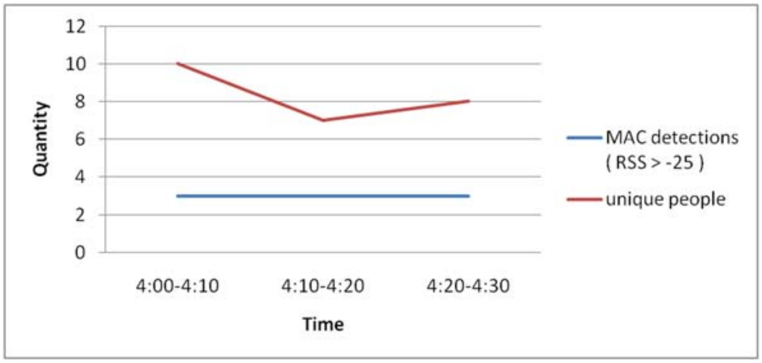


Fig. 69. *MAC detections vs. unique people in 3 consecutive 10-minute time periods (May 31).*

The results from Fig. 69 show that 3 identical devices were detected in all cases. The OUIs of the three MAC addresses, as shown in Tab. 32, reveal that all three devices are permanent devices (2 Wi-Fi access points and 1 Raspberry Pi sensor), which means the sensor network did not detect any devices carried by any of the unique occupants counted. The results show that the system is incapable of detecting any Wi-Fi devices moving along the stairway.

To conclude, the central node arrangement cannot provide any reliable data for measuring non-localized occupants on presence or count. This arrangement also cannot provide any information on activity.

MAC Address	Manufacturer
E84E0634F656	EDUP International
E84E0634F6BF	EDUP International
B827EBB709FD	Raspberry Pi

Tab. 32. *MAC address identification.*

5. Raspberry Pi Passive infrared (PIR) people counter experiment

This experiment aimed to examine a low-cost PIR sensor people counter with non-localized occupants passing through the space over a very short period of time

5.1 Basic setup

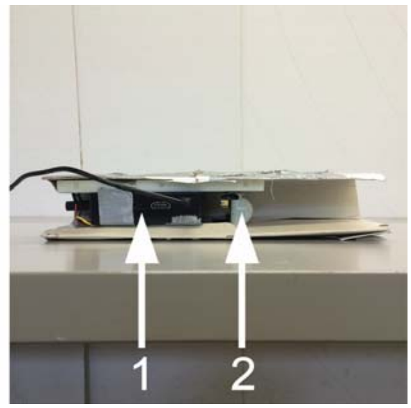


Fig. 70 (left). *Perspective view of Raspberry Pi people counter with power cable plugged in.*

Fig. 71 (middle). *Side view of Raspberry Pi people counter with power cable plugged in.*

Fig. 72 (right). *Sectional view of Raspberry Pi people counter. (1) Raspberry Pi 3 Model B Quad-Core 1.2 GHz 1 GB RA. (2) Adjustable PIR sensor (Product Code: RB-Ite-116). Sentry distance: Max 7 m.*

Fig. 73. *Enlarged photo of adjustable PIR (motion) sensor.*

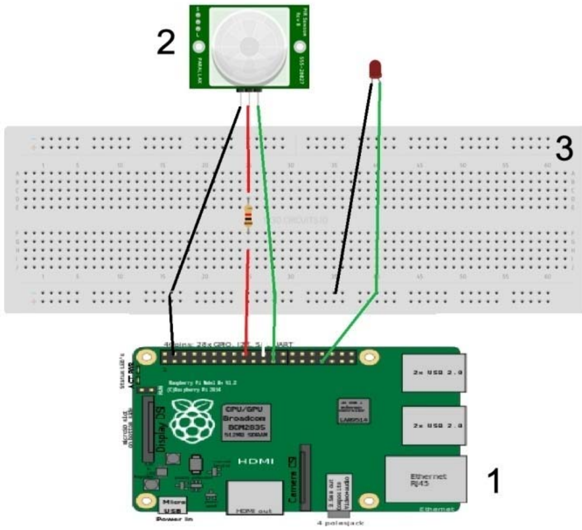


***Fig. 7*4.** *Raspberry Pi people counter wiring diagram. (1) is Raspberry Pi compute3. (2) adjustable PIR sensor. (3) Breadboard.*

The Raspberry Pi 3 (R-Pi) computer is a credit-card sized computer. With a monitor, keyboard, and mouse connected to it, the R-Pi computer runs as a regular computer. In this project, an operating system called Ubuntu MATE was installed on the R-Pi. A Python Script was written to operate the PIR sensor to passively detect any disturbance to the infrared signal in front of the sensor. Every increment of change in the infrared energy received will trigger a positive register of one count. The sensitivity level of the PIR sensor was calibrated to minimize false detection due to movement and changes in illumination level. The calibration was carried out by adjusting the trimpot located on the back of the sensor. The distance sensitivity which has a maximum of about 7 m, however, is not adjustable and therefore, the sensor works the best when it is pointing toward a wall. The wiring diagram of the people counter is shown in Fig. 74.

A long rectangular box , as shown in Fig. 70 - 72, was custom-made to contain the device with the globe-like sensor (see Fig. 73) recessed about 700 mm from the rectangular-shaped opening. The results show that this recess narrows down the more globe-like detection range to one that is more beam-like and directional. This enables the sensor to focus on detecting any disturbance in front of it, instead of the movement on the two sides.

The experiment was carried out on July 12 at 7 PM inside the main entrance to the Student Learning Center (SLC) at Ryerson University (Fig. 75). The device was positioned at about 80 cm above ground, with the sensor positioned perpendicular to the direction of subjects' path of walking, as shown in Fig. 76. The device was held against the top of a chair to stabilize it. The three pairs of double doors did not obstruct the sensor detection as they did not open in the range of the sensor.

A station was set up on the other side of the lobby and the sensor was connected to a monitor, keyboard, mouse, and power outlet (Fig. 78). The measurement period lasted for 20 minutes and a physical count was also carried out at the same time. A measurement period of 20 minutes was selected because previous experiments carried out using the same people counter show that the counter started to detect disturbance incorrectly after about 30 minutes. Fig. 76 & 77 illustrate an instance of single travel and group travel respectively.

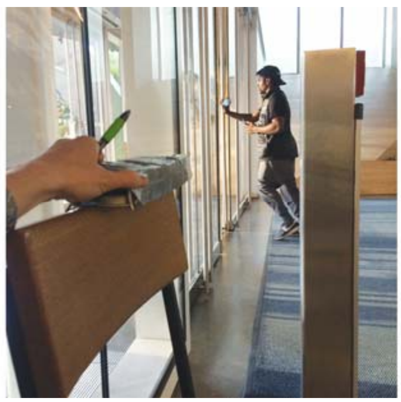
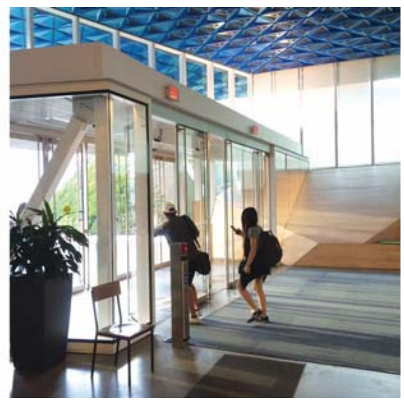




Fig. 75 (left). *Entry lobby at SLC Building.*

Fig. 76 (middle). *Raspberry Pi Sensor detecting a single travel.*

Fig. 77 (right). *Example of a group travel.*

Fig. 78. *Experiment setup at SLC entry lobby.*

5.2 Results

Experiment results show that the sensor is only able to detect and register one increment of disturbance in front of the sensor at a time. This means that the system cannot distinguish between the movement of one subject or a group of subjects. It was found, for example, that a group of nine occupants were only registered as one disturbance. The problem of this particular sensor tested is that it requires a no-disturbance period of 2 - 3 seconds before it can register another disturbance.

As shown in Table 33, in the test period of 20 minutes, the physical count shows that there were a total of approximately 53 times travelers walked passed (see Appendix D), in which 20 times were of single travelers and 33 times were group travelers. In terms of the number of people, there were 115 occupants in group travels and a total number of 135 occupants in all travels. Single travel means that only one person is walking past the sensor at a time. Group travel means that more than one person is walking past the sensor. The people can be following each other and/or traveling in opposite directions. In addition, they can be walking side by side.

Total number of people traveled =	136
Total number of travels (single + group) =	53 (20 + 33)
Total number of detection by R-Pi people counter =	61

Tab. 33. *Results from Raspberry Pi people counter on July 12.*

As for the people counter, it registered a total of 61 spaced travels (see Appendix E), which is close to the actual number (53 times) counted. The difficulty in determining the number of group travels when the occupants are not walking closely together may have contributed to the discrepancy between the two numbers. However, this registered number of detections is far from the total occupant count of 135, and there is no relationship between the two numbers.

To conclude, this Raspberry Pi PIR people counter can detect presence and level of activity for non-localized occupants passing through a particular point. However, the counter cannot provide any useful information on total occupant number.

6. *Discussion*

For the measurement of localized occupants, the results show that the proposed Wi-Fi sensor network can detect presence and provide an estimate of count with limited accuracy in both configurations A and B. The sensor network also appears to be capable of estimating the overall occupancy pattern (general trend) of these localized occupants, but not the absolute number of occupants. However, the network is unable to provide any useful occupant information for non-localized occupants. As for the Raspberry Pi PIR people counter, it is capable of measuring the number of spaced travels, but cannot distinguish and count the number of individual people passing by it.

6.1 *Wi-Fi sensor network in measurement of localized occupants*

Configuration A vs. configuration B

Overall, the results show that a Wi-Fi sensor network is able to estimate the overall occupancy pattern of localized occupants, which means that there are generally higher number of MAC detections when there are more occupants present. However, both configurations appear to be incapable of measuring correctly every small change in occupancy pattern between two 1-hour intervals. The multipliers (detection ratios) also appear to vary from hour to hour, and from day to day in both configurations. The use of a multiplier is not particularly applicable in determining the accuracy of both configurations.

According to the ANOVA analysis, configurations A and B have statistically different multiplier averages. However, the results do not indicate which configuration is more capable of estimating the overall occupancy pattern or count. Although configuration A tends to detect a few devices outside the measurement area, this inaccuracy does not appear to undermine configuration A's capability in estimating the overall occupancy pattern. On the other hand, configuration B requires less nodes, and this may suggest that configuration B is more efficiently organized and is thus more capable of deploying the Wi-Fi sensor network.

Incorrect triangulation of Wi-Fi devices in configuration A

Results show that the perimeter node application is susceptible to giving incorrect data due to the inaccurate triangulation of the Wi-Fi devices. By verifying some of the MAC addresses of devices placed outside the nodes' perimeter, it was found that some of these devices were mistaken by the system as being physically inside the defined perimeter. This suggests that some of these devices have had their coordinates detected as being inside the nodes' perimeter, and the associated RSS must be larger than the RSS cut-off value. In order to verify some of these incorrect triangulations, device M was placed in the office outside the nodes' perimeter, as shown on Fig. 75. The results show that, even though device M's location was separated from the nodes by two layers of walls, Node 2 still detected it with a RSS value ranging from - 38 to - 54 dBm throughout the day of June 14 (See Tab. 34). It also falsely detected it to be inside the nodes' perimeter 30 times between 8:29 AM and 5:38 PM. However, the device was never present inside the studio.

Toronto Time	MAC	Lvl	Lat	Lng	x axis	y axis	Coordinates Filter	Node	RSS (Highest)
6/14/16 8:29 AM	Device M	0	43.659613	-79.377867	79.377867	43.659613	1	Node 2	-47
6/14/16 8:29 AM	Device M	0	43.659616	-79.377869	79.377869	43.659616	1	Node 2	-46
6/14/16 8:32 AM	Device M	0	43.659625	-79.377852	79.377852	43.659625	1	Node 2	-49
6/14/16 8:32 AM	Device M	0	43.659626	-79.377853	79.377853	43.659626	1	Node 2	-49
6/14/16 8:39 AM	Device M	0	43.659621	-79.377868	79.377868	43.659621	1	Node 2	-44
6/14/16 8:44 AM	Device M	0	43.659619	-79.377885	79.377885	43.659619	1	Node 2	-38
6/14/16 8:44 AM	Device M	0	43.659619	-79.377886	79.377886	43.659619	1	Node 2	-38
6/14/16 8:49 AM	Device M	0	43.659585	-79.377831	79.377831	43.659585	1	Node 2	-54
6/14/16 8:57 AM	Device M	0	43.659611	-79.377831	79.377831	43.659611	1	Node 1	-57

Tab. 34. *Fluctuation in RSS detections of Device M.*

In addition, devices located right outside the measurement area and are not physically separated by a wall are more easily detected to be inside because of their high RSS values. Other identified devices that were shown falsely inside the nodes' perimeter were actually located on the other side of the MBSc studio (see Fig. 79). Without any physical barrier between the two sides of the studio, these devices were easily detected by Nodes 3 & 6 with high RSS values. This level of location inaccuracy is actually larger than the range described in the Accuware's product literature. The project's node spacing of less than 12 -15 m is supposed to produce an average accuracy of 2 - 3 m. For a space with small occupancy, this level of inaccuracy can include a proportionally significant number of occupants.

The high level of inaccuracy in this research is possibly due to the high amount of noise and interference inside the test area. According to El Amine (2014) and Mardini et al. (2014), obstacles and walls can contribute greatly to the environmental noise. The MBSc studio was filled with partitions, models, and building materials during the measurement period. In addition, the presence of water inside the water pipes that the sensors were attached to may also have created more noise in the RSS measured (Accuware, 2015). Study by Osa et al. (2012) shows that the inaccuracy in the triangulation of devices is much higher in an environment with a higher noise level.

Furthermore, a study by Tsai et al. (2012) indicates that a location accuracy level of no more than 6.2 m was shown in 50 % of the developed applications for indoor localization. This number is much higher than 2 - 3 m as stated by Accuware. The lower location accuracy level achieved in this research project is possibly due to the high noise level in the studio. This high level of noise reduced the performance of the perimeter node configuration to only be able to estimate devices at room-level accuracy. As Locher et al. (2015) pointed out, the fluctuation of RSS values has a less significant impact for localization estimation over a longer period of time when the required level of accuracy is reduced from location level to room level. This suggests that a perimeter node arrangement can still achieve room-level accuracy with the presence of noise for localized occupants. Therefore, perimeter node configuration performs similarly as central node configuration on measuring occupant count and presence.

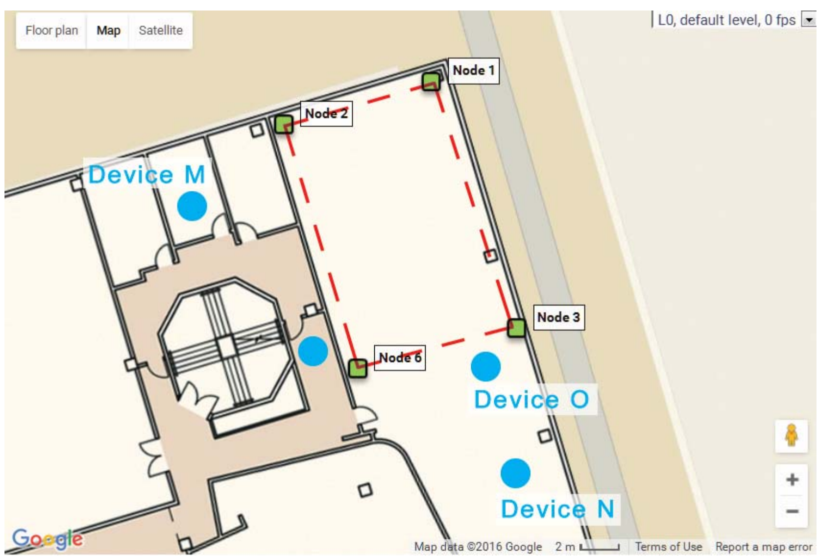


Fig. 79. *Devices (denoted by blue dots) falsely detected as inside the measurement area.*

Nodes as Wi-Fi access points

Although both node configurations appear to have similar performance in measuring occupancy , it seems more desirable to locate the nodes at the center of each bay. This is because central node arrangement is similar to the layout of Wi-Fi access points in a space, allowing the sensors' nodes to be integrated with Wi-Fi access points to provide wireless network access. In fact, the current node locations in the studio are fairly close to the existing Wi-Fi access points, as shown in Fig. 80. It makes sense because this arrangement provides the highest coverage area with the least number of access points. Compared with configuration A with four nodes, configuration B only uses two nodes at the MBSc Studio for occupancy measurement.

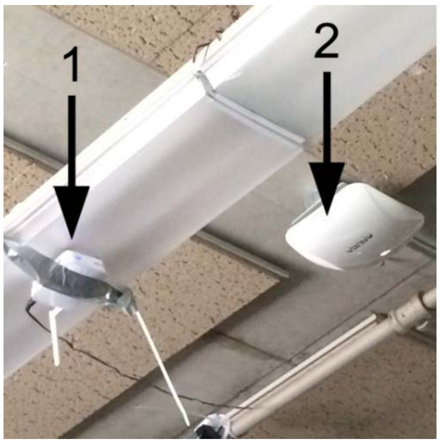


Fig. 80. *Location proximity of node to existing Wi-Fi access point. (1) Node. (2) Existing Wi-Fi access point at MBSC Studio.*

6.2 General system limitations

Since the experiment at the MBSc Studio shows that devices outside the measurement area at the end of the studio were constantly being detected by the nodes, an additional sensor node was added to cover this area to try to improve the Wi-Fi network's capability in estimating occupancy pattern and count. The results show no noticeable improvement in either area. This is possibly due to the general limitations of the Wi-Fi sensor network, which limit the capability of the system to measure only the overall occupancy pattern for localized occupants over a longer period of time. These limitations are discussed below:

Difficulty in relating number of MAC detections to number of unique occupants

At the beginning of this research, it was hypothesized that an average student working inside an area, like the Building Science Studio, would have approximately two active Wi-Fi devices. Therefore, it was expected that by detecting the number of these devices and dividing this number by two, it was possible to obtain a fairly accurate count of occupants in the studio. However, the results show that the proposed strategy is not valid based on the reasons listed below. It was found that some short-term occupants used their Wi-Fi devices, especially smartphones, quite intensively during their short duration of stay, and their MAC addresses were registered by the nodes. On the other hand, there were occupants working in the studio for the whole hour, but they were not detected by the system since they were not using any Wi-Fi devices.

In addition, the number of Wi-Fi devices per student varies significantly even in the MBSc Studio and would likely vary significantly for other spaces. These devices include smartphones, personal computers, tablets, or iPods. There are also students who never turn on the Wi-Fi buttons on their smartphones. The variations in the number of Wi-Fi devices per occupant and occupant's Wi-Fi usage habit within the same occupant type makes it difficult in directly relating the number of MAC detections and the number of unique occupants. The association of multiple devices to one occupant is consistent with the findings in the building occupancy estimation carried out by Christensen et al. (2014) and Martani (2012). Christensen et al. (2014) further stated in the study that the number of devices per occupant varies on a daily basis and there is no consistency at all.

For the measurements carried out in the Lecture Room during a lecture at a convention, all the participants were from outside the university. Almost none of them were using a laptop. It was, however, unknown how many of the smartphones had the Wi-Fi buttons turned on. With an occupant type different from university students, it is still difficult to relate the number of MAC detections with the number of unique occupants.

Lack of consistency in MAC address detection frequency

The research shows that different Wi-Fi devices have different ranges of detection frequency, regardless of Wi-Fi activities performed on the devices. First, it is found that a device can almost always be detected when its Wi-Fi radio button is turned on from an OFF mode, or when the device uses Wi-Fi for the first time in the measurement area. However, if the device stays idle, or is not using Internet services actively, it may not be detected even once in the next hour.

Second, it is found that Mac laptops (MacBooks) manufactured by Apple show a consistently lower detection frequency than laptops (PC) made by other companies. With normal Internet usage, Macs showed a detection frequency of about 1 - 10/hour while PCs showed a frequency of about 1-90/hour in the same experiment. Also, some PCs, for example the Alienware laptops, showed a consistently much higher detection frequency of about 150 - 400/hour. In one particular case, an iPad constantly streaming a TV show had only a detection frequency of 10 - 20/hour. As for smartphones, they showed a detection frequency range of 1 - 20/hour. According to studies by Accuware (2015), it is more difficult to count or track Apple devices installed with an operating system of 9 or newer. It is because the newer operating systems are programmed to broadcast random MAC addresses, which are by default filtered out by the Accuware server. This is implemented as a way to protect user privacy by preventing Apple devices from being tracked. As a result, Mac laptop devices are harder to detect, and that is why they tend to have a lower detection frequency. Tab. 35 shows that even an Apple MacBook actively using Wi-Fi was only detected once or twice by the Wi-Fi sensor network within the period of an hour.

June 13 15:00 - 16:00 PM			
Unique Wi-Fi devices detected	Detection freq	No. of devices w/ detection freq > 100	No. of devices w/ detection freq < 100
		4	13
Device I (Macbook)	1	0	1
Device Q (smartphone)	2	0	1
Device A	27	0	1
Device B	5	0	1
Device C	58	0	1
Device D (Wi-Fi access point)	453	1	0
Device E (Wi-Fi access point)	166	1	0
Device J (Macbook)	9	0	1
Device F	1	0	1
Device G (PC)	427	1	0
Device N (smartphone)	4	0	1
Device O (smartphone)	2	0	1
Device K	110	1	0
Device L	54	0	1
Device R (smartphone)	4	0	1
Device P (PC)	80	0	1
Device H (smartphone)	2	0	1

Tab. 35. *Low detection frequency of Macbooks and smartphones.*

Difficulty in selecting a suitable RSS cut-off value

In both configurations A & B, the RSS cut-off value application is crucial in eliminating MAC addresses possibly detected outside the concerned measurement area. Application of RSS cut-off value is more important in configuration B as devices are detected entirely based on their associated RSS values. The RSS calibrations performed for each experiment has revealed that RSS values are not always inversely proportional to distance. It was found that in MBSc and MArch studios, both iPhones 5s and 6s situated close to the corner windows were detected with higher RSS values by the node that was further away from the window than a closer node. It suggests that the architecture of a space has influence over the propagation of wireless signals, in addition to the fact that building materials affect RSS values (Davies et al., 2008). As stated by El Amine (2014), Mardini et al. (2014), and Locher et al. (2015), the RSS noise is heavily influenced by the indoor environment, which includes physical layout, construction materials, and different obstacles present in the space between the devices and the sensors. These factors have caused the RSS values measured to not be inversely proportional to distances. As a result, each dissimilar space has to be individually calibrated.

In addition, the RSS values detected from a location-static device are not always constant. The values fluctuate and they spread over a range of ± 10 dBm with the majority of the detected signal strengths being inversely proportional to distances. These findings are consistent with the results in a study carried out by Locher et al. (2015). Their study shows that RSS values not only fluctuate considerably over a long period of time as a result of noise and interference, but they also follow a normal distribution curve. Furthermore, Osa et al. (2012) pointed out in their research on triangulation of wireless devices that "the measured RSS value can vary up to 10 dB from one device to another" for the same position, which is consistent with RSS fluctuation range observed in this research project.

The limitations mentioned above were evident in the experiment at the MBSc Studio using a central node arrangement with an additional node to cover the other end of the studio. It was thought that this extra node could improve the system's performance in measuring occupancy by detecting the few devices (1 - 3) on the other side that were previously mistakenly measured in the experiment. However, the two experiments show no noticeable difference, which suggests that within a group of 10 to 20 devices, the ability to detect a few more devices correctly is not as significant as the influence of the Wi-Fi sensor network's limitations. To conclude, the results suggest that the sensor network measures occupancy at a macro scale, and its performance is unaffected by small changes in occupancy. This finding is coherent with the overall observation that the system can only predict occupancy pattern over a longer period of time for localized occupants.

6.3 Wi-Fi sensor network in measurement of non-localized occupants

Configurations A & B

Overall, the results show that for both configurations A and B the Wi-Fi sensor network is not able to estimate neither the count nor the occupancy pattern of the measured areas with any useful level of accuracy. While the system can detect less than a third of the occupants in the circulation area, it can detect none at the stairway. Because of its inability to detect non-localized occupants, it is not suitable to be used for determining occupant presence or movement through the space.

Long scanning rate

During the physical count, it was observed that the majority of occupants were not using their devices while they were maneuvering up and down the stairway. The central node was placed at the middle of the flight of stairs and the RSS cut-off value was set to -25 dBm for a corresponding detection distance of about 2 m, which was the width of the stairway. It was observed that each occupant spent no more than 2 - 4 seconds in the middle of the flight of stairs. The results show that no devices were detected. To ensure that the lack of Wi-Fi device detections was not due to an overly high RSS cut-off value, a lower RSS cut-off value of greater than or equal to - 35 dBm, which corresponds to a detection distance of about 4 m, was used to check if more devices could be detected. Tab. 36 shows that the results remain about the same with only 2 more devices being detected in the range.

May 31			
Time	Number of unique occupants counted	RSS > - 36 dBm	RSS > - 26 dBm
		Number of MAC detections (not including permanent Wi-Fi devices)	Number of MAC detections (not including permanent Wi-Fi devices)
16:00 - 16:10	10	2	0
16:10 - 16:20	7	0	0
16:20 - 16:30	8	0	0

Tab. 36. *Number of MAC detections with RSS > - 36 dBm and RSS > - 26 dBm.*

As for the circulation area, some of the occupants used their smartphone devices while they were going through the space. It was observed that an average occupant spent about 8 - 14 seconds in the area, excluding those actually holding a conversation there. Still, the results show no or a small number of MAC detection. According to Vebree et al. (2013), a long scanning rate is the major reason for the lack of

Wi-Fi detections in the measurement of non-localized occupants. Although Accuware sets the Open Mesh to scan Wi-Fi devices every five seconds, in reality, the scanning time is much longer. Even with a scanning rate of every five seconds, the interval between two scans can be as long as one to two minutes (Vebree et al., 2013). This is because the active scanning has to coincide with the probe requests sent out by the devices in order to produce a successful scan. When a device is asleep, a probe request is only sent out every minute. When a device is on stand-by mode, a probe request is sent out every 4 - 6 seconds. As a result, even a device that is actively sending out Wi-Fi signal for five seconds may not be scanned by the sensor successfully in 5 seconds. Vebree et al. (2013) further pointed out that the performance of their experiment did not improve even with a shorter scanning rate, as it did not alter the frequency of probe requests. Therefore, in the measurement of non-localized occupants, their short duration of stay in the middle of the stairway and circulation area did not allow enough time for their devices to be scanned even if the occupants were actively using their devices.

Incorrect triangulation due to openness of circulation area

The results show that the perimeter node arrangement is only able to detect some MAC addresses in the 30-minute time period. As mentioned previously, the inaccuracy in the triangulation of devices is further amplified by the openness of the sensor environment. The circulation area is not enclosed by any wall on the x-y plane; it is also connected to the balcony above by two vertical atriums adjacent to it. As pointed out by Davies et al. (2008), concrete wall and slab can reduce RSS by up to 15 dBm. Without the concrete wall separation, the devices in the immediate open area were included in the measurement from time to time. Therefore, the openness of a circulation space makes the sensor system vulnerable to false detections.

Other issues / drawbacks

Although the Wi-Fi sensor network is relatively easy and economical to install, the data processing requires complex procedures and the development of an application program interface (API) (Zhao et al., 2015) to produce meaningful occupancy information. This is one of the reasons why this project has subscribed to Accuware's data processing and nodes-monitoring services. Also, the MAC detection system is entirely terminal-based and occupants may feel that they are being monitored (Zhao et al., 2015). In addition, the system is not as user-friendly as promoted in the Accuware product literature

(Accuware, 2015). It is observed that the sensor nodes do not always function properly. Malfunctions can occur when the nodes fail to upgrade their firmware, and due to other unknown reasons. Unlike an Internet router, there are no reset buttons on the nodes. They have to be physically taken down and plugged into a computer through an Ethernet cable for a manual reset. This has proven to be time-consuming and technically challenging for an average person. It also suggests that the system has to be constantly monitored.

6.4 Raspberry Pi PIR people counter in measurement of occupants

When used alone as a people counter, the Raspberry Pi passive infrared motion sensor is non-terminal based and it can detect presence by sensing occupants going into a room or a building. Since the system cannot count accurately, it is impossible to determine if all occupants have left the room. As a result, the system is not capable of determining if a room is continuously occupied. Also, the sensor cannot provide occupant information about their activity.

However, in a scenario involving non-localized occupants such as people walking up and down a stairway, this system is able to determine when and whether such space is being traveled. With the ability to provide occupant information regarding frequency of usage, this exceptionally low-cost device (CAN $100 for a Raspberry Pi computer and CAN $5 for a passive infrared motion sensor) can be used easily to compare the relative space usage among different circulation spaces and at different time intervals. However, as a passive infrared sensor, the Raspberry Pi people counter is susceptible to false detections due to the changes in illumination level or non-occupant related movement in the measured environment. The experiment at SLC was not affected by the changes in light level because the measurement area faces south and the experiment was carried out at 7 PM when the influence from the sun was on the west. Also, there were no other student activities in the vicinity and the sensor was pointing to a wall.

Raspberry Pi passive infrared motion sensors are classified as an open source sensor, which means they are non-proprietary commercial products that can be bought off the shelves. Their main advantage is that they are affordable and can be modified by users to match special needs (Weekly et al., 2014). However, the Raspberry Pi sensors also share some of the same main drawbacks suffered by other open source devices. First, although the purchasing cost of the components is low, it does not include the time value of labour involved in constructing, programming, and calibrating the device (Weekly et al., 2014). Second, there are many potential sources of errors from manually assembling the parts by the users themselves who may not have the needed expertise (Weekly et al., 2014). In the construction of the Raspberry Pi sensor for this research project, there were errors in the scripts and codes that were freely downloaded from the Internet. These challenges make it difficult for average users to build their own sensors.

6.5 Examples of Wi-Fi sensor network's applications

The previous experiments show that a Wi-Fi sensor network is capable of predicting the overall occupancy pattern (trend) of localized occupants throughout the day. To demonstrate how the network can potentially be used to improve building performance, real-life applications of the network were carried out at the Gallery (see Fig. 81) and lecture room (Pit) in the Architecture Building (see Fig. 82).

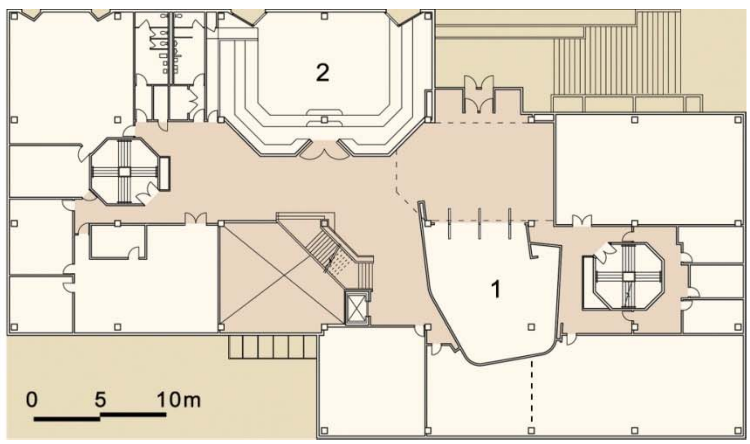


Fig. 81. (left) Paul H. Cocker Gallery.

Fig. 82. (right) Second floor plan of the Architecture Building. (1) Gallery. (2) Room ARC 202 - Lecture room (Pit).

Example 1 at Gallery - MArch students' thesis presentation

This example aimed to demonstrate how the real-time MAC detections produced by the use of a Wi-Fi sensor network can be used to control an HVAC system more effectively and improve IAQ and thermal comfort for localized occupants who use the space over a longer period of time. The experiment took place when the students were having a sit-down thesis presentation.

Node 3 was installed underneath the lighting power supply track at about 500 mm away from the ceiling at the center of the Gallery (see Fig. 83) from August 23 to August 24. A "1% CO2 + RH/T" Data Logger (see Fig. 84) manufactured by CO2 Meter was also installed next to the sensor node underneath the adjacent power supply track. A RSS cut-off value of greater than or equal to -39 dBm was chosen. It was the same as the cut-off value used in the single node application in MArch studio as the nodes in both the Gallery and MArch Studio were using a similar detection radius.

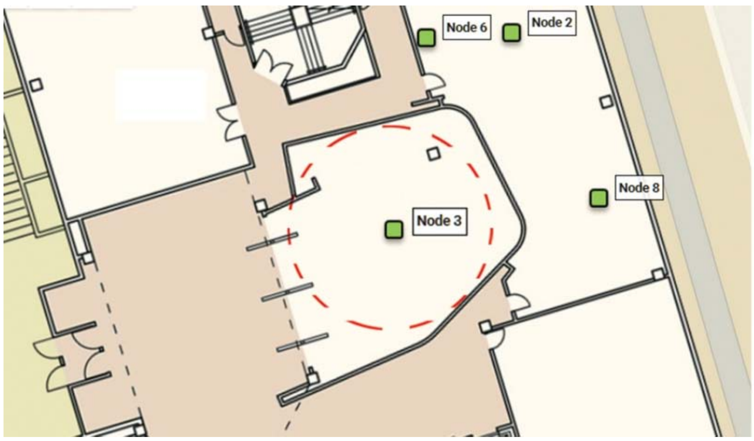


Fig. 83. (left) Single node application at Gallery.

Fig. 84. (right) 1% CO2 + RH/T Data Logger of model# CM-0018AA.

The results from Fig. 86 show that room temperature, relative humidity and CO_2 concentration all reached their peak at around 3 PM. In terms of IEQ, at 3 PM, the room temperature increased from 28.5^{0}C to 30.2^{0}C; the relative humidity increased from 34% to 42%; the CO_2 concentration increased by more than 300% from 400 ppm to 1,400 ppm. At the same time, the Wi-Fi sensor network also detected the maximum number of MAC detections at 3 PM (see Fig. 85). The above three IEQ parameters and the number of MAC detections reached their peak at the same because their increases were mainly due to an increase in the number of occupants present. This further confirms that the sensor network is capable of predicting real-time occupancy pattern.

In addition, similar measurement results were recorded on August 24 as shown in Fig. 87 & 88. The results show that the room temperature and the CO_2 concentration increased to their maximum levels of about 19.7^{0}C and 900 ppm, respectively, between 1:30 PM and 6 PM. This trend aligned with the occupancy pattern measured by the sensor network.

Results on August 23

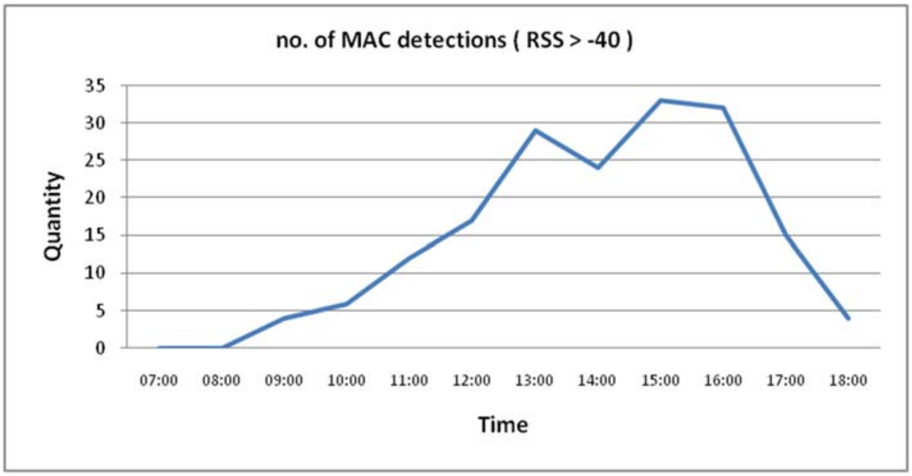


Fig. 85. *Number of MAC detections in each 1-hour time frame at RSS > - 40 dBm. Note: Time without daylight saving.*

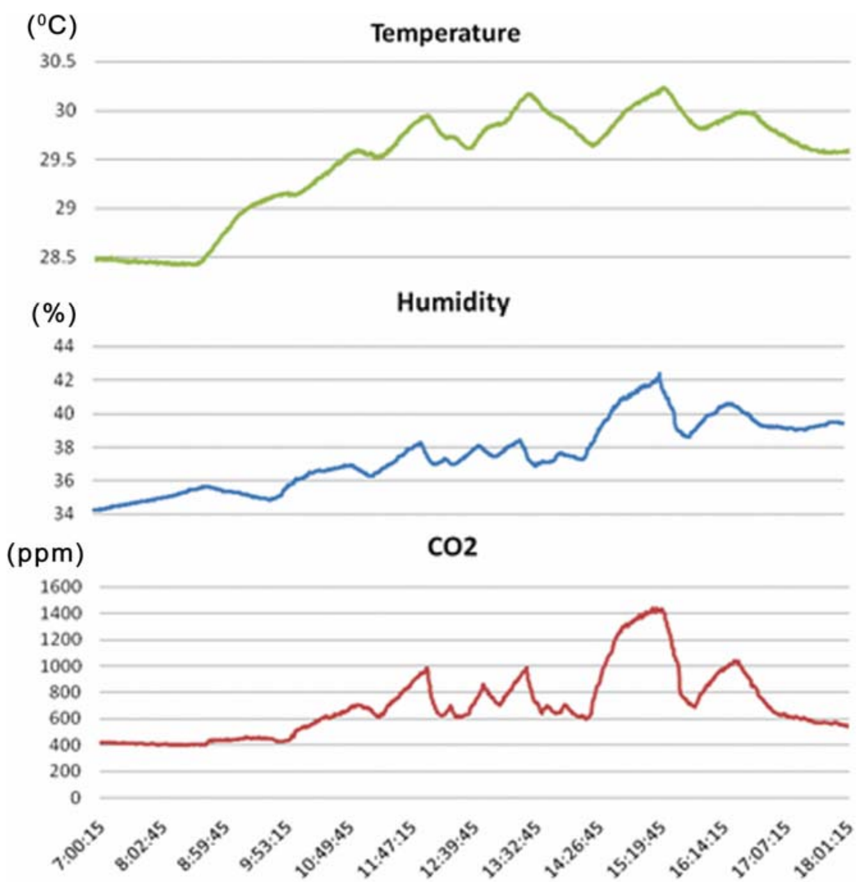


Fig. 86. *Temperature (^{0}C), relative humidity (%) and CO_2 concentration (ppm) measured at Gallery. Note: Time without daylight saving.*

Results on August 24

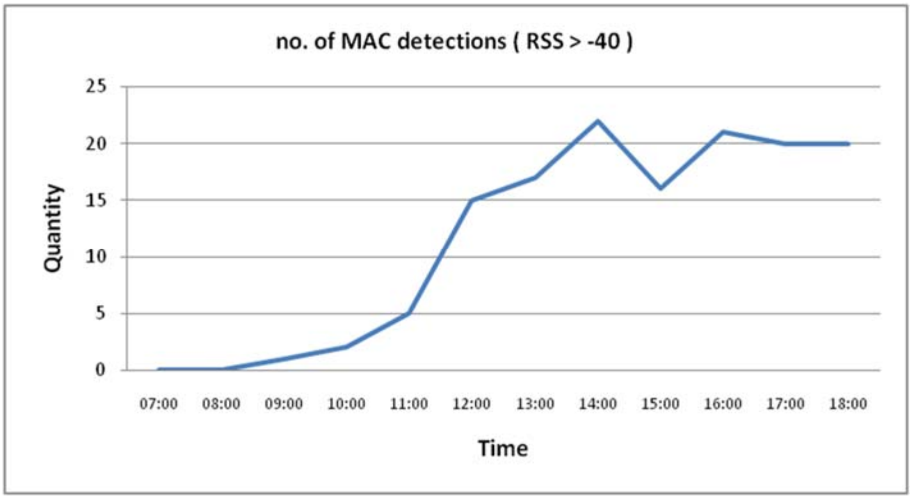


Fig. 87. *Number of MAC detections in each 1-hour time frame at RSS > - 40 dBm. Note: Time without daylight saving.*

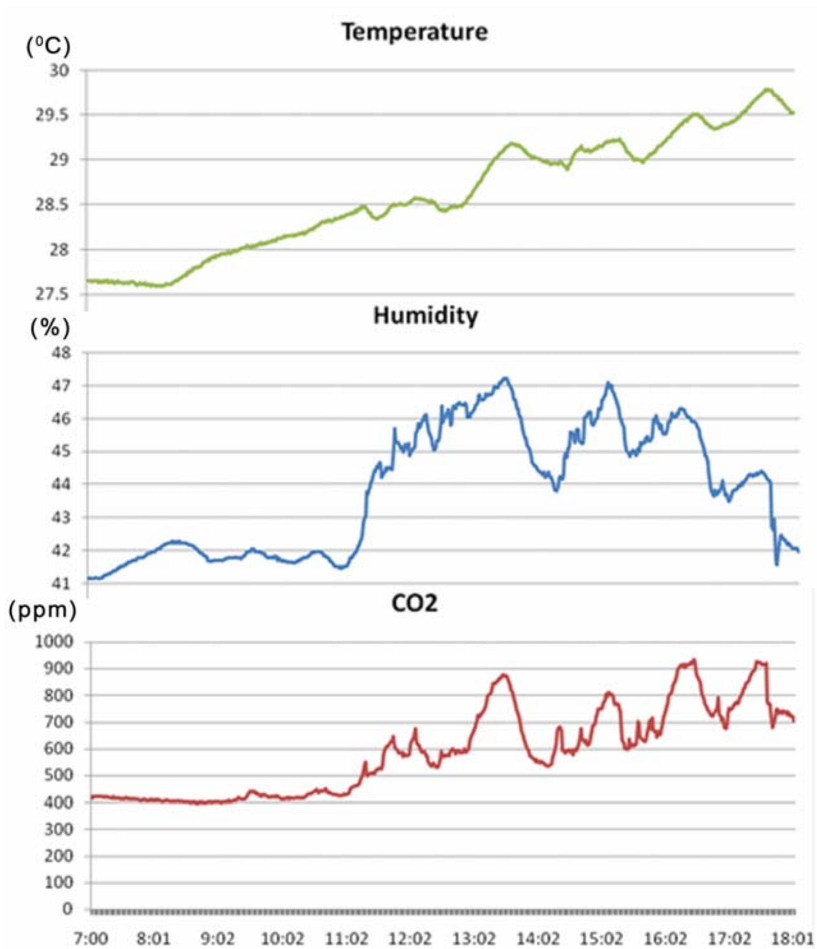


Fig. 88. *Temperature (^{0}C), relative humidity (%) and CO_2 concentration (ppm) measured at Gallery. Note: Time without daylight saving.*

This example shows that it is possible to use the real-time occupancy trend exhibited by the changes in the number of MAC detections to control the supply of conditioned and/or fresh air and thereby improve the IAQ and thermal comfort in the Gallery. It was observed that the Gallery currently was not connected to any HVAC systems and it simply relied on opening the doors for any air exchange with the conditioned atrium to improve its IEQ. Interestingly, Fig. 85 & 86 also shows that temperatures continued to remain above 29.5^{0}C between 4:00 PM and 6:00 PM while the number of MAC detections was decreasing. In this case, a HVAC control system using a real-time occupancy trend can potentially save electrical energy by reducing or cutting off its supply of conditioned air. This energy savings approach due to decreasing or no occupancy may not be possible with the use of an IEQ data logger alone, since an uncomfortable IEQ may not require conditioning.

Example 2 at lecture room (Pit) - Class of 2020 undergraduates orientation

A similar setup using Node 5 and an IEQ data logger was installed in the lecture room (see Fig. 89) on August 30. The same RSS cut-off value of greater than or equal to -46 dBm, as previously employed for the single node application, in the lecture room was used. The results (see Fig. 90 & 91) are similar to the ones shown in the Gallery example. A HVAC control system using real-life occupancy data provided by the sensor network has the potential to improve the temperature, relative humidity and CO_2 concentration in the lecture room between 10:30 AM and 5:00 PM.

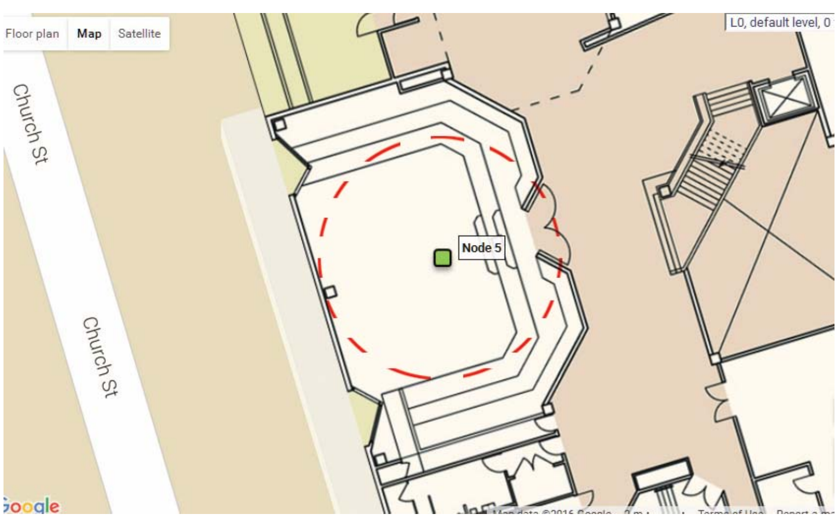


Fig. 89. Single node application at lecture room.

Results on August 30

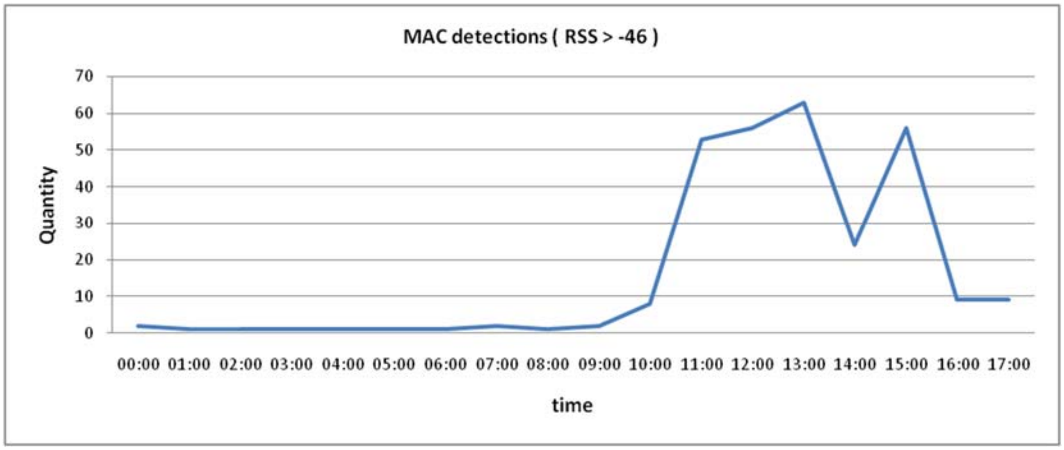


Fig. 90. *Number of MAC detections in each 1-hour time frame at RSS > - 46 dBm. Note: Time without daylight saving.*

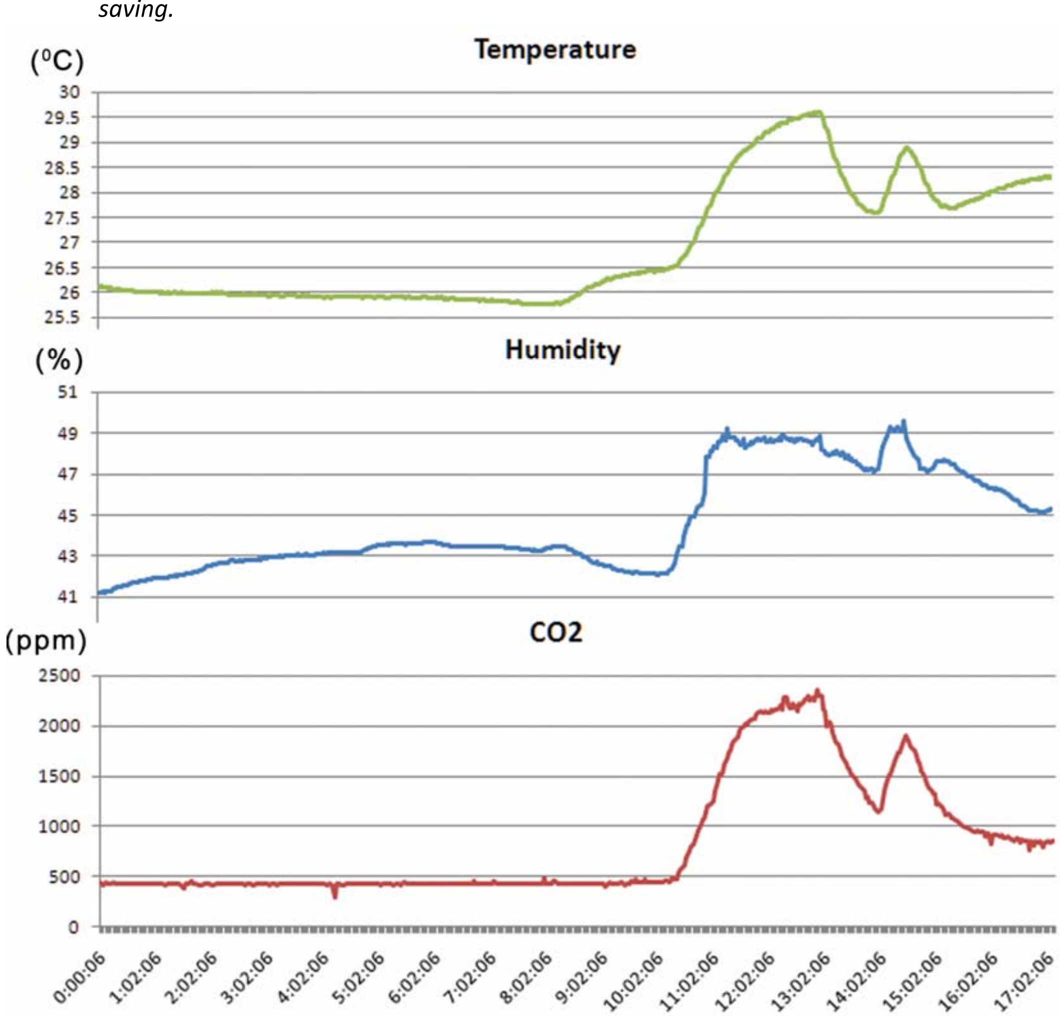


Fig. 91. *Temperature (^{0}C), relative humidity (%) and CO_2 concentration (ppm) measured at lecture room. Note: Time without daylight saving.*

Another advantage of using Wi-Fi sensor networks is to more effectively control building systems such as the HVAC system is that it detects Wi-Fi devices (occupants) instead of indoor environmental conditions. It is very likely that an increase in the number of MAC detections is due to an increase in the number of occupants present. For example, the presence of an occupant in a lecture room can cause an increase in the number of MAC detections. This can trigger the HVAC supply in this room. However, a system using only CO2 concentration as the occupant detection system may not detect any change in CO2 level due to the presence of one occupant. As a result, no HVAC will be supplied and this will result in an uncomfortable indoor condition.

Also, Wi-Fi devices such as smartphones mostly belong to one individual. Therefore, it is possible to use a Wi-Fi device within a Wi-Fi sensor network to control building systems to provide an individualized comfort setting in a location that is occupied by one person, such as an office. When a Wi-Fi sensor network detects a specific MAC address in the preset detection range, it can theoretically operate different building systems, such as lighting, heating, and fan, to their set-points which are decided based on predefined values to ensure personalized comfort. According to Sarkar (2015), this automatic building system control to achieve less energy consumption is already possible using a smartphone application.

In addition, Wi-Fi sensor networks are able to provide information regarding space utilization. This information is valuable in understanding how often a space is being used. According to Sensible Building Science (2014), overall occupancy pattern obtained from the sensor network can be used as a reference tool in space when planning for existing and new buildings to increase cost-efficiency in space utilization. It is also possible to gain insight into how the usage of a space is affected by its architectural design through measuring occupancy. This may assist architectural planners in designing buildings that can function closer to what is intended in the building design.

7. Conclusion

7.1 Results in response to research questions

The experiment shows that the proposed Wi-Fi sensor network is not capable of accurately measuring the number of occupants who occupy a room, for example a lecture room, for a longer time period. The Wi-Fi sensor network is also not capable of measuring how many people pass through a particular point in a circulation space.

In the measurement of occupants who use a room for a longer time period, the Wi-Fi sensor network, in general, detects more MAC addresses when there is a larger group of occupants. However, there is no consistent relationship between the number of MAC detections and the number of occupants. The results show that the Wi-Fi sensor network cannot always correctly estimate the small changes between each 1-hour interval, but it can estimate the overall occupancy pattern in the course of a day and in a longer time period. The system can predict when there is occupant presence, and if the occupancy is overall increasing, decreasing, at its peak or at its lowest point in the course of a day.

In measuring how many people pass through a particular point, the Wi-Fi sensor network cannot detect any Wi-Fi devices that are only present for a very short period of time and are with no or limited Wi-Fi activities. Occupants have to be actively exchanging Wi-Fi signals with the sensor network while the device is being scanned for a successful detection.

7.2 Wi-Fi sensor network compared with other major occupant detection systems

In terms of fine-grained occupancy information, the Wi-Fi sensor network can detect occupant presence and can estimate the general trend in occupancy pattern, but it cannot provide accurate information regarding occupant count and activity.

Compared to other occupant detection systems, its major advantage is its easy deployment. The Wi-Fi sensor network installed had 10 nodes and it only took 4 hours to install them. The installation process included connecting the power and Ethernet cables, and mounting the nodes to the ceiling. This process did not require any particular knowledge in networking. The sensor network was fully operating within 24 hours after installation. Unlike PIR systems, Wi-Fi sensor networks do not require a clear line of sight.

And unlike CO_2, PIR, ultrasonic and audio based systems, Wi-Fi sensors networks are not susceptible to changes in environmental factors. The only factor to be calibrated in a Wi-Fi sensor network is the RSS cut-off value. For an open-concept office space, RSS calibration can be carried out simply using the slide bar inside the Accuware Analytics dashboard.

Its other major advantage is its low infrastructural cost. To install a system using Accuware services, there is only the cost associated with the sensor nodes and the subscription services. And if occupant data can be extracted from existing Wi-Fi network, there will be no infrastructural cost at all. Other detection systems such as vision-based systems, RFID tags systems and PIR people counters involve expensive equipment and installation costs.

The major disadvantage of a Wi-Fi sensor network system is that it cannot detect and deliver an accurate occupant count. Also, the effectiveness of a Wi-Fi sensor network in detecting occupancy information is entirely based on how many active Wi-Fi devices are present. Unlike CO2, PIR, and ultrasonic audio and vision based systems, Wi-Fi sensor networks do not detect any actions except the Wi-Fi activities carried out by the occupants. And unlike CO2 and audio based systems, which can be calibrated to improve their accuracy in providing a count of all occupants, Wi-Fi systems cannot be further calibrated once a RSS cut-off value is set. Therefore, Wi-Fi sensor networks cannot provide occupant count, but only the general trend in occupancy pattern. In addition, the performance of Wi-Fi sensor networks is highly dependent on the user types and the functions of the spaces measured. Wi-Fi sensor networks are very likely to perform poorly in certain locations, for example a concert hall or a gymnasium, where the use of any Wi-Fi devices is minimal.

To conclude, Wi-Fi sensor networks can detect occupant presence and estimate overall occupancy pattern for localized occupants. With its low infrastructural cost and ease of deployment, there is great potential to develop more Wi-Fi sensor networks to improve building performance in the future.

7.3 Contributions

Unexpectedly, one important finding from the experiments carried out is that the central node application seems to perform as well as the perimeter node application in measuring localized occupants. This finding is contradictory to what is suggested in the Accuware's product literature. It is possibly because the product literature is more concerned with the tracking of Wi-Fi device locations, which is dependent on the triangulation of devices. As a result, a perimeter node arrangement is preferred. For the purpose of improving building performance, high location accuracy is not important as long as the occupants are within the served area. This finding also economizes the number of sensor nodes needed for estimating occupant count.

In addition, the limitations of the proposed Wi-Fi sensor network were identified in this research project. The proposed Wi-Fi system is only capable of estimating the overall occupancy pattern of occupants who use the space for a long time period. This system is incapable of estimating occupant count due to the system's incapability in detecting all devices, and the lack of constant relationship between the number of devices and the number of occupants.

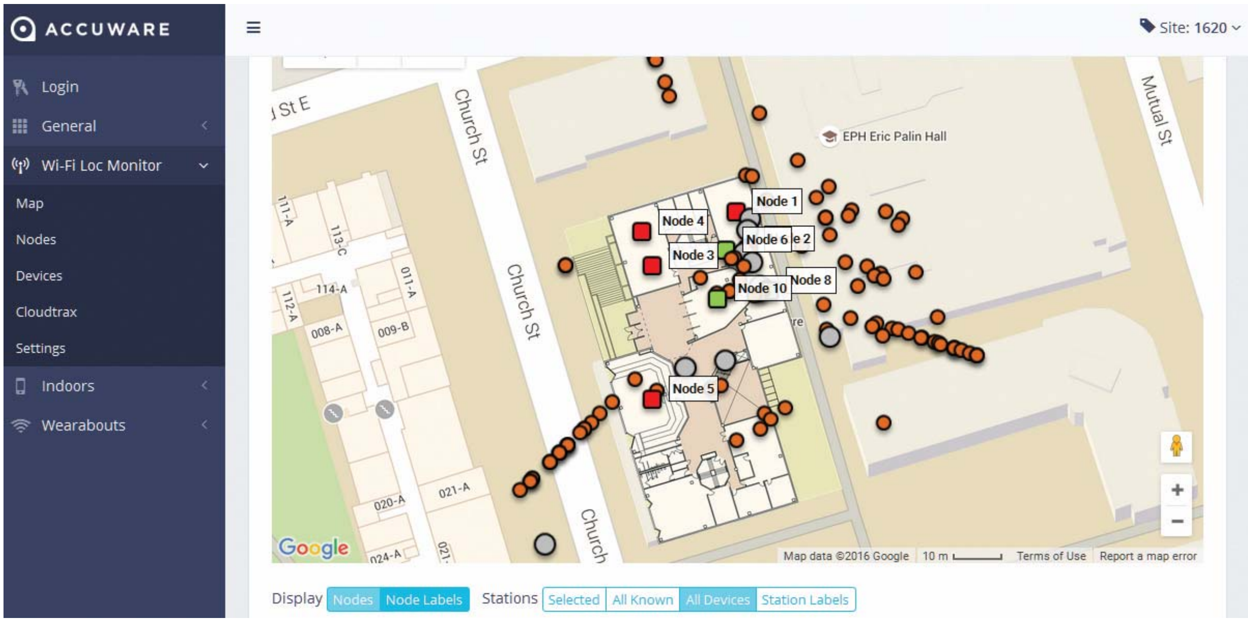
7.4 Future work

It is recommended that the experiments be carried out with more occupants involved to further investigate the level of accuracy in estimating occupant count and pattern. Unfortunately they were not achieved by the proposed Wi-Fi sensor network. Current experiments took place in the summer semester when occupancy was relatively lower than when the university was built is in full session.

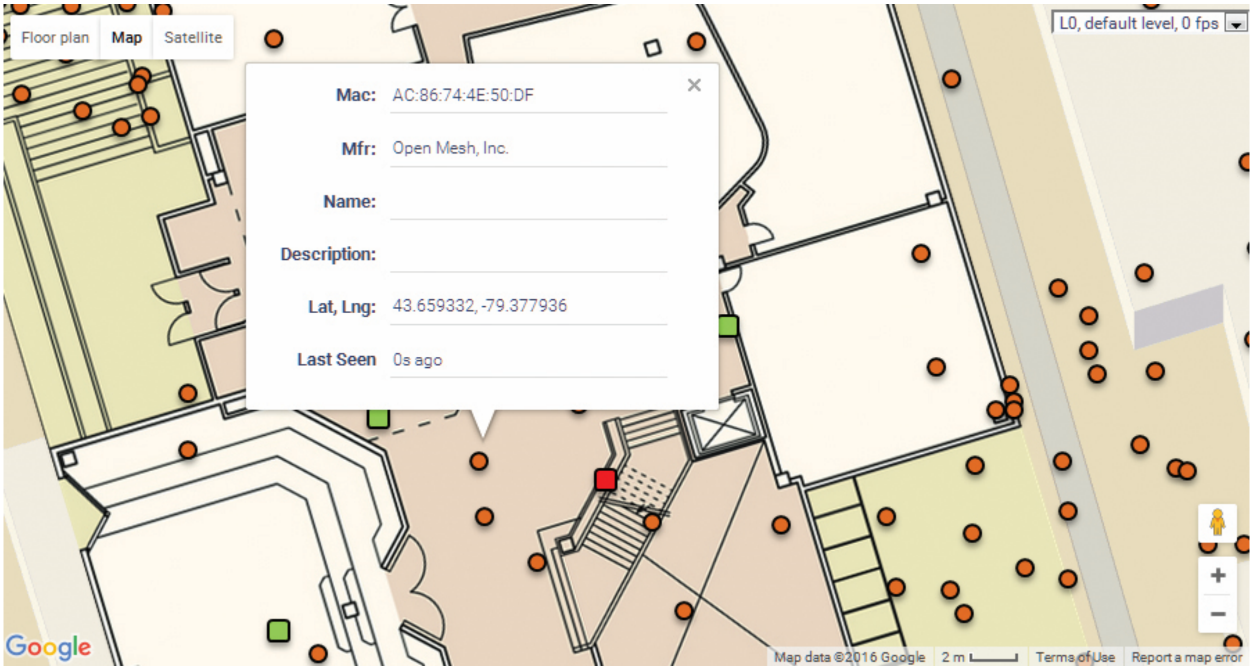
Also, there is potential to investigate the intensity of space usage by occupants at different locations throughout the floor plan. This investigation will have to be carried out with the use of more nodes to cover the complete floor. It will require a more developed heat density map tool by Accuware. Currently, the tool is only in its developing stage and the results generated are not able to accurately represent the changing occupant density throughout the day.

Appendix A Accuware dashboard

1. Accuware dashboard showing MAC detections at the Architecture Building.

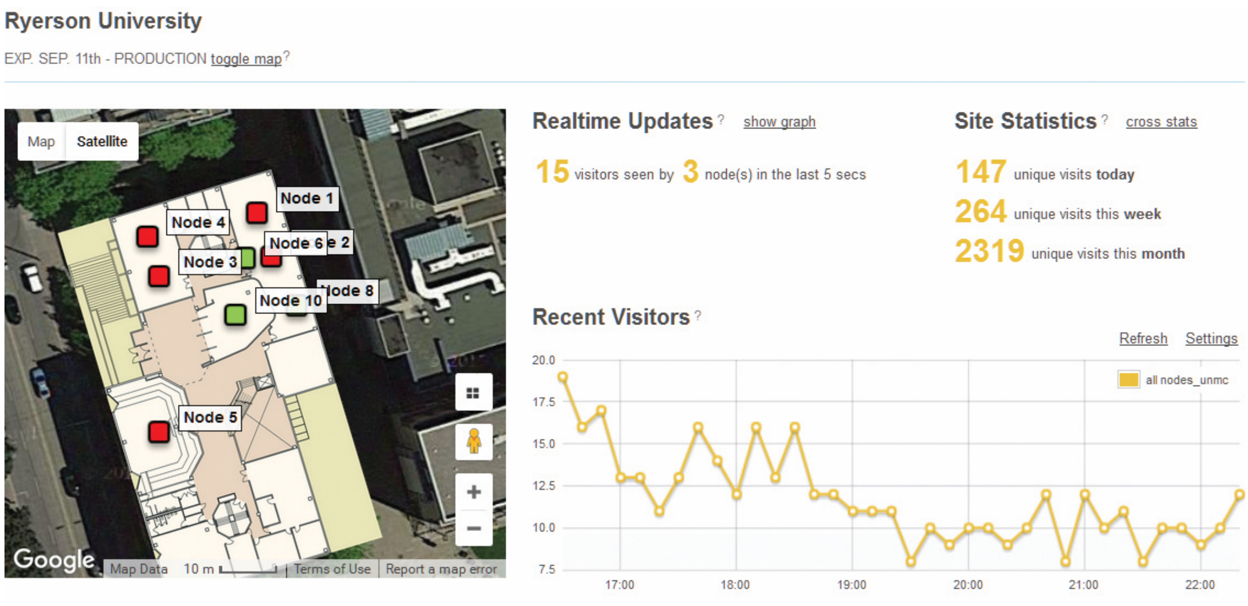


2. Accuware dashboard showing details of each MAC detection at the Architecture Building.



Appendix B Accuware Analytics dashboard

Accuware Analytics dashboard showing real-time site statistics at the Architecture Building.



Appendix C Example result from Experiment phase 1: Configuration A at MBSc Studio

(Localized occupants), RSS > - 40 dBm

8:00 - 9:00 AM

Unique Wi-Fi devices detected	Detection freq	No. of devices w/ detection freq > 100	No. of devices w/ detection freq < 100	Physical count
		0	7	n. a.
Device X	2	0	1	
Device A (smartphone)	1	0	1	
Device Y	1	0	1	
Device Z	2	0	1	
Device B (smartphone)	2	0	1	
Device C (PC)	3	0	1	
Device D (PC)	7	0	1	

9:00 - 10:00 AM

Unique Wi-Fi devices detected	Detection freq	No. of devices w/ detection freq > 100	No. of devices w/ detection freq < 100	Physical count
		1	6	n. a.
Device A (smartphone)	4	0	1	
Device E	1	0	1	
Device C (PC)	3	0	1	
Device AA	3	0	1	
Device AB	2	0	1	
Device AC	2	0	1	
Device D (PC)	217	1	0	

10:00 - 11:00 AM

Unique Wi-Fi devices detected	Detection freq	No. of devices w/ detection freq > 100	No. of devices w/ detection freq < 100	Physical count
		1	3	n. a.
Device F (Macbook)	4	0	1	
Device B (smartphone)	1	0	1	
Device G (PC)	184	1	0	
Device H (smartphone)	4	0	1	

11:00 - 12:00 PM

Unique Wi-Fi devices detected	Detection freq	No. of devices w/ detection freq > 100	No. of devices w/ detection freq < 100	Physical count
		2	15	6
Device I (Macbook)	5	0	1	
Device A (smartphone)	1	0	1	
Device AD	1	0	1	
Device AE	1	0	1	
Device J (Macbook)	5	0	1	
Device K	1	0	1	
Device L (Macbook)	3	0	1	
Device G (PC)	397	1	0	
Device C (PC)	6	0	1	
Device M (PC)	126	1	0	
Device N (smartphone)	3	0	1	
Device O (smartphone)	1	0	1	
Device AF	76	0	1	
Device AG	1	0	1	
Device AH	28	0	1	
Device P (PC)	42	0	1	
Device H (smartphone)	5	0	1	

12:00 - 13:00 PM				
Unique Wi-Fi devices detected	Detection freq	No. of devices w/ detection freq > 100	No. of devices w/ detection freq < 100	Physical count
		2	12	6
Device I (Macbook)	1	0	1	
Device Q (smartphone)	3	0	1	
Device AD	5	0	1	
Device AI	8	0	1	
Device AJ	4	0	1	
Device AK	11	0	1	
Device G (PC)	402	1	0	
Device C (PC)	1	0	1	
1C56FE188A1A	2	0	1	
Device AF	178	1	0	
Device AH	58	0	1	
Device R (smartphone)	18	0	1	
Device P (PC)	74	0	1	
Device H (smartphone)	4	0	1	

13:00 - 14:00 PM				
Unique Wi-Fi devices detected	Detection freq	No. of devices w/ detection freq > 100	No. of devices w/ detection freq < 100	Physical count
		2	19	10
Device I (Macbook)	3	0	1	
Device Q (smartphone)	3	0	1	
Device A (smartphone)	1	0	1	
Device AD	1	0	1	
Device AI	16	0	1	
Device AJ	10	0	1	
Device AK	53	0	1	
Device L (Macbook)	4	0	1	
Device G (PC)	135	1	0	
Device S (smartphone)	6	0	1	
Device T (smartphone)	1	0	1	
Device U (ipod)	2	0	1	
Device V (smartphone)	1	0	1	
Device N (smartphone)	3	0	1	
Device O (smartphone)	1	0	1	
Device AF	141	1	0	
Device AH	50	0	1	
Device R (smartphone)	7	0	1	
Device P (PC)	75	0	1	
Device W (smartphone)	1	0	1	
Device H (smartphone)	6	0	1	

14:00 - 15:00 PM				
Unique Wi-Fi devices detected	Detection freq	No. of devices w/ detection freq > 100	No. of devices w/ detection freq < 100	Physical count
		4	19	8
Device I (Macbook)	1	0	1	
Device Q (smartphone)	1	0	1	
Device A (smartphone)	9	0	1	
Device AI	6	0	1	
Device AJ	4	0	1	
Device AK	54	0	1	
Device AL	380	1	0	
Device AM	154	1	0	
Device E	1	0	1	
Device G (PC)	288	1	0	
Device S (smartphone)	12	0	1	
Device C (PC)	6	0	1	
Device T (smartphone)	1	0	1	
Device M (PC)	1	0	1	
Device AN	1	0	1	
Device AO	3	0	1	
Device O (smartphone)	4	0	1	
Device AF	109	1	0	
Device AH	50	0	1	
Device AP	1	0	1	
Device P (PC)	84	0	1	
Device AQ	1	0	1	
Device H (smartphone)	1	0	1	

15:00 - 16:00 PM				
Unique Wi-Fi devices detected	Detection freq	No. of devices w/ detection freq > 100	No. of devices w/ detection freq < 100	Physical count
		4	13	7
Device I (Macbook)	1	0	1	
Device Q (smartphone)	2	0	1	
Device AR	27	0	1	
Device AD	5	0	1	
Device AK	58	0	1	
Device AL	453	1	0	
Device AM	166	1	0	
Device J (Macbook)	9	0	1	
Device AS	1	0	1	
Device G (PC)	427	1	0	
Device N (smartphone)	4	0	1	
Device O (smartphone)	2	0	1	
Device AF	110	1	0	
Device AH	54	0	1	
Device R (smartphone)	4	0	1	
Device P (PC)	80	0	1	
Device H (smartphone)	2	0	1	

16:00 - 17:00 PM				
Unique Wi-Fi devices detected	Detection freq	No. of devices w/ detection freq > 100	No. of devices w/ detection freq < 100	Physical count
		4	13	7
Device Q (smartphone)	1	0	1	
Device AR	4	0	1	
Device AD	1	0	1	
Device AK	72	0	1	
Device AL	440	1	0	
Device AM	161	1	0	
Device J (Macbook)	4	0	1	
Device G (PC)	426	1	0	
Device AT	1	0	1	
Device N (smartphone)	1	0	1	
Device O (smartphone)	10	0	1	
Device AF	116	1	0	
Device AH	57	0	1	
Device R (smartphone)	15	0	1	
Device P (PC)	76	0	1	
Device AU	1	0	1	
Device H (smartphone)	4	0	1	

17:00 - 18:00 PM				
Unique Wi-Fi devices detected	Detection freq	No. of devices w/ detection freq > 100	No. of devices w/ detection freq < 100	Physical count
		3	19	11
Device Q (smartphone)	1	0	1	
Device AD	2	0	1	
Device AJ	5	0	1	
Device AK	50	0	1	
Device AL	418	1	0	
Device AM	150	1	0	
Device AV	1	0	1	
Device AW	15	0	1	
Device L (Macbook)	2	0	1	
Device G (PC)	11	0	1	
Device AT	33	0	1	
Device AX	2	0	1	
Device N (smartphone)	1	0	1	
Device AY	8	0	1	
Device O (smartphone)	5	0	1	
Device AZ	1	0	1	
Device AF	109	1	0	
Device AH	36	0	1	
Device R (smartphone)	6	0	1	
Device P (PC)	78	0	1	
Device W (smartphone)	2	0	1	
Device H (smartphone)	2	0	1	

18:00 - 19:00 PM				
Unique Wi-Fi devices detected	Detection freq	No. of devices w/ detection freq > 100	No. of devices w/ detection freq < 100	Physical count
		2	6	n. a.
Device I (Macbook)	1	0	1	
Device BA	1	0	1	
Device AL	217	1	0	
Device AM	164	1	0	
Device J (Macbook)	4	0	1	
Device BB	2	0	1	
Device E	2	0	1	
Device AF	41	0	1	

19:00 - 20:00 PM				
Unique Wi-Fi devices detected	Detection freq	No. of devices w/ detection freq > 100	No. of devices w/ detection freq < 100	Physical count
		2	5	n. a.
Device A (smartphone)	1	0	1	
Device AL	159	1	0	
Device AM	256	1	0	
Device B (smartphone)	4	0	1	
Device BC	1	0	1	
Device BD	2	0	1	
Device D (PC)	5	0	1	

Appendix D Physical count from Raspberry Pi PIR people counter experiment

(at Ryerson University Student Learning Centre on July 12, 2016)

July 12 (Tuesday) Physical count at Student Learning Center					
Time	**Single travel**	**Group travel**	**Time**	**Single travel**	**Group travel**
19:00 PM		2			2
		2			2
		4			2
		2			4
	1			1	
		3			3
	1				3
	1			1	
		2			3
	1				3
		5			5
		3			8
	1				2
		2			3
		2		1	
		4		1	
	1				3
		5			9
	1				2
		3			8
		5		1	
	1				3
		3		1	
	1				4
	1			1	
	1		**19:20 PM**	1	
	1				

Total number of people traveled =	**136**
Total number of travels (single + group) =	**53 (20 + 33)**
Total number of detection by R-Pi people counter =	**61**

Appendix E *Partial data recorded by Raspberry Pi PIR people counter*

(at Ryerson University Student Learning Centre on July 12, 2016)

2016-07-12 19:20:25.051104 Five min
2016-07-12 21:05:24.240268 Hours Plus
No intruders 0

2016-07-12 19:17:31.218780
2016-07-12 19:20:25.051104 Five min
2016-07-12 21:05:24.240268 Hours Plus
No intruders 0

2016-07-12 19:17:32.220173
2016-07-12 19:20:25.051104 Five min
2016-07-12 21:05:24.240268 Hours Plus
No intruders 0

2016-07-12 19:17:33.221542
2016-07-12 19:20:25.051104 Five min
2016-07-12 21:05:24.240268 Hours Plus
No intruders 0

2016-07-12 19:17:34.222920
2016-07-12 19:20:25.051104 Five min
2016-07-12 21:05:24.240268 Hours Plus
No intruders 0

2016-07-12 19:17:35.224317
2016-07-12 19:20:25.051104 Five min
2016-07-12 21:05:24.240268 Hours Plus
Intruder detected Total number of people : 49

2016-07-12 19:17:38.227722
2016-07-12 19:20:25.051104 Five min
2016-07-12 21:05:24.240268 Hours Plus
No intruders 0

2016-07-12 19:17:39.229125
2016-07-12 19:20:25.051104 Five min
2016-07-12 21:05:24.240268 Hours Plus
No intruders 0

2016-07-12 19:17:40.230518
2016-07-12 19:20:25.051104 Five min
2016-07-12 21:05:24.240268 Hours Plus
No intruders 0

2016-07-12 19:17:41.231918
2016-07-12 19:20:25.051104 Five min
2016-07-12 21:05:24.240268 Hours Plus
No intruders 0

Appendix F Macro script for coordinates filter

```
Function PointInPolygon(rXY As Range, rpolyXY As Range) As Boolean
 ' Function checks if X,Y given in rXY falls within complex _
  polygon as defined by node list rpolyXY. _
  rXY to be 2 cell range with one X and one Y value _
  rpolyXY to be 2 column range with for each node on the polygon _
  the X and the Y point

 Dim i As Integer, j As Integer, polySides As Integer
 Dim oddNodes As Boolean
 Dim x As Double, y As Double
 Dim aXY As Variant

 oddNodes = False
 x = rXY.Cells.Value2(1, 1)
 y = rXY.Cells.Value2(1, 2)
 aXY = rpolyXY.Value

 polySides = rpolyXY.Rows.Count
 j = polySides

 For i = 1 To polySides
  If (((aXY(i, 2) < y And aXY(j, 2) >= y) _
   Or (aXY(j, 2) < y And aXY(i, 2) >= y)) _
   And (aXY(i, 1) <= x Or aXY(j, 1) <= x)) Then
   oddNodes = oddNodes Xor (aXY(i, 1) + (y - aXY(i, 2)) / (aXY(j, 2) - aXY(i, 2)) * (aXY(j, 1) - aXY(i, 1)) < x)
  End If
  j = i
 Next i
 PointInPolygon = oddNodes
End Function
```

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