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## Using existing network infrastructure to estimate building occupancy and control plugged-in devices in user workspaces

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**Abstract:** Buildings are a major consumer of energy. We believe that energy can be saved with the notion of implicit occupancy sensing where existing IT infrastructure can be used to replace and/or supplement explicit dedicated sensors to determine building occupancy and drive building operation. Implicit sensing has the promise to be both lower in cost than explicit sensing based on PIR and ultrasound sensors and to offer additional useful data about the occupants of a building. Our implicit sensing methods are largely based on monitoring IP and MAC addresses in Wi-Fi access points and in routers, and then correlating these addresses to the occupancy of a floor, area, or room of a building. We experimentally evaluate the feasibility of this dual-use of IT infrastructure. We demonstrate an application of implicit sensing to sense the pending occupancy of a user workspace and automatically control the plugged-in devices in the workspace.

**Keywords:** green buildings; existing network infrastructure; occupancy detection; implicit sensing; facilities management.

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## 1 Introduction

In the USA, buildings are responsible for about 39% of CO<sub>2</sub> emissions and 73% of electricity consumption (US DOE, 2011). Lighting, HVAC, IT infrastructure, and plug loads are the major consumers of electricity in buildings. Plug load is the power consumed by electrical devices connected, or plugged-in, to an outlet including

computers, monitors, printers, speakers, desk lamps, coffee makers, and so on. This load is estimated to be 15 to 35% of the total building energy consumption (Kushki et al., 2007). Reducing the energy consumption of buildings is a societal priority with major efforts towards Net-Zero Energy buildings – that is, green technology to enable fully sustainable buildings – being funded by the National Institute for Standards and Technology (2011) in the USA and by other agencies worldwide.

Knowledge of building occupancy is central to reducing energy consumption (National Institute of Standards and Technology, 2010). Occupancy information can be used directly by control systems to reduce the energy consumption of lighting, HVAC, IT infrastructure, and plug load (California Energy Commission, 1993; Garg and Bansal, 2000). Occupancy detection can provide information to these existing and future building systems to allow these systems to operate proportionally to the number of occupants in the building. In Harle and Hopper (2008), it is shown that for lighting there are potential energy savings of 50% with good occupancy detection. For HVAC, (Erickson and Cerpa, 2010) shows that occupancy-driven control could enable energy savings of 20%. Significant energy savings are possible by controlling desktop PC power on and sleep states as a function of usage. This is evidenced by a growing number of commercial products (for example, Verdiem, 2011) and research efforts in this area (for example, Reich et al., 2010). At the heart of these methods is occupancy detection of PC users. Energy savings in the building network infrastructure – both wired (Bleakley et al., 2011; Barroso, 2011) and wireless – and in data servers (Kist, 2011) have also been shown to be achievable. A specific focus on reducing energy consumption of PCs in homes (as driven by home occupancy) was addressed in Hlavacs et al. (2010).

Occupancy detection in current buildings is typically accomplished using passive infrared (PIR) and ultrasonic motion sensors. These dedicated – or explicit – occupancy sensors are installed expressly to determine occupancy and control building systems to reduce energy. Drawbacks to explicit occupancy sensing include the cost of installing and maintaining sensors, limited accuracy, and lack of networking capabilities for data fusion and collection. In Von Neida et al. (2001), it has been shown that energy savings from using PIR sensors to control lights can vary from 10% to 45% depending on the type of room and the detector settings. PIR sensors are particularly effective for controlling lighting in infrequently occupied closed spaces such as storage rooms, but are ineffective for more open layouts such as offices (Dodier et al., 2006; Von Neida et al., 2001). The lack of communication among these sensors precludes the sharing of occupancy information with other systems and fusion of information from multiple sensors. Existing explicit sensors provide limited occupancy information. For example, most existing sensors cannot provide identity, location, or movement information, which hampers their ability to improve building functionality and reduce energy use (Dodier et al., 2006; Von Neida et al., 2001). This is one of the reasons why explicit occupancy sensors usually control only lighting and not other building systems.

In this paper, we explore an approach to occupancy detection using existing IT infrastructure common to many (if not most) building types. This approach, first proposed in Nordman and Meier (2009) (unpublished) and later in Melfi et al. (2011), is called implicit occupancy sensing. Instead of directly measuring physical occupancy, the occupancy is derived from sources not originally intended for occupancy sensing. By using existing infrastructure, occupancy information can be gathered inexpensively and with reduced energy overhead. Implicit sensing can also provide additional information

about the occupants such as identity, activity, and environmental conditions. The contributions of this paper are:

- a definition and taxonomy of building occupancy measures
- a broad description of implicit sensing and the evaluation of several implicit sensing methods
- a demonstration of using implicit sensing to control plugged-in devices in a user workspace.

This paper is a revised and expanded version of Melfi et al. (2011) and includes a deeper analysis of implicit sensing including a study of a conversion factor and a demonstration of using implicit sensing to reduce energy use in buildings by controlling plugged-in devices in user workspaces. In the remainder of this paper, we formally define occupancy measures and how occupancy sensing can be evaluated. We then describe several new implicit sensing methods that have potential for providing high-resolution occupancy information. We evaluate these methods through experiments performed in two different buildings. We use our collected data to explore the notion of a conversion factor to improve the accuracy of predicting occupant counts of implicit sensing. Finally, we demonstrate how user workspace plugged-in devices can be controlled using implicit sensing methods. At the end of the paper, we describe related work, make conclusions, and propose future work.

## **2 Measures of occupancy**

We define building occupancy along the dimensions of resolution and accuracy. An explicit occupancy sensor, such as a PIR sensor, outputs a binary value indicating that the area it is monitoring has people in it or not. This binary measure of occupancy is not adequate when compared to more sophisticated sensors (to be developed in this paper) which provide additional occupancy related information such as the number of occupants. Such more sophisticated sensors may facilitate control strategies not possible with PIR sensors. For example, consider an area, such as a cubicle farm or ‘bullpen’, with multiple PCs used by multiple users. A PIR sensor will not differentiate among occupants and so could not control individual work spaces. Occupancy sensing that identifies occupants could appropriately power-up and power-down occupants’ specific work spaces. Occupancy measurement should include information about the space, occupants, and time span.

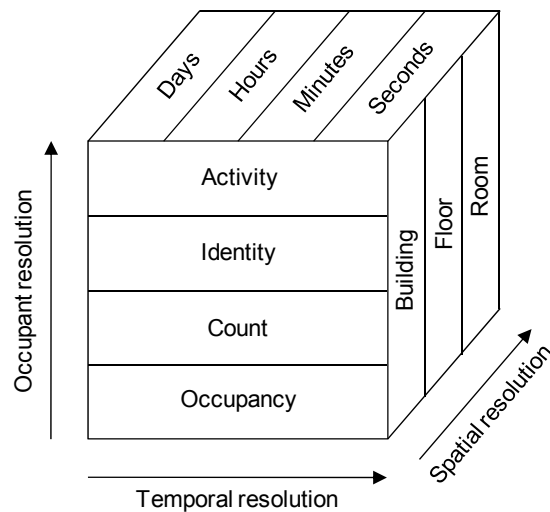
The quality of information provided by different types of sensors varies widely and can be thought of as the occupancy resolution of the sensor. Generally, as measured resolution increases the space becomes smaller, the occupant becomes more defined, and the information is available more quickly. For instance, a low resolution sensor might indicate that a building was occupied by one or more unidentified people in the last hour. A high resolution sensor might indicate that a specific room was occupied by three identified people in the last minute. Figure 1 shows occupancy resolution along three dimensions – occupant knowledge, temporal, and spatial. The spatial resolution of occupancy is definable in terms of building structures (for example, by floors, areas, and rooms) which are referred to as zones in this paper. Temporal resolution is the smallest time span in which changes in spatial and occupant resolution can be reported by a given

sensor. Occupant knowledge resolution is less simple. We define four levels of occupant knowledge resolution:

- occupancy – a zone has at least one person in it
- count – how many people are in a zone
- identity – who the people are a zone
- activity – what the people are doing in a zone.

Occupancy error, or accuracy, indicates how far from the ground truth any occupancy measurement is. Given a number of readings from a sensor and the ground truth (or actual) occupancy, accuracy is the relative error of the measured value from the ground truth. The inaccuracies in explicit sensors are apparent when lights are turned off when an occupant is present or turned on when there are no occupants. If the consequences of an incorrect decision are acceptable then low accuracy is also acceptable. Sensor accuracy affects what types of control strategies can be implemented using the sensor. While some applications may require high accuracy, others, such as control of HVAC temperature set points and ventilation, may not. For example, ventilation rates can be keyed to whether no one is present, or to a rough estimate of the number of people in a zone. The typical approach to HVAC control is to use a fixed schedule for controlling set points and ventilation rates (and furthermore to assume maximum occupancy). With sensing, the start-of-day and end-of-day modes can be keyed to occupancy and not to a fixed schedule that may be incorrect on some days of the week. For HVAC, set points could be keyed to the number of people present, so that when fewer people are present larger deviations from the ideal set points are allowed. One feature of implicit occupancy sensing is that holidays and other low-occupancy days are automatically detected; there is no need to rely on a building manager to manually input such information on an ongoing basis. In many of these cases, the relevant comparison is not to widely distributed explicit sensors – the practical alternative to implicit occupancy sensing is no occupancy sensing at all.

**Figure 1** Occupancy resolution



### 3 Implicit occupancy sensing

Implicit occupancy sensing is the use of existing building infrastructure that is not originally intended for occupancy detection to measure occupancy. Implicit sensing relies on the notion that the effects occupants have on these building systems can be used to determine occupancy information. We refer to such effects as implicit measures of occupancy and the building systems as implicit occupancy sensors. Some building systems can be modified to add implicit occupancy sensing capability to make them implicit sensors. We use the degree of modification to classify implicit occupancy sensing into three tiers:

- Tier 1 requires no modification to existing systems other than a data collection and processing point.
- Tier 2 involves the addition of software to existing infrastructure to make existing occupancy related data available.
- Tier 3 involves the addition of software and hardware to introduce new sources of occupancy data to existing systems.

We have identified several implicit occupancy measures and observed how these measures relate to occupancy at two locations: the Engineering Building (ENB) at the University of South Florida (USF) and Building 90 (B90) at Lawrence Berkeley National Laboratory (LBNL). ENB is the main ENB at USF and is a four-floor multi-purpose building that houses single occupant offices, conference rooms, classrooms, large communal areas, and research labs. B90 is a four-floor multi-purpose office building on the LBNL campus that includes private offices, workstations in communal areas, and conference rooms.

#### 3.1 Tier 1 implicit sensing

The Address Resolution Protocol (ARP) is used by hosts and routers to determine the Ethernet or Wi-Fi Medium Access Control (MAC) address of all hosts on a subnet and associate the MAC address with the host's IP address. Routers use the ARP protocol to maintain a table, or ARP cache, of associated IP and MAC addresses to enable forwarding of packets from a router to a host. The ARP table can be used as a measure of the number of active hosts in a subnet. While some devices are 'fixed' infrastructure, such as printers, servers, switches, and access points (AP), most are directly associated with individual people. We consider the fixed infrastructure to be the base load. ARP data collected from wired routers or wireless Wi-Fi AP within a building can serve as implicit occupancy measures.

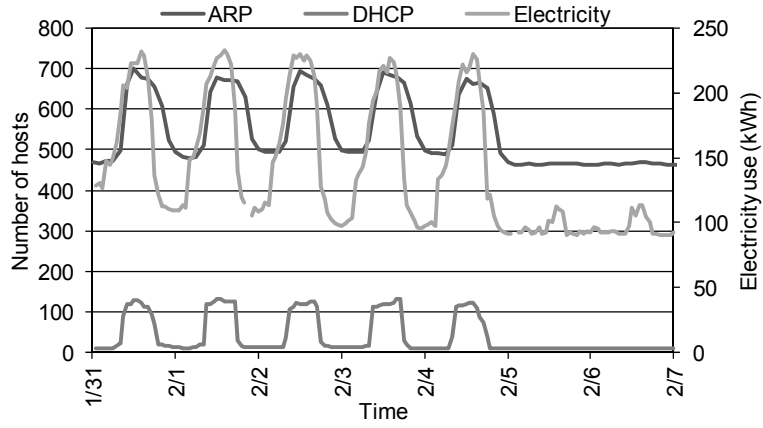
The Dynamic Host Control Protocol (DHCP) can be used in a similar manner as ARP to determine the number of hosts in a network. DHCP is typically used by non-permanent mobile hosts to lease an IP address for a temporary period of time. A DHCP server has a pool of IP addresses and maintains a table of which addresses are currently leased-out. In Wi-Fi networks the majority of (if not all) hosts use DHCP to obtain an IP address. Thus, the DHCP lease data is a measure of the number of mobile hosts active on the network (this does not include the permanent hosts with fixed IP addresses – ARP data includes both permanent and mobile hosts). Additional information that can be gleaned from

DHCP includes the number of new hosts, the number of hosts which hop between APs, and the number of hosts whose leases have expired. These additional DHCP measures may relate to occupancy measures of people entering the building, moving within the building, and leaving the building within the last DHCP timeout period.

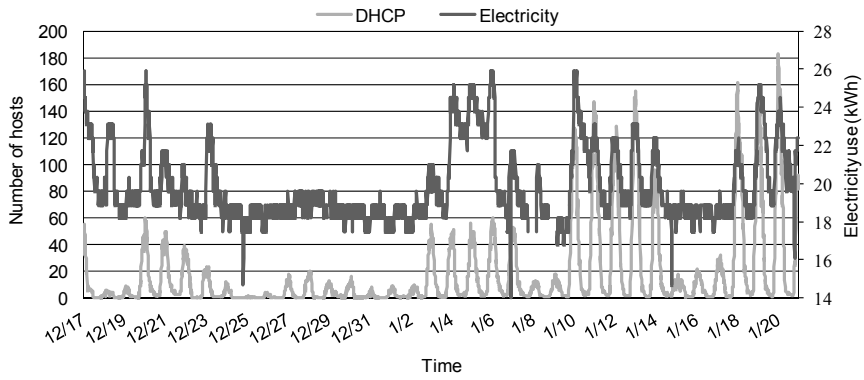
For both the ARP cache and DHCP lease table, hosts that have powered-down or otherwise left the network are detected and deleted from the respective table. For DHCP the mechanism is a timeout set by the network administrator. If a host does not renew its DHCP lease within the timeout period then that host is assumed to be gone and its IP address is returned to the available address pool. ARP cache entries are removed after there have been no packets sent to an address for an administrator-defined ARP timeout period.

We have found that the number of hosts in a building as indicated by ARP and DHCP tend to follow trends similar to the number of building occupants. Figure 2 shows variation in the total number of hosts as indicated by ARP and DHCP records from B90 routers and APs and building electricity use as a function of time of day. The x-axis of the graph shows time beginning on a Monday and the primary y-axis shows the number of unique MAC addresses seen within 2 hour intervals for ARP and 10 minutes for DHCP. The secondary y-axis shows the electricity use of B90. The changes in ARP measurements, DHCP measurements, and electricity use are similar to those one would expect from occupancy in a laboratory or office; increase in the morning, stabilisation around lunch, a decrease towards evening, and lower levels during the weekend than during week days. Figure 3 shows the number of measured active Wi-Fi hosts and the building energy use for ENB as measured by the electricity meter for ENB for five weeks beginning December 17, 2010. The figure shows the number of unique Wi-Fi hosts as a function of day on the left Y-axis graph and the actual measured electricity use of ENB on the right Y-axis. The correlation between these values can be seen in the scatter graph of Figure 4 and is quantified by the Pearson correlation coefficient, which measures linear correlation between two data sets (with 1.0 being a perfect positive linear correlation). For the data in Figure 3 the Pearson correlation coefficient is 0.59 indicating a partial positive linear correlation between the electricity use and number of Wi-Fi hosts (that is, as the number of Wi-Fi hosts increases so does electricity use). A similar data set was collected for the week of September 7, 2010 to September 13, 2010 (a non-holiday period) where the Pearson correlation coefficient was found to be 0.89. In ENB the HVAC is running 24/7 and the lighting in communal areas, including hallways, is always on. This suggests that the increase in electricity use during the day is likely dependent on environmental changes and occupancy. Since the changes in electricity use are at least partially a function of occupancy, the correlation between Wi-Fi data and electricity use indicates that Wi-Fi host count is an indicator of building occupancy. The occupancy patterns in ENB have more complexity than a simple occupied/unoccupied model. In addition to normal occupancy patterns, implicit measures can reveal occupancy patterns that are unusual due to special events or holidays. For instance, Martin Luther King Day is apparent in the DHCP data. Also apparent is the end-of-year winter holiday for both ENB and B90.

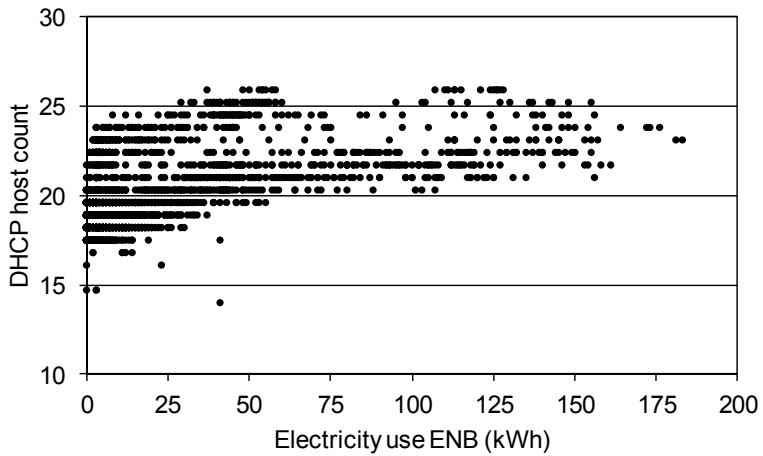
**Figure 2** DHCP, ARP, and electricity use in B90



**Figure 3** DHCP and electricity use in ENB



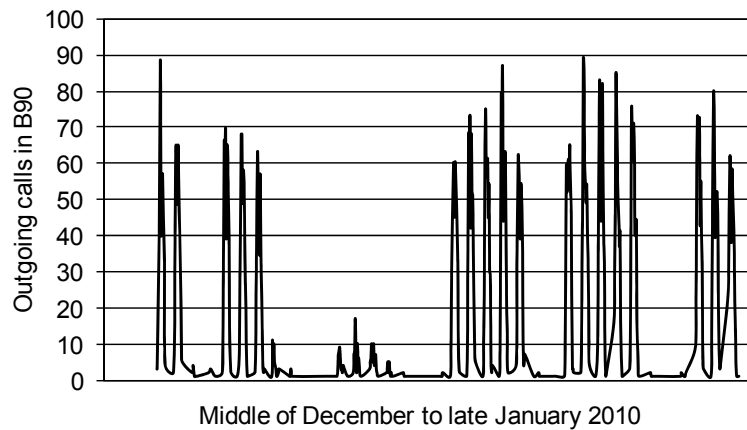
**Figure 4** DHCP versus electricity use in ENB





Other tier 1 measures include outgoing telephone calls, security door sensors being triggered, and security badging systems. Figure 5 shows the number of outgoing telephone calls from B90 from mid December to late January (here again the winter holiday is apparent). Each spike in the number of calls can be seen to correspond to a day. Weekdays and weekends can be clearly delineated from the data – on weekends building occupancy is lower than on weekdays. All of these measures have the ability to reveal detailed information about the occupancy level of a building.

**Figure 5** Outgoing telephone calls in B90



### 3.2 Tier 2 implicit sensing

Wi-Fi can be used to locate occupants in a building by triangulating on signal strength of multiple APs. This ability has been explored in Kushki et al. (2007) and by others where specialised software running on user hosts report all the available APs and their respective signal strengths. This information can be used to triangulate occupants with Wi-Fi devices since all the nodes available to that occupant are known as opposed to only knowing which one was connected to through DHCP. This is an example of tier 2 implicit sensing where additional software can make use of data in the existing IT infrastructure for a new purpose.

Another indication of occupancy is keyboard and mouse use (for example, of a desktop PC in a user's office or workspace). Operating systems provide functions to detect keyboard and mouse activity, but additional software is needed to collect this activity data and make it available remotely. We have implemented a software method to gather this information called the User Activity Monitor. The User Activity Monitor calls the `GetLastInputInfo()` function from the Windows API which returns the time of the last keyboard or mouse activity. If there was activity within the last one minute then the User Activity Monitor software logs a '1' otherwise it logs '0' to a log file. This log data is made available remotely using the Simple Network Management Protocol (SNMP). SNMP provides a standard way to centrally gather data recorded by the User Activity Monitor running on multiple computers. In Harle and Hopper (2008), occupancy patterns were observed in several offices, and it was found that employees spend 76% of their

time in their private office where their PCs are located. Thus, monitoring computer activity could be a good predictor of total building occupancy.

Other tier 2 methods include the use of existing microphones and webcams to detect occupancy. Microphones on PCs, notebooks, and phones could provide occupant counts and identification based on sound levels or conversations. In Dong et al. (2010), work was done in relating acoustics to occupancy using dedicated sensors. The use of a webcam to detect occupants in front of a computer is also possible and has been demonstrated in Dalton and Ellis (2003). Clearly, privacy issues need to be considered. Privacy of wireless infrastructures is considered in So-In et al. (2012).

### 3.3 Tier 3 implicit sensing

Tier 3 methods require the addition of hardware and software to existing systems. The difference between this and dedicated sensors is that tier 3 implicit sensing makes use of the existing IT infrastructure to enable the sensing and provide communication and processing. Tier 3 methods could be used, for example, for measuring environmental conditions (such as area temperature) as a component of the measure of occupancy. For example, an inexpensive USB thermometer could be connected to a desktop PC and used for remote monitoring of zone temperature in the area of the PC (this may entail waking-up the PC periodically if it is sleeping). We do not implement or evaluate tier 3 methods in this paper.

## 4 Experimental evaluation of implicit sensing

We conducted an experimental evaluation of several implicit occupancy information sources in both ENB and B90. The experiments were intended to answer the following four questions:

- 1 What is the accuracy of implicit sensing as a measure of occupancy levels?
- 2 What is the accuracy of implicit sensing as a measure of individual occupant location?
- 3 How does the accuracy of implicit occupancy measures compare to that of explicit sensors?

We designed three experiments, one for each of the above questions.

### 4.1 Experiment testbeds

Our experiments used the wireless network infrastructure in ENB and B90. ENBs wireless network covers all four floors and consists of 44 APs. The AP names correspond to the floor and room in which the AP is found. B90 has three APs per floor except for the fourth floor which has one AP for a total of 10 APs. A communal location in ENB called the 'Fishbowl' and the entire fourth floor of B90 were isolated for purposes of counting ground truth occupancy. The Fishbowl is an area furnished with a number of circular tables which are typically used by groups of students to study and socialise. The area generally has 5 to 50 occupants. Wireless coverage for this area is redundant with about seven accessible APs. The fourth floor of B90 has 80 offices, a number of them

private, which surround an open office area in the middle. The floor generally has 20 to 60 occupants. There is only one AP on the fourth floor, but it is possible to connect to a third floor AP as well. For experiments in ENB, the Wi-Fi device used was a BlackBerry mobile phone and in B90 an iPhone 4 was used.

#### 4.2 *Experiment design*

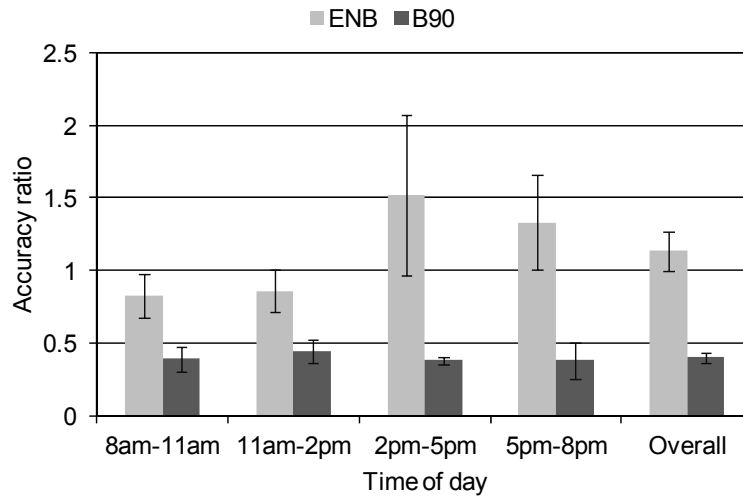
The three experiments designed were:

- *Occupancy count:* For this experiment we measured the number of hosts on the seven APs which generally serve the Fishbowl area of ENB as indicated by DHCP leases. We also visually counted the number of occupants to establish the ground truth occupancy. We repeated this measurement on the fourth floor of B90 for the single AP. The procedure for this experiment was as follows:
  - 1 at a given time visually record the number of occupants and count the number of hosts as indicated by DHCP leases
  - 2 repeat step (1) approximately ten times within the following intervals, 8am to 11am, 11am to 2pm, 2pm to 5pm, and 5pm to 8pm for four weeks.
- *Localisation:* For this experiment a walking path through a building was selected. The walking path was about 15 minutes in duration and included stops (of duration several minutes) in multiple rooms. The intent was to mimic the behaviour of a building occupant entering a building, checking their mail, going to their workspace, and so on. The experiment procedure was as follows:
  - 1 Walk the predetermined path with a Wi-Fi device on the person. Log the actual locations and the AP indicated locations from DHCP leases by time.
  - 2 Repeat step (1) at least three times for each path.
- *Comparison of implicit and explicit sensors:* To understand how implicit and explicit occupancy measures compare, a work area was selected which had Wi-Fi coverage, a desktop PC was instrumented with the User Activity Monitor software (see Section 3.2), and a PIR sensor was connected to the monitor of the PC facing the user's seat. The explicit sensor used was a USB PIR motion sensor (part number CGUSBPIR) from CircuitGizmos.com. The sensor is a PIR module combined with a U421 USB interface which allows recording via a PC through the USB interface. The sensor had a range of about 20 feet and costs about \$45. The measurements from the User Activity Monitor software, the PIR sensor, and the DHCP leases were recorded while the following procedure was executed four times for  $t = 5$  minutes, two times for  $t = 10$  minutes, and one time for  $t = 15$  minutes:
  - 1 An occupant carrying a Wi-Fi enabled device approaches the instrumented desktop PC at their workspace and logs the time he or she sat down. The Wi-Fi device should remain active and auto-connect to APs.
  - 2 The occupant remains seated for  $t$  minutes while normally interacting with the PC.
  - 3 The occupant logs the time then leaves the area for two minutes.

### 4.3 Experiment results

The results for the occupancy count experiments in ENB are shown in Figure 6. The average error for DHCP as a measure of occupancy for several time periods during the day is shown with a 95% confidence interval computed and shown. The number of samples for each time period and location are in Table 1. The overall average accuracy and confidence interval for all of the samples from ENB and B90 were respectively  $1.13 \pm 0.13$  and  $0.40 \pm 0.036$ .

**Figure 6** Accuracy of DHCP counts

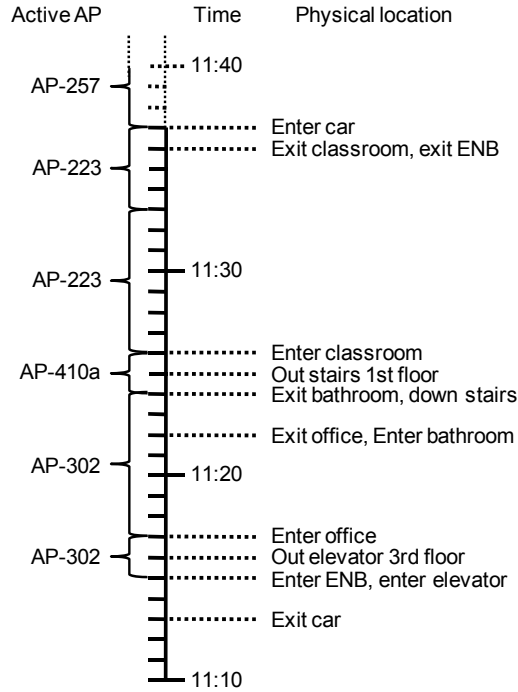


**Table 1** Number of samples for count experiment

<i>Time of day</i>	<i>No. of samples (ENB)</i>	<i>No. of samples (B90)</i>
8am to 11am	16	10
11am to 2pm	14	9
2pm to 5pm	5	11
5pm to 8pm	7	4
Overall	42	34

The results from one trial of the localisation experiment in ENB are shown in Figure 7. The left side of the figure shows the time, location, and duration of the DHCP leases and the right side shows the actual time and locations of the Wi-Fi device. The results from all trials and both locations can be seen in Table 2. The accuracy is the percentage of time that the DHCP logs correctly localised the occupant to the building, the floor, and individual rooms. For example, in the first trial DHCP correctly detected the occupant in or not in the building 71% of the time.

**Figure 7** Walking paths in ENB



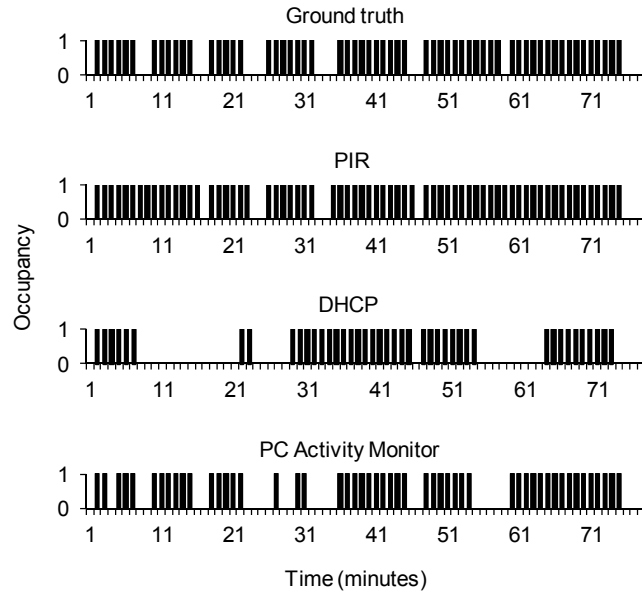
**Table 2** Location accuracy of DHCP sensor

Trial	ENB		B90	
	Building	Floor	Building	Floor
1	71%	31%	75%	41%
2	71%	42%	78%	50%
3	94%	84%	78%	44%

Finally, the results of the implicit versus explicit sensing experiment are shown in Figure 8. A reading of 1 for each sensor indicates occupancy and a 0 indicates a vacancy. The DHCP measure represents occupancy at a floor level resolution. The accuracy for detecting occupancy, vacancy, and total accuracy is shown in Table 3. Occupancy accuracy here is the percentage of time the seat was occupied and the sensors detected occupancy. Vacancy accuracy is the percentage of the time the seat was unoccupied and the sensors did not detect occupancy. Overall accuracy is the weighted average of vacancy and occupancy accuracy based on the time spent in each state.

#### 4.4 Discussion of experiment results

There are two main issues which affect the accuracy of DHCP as an implicit occupancy measure in the count and localisation experiments: overlap of AP coverage, and inconsistent Wi-Fi connectivity of mobile phones.

**Figure 8** Accuracy of explicit and implicit sensing**Table 3** Accuracy of explicit and implicit sensing

<i>Device</i>	<i>Vacancy</i>	<i>Occupancy</i>	<i>Overall</i>
PIR	61%	100%	91%
PC activity	100%	85%	89%
DHCP	61%	59%	59%

As AP coverage areas often overlap, devices sometimes connect to APs that are not in the same area as the occupant. For instance, a device may connect to an AP on the second floor when the occupant is on the third floor. This occurred frequently in experiments involving occupant localisation. Floor and room level accuracy was greatly reduced due to this issue. This issue also creates difficulty in mapping a physical area to a set of APs because AP coverage is not bounded by physical spaces such as rooms or floors. This causes inaccuracies in the measurement of occupant levels for specific floors and rooms. This was apparent in the count experiments performed at ENB where the APs available in the Fishbowl covered an area much greater than the Fishbowl itself. This could account for the change in accuracy for night hours, as the areas outside of the Fishbowl could have had occupancy patterns different from the Fishbowl. Given the data, it is likely that an area with high night time occupancy (such as a computer lab on the second floor) was counted by the DHCP measure. For the occupancy count experiment at B90 a single AP was selected whose coverage closely matched the fourth floor while other APs (though available to the fourth floor) were ignored in the data collection. This may account for the low variability in the accuracy for occupancy count measurements at B90.

Inconsistency in Wi-Fi connectivity of mobile phones results in devices losing network presence, which causes false negatives. It also means that fine grain movement (room to room) cannot be tracked with DHCP due to delays in reconnecting to the

wireless network after an occupant has moved to another area. This issue is rooted in the Wi-Fi settings in individual devices. Android devices allow for Wi-Fi to be kept powered-on or powered-off when the device sleeps. The default setting may vary by device vendor. Acquiring data services through building Wi-Fi is usually lower cost, higher performance, and uses less battery charge than acquiring the same services through a mobile data plan. Thus, it is reasonable to expect that more smartphones and similar devices (such as tablets), will have Wi-Fi powered-on at all times in the future.

Results from the sensor comparison experiment indicate that the PIR sensor was most accurate in measuring overall occupancy. It was however prone to false positives caused by other occupants entering the area. On the other hand, the User Activity Monitor software was prone to false negatives indicating that the space was not in use when the occupant was present, but not using the PC. It is important to note that the implicit measures provided occupancy information (that is, via the network connection) including occupant activity and identity not provided by the PIR sensor. This experiment also indicates that sensor redundancy may be necessary for a more accurate measurement of occupancy and for more complex energy saving control strategies.

## 5 A conversion factor for occupancy count prediction

As described in the previous sections of this paper, we have shown that there is a direct correlation between the DHCP count and the ground truth (or observed) number of occupants – our measure of accuracy is the relative difference between these two counts. Based on the ratio of DHCP count to observed count, we seek to identify a conversion factor to enable a more accurate prediction of occupancy. A study was done to specifically estimate a conversion factor.

Over a two-week period in March 2011, the total number of occupants on the fourth floor of B90 was counted at random times of the day. A total of 34 different observed occupant counts were made: 10 for 8am to 11am, 9 for 11am to 2pm, 11 for 2pm to 5pm, and 4 for 5pm to 8pm. From the DHCP log, the number of wireless devices connected to the fourth floor AP, for the same times, were collected and compared to the observed counts. The results are shown in Figure 9. The ratio of DHCP count to observed occupant count for this time period is about 0.40 with the 95% confidence interval being  $\pm 0.036$  (or about  $\pm 10\%$ ). A ratio of 1 would mean that each occupant is carrying one wireless device that is connected to the AP. The data suggests that around 40% of occupants are carrying a connected wireless device. Another potential factor reducing the ratio could be that not all wireless devices are connecting to the fourth floor AP even though it is the horizontally closest access point. Some wireless devices could have connected to an access point on the third floor due to a stronger signal strength. The DHCP log data does not directly translate to an accurate occupant count, but since the variability is generally low (as indicated by the ‘tight’ confidence interval), DHCP log data does reflect occupant trend data, and with a conversion factor could produce a highly accurate predicted occupant count. The conversion factor from DHCP lease count to predicted occupant count is the reciprocal of the ratio between DHCP lease count and observed occupant count. For the fourth floor of B90, the approximate ratio of 0.40 leads to a reasonably accurate estimated conversion factor of 2.5 from DHCP lease count to predicted occupant count. For example, a DHCP lease count of 16, using the conversion factor of 2.5, means a predicted occupant count of 40.

Out of the 34 observed counts recorded in March 2011, nine were recorded on Tuesday, March 15th. The scatter plot in Figure 10 shows dots representing counts (actual and implicit) taken on March 15th. The conversion factor becomes more stable for data points all within a single day than for data points taken over the course of two weeks. This is likely due to specific individuals carrying certain wireless devices on that particular day, and illustrates that a noticeable portion of the variability of the ratio depends on the behaviour of the occupants on that specific day and what devices those occupants carry. It is likely that each office building, will have a different conversion factor depending on wireless use and the demographic of the occupants of the building, and that conversion factors may need to be recalculated on a periodic basis. We note that some occupants may have multiple Wi-Fi devices (and this may also change over time) and this needs to be considered so as not to ‘double count’ individual occupants. Calibration of a conversion factor is a subject of future work.

Figure 9 DHCP and observed counts for B90

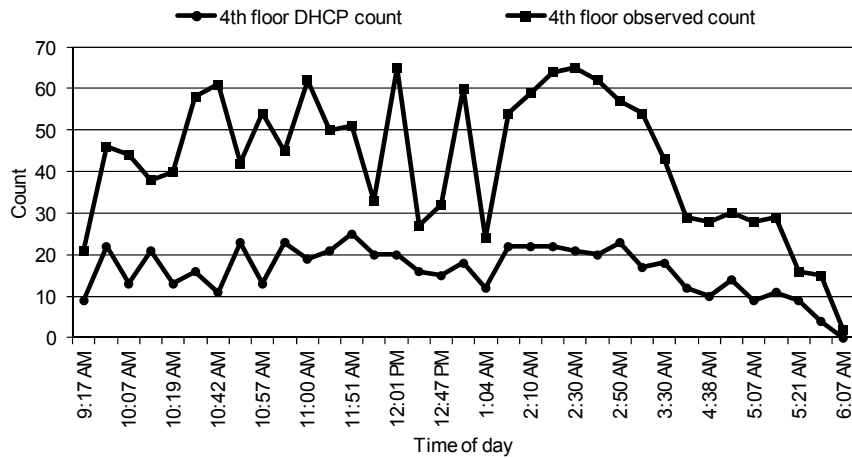
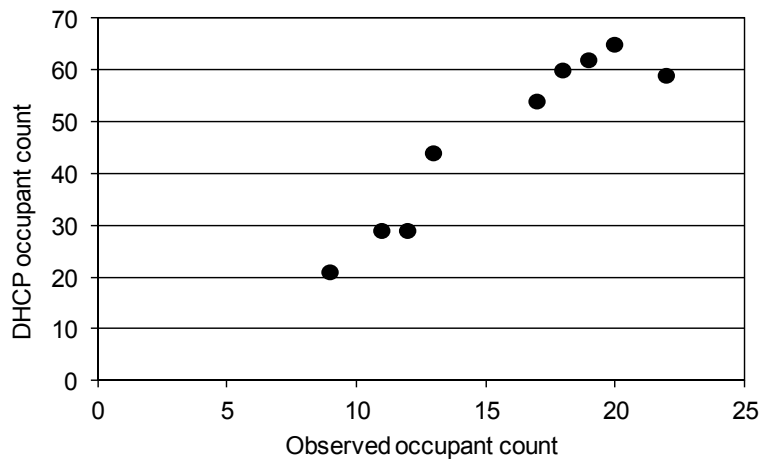


Figure 10 Scatter plot for data collected on March 15th for B90





## 6 Implicit power control – controlling plugged-in devices

We developed a prototype system to explore the efficacy of implicit sensing to reduce wasted energy from plugged-in devices in a user workspace. A typical cubicle workspace in an office building may include a desktop PC, one or more monitors, a desktop lamp, and other electrical or electronic equipment plugged-in to a single power strip. This equipment often remains powered-up even when the workspace is unoccupied (such as when the occupant is out to lunch). Figure 11 shows an example workspace with plugged-in devices. Our prototype system used the detected presence (or absence) of a Wi-Fi smartphone – associated with the user of the workspace – as the implicit sensing signal for occupancy. The goal was to be able to power-down a workspace when its occupant had left it and to power it back up immediately before the arrival of its occupant. The power-up before arrival of the occupant is critical to prevent user annoyance from having to wait for a desktop PC to resume full operation from a sleep or hibernation state.

**Figure 11** Office workspace showing plugged-in devices (see online version for colours)



Our prototype used a Smart Strip auto-switching surge protector power strip (Bits Limited, 2011) to enable the power state of a desktop PC to control the power state of all equipment plugged into the Smart Strip. Figure 12 shows a Smart Strip. The Smart Strip uses the power draw from a single ‘sensing outlet’ as an indicator to turn on or off other outlets on the strip. The Smart Strip has two states:

- 1 when the current load (or power draw) from the sensing outlet is high, all controlled outlets are powered, and equipment plugged into these outlets can draw power
- 2 when the power draw from the sensing outlet is low, all controlled outlets are depowered, and equipment plugged-in to these outlets cannot draw power.

We plugged-in the workspace desktop PC to the sensing outlet. When the desktop PC goes to sleep its power draw drops to about 50 mA (corresponding to a sleep power draw of about 5 W) – this triggers the Smart Strip to depower its other outlets to which the

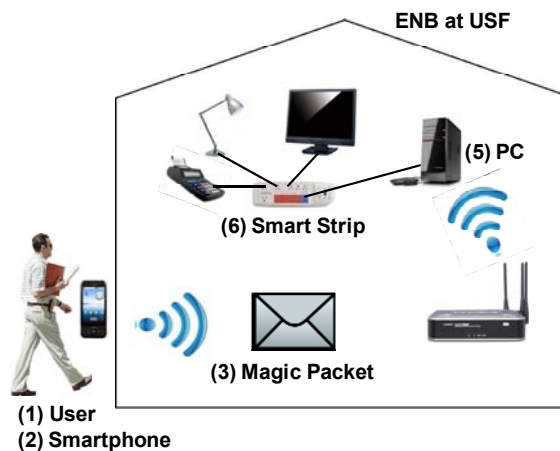
workspace monitors, lamp, and other equipment are plugged in. Thus, the power state of the desktop PC controls the power state of all other plugged-in devices in the workspace. The power state of the PC was automatically controlled remotely from the smartphone using a Magic Packet (Advanced Micro Devices, 1995) and a newly architected Sleep Packet.

Figure 13 shows the packet flows and operation of our system as implemented in an Android App. When a user (1) carrying a Wi-Fi-enabled smartphone (2) enters his or her building (or otherwise gets close to his or her work space within a building) the smartphone detects that it is connected to the workspace AP. This detection of Wi-Fi connection to workspace AP causes the smartphone App to send a Magic Packet (3) to the workspace desktop PC (5) via the now connected AP (4). The Magic Packet wakes the PC, which then triggers the Smart Strip to activate its controlled outlets. When the user departs the building, a Sleep Packet is sent to the desktop PC. Departure is detected by decreasing Wi-Fi signal strength from the workspace AP (alternatively, the Sleep Packet could be sent via the smartphone data service and not via Wi-Fi on detecting loss of connection to the workspace Wi-Fi AP). Figure 14 is the pseudocode description of the Android App that implements the above (not shown in the pseudocode is a handshake to stop sending packets when the PC has powered-up from a Magic Packet or gone to sleep from a Sleep packet). Figure 15 shows the Wi-Fi sleep policy settings screen from an Android smartphone. The ‘never sleep’ option is selected – the effects of setting this option on battery discharge time were studied in the evaluation of the method (described in Section 5.2). The smartphone would sleep (and its App suspend) until the connection to an AP would trigger the smartphone to wake-up (and the App to restart execution).

**Figure 12** Smart strip with auto-sensing capability (see online version for colours)



**Figure 13** Packet flows for implicit power control method (see online version for colours)

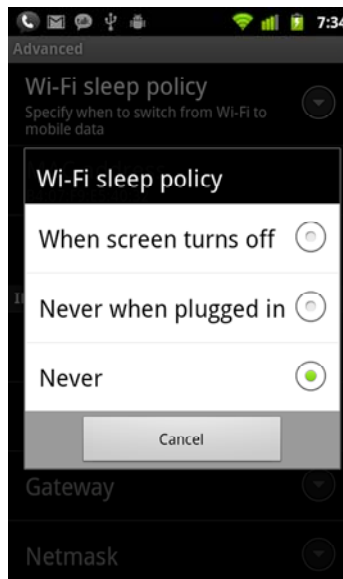


**Figure 14** Pseudocode for smartphone application

```

while (true)
  if (Wi-Fi enabled)
    if (connection established to AP)
      if (connected to workspace AP)
        send Magic Packet
      else
        send Sleep Packet
    end
  end

```

**Figure 15** Wi-Fi sleep policy options for an android smartphone (see online version for colours)

### 6.1 *The sleep packet and PC user activity monitor agent*

The Magic Packet (Advanced Micro Devices, 1995) is an existing MAC-level packet supported by Ethernet and Wi-Fi interfaces. When an interface receives a Magic Packet it triggers an internal system-level interrupt which can force a system to power-up from a sleep or hibernate state. To achieve Implicit Power Control we architected and implemented a UDP packet to trigger a system to enter a sleep state. This entailed developing and installing a software agent in the workspace desktop PC. This agent would listen for the new Sleep packet and then issue a sleep command to the desktop PC when the packet was received. In Windows, a PC can be put to sleep using the `SetSuspendState()` function call. For our prototype, the Sleep Packet was a direct-addressed UDP packet containing the ASCII string 'sleep'. Figure 16 is the pseudocode for the desktop PC agent.

**Figure 16** Pseudocode for desktop PC agent

```
while (true)
  receive the UDP packet
  if (received packet = "sleep")
    put computer to sleep
end
```

## 6.2 Evaluation of the implicit power control prototype

Our evaluation addressed three open questions, which were:

- 1 Can plug-load energy consumption be reduced in a user workspace?
- 2 Will there be a new, or increased, level of user annoyance?
- 3 What is the effect of the Wi-Fi do-not-sleep setting and new App on smartphone battery discharge time?

To answer these three questions we defined three experiments:

- *Leaving the office:* The occupant leaves their workspace by walking away. The metric is the percentage of cases the workspace powers-down as expected.
- *Entering the office:* The occupant enters the building and goes directly to their workspace. The metric is the percentage of cases the workspace powers-up as expected (that is, it powers-up when the occupant arrives).
- *Smartphone battery discharge:* The battery discharge rate of the Android smartphone is measured when the Wi-Fi enabled at all times as well as under normal use when it is disabled when the phone is asleep.

These experiments were conducted in a shared laboratory area in the ENB building – Figure 11 shows the workspace. Table 4 shows the results from the leaving and entering the office experiments based on 20 trials for each. On leaving the office, in 90% of the cases the workspace powered-down as expected and on entering the office in 75% of the cases the workspace was powered-up correctly. The cases when operation was not correct were due to connections with an AP not being made correctly by the smartphone. We are not sure why this occurred and this needs further investigation. Nonetheless, it can be seen that the workspace is controlled correctly in the majority of cases. Table 5 shows the results from the battery discharge experiment as battery discharge for one hour. The smartphone used was a Google G1. Here, it can be seen that when the smartphone has Wi-Fi enabled and is not connected to an AP that the battery discharge rate is somewhat higher than when connected to an AP. This is, we believe, due to the constant polling of the smartphone Wi-Fi for an available AP. The battery discharge rate is high, but probably not unacceptable. Further, work is needed in this area. The addition of the App – which suspends whenever the smartphone sleeps – did not affect battery discharge time.

**Table 4** Results from leaving and entering office experiments

<i>Experiment</i>	<i>Powered-up correctly</i>	<i>Powered-off correctly</i>
Arriving	75%	25%
Leaving	10%	90%

**Table 5** Results from smartphone battery discharge experiment

<i>App installed</i>	<i>Connected to AP</i>	<i>Battery discharge</i>
Yes	Yes	0%
Yes	No	5%
No	Yes	1%
No	No	4%

Not evaluated are possible issues with security – can a malicious outsider use the Magic Packet and Sleep Packet to trigger spurious wake-ups and sleep cycles? This should be addressed in future work, but these vulnerabilities largely already exist in large desktop PC infrastructures.

## 7 Related work

HVAC represents a major energy use component in buildings. Recent work has shown that having occupancy information can result in better control of HVAC and achieve energy savings. In Agarwal et al. (2011), a dedicated sensor network is used to detect occupancy levels in building zones and control the HVAC as a function of occupancy. This is in contrast to the typical fixed-schedule HVAC control, which can be wasteful. This work shows that energy savings of 10 to 15% can be achieved in HVAC with occupant sensing. Another recent work on controlling HVAC systems as a function of occupancy is Erickson et al. (2009). In this work a wireless camera sensor network is used to collect occupancy data to drive the setting of HVAC system. A reduction of 14% in HVAC energy use is reported [roughly similar to that reported in Agarwal et al. (2011)]. In Erickson et al. (2011), the same authors develop a Markov chain-based statistical method for estimating occupancy based on inputs from a sensor network. The goal is to improve the accuracy of occupancy estimation to approach that of ground truth. Our work can, we believe, achieve the necessary occupancy sensing needed for HVAC control without needing a dedicated sensor network (and its associated installation and maintenance cost).

There have been several efforts to improve the accuracy of dedicated occupancy sensors by allowing such sensors to communicate (Dodier et al., 2006; Hutchins et al., 2007). Other researchers have tried to create a general occupancy model capable of incorporating occupancy information from multiple sources (Liao and Barooah, 2010; Meyn et al., 2009). Bayesian modelling was used in Dodier et al. (2006) to improve sensor accuracy through sensor communication. A convex optimisation algorithm named SUN was developed in Meyn et al. (2009) that incorporates prior information, real time sensor readings, and the network configuration to estimate occupancy. Markov models were used in Liao and Barooah (2010) to improve the accuracy of a network of explicit

sensors. Each of these works tries to improve dedicated sensors through modelling and communication.

Implicit sensors have been explored in Chintalapudi et al. (2004), Dalton and Ellis (2003), Harris and Cahill (2005), and Kushki et al. (2007). In Dalton and Ellis (2003), a programme called Face Off which uses a PC's webcam in order to detect occupancy is developed. In Harris and Cahill (2005), a Bluetooth device is used as a proximity sensor to turn on and off a user's computer. In Chintalapudi et al. (2004), and Kushki et al. (2007), a wireless card and Wi-Fi routers are used to calculate the position of a wireless device. This localisation method is more accurate than DHCP leases since it is active on the part of the wireless hosts and may resolve the two open issues found in our experimentation. These methods are all tier 2 in that they require additional software to gather information from the devices. There has also been some work in the area of tier 3 sensing, which incorporates environmental sensors (using additional hardware) to detect occupancy. In Dong et al. (2010), a wireless sensor network (WSN) test bed of air quality and CO<sub>2</sub> sensors in an office space was implemented for occupancy detection. Using hidden Markov models to process the information from the sensors they could count the number of occupants (ranging from 1 to 5) with an average accuracy of 75%. It was concluded that the factors most related to occupancy in this situation were acoustics and CO<sub>2</sub> levels. Data mining analysis on sensor information for a WSN containing temperature, light, and humidity sensors was performed in Wu and Clements-Croome (2007). It was concluded that measurements from these sensors contain noise due to inaccuracies and imprecision in the sensors. It was also found that many of the sensors exhibited spatial and temporal correlation, which has implications for applying predictive models such as Bayesian Networks to these sensor networks. Since these methods require costly WSNs it is important to address whether these tier 3 sensors can provide additional accuracy over the less expensive tiers 1 and 2 counterparts. In Kim et al. (2010), the relationship of measured zone energy use as a function of IP traffic was explored. Work by Vaccari et al. (2009) in the context of MIT's Enernet have shown that "...WiFi activity can be used as a surrogate to at least the daily profile of human occupancy within buildings, and in some cases perhaps even a scaled measurement of occupancy itself". This work by Vaccari et al. (2009) and Kim et al. (2010) is the closest to our work and reinforces the ideas described in our work.

Control of plug load and lighting has been explored by several researchers. In Weng et al. (2011), a method of managing plug load in buildings is developed and evaluated. The method uses a smart meter that can be controlled by a build manager. The authors have experimented with using occupancy information noting that unoccupied rooms are good candidates for load shedding. The use of occupancy information built on the work in Agarwal et al. (2011). In Krioukov et al. (2011), a web-based personal lighting control system is developed and evaluated. This system puts control of building lighting in the hands of users – albeit in the form of manual control – replacing typical time-of-day control. There exist commercial products (for example, from JouleX, 2011) that can trigger wake-up of desktop PCs based on the location of a user using GPS services in a smartphone. GPS does not work well within buildings and typically consumes more battery charge than only using Wi-Fi. As such, we believe that our Wi-Fi approach to implicit power control is better. There are no existing methods, to the best of our knowledge, which can implicitly power-up PCs (as our method can).

This related work and our work show the importance of occupancy measurement to the control of building functions. The potential for implicit sensing and the use of this sensing data for automatic control of user workspaces in buildings to reduce energy use and achieve a higher degree of sustainability is significant.

## **8 Conclusions and future work**

In this paper, we have shown that no cost, implicit occupancy sensors are already available within existing building infrastructure. We evaluated the accuracy of several implicit sensors in terms of occupancy counts and location. We demonstrated the feasibility of implicit occupancy sensing. Implicit sensing was shown to have several advantages over sensing with dedicated sensors. These advantages include:

- no additional cost in terms of hardware, installation, operation, or maintenance of sensors
- availability of sensor readings over existing IT networks
- providing better information (such as occupancy resolution with respect to occupant count, identity, and activity) not available from dedicated sensors.

The overriding question of what level of accuracy is needed for effective control is future work to be addressed. While some applications require high accuracy occupancy information to be useful, others, particularly HVAC, may be able to utilise fairly inaccurate data and still save energy because the alternative is non-dynamic fixed building control schedules. A better understanding of the ratio between implicit occupancy measures and ground truth occupancy is critical if accuracy better than approximately  $\pm 10\%$  is needed for building controls (and it is not clear that better than  $\pm 10\%$  is needed for all cases, or even many cases). Probabilistic models, for example, as in Dodier et al. (2006), Hutchins et al. (2007), Liao and Barooah (2010), Meyn et al. (2009), may lead to a more accurate conversion factor between implicit occupancy measures and occupancy count predictions.

We developed and demonstrated one application of implicit sensing – implicit power control of the plugged-in devices of a user workspace. This demonstration showed the potential for using existing infrastructure to control energy use in buildings. This application also further highlighted how Wi-Fi devices may not always connect to the nearest AP – additional work is needed in better understanding how a Wi-Fi device determines which AP to connect to and if/how this connection can be controlled to always occur to the nearest AP. Additional work is also needed in calibrating conversion factors.

Future work needs to better address the question of accuracy – what level of accuracy can be attained with both implicit and explicit sensing, and what level of accuracy is actually needed for effective control of building functions to maximise the reduction in building energy consumption. The notion of conversion factors may be key to this future exploration of accuracy. The responsiveness of implicit versus explicit sensing also needs to be further explored.

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